Role of Heterosynaptic Interaction and its effect on Development of Receptive Field Structure in Primary Visual Cortex

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ABSTRACT

Many modeling studies have been performed to investigate and find a specific learning mechanism suitable or responsible for the development of simple cell receptive field structure (SCRFS).

In this work, it is shown that the mechanism of spike timing dependent plasticity (STDP) when combine with heterosynaptic interaction is suitable and sufficient for development of simple cell receptive field structure.

Furthermore, with this study it is confirm that in the formation of simple cell receptive field structure the required temporal and spatial relationship is provided by STDP and heterosynaptic interaction respectively.

Keywords

Receptive field structure, synaptic modification, Heterosynaptic interaction,

1. INTRODUCTION

Experimental studies have shown that synaptic modifications induced at one synapse are accompanied by heterosynaptic changes at specific neighbouring sites that did not experience the induction activity[3,4,6,9,11].

Heterosynaptic interaction is a cellular property that has not been linked with sequence learning. Heterosynaptic competition for synapse growth or total synaptic strength has been documented at both pre and post synaptic neurons. For example, post synaptic neurons balance activity dependent potentiation of input synapse by inducing heterosynaptic depression among other input synapses, conserving the total synaptic weight on to the neurons[12].

The heterosynaptic sharing of plasticity represents a dynamic, short-term synaptic enhancement of synaptic inputs onto a common postsynaptic target. The heterosynaptic interaction changes the synapses while they were not active during the induction. Since only a fraction of the neuron's inputs is active at a given time, or is involved in activity during a certain induction protocol, potential targets of hetero-synaptic plasticity are much more numerous.

Garg, et. al[7] proposed a computational model for the formation of simple cell RF structure with the inclusion of both presynaptic and post synaptic heterosynaptic interaction. His computational model is sufficient for inputs to segregate and to maintain this segregation: starting from homogenous state to segregated ON- and OFF- inputs for the simple cell receptive field. Furthermore, there is no requirement to include additional constraints such as normalization, fixed intra-cortical synaptic strengths and hard bounds on synaptic strengths.

In this work describe an integrate- and fire- neuron model has been used to each of the cortical cells. In this model spike timing dependent plasticity (STDP) is used as a learning mechanism for development of receptive field structure (RFS) in the cortical neuron in presence of inhibition. The model also incorporates heterosynaptic competition for synapse growth only for post synaptic neuron. Though, in biological system synaptic strength has been documented at both pre and post synaptic neuron.

2. MATERIAL AND METHODS

The mathematical model which used for development of RFS is a set of ON-and-OFF centre Lateral Geniculate Nucleus (LGN) neurons converging on to an array of cortical neurons. The primary visual cortex (PVC) is modelled as a 2-D array of neurons. The neurons of the PVC are innervated by the ON-and OFF channels of the LGN; which are also modelled as 2-D array of neurons. For the development of thalamocortical connections a two layer structure is assumed as shown in the Figure 1. The output layer composed of a single cortical cell, which represent cell of layer IV C of cat primary visual cortex. Though in the figure there is large number of cortical neurons. The input layer, which represents the corresponding LGN layer, is subdivided into two dimensional sheets. One sheet labelled "ON" consisting of ON-type LGN cells and other sheet labeled "OFF" consisting of OFF type-LGN cells [2][10].

Cells in LGN layer are given by two dimensional position vector i, j, … etc. where, $i = (i_1,i_2)$ and $j = (j_1,j_2)$ and so on. Similarly the location of cortical cells are given by two dimensional position vector x,y, …. etc.

where, $x = (x_1,x_2)$ and $y = (y_1,y_2)$ and so on. To equate the locations in the three sheets common coordinates has been used i.e. all the sheets are considered to be lying in the same spatial location.

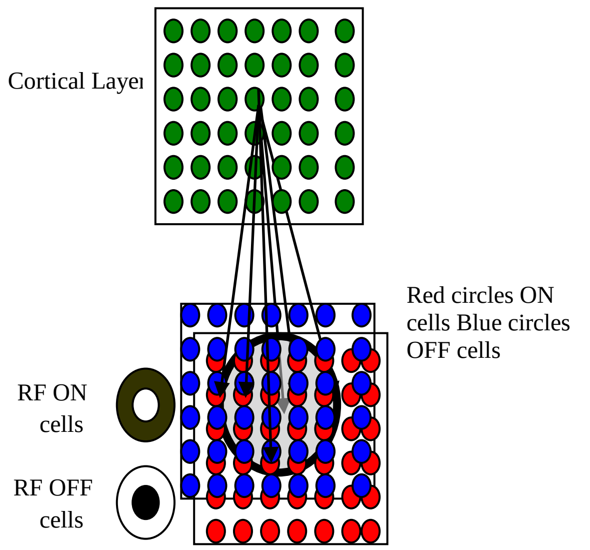


Fig 1: Schematic of model architecture: Two layer structure: one layer for LGN ON and OFF cells and the other layer for cortical cells.

