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Competitive and Temporal Inhibition Structures with Spiking Neurons

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Abstract. The paper describes the implementation of competitive neural structures based on a spiking neural model that includes multiplicative or shunting synapses enabling non-saturated stable states in response to different stationary inputs as well as controllable transient responses. A VLSI-viable implementation of this model has been previously proposed and tested [1]. It has the possibility of modulating the output spike frequency by an additional input without affecting other neuron variables such as the membrane potential. This feature is exploited in the simulation of a Selective Temporal Inhibition network that is suitable for implementing attentional control systems.

Key words: spiking neurons, competitive processing, temporal inhibition, attentional control mechanisms, bio-inspired neural systems.

1. Introduction

In the approach presented here, the main motivation for using spiking neurons arises from the implementation issues. An inter-neuron communication scheme based on instantaneous events that can be multiplexed in shared connection channels enables to take advantage of inter-chip communication schemes [2–6] that make multiple-chip architectures viable. Furthermore, the incoming pulses can be directly integrated at the target synapses, thus enabling single synapses to process spikes from several source neurons, therefore reducing the number of synapse modules required to implement convergent synaptic trees, like the many-to-many connections required in on-centre–off-surround topologies.

A competitive structure based on the cell model described in Section 2 is simulated. In some perception processing schemes like saliency maps [7], competition between the different features extracted makes it possible to perform selective attentional control that can drastically reduce the reaction times in complex environments. An attentional shifting mechanism, based on Selective Temporal Inhibition (STI) structures, is also simulated in Section 3. This attentional mechanism takes advantage of the representation provided by a competitive structure in which different intermediate states of active nodes are preserved and taken into account. A competitive layer made up of the proposed STI elements selectively inhibits the firing nodes in response to a global reset signal giving a chance to other less active nodes.

Section 2 of the paper briefly presents the neuron model; Section 3 describes simulation results of a competitive structure and a Selective Temporal Inhibition node based on the presented neuron model. Section 4 summarises some concluding remarks.

2. Neuron Model

2.1. GLOBAL NEURON DESCRIPTION

The schematic diagram of the neuron model is shown in Figure 1, where $F_j^{+/-}$ and $F_i^{+/-}$ denote the spike frequencies at the respective frequency-controlled current-sources and conductances. F_R is a frequency input to set the leakage or passive decay term of the neuron. The output circuit can be seen as a Voltage to Frequency Converter (VFC); it converts the membrane potential into short voltage pulses to interact with other cells.

The membrane potential V_x at the capacitance C_x represents the state of the cell. Inputs and contributions from other neurons are integrated through several synapses that can be modelled as frequency controlled current sources (FCI) or as frequency controlled conductances (FCG). A cmOS circuit implementation of this neuron model has been previously proposed and tested in [1], illustrating its controllable transient responses to well-defined neuron states.

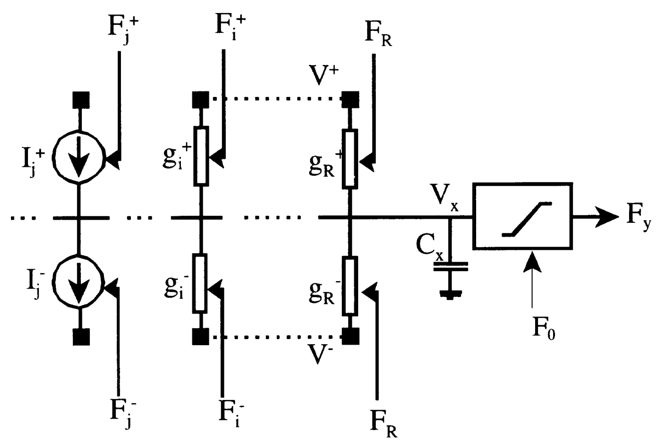


Figure 1. The cell model includes frequency controlled current sources (FCI) and frequency controlled conductances (FCG); these two modules are used as additive and shunting synapses respectively, integrating the input contributions into a membrane capacitance (C_x). An output circuit converts the membrane potential (V_x) into short voltage pulses that are transmitted to other neurons. Two shunting synapses (g_R^+ and g_R^-) receiving a constant input frequency (F_R) can be used to implement the passive decay term that leads the membrane potential to a well defined resting state (V_R) in the absence of other input stimuli.

