Analysis of spike propagation in feed–forward neural networks

A thesis submitted towards partial fulfilment of
BS-MS Dual Degree Programme

by

Himanshu Rajmane
20101017
BS-MS
IISER-Pune

Under the supervision of -
Dr. Suhita Nadkarni,
Assistant Professor,
IISER Pune

Indian Institute of Science Education and Research, Pune

Acknowledgements

Being a part of the Indian Institute of Science Education and Research Pune I would like to thank Dr. Suhita Nadkarni for giving an opportunity to carry out this project and Dr. Collins Assisi for his guidance. Dr. Aurnab Ghose, my thesis advisory mentor. My parents, Dr. M.S.Madhusudhan and Dr.L.S.Shashidhara who have helped me a lot dedicating their valuable time for supportting my final year project work.

Certificate

This is to certify that this dissertation entitled ''Analysis of spike propagation in feed-forward networks'' submitted towards the partial fulfilment of the BS-MS dual degree programme at the Indian Institute of Science Education and Research Pune represents original research carried out by ''Himanshu Rajmane'' at ''IISER Pune'', under the supervision of ''Dr. Suhita Nadkarni, Assistant Professor, Biology'' during the academic year 2014-2015.

Supervisor: Date:

Declaration

I hereby declare that the matter embodied in the report entitled “Analysis of spike propagation in feed-forward networks” are the results of the investigations carried out by me at the Department of Biology, Indian Institute of Science Education and Research, Pune, under the supervision of Dr. Suhita Nadkarni and the same has not been submitted elsewhere for any other degree.

Student: Date:

Abstract:

Propagation of spiking activity in networks of neuron is the key to how information is presented in the brain. The precise arrival times of spikes encode different kinds of incoming information. It has been shown that parameters like the number of spikes and the variability in timing of spikes determine the propagation of input across the network (Diesmann, Gewaltig, & Aertsen, 1999b). We want to determine the conditions under which the activity propagates across layers of neurons in a feed-forward network (Diesmann, Gewaltig, & Aertsen, 1999a; Kumar, Rotter, & Aertsen, 2010a; Rossum, Turrigiano, & Nelson, 2002) Also we look for the conditions under which spike volleys with spread in spike times synchronise and vice-versa. Feed-forward networks are embedded in many brain areas (Doupe, Solis, Kimpo, & Boettiger, 2004; Fee & Scharff, 1969; Gewaltig, Diesmann, & Aertsen, 2001a; Hanuschkin, Diesmann, & Morrison, 2011; Mittmann, Koch, & Häusser, 2005; Teramae & Fukai, 2008) and an understanding of activity propagation in canonical feed-forward network will help us understand dynamics of neural networks in general and also form a good framework for understanding sensory computation.

List of figures

Illustration	Description	Pg. no.
1	Leaky integrate and fire neuron with K-conductance	15
2	Synapse dynamics	15
3	*Change in membrane potential on receiving 1 spike*	16
4	*Background spiking due to noise is at 1.88 Hz for a group containing 100 neurons, runtime 90 ms*	18
5	*Stable propagation with initial spike volley having a spike count 'a' of 50 spikes and temporal dispersion 'sigma' between the spikes of 0 ms*	18
6	*Unstable propagation with initial spike volley having a spike count 'a' of 48 spikes and temporal dispersion 'sigma' between the spikes of 0 ms.*	19
7	*a,sigma estimation*	20
8	*Phase portrait with number of neurons per layer, 100.*	21
9	*Activity propagation phase diagram. a, spike count and sigma is the variation in spike time.*	22
10	*Average membrane potential*	23
11	*Isoclines for w 90*	24
12	Phase portrait with neurons per group, 90	24
13	Phase portrait with neurons per group, 100	24
14	*Isoclines for w 100*	24
15	Phase portrait with neurons per group, 110	24
16	*Isoclines for w 110*	24

17	*Sigmoidicity of spike response probability*	25
18	*Spread in output versus the spread in input is linear*	26
19	*Phase portrait for network without inhibition: w = 125, grid 30x30*	27
20	*Phase portrait for network with Inhibition: w = 125, weight of inhibition = -69.4, grid 30x30*	28
21	*A 3D plot with positive X & Y axis being sigma and neuron number. Z-axis is the weight of inhibition*	28
22	*Wi = -34, w = 125, Inhibition rate = 2Hz*	29
23	*Wi = -34, w = 125, Inhibition rate = 4.6Hz*	30
24	*Wi = -34, w = 125, Inhibition rate = 19Hz*	30
25	*A 3D plot with positive X & Y axis being neuron number & sigma. Z-axis is the rate of inhibition*	31
26	*Wi = -34, w = 125, Probability = 0.7*	32
27	*Wi = -34, w = 125, Probability = 0.89*	32
28	*Wi = -34, w = 125, Probability = 0.97*	33
29	*Wi = -34, w = 125, Proportion = 0.17*	34
30	*Wi = -34, w = 125, Proportion = 0.64*	34
31	*Wi = -34, w = 125, Proportion = 0.85*	35
32	*A 3D plot with positive Y & X axis being neuron number & sigma. Z-axis is the proportion of noise inhibitory neuron to excitatory neuron*	36
33	*A 3D plot with positive Y & X axis being neuron number & sigma. Z-axis is the proportion of noise*	37