It is assumed that cells of each center type are present at all locations in both the sheets of the LGN layer. Each LGN cell is constrained to always arborize over a fixed, topographically appropriate circular patch of cortical cells with diameter of 13 grid units. Thalamic projection of 13x13 corresponds to inputs from approximately 4^ox4^o visual space [8,13]. Also, in the beginning each cortical cell is connected to both types of all the LGN cells lying in topographically appropriate circular region in the LGN layer. For computational convenience all the synaptic contacts between one LGN cell (ON or OFF) and one cortical cell are lumped together and are represented by a single quantity i.e. synaptic strength [2][10].

The value of the synaptic strength at time t between LGN cell i in sheet labeled "ON" and cortical cell x is described by its peak synaptic conductance $\mathbf{g^{ON}_{xi}(t)}$. Similarly the synaptic strength between LGN cell i in sheet labeled "OFF" and cortical cell x is given by $\mathbf{g^{OFF}_{xi}(t)}$.The synaptic strength of the feed forward connection between LGN cell and cortical cell is considered to be modifiable and an integrate-and-fire neuron model describes each of the cortical cells.

STDP is a biological process that adjusts the strength of connections between neurons in the brain. The process adjusts the connection strengths based on the relative timing of a particular neuron's output and input action potential which are generally known as spikes.

As mention earlier that synaptic strength of the feedforward connection between LGN cell and cortical cell is considered to be modifiable. An integrate-and-fire neuron model describes each of the cortical cells. The membrane potential of the integrate-and-fire model neuron of the cortical cell located at location **"x"** in the cortical sheet in the presence of inhibition changes according to

$$\tau_m \frac{dV^x}{dt} = V_{rest} - V^x(t) + G^x_{ex}(t)\big(E_{ex} - V^x(t)\big) - 0.2 * G^x_{inh}(t)\big(E_{inh} - V_{cl}(t)\big) \qquad \ldots(1)$$

Where the initial values of G^x_{ex} and G^x_{inh} are calculated as

$\boldsymbol{G^x_{ex}}$= *nSe*fe*tampa*gampa/1000* …(2a)

where *nSe* is the number of excitatory connections, *tampa* is the time constant, gampa is the maximum value of synaptic conductance for excitatory synapse.

$\boldsymbol{G^x_{inh}}$ = *nSi*fi*tgaba*ggaba/1000* …(2b)

Where *nSi* is the number of inhibitory connections, *tgaba* is the time constant, ggaba is the maximum value of synaptic conductance for inhibitory synapse. Also,

τ_m = 20ms, V_{rest} = -60mV and E_{ex} = 0 mV. E_{ex} is the reversal potential for the excitatory synapses and $V^x(t)$ is the membrane potential at time step t of the cortical cell located at location *"x"* in the cortical sheet. When the membrane potential of the neuron reaches the threshold value of –54 mV, the neuron fires an action potential and subsequently membrane potential is reset to -60 mV [1]. Here, $G^x_{ex}(t)$ and $G^x_{inh}(t)$ are the excitatory and inhibitory synaptic conductance at time step t of the cortical cell at location *"x"* in cortical sheet. This is measured in the units of the leak conductance g_l of the neuron. Whenever a particular ON (OFF) type of LGN cell fires, the corresponding peak synaptic conductance contributes towards the value of excitatory synaptic conductance G^x_{ex}:

$$\boldsymbol{G^x_{ex}(t+1)} = \boldsymbol{G^x_{ex}(t)} + \textstyle\sum_i^M \boldsymbol{g^{ON}_{xi}(t)}.\boldsymbol{I^{ON}_i(t)} + \sum_i^M \boldsymbol{g^{OFF}_{xi}(t)}.\boldsymbol{I^{OFF}_i(t)} \quad \ldots(3)$$