2.2. SYNAPTIC MODULES

An excitatory FCI synaptic module changes the membrane potential by a constant factor, according to Equation (1), each time it receives a spike. Therefore a neuron receiving only a constant input frequency of spikes through one of these modules responds with a linear excitation transition up to the high saturation level.

$$\Delta V_x = B \cdot (V^+ - V_{ref}) \tag{1}$$

B is a constant factor defined by the particular implementation of the module, V^+ is a reference voltage that works as the upper limit of the membrane potential and V_{ref} is a reference input that can be used, in the case of FCI modules, to modulate the synaptic weight.

The way an excitatory FCG synaptic module changes the membrane potential for each received spike is described by Equation (2).

$$\Delta V_x = D \cdot (V^+ - V_{X0}) \tag{2}$$

V_{X0} is the initial membrane potential when the input spike reaches the synapse. Therefore the contribution of each pulse depends not only on the synaptic weight (in this case controllable only by the factor D) but also on the current neuron state (V_x).

Assuming small contributions of single spikes in the different synapses, the dynamics of the different modules of Figure 1, i.e. Frequency Controlled Conductances (FCG) and Frequency Controlled Current Sources (FCI), can be approximated by the differential Equations (3).

$$\begin{aligned}
\mathrm{FCG}_{\mathrm{Exc}} &: \tfrac{dV_x}{dt} = D_i^+ \cdot (V^+ - V_x) \cdot F_i^+ \\
\mathrm{FCG}_{\mathrm{Inh}} &: \tfrac{dV_x}{dt} = -D_i^- \cdot (V_x - V^-) \cdot F_i^- \\
\mathrm{FCI}_{\mathrm{Exc}} &: \tfrac{dV_x}{dt} = B_j^+ \cdot (V^+ - V_{r,j}) \cdot F_j^+ \\
\mathrm{FCI}_{\mathrm{Inh}} &: \tfrac{dV_x}{dt} = -B_j^- \cdot (V_{r,j} - V^-) \cdot F_j^-
\end{aligned} \tag{3}$$

Thus, for a neuron such as the one shown in Figure 1, with excitatory and inhibitory synapses, including FCI and FCG ones, and a pair of FCG synaptic modules (with factors D_R^+ and D_R^-) implementing the leakage or passive decay term, the cell dynamics can be approximated by the differential Equation (4),

$$\begin{aligned}
C_x \cdot \frac{dV_x}{dt} &= -g_R(F_R) \cdot (V_x - V_R) + \sum_{j,exc} B_j^+ \cdot (V^+ - V_{r,j}) \cdot F_j^+ \\
&- \sum_{j,inh} B_j^- \cdot (Vr,j - V^-) \cdot F_j^- + \sum_{j,exc} D_i^+ \cdot (V^+ - V_x) \cdot F_i^+ - \sum_{i,inh} D_i^- \cdot (V_x - V^-) \cdot F_i^-
\end{aligned}$$

where

$$g_R(F_R) = D_R^+ \cdot F_R + D_R^- \cdot F_R \quad ; \quad V_R = \frac{D_R^+ \cdot F_R \cdot V^+ + D_R^- \cdot F_R \cdot V^-}{D_R^+ \cdot F_R + D_R^- \cdot F_R} \tag{4}$$

$V_{r,l}$ are the specific reference voltages of FCI synaptic mocules, and the resting state (V_R) and conductance (g_R) are set by means of two FCG synapses receiving a constant pulse frequency (F_R). Equation (4) describes a general model that can be simplified if the neuron includes only FCI or only FCG synapses. In fact, the equation can be rewritten in terms of only linear contributions by rearranging the multiplicative terms to include the factors $D_i^+ \cdot V^+$ and $D_i^- \cdot V^-$ in the passive-decay term. However, in its present form, the model allows an independent control of the passive-decay and the synaptic time constants, making short-term memory states (i.e. high passive-decay time constant) compatible with fast responses to input stimuli [8]. This feature is exploited in the STI structure of Section 3.

