

Modeling Figure/Ground Separation with Spiking Neurons

Marc Ebner

Ernst Moritz Arndt Universität Greifswald
Institut für Mathematik und Informatik
Walther-Rathenau-Str. 47
17487 Greifswald, Germany
marc.ebner@uni-greifswald.de

Stuart Hameroff

Departments of Anesthesiology and Psychology
and Center for Consciousness Studies
The University of Arizona
Tucson, Arizona 85724, USA
hameroff@u.arizona.edu

Abstract—The human brain routinely performs figure/ground separation like picking up a cup on a table, or grasping an apple from a tree. Figure/ground separation is used not only in vision, but in separating voice from chatter, touch and other modalities, and remains a challenge in artificial intelligence and machine learning. To approach this problem we’ve shown figure/ground separation in a laterally-connected sheet of ‘integrate-and-fire’ spiking neurons. Biologically, the lateral connections and sheet are based on ‘gap junction’ electrical synapses between dendrites and soma of brain neurons, e.g. cortical layer 5 pyramidal cells and interneurons. The method is based on locally computing the average integration potential for each neuron using lateral connection inputs as well as direct sensory inputs. We show results for artificial as well as real world images in which the model adaptively extracts a figure from background, irrespective of actual numerical value of the figure’s pixels. Lateral modulation enables collective integration and synchronized firing/spiking of large groups of neurons. As lateral connections open and close, a zone of integration moves through the larger system. With further development, such ‘mobile zones’ offer models for executive agency, causal action, attention and correlates of consciousness in intelligent systems.

Index Terms—Figure/ground separation; visual perception; spiking neurons; lateral-coupling; gap-junctions; gamma-oscillations

I. INTRODUCTION

The human brain excels at many tasks involving ‘Figure/Ground separation’, e.g. recognizing salience and meaning in an object or pattern from its background. Understanding how the brain discriminates ‘Figure’ from less important ‘ground’ may help design computer systems for artificial intelligence (AI).

In the brain, figure/ground separation in conscious perception depends on sensory inputs reaching thalamus, and then on to cerebral cortex in a 3-step hierarchical process. For example in visual processing, optical inputs are mapped onto (‘retino-topic’) sheets of rod and cone cells in retina, and then relayed to thalamus. From thalamus, the first wave of activity relays sensory inputs to primary cortex, e.g. for vision in V1 in the very back of the brain’s occipital lobe, still maintaining retino-topic representation. From there, secondary ‘associative’ processes project in feed-forward pathways to frontal areas including prefrontal ‘executive’ cortex. Finally, from there, a third wave of ‘recursive’ feedback projects

to other cortical and sub-cortical areas and correlates with consciousness [1]. This third wave matches a philosophical approach termed ‘higher order thought’ (‘HOT’, [2], [3]) which suggests recursive feedback projection from pre-frontal cortex to other brain regions correlates with consciousness. Lee et al. [4] showed this third wave activity is selectively sensitive to anesthetics of all types, i.e. gas molecules, propofol and ketamine.

Third wave activities terminate at the apex of the brain’s hierarchy, cortical layer V giant pyramidal neurons which are unique in several ways. Their apical dendrites arise vertically to the cortical surface, and are primarily responsible for EEG signals. Basilar dendrites of pyramidal neurons spread laterally, parallel to brain surface, forming, along with interneurons, sheet-like networks throughout cortex. They are likely biological sites for conscious perceptions, and figure/ground separation.

But how are certain activities within the sheet recognized as ‘figure’ rather than ground, and assigned meaning? Various ‘spotlight’ attentional theories require a spotlight operator. We’ve approached the problem with a self-organizing mobile zone of integrative activity within a larger sheet of integrate-and-fire spiking neurons.

Neurons consist of multiple dendrites and cell body, or soma, which receive and integrate synaptic inputs by chemical messengers to a threshold potential for all-or-none firing, or spiking along a single long axon, giving unidirectional information flow. However the brain also utilizes electrical synapses, or ‘gap junctions’ which physically fuse neuronal membranes, create window-like connections between adjacent neuronal interiors, and synchronize membrane depolarizations, e.g. in gamma synchrony EEG. Although gap junctions are prevalent in the brain, more primitive than chemical synapses and highly conserved in evolution, their true function is not understood.

In networks of integrate-and-fire (spiking) neurons, inputs from dendritic-dendritic (and dendritic-somatic) gap junctions have been proposed to modulate integration and regulate firing/spiking. Gap junction lateral connections may enable groups of neurons to function collectively, and more intelligently. We applied this principle in a computational model

system for figure/ground separation.

We previously described figure/ground processing using a sheet of spiking neurons with lateral connections [5]–[7]. It is assumed that the neurons’ ‘pre-spiking’ dendrites are laterally connected through gap junctions to neurons in their immediate vicinity. This is an extension to the traditional spiking neuron model which does not include lateral connections.

In our model, if an open gap junction exists between two neurons then the neurons are resistively coupled, allowing for a current flow, or voltage gradient, from the neuron having a higher activation to the neuron having a lower activation. As a result, neurons connected via an open gap junction are able to integrate collectively and synchronize their firing behavior. Neurons cause gap junctions to open and close based on activation or other factors. If a gap junction closes, the lateral connection between two neurons is severed, and they integrate individually and fire asynchronously.

While gap junctions are either open or closed, we assume an additional permanent network of lateral connections. This may occur biologically (e.g. in layer 5 cortical pyramidal neurons) by cortical inter-neurons, and used to compute a spatial average of the input. This average is then used to determine whether neurons close or open their gap junctions. If a neuron’s activation is above the spatial average, then this neuron will open its gap junctions. Neurons connected by lateral gap junctions can collectively respond to a given stimulus, and fire synchronously with a specific frequency which can be used to discern different stimuli. Neurons which do not respond may fire asynchronously.

Our model uses visual information from a sheet of neurons whose output corresponds basically to a topological representation of the retina, e.g. retinal outputs serve as inputs to our model which is comparable to neurons found in V1. Our sheet of laterally connected neurons then performs figure/ground segmentation.

The brighter part of the image is extracted if neurons whose activation is above the spatial average open their gap junctions, irrespective of the actual maximum output of a single input neuron. The neurons adjust themselves such that whichever region appears brighter than the surrounding will be extracted as figure while the remaining area is considered as background. We could extract arbitrary types of regions (e.g. regions having a certain color or texture) by transforming the input through additional sheets of neurons placed in front of the sheet that we describe here.