Here M is the total number of ON (OFF) type LGN cells (13X13 in our model) connected to a particular cortical cell. Looking onto the above equation it can be seen that only active presynaptic cells are contributing toward the increase of the value of excitatory synaptic conductance. During the time *dt* when there are no presynaptic activity this synaptic conductance decays exponentially i.e.

$$\boldsymbol{\tau_{ex}} \frac{\boldsymbol{dG^x_{ex}}}{\boldsymbol{dt}} = -\boldsymbol{G^x_{ex}} \qquad \ldots(4)$$

$$\boldsymbol{\tau_{inh}} \frac{\boldsymbol{dG^x_{inh}}}{\boldsymbol{dt}} = -\boldsymbol{G^x_{inh}} + \textit{Sum of randomly selected inhibitory conductance} \qquad \ldots(5)$$

In addition to the STDP learning rule, the modifications in the synaptic strengths are also dependent upon distance-based heterosynaptic interactions i.e. modifications at one set of synapse are accompanied by changes at nearby synapses. The post- synaptic interactions are implemented in a way that some portion of every local alteration in synaptic strength is propagated to nearby synapses of the same postsynaptic cell. Gaussian shape of interaction has been chosen to incorporate the effect of these heterosynaptic interactions. Thereby it assumes rotational and translational symmetry. Hence, the changes in the individual synaptic weight due to both the competition and distance based heterosynaptic interactions can be given by the following equations:

$$\boldsymbol{dSN1_i} = \textstyle\sum_{i'} \boldsymbol{k} \ \ \boldsymbol{h_{ii'}}\Delta \boldsymbol{g^{ON}_{ii'}}\ (\boldsymbol{t}) \qquad \ldots(6)$$

$$\boldsymbol{dSF1_i} = \textstyle\sum_{i'} \boldsymbol{k} \ \ \boldsymbol{h_{ii'}}\Delta \boldsymbol{g^{OFF}_{ii'}}\ (\boldsymbol{t}) \qquad \ldots(7)$$

$$\boldsymbol{h_{ii'}} = \boldsymbol{exp}\left(-\frac{\boldsymbol{d^2_{ij}}}{\boldsymbol{rho}}\right) \qquad \ldots(8)$$

Here, k is a constant. $h_{ii'}$ is the distance based function and d_{ij} is the distance between $\boldsymbol{i}$ to $\boldsymbol{j}$ cell(ON cell to ON cell and OFF cell to OFF cell). In each of the above equation besides $\Delta g^{ON}_{ii'}(t)$ and $\Delta g^{OFF}_{ii'}(t)$ there is a term describing the redistribution of change synaptic weight of connections between different presynaptic cells and the same postsynaptic cell and is termed as postsynaptic interaction. These are calculated by taking the difference of weight between *t-1* and *t* time. Now update the synaptic conductance using following equations:

$$g_i^{ON}(t) = g_i^{ON}(t) + dSN1_i \quad \ldots(9)$$

$$g_i^{OFF}(t) = g_i^{OFF}(t) + dSF1_i \quad \ldots(10)$$

3. RESULT AND ANALYSIS

In this work an analytical approach has been used for development of receptive field structure in the primary visual cortex as discussed in the previous section. Eq 1 describes the change in the membrane potential of a cortical neuron. Whenever a particular ON (OFF) type of LGN cell fires, the corresponding peak synaptic conductance increases as per eq.2, otherwise it will decay according to eq 4 and 5.

Receptive field structure with only STDP learning mechanism for any random input activity is shown in figure 2.Coresponding orientation tuning curve and contour map is also shown in the same figure. We can visualise that the RFS is not in proper shape and the orientation tuning curve is also not sharp. The required no. of iteration for development of RFS is about 100000.

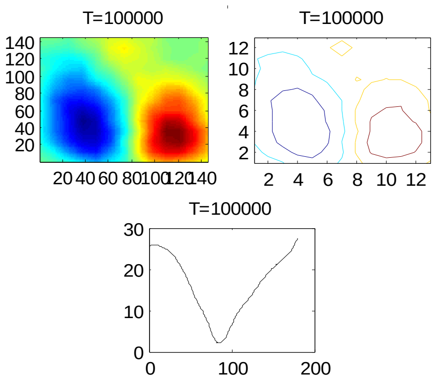


Fig2: Development of Receptive field structure with only STDP mechanism

The changes in the individual synaptic weight due to both the competition and distance based heterosynaptic interactions is given by equations 6 and 7while eq 9 and 10 gives the change in the synaptic weight due to postsynaptic interaction.

