Scalability of large neural network simulations via activity tracking with time asynchrony and procedural connectivity

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Abstract

We present a new algorithm to efficiently simulate random models of large neural networks satisfying the property of time asynchrony. The model parameters (average firing rate, number of neurons, synaptic connection probability, and postsynaptic duration) are of the order of magnitude of a small mammalian brain, or of human brain areas. Through the use of activity tracking and procedural connectivity (dynamical regeneration of synapses), both computational and memory complexities of this algorithm are proved to be theoretically linear with the number of neurons. These results are experimentally validated by sequential simulations of millions of neurons and billions of synapses running in few minutes on a single equivalent CPU computer, without using parallelization.

Keywords: Brain neuronal networks; Random models; Point processes; Stochastic simulation; Discrete event systems; Activity Tracking with Time Asynchrony and Procedural connectivity (ATi-TAP); Hawkes processes.

1 Introduction

There are more and more vast research projects, whose objective is to simulate brain areas, or even complete brains, in order to better understand their functioning. Examples are the Human

Brain Project in Europe, the Brain Mapping by Integrated Neurotechnologies for Disease Studies (Brain/MINDS) in Japan or the Brain Initiative in the United States. Several approaches can be considered for this purpose. There is the biochemical approach (see for example [37]), which cannot succeed for systems as complex as the brain. A more biophysical approach has been used (see for example [13]) where cortical barrels have been successfully simulated. This approach is limited to about 10^5 neurons. However, the human brain contains about 10^{11} neurons while a small monkey, like marmosets [6], already has 6×10^8 neurons [22] and a larger monkey, like a macaque, has 6×10^9 neurons [22].

To simulate such huge networks, the models have to be simplified. In particular, a neuron has no physical form and is just represented by a point in a network, possibly with a certain voltage. The Hodgkin-Huxley equations [32] are able to reproduce the shape of the action potential by taking into account the dynamics of the ion channels, but the complexity of these coupled equations [18], makes the system quite difficult to simulate for huge networks. If the dynamics of the ion channels are neglected, the simplest voltage model is the Integrate-and-Fire (IF) model. With such models, it has been possible to simulate on supercomputers a neural network reaching about 68×10^9 neurons [54].

However, there is another range of simplified models, which can simulate such massive networks. Indeed, we can use much more random models to reproduce the essential dynamics of neurons: their firing pattern. Randomizing not only the connectivity graph but also the dynamics on the graph makes the model closer to real data and explains to some extent their variability. The introduction of randomness is not new and has been done in the models mentioned above: Hodgkin-Huxley [12] or Leaky Integrate-and-fire (LIF) [28].

Here we want to focus on particular random models: point processes [50], which model only spike trains. Point processes have usually the property of time asynchrony, i.e., two different neurons cannot produce spikes at exactly the same time. This includes Hawkes models and its variants such as generalized linear models, Wold processes, Galves-Löcherbach models, and even some random LIF models with random or soft thresholds [50, 4, 43, 40, 41, 14, 45]. As one can see in these references, all these point process models have been used to study different real datasets. Some of these point process models can be related to IF models. Indeed, as noted in [15] (Chapter 9), IF models can be made noisy, using "escape noise". In an escape noise model, IF neurons can fire

even if the threshold has not been reached or can remain quiescent even if the threshold has been transiently exceeded. As indicated in the same book (chapter 10), this formulation is very close to the generalized linear models [40], which are in fact known in mathematics as Galves-Löcherbach models [14] or the more classical version without reset: Hawkes models [43]. In this sense, Hawkes processes, which are used in the present work, can be seen as a noisy version of an IF model.

The time asynchrony property of point processes [2, 4], combined with the sparsity of the graph led to a new algorithm for point process network simulation, whose computational complexity is theoretically controlled. We called this algorithm ATiTA, for Actitivity Tracking with Time Asynchrony, in [31]. Thanks to time asynchrony and activity tracking [33], we showed in particular that, if the graph is sparse, the complexity cost of the calculation of a new point in the system is linear with the number of neurons. However the memory cost of this former work was too high to reach networks of 10^8 neurons.

In a preliminary work on the mathematical aspects of the mean field limits of LIFs [17], we also found a way to optimize the memory cost in the framework of random graphs: it is enough not to keep in memory the whole network but just to regenerate it when needed. However, this trick was not put into practice and its memory cost was not theoretically calculated in [17]. Both new aspects are treated in the present article. This approach is inspired by dynamic-structure discrete event systems [35]. It has already been applied to track the activity and addition/deletion of cells and neighborhood connectivity in cellular automata [34]. Recently, the same idea under the name of procedural connectivity, has been successfully applied on LIF models using Graphics Processing Units (GPU) [26]. Thanks to GPU parallel programming, and without using time asynchrony, the authors of [26] were able to simulate in parallel a network of 4×10^6 neurons and 24×10^9 synapses on a GPU computer with 4600 cores.

In comparison to [26], by combining procedural connectivity with activity tracking and time asynchrony, the new algorithm of the present work, called ATiTAP, obtains a smaller memory cost and a range of computational costs, which is much smaller than the sum of the costs of 4600 cores, and this, by using a single processing unit (PU) (either processor or core) instead of using several parallel PUs.

Indeed, classical parallel computing generally uses a discrete simulation time and computes for all neurons (or synapses) what happens at each time step in a parallel way. However, the spikes

must be transmitted between pre and post synaptic neurons, between two time steps. With more advanced techniques such as hybrid parallel computation [19], the spikes are computed in parallel for each neuron thanks to discrete event programming, while the exchange at the level of the synapses can be done at a less fine scale in a discretized way [36, 3, 44, 49]. Nevertheless, in both cases (classical or hybrid parallel computation), the synchronization between neurons is necessary to propagate the spikes at the synapses, even if it is not done at the same time scale.

With ATiTAP, thanks to time asynchrony, we can exploit discrete event computations [55, 33] to track the activity, not of each neuron independently, but of the whole neuronal network, over time, by jumps (from one spike in the network to another spike in the network). Synaptic transmissions are updated on the fly only for the neurons impacted by a spike. Therefore, a single PU can be used to sequentially compute each spike and each synaptic transmission. Being alone, the single PU can then compute the dynamics of the entire network as quickly as possible without waiting for the synchronization with other PUs. This reduces the overall computation time (compared to the summed time of all cores), which makes our sequential computation technique competitive with parallel computation techniques. Indeed, being able to simulate an entire large neural network on a single core opens the possibility of using the other cores to run simulation replicas in parallel. It is then possible to simulate many models in parallel instead of a single model in parallel, with reasonable execution time.

To summarize, ATiTAP, the new algorithm proposed here, allows simulating large neural networks through activity tracking with time asynchrony and procedural connectivity. Thus, a realistic network of 10^8 neurons can be sequentially simulated on a single PU, with memory and computational costs roughly comparable to other available algorithms (which require a parallel implementation on multiple PUs) [24, 26, 46]. Moreover, these costs can be controlled analytically in advance: in particular, they remain linear with the number of neurons in the network.

In Section 2, after discussing more precisely the differences and links between Hawkes processes and classical Integrate-and-Fire, we explain the main features of the benchmark (the hybrid simulation algorithm for IF [19]) and the ones of our new algorithm ATiTAP. We also derive the theoretical memory and computational costs and compare it to simulations on a realistic range of parameters with respect to human brain areas. In Section 3, we give the main mathematical ingredients to calibrate our simulations. In Section 4, we discuss the results we obtained in view of the various

benchmarks of the existing algorithms to simulate huge realistic neuronal networks.

