

Computational Modeling of Robust Figure/Ground Separation

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Abstract—It is unknown which computational method the brain uses to perceive a visual scene. Given current advancements, it is now possible to model perceptual processes of the brain using spiking neural network models. We have developed a computational model for robust figure/ground separation. The model is based on a laterally connected sheet of spiking neurons. The sheet of neurons receives its visual input from a virtual retina. It is assumed to be located inside V1 or a higher visual area. The neurons are assumed to be laterally connected to their nearest neighbors through gap-junctions. These lateral connections allow the neurons to exchange information and therefore allow for robust figure/ground separation. Even though we only show results for visual signals, the method is quite general and may be used in various areas of the brain. A result of the lateral coupling is that the neurons synchronize their firing behavior resulting in the so called gamma-synchrony which is also a result of our computational model.

Index Terms—visual perception; spiking neurons; lateral-coupling; gap-junctions; gamma-oscillations

I. INTRODUCTION

In computational neuroscience, one tries to understand how the brain actually processes information at the neural level. The goal is to seek an algorithmic description. Once this description is obtained it may be used to simulate the same behavior in another medium, i.e. on a computer. We are still a long way from being able to fully understand how human visual processing works. However, we have been able to show how the brain can process visual information using a sheet of spiking neurons. Our sheet of neurons is laterally connected to neighboring neurons. The connections (assumed to be due to gap junctions) allow the neurons to exchange data with their neighbors and therefore tune their firing behavior such that the relevant neurons collectively respond to a certain stimulus. Our contribution is to extend the spiking neuron model to include lateral connections. We provide a complete algorithmic description of our theoretical model which can be used for comparison with real data or for predictions. We show how the sheet of neurons automatically adapts its behavior so as to robustly extract a figure from ground.

In our simulations, we model a single sheet of neurons. The input to this sheet of neurons is assumed to come from a virtual retina, i.e. from neural cells responding to visual stimuli. Hence, the sheet of neurons perceives and represents a visual

scene. Even though we only show results for visual stimuli, the method is quite general and may be used to process arbitrary signals. It could also be used to process haptic or auditory information. Our model assumes that cells performing a related function are connected through gap junctions while no lateral connection exists between cells tuned to process different kinds of information. Since a gap-junction can be modeled as a resistive connection, the entire set of interconnected neurons form a resistive grid. This resistive grid causes the neurons to laterally exchange part of their activation level with nearby neurons provided that the connected gap junction is in an open state. The resistive grid is also used to temporally and spatially average the incoming spikes. This enables the network to tune their behavior and to perform robust figure/ground separation. The temporally and spatially averaged signal is used as an adjustive signal for the neuron. Depending on this signal, the gap junctions open or close. When the temporal average of the neuron's dendritic input is above the spatial average of the neuron's dendritic input, then the gap junction opens its connection. If the temporal average is below the spatial average, then the gap junction closes. Once, the gap junction between two neurons is open, then these two neurons exchange part of their activation, thereby synchronizing their firing behavior. Eventually, other nearby neurons will also open their gap junctions, thereby forming an extended zone of laterally connected neurons with synchronized firing behavior. All of the neurons whose receptive field shows part of the figure will fire in synchrony. Neurons for which the figure is outside the receptive field will fire out of sync and at a much lower rate.

II. SPIKING NEURAL NETWORKS

Sensory perception, motor control and learning are due to the neural processing which occurs inside the brain. The brain itself is usually modeled as a set of spiking neurons [2]. In this standard model, each neuron independently integrates the electrical inputs which it receives from other neurons. This happens until the activation of the neuron rises above a certain level or threshold. Once this happens, the neuron is said to fire. The neuron then sends an electrical impulse or signal along the axon. This signal may then be integrated by other neurons which eventually will also fire.

It is standard practice to only model the spiking behavior of neurons as this is thought to be the most relevant aspect of neural information processing. It is assumed that the entire function of the neuron can be replicated by only modeling the spiking behavior of the neuron. Low level interactions between neurons, i.e. at the level of neuro transmitters and ion channels, are thought not to be relevant to replicate neural processing. Hence, these aspects are usually omitted in computational modeling. By abstracting and given powerful computational resources, it is possible to even model thalamocortical systems [1].

