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DAMNED: A Distributed And Multithreaded Neural Event Driven simulation framework

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ABSTRACT

In a Spiking Neural Networks (SNN), spike emissions are sparsely and irregularly distributed both in time and in the network architecture. Since a current feature of SNNs is a low average activity, efficient implementations of SNNs are usually based on an Event-Driven Simulation (EDS). On the other hand, simulations of large scale neural networks can take advantage of distributing the neurons on a set of processors (either workstation cluster or parallel computer). This article presents DAMNED, a large scale SNN simulation framework able to gather the benefits of EDS and parallel computing. Two levels of parallelism are combined: Distributed mapping of the neural topology, at the network level, and local multithreaded allocation of resources for simultaneous processing of events, at the neuron level. Based on the causality of events, a distributed solution is proposed for solving the complex problem of scheduling without synchronization barrier.

KEY WORDS

Spiking Neural Networks, Event-Driven Simulations, Parallel Computing, Multi-threading, Scheduling.

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1 Introduction

Advancing the knowledge on cognitive functions, simulations of Spiking Neural Networks (SNNs) represent a bridge between theoretical models and experimental measurements in neuroscience. Unlike usual threshold or sigmoid neurons, models of spiking neurons take into account the precise times of spike emissions. Therefore, SNNs help to simulate biologically plausible interactions between neurons and to study the influence of local parameters, at the neuron level, on the network global behavior, at the functional level. Results of very large scale SNN simulations can be analyzed the same way as experiments on animal or human, e.g. LFP [1] or EEG [2] recording, thus helping to understand how the brain works [3, 4]. From a complementary point of view, theoretical studies [5, 6] give large hope in the computational power of SNNs. Subject to the discovery of convenient learning rules [7, 8], simulations of large scale SNNs would provide efficient new solutions for many applications such as computer vision [9], adaptive control, real-time systems or autonomous robotics.

For developing very large scale SNNs, supporting a wide variety of spiking neuron models, a general purpose and fast running simulation framework is necessary. The well known GENESIS [10] and NEURON [11] are good for simulating precise biophysical models of neu-

rons, but based on time driven simulation, i.e. scrolling all the neurons and synapses of the network at each time step, they are not specifically designed for fast simulation of very large scale SNNs. In accordance with biological observations, the neurons of an SNN are sparsely and irregularly connected in space (network topology), and the variability of spike flows implies they communicate irregularly in time (network dynamics) with a low average activity. Since the activity of an SNN can be fully described by emissions of dated spikes from pre-synaptic neurons towards post-synaptic neurons, an Event-Driven Simulation (EDS) is clearly suitable for sequential simulations of spiking neural networks [12, 13, 14, 15, 16]. More generally, event-driven approaches substantially reduce the computational charge of simulators that control exchanges of dated events between event-driven cells EC, without checking each cell at each time step. On the other hand, since parallelism is an inherent feature of neural processing in brain, simulations of large scale neural networks could take advantage of parallel computing [17, 18] or hardware implementations [19, 20, 21]. A few studies coupled parallel computing and EDS, for general purpose systems [22], and for SNN simulation [23, 24, 25].

Our simulator belongs to the latter family and is close to Grassmann’s work [23, 25], with some additional characteristics. Although it is known for long [26] that a fine grain mapping of the network (e.g. one neuron per processor) is dramatically inefficient, due to high communication overhead, we think that a multithreaded implementation of neurons as event-driven cells EC is efficient. Unlike several simulators [22, 24, 25], we avoid the implementation of a unique controller or farmer processor for scheduling the network simulation. We propose to direct the timing of execution through the times of events, without an explicit synchronization barrier. Hence we propose DAMNED, a “Distributed And Multithreaded Neural Event Driven” simulation framework that gathers the benefits of EDS and distributed computing, and combines two levels of parallelism (multiprocessor and multithread) for taking full advantage of the specific features of SNNs, whatever the models of spiking neurons to be implemented. Designed for efficient simulations either on workstation cluster or on parallel computer, the simulator is written in the object-oriented language C++, with the help of the MPI library to handle communications between distant processors. Section 2 develops the speci-

ficity of temporal events in SNNs. Section 3 defines the distributed multiprocessor architecture and specifies the role of the multithreaded processes. Section 4 details the algorithms and addresses the synchronization problem. In section 5, we conclude with an outlook on DAMNED exploitation.