	inhibitory neuron to excitatory neuron from 0.5 to 1.0	

Table of contents

Chapter 1 – Introduction (8-11)
- 1.1 Synchrony and need for neural assemblies (8)
- 1.2 Topology of the network (9)
- 1.3 Noise – Sources and its role (10)
- 1.4 Role of Inhibition (10)
- 1.5 Balance of Excitation and Inhibition (11)

Chapter 2 – Methods (12-20)
- 2.1 Dynamics of the Integrate & Fire neuron (12)
- 2.2 Synapse (13)
- 2.3 Network Connectivity (14-15)
  - 2.3.1 Excitatory feed-forward network (14)
  - 2.3.2 Excitatory-Inhibitory feed-forward network (15)
  - 2.3.3 Excitatory-Inhibitory feed-forward network with intra-layer connection (15)
  - 2.3.4 Excitatory-Inhibitory feed-forward network with connection probability (15)
- 2.4 Background activity (15)
- 2.5 Spiking activity propagation (16)
- 2.6 Estimation of spike number & temporal spread (17)
- 2.7 Phase portrait to understand propagation (18)
- 2.8 Finding the stable & saddle fixed points (19)

Chapter 3 – Results (20-35)
- 3.1 Average membrane potential & activity propagation for various neuron pool sizes (21)
- 3.2 Spike response probabilities (23)
- 3.3 Spike activity propagation in an excitatory-inhibitory feed-forward network (24)
- 3.4 Rate of inhibition & its effect on propagation (27)
- 3.5 Introduction of connection probability in EI-FFN (29)
- 3.6 Balance of excitation & inhibition in EI-FFN (31)

Chapter 4 – Discussion (36-37)

Chapter 5 – Conclusion (38)

Chapter 1

Introduction:

"A writer is like a tuning fork: We respond when we're struck by something. The thing is to pay attention, to be ready for radical empathy. If we empty ourselves of ourselves we'll be able to vibrate in synchrony with something deep and powerful. If we're lucky we'll transmit a strong pure note, one that isn't ours, but which passes through us. If we're lucky, it will be a note that reverberates and expands, one that other people will hear and understand."
—Roxana Robinson

A neural code is a collection of spikes that may be used by the brain to encode,decode and process cognitive information. Brain is a highly modular structure and spiking activity propagates from one region to another in a manner where the collective spikes either have a low temporal difference or high temporal difference depending on the network and the synapses (Diesmann et al., 1999a; Gewaltig, Diesmann, & Aertsen, 2001b). Thus to understand the neural code it is necessary to understand the conditions under which the spiking activity propagates.

1.1 Synchrony and need for neural assemblies:

Even though the brain is densely packed with neurons, a very small fraction of them are activated in response to a stimulus. Many studies that recorded single neuron activity suggested that repeated presentation of the same stimulus activates roughly the same set of neurons each time. This fact is the basis for the concept of neural assembly (Gerstein, Bedenbaugh, & Aertsen, 1989; Harris, 2005; Hebb, 1949).

Intrinsic properties of the neurons and the synaptic connectivity plays a role in the network's operation. Activity propagation by individual neurons solely can't be mediated in a noisy environment reflecting fluctuations in the synaptic input and hence are incapable of transmitting signals with millisecond precision. Hence a population of neuron becomes necesary for the transfer of signal (Gerstein et al., 1989). On the other hand it is evident that neural computations are very fast as in a task of categorizing complex visual scenes takes about 150msec (Fabre-Thorpe, 2011) which is fascinating as the signal has to go through many synapses for this computation. Also from the brain recordings of Songbirds it is known that the preplay and replay events have a very small timescale of hundreds of milliseconds (Doupe et al., 2004; Long, Jin, & Fee, 2010). By collecting spikes from a population of many independent neurons from a layer the readout can be made reliable.