In the standard so called integrate and fire model, each neuron is viewed as a functional unit. The neuron integrates the input received through the dendrites. Once a given threshold is reached, then the neuron is said to fire. The input of a neuron is due to electrical signals received via axons from other neurons. Whenever a neuron fires, then a voltage spike is sent along its axon. This electrical signal is received by other neurons through their dendrites (and also via their cell bodies). Each neuron integrates its input over time resulting in a buildup of the activation potential. If the activation potential of a cell is high enough, then the neuron will again send a spike down its axon. This signal will be integrated by other neurons and the process continues.

Let V_i be the activation potential of neuron i of a larger network. The change of the activation potential V_i can be modeled by the following equation (modified from [3]):

$$C \frac{dV_i}{dt} = g_i(E_i - V_i) + I_{\text{tonic}} + I_i + \sum_{j=1}^N w_{ij} K_j \quad (1)$$

Here, C is the capacitance of the neuron. The factor g_i is the leakage conductance. This factor will determine the speed with which the cell will eventually reach the resting potential E_i if no input is received. A tonic current can be modeled through the term I_{tonic} . An input current to neuron i from an external source can be provided through the term I_i . Let K_j be the input received from neuron j . Each input will be weighted with factors w_{ij} describing the connection strength between neurons i and j . The connection strengths can be tuned through neural learning. The input of a neuron is the weighted sum over all its inputs received from other neurons.

In this standard neural model, an important ingredient is missing. Lateral connections between neurons are not considered. We find such lateral connections between neurons to be highly useful for signal processing. The lateral connections allow the neurons to exchange data with their immediate neighbors and thereby to collectively tune the response to a given stimulus.

III. LATERAL CONNECTIONS

Our model neuron extends the standard model by also including lateral connections between neurons. Similar to the standard model, the neuron temporally integrates the incoming spikes. This leads to a rise of the activation voltage until a particular threshold is reached. Once this happens, the neuron

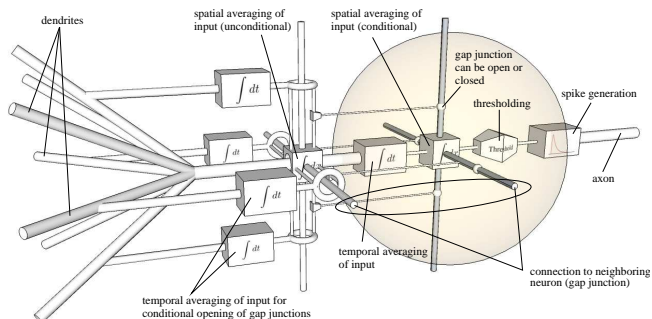


Fig. 1. Artificial neuron. Each neuron is laterally connected via gap junctions to several other neurons (only 4 gap junctions are shown).

sends a spike along its axon, i.e. it fires. In contrast to the integrate and fire model, our neuron includes lateral connections which as assumed to be due to gap junctions between neurons. Only neurons which perform a similar function are assumed to be laterally connected. During development, lateral connections may just occur completely at random. In the course of time, some neighboring neurons will fire together by chance. This may lead to gap junctions between these neurons. The laterally connected neurons will form a sub-network. A gap junction can be modeled as a resistive connection between neurons [4], [5]. Hence, the connected neurons form a resistive grid. Since the gap-junctions are always there, the gap-junction connections form an unconditional resistive grid. This resistive grid is used to adaptively tune the neuron to a given stimulus.

A gap junction may be in one of two states. It can be open or closed. The state that is chosen is voltage dependent. A voltage dependent conductance of gap junctions was also used by Traub et al. [6]. In our model, a channel is opened for each open gap junction allowing the connected set of neurons to exchange part of their activation. This leakage current causes the conditionally connected neurons to synchronize their firing behavior. In computational modeling, an open gap junction is modeled as a resistor. The synchronization of laterally connected neurons occurs in the same way that chaotic or non-linear electrical circuits synchronize their behavior if they are resistively connected, i.e. a signal is exchanged between the two circuits [7]–[9].