2 Results

2.1 Models features

As said in the introduction, some point processes and especially Hawkes processes have some common features with more classical Integrate-and-fire models. Point processes are usually defined by their conditional intensities, which describes the probability for a spike to happen on a given neuron, given every other spikes that have happened in the network in the past [4]. It has been shown (see for instance [23] with experiments on motor neurons), that the conditional intensity of a spike train is a function of the membrane voltage. From a model point of view, we can assimilate more or less one to the other : the higher the voltage, the more likely the neuron spikes. This is also the spirit of the equivalence derived in chapters 9 and 10 of [15]. In this sense, one derives an equivalence between the formula of the conditional intensity of a Hawkes process and the voltage dynamic of an Integrate-and-Fire model. Modeling the activity of M neurons by a Hawkes process means that the conditional intensity of neuron i, which models the spike train N^i, is given by

$$\lambda^i(t) = \Phi\left(\nu^i + \sum_{j=0}^{M} \sum_{T \in N^i, T<t} h_{j\to i}(t-T)\right), \tag{1}$$

In this formula, from a point process point of view, ν_i represents the spontaneous activity of the neuron i if the other neurons do not fire, whereas $h_{j\to i}$ is the interaction function, that is $h_{j\to i}(u)$ is the increase (if positive) or decrease (if negative) that the firing rate of neuron i suffers due to a spike on j, which has taken place u seconds before. The increasing function Φ is the transfer function, which is usually the positive part, i.e. $\Phi(x) = \max(x, 0)$. Indeed, if the interaction functions $h_{j\to i}$ are too negative, the overall sum might be negative and the positive part ensures that the conditional intensity is just null in this case : this corresponds to the fact that the neuron is so inhibited that it does not emit any spike anymore. Some authors also uses the exponential transform $\Phi(x) = \exp(x)$ (see [40] for instance).

From a voltage/IF point of view, we can interpret

$$\nu^i + \sum_{j=0}^{M} \sum_{T \in N^i, T<t} {}_{j\to i}(t-T)$$

as the voltage membrane of the neuron, ν^i being the resting potential and the functions $h_{j\to i}$, the respective excitatory or inhibitory post-synaptic potentials that are summed after each received spikes. In the IF model, especially the one used in [19], these functions are solutions of differential equations (the most classic, the exponential, being represented in blue on Figure 1, less classic functions with synaptic delays for the transmission being represented in black).

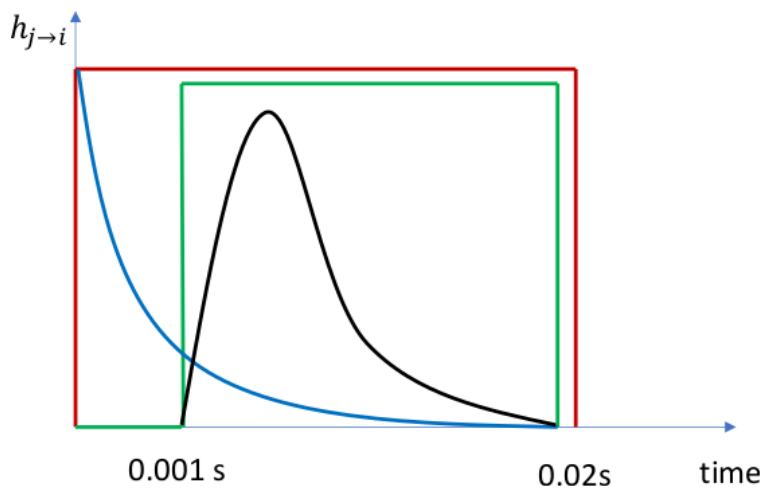


Figure 1: Examples of interaction functions $h_{j\to i}$ from a neuron j to a neuron i: in red a piecewise constant function with no delay ; in green a piecewise constant function modeling a synaptic transmission delay ; in black a continuous interaction function with the same synaptic delay ; in blue the exponential interaction function, obtained in the most classic Integrate-and-Fire models.

Once this parallel is done, there are several features that Hawkes processes have that might help to understand why we choose this model over various other representations.

First of all, because Hawkes processes are defined by a conditional intensity, they are simple [2] and therefore do possess the time asynchrony property, that is, two neurons cannot produce spikes at exactly the same time. This property is not satisfied by classical Integrate-and-Fire models, which fire each time the voltage of a given neuron exceeds a given threshold. It has been shown mathematically that unrealistic blow-up phenomena can appear for IF because of this absolute rule: a massive proportion of the neurons can exceed the threshold at the exact same time, whereas Hawkes models do not have this caveat [5, 7].

Second, and this is true for all point processes defined by a conditional intensity, one can always thin a rougher process into a more complex one [38, 31]. Indeed as soon as we are able to simulate a process with a larger intensity, we can reject some of the points, via a particular mathematical procedure called *thinning*, to create a process with a smaller intensity.

Third, in the case of excitatory interaction functions and transfer function $\Phi(x) = x$, we can easily predict mathematically the number of spikes that will be produced (see Section 3 for more details). This helps us design beforehand numerical experiments with a given highly variable distribution of the firing rates, as one can observe on real data.

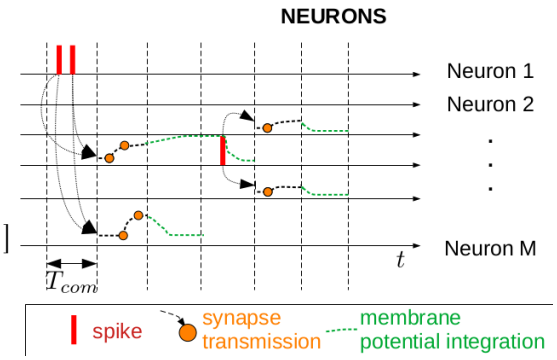
Finally, in the case of non negative piecewise interaction functions, thinning is not necessary [31] and we are able to precisely compute the theoretical memory and computational costs (see Sections 2.3 and 2.4) as a function of : M, the number of neurons; d the average degree of the network; $\bar{m}$, the average firing rate in the network; τ , the largest possible interaction duration, that is the maximal support of the functions $h_{j\to i}$ and A, the maximal number of breakpoints in the piecewise constant functions $h_{j\to i}$.

In the sequel, we restrict ourselves to non negative piecewise constant interaction functions (and $\Phi(x) = x$) for the computation and simulation. Note that taking negative piecewise constant functions is not a problem for ATiTA and ATiTAP, and that the resulting process will always have less points than the one without inhibition. Memory cost and numerical complexity are therefore upper bounded by the pure excitatory case, where negative interaction functions are discarded. Also it is always possible to thin this process into a more complex one with smoother interaction functions for instance, as long as the interaction functions are upper bounded by piecewise constant functions (see Figure 1). Again this procedure will only diminish the number of points. However the theoretical complexity of this thinning step cannot be well evaluated. Therefore the benchmarks that are given in the present work have to be understood as a proof of concept that such huge simulations can be done on a single PU. Of course, we can also make the interaction functions smoother by increasing the number of breakpoints of the piecewise interaction functions (A). However, it is likely that this would be more time consuming than pure thinning.