Below, we fully describe our theoretical model of a spiking neuron including its lateral connections. We show how a sheet of such neurons is able to separate figure from ground for several real world images. We show only results for visual input data. However, the method can also be used to separate figure from ground in any kind of spatially distributed signal.

For example, suppose we take a topological map of neurons representing different regions of the body and pressure, touch or proprioception are the relevant signals. Our method would be able to locate the signal irrespective of the amount of pressure exerted. The corresponding neurons of a certain

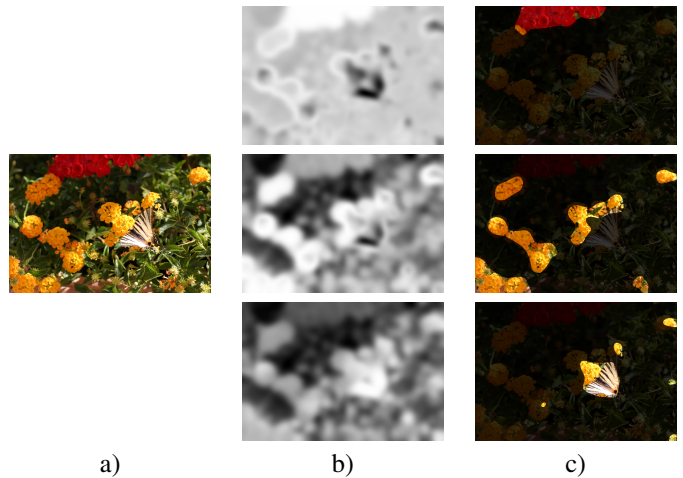


Fig. 1. a) Input image. b) gaussian blur of squared color differences highlighting areas which have the colors (from top to bottom): red, yellow, white) c) extracted areas: red flowers, yellow flowers, butterfly.

region would only have to fire, or fire with a larger frequency when this area is touched. All neurons responding to the same touch would fire in synchrony.

II. FIGURE/GROUND SEPARATION

The ability to separate figure from ground is very important to many daily tasks. If one grasps a cup on a table top, the brain determines what part of the scene corresponds to the cup and what part corresponds to the table top. A similar ability is probably required by all animals processing visual information in nature. Locating red apples on a tree or strawberries in a field require a similar ability.

Figure 1 illustrates how different objects can be extracted based on their color. The first column shows the input image. First, squared differences are computed. The second column shows the results after computing squared differences with the colors $[0.82, 0.43, 0]$, $[0.63, 0.02, 0.04]$, $[0.90, 0.78, 0.62]$ and applying Gaussian blur with a standard deviation of 10 pixels. Let $a(x, y)$ be the output of the blur operator, i.e. a local spatial average and let \bar{a} be the global average of this output. The third column of images shows areas for which $a(x, y) \geq f\bar{a}$ holds with $f = \{1.4, 1.16, 1.7\}$. Extracted objects are shown in Figure 1c). This rather simple example shows how different colored objects (red flowers, yellow flowers or butterfly) can be separated from their background based on their color.

A cup on a table may be more difficult to extract. However, we can of course take additional information such as depth or texture into account. Then we would extract areas which have a unique texture and a depth different from the surrounding area.

Below, we will show how a figure can be separated from ground using a network of laterally connected neurons. But first, we will describe the basic model of a spiking neuron followed by our extension which also includes lateral connections.

III. SPIKING NEURAL NETWORKS

The brain consists of a large set of ‘integrate-and-fire’ spiking neurons interconnected by variable strength chemical synapses in feed-forward networks [8].

These neurons exchange electro-chemical signals, resulting in network patterns of activity which correlate with sensory perception, motor control and learning. Each neuron sends out sequences of spikes along its axon to other neurons, the sequence depending largely (but not entirely) on integration of electro-chemical membrane signals the neuron receives from other neurons.

Each neuron receives and integrates synaptic inputs to its dendrites and cell body/soma in the form of an integrated activation potential. When this potential reaches a threshold potential, an all-or-none firing, or spike is triggered down the axon. However in brains of awake animals, threshold for firing varies spike-to-spike, suggesting some other factor contributes to integration, possibly via gap junctions [9].

In standard computational models, only algorithmic integration and a fixed spiking threshold are considered. Other potentially relevant aspects are usually not included, for example lower level synaptic and cytoskeletal interactions and lateral gap junction influences. Using a spiking neural model based on membrane capacitance, resting potential, threshold potential, a recovery variable, dendritic and synaptic currents and other parameters, a large-scale approximation of mammalian thalamo-cortical systems can be constructed [10].

In simulations, we model a large network of neurons. Consider a single neuron i with activation potential V_i . The change of the activation potential $\frac{dV_i}{dt}$ can be described by (modified from [11]):

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

where C is the capacitance of the neuron, g_i is the leakage conductance, E_i is the resting potential and I_{tonic} is a tonic current. The leakage conductance will determine the speed with which the activation potential will reach the resting potential if no input is received from other neurons. External input to the neuron can be modelled using I_i while the input received from other neurons is modelled by K_j . The input received from other neurons will depend on the strength of the synaptic connection w_{ij} between the two neurons i and j . Neural learning is thought to basically modify the connection strengths w_{ij} .

This standard model only considers input from other neurons received via synaptic connections, with learning achieved by tuning the connective weights. Lateral connections created by gap junctions are not included in this standard model. Below, we will show that these lateral connections enable exchange of activation between neighboring neurons, allowing them to tune their response to a given stimulus. Thus neurons connected via open gap junctions can collectively integrate inputs and memory, fire synchronously and efficiently separate figure from ground.

IV. LATERAL CONNECTIONS VIA GAP JUNCTIONS

Our model neuronal network also includes lateral connections via gap junctions. Neurons in our model network receive and temporally integrate incoming spikes as in the standard model, activation potential slowly rising toward threshold. And like the standard model, once activation potential reaches a particular threshold, the neuron ‘fires’, or ‘spikes’, and sends a spike along its axon to the next synapse. Our model adds another factor during integration and activation which regulate firing/spiking, inputs from lateral ‘gap junction’ and interneuron connections.

Laterally-connected neurons are able to exchange part of this activation via open gap junctions. A current will flow, i.e. a voltage gradient exists, from a neuron with a higher activation potential to a neuron with a lower activation potential. In our model, this current flow/gradient between neighboring neurons can be turned on or off by opening or closing the gap junction. Only neurons which perform a similar function, i.e. which respond to the same type of signals are assumed to be connected. Such neurons inter-connected by open gap junctions will collectively respond to the same stimulus.