The input spikes passing next to each gap-junction are temporally integrated and, through the resistive grid, also spatially averaged. The spatially averaged input results in an adjustive signal for the neuron. Gap junctions open and close depending on this signal. In our model, we call this signal the sync-threshold. Gap junctions open if the temporal average of a neuron's input is above the spatial average. Otherwise, the gap junctions close.

An illustration of our neuron including lateral connections is shown in Figure 1. The lateral connections are shown extruding from the body of the neuron in order to make clear that this

is a connection to other neurons on the same level. In reality, the gap-junctions are located on the dendrites which are shown on the left part of Figure 1 leading up to the neuron body. The neuron receives its input through the dendrites. This input is temporally integrated as is illustrated by the center box labeled “ $\int dt$ ”. The same input is also temporally integrated (although with a different factor) and also spatially averaged at each gap-junction as illustrated by the boxes “ $\int dt$ ” and “ $\int dx$ ”. Figure 1 shows 8 dendritic connections but only 4 gap-junctions in order not to overload the figure. In an actual neuron, the connections are not necessarily uniformly distributed. For each gap-junction, two connections are shown. One dark connection and one light connection. The lighter connection illustrates the resistive grid that is formed because the gap-junction exists. The darker connection illustrates the conditional connection between neighboring neurons as the gap junctions open or close (sphere on the dark lateral connection). If the temporal average of the incoming signal is clearly above the spatial average, then the gap junctions open. If the temporal average is below the spatial average, then the gap junctions close. The dendritic input to the neuron is integrated by the second box labeled “ $\int dx$ ”. Note that this input passes through the first box labeled “ $\int dx$ ” which is the integration due to the unconditional resistive grid. If the gap junction is open, part of the activation will be exchanged between the connected neurons. The current will flow from the neuron having a higher activation to the neuron having a lower activation. This causes the connected neurons to synchronize their firing behavior. If the activation of the neuron rises above a threshold (illustrated by the “Threshold”-box), then the neuron will fire. In this case, an electrical impulse is sent along the axon. This is illustrated by the box with the spike.

A connected network of such neurons is able to extract an arbitrary signal which is above the average. The same function could also be achieved with multiple interconnected neurons. It could be that the above behavior illustrated within a single neuron is actually spread over multiple neurons inside a cortical column. See Mountcastle [10] for a review of columnar organization of the neocortex.

IV. ROBUST FIGURE/GROUND SEPARATION

In order to evaluate our model, we first start off using virtual stimuli. A sheet of 1000 laterally connected neurons is simulated. This sheet of neurons processes input from a virtual retina. The 1000 neurons are randomly placed inside a $100 \times 100 \times 2$ area. It would suffice to model a two-dimensional sheet of neurons. However, we have used a three-dimensional sheet in order to include the fact that actual neurons are not perfectly positioned inside a two-dimensional plane. Let (x_i, y_i, z_i) be the position of the i -th neuron inside the three-dimensional area. Each neuron is laterally connected to its 6 nearest neighbors the sheet. Input to neuron i is provided by a virtual retina. The receptive field of neuron i is mapped topographically from its position inside the sheet to the retinal neurons. Let $x_i, y_i,$ and z_I be the normalized coordinates with range $[0, 1]$, then neuron i receives its input from position

$(wx_i + x_r, hy_i + y_r)$ where w is the width of the retina and h is the height of the retina and (x_r, y_r) is a random offset selected from $-1, 0, 1$.

Our sheet of neurons could theoretically be located inside V1, however, it is more likely to be located in some higher visual area. It could be used wherever a signal has to be separated from ground. Below, we will show how the network can be used to separate a lighter signal from a darker background. The same network, however, can also be used to separate more complicated signals which depend on motion or texture. Neurons processing these features would be located in V3 or V5 or inside higher areas [11], [12].