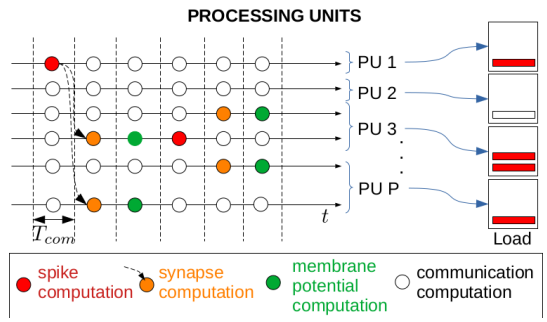
2.2 Description of the algorithms

Parallel simulation and the hybrid algorithm The simulation of large neural networks is usually performed in parallel with regular synchronizations of all the computing cores. Of course, this depends on both the mathematical model and the simulation algorithm. However, for most models, differential equations are used to compute the time evolution of the membrane voltage for each individual neuron. Usually, these equations are (approximately) solved by classic discrete-time numerical schemes [26]. One of the most advanced algorithms nowadays to simulate neuronal networks is called hybrid parallel computing [19] and it works with an Integrate-and-Fire model. It supersedes the previous discrete-time numerical schemes by using discrete-event simulation to directly produce the next spike of a neuron once all synaptic transmissions to this neuron have been planned.

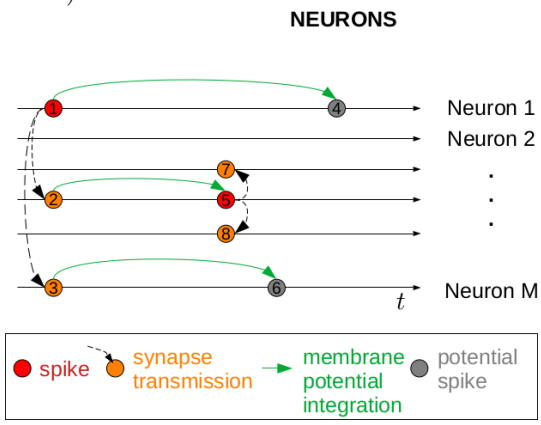
The hybrid parallel algorithm is represented on the top part of Figure 2 (a. and b.). There are two ways to understand the computations: either from a neuron point of view or from a PU point of view. From a neuron point of view, when a presynaptic neuron emits a spike at time t (red ticks on Figure 2a), the postsynaptic neurons receive this information at time $t+T_{com}$ (orange dots on Figure 2a) because synaptic transmission is not instantaneous biologically speaking. Between two synaptic transmissions, the membrane potential of a neuron evolves independently from the other neurons and can be calculated in parallel (green dashed lines on the figure 2a). From a processor point of view (cf. Figure 2b), a processor takes in charge the computation of a group of neurons. Because of the delay T_{com}, every multiple of T_{com}, the processors must synchronize to be able to anticipate, over the next interval of length T_{com}, the synaptic transmissions that are going to take place, before computing independently the membrane voltage. Notice therefore that since the firing rate is quite low in the network, a lot of PUs could have pursue their computations without synchronization, but are forced to wait. Hence the load of each PU is sub-optimal on average.



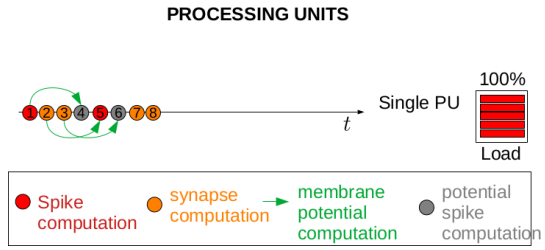
(a) Hybrid (discrete-time and discrete-event) approach for parallel simulation (at neuronal level)



(b) Hybrid (discrete-time and discrete-event) approach for parallel simulation (at processor level)



(c) Discrete-event approach for sequential simulation (at neuronal level)



(d) Discrete-event approach for sequential simulation (at processor level)

Figure 2: Schematic view of the hybrid algorithm [19] (Figures (a) and (b)) and ATiTA(P) (Figures (c) and (d)). Figures (a) and (c) represent the neuronal network point of view, whereas the PU point of view is displayed in Figures (b) and (d). Everywhere, spikes are in red, synaptic transmission events in orange, prediction of next spike in green, thanks to integration of membrane potential or intensity. For ATiTA(P), also grey refers to potential spikes that are computed and then discarded. In (a) thanks to the synaptic delay of size T_{com} spikes are received by the neurons in the next bin of size T_{com} and then integrated to compute the membrane potential. In (b) the computations per PU are then done per bin of size T_{com} and need to be synchronized every T_{com}. Depending on the number of PUs, it is likely that some PUs wait the other ones without computing much and therefore their load is low. In (c), for ATiTA(P), the discrete-event approach is used at the network level: the computation makes jumps to the next potential spikes. The smallest one is kept as the actual next spike. Then synaptic transmission, update of the corresponding intensities and new computations for the next potential spikes, are done only for the post synaptic neurons. In (d), the different operations of (c) are put in the order of the successive operations that are done by the single PU, which has therefore a full load over time.

ATiTA and ATiTAP In [31], we proposed a discrete-event algorithm, ATiTA, to simulate point processes with stochastic intensities. This algorithm is based on the theory of local independence

graphs [9], which corresponds to the directed neuronal network in our present case. ATiTAP follows the same principle and we refer to both algorithms as ATiTA(P). Computationnally, ATiTA(P) work as follows (see Figure 2c).

From a neuronal network point of view, the spike events happen in continuous time in the system (up to the numerical precision). Once a spike on a particular presynaptic neuron happens (red dots in Figure 2c), the postsynaptic neurons are updated (orange dots in Figure 2c). The presynaptic and the post synaptic neurons compute their respective intensities and forecast their evolution (green arrows in Figure 2c) if nothing in between occurs in the system. They are therefore able to forecast their potential next spike (gray dots in Figure 2c). The algorithm maintains a scheduler containing all potential next spikes on all neurons. This particular data structure [31] can efficiently maintain a sorted list of numbers. ATiTA(P) decides that the next neuron to fire effectively is the one corresponding to the minimum of these potential next spikes. For more details, we refer to [31]. The computational gain comes from the fact that neurons that are not firing a lot, do not require a lot of computations either. In particular we do not have to update all neurons at each spike but only the pre and post synaptic neurons that are involved in the spiking event. This is the main difference with the hybrid algorithm detailed above, which requires each PU to wait for the others to finish at each bin of size T_{com}, even if it does not receive any input. The other difference is that we are working at the classical numerical precision of 10^{-15}, without impeding the time complexity of the algorithm. Note that the whole algorithm is possible only because two neurons in the network will not spike at the same time: the whole concept is based on time asynchrony to be able to jump from one spike in the system to the next spike in the system. Of course, this is true only up to numerical precision: if two potential next spikes (gray dots on Figure 2c) happen at the exact same time with resolution 10^{-15}, by convention the neuron with the smaller index is said to fire. But the probability of such event is so small that this is not putting the simulation in jeopardy. Also note that this does not prevent neurons to eventually synchronize quite frequently over few milliseconds, as defined for instance in [51] and the references therein.