2.3. OUTPUT MODULE

The output spikes of the neuron are produced by a module [1] that behaves as a Voltage to Frequency Converter (VFC) with a pseudo-linear characteristic function described by Equation (5),

$$\mathrm{VCF}_{\mathrm{NeuronOutput}} : F_y(V_x) = A \cdot (V_x - V_{th}) \cdot F_0 \tag{5}$$

where V_{th} is a reference voltage that acts as the firing threshold and F_0 is a reference frequency which can be used to control, in a multiplicative way, the neuron output without affecting the membrane potential (V_x). This reference frequency can be either experimentally set or driven by the outputs of other neurons.

3. Simulation of Functional Blocks

3.1. CONTRAST-ENHANCEMENT COMPETITIVE LAYER

In a competitive topology (see Figure 2) the neuron (or group of neurons) that receives the highest excitation becomes active, inhibiting the other cells of the same layer. Each cell of the competitive layer receives excitatory connections from itself and from its corresponding input element, and inhibitory connections from all the other neurons in the same layer. If only FCI synapses were used, the input pattern would lead the neurons of the competitive layer either to the low or the high saturation level. The winning node (or neural group) would reach the high saturation state at the same time as it inhibited the other nodes to the low saturation level.

A competitive layer of 20 neurons with the topology of Figure 2 has been simulated. The simulation results in Figures 3 and 4 show the final state, i.e. the final membrane potential level (continuous line), after an input pattern (dashed line) is presented. In these experiments the weights used are $W_{exc} = 1$, $\mathrm{W}_{inh} = -1$ and $W_{inp} = 4$ (these weights are referred as D terms in Equations (3) and (4)), to enable the input pattern to override the previous layer state. Each cell includes a pseudo-linear output module (VCF) with a firing threshold $V_{th} = 2$ V.

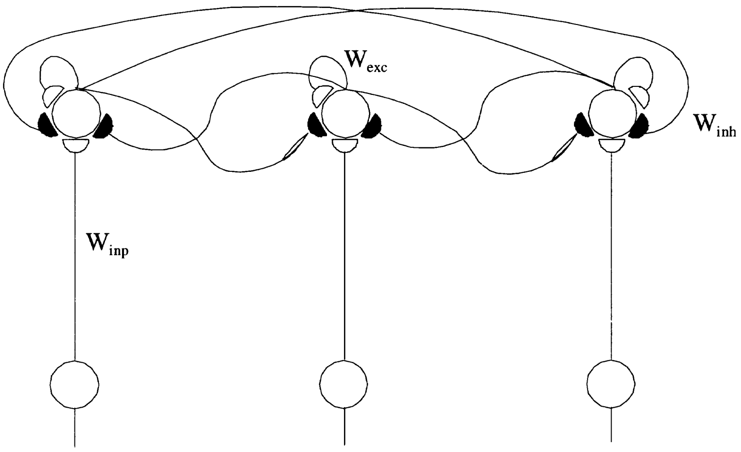
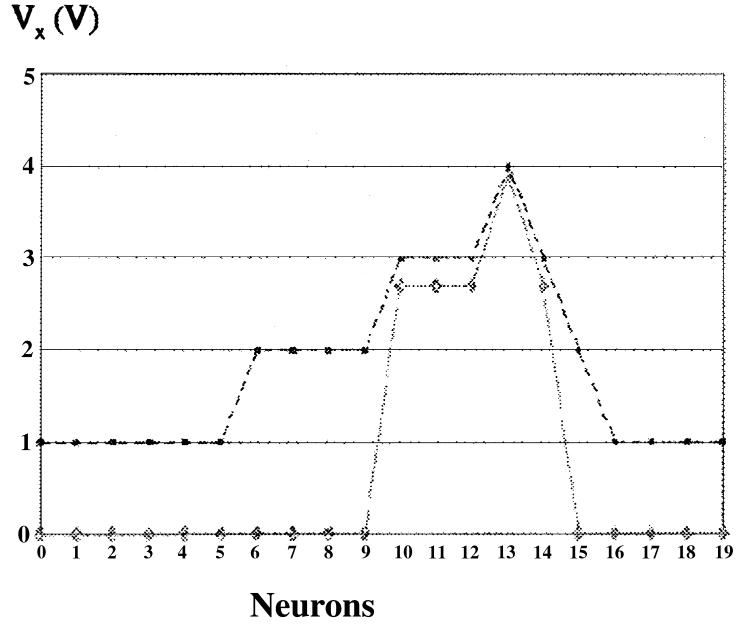


