A COMPUTATIONAL MODEL FOR CONSCIOUS VISUAL PERCEPTION AND FIGURE/GROUND SEPARATION

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Abstract: The human brain is able to perform a number feats that researchers have not been able to replicate in artificial systems. Unsolved questions include: Why are we conscious and how do we process visual information from the input stimulus right down to the individual action. We have created a computational model of visual information processing. A network of spiking neurons, a single layer, is simulated. This layer processes visual information from a virtual retina. In contrast to the standard integrate and fire behavior of biological neurons, we focus on lateral connections between neurons of the same layer. We assume that neurons performing the same function are laterally connected through gap junctions. These lateral connections allow the neurons responding to the same stimulus to synchronize their firing behavior. The lateral connections also enable the neurons to perform figure/ground separation. Even though we describe our model in the context of visual information processing, it is clear that the methods described, can be applied to other kinds of information, e.g. auditory.

1 MOTIVATION

To fully understand how cognitive information processing works, we will have to replicate all essential functions of the brain either in simulation or by building an artificial artifact. Only if we are able to build an artificial entity, which is able to perform similar tasks as the human brain, then we have understood how the brain actually works. Sensory perception, motor control and learning are assumed to be a result of the neural processing occurring inside the brain. It is assumed that the processing occurs through so called integrate-and-fire neurons. Such neurons integrate the electrical inputs received through axons from other neurons. Once the activation of a neuron reaches a certain threshold, then it fires. It itself sends an electrical impulse along its axon. An essential marker of consciousness cognition is the synchronized electrical activity of neurons inside a particular frequency band (30 to 90 Hz) of the electroencephalogram (EEG), called gamma synchrony EEG (Gray and Singer, 1989; Ribary et al., 1991). Singer (1999) gives a review on how gamma synchrony correlates with perception and motor control. Gamma synchrony is mediated largely by inter dendritic gap junctions. According to the Hameroff 'conscious pilot' model (Hameroff, 2010), synchronized zones of activation move through the brain as gap junctions open and close. The synchronized zones convert non-conscious cognition, i.e. cognition on auto-pilot, to consciousness.

Kouider (2009) has reviewed several different neurobiological theories of consciousness. Many seemingly different theories of consciousness (e.g. Tononi and Edelman's reentrant dynamic core hypothesis (Tononi and Edelman, 1998) or Lamme's local recurrence theory (Lamme, 2006) assume recurrent processing of information. Zeki (2007) has put forward the microconsciousness theory. He suggests that multiple consciousnesses are distributed across processing sites and that attributes such as color, form or motion are eventually bound together giving rise to macroconsciousness possibly also involving linguistic and communication skills which would then be a unified form of consciousness.

With this contribution we focus on Zeki's micro-consciousness using recurrent information processing. We present a theoretical model on how a sheet of neurons interacts laterally through gap junctions to perceive and represent a visual scene. Even though we only show results for the processing of visual information, the same method can also be used to perceive auditory or haptic information. In our model, neurons are connected laterally through gap junctions. We assume that within a sheet of neurons, neurons with a similar function are connected through such gap junctions. Completely unrelated functions are not connected through gap junctions. We model a single sheet of laterally connected neurons processing visual input from a virtual retina using real scenes as input.

The interconnected neurons are assumed to form a resistive grid which is used to temporally and spatially average the out-going spikes. The spatial average of the out-going signal is used as a feedback signal which determines whether the gap junctions between two adjacent neurons open or close. Gap junctions open if the temporal average of the neuron's input is above the spatial average of the averaged output, otherwise they close. This enables the set of neurons to perform figure/ground separation. If a gap junction between two adjacent neurons is open, then these neurons synchronize their firing behavior. Thus, eventually all of the neurons receiving input from the "figure" will fire in synchrony. We show how this works by presenting the sheet of neurons different photographs. The virtual retina gazes at these photographs. As the object moves across the retina, the object is extracted and tracked by a zone of synchronized activity.