The human visual system uses two different types of receptors: rods and cones. The cones are used for color vision. Three different cones can be distinguished. Their peak response lies either in the red, green or blue parts of the spectrum [13]. The retinal receptors measure the light falling onto the retina. The information is then passed on to the lateral geniculate nucleus and finally reaches V1. By the time, the visual information has reached the visual cortex, it has been transformed from a red-green-blue coordinate system to a rotated coordinate system. This rotation is caused by color opponent and double-opponent cells. The axes of the rotated coordinate system are: bright-dark, red-green and yellow-blue [14]. For our experiments, we will be using only the bright-dark channel (also called lightness). We process data which is stored as computer images. The transformation from red, green, and blue non-linear pixel intensities (R, G, B) is given by $L = 0.299R + 0.587G + 0.114B$ [15]. Each neuron i of our sheet receives lightness L from 3 different positions of the virtual retina. The mapping from neurons to their input is defined as described above. Thus, we have for the output o_i of the retinal neuron i : $o_i = L(x'_i, y'_i)$ with $(x'_i, y'_i) = (wx_i + x_r, hy_i + y_r)$.

Each neuron is fully described by the following state variables: a_i activation, t_i fire-threshold, o_i output voltage, \tilde{a}_i , temporal average of incoming spikes, \bar{a}_i spatial average of temporal average. The variable \tilde{a}_i is actually associated with every gap-junction. However, we have used one variable per neuron to speed up the simulation. The algorithm which is run by each neuron i is shown in Figure 2. Due to the leakage factors, the state variables can be initialized with random values at the start of the algorithm. For our experiments, we have used the following parameters: $\alpha_a = 0.9995$ decay of activation potential, $\alpha_o = 0.5$ decay of output voltage, $\alpha_t = 0.001$ temporal averaging factor of gap-junction, $\alpha_s = 0.0001$ spatial averaging factor of gap-junction input, $\epsilon = 0.0001$ leakage to adjacent neurons upon firing, $\gamma = 0.0005$ reduction of fire-threshold, $\omega = 1.999$ factor for over-relaxation, $\Delta t_r = 10$ refractory period of neuron, $w_{ij} = 1$ weight between neurons i and j . We have used only positive unit weights because the input image is directly processed by the neural sheet. In the brain, the weights can be found using neural learning, e.g., Hebbian learning [16]. Of course, it is also possible to include negative weights. Negative weights would represent inhibitory signals. The type of weights that have to be used, are of course

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(01)  $o_i = (1 - \alpha_o)o_i$  // decay of output
(02)  $a_i = (1 - \alpha_a)a_i$  // decay of activation
(03)  $a_i = a_i + \alpha_a \sum_j w_{ij}o_j$  // integrate input
(04)  $\tilde{a}_i = (1 - \alpha_t)\tilde{a}_i + \alpha_t \sum_j w_{ij}o_j$  // temporal average
(05)  $\bar{a}'' = \bar{a}_i$  // save previous result
(06)  $\bar{a}' = \frac{1}{1+|N|} \sum_{j \in N} \bar{a}_i$  // compute spatial average
(07)  $\bar{a}_i = (1 - \alpha_s)\bar{a}' + \alpha_s \bar{a}_i$  // add temp. average
(08)  $\bar{a}_i = (1 - \omega)\bar{a}'' + \omega \bar{a}_i$  // use over-relaxation
(09) if ( $\tilde{a}_i > \bar{a}_i$ ) open gap junctions
(10) else close gap junctions
(11) if Neuron  $i$  fired within  $\Delta t_r$  return
(12)  $N = \{j | \text{Neuron } j \text{ is laterally connected to}$ 
(13)  $\text{neuron } i \text{ via open gap junction}\}$ 
(14)  $a' = a_i; n = 1$  // initialize spatial averaging
(15) for all  $j \in N$  do : if Neuron  $j$  did not fire within  $\Delta t_r$ 
(16)  $\{ a' = a' + a_j; n = n + 1 \}$ 
(17)  $a_i = a'/n$  // spatial averaging completed
(18) // distribute sp. avg to neighboring neurons
(19) for all  $j \in N$  do : if Neuron  $j$  did not fire within  $\Delta t_r$ 
(20)  $\{ a_j = a_i; \}$ 
(21)  $t_i = \max[0, 1 - \gamma \cdot N_s]$  // comp. fire-threshold
(22) if ( $a_i > t_i$ ) { // does the neuron fire?
(23)  $a_i = 0$  // reset activation
(24)  $o_i = 1 - \epsilon |N|$  // output rises to 1
(25) for all  $j \in N$  do :  $a_j = a_j + \epsilon$  // distribute leakage
(26) }
    