RFS for the same input activity and with the inclusion of heterosynaptic interaction is shown in figure 3. The effect of heterosynaptic interaction is clearly depicted in the figure. A good RFS has obtained and a sharp orientation tuning curve is also obtained. Also the no. of iteration required is about only 40000. Thus with the inclusion of HIS effect, computer simulation time is greatly reduced.

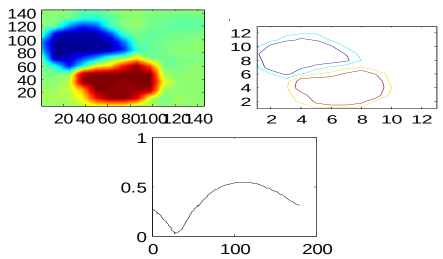
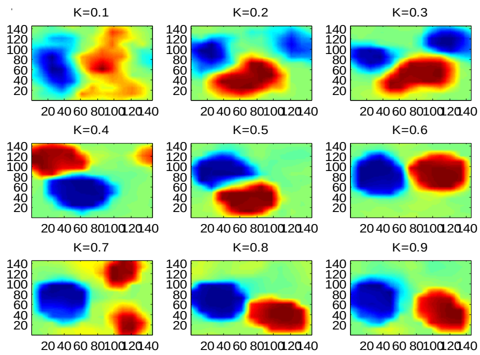
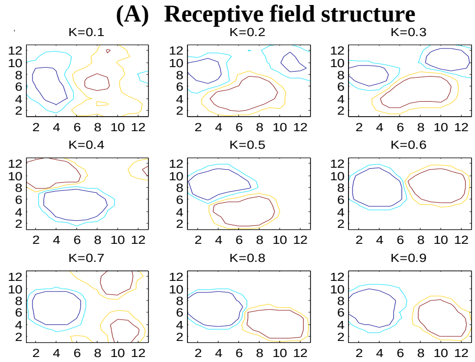


Fig 3: Development of Receptive field structure with STDP mechanism along with Heterosynaptic Interaction

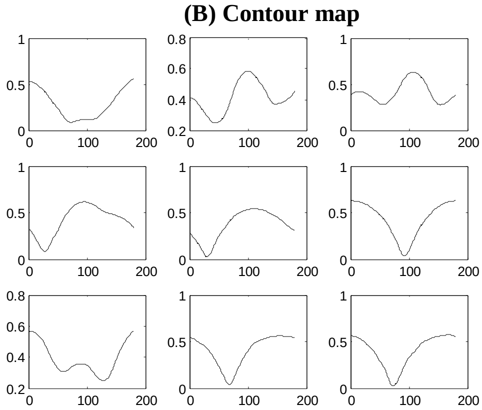
In this model the post synaptic interaction i.e. interaction between axons of different LGN cells connected to common cortical cell is controlled by factor k as mentioned in Eq 6 and 7. This HSI constant k controls the HSI effect. Lesser value of this constant means the nearby synapses which are under this interaction effect, grow at lesser strength. As this constant k increases, the interaction effect on the nearby synapses are more pronounced, thus the synaptic strength of these synapse are grow in large manner. The effect of this constant on the RFS is shown in the figure in 4. The related contour maps and orientation tuning curves are shown in the figure 4. These figures indicates that at a very small or a very large value of this constant, the well segregation of RFS do not take place. At very small value of this constant k (0.3), it will work just like as STDP learning mechanism. As the number of iteration are less hence at lower values of k, segregation will not occur. Figure 4 indicates the receptive field structure when variable k is varied from 0.1 to 0.9.The optimal value of this HSI constant which found by simulations in this model comes to be 0.5.



(A) Receptive field structure



(B) Contour map



(C)Orientation tuning curve

Fig4: Effect of heterosynaptic interaction factor on the development of Receptive field structure

4. CONCLUSION

In this work STDP learning mechanism for segregation of receptive field structure and orientation selectivity as this mechanism is present in biological system.

The work also introduced the heterosynaptic interaction in the form of propagation of change taking place at one location on to other location provides the mechanism for cooperation among nearby synapse. With the inclusion of heterosynaptic interaction the dependency on the activity is greatly reduces. Also due to less no. of iteration simulation time is also reduced.

5. REFERENCES

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