Our model only requires local connections between neurons. Global connections are not required. Local connections have also been used by Wang (1995) and König and Schillen (1991) to establish synchronous firing. Our model uses different firing rates of segmented regions to distinguish between different objects, i.e. neurons of regions of different sizes will be synchronized within a region but desynchronized across regions. Terman and Wang (1995) achieve desynchronization between different objects using a global inhibitor while Schillen and König (1991) use long range excitatory delay connections. Zhao and Breve (2008) have used chaotic oscillators for scene segmentation. They segmented static input. They worked with Wilson-Cowan neural oscillators (Wilson and Cowan, 1972). In their model, neurons which respond to the same object synchronize their behavior while neurons responding to a different object are in another chaotic orbit. Eckhorn et al. (1990) have simulated two one-dimensional layers of neurons simulating results from cat visual cortex. They also performed experiments with a moving stimulus. However, they used long range feeding connections between neurons of the same layer.

Our model is quite simple and shows how the synchronized zones of activity, the neural correlate of consciousness, arise and how they move around in a sheet of neurons. In the brain, similar synchronized zones of activity correlate with conscious perception and control.

2 COMPUTATIONAL MODELING

Traditionally, only the spiking behavior of neurons is modeled. The spiking behavior is assumed to be the most relevant aspect of the neuron's function. If this is indeed the case, then the function of a neuron can be replicated by only modeling the spiking behavior. Other aspects, such as interactions at the level of neuro transmitters and ion channels are assumed to be not relevant and can be omitted in the computational modeling. Eventually, large scale modeling of all of the brain's neurons may lead to a better understanding of how the brain functions (Izhikevich and Edelman, 2008). The neuron is viewed as a functional unit which integrates the input, and once a particular threshold is reached, the neuron fires. This is the standard integrate and fire model (Gerstner and Kistler, 2002).

The input is received from axons of other neurons. A voltage spike train travels along the axons. This signal is received through the dendrites of a neuron (and also the cell body/soma). The signal is integrated over time, building up the so called activation potential of the neuron. Once the activation potential is high enough, i.e. above the firing-threshold, then the neuron itself will fire. A spike is sent down along the axon. This signal will then be received by other neurons where the process continues.

The change of the activation potential V_i of neuron i is described by the following equation (Thivierge and Cisek, 2008)

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

where τ is a time constant. Without any input, the cell activation potential will slowly decay and eventually reach the resting potential E_i. The factor g_i is the leakage conductance, i.e. the speed of the decay. An input current from an external source can be modeled using the term I_i. A tonic current can be specified through I_{tonic}. The input from other neurons K_j is weighted through factors w_{ij} which describe the strength between the neurons i and j. This standard model lacks an important ingredient: lateral connections between neurons. Such lateral connections will allow a set of neurons to perform figure/ground segmentation. They will also cause neurons responding to the same object to synchronize their firing behavior.

3 NEURON WITH LATERAL CONNECTIONS

In our model, the neuron performs a temporal integration of the incoming spikes. The activation of the neuron rises until a particular threshold is met. Once the threshold is met, the neuron fires. This is exactly the traditional integrate-and-fire-model. Extending the standard model, a neuron is connected to nearby neurons performing a similar function through gap junctions. The connected neurons form a resistive grid because each gap junction can be modeled as a resistor (Herault, 1996; Veruki and Hartveit, 2002). This connection between two neurons, i.e. the resistor, is always there. It is an unconditional connection. However, a gap junction may also be in one of two states: open or closed. Which state is chosen is voltage dependent. Traub et al. (2001) have also used a voltage dependent conductance of gap junctions in their simulations. If a gap junction is open, then an additional resistive connection is created between the two neurons allowing for the connected neurons to collectively integrate their input. Because of this conditional resistive coupling, connected neurons synchronize their firing behavior. They fire in synchrony, i.e. we obtain the so called gamma synchrony. The neurons synchronize in the same way that chaotic or non-linear electrical circuits synchronize if a signal is exchanged between them (Carroll and Pecora, 1991; Pecora and Carroll, 1990; Volos et al., 2008).

The output spikes of the neuron are temporally integrated and spatially averaged because of the resistive grid. The spatially averaged output forms a feedback signal. This feedback signal is used to determine whether gap junctions open or close. We call this feedback signal the sync-threshold. If the temporal average of the neuron's output is above the sync-threshold, then its gap junctions open. If the temporal average of the neuron's output is below the sync-threshold, then the gap junctions close.