From a PU point of view (cf. Figure 2d), a single PU computes sequentially (potential) spikes, synaptic and membrane potentials for all the neurons in the network. Notice that the load of this single PU is always optimal, as it is computing all the activities in the network. At the difference with the hybrid algorithm, no load balancing is required to attribute PUs to groups of neurons.

Computational performances only depend on the capacity of a single PU to compute activities as fast as possible.

The additional feature of ATiTAP with respect to ATiTA is the procedural connectivity [17, 26]. One of the memory burden of the hybrid algorithm and of ATiTA, comes from the fact that a classic implementation stores the whole connectivity graph, which is huge for brain scale models. If the connectivity is the result of a random graph and that each presynaptic neuron is randomly connected to its postsynaptic neurons, one can store the random seed instead of the result of the random attribution. Hence the whole graph is never stored in full but only regenerated when need be. The random connectivity is regenerated at each spike taking advantage of the deterministic nature of the pseudo-random generator used in the simulation. Storing the generator initial seed, the seed of each neuron is computed based on initial seed value and neuron index (see Figure 3). With this method, only the initial seed is stored in memory. Of course this dynamic regeneration at each spike has a cost in terms of time complexity, but this cost is negligible with respect to the other computations that need to be made and this saves memory. In the sequel, the random graphs that are considered are Erdös-Renyii (see Section 3).

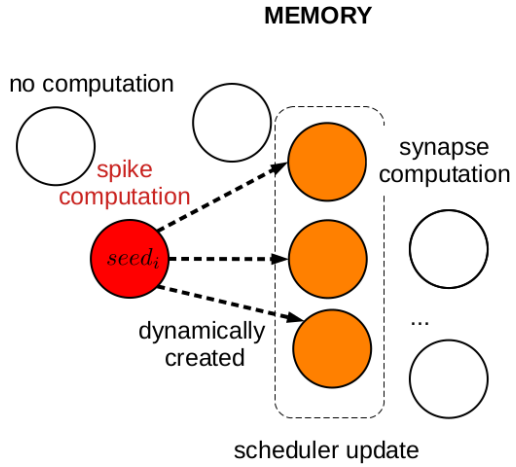


Figure 3: Time asynchrony and procedural connectivity at both computational and memory levels. When a spike occurs in neuron i, corresponding seed is computed based on neuron index i and the indices of the corresponding post-synaptic neurons are then generated. Later, the next potential spikes of these post-synaptic neurons are computed. Colors represent the computational order of magnitude: white meaning no computations, orange corresponding to the computation of the next potential spike and red to the computation of the next potential spike plus the seed computation and local regeneration of the graph.

2.3 Theoretical computational cost of ATiTA(P)

In [31], an accurate estimate of the complexity of ATiTA has been derived (*cf.* Equation 7 of [31]). This can be completed to compute the computational complexity of ATiTAP, when the procedural connectivity step is added. The overall time complexity of our algorithm is of the order of

$$\mathcal{O}\left(TM\bar{m}\left[d^2 A\tau\bar{m} + d\log(M) + d\right]\right). \tag{2}$$

More precisely, since M is the number of neurons, $\bar{m}$ the average firing rate and T the simulation time, the factor $TM\bar{m}$ corresponds to the average number of points that are produced by the algorithm. For each of these points, one needs to decompose the algorithm in a few steps to understand the different elements of this complexity formula.

(a) *Update of the intensities of the presynaptic neuron and of all the d (in average) post-synaptic neurons and computation of their possible next point:* The intensity of a given neuron is piecewise constant, more precisely it is a sum of (in average) d piecewise constant functions, corresponding to each interaction functions (see (1)). Moreover a term like $\sum_{T\in N^j T<t} h_{j\to i}(t-T)$ is piecewise constant in t with as many breakpoints as: A (number of breakpoints in $h_{j\to i}$) times the number of spikes that are appearing in a range τ (support of the function $h_{j\to i}$). So globally, the intensity of a given neuron is a piecewise constant function with (in average) $dA\tau\bar{m}$ breakpoints. Updating $d+1$ intensities and computing for each of them, their next potential point is therefore proportional to $d^2 A\tau\bar{m}$.

(b) *Update of the scheduler containing all the possible M next points*: Updating one time in a scheduler requires $\log(M)$ iterations. Hence updating $d+1$ points in the scheduler requires $d\log(M)$ iterations.

(c) *Procedural connectivity*: This step is the only difference between ATiTA and ATiTAP. It does not exist for ATiTA. For ATiTAP, at each spike, we regenerate the d (in average) postsynaptic neurons of the random graph. This costs d. Note that step (c) is negligible with respect to step (b) and therefore ATiTA and ATiTAP have roughly the same computational complexity.

Note that for general point processes, the main change in this evaluation would be the complexity of the intensity in step (a), which would also impact the computation of the next point. If thinning

is involved, that is if we simulate a rougher process and then precisely reject all the unnecessary points, the global factor will be larger than the actual number of points ($TM\bar{m}$), since it would count the number of points of the rougher process. However, if the evaluation of the more complex intensity at a given point is not too time consuming [38], the complexity (for a given point of the rougher process) of step (a), (b) and (c) can be roughly the same.

2.4 Theoretical memory cost of ATiTA(P)

In [31], the memory cost of ATiTA was not computed. Here we evaluate this cost for both ATiTA and ATiTAP. There are several costs, some necessary whatever the aim of the simulation, some depending on what is the purpose of the simulation.:

(a) *Library cost:* As in [27, 24], some libraries and other code need to be stored in memory. We denote this cost by ρ. Since there is only one PU and we are not using a parallel simulation, we pay this cost only once.

(b) *Random seed:* For ATiTA or ATiTAP, random numbers are necessary to produce the points of the process. For reproducibility purpose, one can store the first random seed and then obtain the other ones based on neuron indexes. Hence only the first one needs to be stored. This cost is η.

(c) *Connectivity cost:* For ATiTA, one can use the Yale format [11] to store the synaptic connections of the neural network. This format consists of storing for each pre-synaptic neuron the set of post-synaptic neurons (both of them represented as indices). So the memory cost if $dM\omega$, with ω the number of bytes to store an index (integer or long integer). For ATiTAP, we also need to store the first seed for the generation of the random graph. Then ,the other ones, for each neuron of the graph, are obtained thanks to their index (see Figure 3). Finally, at each iteration of the algorithm we need to store, in average, the d indices of the d post synaptic neurons that are regenerated on the fly. The whole cost is therefore $\eta + d\omega$.

(d) *Parameters cost:* In general, for ATiTA, it should be necessary to store all the ν_i's and all the $h_{j\to i}$'s that are non zero. This would cost roughly $MdA\epsilon$, where ϵ is the number of bytes necessary to represent a spiking time. In the set-up of the present simulation, for ATiTAP,

the ν_i's are different to have a large heterogeneity in the spiking rates and we use the same interaction functions for all neurons as soon as they are non zero. The cost is therefore $(M + A)\epsilon$.

(e) *Storage of the intensities:* As said previously in Section 2.3, an intensity has in average $dA\tau\bar{m}$ breakpoints. Hence, storing all the M intensities roughly costs $MdA\tau\bar{m}\epsilon$.

(f) *Scheduler of the possible next spikes:* This scheduler is of size M, hence the cost is $M\epsilon$.

