Analogue circuits of a learning spiking neuron model

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Introduction: Biological neurons communicate via sequences of calibrated pulses or spikes. The behaviour of spiking neurons is the following: input spikes from pre-synaptic neurons are weighted and summed up yielding a value called membrane potential. The membrane potential is time dependent and decays when no spikes are received by the neuron. If however spikes excite the membrane potential sufficiently so that it exceeds a certain threshold, a spike is emitted and transmitted through its axon via synapses to other neurons. After the emission of a spike the neuron is unable to spike again for a certain period called refractory period.

Recently, a new theoretical formulation has been proposed by Gerstner [1]. The computational power of neural networks based on temporal coding by spikes, rather than on the traditional interpretation of analogue variables, has been investigated by Maass [2]. It is shown that simple operations on phase-differences between spike-trains provide a powerful computational tool.

The integrate-and-fire model: Spiking neuron models are biophysical models which try to take properties of real neurons into account without descending to the level of ionic current but by modelling the integrated signal flow through part of the neuron.

Let N be a network of spiking neurons and assume that each neuron $i \in N$ has a set P_i of n_i immediate pre-synaptic neurons. Let F_i be the set of all firing times $t_i^{(f)}$ for neuron $i \in N$. In the case of the integrate-and-fire model, neuron i activity depends on its membrane potential $u_i(t)$ and its stimulation current $I_i(t)$ as shown in figure 1.

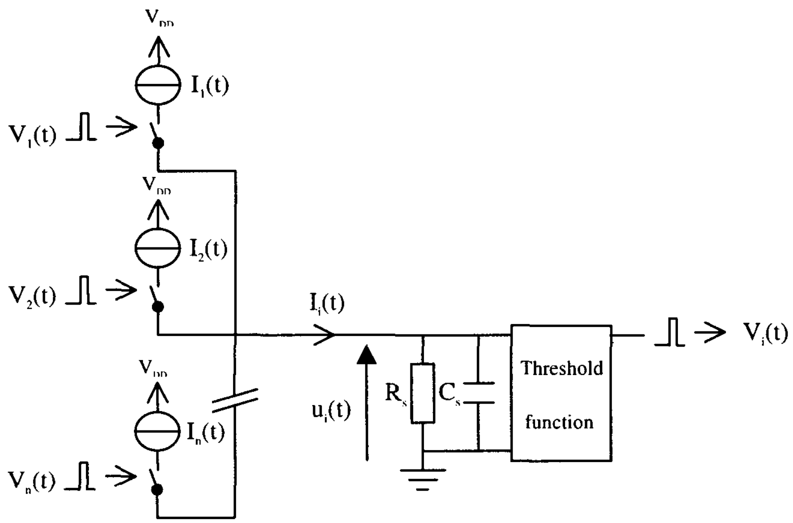

Figure 1: integrated-and-fire model

Let's consider now an input spike emitted by neuron $j \in P_i$. Its current contribution is:

$$I_j(t) = w_{ij}\alpha\left(t - t_j^{(f)}\right) \tag{1}$$

The synaptic weight w_{ij} defines the amplitude of $I_j(t)$ and α its shape versus time. Thus, the membrane potential $u_i(t)$ varies according to:

$$R_s C_s \frac{du_i}{dt} + u_i(t) = R_s \sum_j \sum_{t_j^{(f)}} w_{ij}\alpha\left(t - t_j^{(f)}\right) \tag{2}$$

Finally, neuron i fires when

$$u_i(t) = \sum_{j \in \Gamma_i} \sum_{t_j^{(f)} \in F_j} w_{ij}\varepsilon_{ij}(t - t_j^{(f)}) + \sum_{t_i^{(f)} \in F_i} \eta_i(t - t_i^{(f)}) \tag{3}$$

reaches the threshold value θ. ε_{ij} models post-synaptic potentials at the soma of neuron i, which result from the firing of neuron j at time $t_j^{(f)}$. η models the response of neuron i to its own firing.

Proposed circuits: Many hardware implementations of neural networks using pulsed computation have been developed by researchers [3] [4]. One of the main reasons for using analogue electronics to realise neural network hardware is that several of the operations in neural networks can be carried out by simple circuits. In order to be realistic, analogue VLSI neural networks must be based on low-precision computations of relatively simple processing elements [5] as are biological neural systems and use asynchronous signalling throughout the system.

In figure 2, we show the synapse circuit connecting neuron j to neuron i.