2 Temporal events in SNNs

In a typical neural network, at any time, each neuron can receive on its dendritic tree some signals emitted by other neurons. An incoming signal arrives with a delay d_{ij} and is weighted by a synaptic strength w_{ij} to be processed by the soma. The values of d_{ij} and w_{ij} are specific to a given connection, from a presynaptic neuron N_i to a postsynaptic neuron N_j . The membrane potential of a neuron varies in function of time and incoming signals. The neuron emits a spike, i.e. an outgoing signal on its axon, whenever its membrane potential overcomes a given threshold θ . In experimental setting, and thus for simulations, firing times are measured with some resolution Δt , yielding a discrete time representation. Hence each spike can be considered as an event, with a time stamp, and each neuron can be considered as an event-driven cell EC_j , able to forecast its next spike emission time, as result from the integration of incoming spikes.

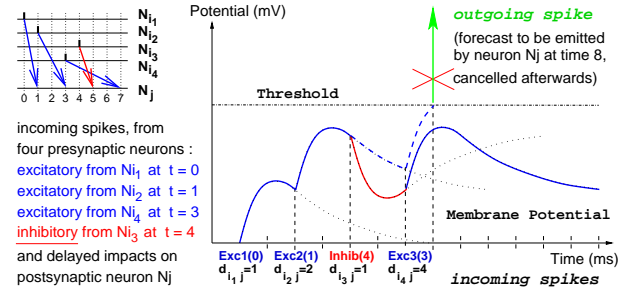


Figure 1: Variations of membrane potential for a postsynaptic neuron N_j . Three successive incoming Excitatory spikes let forecast an outgoing spike that must be cancelled afterwards, due to a further incoming Inhibitory spike, with a smaller delay d_{i_3j} .

However, the way to compute the future time of spike emission can be complex, depending on the model of neuron. For instance, if EC_j manages the incoming delays, a

further incoming spike, with inhibitory synapse, can cancel the forecast of an outgoing spike before the stamp associated to this event (see Figure 1). Hence we have to address the delayed firing problem (see [23, 14, 13]).

Since the activity in the network is unpredictable, in order to preserve the temporal order of events, for the sake of biological plausibility, we ought to control the uncertainty of spike prediction. In the context of C++ language programming, we have chosen the following data structure for classes of “events objects” :

CM event (resulting from <i>ComMunication</i>) = incoming spike, to be computed		
label of target neuron N_j (integer)	label of source neuron N_i (integer)	time stamp of spike emission st_i (integer)
CP event (resulting from <i>ComPutation</i>) = outgoing spike, to be emitted		
label of source neuron N_i (integer)	time stamp of spike emission st_i (integer)	certification flag crt (boolean)

where crt is true only if the typical time of local run, on the processor implementing the neuron N_i , is high enough to guarantee that no further incoming spike could ever cancel the CP event (see section 4 for further details).

Each class of “event-driven cells” EC objects is in charge of the computation methods associated to a model of spiking neuron, e.g. Integrate-and-Fire (IF, LIF), Spike Response Model (SRM), or other (see [27, 28]), so that different neuron types can be modeled in an heterogeneous SNN. Classically, an EC_j object modeling a neuron N_j has among its attributes the firing threshold θ_j of the neuron, the synaptic weights w_{ij} and the delays d_{ij} of the connections from all the presynaptic neurons N_i able to emit a spike towards N_j .