Figure 1 shows our model of a neuron with lateral connections. The neuron illustrates the different functional components. The temporal averaging (indicated by the box "$\int dt$") occurs first. The spines extending laterally to nearby neurons illustrate lateral connections caused by gap junctions. In the illustration, we have connections to four other neurons. It is of course clear that these connections are not necessarily uniformly distributed in an actual neuron. For the biological neuron, the gap junctions are actually found between dendrites of neighboring neurons. The darker lateral connections (see Figure 1) form the conditional resistive grid which can be in one of two states: open or closed. These connections cause connected neurons to fire in synchrony (indicated by the box "$\int dx$"). If the neuron activation is sufficiently high (indicated by the "Threshold"-box), then the neuron fires (indicated by the box with the spike), sending a spike down the axon. The outgoing spikes are temporally integrated (indicated by the upper "$\int dt$"-box). This signal is also spatially integrated (indicated by the outer circular ring). If this spatially integrated signal is above the temporally integrated signal, then the gap junctions open otherwise they close. Even though the we model the behavior just described using only a single neuron, it could be that these functions are actually spread over multiple neurons inside a cortical column. Mountcastle (1997) gives an excellent review of the columnar organization of the neocortex.

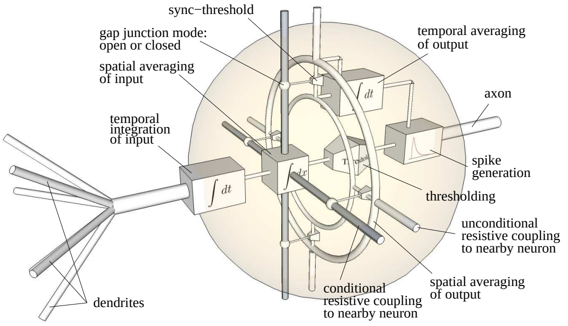

Figure 1: Artificial neuron. Each neuron is laterally connected to other neurons (via gap junctions) which perform a similar function.

4 EXPERIMENT ON VISUAL FIGURE/GROUND SEPARATION

In order to test our model, we have created a virtual retina to provide visual input to a simulated sheet of 1000 neurons. The neurons are randomly distributed over a $100 \times 100 \times 10$ area. Each neuron i receives input from the corresponding position of the retina with a small random displacement. Let (x_i, y_i, z_i) be the position of the neuron. We assume coordinates to be normalized to the range $[0,1]$. Then neuron i will receive its visual input from position $(wx_i + x_r, hy_i + y_r)$ where w and h are the width and height of the original image in pixels and x_r and y_r are random offsets from the range $[-1,1]$. The third dimension (z) is not really required and the model would also work if we spread out our sheet of neurons exactly on a two-dimensional plane. However, biological neurons are assumed not be perfectly positioned on a two-dimensional plane.

The processing that we simulate is assumed to take place inside some higher area of the visual cortex. It could take place in V1. However, according to Crick and Koch (1995) humans do not appear to be aware of the processing occurring inside V1. Thus, we assume that higher visual areas are involved. Higher visual areas have to be involved anyway if other features such as form or motion are used (Zeki, 1978, 1993).

The retinal receptors (cones) respond to light in the red, green and blue parts of the spectrum (Dartnall et al., 1983). The visual stimulus is transformed by the time it has reached the visual cortex by color opponent and double-opponent cells. The visual stimulus is processed inside a rotated coordinate system where the three axes are: bright-dark, red-green, and yellow-blue (Tovée, 1996). In our experiments, we focus on the bright-dark stimulus, the lightness. Lightness L is computed from R, G, B, non-linear pixel intensities using (Poynton, 2003)