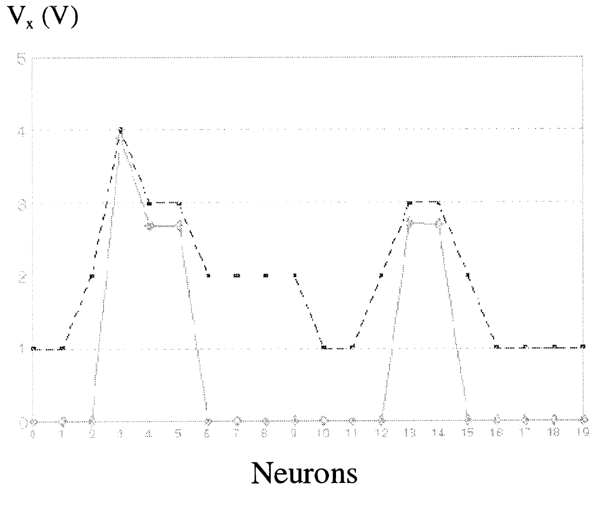
Figure 2. Competitive Topology. The connectivity is defined by excitatory (W_{exc}) and inhibitory (W_{inh}) weights in the competitive layer while the input excitatory weights (W_{inp}) transfer the input pattern between layers.

In Figure 3(a), the competition process leads the structure to a stable state in which the 13th neuron exhibits the greatest membrane potential, corresponding to its highest input component. Another four neurons are not completely inhibited because their input cells fire spikes continuously, as long as their cell states remain over the VCF threshold (V_{th}). If the input pattern is changed (see Figure 3(b)) the structure evolves to a new state where the 3rd neuron dominates the competition due to its greater input component, although other cells remain active. In this way Figure 3 shows a direct transition (without extinguishing the input signals) between two stable states set by two different patterns in a contrast-enhancement process.

In some applications it is of interest to keep several relevant features active in a saliency map [7] after a competition process, and therefore to have some active cells with different membrane potential levels. In other cases it may be convenient to have a stronger competitive process where a single neuron wins and completely inhibits all the other cells of the layer. This can be achieved either by stronger feedback weights (W_{exc} and W_{inh}) or by temporarily extinguishing the input pattern to complete the evolution of the nodes in the absence of input signals, as shown in Figure 4. In the first stage the 13th neuron wins the competition in the presence of the first input pattern, but other cells remain active due to their significant input components (see Figure 4(a)). In the second stage, the input pattern is extinguished and the competitive process goes on, leading the 13th neuron to the highest activity level and completely inhibiting the rest of the nodes in the layer (Figure 4(b)). In the third stage another input pattern is presented, making the 3rd node dominate the competition (Figure 4(c)). Again, when the inputs are extinguished the network evolves to a state with a single active node (Figure 4(d)).