Our perspective is to look at the collective activity of populations of neurons with respect to synchrony transfer or propagation with change in the temporal structure of the spikes in the presence of noise arising from various sources. In context of temporal coding in the brain well-timed and reliable spikes are of prominent importance. Abeles formalized the idea of synfire chain, groups of neuron are connected in a feed-forward manner where a large enough pool of depolarising neurons tend to align their action potentials to propagate activity synchronously (Abeles, 1991). Precision of neuron's action potential is accessed based on the timing of those of its neighbouring neurons which share the same pool. The quality of timing determines whether the synchronous spiking is sustained or it dies out (Diesmann et al., 1999a).

A neural code can be characterized on several biophysical dimensions like the time constants of different synaptic channels involved (Liu, Xu, Kang, & Nedergaard, 2005), transmitter release depending on the calcium concentration in the presynaptic terminal (Fiacco & McCarthy, 2004; Helmchen, Borst, & Sakmann, 1997; Zhai & Bellen, 2004), astrocytes which phospharylate the post synaptic terminal channels affecting their conductances (Volman, Ben-Jacob, & Levine, 2007), etc.,.

We look at the two basic dimensions of neural representations needed for characterizing a neural code. Spatial: sensory processing is based on size of distributed populations of neurons from small neural ensemble to populations of neurons spread across brain areas.) Temporal: neural responses evolve over time, and the temporal structure of neural activity is often required to explain speeded reactions (Overath et al., 2007). Neglecting the temporal dimension of neural activity results in a less detailed representation of the sensory input. Synfire coding is therefore necessary where a stable propagation of signal is required.

1.2 Topology of the network:

The topology of connections within a feed-forward network (FFN) can determine the degree to which it synchronizes the incoming signal. The probability of connections across layers can also play a role in determining whether activity propagates across the network or steadily dissipates as it traverses multiple layers. In a bilogical scenario FFN is a part of a network with both back and forth connections (Kumar, Rotter, & Aertsen, 2010b) and it becomes important to study the dynamics of the FFN and that of the embedding feedback-feedforward network. One way to study the dynamics of the FFN under realistic conditions is by randomly choosing a group of neurons and identifying another group that is directly connected to the first group with certain probability. Repeating this N times, N layers of FFN can be identified (Vogels & Abbott, 2005). In Neocortex where neurons are weakly connected, only sparsely connected FFNs can be identified (Izhikevich, Gally, & Edelman, 2004; Vogels & Abbott, 2005). Evidences from neuroanatomy suggest that there are 10000 synapses per neuron where individual synapses are weak and unreliable suggesting that collective activation of multiple presynaptic neurons is necessarg to elicit an action potential in a postsynaptic neuron (Binzegger, Douglas, & Martin, 2004; Garey, 1999). By systematically varying the intralayer and interlayer connectivity we study the effects on the dynamics of the network.

1.3 Noise - Sources and its role:

Another key aspect that needs to be investigated is the role of noise that it plays in the propagation of signal. Experimental evidences from in vivo extracellular recordings suggest that a neural network can be considered as a complex nonlinear dynamical system exhibiting chaotic dynamics (Segundo,2003;van Vreeswijk & Sompolinsky, 1996). The information propagation across multiple layers of brain imposes important constraints that previous studies lack. First is to retain information about the stimulus, small stimuli should propagate whereas strong stimuli shouldn't saturate the response. Second, synchronisation must not be lost for synfire coding in presence of noise from various possible background sources like noise in the spike generator, spontaneous quantal events (Bekkers, Richerson, & Stevens, 1990), input from neural ensemble in a network maintaining an asynchronous low-activity state (van Vreeswijk & Sompolinsky, 1996), heterogeneity in the excitability of the cell (Wilson & Cowan, 1972) or stochastic vesicle release (Maass & Natschläger, 2000).

The membrane potential of neocortical neurons in-vivo is found to be continously fluctuating due to the presence of synaptic background activity which reflects ongoing activity in the cortical network (Destexhe & Paré, 1999). In cat parietal cortex it was found that background activity accounts for upto 80% of the input conductance (Destexhe & Paré, 1999). A significant conductance increase due to background activity has also been observed in cerebellar Purkinje cells (Häusser & Clark, 1997). High-amplitude membrane potential fluctuation is a consistent feature of intracellular recordings in-vivo, which are rarely taken into account. The membrane potential fluctuations have been shown to play a positive role in increasing the responsiveness of neocortical pyramidal neurons in presence of synaptic background activity by lowering the threshold of firing (Hô & Destexhe, 2000a). In a network level increased responsivess will lead to detection of small signals which are below threshold. This is in line with the observation that background activity is particularly intense in intracellularly recorded cortical neurons of awake animals (Steriade, 1999) where it can be an active component of arousal or attentional mechanisms. Hence noise in a way helps in propagation of such small signals in a network.