It can be envisioned that initially, i.e. during early development, many lateral connections randomly form, and are then pruned to form sub-networks able to collectively respond to a stimulus. Gap junction-defined sub-networks then specialize themselves to respond to different types of stimuli by tuning their synaptic weights.

A gap junction can be treated as a resistive connection between neurons [12], [13]. The set of all neurons interconnected via gap junctions form a resistive grid where the node points are the neurons and the gap junctions the resistors. If a gap junction exists, it is always there, i.e. a permanent connection between two neurons, though it may be open or closed. We assume that this connection forms an unconditional resistive grid. Therefore, some information is always exchanged between these laterally connected neurons. This network could be used to compute a global average among interconnected neurons.

Traub et al. [14] have used a voltage dependent conductance of gap junctions. In our model, each gap junction is also able to change its state. It can open or close, i.e. the conductance depends on an internal state of the neuron. This creates a second network whose connections can be modified over time. The two networks are illustrated in Figure 2. If a gap junction is open between two neurons then these neurons will synchronize their firing behavior. It is well known that chaotic or non-linear electrical circuits will synchronize their behavior if they are resistively connected [15]–[17]. The same will happen with neurons whose firing pattern is chaotic whenever they are resistively connected to other neurons.

The unconditional network is assumed to spatially average the input spikes. This allows each neuron to become aware of the global average firing pattern of all other laterally connected neurons. This signal which we call the sync-threshold, is used to adjust the adaptive resistive network. Each neuron can of

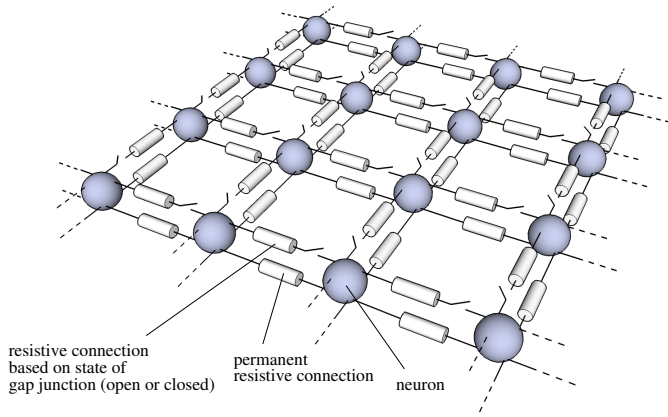


Fig. 2. Gap junctions between adjacent neurons give rise to two resistive networks: a fixed resistive network and a modifiable resistive network defined by the state of the gap junction (open or closed).

course also compute a temporal average of its firing pattern. If the average firing pattern is above the global average, i.e. the sync-threshold, then the network will open its gap junctions. Otherwise it will close its gap junctions. This results in synchronized firing of all neurons responding to the figure, i.e. which have an average firing rate above average.

Figure 3 shows our model neuron which is also laterally connected to four other neurons. Of course, neurons may also have fewer or more gap junctions. Similarly, neurons may have an other number of dendritic inputs and the connections will not be uniformly distributed. In Figure 3, the lateral connections extrude from the neuron body. This is meant to illustrate that information is exchanged through this connection on the same level. For actual neurons, gap-junctions are generally located on the dendrites, shown on left in the illustration. The dendrites lead up to the neuron soma, or cell body which also receives and temporally integrates inputs.

Inputs received and temporally integrated are indicated by the box labeled with $\int dt$. This input is also temporally and then spatially integrated as indicated by the boxes labeled with $\int dt$ and $\int dx$. Gap junctions allow for an exchange of this signal with laterally connected neurons, provided these gap junctions are open. Two connections are shown for each gap junction. The connection extending from the sphere illustrates the conditional connection between neighboring neurons. The small sphere on this connection indicates that the gap junction can be opened or closed. This connection is controlled via the input from the sync-threshold which in turn is determined by the spatially averaged input signal obtained from the unconditional network (formed by the lateral connections protruding in between the dendrites and the large sphere, and biologically by interneurons). The neuron will fire if its activation potential is above the threshold. This operation is indicated by the threshold box. Whenever the neuron fires, a spike (as indicated by the spike shown on the last box on the right) is sent along the axon.

It may also be that some of the functions just described, are spread over two or three interconnected neurons inside a

cortical column. Mountcastle [18] gives a review of columnar organization of the neocortex. These neurons would then have different shapes due to the different function performed by the neuron. A lateral network formed by such neurons will extract any kind of spatial signal which is above the average. This is more useful than using a fixed threshold per neuron. A set of neurons which extracts a signal with a fixed threshold will fail to detect a faint signal. It will also fail to generate synchronized firing behavior.

V. SIMULATION OF A SHEET OF LATERALLY CONNECTED NEURONS

We evaluate our model using real world photographs as visual stimuli. We simulate a sheet of laterally connected neurons. Each neuron is randomly connected to other neurons in its immediate surrounding. All neurons of this sheet receive their input from a virtual retina. This input can also be viewed as coming from V1 with some additional transformation of the visual stimulus.

The sheet of neurons is assumed to extend over an area of $1000 \times 1000 \times 2$ units, i.e. a square area of non-zero height. We simulate 4000 neurons inside this area. The non-zero height is modeled because actual neurons are not perfectly arranged on a two-dimensional plane inside the cortex. In our simulation, each neuron i is located at position (x_i, y_i, z_i) inside the three-dimensional sheet. It is laterally connected to its 6 nearest neighbors.

The human visual system processes visual information using three channels, bright-dark, red-green and yellow-blue [19]. Our sheet of neurons processes only information from the bright-dark channel (also called lightness). Data is extracted from computer images which are stored using red, green, blue components. This data is transformed to lightness for each image pixel. Let (R, G, B) be the red, green and blue non-linear pixel intensities, then lightness is given by $L = 0.299R + 0.587G + 0.114B$ [20].

A topological mapping is used to determine the input received by neuron i . Let the coordinates x_i, y_i, z_i of neuron i be normalized to the range $[0, 1]$. For each input signal, we determine offset coordinates $(x_{r,i}, y_{r,i})$ randomly selected from $-1, 0, 1$. The neuron j where neuron i receives its input from is given by $(wx_i + x_{r,i}, hy_i + y_{r,i})$ where w and h are the width and height of the input image. Each neuron i receives input from three neurons of a lower sheet. The output provided by neuron j from a lower sheet is taken as $o_j = L(x_j, y_j)$ where L is simply the lightness of the corresponding image pixel at position (x_j, y_j) .