3 Distributed architecture and threads

The neural network topology must be distributed on P processors according to a static mapping, to be defined as convenient for the application to be simulated. Each processor Pr_p implements a certain amount of EC objects, labelled by their neuron number N_i . Each processor Pr_p

runs simultaneously two main threads so called CMC and CPC, for “ComMunication Controller” and “ComPutation Controller” respectively and as many extra threads as simultaneously computing neurons (see Figure 2). Incoming spikes intended to be computed by every neurons N_i belonging to processor Pr_p are stored in a priority queue of CM events, ordered by their spike time stamp. Outgoing spikes resulting from computations of neurons N_i belonging to processor Pr_p are stored in a priority queue of CP events, ordered by their spike time stamp. They are intended to be sent by the CMC process to all the target neurons N_j of N_i , whatever they belong to Pr_p or to another processor. Processor Pr_p knows the tables of postsynaptic neurons (neuron numbers N_j and number m of processor Pr_m implementing N_j) for all its neurons N_i . For local target neurons, i.e. $N_j \in Pr_p$, a CP event $[N_i, st_i, crt]$ from the CPC queue generates CM events $[N_j, N_i, st_i]$ in the CMC queue of the same processor. For distant target neurons, each CM event $[N_k, N_i, st_i]$ is packeted into a message to be sent to processor Pr_m implementing N_k .

As illustrated by Figure 2, each processor runs in parallel: two main threads, CMC and CPC, with mutual exclusion for accessing each other priority queue. The CMC and CPC threads continuously run each an infinite loop, on the following procedures

CMC, ComMunication Controller

1. *message reception*: If messages from other processors are available, then place all the received CM events $[N_j, N_i, st_i]$ inside the CMC priority queue, ordered by their time stamp st_i (or by arrival time, if equal time stamps exist),
2. *emission control*: If the next outgoing spike $[N_i, st_i, crt]$, at the top of the CPC queue, is authorized, then look at the table of target neurons of N_i , create the CM events $[N_j, N_i, st_i]$ for all the postsynaptic neurons N_j and place them either in the local CMC queue, if $N_j \in Pr_p$, or in packets prepared for further message sending,
3. *message sending*: If packets are ready, then send them to the target processors.

All messages are sent and received according to MPI communication protocols. The *receive* and *send* procedures do not stall waiting for effective messages at each

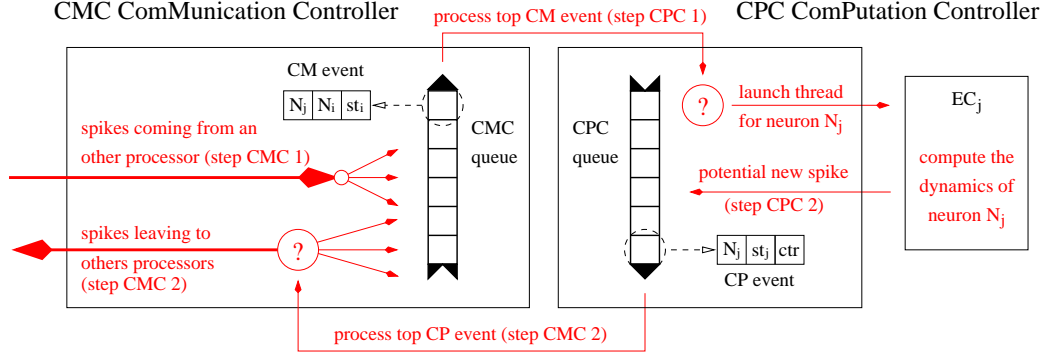


Figure 2: Architecture of a processor Pr_p , for $p \neq 0$. Several threads run simultaneously: A CMC thread, a CPC thread and as many threads as currently computing neurons. CMC receives spike events coming from other processors (step CMC 1). CMC inserts the incoming events in the CM priority queue according to their time stamp st_i . CPC checks if the top CM event is authorized for computation (step CPC 1). If authorisation is granted, the thread associated to EC_j processes the $[N_j, N_i, st_i]$ CM event. If N_j triggers, the resulting spike generates a new CP events that are inserted in the CPC priority queue (step CPC 2). CMC checks if the top CP event is authorized for emission. If so, the spike event is dispatched towards all the target neurons, generating CM events that are inserted either in the CMC queue or in packets to be sent to other processors.

loop step. They only check if messages are present in their communication buffers. They process them if relevant, otherwise the loop goes on.