1.4 Role of Inhibition :

Inhibition is found to play a key role in providing a time window for integration of spikes. It is observed that when inhibition is blocked pharmacologically, it leads to epilepsy. In this condition the neurons are no more selective to stimulus form (Cossart et al., 2001).

1.5 Balance of Excitation and Inhibition:

In cortex it has been sen that neurons tend to show random spiking activity which suggests that if neurons were solely to remain in a depolarised state the individual random spikes won't be able to illicit any action potential, but it is observed that it can illicit an action potential suggesting that there's constant excitation comming in which keeps the membrane potential of the neurons just below the firing threshold (Hô & Destexhe, 2000b). A balance between this inhibition and excitation thus helps in increased responsivess to stimulus, decides the selective window for spike integration based on the level of inhibition present thus neural computation, and it also enables the long distance propagation of signals in a network connected with lower probabilities (Haider, Duque, Hasenstaub, & McCormick, 2006). Since synchrony transfer is been investigated incorporating inhbition in the network will better help understand the ability of the signal to propagate through the layers and the interplay between excitation and inhibition to keep the neuron ready for firing depending on the form of stimulus.

Chapter 2

Methods:

Simulations were done using the BRIAN simulator in Python 2.7.

"The network model used in the present study was obtained from ModelDB (accession number 153988)".

In the model a feed-forward network of 100 neurons present in 10 subsequent layers was created. Connectivity among neurons within a layer was absent. All the 100 neurons from one layer form synapses with neurons in the next layer only. In total the network had 1000 neurons and 90000 synapses. Neurons were modelled using Integrate-and-fire neurons with leaky K-conductance having a resting membrane potential, -70 mV and firing threshold, -55 mV and an absolute refractory period of 1 msec. Exponential form of alpha synapses with reversal potential of 0 mV having a fall time of 0.325 ms where choosen to yield a realistic 0.14 mV bump in the post synaptic potential. To incorporate the ongoing background cortical network activity, every neuron in the network received a synaptic current with 25.27 mV mean and a standard deviation of 6.264 mV, such that the frequency of background firing was 1.88 Hz.

2.1 Dynamics of the Integrate-and-fire neuron (Stein, 1967):

A leaky IF neuron model is a simplistic neuron model which is computationaly fast and is ideal for network simulations, given by the ODEs, where (1) is the voltage derivative, (2) conductance derivative and (3) exponential synapse.

Equations:

