# LIST OF FIGURES

1.1 Structure of a Neuron. .................................................. 4
1.2 Parts of the Brain. ....................................................... 5
1.3 Brain areas or cortices associated with different sensory, motor 6  
and associative functions.

2.1 Layout of a pFET floating-gate MOSFET. ......................... 23
2.2 Basic model of four terminal floating-gate pFET ‘synapse’. ...... 24
2.3 Shows variation in Injection and Tunnel current as a function of $V_{fg}$ 27  
with constant terminal voltages $V_{Tun} = 12.8V$, $V_{D} = 0V$, $V_{G} = 0V$,  
and $V_{S} = 6.0V$. The ‘gradient of $V_{fg}$’ ($= I_{tunnel} - I_{injection}$) passes through  
two crossover points that characterize the adaptation dynamics of  
floating-gate pFETs.

2.4 Depiction of the WTA learning cell (a) is the actual circuit and (b) is 31  
the abstract model. Device D is a voltage buffer which isolates the  
voltage $V_{s}$ from loading effects. Devices I, and T are feedback devices  
which are almost linear dependent voltage sources for both the  
injection and tunnel nodes.

2.5 Depiction of Tunnel feedback device ‘T’ and Injection feedback device 34  
‘I’ along with buffer device ‘D’ and their equivalent circuits.

2.6 Depiction of temporal development of floating gate voltages and 36  
currents for values of $\alpha > 1$ for the initial bias condition ($V_{fg}i > V_{fg}o$).

2.7 Depiction of temporal development of floating gate voltages and 38  
currents for $\alpha < 1$ for the initial bias condition ($V_{fg}i > V_{fg}o$).

2.8 Lazzaro’s WTA (L-WTA) circuit. .................................... 41

2.9 Feature Selectivity with ts-WTA. ..................................... 43
2.10 Depiction of the effect of learning parameter, $\gamma$, on ts-WTA. 46
2.11 Operation of ts-WTA after learning has ceased. 47
2.12 Extendibility in the design of ts-WTA. 48
2.13 Layout of WTA Cell 51
3.1 Shows diffusive interaction among a pair of oppositely biased ts-WTA cells. 53
3.2(i) Simulations of MATLAB model of feature selective cell to study its clustering behavior when the cell is surrounded by neighbors with similar initial bias, the difference between the two floating gate voltages amplifies i.e. the cell develops with its own bias in communion with neighborhood. 54
3.2(ii) Simulations of MATLAB model of feature selective cell to study its clustering behavior when the cell is surrounded by neighbors with opposite initial bias, the difference between the two floating gate voltages reverses and then amplifies i.e. the cell adapts its bias in communion with the neighborhood. 55
3.2(iii) Simulations of MATLAB model of feature selective cell to study its clustering behavior when cell’s neighborhood has equal number of cells in favor and against its bias, the difference between the two floating gate voltages diminishes i.e. the cell becomes unbiased or responds equally to both inputs, albeit weakly. 56
3.3 Diffusive interaction between learning cells implemented in an actual circuit by means of a 1-D RC network between neighboring cells. 58
3.4 Development of three cells 1, 2, 3, which are cells 4, 5, 6 of figure 3, respectively over 1000 epochs. Left/right dominated cell has a large difference between left and right floating-gate voltages, but a binocular
cell has nearly equal floating gate voltages in the left and right arms, which are relatively weak as compared to a dominated cell.

3.5 Experimental data depicting ocular dominance (a) as observed in a monkey, (b) as observed in a cat in area 17, (c) after filtering out the noise from (b). White (black) symbolizes dominance by left (right) eye and grey symbolizes binocular cells.

3.6 Depiction of a 2-D RC network for Ocular Dominance map simulation.

3.7 Simulation data depicting Ocular Dominance map with 100x100 cells, with periodic boundary conditions.

3.8 Modified form of figure 3.3 with two RC networks for u i.e. activator or injection and v i.e. inhibitor or tunnel. \(R_uC\) determines diffusion constant \(D_u\), similarly \(R_vC\) determines diffusion constant \(D_v\). The relative impact of activator and inhibitor is controlled by reaction term \(R\).

3.9 Formation of the ocular dominance pattern for different value of \(D_u\) and \(D_v\) showing variations in stripe widths and hence greater control on stripe formation.

4.1 Depiction of Orientation Selectivity in the visual cortex.

4.2 a) The 3 layer abstract feed-forward model of Orientation Selectivity. The first layer, retina, is the layer that receives inputs. The second layer is the LGN. There is one-to-one mapping between retina and LGN cells. The third layer is the cortex.

b). The elongated ON-Centred, OFF-Surround receptive field of a cortical cell (Inspired by Hubel and Wiesel’s model of Orientation Selectivity).

c). The elongated OFF-Centred, ON-Surround receptive field of a
cortical cell.