(g) *Storage of all the generated points:* Depending on the problem, one might want to store all the spikes that have been generated, or only summary statistics (like firing rates, etc.) that are less costly. In the case where we want to store all the generated points, the cost is $TM\bar{m}\epsilon$.

Hence without counting case (g), we have for a general ATiTA algorithm with various interaction functions a memory cost of

$$O(\rho + \eta + Md(\omega + A\epsilon + A\tau\bar{m}\epsilon) + M\epsilon), \tag{3}$$

whereas ATiTAP with one common interaction function is of memory cost

$$O(\rho + \eta + d\omega + MdA\tau\bar{m}\epsilon + (M + A)\epsilon). \tag{4}$$

Usually, $\eta = \omega = \epsilon = 64$, the precision of a double / long integer type.

2.5 Choice of brain scale parameters

Because of the precision of actual measurements and their intrinsic variability, it is difficult to estimate quantitatively both physiological (number of synapses per neuron, etc.) and dynamic parameters (average firing rate, etc.) of neuronal networks in primates [22] and humans [21]. Only rough estimates are available. We give in this section, rough estimates of the main quantities of a human brain in order to see the scalability of ATiTA(P) to reach human brain areas.

To our knowledge, the best documented region of the human brain is the (neo)cortex. Based on the structural statistics (number of neurons and synaptic connections) of neuronal networks in the (neo)cortex, we extrapolate here their representative parameter values for the whole brain.

The *firing rate of a neuron* in the brain can be estimated by the limited resources at its disposal, especially glucose. Measures of ATP consumption have shown (see [29]) that the firing rate of a neuron in human neocortex can be estimated around $0.16Hz$. Still based on ATP consumption, only 10% of the neurons in the neocortex can be active at the same time. So it seems coherent to choose an average of $0.16Hz$. These values can be extrapolated to the whole brain[1], as follows.

The neocortex represents 80% of the volume of the brain [48] and consumes 44% of its energy [29]. Considering that the energy consumed by the brain is proportional to the firing rate of the neurons, we obtain that

$$\frac{P_{cortex}}{P_{brain}} \sim \frac{V_{cortex}\bar{m}_{cortex}}{V_{brain}\bar{m}_{brain}},$$

with $\bar{m}_{cortex}$ the mean firing rate of individual neurons in the neocortex (resp. in the brain) and V_{cortex} the volume of the neocortex (resp. in the brain). The *average firing rate of the brain* then consists of $\bar{m}_{brain} = 0.8 \times \frac{0.16}{0.44} \simeq 0.3\ Hz$ per neuron.

This average firing rate should not be confused with the fact that particular neurons may have a much larger firing rate. Particularly, groups of neurons synchronize together to achieve a particular cognitive task: this is the concept of neuronal assemblies [16]. In an assembly, neurons can usually increase their rates to tens Hz (possibly $50Hz$) over a short duration. Therefore, we choose a firing rate distribution where most of the neurons have a firing rate of $0.3Hz$ but some have a much higher firing rate (up to $50Hz$) using an heavy tailed distribution (see Section 3).

The average number of synaptic connections in a human brain is hard to estimate and depends heavily on the neuron types and brain regions. For example, in the brain, it is assumed that the majority of neurons are cerebellum granule cells [47]. In [30], the number of synaptic connections to granule neurons is estimated to an average of only 4 connections, matching those observed anatomically. On the other hand, Purkinje neurons can have up to $200,000$ synapses on only one dendrite in the human brain [47]. The approximate number of synapses in the cortex is 0.6×10^{14} [10]. Assuming that the volume of the cortex represents around 80% of the volume of the brain, the number of synapses in the brain is of order 10^{14}. Considering that the number of neurons in the human brain is of order 10^{11} [21], we find that the average number of synapses is about $1,000$

[1]This calculus can be found on AI impact project webpage: `https://aiimpacts.org/rate-of-neuron-firing/` (lastly verified: 02/09/2021)

synapses per neuron[2]. In the present work, the parameter d, the average number of pre / post synaptic neurons, is therefore evolving between 250 and 1000.

Finally, an action potential arriving on one pre-synaptic neuron produces an Excitatory Post-Synaptic Potential (EPSP), or an Inhibitory PostSynaptic Potential (IPSP), in the postsynaptic neuron. The duration of these postsynaptic potentials is about $\tau = 20ms$ [47] (see Section 2.1 for the link with the support of the interaction functions).

Therefore the parameters that we used in the simulation are indicated in Table 1.

Simulation duration	$T = 5s$
Mean firing rate	$\bar{m} = 0.3Hz$
Number of neurons simulated	$M \in \{10^5, 10^6, 10^7, 10^8\}$
Synaptic connection in average	$d \in \{250, 500, 1000\}$
Postsynaptic duration	$\tau = 0.02s$

Table 1: Parameters used in the simulation

2.6 Software and hardware configurations

The simulations have been run on a Symmetric shared Memory multiProcessor (SMP) computer, called IRENE, equipped with Intel CascadeLake@2.6GHz processor[3]. This kind of computer is used here to have access to larger memory capacities. At computational level, only one processor was used for the simulations. The implementation of the algorithm is written in C++ (2011) programming language and compiled using g++ 9.3.0.

2.7 Firing rate at network level

As detailed above, the firing rates in the brain are highly inhomogeneous. Therefore, to be more realistic, it was important to simulate this heterogeneity. Also this heterogeneity is advantageous to ATiTA(P) since the whole algorithm does not spend time on almost silent neurons to concentrate

[2]Calculus on AI impact project webpage: `https://aiimpacts.org/scale-of-the-human-brain/` (lastly verified: 02/09/2021).

[3]We used the partition v100l on Joliot-Curie supercomputer at TGCC as a Fenix Infrastructure resource. The PU consists of two (linked) Intel CascadeLake@2.6GHz processors, each with 18 cores. A dual-socket mother board contains the 2 CPUs, which are not used in parallel. So they can be considered as one equivalent PU. Each core has a memory of 10 GBytes, so the total amount of available memory is 360 GBytes.

all the computations of the single PU on the most active neurons. Therefore, before looking at execution time and memory imprint we wanted to check this heterogeneity.

Table 2 presents classical elementary statistics on the simulated firing rates, whereas Figure 4 presents the corresponding densities. As one can see in Section 3, the system is initialized with a lot of neurons whose spontaneous spiking activity is null (see (1), with $\nu_i = 0$). The system needs to warm up to have almost all neurons spiking. This explains why the density at $T = 5$s is still rippled whereas, at $T = 50s$, it looks much smoother. As detailed in Section 3, the parameters of the Hawkes model (in particular the spontaneous spiking activity) have been fixed to achieve a certain stationary distribution of the firing rates (with mean 0.3Hz), which is heavy tailed to achieve records as large as 50 Hz. This is close to the distribution at $T = 50$ s. However these simulations show that, even if at $T = 5$s the system is not warmed up yet with a lot of non spiking neurons, one can still achieve the desired average firing rate and heterogeneity (extremal values) and that this does not vary a lot with T (see Table 2). Note that the density plots are roughly the same for all configurations: with ripples at $T = 5$s and smooth curves at $T = 50$s.