Our sheet of neurons is probably located in some higher visual area which is in charge of figure/ground separation. For our experiments, we use the input directly from the image. Since multiple inputs from all three color bands are used, this amounts to using only the black and white channel as input. Any type of color could be extracted by simply computing squared differences to certain colors or by correlating the input signal with a given signal.

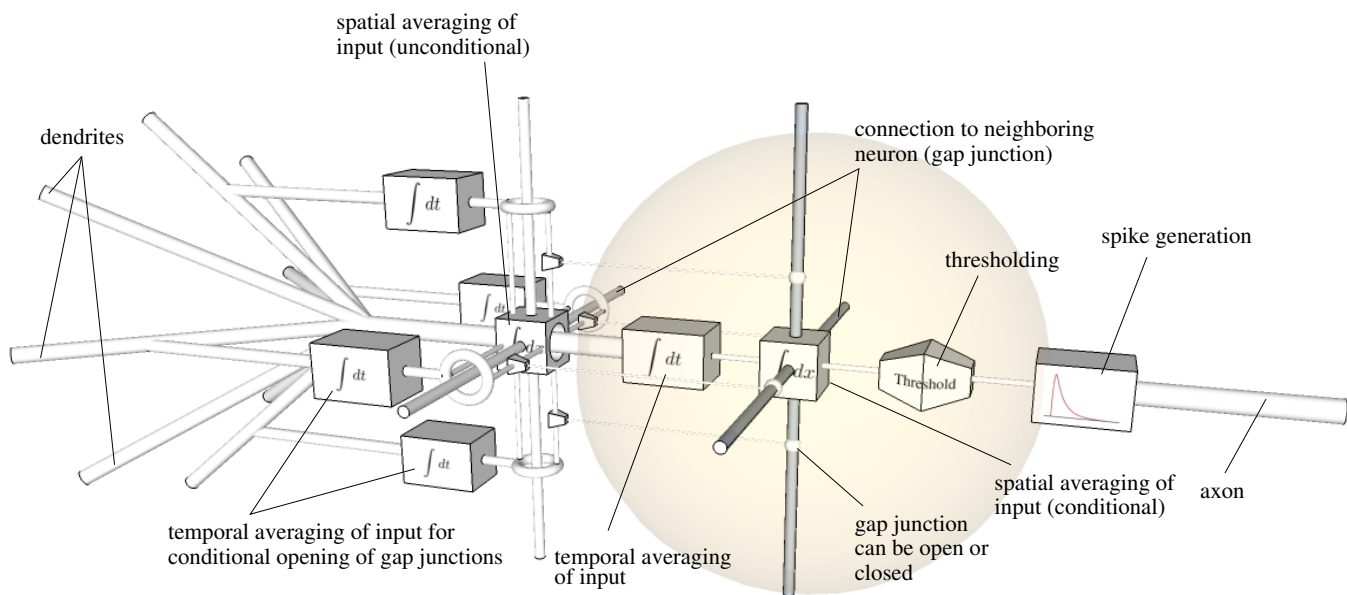


Fig. 3. Artificial neuron, laterally connected to 4 other neurons via gap junctions.

Neurons found in V3 respond to different types of oriented lines [21], [22]. Hence, neurons receiving input from V3 could be used to separate figure from ground based on texture. Neurons found in V5 respond to lines moving in a certain type of direction. Some neurons also respond to the global motion of an object. This contrasts with the response of neurons found in V1 which only respond to local image motion. Thus, neurons receiving input from V5 could be used to separate a figure moving in a certain direction while the background is either stationary or moving in a different direction.

In our computer model, the state of our laterally connected neuron i is described by the following 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 spatial average is computed using the unconditional network formed by the gap-junctions. The model shown in Figure 3 shows temporal averaging per dendrite. Since these temporally averaged signals are eventually spatially averaged, we use only one variable \tilde{a}_i for the neuron i to speed up the simulation. The update equations which modify these state variables are shown in Figure 4. Compared to our earlier model [6], we have modified the algorithm slightly in that the activation is not distributed to neighboring neurons but simply averaged. In other words, a current flows, or voltage gradient exists from the neuron having a higher activation to a neuron having a lower activation.

The state variables can be initialized with random values. The exact values, which are used to initialize the simulation, are not relevant. Due to the leakage factors the simulation will converge to the same type of response if the input is kept constant. The following values were used for our experiments: decay of activation potential $\alpha_a = 0.9995$, decay of output voltage $\alpha_o = 0.5$, temporal averaging factor of gap-

junction $\alpha_t = 0.001$, spatial averaging factor of gap-junction input $\alpha_s = 0.0001$, leakage to adjacent neurons upon firing $\epsilon = 0.0001$, reduction of fire-threshold $\gamma = 0.0005$, factor for over-relaxation $\omega = 1.999$, refractory period of neuron $\Delta t_r = 10$.

All weights between neurons i and j are set to $w_{ij} = 1$. Learning could be used to tune these weights. For our experiments, we only process the luminance signal to extract objects with maximum luminance. Hence, learning is not necessary. Simple Hebbian learning [23] could tune these weights in a way that objects having certain colors are extracted. Alternatively, learning and memory could occur within each neuron, e.g. in the cytoskeleton. Negative weights could also be used. Such weights would model inhibitory signals.

The behavior of a single neuron is fully described by the algorithm shown in Figure 4. Each line of the algorithm describes one small state change. If all updates are completed, then the algorithm starts over. First, the output voltage decays (01), then the weighted input is computed (02). If we were to add learning, we would have to tune the weights w_{ij} .

Each neuron computes the temporal average of the input using the parameter α_a (03). Next, another temporal average is computed using the parameter α_t (04). The spatial average of \tilde{a} is computed in lines (05-08) using the unconditional network formed by the gap junctions. Over-relaxation is used in line (09) to speed up the simulation. If the temporal average \tilde{a} is above the spatial average \bar{a} , then we open all gap junctions, otherwise we close all gap junctions (10-11). This spatial average is an adaptive threshold. It depends on the average spatial output produced by the previous sheet of neurons. Only neurons whose input is above the spatial average will fire vigorously and also connect with adjacent neurons which allows for figure/ground separation.

