FACETS

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Fast Analog Computing with Emergent Transient States

Deliverable D17
Report on hardware simulations of single-cell and network benchmarks

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DELIVERABLE SUMMARY SHEET

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Short description:

The whole hardware system developed in WP6 is used for network simulations. In this deliverable, we study the activity of excitatory neurons network with all-to-all connectivity and STDP algorithm, and the influence of synaptic noise inputs with different rates and different correlations. We present some results among more than one hundred simulations.

Partners owning: ENSEIRB (3)

Partners contributed: ENSEIRB (3) CNRS (6a)

Made available to: all

I. Overview

This report details the execution of the Task1 described in WP6. For this task, ENSEIRB (Partner 3) and Alain Destexhe's Group (CNRS – Partner 6a) work in closed collaboration for the single cell simulations and to define network benchmark experiments. In this report, we will first describe the single-cell simulations and then we will present the network topologies features and a STDP algorithm which is implemented for the experiments. Next, we will describe the experimental protocols for the network tests. At last, we will present the associated results.

II. Single Cell Simulations

The implemented model is based on the Hodgkin-Huxley formalism. The detailed model presentation was already done in D18 (WP6) [1] and the behaviors comparison between our ASIC and software was done in D15 (WP5) [2]. We briefly present here the previous results to easier introduce network simulations (see Figure 1).

The hardware neuron contains two ionic channels (sodium and potassium) and one leak channel. This configuration authorizes to simulate fast spiking neurons (FS). A third ionic conductance has been implemented to simulate regular spiking neurons (RS). This conductance named modulator channel and noted I_{mod} emulates the calcium channel and the calcium-dependent potassium channel, in other words emulates a slow voltage-dependent potassium conductance for spike-frequency adaptation. The maximal conductance value is chosen among four possibilities: RS0 for $gmax\_I_{mod}$ = 45,5 mS / cm²; RS1 for $gmax\_I_{mod}$ = 90,9 mS / cm²; RS2 for $gmax\_I_{mod}$ = 136,4 mS / cm² and RS3 for $gmax\_I_{mod}$ = 181,8 mS / cm².

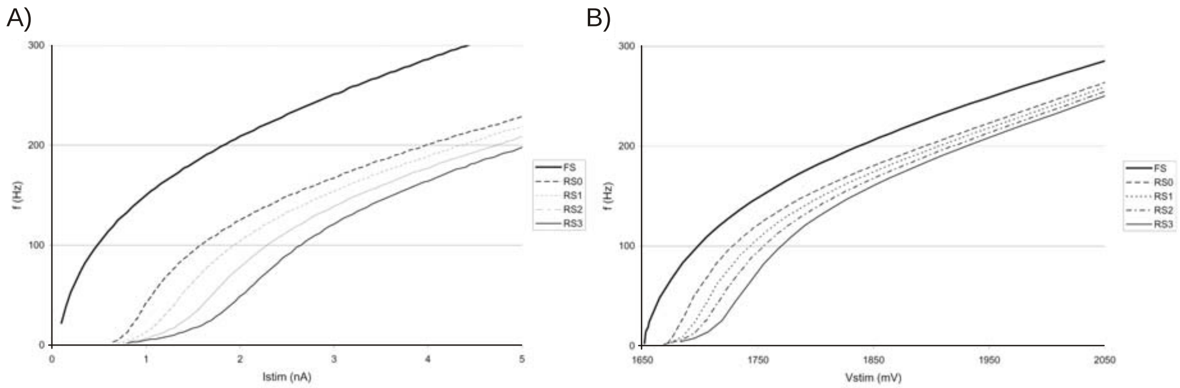

Figure 1: Frequencies vs stimulation current curves for software and hardware models. The behavioral differences between software and hardware are due to fabrication process mismatch. A) Software simulations. B) Hardware simulations where Vstim is the applied voltage on the ASIC. On this chip generation, we can not measure the current stimulation for an applied voltage.