$$\frac{dV}{dt} = \frac{(-(V - Vr) + x)}{taum} \tag{1}$$

$$\frac{dx}{dt} = \frac{(-x + y)}{taupsp} \tag{2}$$

$$\frac{dy}{dt} = \frac{-y}{taupsp} + 25.27 + \sqrt{39.24} * nrand \tag{3}$$

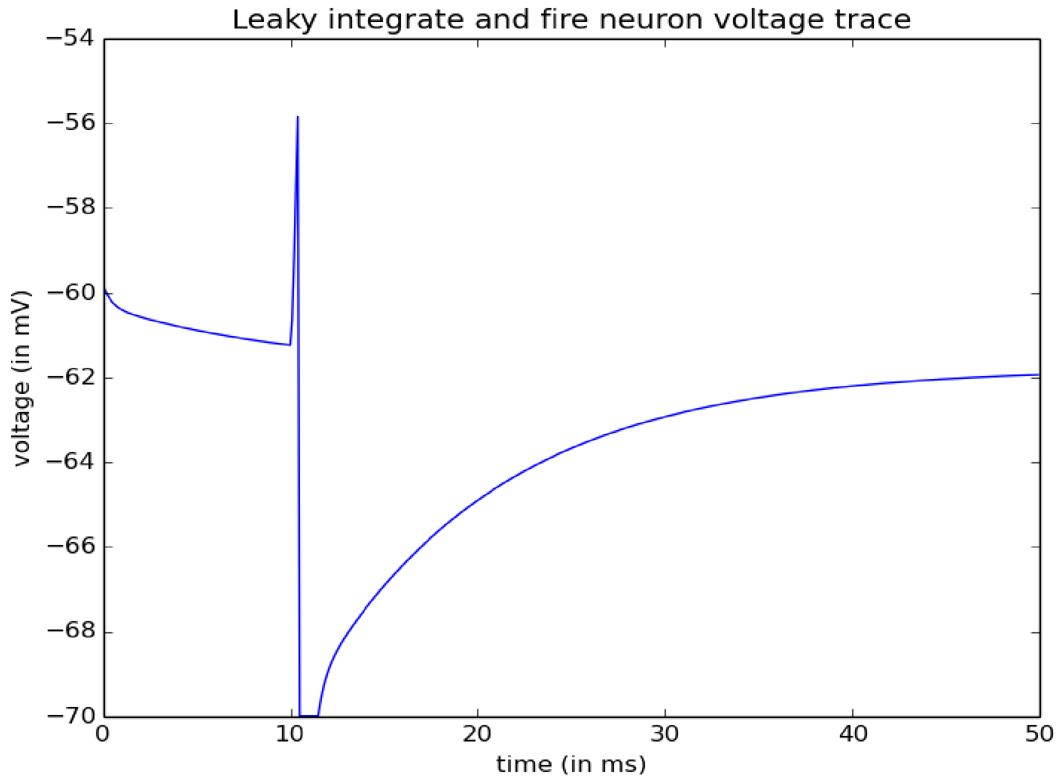


Illustration 1: Leaky Integrate and Fire neuron with K-Conductance. Resting potential, -70 mV; Firing threshold, -55 mV; Abs. refrac. period, 1 msec;

2.2 Synapse:

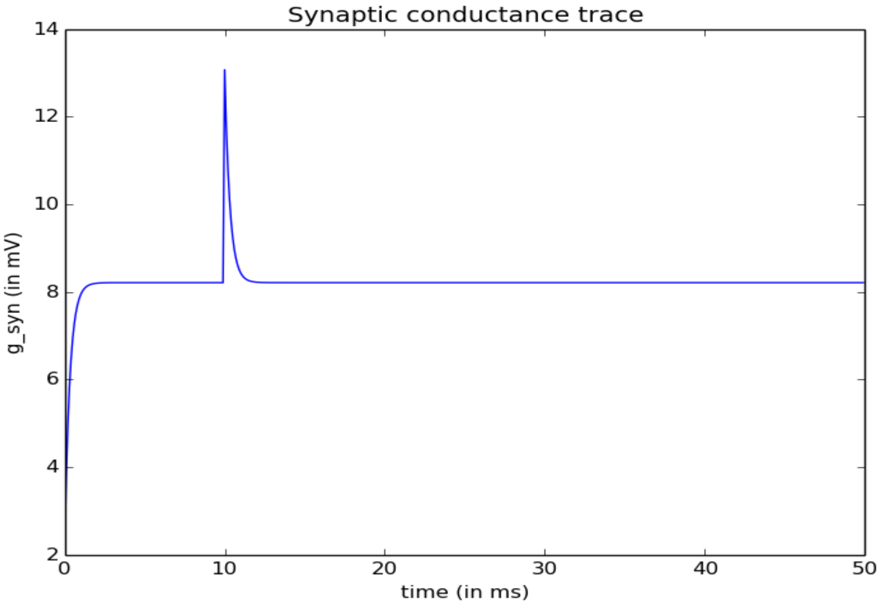


Illustration 2: Synapse dynamics:A single spiking event triggers the synapse which has a fall time of 0.325 msec which contributes to a 0.14 mV jump in the membrane voltage.

Exponential synapse with a fall time of 0.325 ms is used (Equation 3). The synaptic connection between two neurons was made such that a presynaptic neuron when spiked contributed 0.14 mV of PSP in the postsynaptic neuron with a synaptic conductance of 13 mV.