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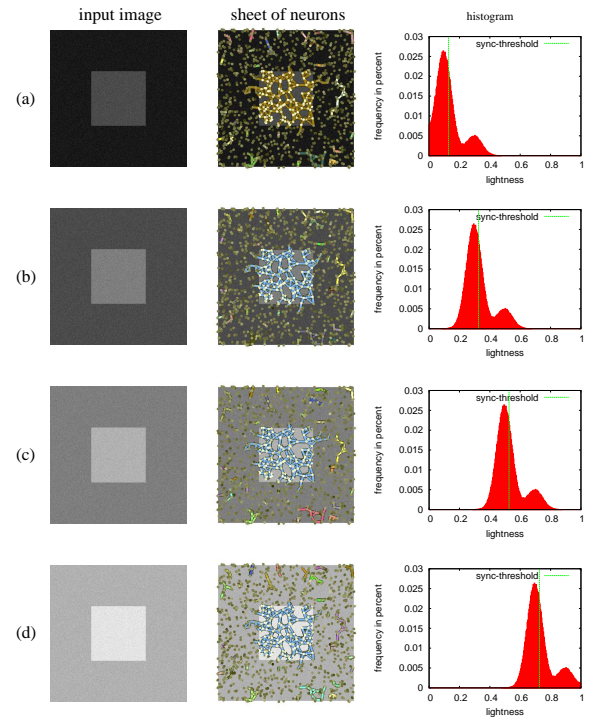
 Fig. 2. Algorithm of neuron i

dependent on the problem that has to be solved. For our task, unit weights suffice. The parameter N_s denotes the number of neurons in the sub-network.

In the following, we will refer to the line numbers of Figure 2 in order to explain what the neuron does. First, the output voltage (01) as well as the activation (02) decays. Each neuron integrates the input (03). The gap junctions are controlled depending on whether the temporal average of the input is above the spatial average (09-10). The temporal average of the input is computed in (04). The spatial average of the temporal average is computed using over-relaxation in (05-08). This spatial average is basically an adaptive threshold which allows for adaptive figure/ground separation.

Note that in an earlier model [17], we have used the firing signal of the neuron as a feedback signal to control all of the gap-junctions at the same time. It is probably more accurate, that each gap-junction is controlled independently by the temporal average of the signal passing through the dendrite where the gap-junction is located. Thus, according to our theory, each gap-junction opens or closed independently of the other gap-junctions depending on the signal that passes through its dendrite. The algorithm that we use for our simulation, nevertheless takes the signal running through all of the dendrites as a single input and controls all gap-junctions of a neuron at the same time. This allows for faster simulation of the entire sheet of neurons.

Condition (09) ensures that the brightest stimulus is extracted. Parts of the image with high lightness correspond to the figure whereas other parts with low lightness correspond to the background. Processing continues if the neuron is not


 Fig. 3. Experimental results for different noisy input images (zero mean, standard deviation 0.05). The relationship between background lightness L_b and figure lightness L_f is (a) $L_b/L_f=0.1/0.3$ (b) $L_b/L_f=0.3/0.5$ (c) $L_b/L_f=0.5/0.7$ (d) $L_b/L_f=0.7/0.9$

longer in its refractory period (11). Lines (12-20) distribute part of the activation across open gap junctions. The activation flows from the neuron having a higher activation to neighboring neurons having a lower activation. This causes adjacent neurons with open gap-junctions to synchronize their firing behavior. The fire-threshold is set depending on the size of the connected sub-network (21). If the connected sub-network is large, then the threshold is lowered, whereas if the connected sub-network is small, then the threshold is higher. This causes neurons belonging to a larger object to fire with a higher frequency. Once the neuron fires (22-26), most of the activation is sent along the axon. However, part of the activation is also distributed to neighboring neurons.