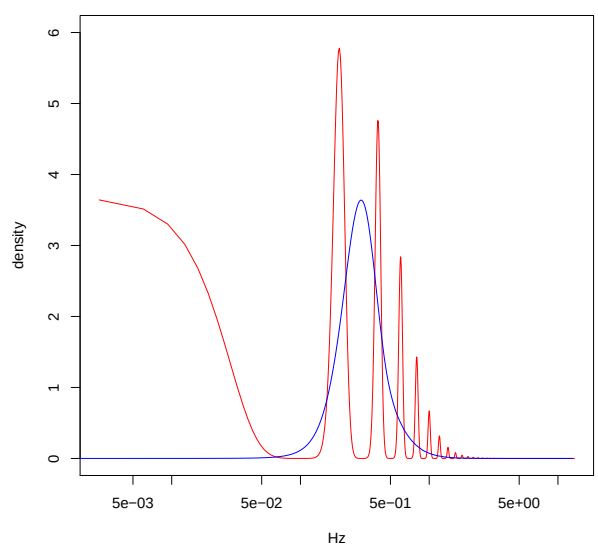


Figure 4: Densities (on a logarithmic scale) of the simulated firing rates in the network with $M = 10^6$ neurons and $d = 1000$ post-synaptic connections in average. In red, for $T = 5$s and in blue for $T = 50$s. These densities are obtained with a Gaussian kernel estimator with bandwidth 0.02 Hz.

M	d	Average freq.	Freq. min.	Freq. max.	Freq. std.	Percentage of non spiking neuron
1e5	250	0.279 (0.279)	0 (0)	14 (13.94)	0.315 (0.222)	31.2 (0.01)
1e5	500	0.334 (0.333)	0 (0.02)	6.6 (5.76)	0.328 (0.218)	23.5 (0)
1e5	1000	0.399 (0.398)	0 (0.04)	10.4 (11.64)	0.345 (0.220)	16.9 (0)
1e6	250	0.267 (0.267)	0 (0)	19.2 (20.84)	0.308 (0.217)	33 (0.01)
1e6	500	0.322 (0.324)	0 (0)	38.4 (39.38)	0.329 (0.225)	25.1 (0.00)
1e6	1000	0.383 (0.387)	0 (0.02)	13.4 (12.9)	0.344 (0.223)	18.5 (0)
5e6	250	0.26 (0.261)	0 (0)	27.4 (28.5)	0.307 (0.217)	34.1 (0.02)
5e6	500	0.315 (0.316)	0 (0)	34.2 (34.1)	0.324 (0.220)	26 (0.00)
5e6	1000	0.377	0	19.8	0.342	19
1e7	250	0.258 (0.259)	0 (0)	23.2 (21.62)	0.306 (0.217)	34.4 (0.02)
1e7	500	0.311	0	21.6	0.322	26.4
1e7	1000	0.374	0	21.8	0.342	19.3
5e7	250	0.253	0	38.2	0.304	35.4
5e7	500	0.305	0	50.6	0.321	27.2
1e8	250	0.251	0	46.2	0.303	35.7

Table 2: Firing rates elementary statistics (average, minimum, maximum and standard deviation) obtained by simulation for different sizes of neural networks and different numbers of synaptic connections and $T = 5s$. The number between parentheses displays the results at $T = 50s$. We were able to run these long simulations of 50s only for the less demanding set of parameters (typically not 10^7 neurons and 1000 synapses).

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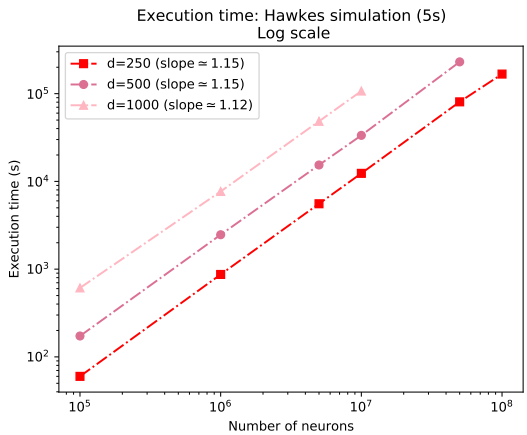
2.8 Execution times and memory usage

The simulation execution times are presented in Figure 5a for different M (number of neurons) and different d (average number of pre/post synaptic connections). The experimental execution times obtained are in agreement with (2): the curves (in the log scale) are almost linear, with slopes around 1.1, which corresponds to the theoretical growth in $dM\log(M)$ with respect to the number of neurons. Also since d, the number of post-synaptic connections, acts like a multiplicative factor, this explains the parallel equispaced lines in the log-scale.

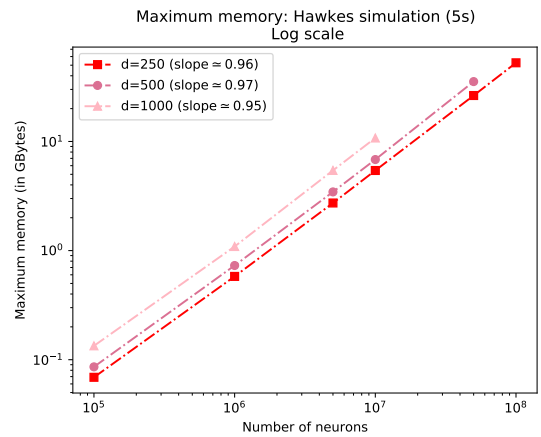
The total amount of used memory is displayed in Figure 5b. They are also in agreement with ATiTAP theoretical memory complexity, computed in Equation (4): it is almost linear in M, with slopes around 1, whatever d.

Note that a mouse cortex or a human hippocampus have roughly $M = 10^7$ neurons [53]. Figure 5 says that in this case, with $d = 1000$, we need a few hours and about 10 GigaBytes of memory

to simulate it. Because of the configuration we used, Figure 5 therefore shows that this could have been achieved on a simple desktop computer.



(a) Simulation execution times for different sizes of networks.



(b) Memory usages for different sizes of networks.

Figure 5: Simulation execution times (5a) and memory usage (5b) of ATiTAP for different sizes of networks.

3 Material and Method

3.1 Details on the model

For a set of M neurons, we first design the graph of interactions by saying that neuron j influences neuron i if a Bernoulli variable $Z_{j\to i}$ of parameter p is non zero. The resulting network is an Erdös-Rényii graph. Once the network is fixed, we design the spike apparition thanks to a Hawkes process (see (1), with $\Phi(x) = x$).

One of the advantage of (linear) Hawkes processes is that one can evaluate the firing rate distribution and that this evaluation only depends on the integral of the interaction function. In this sense, having piecewise constant functions, or shifted piecewise constant functions to take into account synaptic delays, or even more intricate (like exponential etc.) interaction functions, will absolutely not change the evaluations that are made as long as the integral is known (see Figure 1).

We are interested in a particular case of the Hawkes process where all the interaction functions

are always the same when they are non null. More precisely, we set the interaction function

$$h_{j\to i} = Z_{j\to i}\theta h,$$

where h is a fixed positive interaction function of integral 1 and θ is a tuning parameter that we need to calibrate to avoid explosion of the process. We also set $h_{i\to i} = 0$ (no self interaction). We take $h = 50 \times \mathbb{1}_{[0,0.02]}$, so that h is of integral 1 and non zero $h_{j\to i}$ are of integral θ.