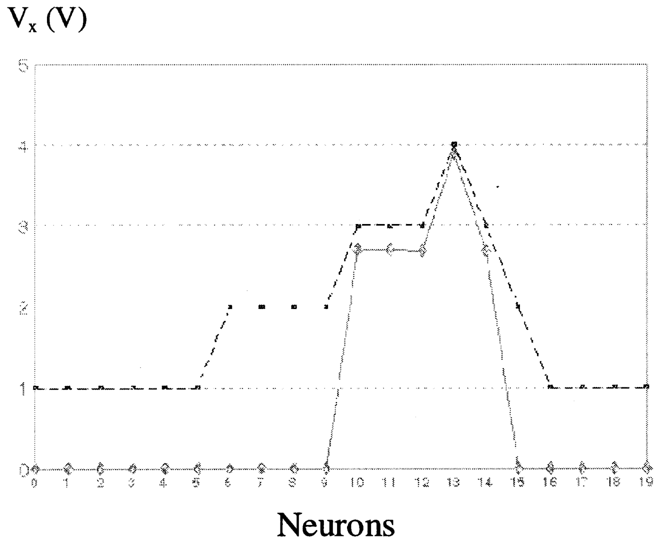


(3.a)

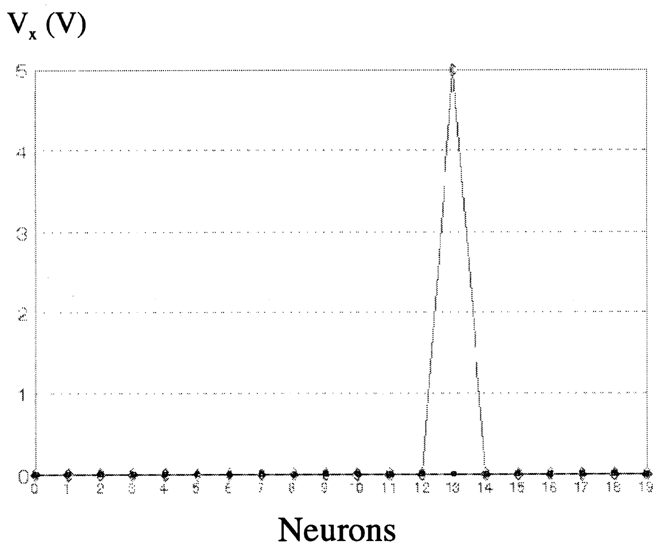


(3.b)

Figure 3. Direct transition between two different states due to consecutive patterns. The nodes whose input components are above the firing threshold (V_{th}) stay active because they keep on receiving spikes from the input layer.

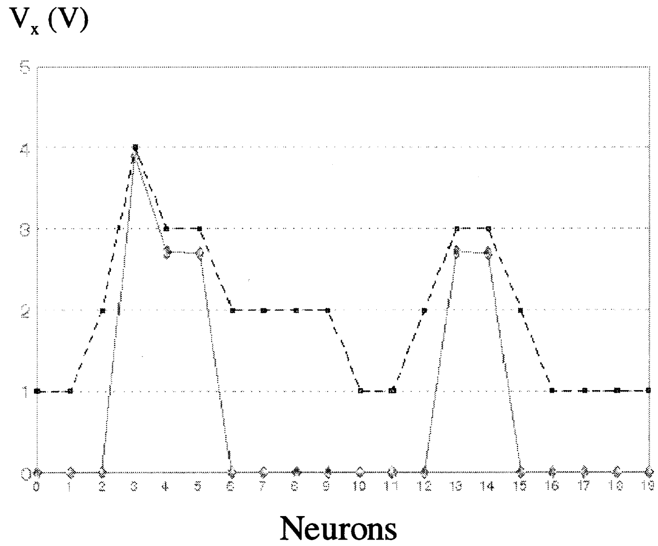


(4.a)