Here, all gap junctions are modified at the same time. This

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(01)  $o_i = (1 - \alpha_o)o_i$  // decay of output
(02)  $I = \sum_j w_{ij}o_j$  // compute weighted input
(03)  $a_i = (1 - \alpha_a)a_i + \alpha_a I$  // temporal average of input (activation)
(04)  $\tilde{a}_i = (1 - \alpha_t)\tilde{a}_i + \alpha_t I$  // temporal average of input (dendrites)
(05)  $\bar{a}'' = \bar{a}_i$  // save spatial average from previous time step
(06)  $N = \{j | \text{Neuron } j \text{ is laterally connected to neuron } i \text{ via gap junction}\}$ 
(07)  $\bar{a}' = \frac{1}{1+|N|} \left( \bar{a}_i + \sum_{j \in N} \bar{a}_j \right)$  // compute spatial average
(08)  $\bar{a}_i = (1 - \alpha_s)\bar{a}' + \alpha_s \tilde{a}_i$  // add temporal average
(09)  $\bar{a}_i = (1 - \omega)\bar{a}'' + \omega \bar{a}_i$  // use over-relaxation
(10) if ( $\tilde{a}_i > \bar{a}_i$ ) open gap junctions // open gap junctions
(11) else close gap junctions // close gap junctions
(12) if Neuron  $i$  fired within  $\Delta t_r$  return // done if neuron fired recently
(13)  $N = \{j | \text{Neuron } j \text{ is laterally connected to neuron } i \text{ via open gap junction}\}$ 
(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)  $N_s = \{ \text{number of neurons in sub-network created via open gap junctions} \}$ 
(19)  $t_i = \max[0, 1 - \gamma \cdot N_s]$  // compute fire-threshold
(20) if ( $a_i > t_i$ )  $\{$  // does the neuron fire? (activation above fire-threshold)?
(21)  $a_i = 0$  // reset activation
(22)  $o_i = 1 - \epsilon / |N|$  // output rises to 1 minus some loss
(23) for all  $j \in N$  do :  $a_j = a_j + \epsilon$  // distribute leakage to adjacent neurons
(24)  $\}$ 

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Fig. 4. Update equations which change the state variables of neuron i over time.

is probably not the case for actual neurons. We have used this simplification to allow for faster simulation of the model. Currently, it takes 3.7ms to simulate one update of a sheet of 4000 neurons on a 2,8 GHz Intel Core i7. In real neurons, gap-junctions probably open and close independently of the other gap-junctions. The state of the gap junction is probably controlled by the signal passing through its dendrite.

We are done if the neuron fired recently (12). Next, the neuron computes the spatial average of activation across open gap junctions (13-17). This operation allows activation to flow from a neuron having a higher activation to a neighboring neuron with a lower activation. Then the fire threshold is computed (18-19). This threshold depends on the number of neurons in the sub-network formed by neurons connected through open gap junctions. For larger networks the threshold will be lowered such that neurons belonging to a large set of neurons will fire with a higher frequency. An adaptive firing threshold is not really required. However, it allows to distinguish larger figures from smaller figures in higher visual areas.

Whenever the neuron fires (20), i.e. the activation is above the fire-threshold, then the activation is reset (21) and the output rises to 1 minus some leakage (22). This leakage is distributed to adjacent neurons (23).

It should be clear that our sheet of neurons is capable of adaptive figure/ground separation irrespective of the actual lightness values. Figure 5 shows how the sheet of neurons responds to images of a gray square on a slightly darker background. The input images are shown on the left hand side. Noise with a mean of zero and a standard deviation of 0.5 has been applied to these images as real world signals

always contain some noise. The noisy input signal is shown in the middle. The sheet of neurons is shown overlaid on this input signal. Each neuron is represented by a dot. The brightness of the dot is proportional to its activation. Open gap junctions between two neurons are represented by thick lines. The color of the lines is chosen in a way that each sub-network has a unique color.

On the right hand side, the lightness histograms are shown. It should be noted that the lightness of the background in case (d) is higher than the lightness of the square in case (a) and (b). Nevertheless the square is correctly separated from the background in case (d). A single neuron which may be capable of simple bright/dark classification based on a fixed threshold would not be able to correctly separate the figure from ground in all four cases shown in Figure 5.

Figure 6 and Figure 7 shows the response of individual neurons for two different types of input stimuli. The input stimulus is shown on the left hand side. Selected neurons are marked with a circle and a number. Three neurons are located on the figure (bright square) while three other neurons are located on the background. The spiking sequences are shown on the right hand side. Neurons 1 to 3 whose receptive fields lie on the bright square fire in sync, while neurons 4 to 6 whose receptive field lie on the background fire out of sync. All neurons located on the figure are connected via open gap junctions to neighboring neurons. It can also be seen that the neurons located on the larger square fire with a higher frequency compared to the neurons located on the smaller square. This behavior is due to the adaptive firing threshold used in line (19) of Figure 4. Higher visual areas may make use of the different firing rates for tracking of different objects.

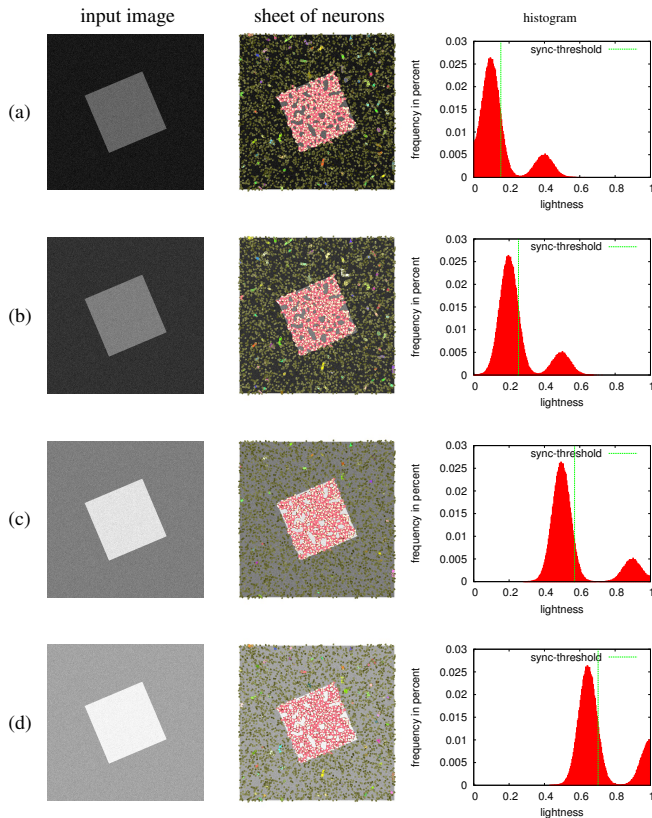


Fig. 5. Results for a brighter sphere in front of a darker background. Noise has been applied with zero mean and standard deviation 0.05 (pixel range [0,1]). Background lightness L_b and figure lightness L_f were chosen as follows (a) $L_b = 0.1$, $L_f = 0.4$ (b) $L_b = 0.2$, $L_f = 0.5$ (c) $L_b = 0.5$, $L_f = 0.9$ (d) $L_b = 0.65$, $L_f = 1.0$