Let us denote $H_{j\to i} = \int_0^{+\infty} h_{j\to i}(t)dt$ and $H = (H_{j\to i})_{i,j=1,\dots,M}$ the corresponding matrix (line i corresponds to a postsynaptic neuron, column j to a presynaptic neuron).

Hawkes processes may explode that is, it produces an exponentially increasing number of point per unit of time (see [8]), but this does not happen if the spectral radius of H is strictly smaller than 1 [20]. In this case, a stationary version exists and the corresponding vector of mean firing rates $m = (m_i)_{i=1,\dots,M}$ is given by

$$m = (I - H)^{-1}\nu. \tag{5}$$

Note also that if we start the simulation without points before 0 in this case, the process is not stricto sensu stationary but it converges to an equilibrium given by the stationary state and that the number of points that are produced in this case is always smaller than the stationary version.

Before running the simulation, we want to calibrate parameters so that (i) we avoid explosion and (ii) we reach a certain realistic heterogeneous distribution of the firing rates (vector m), that is an average around 0.3 Hz and records around 50 Hz. Both of these calibrations can be done mathematically beforehand in the Hawkes model: we can guarantee the behavior of the whole system even before performing the simulation, whereas this might be much more intricate for other models such as LIF.

3.2 Choice of θ or how to avoid explosion

Note that $H = \theta\mathcal{Z}$, with $\mathcal{Z} = (Z_{j\to i})_{i,j=1,\dots,M}$. So if we can compute the largest eigenvalue of $\mathcal{Z}$ or an upper bound, we can decide how to choose θ.

We can use Gershgorin circles [52] to say that any complex eigenvalue λ of $\mathcal{Z}$ satisfies (because

the diagonal is null),

$$|\lambda| \leq \max_{i=1,\dots,M} \sum_{j \neq i} Z_{j \to i}.$$

Therefore the spectral radius is upper bounded by $\max_{i=1,\dots,M} B_i$, where $B_i = \sum_{j \neq i} Z_{j \to i}$. This random quantity can be computed for small networks but it is clearly too intensive in our setting: indeed, with the procedural connectivity implementation, it is always easy to access the children ℓ of a given i, i.e. such that $i \to \ell$ is in the graph, but we need to look at all the neurons in the graphs to find out the set of parents j of i, i.e. such that $j \to i$ is in the graph. However, probabilistic estimates might be computed mathematically. Indeed B_i is a sum of i.i.d. Bernoulli variables. So by Bernstein's inequality [1], for all positive x,

$$\begin{aligned}
&\forall i = 1, \dots, M, \\
&\mathbb{P}(B_i \geq (M-1)p + \sqrt{2(M-1)p(1-p)x} + x/3) \leq e^{-x},
\end{aligned}$$

and, by union bound,

$$\mathbb{P}(\max_{i=1,\dots,M} B_i \geq (M-1)p + \sqrt{2(M-1)p(1-p)x} + x/3) \leq M e^{-x}.$$

Therefore for a fixed level α (say 1%), and with $x = \log(M) + \log(1/\alpha)$, we obtain that with probability larger than $1 - \alpha$, the spectral radius of $\mathcal{Z}$ is upper bounded

$$\rho_{\max} = (M-1)p + \xi_\alpha$$

with

$$\begin{aligned}
\xi_\alpha = \sqrt{2(M-1)p(1-p)[\log(M) + \log(1/\alpha)]} \\
+[\log(M) + \log(1/\alpha)]/3
\end{aligned}$$

Note that $\rho_{\max}$ is roughly $(M-1)p$, which is the largest eigenvalue of $\mathbb{E}(\mathcal{Z})$. Finally if we take $\theta < 1/\rho_{\max}$, the process will not explode with probability larger than $1 - \alpha$. In practice, to ensure a strong enough interaction, we take $\theta = 0.9\rho_{max}^{-1}$.

Choice of ν_i or how to constraint the distribution of the firing rates

The first step consists in deciding for a target distribution for the m_i's. We have chosen to pick the m_i's independently as $0.1X$ where X is the absolute value of a student variable with mean 3 and 4 degrees of freedom. The choice of the student variable was driven by the wish of having a moderate heavy tail, which will ensure records around 50 Hz and a mean around 0.3Hz.

The problem is that the m_i's are not parameters of the model, so we need to tune the ν_i's to get such m_i's. Note that by inverting (5), we get that

$$(I - H)m = \nu$$

(see also [42]) that is for all i

$$\nu_i = m_i - \theta \sum_{j \neq i} m_j Z_{j \to i}.$$

This means that the spontaneous rate that we need to put is the mean firing rate m_i minus what can be explained with the parents of i.

So in theory, the Hawkes model is very easy to tune for prescribed firing rates since there is a linear relationship between both. However, and for the same reasons as before, it might be too computationally intensive to compute this explicitly.

One possible way is to again use concentration inequalities, but this time on $\sum_{j \neq i} m_j Z_{j \to i}$ and not on B_i. However a simpler trick works well (as seen in Figure 4).

Indeed $\sum_{j \neq i} m_j Z_{j \to i}$ is a sum of about $(M-1)p \simeq 1000$ i.i.d variables with mean $\bar{m} = 0.3$Hz. Hence it should be close to $\bar{m} B_i$. With the previous computations, we know already that ν_i should therefore be larger than $m_i - \theta \rho_{\max} \bar{m}$.

Therefore, with the previous choice of $\theta = 0.9 \rho_{\max}^{-1}$, we take the ν_i's as follows:

$$\nu_i = \max(m_i - 0.9\bar{m}, 0).$$

Note that ν_i remains positive or null, which guarantees that the Hawkes process stays linear. However, this also means that a non negligible portion of the neurons start with a null spontaneous firing rate, which explains the ripples of Figure 4.

With this choice, we cannot hope to have exactly the same distribution as the desired m_i's, but it conserves the same heavy tail and roughly the same mean firing rate, as one can see on Table 2.

4 Discussion

The ATiTAP algorithm is based on Activity Tracking with Time Asynchrony and Procedural connectivity and is derived from another algorithm, ATiTA [31] which has a much higher memory cost. The aim of this study is a proof of concept that simulations of huge neuronal networks on single PU are possible and that this may open the way for a new point of view on neuronal simulations.

More specifically, we have been able to theoretically compute ATiTA(P) computational cost and memory burden (see Sections 2.3 and 2.4) and to perform simulations in a range of parameters that are of the order of magnitude of human brain areas or small mammalian whole brains (see Section 2.5). Moreover we have been able to reproduce a large heterogeneity in the firing rates (see Section 2.7) and to prove that on a desktop computer we can easily reach 10^7 neurons, that is the size a human hippocampus [53] or of a mouse.

Comparison with existing algorithms is tricky. First because the models are not completely equivalent (for instance Integrate-and-Fire in [19, 26] versus Hawkes for ATiTA(P)), second because the other algorithms use super-computers with massive parallel computations, thirdly because depending on the model, it is more or less difficult to compute theoretical memory and computational costs (see for instance [27, 24]).

In Section 2.1, we have shown the similarities and dissimilarities between Hawkes processes and Integrate-and-Fire. We believe that it is a matter of taste for preferring one to the other: Hawkes processes have been shown to fit real data (see [43, 40]), Integrate-and-Fire models have a nice voltage interpretation. But there are links between both, especially because the intensity of the process can be thought as a function of the voltage.