III. NETWORK AND STDP FEATURES

NETWORK FEATURES

The network is composed of 6 excitatory neurons which can be connected by synapses. The modeled synapses implement kinetic model of glutamate [3] (only excitatory synapses are functional). This synapses model is designed such as to compute any number and frequency of pre-synaptic signals, and therefore can represent multiple synapses. This model uses "exponential" synapses, where the synaptic conductance increases of a given "quantal conductance" when a pre-synaptic spike occurs, then relaxes exponentially to zero. The associated post-synaptic current I_{SYN} is given in (1) and (2), where g_{MAX} is the maximal conductance, E_{SYN} the reverse synaptic potential, V_{MEM} the post-synaptic membrane potential, r the fraction of receptors in open state, α and β voltage-independent forward and backward rate constants, [T] the transmitter concentration.

$$I_{SYN} = g_{MAX} .r.\left(V_{MEM} - E_{SYN}\right) \quad (1) \qquad\qquad \frac{dr}{dt} = \alpha\left[T\right].(1-r) - \beta.r \quad (2)$$

Figure 2 illustrates the time-variation of the synaptic conductance g when a transmitter concentration pulse [T] occurs, assuming that the transmitter is released when a pre-synaptic action potential appears. As the quantum Δg is proportional to the Δt pulse width, this later parameter will be exploited to modulate Δg.

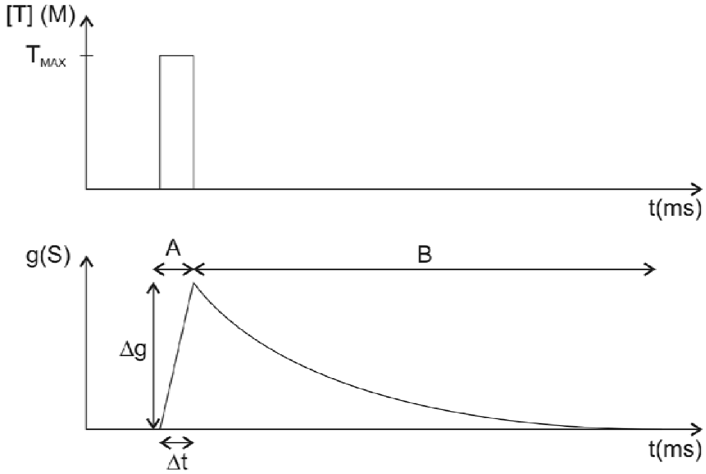

Figure 2: Exponential decay synapse principle

STDP FEATURES

Plasticity rules are only applied to excitatory synapses, according to spike-timing dependent plasticity algorithms (STDP) [4] [5], where the synaptic weight varies as a function of the relative timing of pre- and post-synaptic spikes. For a synaptic weight ω_{ji} from pre-synaptic neuron j to post-synaptic neuron i, the implemented algorithm follows the equation (3)

$$\frac{d\omega_{ji}}{dt} = -\varepsilon_i \varepsilon_j \left[F_{LTP}(t).\left(\omega_{ji} - \omega_{LTP}\right) + F_{LTD}(t).\left(\omega_{ji} - \omega_{LTD}\right)\right] \quad (3)$$

ε_i and ε_j are spike eligibility factors account for non-linear interactions arising for multiple pairs. They are implemented with the equations (4) and (5)

$$\varepsilon_i = 1 - \exp\left[-\left(\frac{t - t_i^{last}(t)}{\tau_s^{post}} \right) \right] \quad (4) \qquad \varepsilon_j = 1 - \exp\left[-\left(\frac{t - t_j^{last}(t)}{\tau_s^{pre}} \right) \right] \quad (5)$$

where $\tau_s^{pre} = 28\,\text{ms}$, $\tau_s^{post} = 88\,\text{ms}$ and $t_k^{last}(t)$ gives the time of the last spike in neuron k.

$F_{LTP}(t)$ and $F_{LTD}(t)$ are functions describing the coincidence between pre- and post-synaptic spikes.

$$F_{LTP}(t) = \sum_{t_i, t_j} A_P.\exp\left(-\frac{t - t_i}{\tau_P} \right).\delta(t - t_i) \quad (4)$$

$$F_{LTD}(t) = \sum_{t_i, t_j} A_Q.\exp\left(-\frac{t - t_j}{\tau_Q} \right).\delta(t - t_j) \quad (5)$$

where $\tau_P = 14{,}8\,\text{ms}$, $\tau_Q = 33.8\,\text{ms}$, $A_P = 0{,}1$ and $A_Q = 0{,}05$. These functions define time window of interactions between spikes, in other words they define the time "STDP function".

