Modeling organization of spiking neural nets in DEVS for high performance parallel simulation

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Introduction

- Discrete events already used for the modeling and simulation of neural nets (Brette *et al.* , 2007).
- With DEVS: Original neuron models (Zeigler, 2005) or to abstract neural nets (Zeigler, 1975).
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- Markov model components as DEVS pseudorandom systems
- Markov matrix models to predict the speed-up of parallel simulations
- Application to symmetric multiprocessor (SMP)
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Neuron dynamic model

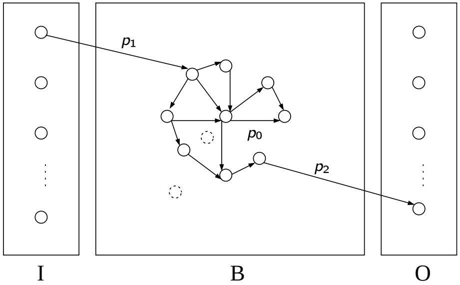
Usual *leaky integrate-and-fire model*, at time $t \in \mathbb{N}$, the *membrane potential* $s(t) \in \mathbb{R}$ of a neuron consists of:

$$s(t) = \begin{cases} rs(t-1) + \Sigma_{j=1}^{m} w_j x_j(t) & \textit{if } s(t-1) < \tau \\ 0 & \textit{otherwise} \end{cases}$$

with $r \in [0, 1]$ the *remaining coefficient*, w_j the *synaptic weight* from neuron j.
Spike emission $x(t)$ depends on *threshold* $\tau \in \mathbb{R}^+$:

$$x(t) = \begin{cases} 1 & \textit{if } s(t-1) \geq \tau \\ 0 & \textit{otherwise} \end{cases}$$

Neuron graph model



Parallel simulation

- Simulation parameters
  - probabilities: $p_1 = p_2 = 0.9$, $p_3 = 0.5$, p_0: variations,
  - all *high activity* neurons: $a = r = 1$, each threshold $\tau_i \sim \mathcal{N}(m, \sigma^2)$, with $m = 20$ and $\sigma = 1$
  - Generator period: *1*
  - No internal couplings inside input and output layers
- Parallel implementation
- Multithreaded SMP machine (80 physical cores, 160 logical ones)
  - Each coordinator with own parallelized scheduler
  - DEVSJava extension

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Parallel simulation

- Variations of:
  - Number of threads (1,5,10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160)
  - probability p_0 (internal coupling of middle layer)
  - Number of neurons in each layer (1, 5, 10, 100, 500)
- Model each coupled model execution time reduction

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Preliminary results

Input layer (simple stochastic generators)

Nb of neurons in middle layer	Elapsed time one thread	Best time	Speed-up ratio
1	0,520717	0,420232	1,2391179158
5	0,495051	0,495051	1
10	0,52735	0,52735	1
100	0,661288	0,661288	1
500	5,65755	5,65755	1

Rk: Each result is replicated 20 times with good confidence interval

Preliminary results

- Middle layer (send/receive neurons with int. couplings)
- gain = proba*NbNeurons

Proba	0,1			
Nb of neurons in middle layer	Elapsed time one thread	Best time	Speed-up ratio	proba*NbNeurons
1	-	-	-	0,1
5	0,369873	0,369873	1	0,5
10	0,326683	0,326683	1	1
100	1,77223	1,352	1,3108210059	10
500	44,4226	25,8828	1,7162980821	50

Proba	0,9			
Nb of neurons in middle layer	Elapsed time one thread	Best time	Speed-up ratio	proba*NbNeurons
1	-	-	-	0,9
5	0,400321	0,400321	1	4,5
10	0,403413	0,403413	1	9
100	2,7502	1,58617	1,7338620703	90
500	75,207	35,8044	2,1004960284	450

Preliminary results

Output layer (simple receiving neurons)

Nb of neurons in middle layer	Elapsed time one thread	Best time	Speed-up ratio
1	-	-	-
5	0,089175	0,089175	1
10	0,122071	0,122071	1
100	1,25386	0,860517	1,4571007894
500	32,2965	13,4208	2,4064511803

Sum-up

All layers

P0=0,1					P0=0,9		
Neurons	Input	middle	output		input	middle	output
5	0,50	0,37	0,89		0,45	0,40	0,16
10	0,53	0,33	0,12		0,49	0,40	0,18
100	0,66	1,77	1,25		0,52	2,75	1,31
500	5,66	44,42	32,30		6,12	75,21	32,44

Conclusion

- Simulations with more overhead are running
- First model of random graph based coupled models run in parallel
- Next steps [test composition of Markov models (of each layer)]:
    - Collect new results and achieve better models
    - Account for negative weights percentage for the gain (proportional)

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