CPC, ComPutation Controller

1. *computation starter*: If the next incoming spike $[N_j, N_i, st_i]$ at the top of the CMC queue, is authorized, then launch the thread associated to EC_j that implements neuron N_j
2. *result collector*: If a new spike $[N_j, st_j, crt]$ has been generated by EC_j , then place the event inside the CPC priority queue, ordered by its time stamp st_j (or default, arrival time if some other time stamps are equal)

Each time an incoming spike is computed by a neuron N_j , the associated thread is activated. Since the CPC runs an infinite loop on the *computation starter* and *result collector* procedures, several other threads, on EC objects, can be active simultaneously, thus implementing concurrent computation of several neurons, locally on processor Pr_p (Figure 2). On each processor, $nbth_p$ represents the number of active threads on Pr_p . The variable $nbth_p$ is incremented by the *computation starter* procedure each time a thread is activated for an EC object, and decremented by the *result collector* procedure each time

a thread ends. The EC object keeps a pointer to every CP event it has generated as far as the event is present in the CPC queue. Hence the EC object can modify some certification flags if a new information allows it to authenticate some old-queued events that have not yet been emitted. For complete explanation of how to manage the delayed firing problem, let us define two other local variables:

et_p is the current *emission time* on processor Pr_p
 pt_p is the current *processing time* on processor Pr_p

The variable et_p switches to its opposite negative value if the CPC queue (spikes to be emitted) becomes empty, and switch back to opposite positive value when new events arrives in CPC queue. Same behavior for the variable pt_p according to the state of the CMC queue (spikes to be processed). Those two variables play a fundamental role for controlling the scheduling on the set of processors and for defining the conditions of emission and computation authorizations, as detailed in section 4.

A last point about the distributed architecture: The neural network topology is spread onto P processors. However, a realistic simulation requires an interaction with the environment. Hence an extra processor Pr_0 is necessary to send the environment stimuli to input neurons (distributed on several Pr_p , with $p \geq 1$) and to receive the

response from output neurons (also distributed on several Pr_q , with $q \geq 1$). We prevent the processor Pr_0 to be a controller or a farmer, but the way it helps the scheduling of the whole simulation is also fundamental, as explained in next section.

4 Synchronization control methods

The main point is to keep an exact computation of firing times for all the neurons of the network, and to prevent all the processors from deadlock situations, despite of the may-be irregularly distributed firing dynamics that can result from the environment data. The processor Pr_0 is in charge to send to the neural network all the input stimuli generated by the environment (e.g. translation in temporal coding of an input vector) and to receive all the spikes emitted by the output neurons of the network.

Pr_0 knows the actual time T of the environment, and its current *emission time* et_0 . At initial time, all the processors emission times et_p are set to 0. While the simulation runs, each processor, including Pr_0 , may have a partial and obsolete view of the clocks of the other processors. Each processor Pr_m , $0 \leq m \leq P$, owns a local clock array $Clk(m)$ storing the emission times it currently knows, for all the processors Pr_p , $0 \leq p \leq P$

$$Clk(m) = \begin{bmatrix} et_0(m) & et_1(m) & \dots & et_P(m) \end{bmatrix}$$

Each time a processor Pr_p sends a packet of events (spike emissions) to a processor Pr_m , the message is encapsulated with the local clock $Clk(p)$. Hence the clock $Clk(m)$ can be updated each time Pr_m receives a message. We assess that the whole network scheduling can be achieved this way, due to the local management of event causality. Since this way of controlling synchronization does not require “look-ahead” query-messages, we propose a more flexible method than the “safe window” solution described in [23].

Environment processor Processor Pr_0 is the only one that is not subject to the delayed firing problem since the environment processor relays all the input stimuli towards the neural network. Hence Pr_0 knows exactly the dates of all the external spikes that will trigger the input neurons of the SNN. Each time Pr_0 increments the actual time to

T , all the packets with time stamps $T-1$ are ready for immediate sending. Messages are sent to all the processors Pr_m , $m \geq 1$, with the following information:

- the current update of the clock $Clk(0)$, where et_0 has just been incremented to T
- if relevant, all the CM events $[N_j, Ext, T-1]$ that will generate spike emissions at time T on N_j input neurons owned by processor Pr_m

Even if a processor Pr_m does not own input neurons, or if it owns input neurons that do not trigger at time T , it will receive a message with the clock $Clk(0)$. Note that the environment processor Pr_0 is the only one that can send messages reduced to the clock. Since all the processors are aware of the last update of et_0 “immediately”, or as soon as the message can be transmitted [we assume reliable communication channels], the argument (m) will be next omitted in notation $et_0(m)$.