Besides the fact that Hawkes processes allow us to compute theoretical complexities, we believe that one of the main advantage of Hawkes processes is that they satisfy time asynchrony, which allows us to spend computational time only on the neurons that are very active. Let us quantify this more specifically. In Section 2.2, we have described in details the benchmark hybrid algorithm [19] versus ATiTA(P). The main burden with parallelization, even in the hybrid algorithm, is that PUs

have to wait for each other every discretization step T_{com}. The nice idea of the hybrid algorithm is that this step is not the thinnest possible but of intermediate size, so that this synchronization does not happen often ($T_{com} = 0.001$s in their case). Still, at every discretization step, the whole system has to check the state of all neurons, that is a total of MT/T_{com} operations just for the synchronization. For a classic network of $M = 10^6$ neurons and 1s of simulation, we end up with 10^9 operations, only for synchronization. To give an order of magnitude, ATiTA and ATiTAP have a complexity cost of 6×10^9 thanks to (2) for 1000 post-synaptic neurons in average, for the full simulation.

Table 3 compares both execution times and memory imprints of the latest simulations of large-scale spiking neural networks in the literature. Because the models are very close dynamically and structurally, it is a good way to evaluate roughly the memory and computational performances of corresponding simulators and hardware solutions. Indeed, simulations in [26, 46, 24] use LIF models that are dynamically very close to the Hawkes model used here (see Section 2.1). Structurally, we compare networks of similar size and connectivity. Remains the choice of the parameters. Comparing all corresponding simulations with respect to memory and computational costs should be easy to achieve analytically, if everyone provides the same parameter values (*cf.* Table 1) and both computational and memory complexities of their solutions. However, in [26, 46, 24] we were not able to find the mean firing network rate and there is no computational complexity except in [24], where only the memory complexity is provided. Still these simulations are meant to be biologically plausible and therefore should have been run on realistic parameter ranges. Hence they should be roughly comparable to ours. This comparison is thus a first baseline that can be further enhanced providing either firing rates or analytical complexities. In the mean time it is, as far as we know, the first attempt to unify both experimental and formal benchmarks in a common framework.

Let us now comment more precisely Table 3. In [27, 24], a Message Passing Interface (MPI) parallel process is attached to each computational node (or CPU). This decreases the memory usage of each node as well as the execution time but this comes with a huge total memory cost. Furthermore algorithms of [27, 46] are able to embed models of synaptic plasticity, which force the storage of the whole connectivity matrix, with the synaptic weights. This also explains the huge memory cost. The other work on procedural connectivity [26] drastically reduces both memory cost and execution times of the parallel simulations but it does not implement plastic synapses.

While all these works have used at least 1000 PUs, ATiTA(P) has been run with 10 times less synapses but on only one single PU. Thanks to the theoretical complexities (2) and (4), we can compute the theoretical scaling factor that should take place if the number of synapses is multiplied by 10.

Clearly the memory cost of ATiTAP is the lowest, even when we compare to [26], which is also using procedural connectivity. If we do the computation for ATiTA, and if we keep all interaction functions in memory, we obtain a memory cost comparable to [46]. Note that storing all the synaptic weights is a bottleneck that cannot be easily passed as soon as one wants to simulate synaptic plasticity, which is not the purpose of the present work.

The computational cost is clearly more important for ATiTA(P), at least by a factor 60, but this has to be put into perspective with the usage of at least 1000 PUs by the other algorithms, whereas ATiTA(P) only uses one.

Simulator	PUs	Size order	Memory	Execution time
NEST1 [46]	JUQUEEN 1024 CPUs	10^6 neurons 10^{10} plastic synapses	2 10^{12} Bytes	17min
NEST2 [24]	K with 8192 CPUs	10^6 neurons 10^{10} plastic synapses	huge*	16s
GeNN [26]	GPU with 4600 cores	10^6 neurons 10^{10} synapses	$10^{11} Bytes$	14.4min
ATiTAP (sim)	IRENE with 1 equivalent CPU	10^6 neurons 10^9 synapses	$10^9 Bytes$	25min
ATiTAP (th. est.)	IRENE with 1 equivalent CPU	10^6 neurons 10^{10} synapses	8.7 $10^9 Bytes$	36× 25min ≃ 15h
ATiTA (th.est.)	IRENE with 1 equivalent CPU	10^6 neurons 10^{10} synapses	2.8 $10^{12} Bytes$	36× 25min ≃ 15h

Table 3: Comparison of execution times and total memory cost for each simulator and comparable network sizes for 1s of biological time. For **NEST2**, comment on * : although the precise memory cost is not indicated in the study it is "huge" compared to other approaches described here: authors in the publication indicate a memory cost of 10^{15}Bytes for 10^9 neurons and 10^{13} synapses. For ATiTAP (see Section 2 and Figure 5) the case $d = 1000$, $M = 10^6$ corresponds to a total number of synapses of 10^9. To understand the theoretical scaling for ATiTAP and ATiTA with 10^{10} synapses, we apply for the computational cost, the theoretical multiplicative factor given by the ratio of (2) between $d = 10^4$ and $d = 10^3$. The same computation is done for the memory cost with (4) in the case where ρ and η are neglected and where $\omega = \epsilon$, that is same accuracy for a spiking time and an index in the network. Note that in **NEST1** and **NEST2**, synapses are plastic, that is, a certain form of update of the synaptic weights is embedded in the code.

So overall, our algorithm provides the best memory cost but not the best computational cost with respect to other existing methods, but this has to be put in perspective with respect to the purpose of simulations. Indeed, especially for randoms models (but this can also hold as soon as we want to test several set of parameters), the purpose of simulations is not to make just one simulation but to do replicas. In this sense, it is important to think that if we use the totality of the PUs to perform one simulation, doing replicas can only be done in a serial way. In this sense, ATiTA(P) allows us to have one PU per replica.

Table 4 gives an idea on how well ATiTA(P) could perform in terms of numbers of replicas with respect to the other algorithms, if we only consider the computational cost. If we think in terms of memory burden, one could easily perform thousand of replicas and still use about 10^{12} Bytes, with ATiTAP. The memory burden is on the other hand exploding for ATiTA.

Simulator	Number of PUs	Number of replicates in 15h	Number of replicates for ATiTA(P) with the same number of PUs
NEST1 [46]	1024	53	1024
NEST2 [24]	8192	3375	8192
GeNN [26]	4600	63	4600

Table 4: Comparison of the number of replicates that could be computed in 15 hours by each algorithm.

There is still room for improvements but this first proof of concept is promising. Among the several possible improvements, ATiTA(P) could be parallelized among the post-synaptic neurons (update and prediction of the next potential spikes). This is particularly important if we want to pass from $d = 10^3$ to $d = 10^4$ post-synaptic neurons in average (even if we showed that $d = 10^4$ seems not to be relevant for realistic simulations). Next, new algorithms for Hawkes processes, based on Kalikow decomposition, have been proved to work even if the neuronal network is infinite [39]. This would theoretically decrease the overall complexity in terms of d. Finally, if we want to have synaptic plasticity, we are forced to work with ATiTA and varying non zero interaction functions that need to be stored. Once they are stored, the update of these functions seems to be as costly that the update of the intensities themselves (see for instance [25] where only local firing rates are needed). This is definitely a source for future work.

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