The hardware system authorizes hard bounds which are digital values: 0 and 255.

The soft bounds, ω_{LTP} and ω_{LTD}, are respectively the maximal and minimal values of the synaptic weight that can be computed by STDP algorithm, and their values obviously belong to the interval defined by the hard bound limits. We have no possibility to measure the synaptic current following the digital synaptic values. Then we can only analyze the results from a qualitative point of view. This inconvenient will disappear in the next hardware system generation.

IV. EXPERIMENTS METHODOLOGY

EXPERIMENTS DESCRIPTION

We have chosen to study the activity of excitatory neurons network with all-to-all connectivity and STDP algorithm, and the influence of synaptic noise inputs with different rates and different correlations.

A) In first time, we define input uncorrelated Poisson-trains with different rates (2.5 , 5 , 7.5 , 10 & 15 Hz) for each neuron. We use these synaptic noise patterns with all-to-all network, synaptic weights initially equal to zero and the STDP described above. For 5 minutes, we record spike trains from all neurons and the evolution of synaptic weights.

B) In second time, we use the same noise patterns and STDP algorithm but the initial synaptic weights are not equal to zero. We did one trial with all weights equal to maximal value (soft bound) and three trials with randomized initial values. We record the same outputs for the same duration.

C) In third time, we change the correlation between synaptic inputs noise. With different correlation rates, we used the same protocols: different noise rates, different initial weights. These parameters are identical than in the both simulations A) and B).

SYNAPTIC NOISE GENERATION WITH DIFFERENT CORRELATION RATES

To define the synaptic noise, we generate time intervals following Poisson distribution. The mean value of time intervals corresponds to the synaptic noise period. For a network of 6 neurons with uncorrelated synaptic noise, we generate 6 independent Poisson distributions. For correlated noise, we generate one Poisson distribution of time intervals, and then we add the intervals to obtain an absolute time distribution. For each event of the Poisson distribution, we generate 6 events (one event per neuron) following Gaussian distribution. The correlation rate between synaptic noises depends on Standard Deviation. The correlation decreases when the SD grows.

V. RESULTS

With all different initial conditions, we obtain more than one hundred results. The computational core (ASIC) is analog then it is necessary to performed several simulations for the same initial conditions. We obtain then several hundred simulations. We present here some results to illustrate the influence of the synaptic noise correlation in STDP efficiency.

We ran the simulation for different noise frequencies, for different initial weights (null, maximal and randomized) and for different correlation rates. The figures 3 to 6 illustrate the instantaneous frequencies of the 6 neurons (above) and the 36 synaptic weights (below). Each simulation lasts 360 seconds in real time.

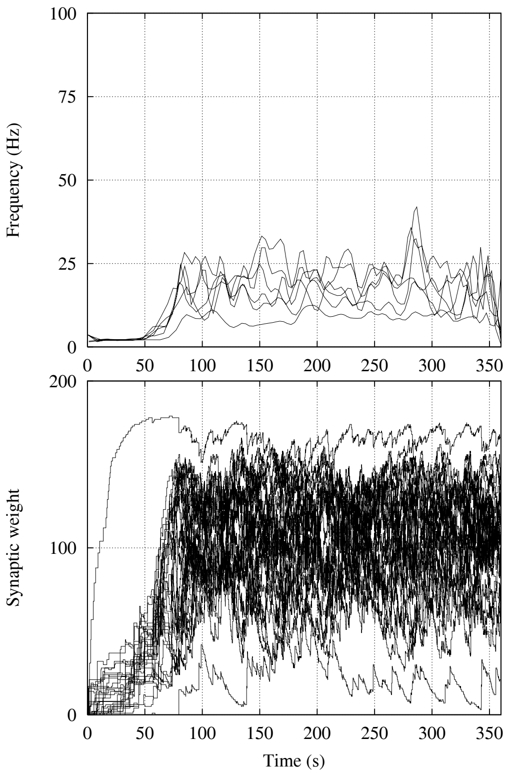

Figure 3: Synaptic noise frequency = 10 Hz; uncorrelated noise and null weights initially.