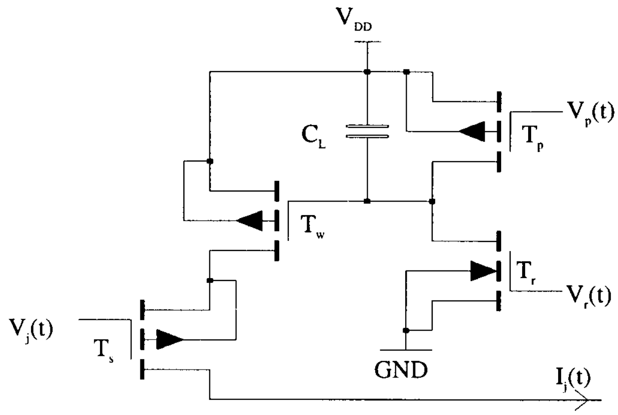

Figure 2: neural input circuit

T_s operating in saturated mode acts as power supply "on/off" switch for synaptic current $I_j(t)$. Since T_s is controlled respectively by the pulse stream output signal $V_j(t)$ from neuron j, the more frequently asynchronous negative pulses arrive at T_s, the more charges are transferred to C_s. T_w behaves as current source and consequently determines the synaptic weight between neurons i and j. Amplitude of the current pulse depends on C_L charge which can be modified by $V_r(t)$ and $V_p(t)$.

As shown in figure 3, weighted synaptic currents $I_1(t)$, $I_2(t)$,..., $I_n(t)$ are summed via Kirchoff's current law to form the input current $I_i(t)$ which is integrated on C_s and give an activity which depends on statistically distributed events occurring asynchronously in time. T_t is used as pulse generator. Thus, with time, $u_i(t)$ increases, eventually reaching T_t threshold θ, causing C_s to discharge through R_p. When C_s voltage reaches the lower threshold, the pulse is complete. In a biological context, T_t simulates the threshold-function in a manner which is acceptable to many neurobiologists as being reasonably realistic for a biological neuron.

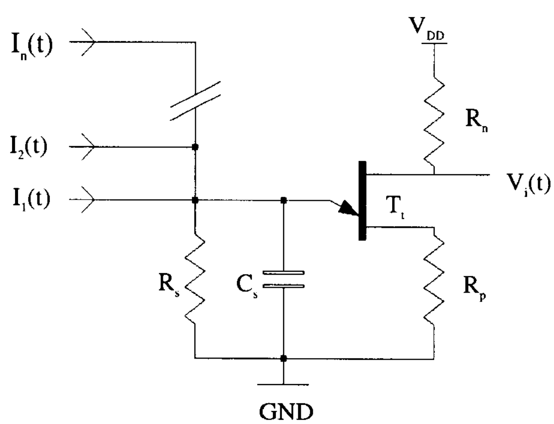

Figure 3: neuron circuit

Simulation: We have simulated a neuron i fully connected to 5 pre-synaptic ones. These 5 neurons receive analogue voltages and transmit short negative pulses $V_1(t),\ldots,V_5(t)$ to neuron i, encoding external information in frequency. To do this, their input electronic circuit differs from other. Additionally, we set w_{i5} to its maximum value at t=200µs and reset w_{i1} to its minimum one at t=500µs to simulate some learning rule.

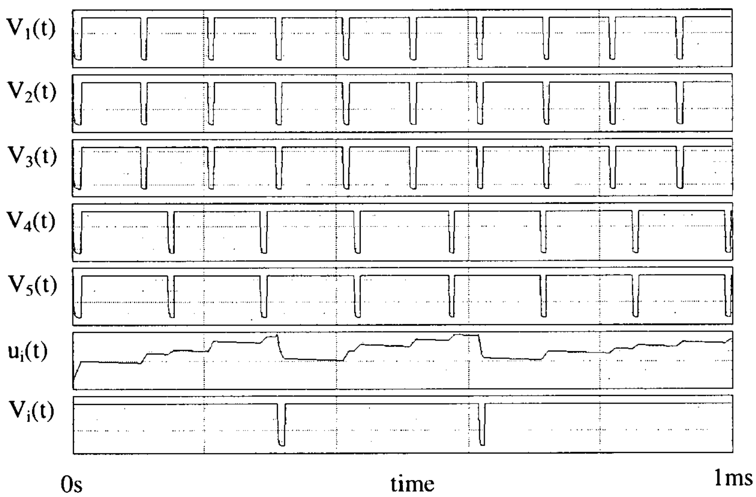

Figure 4: snapshot of simulation results

Results: Inputs voltages, the membrane potential $u_i(t)$ and the output voltage $V_i(t)$ of neuron i are presented in figure 4. Negative pulses instead of positive ones are used to transmit information between neurons which does not appear restrictive in computation. We have deliberately synchronised inputs to show that our model really takes coincidence of spikes into account. Thus, we see that our model has the capability to process signals that have both temporal and spatial significance.

Moreover, it appears that weights modifications clearly affect the current contribution of concerned inputs and consequently the potential membrane of neuron i. Furthermore information can be encoded by using the timing of spikes with frequencies ranging from 1 to 10kHz. Obviously, computation speed, spike characteristics and threshold voltage θ might be scaled-up to be more realistic. However, because of the analogue nature of our model, we estimate that its general behaviour is more important than absolute accuracy.

Conclusions: We have presented a spiking neuron model based on an original analogue circuit. Its behavioural properties have been studied. Computation is based on the explicit firing times of neurons instead of the more common firing rate of neurons. Synaptic weights can simply updated according to the chosen learning rule. Furthermore, our electronic scheme is attractively compact enough to enable an easy integration. Thus, an integrated circuit including a neural network based on our model should soon appear.

References

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