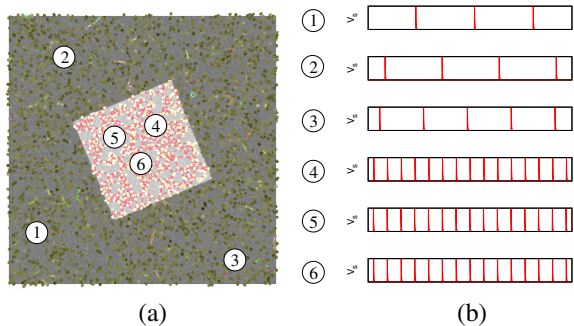


Fig. 6. Sequence of output spikes generated by individual neurons. (a) input stimulus (b) behavior of six different neurons (marked). Neurons 1-3 fire in synchrony. They belong to the sub-network formed by neurons extracting the figure. Neurons 4-6 fire out of sync.

It may also be used for visual servoing [24], [25].

A simulation of the network responding to an image sequence is shown in Figure 8. This sequence simulates a sweep of the eye from one photograph to another photograph. The object in the foreground is extracted by a network of neurons connected via open gap junctions. In the course of time, different neurons respond to the object. The firing rate of neurons with their receptive field above the object will stay

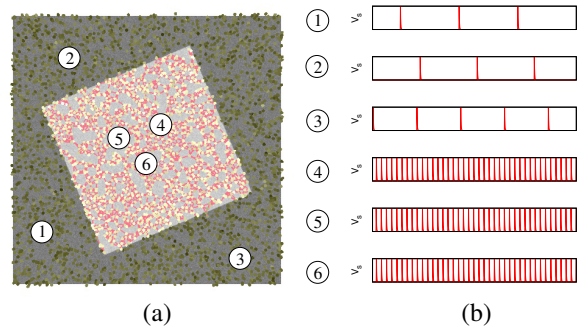


Fig. 7. Sequence of output spikes generated by individual neurons. (a) input stimulus (b) behavior of six different neurons (marked). Neurons 1-3 fire in synchrony. They belong to the sub-network formed by neurons extracting the figure. Neurons 4-6 fire out of sync.

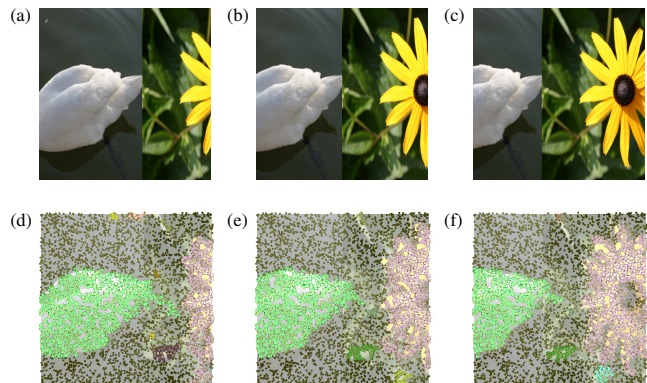


Fig. 8. Results for a moving stimulus (a-c) Snapshots from an image sequence. (d-f) Neurons with a receptive field above the figure respond vigorously. They collectively extract the figure. The sub-network formed by neurons with open gap junctions tracks the figure.

constant as long as the object does not change in size. It is known that the mapping from the retina to the visual cortex can be viewed as a complex-logarithmic mapping [26]–[28]. This transforms the visual input to a size invariant representation.

VI. BASIS OF OUR MODEL

As we have just shown a sheet of laterally connected neurons is able to segment figure from ground. Zhao and Breve [29] have shown that chaotic synchronization in a 2D lattice can be used for scene segmentation. In their work, they have used Wilson-Cowan neural oscillators [30] to segment letters. They only used static input. Quiles et al. [31] have developed a visual selection mechanism using a network of integrate and fire neurons with short range excitatory connections and long-range inhibitory connections. They also used only static images as input. Eckhorn et al. [32] simulated feature linking via synchronization among distributed neural assemblies. They simulated two one-dimensional layers from the visual cortex of the cat including feed forward and backward connections. The backward connections modulate the inputs. A moving stimulus was used as input. Our model addresses synchronization within a sheet of neurons and only relies on local connections. As

gap junctions open and close, a moving zone of collective, synchronized activity tracks and moves with it. Such a zone of activity in the brain is asserted to correlate with conscious perception and control. Self-organizing mobile zones are also possible.

Neurons who have their receptive field above the stimulus will fire in sync while all other neurons will fire out of sync. In the brain, synchronized firing behavior is seen in the electroencephalogram (EEG) especially in the frequency range from 40 to 80Hz [33], [34]. This type of synchronous activity includes gamma synchrony EEG. Singer [35] gives a review on how gamma synchrony correlates with perception and motor control. Gamma synchrony arises because of inter-dendritic gap junctions [36]–[39].

According to the so called “conscious pilot model”, created by Hameroff [40], gap junctions open and close, creating self-organizing synchronized zones of activity moving through the brain. In our model, these zones move because the input stimulus moves. In the ‘conscious pilot’, the zone self-organizes converting non-conscious ‘auto-pilot’ cognition to conscious cognition. Self-organizing mobile zones are candidates for consciousness in the brain, and for an executive ‘causal agent’ in computer systems.

Kouider [41] has reviewed several different theories of consciousness. Tononi and Edelman [42] have developed the re-entrant dynamic core hypothesis. This theory assumes recurrent processing of information. Another theory, the local recurrence theory developed by Lamme [43] also assumes recurrent processing of information, both consistent with the ‘third wave’, also described philosophically by the higher order thought’ (HOT) theory.