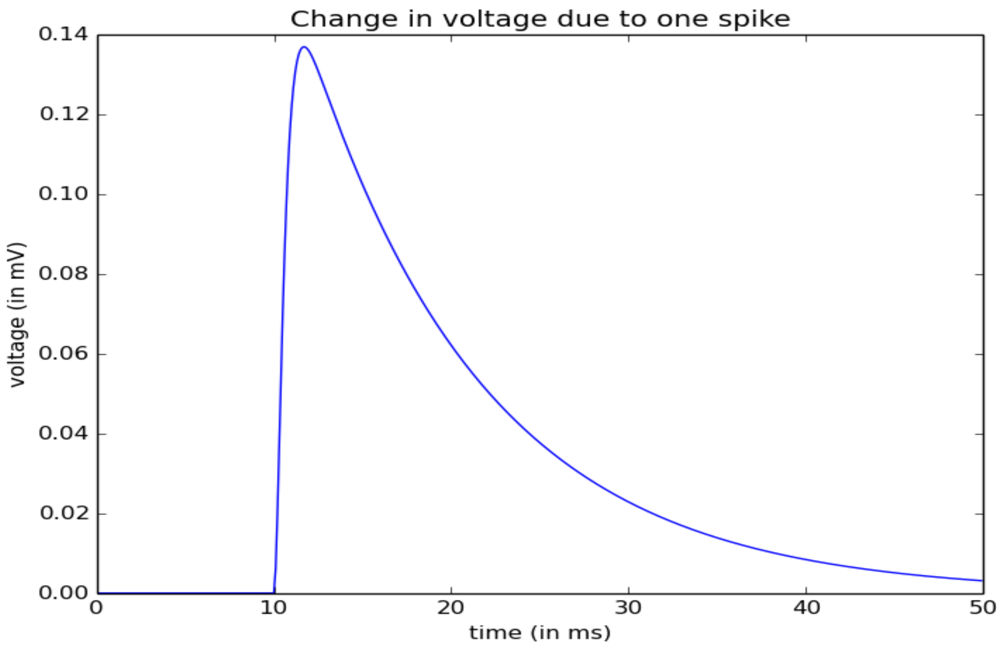
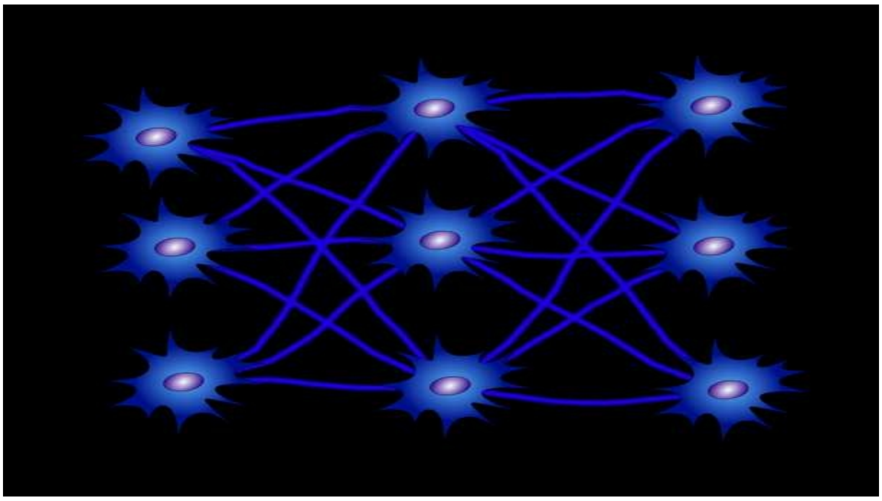


Illustration 3: Change in membrane potential on receiving 1 spike

2.3 Network Connectivity

2.3.1 Excitatory Feed-Forward Network:

In a feed forward network, the neurons from one layer form synapses with neurons in the next layer. Within a layer neurons don't make synapses with each other. The weight of synaptic strength is equal for all the connections. In excitatory FFN, all the neurons are of excitatory nature.



Drawing 1: All the neurons of a layer project to every neuron in the next layer. Intragroup connections are absent.(Source:Created in Neural Network simulator application for Google Android OS 4)

2.3.2 Excitatory-Inhibitory Feed-Forward Network:

Another network composition later used in the work comprises of both excitatory and inhibitory neurons in the ratio 88:12 (Garey, 1999; Mayhew, 1991). The strength of inhibition is equal to that of excitation and connections within a neuron layer is absent.

2.3.3 Excitatory-Inhibitory Feed-Forward Network with Intra-layer connections:

The composition is same as for 2.3.2 but with inhibitory connections made within a neuron layer.

2.3.4 Excitatory-Inhibitory FFN with connection probability:

In this type of network the connections from one group to another are made with certain probability to highlight the fact that neurons synapse with different strength with neighboring layer/group of neurons. This network is used to understand the role of excitation-inhibition balance in spike activity propagation.

2.4 Background activity:

The background activity was modelled by feeding a noise current through exponential synapses to the conductance of the LIF neuron. The noisy events are independently drawn for every single neuron in all the layers. The noise was drawn from a standard normal distribution. Since integration is done by Euler method, the standard deviation and mean were adjusted for the noise. The frequency of spiking events for a group was found to 1.88 Hz (17 spikes/90ms).