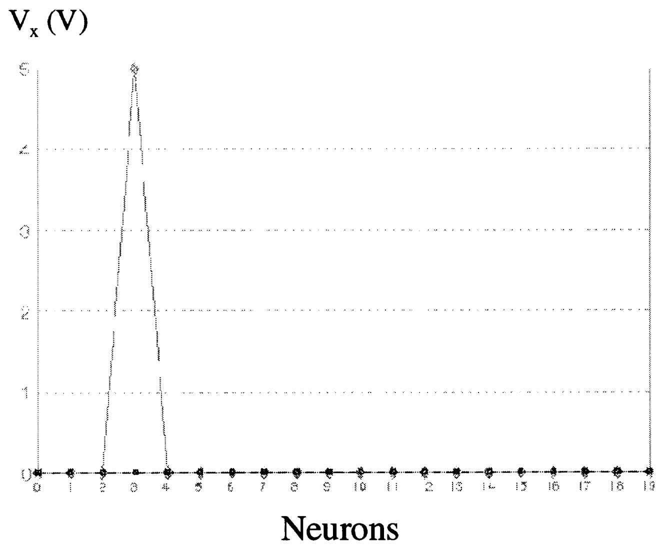


(4.b)

Figure 4. Continued on next page.



(4.c)



(4.d)

Figure 4 (continued). Indirect transitions between states in a competitive layer. On extinguishing the input signals, the network evolves to a state with a single active node.

3.2. SELECTIVE TEMPORAL INHIBITION (STI): ATTENTIONAL SHIFTING

For a given pattern, after a competition has taken place, the current winning element may be inhibited by another subsystem, enabling a new competition process between the remaining active nodes.

The passive decay time constant of a cell can be controlled with a reference frequency (F_R) that can be varied for different neurons in a network. The configuration shown in Figure 5 makes use of this control possibility of the decay time constants by implementing 'Selective Temporal Inhibition' (STI), which is useful to perform attentional shifting in visual processing tasks [7, 9] or in competitive networks [8, 10, 11].

Each STI element is formed by three cells: a neuron (N_i) belonging to a competitive layer such as the one shown in Figure 5 and two inter-neurons (N_iR_1 and N_iR_2) with different passive decay time constants. A global reset signal activates the inter-neurons N_iR_1. The output module of cell N_iR_1 uses the output spikes of neuron N_1 as its reference frequency (F_0 in expression (5)). Therefore, node N_iR_1 does not fire any pulses while neuron N_i in the competitive layer remains below the firing threshold. The cell N_iR_1 receives a high constant inhibition frequency (F_{R1}), exhibiting a short passive decay time constant. If neuron N_i is active its output spikes facilitate the output module of inter-neuron N_iR_1. If the nodes N_iR_1 receive a global reset signal, only those that have their output modules facilitated can fire pulses to excite the second inter-neuron N_iR_2. This node (N_iR_2) receives a constant low frequency of inhibitory spikes (F_{R2}) exhibiting a long passive decay time constant. The activation of this inter-neuron leads to the inhibition of node N_i, which is maintained inactive for a time that depends on the passive decay term of neuron N_iR_2.

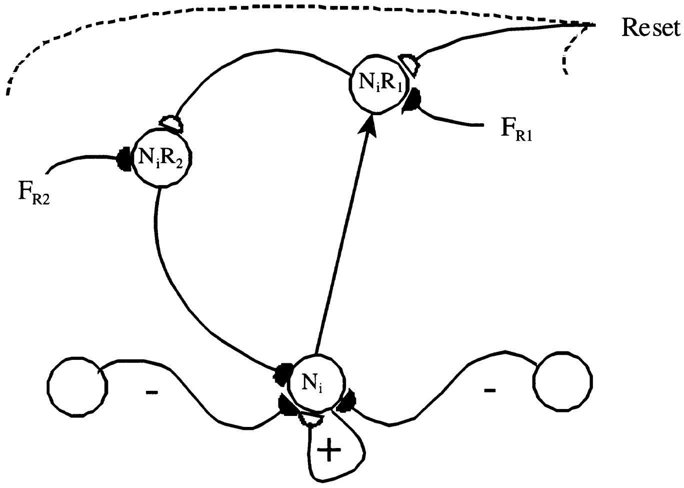


Figure 5. STI Topology. Each STI element is made up of three neurons, N_i, N_iR_1 and N_iR_2.