In the context of theories of consciousness, our model may be seen as a moving zone within the third wave target, e.g. laterally-connected cortical layer 5 pyramidal neurons.

As noted by Crick and Koch [44], humans appear not to be aware of processing occurring inside V1. In this case, V1 is merely in charge of preprocessing visual input and conscious processing starts in higher visual areas. Zeki [45] suggests that multiple consciousnesses are distributed across different processing sites. He calls the conscious processing of different aspects microconsciousness, e.g. of attributes such as color, form and motion bound together. Woolf and Hameroff [46] proposed feed-forward cascades through visual cortex accumulate shape, color, motion and meaning aspects into a conscious visual gestalt. With further unification with other modalities, visual scenes unify into global consciousness. linguistic and communication skills are included. Our model addresses only a single percept, but gap junction-mediated zones may coalesce into larger zones to accommodate full conscious awareness.

So far, we have not modeled synchronization across different sheets but could do so in the future. This would then be macroconsciousness in Zeki’s terms. Wang [47] noted that only local connections can lead to global synchrony. König and Schillen [48] used long range excitatory delay connections to achieve synchronization within two-dimensional layers of

oscillators. Terman and Wang [49] have developed an architecture of oscillator networks in which a global inhibitor is used to achieve desynchronization. In our model, neurons connected via open gap junctions are resistively coupled. They synchronize their behavior, and the connected zone moves through the larger sheet of neurons. With further development, our mobile zone model can serve as a theory for the neural correlate of consciousness, and executive causal agents in artificial intelligence.

VII. CONCLUSION

We extend standard network models of ‘integrate and fire’ spiking neurons to include lateral connections between neurons in a 2-dimensional feed-forward sheet. The lateral connections are based biologically on gap junctions between dendrites and cell bodies of brain neurons. Neurons within the laterally-connected network are shown to perform figure/ground separation by collective integration and synchronized outputs.

Here we implement an artificial system based on laterally-connected neurons and show examples of its ability to discriminate figure from ground. Gap junctions resistively couple adjacent neurons. A gap junction may be in one of two states: open or closed. If a gap junction connects two neurons then it creates a physical connection between the two neurons. A network of resistively coupled neurons forms an unconditional network. In addition to this unconditional network, another network is formed which may be changed over time by opening or closing gap junctions. We use the unconditional network to compute a spatial average of the temporally averaged input. This spatially averaged signal allows the neuron to adaptively respond to the input. If the temporal average of the input signal received by the neuron is above the spatial average, then the neuron opens its gap junctions, otherwise it closes its gap junctions. Neurons connected via open gap junctions synchronize their firing behavior because a current always flows from the neuron having a higher activation to adjacent neurons having a lower activation. Neurons with synchronized firing collectively respond to the figure whereas the remaining neurons fire out of sync. Neurons out of sync respond to the ground. Our model is shown to separate figure from ground for artificial as well as real world images.

REFERENCES

- [1] V. A. F. Lamme and P. R. Roelfsema, “The distinct modes of vision offered by feed-forward and recurrent processing,” *Trends in Neuroscience*, vol. 23, pp. 571–579, 2000.
- [2] R. J. Gennaro, *Consciousness and self-consciousness: A defense of the Higher-Order Thought theory of consciousness*. John Benjamins Publishers, 1996.
- [3] D. Rosenthal, “Consciousness and higher-order thought,” *Macmillan Encyclopedia of Cognitive Science*, pp. 717–726, 2002.
- [4] U. Lee, S. Ku, G. Noh, S. Baek, B. Choi, and G. A. Mashour, “Disruption of frontal-parietal communication by ketamine, propofol, and sevoflurane,” *Anesthesiology*, vol. 118, pp. 1264–1275, 2013.
- [5] M. Ebner and S. Hameroff, “Lateral information processing by spiking neurons – a theoretical model of the neural correlate of consciousness,” *Computational Intelligence and Neuroscience*, 2011.