A single neuron could also perform a bright/dark classification with a proper choice of parameters. However, such a neuron will not be adaptive to the image content. Figure 3 shows the results for different input images with static noise. The input received by the retinal neurons is shown on the left hand side. The sheet of neurons is shown in the middle. Each neuron is marked by a dot. Open gap junctions between neurons are drawn with colored lines. The right hand side shows the distribution of the lightness of the input image. In Figure 3(a) both background and the foreground square (figure) are quite dark. Subsequently, in cases (b-d), the lightness is increased. We can see that for input image (a), a lightness of 0.3 is classified as figure because the background has a lower lightness, e.g., 0.1. However, for case (d), a lightness of as high as 0.7 is classified as background because

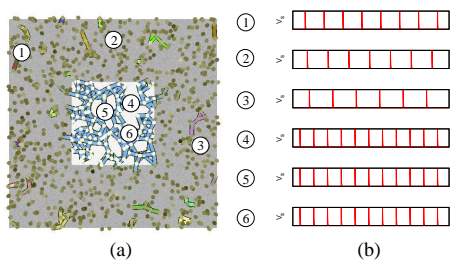


Fig. 4. (a) input stimulus (b) behavior of six different neurons (marked). Neurons 1-3 are located on the figure and show synchronous firing behavior whereas neurons 4-6 are located on the background and fire out of sync.

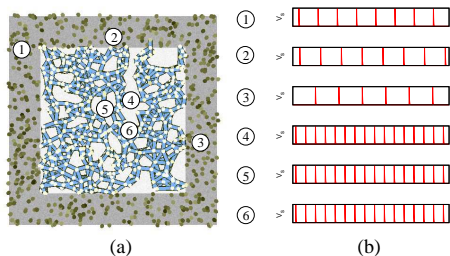


Fig. 5. (a) input stimulus (b) behavior of six different neurons (marked). Neurons 1-3 are located on the figure and show synchronous firing behavior whereas neurons 4-6 are located on the background and fire out of sync.

the figure has a higher lightness of 0.9. Thus, we see that our network is able to adapt to the image content and extract the correct figure. It is also robust in that it is able to cope with noisy input stimuli.

By using other types of input with appropriate weights in (03) and (04), arbitrary stimuli can be extracted. For instance, one could envisage a sheet of neurons processing input from V4 (color) or V5 (motion). Such a sheet could be tuned to extract a moving color stimulus.

Figure 4 shows that the neurons that have their receptive field on the figure fire in synchrony while other neurons fire out of sync. Figure 4(a) shows the neural sheet overlaid on the input image. The output of six different neurons is shown in Figure 4(b). Figure 5 shows what happens for a stimulus of larger size. In this case, the neurons increase their firing rate. This effect is due to the adaptive threshold that is computed in Figure 2(21). Higher visual areas can discern objects of different sizes based on their firing rate.

Figure 6 shows how the network behaves for real input images moving across the virtual retina. As the object or figure moves across the retina, different neurons are activated in the course of time. Neurons of a connected sub-network synchronize their firing rates. Different objects will have different firing rates. This allows for visual servoing techniques [18], [19] which can be used by higher visual areas to track an object.