The simulation starts running by the incrementation of T to 1. Since spike events communication must respect a causal order, the following conditions are always true, on every processor Pr_m (arguments have been omitted):

- $T > 0$ and $et_0 > 0$ all along the run, after simulation start
- $(\forall p \geq 1) et_0 \geq |et_p|$
- T and $(\forall p \geq 0) |et_p|$ are never decreasing
- $(\forall p \geq 0) |pt_p|$ is never decreasing
- $(\forall p \geq 1) et_0 \geq |pt_p|$

The links between *emission time* et_p and *processing time* pt_p are clarified below, where algorithms that govern emission and computation authorizations are detailed.

Each time Pr_0 receives an output event packet, it forwards all the CM events $[Ext, N_i, st_i]$ to environment manager for further external processing, it updates its clock $Clk(0)$, from the received clock $Clk(q)$, as follows:

- $(\forall p \geq 1)$ if $|et_p(q)| \geq |et_p(0)|$ then $et_p(0) \leftarrow et_p(q)$;
- if $(\exists j \geq 1) |et_j(q)| = T$ then $T \leftarrow T + 1$; $et_0 \leftarrow T$;

If T has been incremented, then Pr_0 sends the appropriate messages to all the Pr_m . Note that Pr_0 may receive several output spike events, coming from different processors, between two successive increments of T . Conversely, it is possible that no output neuron send spike emission, at a given time T , and then Pr_0 does not receive any message and does not update its clock. Such a

case would result quickly in stalling all the processors, by blocking their emission and computation authorizations. For preventing the system from deadlock, we assume that a time-out is running on Pr_0 and that T is incremented when time-out expired, which is coherent with the notion of actual time represented by T . Hence et_0 is updated to T and, provided that the time-out is sufficiently long, all the $et_p(0)$ can be set up to $T - 1$. Messages are sent to all the processors, with updated clock $Clk(0)$ and possibly new spike events generated by external stimuli. This time-out is rarely activated but it prevents the system to fall into deadlock when the dynamics of the SNN is reduced to very low overall activity or activity loops that risk to be localized on a single processor or on a cluster with no output spikes.

CMC algorithms for emission authorization

On each processor Pr_p , for $p \geq 1$, the CMC runs an infinite loop on the successive procedures of message reception, *emission control* and message sending (see section 3).

At each message sending, processor Pr_p checks if a packet of required size (minimal packet size $minpak$ is a parameter) is ready to be sent to another processor Pr_m . In case of successful checking, processor Pr_p encapsulates the ready-to-be-sent packet with its current clock array $Clk(p)$ and sends it to the target processor. At each message reception from a processor Pr_q , the CMC of Pr_p inserts the incoming CM events in its priority queue, sets back the processing time to a positive value: $pt_p \leftarrow |pt_p|$, and updates its local knowledge of the et_m on other processors as follows:

$(\forall m \neq p) \text{ if } |et_m(q)| \geq |et_m(p)| \text{ then } et_m(p) \leftarrow et_m(q);$

The *emission control* procedure picks up a new CP event $[N_i, st_i, crt]$ from the top of the CPC priority queue. This event has been computed by a local thread activated by the neuron N_i and has generated a spike emission forecasted for time st_i . In order to respect the causality of events, the CMC process has to check the authorization to communicate this event, by the following algorithm:

if $st_i = et_p$ then emission is authorized;

else if crt then emission is authorized;

else if $st_i \leq pt_p$ then emission is authorized;

else if $nbth_p = 0$ then

if $pt_p < 0$ and $(\forall m \neq p)[st_i \leq et_m \text{ or } et_m \leq 0]$
then emission is authorized;

else emission is delayed;

else emission is delayed;

If the emission is authorized, the CMC process updates the local emission time: $et_p \leftarrow st_i$

If the CP event is authorized then it is removed from the CPC queue. Each time the CPC queue becomes empty, the local emission time is changed to its opposite $et_p \leftarrow -et_p$ in order to indicate that there are no more spike emissions to communicate, at present time, on processor Pr_p . If the emission authorization generates, from the postsynaptic table of neuron N_i , new CM events to be further processed by one or more neurons local to Pr_p , then the processing time pt_p takes back a positive value: $pt_p \leftarrow |pt_p|$.