- [6] —, “Computational modeling of robust figure/ground separation,” in *Proceedings of the Third International Conference on Bioinformatics, Biocomputational Systems and Biotechnologies, Venice/Mestre, Italy*, 2011, pp. 67–72.
- [7] —, “A computational model for conscious visual perception and figure/ground separation,” in *Proceedings of the International Conference on Bio-Inspired Systems and Signal Processing, Rome, Italy*. Portugal: Science and Technology Publications, 2011, pp. 112–118.
- [8] W. Gerstner and W. Kistler, *Spiking Neuron Models*. Cambridge, UK: Cambridge University Press, 2002.
- [9] B. Naundorf, F. Wolf, and M. Volgushev, “Unique features of action potential initiation in cortical neurons,” *Nature*, vol. 440, no. 7087, pp. 1060–1063, Apr. 2006.
- [10] E. M. Izhikevich and G. M. Edelman, “Large-scale model of mammalian thalamocortical systems,” *Proceedings of the National Academy of Sciences USA*, vol. 105, no. 9, pp. 3593–3598, 2008.
- [11] J.-P. Thivierge and P. Cisek, “Nonperiodic synchronization in heterogeneous networks of spiking neurons,” *The Journal of Neuroscience*, vol. 28, no. 32, pp. 7968–7978, Aug. 2008.
- [12] J. Hérault, “A model of colour processing in the retina of vertebrates: From photoreceptors to colour opposition and colour constancy phenomena,” *Neurocomputing*, vol. 12, pp. 113–129, 1996.
- [13] M. L. Veruki and E. Hartveit, “All (rod) amacrine cells form a network of electrically coupled interneurons in the mammalian retina,” *Neuron*, vol. 33, pp. 935–946, Mar. 2002.
- [14] R. D. Traub, N. Kopell, A. Bibbig, E. H. Buhl, F. E. N. LeBeau, and M. A. Whittington, “Gap junctions between interneuron dendrites can enhance synchrony of gamma oscillations in distributed networks,” *The Journal of Neuroscience*, vol. 21, no. 23, pp. 9478–9486, Mar. 2001.
- [15] T. L. Carroll and L. M. Pecora, “Synchronizing chaotic circuits,” *IEEE Transactions on Circuits and Systems*, vol. 38, no. 4, pp. 453–456, Apr. 1991.
- [16] L. M. Pecora and T. L. Carroll, “Synchronization in chaotic systems,” *Physical Review Letters*, vol. 64, no. 8, pp. 821–824, Feb. 1990.
- [17] C. K. Volos, I. M. Kyrianiadis, and I. N. Stouboulos, “Experimental synchronization of two resistively coupled Duffing-type circuits,” *Nonlinear Phenomena in Complex Systems*, vol. 11, no. 2, pp. 187–192, 2008.
- [18] V. B. Mountcastle, “The columnar organization of the neocortex,” *Brain*, vol. 120, pp. 701–722, 1997.
- [19] M. J. Tové, *An introduction to the visual system*. Cambridge: Cambridge University Press, 1996.
- [20] C. Poynton, *Digital Video and HDTV. Algorithms and Interfaces*. San Francisco, CA: Morgan Kaufmann Publishers, 2003.
- [21] S. M. Zeki, “Review article: Functional specialisation in the visual cortex of the rhesus monkey,” *Nature*, vol. 274, pp. 423–428, Aug. 1978.
- [22] S. Zeki, *A Vision of the Brain*. Oxford: Blackwell Science, 1993.
- [23] D. O. Hebb, *The Organization of Behavior*. New York: Wiley, 1949.
- [24] F. Chaumette and S. Hutchinson, “Visual servo control part I: Basic approaches,” *IEEE Robotics & Automation Magazine*, vol. 13, no. 4, pp. 82–90, Dec. 2006.
- [25] —, “Visual servo control part II: Advanced approaches,” *IEEE Robotics & Automation Magazine*, vol. 14, no. 1, pp. 109–118, Mar. 2007.
- [26] E. L. Schwartz, “Spatial mapping in the primate sensory projection: Analytic structure and relevance to perception,” *Biological Cybernetics*, vol. 25, pp. 181–194, 1977.
- [27] —, “Computational anatomy and functional architecture of striate cortex: A spatial mapping approach to perceptual coding,” *Vision Research*, vol. 20, pp. 645–669, 1980.
- [28] P. Cavanagh, “Image transforms in the visual system,” in *Figural Synthesis*, P. C. Dogwell and T. Caelli, Eds. Hillsdale, NJ: Erlbaum, 1984, pp. 185–218.
- [29] L. Zhao and F. A. Breve, “Chaotic synchronization in 2D lattice for scene segmentation,” *Neurocomputing*, vol. 71, pp. 2761–2771, 2008.
- [30] H. R. Wilson and J. D. Cowan, “Excitatory and inhibitory interactions in localized populations of model neurons,” *Biophysical Journal*, vol. 12, pp. 1–24, 1972.
- [31] M. G. Quiles, L. Zhao, F. A. Breve, and R. A. F. Romero, “A network of integrate and fire neurons for visual selection,” *Neurocomputing*, vol. 72, pp. 2198–2208, 2009.
- [32] R. Eckhorn, H. J. Reitboeck, M. Arndt, and P. Dicke, “Feature linking via synchronization among distributed assemblies: Simulations of results from cat visual cortex,” *Neural Computation*, vol. 2, pp. 293–307, 1990.
- [33] C. M. Gray and W. Singer, “Stimulus-specific neuronal oscillations in orientation columns of cat visual cortex,” *Proceedings of the National Academy of Sciences USA*, vol. 86, pp. 1698–1702, Mar. 1989.
- [34] U. Ribary, A. A. Ioannides, K. D. Singh, R. Hasson, J. P. R. Bolton, F. Lado, A. Mogilner, and R. Llinás, “Magnetic field tomography of coherent thalamocortical 40-hz oscillations in humans,” *Proceedings of the National Academy of Sciences USA*, vol. 88, pp. 11 037–11 041, Dec. 1991.
- [35] W. Singer, “Neuronal synchrony: A versatile code for the definition of relations?” *Neuron*, vol. 24, pp. 49–65, 1999.
- [36] R. Dermietzel, “Gap junction wiring: a ‘new’ principle in cell-to-cell communication in the nervous system?” *Brain Research Reviews*, vol. 26, pp. 176–183, 1998.
- [37] A. Draguhn, R. D. Traub, D. Schmitz, and J. G. R. Jefferys, “Electrical coupling underlies high-frequency oscillations in the hippocampus in vitro,” *Nature*, vol. 394, pp. 198–192, Jul. 1998.
- [38] S. G. Hormuzdi, M. A. Filippov, G. Mitropoulou, H. Monyer, and R. Bruzzone, “Electrical synapses: a dynamic signaling system that shapes the activity of neuronal networks,” *Biochimica et Biophysica Acta*, vol. 1662, pp. 113–137, 2004.
- [39] M. V. L. Bennett and R. S. Zukin, “Electrical coupling and neuronal synchronization in the mammalian brain,” *Neuron*, vol. 41, pp. 495–511, Feb. 2004.
- [40] S. Hameroff, “The ‘conscious pilot’ – dendritic synchrony moves through the brain to mediate consciousness,” *Journal of Biological Physics*, vol. 36, pp. 71–93, 2010.
- [41] S. Kouider, “Neurobiological theories of consciousness,” in *Encyclopedia of Consciousness*, W. P. Banks, Ed. Elsevier, 2009, pp. 87–100.
- [42] G. Tononi and G. M. Edelman, “Consciousness and complexity,” *Science*, vol. 282, pp. 1846–1851, Dec. 1998.
- [43] V. A. F. Lamme, “Towards a true neural stance on consciousness,” *Trends in Cognitive Sciences*, vol. 10, no. 11, pp. 494–501, 2006.
- [44] F. Crick and C. Koch, “Are we aware of neural activity in primary visual cortex?” *Nature*, vol. 375, pp. 121–123, May 1995.
- [45] S. Zeki, “A theory of micro-consciousness,” in *The Blackwell companion to consciousness*, M. Velmans and S. Schneider, Eds. Malden, MA: Blackwell Publishing, 2007, pp. 580–588.
- [46] N. J. Woolf and S. R. Hameroff, “A quantum approach to visual consciousness,” *Trends in Cognitive Sciences*, vol. 5, no. 11, pp. 472–478, 2001.
- [47] D. Wang, “Emergent synchrony in locally coupled neural oscillators,” *IEEE Transactions on Neural Networks*, vol. 6, no. 4, pp. 941–948, Jul. 1995.
- [48] P. König and T. B. Schillen, “Stimulus-dependent assembly formation of oscillatory responses: I. synchronization,” *Neural Computation*, vol. 3, pp. 155–166, 1991.
- [49] D. Terman and D. Wang, “Global competition and local cooperation in a network of neural oscillators,” *Physica D*, vol. 81, pp. 148–176, 1995.