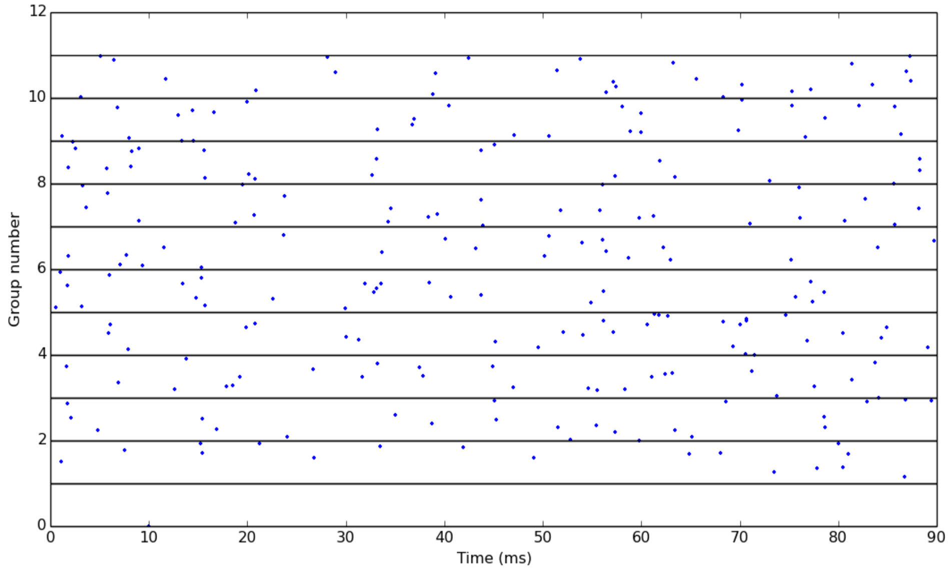


Illustration 4: Background spiking due to noise is at 1.88 Hz for a group containing 100 neurons, runtime 90 ms

2.5 Spiking activity propagation:

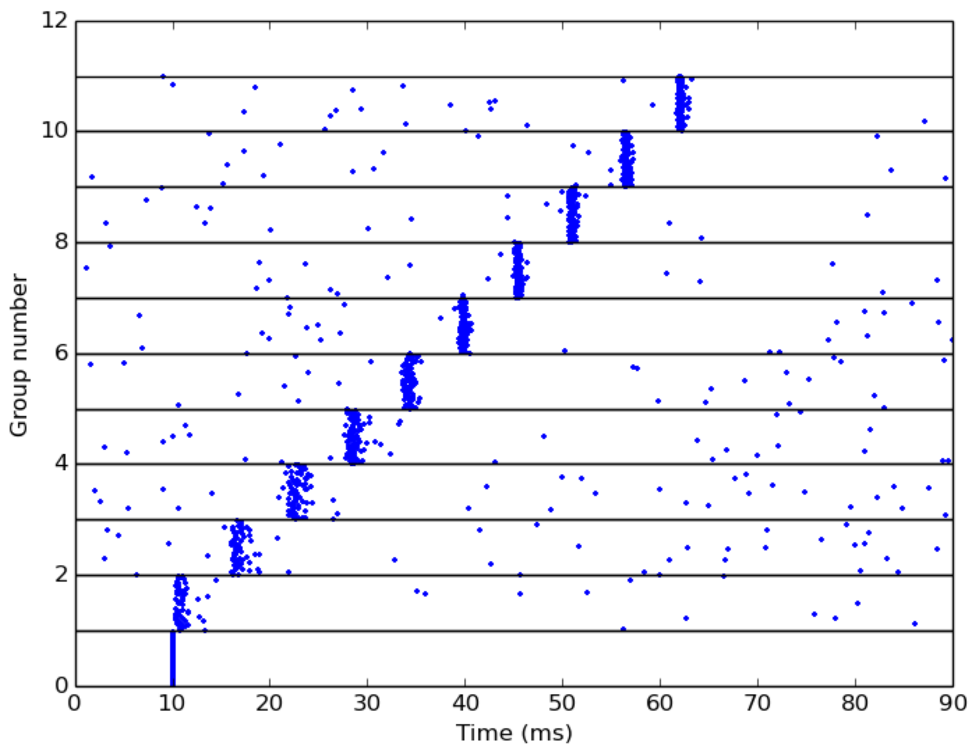


Illustration 5: Stable propagation with initial spike volley having a spike count 'a' of 50 spikes and temporal dispersion 'sigma' between the spikes of 0 ms.