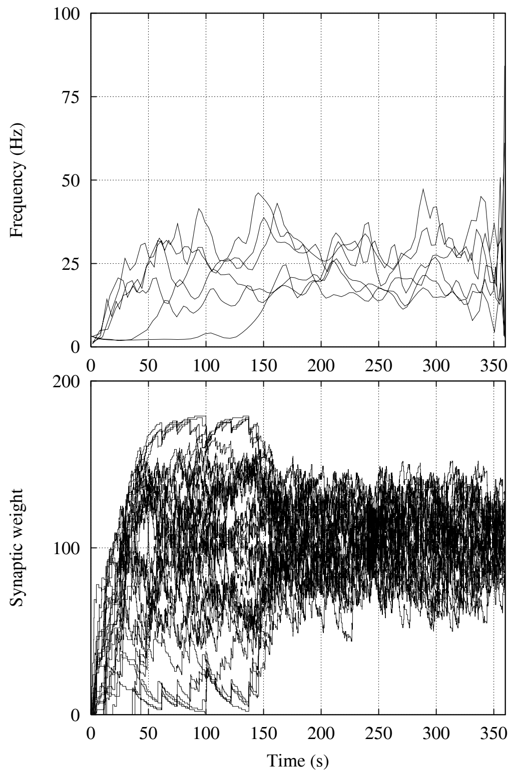

Figure 4: Synaptic noise frequency = 10 Hz; correlation noise = 80 % and null weights initially.

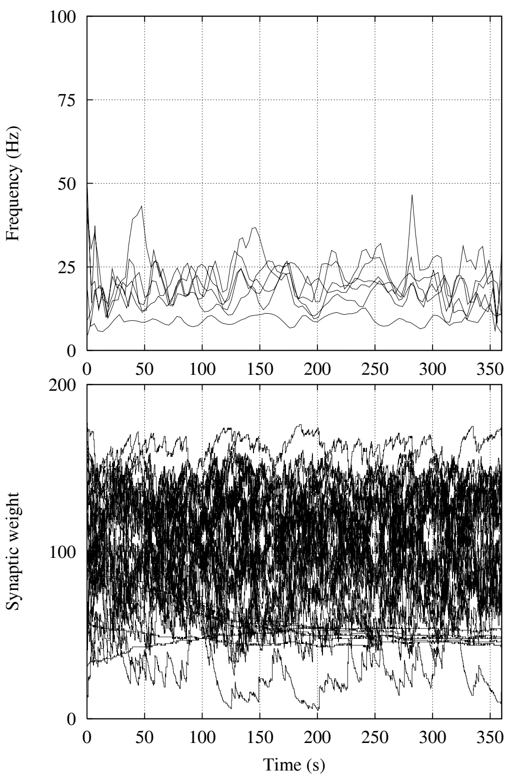

Figure 5: Synaptic noise frequency = 10 Hz; uncorrelated noise and randomized weights initially.

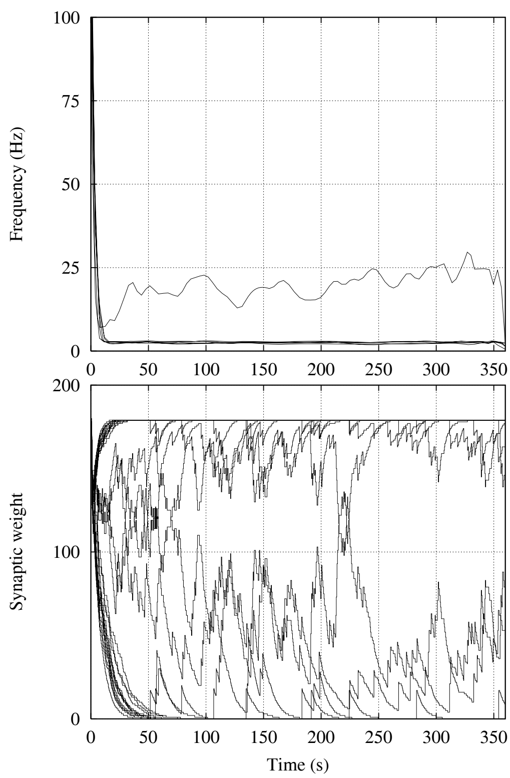

Figure 6: Synaptic noise frequency = 10 Hz; correlation noise = 100 % and maximal weights initially.