4.3 4 ts-WTA cells connected in a row by means of diffusive resistors ($R_D$). The output of each cell ($V_s$) is connected in a feed forward manner using MOSFETs with their drains connected together at node $\text{out}$ which is the feed forward path conveying the self activation or response of the cell. The activation node of each cell ($V_i$) is connected at the diffusion node, $dno$, with feedback resistances ($R_F$). This forms the feedback network of the cell. A small resistance $R_o$ connects $\text{out}$ and $dno$ to keep both these voltages nearly the same. The bias transistor $m_o$ represents the cortical cell.

4.4 Depiction of 2 cortical cells Cell 1 and Cell 2 with a 1x4 (ts-WTA) receptive field. In a) the two cells develop independently. In b) the two cells are connected at the diffusion node ($dno$) by means of a resistance $R_{DIFF}$ for diffusive interaction.

4.5(i) Shows the development of floating gate voltages of the 2 cortical cells of figure 4.4a. Here blue represents the floating gate voltage of the ON-Centered synapse and green represents the floating gate voltage of the OFF-Centered synapse. The cells develop differently according to individual initial biases and inputs. a) Shows the 4 ts-WTAs of Cell 1. The pattern of receptive field is 1100 and b) Shows the 4 ts-WTAs of Cell 2. The receptive field has evolved into 0011.

4.5(ii) Shows the development of floating gate voltages of the diffusively coupled cortical cells in figure 4.4b. Cell 1 which seems to have a stronger bias influences the development of Cell 2 which modifies its original response to become similar to cell 1. a) Shows the unchanged response of cell 1 (1100) and b) shows the response of cell 2 under strong influence of neighbourhood (1100).
4.6 a) Development of floating gate voltages of 10 (1x4) ts-WTA cells in isolation. b) Shows the same 10 cells when they interact diffusively. Near neighbour cells begin to cluster developing similar feature preference. Between two opposite patterns (e.g. 1100 and 0011), there is a gradual variation(1001), see responses of Cells 2, 3 and 4.

4.7 Simplified and distributed layout of a 3x3 portion of the 9x9 receptive field of our Orientation Selective (OR) cell. a) Shows the symbolic representation of a ts-WTA cell. In subsequent figures, the grey square represents a ts-WTA. b) Is the feed-forward MOSFET network that takes the output of the individual ts-WTAs and feeds them to the OR Cell output. This is a read out node from where self activation of the cell can be recorded. c) Shows the diffusive resistance network consisting of $R_D$, that connects the ts-WTA cells to all their neighbours. d) Shows the feedback resistive network consisting of $R_F$ that feeds the output of the cell from dno back to the individual ts-WTAs. Out and dno are connected by $R_o$.

4.8 a) Shows the input patterns that are applied to the orientation cell. b) Shows the orientation tuning curve. Initially the response of the cell is low and similar for all input patterns. As the receptive field develops (see on the right, bottom to top), there is increased response towards that specific pattern as can be seen from the sharpening of the tuning curve. The half width at half height (hwhh) parameter for the best and the worst receptive field has been marked. The sharper the tuning, the lower is the value of hwhh.

4.9 Depiction of the buffer device that isolates the OR Cell Output (out) which conveys the self-activation of the cell, from the Diffusion node (dno) at which other orientation cells connect, to prevent loading of
node out.

a). Shows the characteristic response of the buffer device. The device is linear, and has a double inverting effect on the voltage at node out. The V_{DD} is 6v. b). Shows a typical design of the buffer device. c). Shows an abstract symbol for Orientation Selective Cell along with the buffer device.

4.10 a). Shows the independent development of receptive fields of 3 orientation selective cells with different initial biases and same random inside epoch order of inputs. b). Shows the development of the same three cells with the initial conditions and order of inputs same as a), but with diffusive interaction between neighbors. All the cells develop similar feature preference. c). Two more example of cells developing independently under the same random inside epoch order of inputs but different initial biases. d). Shows the development of the same cells as c) under diffusive coupling. Diffusion causes the cells to develop the same feature preference in each case.

4.11 Variation of current in the resistance, R_{diff}, connecting two orientation selective cells. The current is high (~150μA) during the learning phase. Once the orientation has been learnt, or the floating gate voltages have matured, the current reduces and remains constant thereafter.