V. DISCUSSION AND BASIS OF OUR MODEL

The sheet of neurons segments the scene into figure and ground. Related work for scene segmentation includes the work of Zhao and Breve [20]. They have used Wilson-Cowan

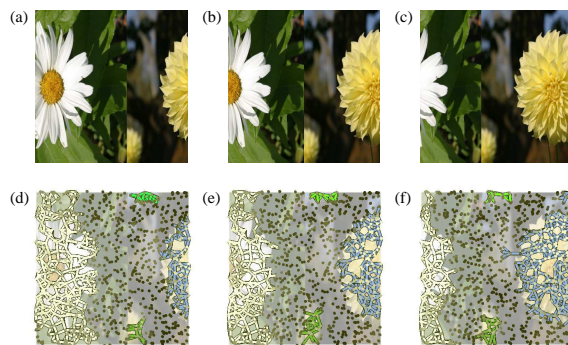


Fig. 6. (a-c) Moving stimulus. (d-f) A connected sub-network tracks the figure.

neural oscillators [21] and segmented static input. Quiles et al. [22] have developed a visual selection mechanism and show how their integrate and fire network responds to different static images. Their model includes short range excitatory connections and long-range inhibitory connections. Eckhorn et al. [23] simulated results from the visual cortex of the cat. They simulated two one-dimensional layers of neurons and used a moving stimulus as input. In contrast to our model, they have used long range feeding connections connecting neurons of the same layer. Our computational model is quite simple, yet it shows how synchronized zones of activity can arise and move around in the brain. These zones of activity are assumed to correlate with conscious perception and control.

Our model of laterally connected neurons show a synchronous firing behavior of neurons responding to the main stimulus (figure) whereas the remaining neurons fire out of sync. Indeed, the electroencephalogram (EEG) shows the synchronized firing behavior of neurons inside the frequency band from 40 to 80Hz [24], [25] This is called gamma synchrony EEG. A review on how gamma synchrony correlates with perception and motor control is given by Singer [26]. The gamma synchrony is due to inter-dendritic gap junctions [27], [28]. Hameroff [29] has put forward the “conscious pilot” model. According to this model, gap junctions open and close, thereby creating synchronized zones of activity. These zones move through the brain and convert non-conscious cognition, i.e. cognition on auto-pilot, to conscious cognition. A review of several different theories of consciousness is given by Kouider [30]. Several theories of consciousness assume re-entrant, i.e. recurrent, processing of information, e.g., the re-entrant dynamic core hypothesis by Tononi and Edelman [31], or the local recurrence theory by Lamme [32]. Crick and Koch [33] have noted that humans appear not to be aware of processing which occurs inside V1. Thus, conscious processing probably starts somewhere above V1. According to Zeki [34], multiple consciousnesses are distributed across different processing sites giving rise to microconsciousness. Attributes such as color, form and motion are bound which then gives rise to macroconsciousness. And finally, there is a global form of consciousness or unified consciousness which involves linguistic and communication skills. Our model is

based on recurrent information processing. Hence, it is in line with theories of Tononi and Edelman as well as the theory of Lamme. In Zeki's terms, our model would be a case of microconsciousness.

Synchronized firing can be achieved through either local or global connections. Our model only uses local connections between neurons. No global connections are required. Nevertheless, global connections could be used to pass information on to higher areas or to provide feedback to lower areas. Wang [35] as well as König and Schillen [36] have used global connections to establish synchronous firing. They use long range excitatory delay connections to achieve desynchronization across different regions. Terman and Wang [37] use a global inhibitor to achieve desynchronization. In our model, neurons responding to the same object will synchronize their firing behavior because they are laterally connected through gap-junctions. Two neurons, each responding to a different object will not be synchronized because of the dependence of the firing threshold on the size of the connected zone of neurons.

VI. CONCLUSION

The standard integrate and fire model does not take lateral connections between neurons into account. The lateral connections are assumed to occur through gap junctions which behave like resistors. A gap junction may be either in an open state or in a closed state. The gap-junctions form two resistive networks. An unconditional network and a conditional network. The unconditional network is used by our model to tune the network to the correct input level. It computes a spatial average of the temporally smoothed input. This spatial average is used to set the sync-threshold by comparing it to the temporal average of the overall input to the neuron. If the overall input is above the spatial average, then the gap junctions open. This causes the neuron to synchronize its firing behavior such that neurons which have their receptive field above the stimulus fire in synchrony. We have shown that our model allows for robust figure/ground separation both on artificial stimuli as well as with real stimuli.

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