$$L = 0.299R + 0.587G + 0.114B. \qquad (2)$$

Figure 2 shows the algorithm that is run by each neuron. Each neuron i is described by the following state variables: activation a_i, threshold t_i, output voltage o_i, temporal average of out-going spikes $\tilde{a}_i$, spatial average $\overline{a}_i$ of temporal average. The initialization of these variables can actually be arbitrary as the activation and the output voltage slowly decay to zero. The parameters used by the algorithm are set as follows: $\alpha_a = 0.01$ decay of the activation potential, $\alpha_o = 0.5$ decay of the output spiking voltage, $\alpha_t = 0.01$ temporal averaging factor, $\alpha_s = 0.0001$ spatial averaging factor, $\varepsilon = 0.001$ activation leakage to adjacent neurons upon firing, $\gamma = 0$ reduction of firing threshold, $\omega = 1.999$ factor for over-relaxation, $\Delta t_r = 10$ refractory period of neuron, N_s number of neurons in sub-network, $w_{ij} = 1$ weight between neurons i and j. For the experiments described here, we have used positive unit weights. The weights can of course in principle be positive or negative. Negative weights would correspond to inhibitory signals which reduce the input to a neuron. Using neural learning, the weights can be dynamically tuned to a given problem. However, for our sample problem, we do not require neural learning. The dendritic input of a simulated neuron j is the lightness L at the corresponding position (x_j, y_j) of the virtual retina. Thus we have, $o_j = L(x_j, y_j)$.

```
$o_i = (1-\alpha_o)o_i$ // decay of output
$a_i = (1-\alpha_a)a_i$ // decay of activation
$a_i = a_i + \alpha_a \sum_j w_{ij} o_j$ // integrate input
if Neuron $i$ fired within $\Delta t_r$ return
$N = \{j |$Neuron $j$ is laterally connected to
        neuron $i$ via open gap junction $\}$
$a' = a_i$; $n = 1$ // initialize spatial averaging
$\forall j \in N :$ if Neuron $j$ did not fire within $\Delta t_r$
        $\{ a' = a' + a_j; n = n + 1 \}$
$a_i = a'/n$ // spatial averaging completed
// distribute sp. avg to neighboring neurons
$\forall j \in N :$ if Neuron $j$ did not fire within $\Delta t_r$
        $\{ a_j = a_i; \}$
$a_i = max[-1, a_i]$ // limit activation
$t_i = max[0, 1 - \gamma \cdot N_s]$ // comp. fire-threshold
if $(a_i > t_i)$ {// does the neuron fire?
    $a_i = 0$ // reset activation
    $o_i = 1 - \varepsilon|N|$ // output rises to 1
    $\forall j \in N : a_j = a_j + \varepsilon$ // distribute leakage
}
$\tilde{a}_i = (1-\alpha_t)\tilde{a}_i + \alpha_t o_i$ // temporal average
$\overline{a}'' = \overline{a}_i$ // save previous result
$\overline{a}' = \frac{1}{1+|N|}\sum_{j \in N} \overline{a}_i$ // compute spatial average
$\overline{a}_i = (1-\alpha_s)\overline{a}' + \alpha_s \tilde{a}_i$ // add temp. average
$\overline{a}_i = (1-\omega)\overline{a}'' + \omega\overline{a}_i$ // use over-relaxation
if $(\tilde{a}_i > \overline{a}_i)$ open gap junctions
else close gap junctions
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Figure 2: Algorithm run by each neuron i

The neuron performs temporal integration of the input and also spatial integration through the resistive grid formed by laterally connected neurons. The feedback signal of the output (again temporally integrated) performs an adaptive determination of the threshold which can be used to separate figure from ground. Since we use lightness as an input, areas with high lightness correspond to the object and areas with low lightness will correspond to the background. Such a separation can of course also be achieved with a standard integrate and fire neuron which is not laterally connected to other neurons. However, in this case, the response of the neuron will no longer be adaptive on the input. Because of the output feedback, our grid of neurons is able to tune its response to the available input. Instead of performing a bright-dark separation, our model can also be used to perform a separation with respect to color, motion or texture. In this case, the sheet of neurons would be located in an area receiving input from V4 (color) or V5 (motion).