The figures 7 to 9 show the output mean frequency of the 6 neurons versus the input synaptic noise frequency. In each one, we show the 5 cases: uncorrelated, correlation at 20%, 50 %, 80 % and 100% for the synaptic noise patterns.

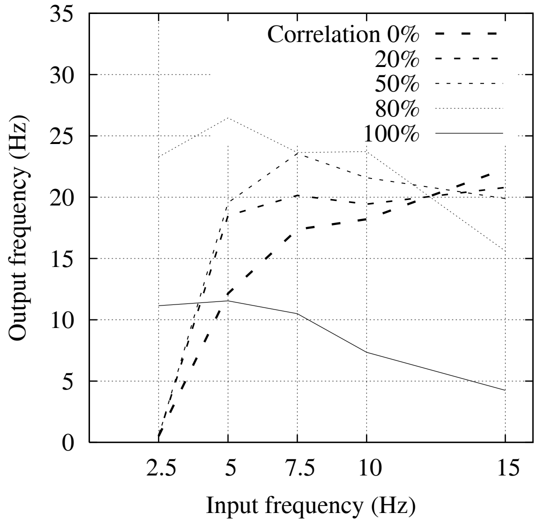

Figure 7: Neurons output mean frequency versus input noise frequency with null weights initially.

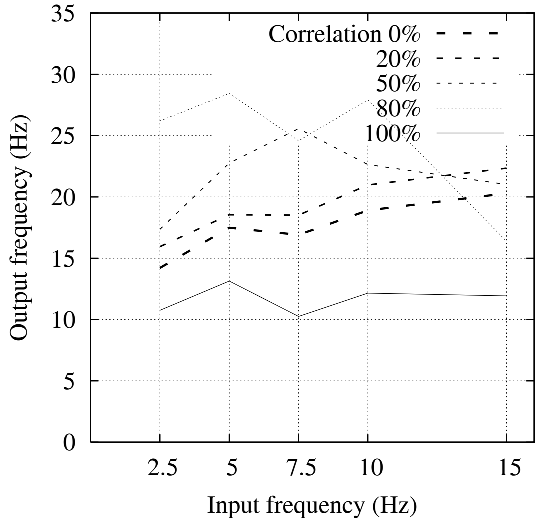

Figure 8: Neurons output mean frequency versus input noise frequency with randomized weights initially.

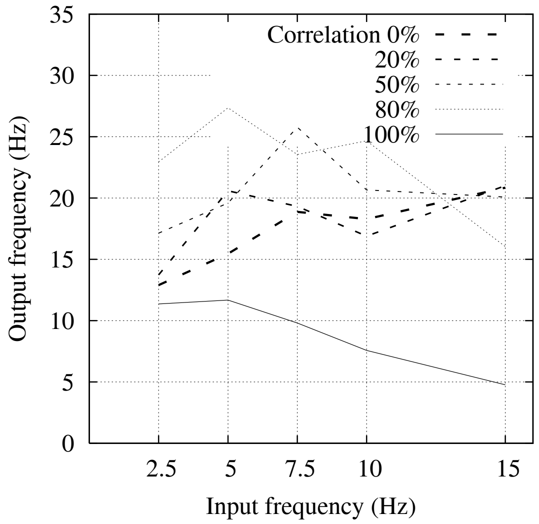

Figure 9: Neurons output mean frequency versus input noise frequency with maximal weights initially.

VI. CONCLUSION

We present in this deliverable some results among more than one hundred of them. Currently we implement a part of these simulations on the Neuron software to establish a benchmark of our hardware system with STDP. In collaboration with Partner 6A, we are also working at building tools to analyze the results.

VII. References

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