4.12 Response of the Orientation Cell to patterns of different spatial frequencies and periodic patterns of different orientations and a). Shows patterns of different spatial frequencies that are applied as inputs to the OR Cell. b). Shows the patterns that the cell learns. Each simulation results in the circuit learning one of the input patterns with equal probability. c). Shows periodic patterns of different orientations that are applied as inputs to the OR cell. d). Shows the periodic patterns
that the cell learns.

4.13 The generic capacity of the developed cell to learn any abstract pattern (numbers, symbols, alphabets etc.). *Left* shows some of the input patterns applied to the cell. *Right* shows the patterns that the cell is able to learn.

6.1 The two-layer model for Quantum-Hebbian Learning. The first layer is the Quantum Layer that is superior and computes all possibilities and the second layer is the classical layer whose development is guided by the first layer. The quantum layer is regulated by attention.

6.2 a) Shows a hypothetical three input Quantum Neural Computer (QNC).

b) Shows all possible input combinations for a 3 input QNC. c) Shows one of the 512 possible weight matrices. d) Shows the functional view of the QNC as a quantum function evaluator, where the inputs are transformed to an output state by means of a unitary transformation represented by the weight matrices.

6.3 Shows how the values of $\alpha$ and $\beta$ are computed for all the inputs and the sample weight matrix shown in figure 2. The matrix $U$ here represents the product between $A$ and $W$ which are the input and weight matrices respectively. The term $(0)1$ represents a product between 0 and 1 and has not been written as 0 here to facilitate the understanding of how $\alpha$ and $\beta$ are computed. $\alpha$ is the sum of all the weights for input $|0\rangle$ where as $\beta$ is the sum of all the weights for input $|1\rangle$.

6.4 Shows the values of $\alpha^2$ and $\beta^2$ over all the 512 weight matrices for 4 different inputs $|100\rangle$, $|101\rangle$, $|110\rangle$ and $|111\rangle$. Here the red dots represent $\alpha^2$ and the green dots represent $\beta^2$. The x-axis has the 512 weight matrices and the y-axis has the values of $\alpha^2$ and $\beta^2$ for each of
them. The values of $\beta^2$ that are 1, are the neural assemblies (or weight matrices) that give the best ‘qualia’ for that particular input.

6.5 Shows subsequent random collapses into different neural assemblies. Each blue dot here represents a collapse and the y-axis represents the ‘qualia’ that the collapse generates. Since there is an inherent randomness with quantum collapses, without a medium that records the physical effect of these collapses, they have no meaning.

6.6 Left Each blue dot represents a collapse. Continuous dots represent collapse to the same assembly or Quantum Zeno Effect. In our algorithm, only when the subsequent collapses happen to the same neural assembly more than a 100 times, does hard wiring happen. Right Each red dot represents a Classical Weight associated with a particular neural assembly on the x-axis. With every collapse to an assembly, its weights get incremented. Only the weights corresponding to the neural assembly to which more than 100 subsequent collapses happen gets hardwired (max weight or highest red dot)

6.7 a) Mind wandering state ($\alpha = 0$), the collapses are completely random. b) QZE, repeated collapses to the same state can be observed from the continuous dots. c) Shows the zombie effect, ($\alpha = 0$), the collapses are determined by the classical weights that have developed the most. d) Free will state.

7.1 Categorization of species into Lower Order and Higher Order Species. Lower Order species have smaller brains, fixed responses to stimuli, show very slow adaptation and only have awareness of body. Higher Order species have larger brains, they adapt or learn very fast and have awareness of both body and mind.

7.2 Shows the Quantum and Classical Regimes in the Brain. The blue lines
represent the limit of axonal communication and the red lines represent
the quantum collapses. In the classical regime the frequency of
quantum collapses (T=\(\hbar/E\)) is lower than the limit of axonal
communication where as in the quantum regime the frequency of
quantum collapses is higher than the limit of axonal communication.
The classical regime is marked by slow processing speeds whereas the
quantum regime is marked by fast processing speeds.

7.3 Different species can be placed at different levels of the Quantum and
Classical Regimes. Different physical and mental phenomena appear at
different levels. e.g. Instinct, Autonomous Body Functions and Sensory
awareness are associated with different levels of the classical regime
whereas Mental Awareness, Thoughts, Cognition and Volition appear
at different collapse frequencies in the Quantum Regime.

7.4 The classical regime is the region of bottom-up or sensory driven
attention. In this regime species do not have control on their attention,
have pre-wired responses or reflex actions to stimuli and show very
slow adaptation. The quantum regime is the region of top-down or
volitional attention. In this regime species can voluntarily control
attention, adaptively form neural assemblies (using attention and QZE)
for unforeseen situations and learn very fast.