The present algorithm controls that an authorization to be emitted can not be delivered to a spike event $[N_i, st_i, crt]$ before its validity has been assured, regarding to the overall run of the simulated SNN. The emission of the spike event is authorized if we are sure that all the further computations of neuron N_i can not invalidate the present spike, either due to other computations locally running on processor Pr_p (controls on et_p , pt_p and $nbth_p$) or to distant spike events further incoming from other processors (controls on et_m , for all $m \neq p$). Even if a spike emission has been delayed only because the local clock $Clk(p)$ was not correctly updated, we avoid to overload the communication network with query messages, since the possible idle state is guaranteed to be ended by the reception of either new incoming events from other processors or clock messages coming from Pr_0 .

CPC algorithms for computation authorization On each processor Pr_p , the CPC runs an infinite loop on the successive procedures *computation starter* and *result collector* (see section 3).

The *computation starter* procedure picks up the top CM event $[N_j, N_i, st_i]$ of the CMC process priority queue. This event notifies that the neuron N_i has emitted

a spike at time st_i towards neuron N_j . The CPC process is in charge to deliver the computation authorization, according to the following algorithm:

if the thread associated to EC_j is already active

then { EC_j gets priority status [for further computation];
computation is delayed; }

else if $st_i = pt_p$ then computation is authorized;

else if $nbth_p = 0$ then

if $(\forall m)[st_i \leq et_m \text{ or } et_m \leq 0]$

then computation is authorized;

else if local deadlock is detected then

if $st_i \leq st_i(\text{next event top of CPC queue})$

then computation is authorized;

else computation is delayed;

with the following condition for local deadlock detection:

if $et_p < st_i$ and $(\forall m \neq p)[st_i \leq et_m \text{ or } et_m \leq 0]$

If the computation is authorized, the CPC updates both the local processing time: $pt_p \leftarrow st_i$

and the number of locally active threads $nbth_p^{++}$. Each time the CMC queue becomes empty, the local processing time is changed to its opposite $pt_p \leftarrow -pt_p$.

The present algorithm authorizes the computation of only one event at a time by a given neuron N_j (the computation is delayed if the thread of EC_j is active) and regulates the computations, via the variable pt_p , according to the whole network advancement state, known by way of the clock $Clk(p)$ (controls on all the et_m). Once again, we avoid communication overhead, even if computation is delayed for a moment, due to an obsolete clock, since the problem will be solved by further reception of messages coming from other processors.

The *result collector* scans the active threads, first for an EC with priority status (if relevant) or in a loop on the number of the currently active threads. If a neuron N_j computation of an event is over (i.e. thread ended), then the number of active threads is decremented $nbth_p^-$. The result of the computation is either null or a new outgoing spike event $[N_j, st_j, crt]$ that the *result collector* inserts in the CPC queue. If the CPC queue was previously empty, then the emission time et_p takes back a positive value: $et_p \leftarrow |et_p|$.

Moreover, the computation of an event for a neuron N_j

induces the certification of old events $[N_j, st_j, crt]$ still present in the CPC queue. $crt \leftarrow \text{"true"}$ each time st_j is less or equal to the currently processed st_i plus the minimal delay $d_j^{min} = \min_i(d_{ij})$ of neuron N_j .

5 Conclusion

We have designed a framework dedicated to event-driven simulation of very large neural networks of biologically plausible spiking neurons. The DAMNED simulator is based on two levels of parallelism: At a coarse grain level, the SNN is distributed on several processors; At a fine grain level, local computations of neurons are multithreaded on each processor. Since local clock updates, based on event causality, are managed via spike events message passing, both time-consuming synchronization barrier and centralized farmer processor can be avoided.

Presently, the simulator has been successfully tested on a toy SNN, with a basic model of spiking neuron. Further work will include implementation of large heterogeneous SNNs. Time measurements and speed-up evaluations will be performed both on workstation clusters and on parallel computers (e.g. at IN2P3 and C3I computation centers).

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