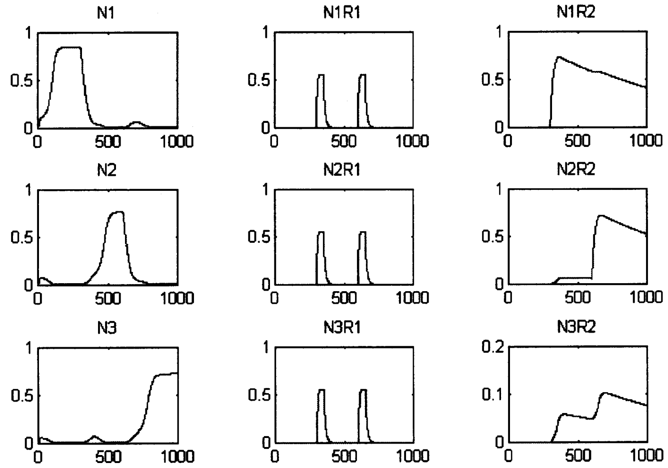


Figure 6. Simulation results of a three element STI competitive structure. Each row of plots represents the activity evolution of the node in the competitive layer (N_i) and its couple of resetting interneurons (N_iR_1 and N_iR_2).

In this way, a global reset signal received by the whole STI structure would temporarily inhibit only the firing nodes (N_i) in the competitive layer, enabling other cells to win the competition.

The simulation results in Figure 6 illustrate the behavior of three STI elements arranged in a winner-takes-all structure. The competitive layer (N_1, N_2 and N_3) receives three input components $E_1>E_2>E_3$. In the first stage neuron N_1 wins due to its greater input component and completely inhibits all the other cells of the same layer. When the system receives a global reset signal it excites the inter-neurons N_iR_1 but only N_1R_1 fires and excites the second inter-neuron N_1R_2. Therefore cell N_1 is inhibited for a time that depends on the passive decay term of node N_1R_2. The inhibition of node N_1 enables node N_2 to win in the competitive layer although it receives a weaker input component. A second global reset inhibits node N_2 enabling N_3 to finally dominate in the competitive layer. In this experiment, strong lateral and self-feedback weights are used in the competitive layer in order to get a winner-takes-all operation. The global reset signal enables different nodes to win the competition consecutively (in an order that depends on the input strengths) without changing the input pattern.

This mechanism may be used to implement attentional shifting processes. In a first stage, a general vision processing layer extracts some elementary features that are combined to create retinotopic saliency maps of broader or higher order visual features initially considered as relevant. In a second stage, a global reset signal is used to temporarily hold down these saliency maps, providing the system with an opportunity to process other, possibly important, features of the visual scene.

4. Concluding Remarks

The spiking neuron model described in Section 2 includes multiplicative terms that enable non-saturated stable states in response to different stationary stimuli. This characteristic is used in an on-centre-off-surround structure in which the steady-state distribution of membrane potentials is a contrast-enhanced version of the input components. The simulations of this structure show how the neurons evolve to new states when the input patterns change, as well as its winner-takes-all operation when the network is allowed to evolve after the input pattern is extinguished.

This kind of competition between significant features can be used in perceptive processing schemes like saliency maps [7] with an attentional mechanism to focus the system resources onto certain regions of the feature maps. An attentional shifting mechanism, based on the Selective Temporal Inhibition (STI) structure, is simulated in Section 3. A competitive layer made up of STI elements responds to a global reset signal selectively inhibiting selectively the firing nodes, giving a chance to other less active nodes that may represent significant features. These attentional mechanisms drastically reduce the reacting time in complex scenes by restricting the regions under study, always considering first the most significant features obtained from primitives implemented in the primary feature extraction layer.

Acknowledgments

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