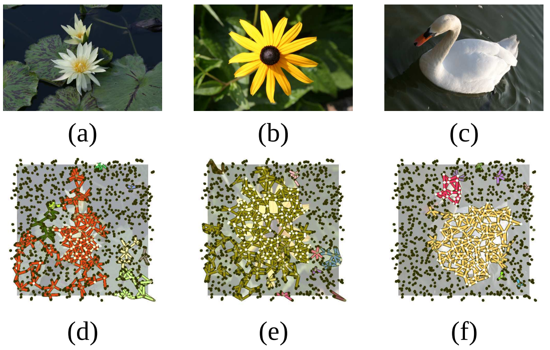
(a) (b) (c)
(d) (e) (f)

Figure 3: Figure/ground separation. (a)-(c) Input images. (d)-(f) The sheet of neurons responds to input from a simulated retina.

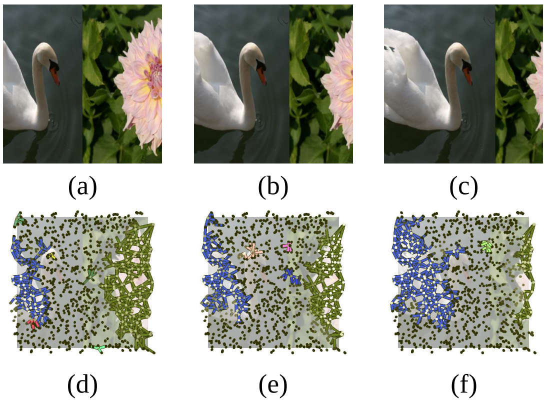
(a) (b) (c)
(d) (e) (f)

Figure 4: Response to moving stimulus. The connected sub-network follows the object.

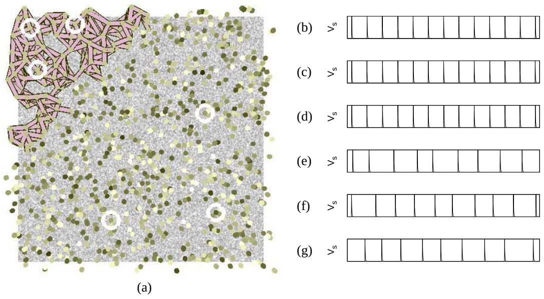

Figure 5: (a) random input stimulus. (b-d) synchronous firing behavior of 3 neurons from the upper left area. (e-g) asynchronous firing of 3 neurons with closed gap junctions.

Or it could be used for adaptive thresholding of auditory information.

The sheet of neurons receives input from the virtual retina. A number of still images are moved across the virtual retina. Figure 3(a)-(c) shows three of the images that the retina was exposed to. The input image is shown in the background. Each dot in the foreground corresponds to a single neuron of our sheet of neurons which receives input from the virtual retina. The output of the sheet of neurons is shown in Figure 3(d)-(f) for the same three images. Open gap junctions are drawn as colored lines between neurons. All connections which belong to the same cluster are drawn with the same color. This indicates synchronous firing. The neurons responding to the "figure" have their gap junctions open. Thus, the figure has been separated from the ground. Figure 4 shows how the same sheet of neurons respond to a moving stimulus. Even though the object moves across the retina, the same sub-network (as indicated by the color of the sub-network) responds to the same stimulus. Higher visual areas are able to process this stimulus using visual servoing techniques (Chaumette and Hutchinson, 2006, 2007) for behaviors such as grasping.

Figure 5 and Figure 6 shows the output of the same sheet of neurons when the gap junctions of several neurons were deliberately opened and a random input was provided to the virtual retina. The neurons located within the connected sub-network synchronize their firing behavior. In order to demonstrate the effect of the size of the sub-network on the firing frequency, the parameter γ was set to 0.001. Hence, the firing frequency depends on the size of the connected sub-network. This can be seen when comparing the spiking frequencies of neurons (b), (c), (d) shown in Figure 5 and Figure 6. Neurons from the connected sub-network shown in Figure 5 have a smaller firing frequency because the size of the sub-network is smaller compared to the size of the sub-network shown in Figure 6. Neurons from the connected sub-network shown in Figure 6 have a higher firing frequency. The difference in the firing frequency can be used to discern different objects by higher visual areas.

5 CONCLUSIONS

In standard neural modeling, neurons are assumed to show an integrate-and-fire-behavior. We have developed a computer simulation which also takes lateral connections between neurons into account. Neurons having the same function, i.e. neurons responding to input in the same way, are assumed to be laterally connected through gap junctions. The neurons integrate their input. If this activation of the neuron is large enough, then the neuron fires. The generated spike train of the neuron is temporally and spatially integrated. If the temporal average of the output is above the average spatial average, then the neuron opens its

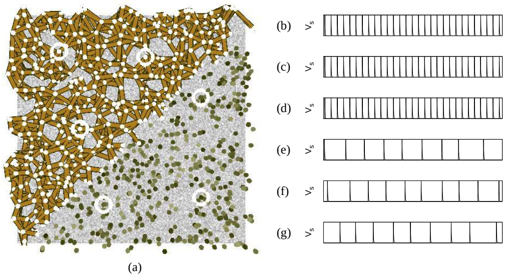

Figure 6: (a) random input stimulus. (b-d) synchronous firing behavior of 3 neurons from the upper left area. (e-g) asynchronous firing of 3 neurons with closed gap junctions.

gap junctions to nearby neurons. Once this happens, then the connected neurons synchronize their firing behavior. This is a marker of consciousness. We have shown how a virtual sheet of neurons responds to visual input on a simulated retina segmenting figure from ground. Higher brain areas can use this data for behaviors such as reaching or grasping.

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