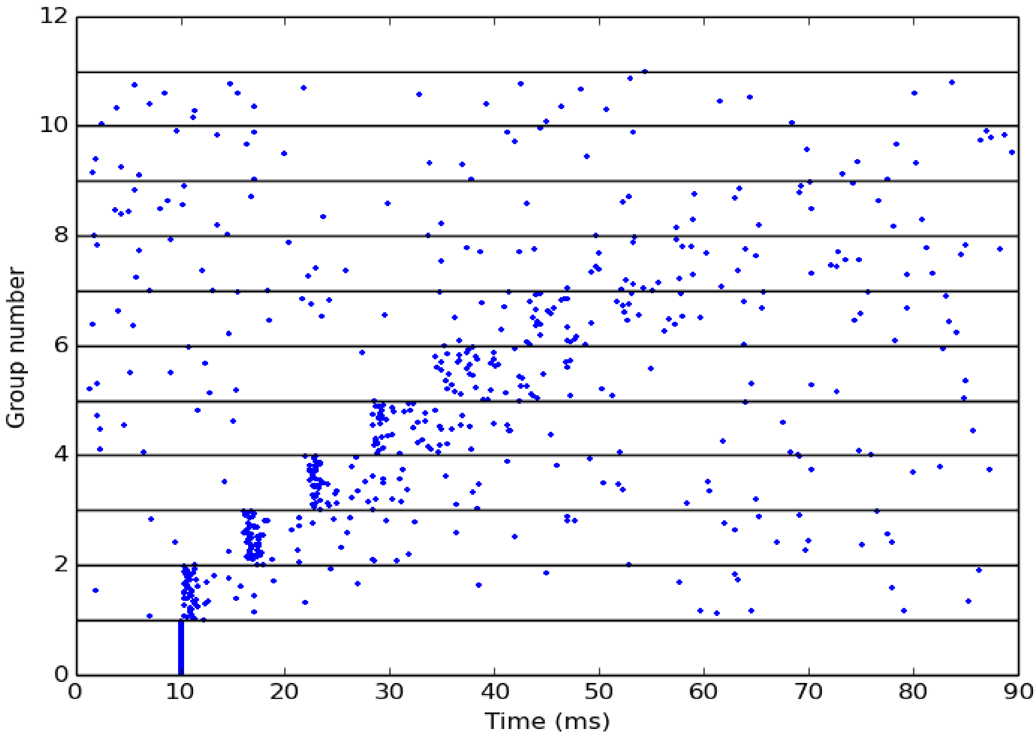


Illustration 6: Unstable propagation with initial spike volley having a spike count 'a' of 48 spikes and temporal dispersion 'sigma' between the spikes of 0 ms.

The spike activity propagation is such that for an input of 50 spikes with 0 ms temporal spread, it is stable or propagates to the last layer with a decreasing or constant temporal spread. And for an input of 48 spikes with temporal spread 0 ms, it is unstable or propagates with an increasing temporal spread. This is in terms with the parameters used to generate figures 1.d & 1.e of Aertsen et. al. 1999.

2.6 Estimation of spike number and temporal spread:

To estimate the temporal spread 'sigma' and spike count 'a' in the subsequent layer following a stimulus is done by drawing a time window of 30 ms around it. The time window is drawn taking care of the synaptic delay present between the first and the nth group for a case where the propagation is stable throughout i.e., for input 100 spike count with 0 ms spread. This key measurement is later used to generate a phase portrait in the paper. Also estimation is done independently again and again for a sample size of 50 for all the simulations so as to get a better estimate of temporal spread in the signal.

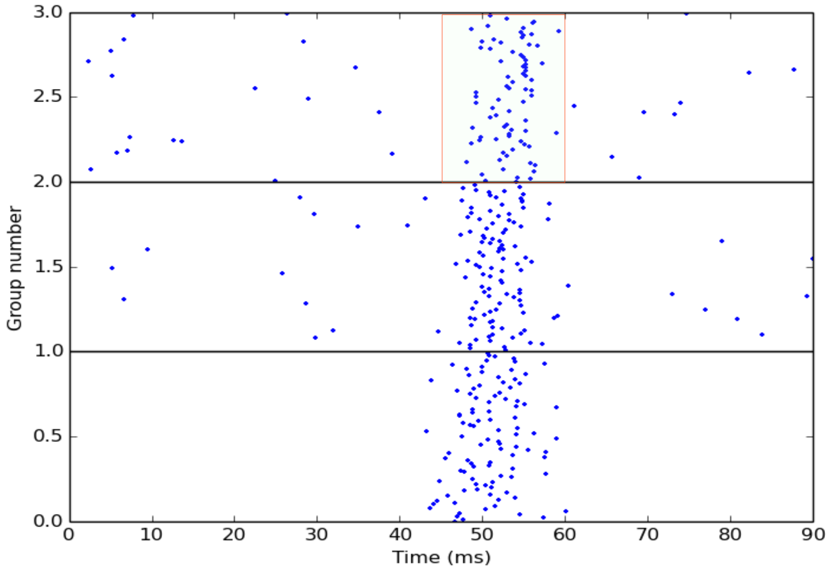


Illustration 7: a,sigma estimation; Red box is the time window for estimation where spike count 'a' is counted and temporal dispersion of the spike times of every neuron is calculated.

2.7 Phase portrait to understand propagation:

Grid of sizes 10x10 and 15x15 with one parameter being spike count 'a' and other temporal dispersion 'sigma' are used for understanding the nature of propagation with changes being made to network, synapse and intrinsic properties of the neurons. Every grid point is an initial condition for a network simulation of duration 90 ms. The final measurement of 'a' and 'sigma' draws a vector in the phase plane indicating the nature of propagation. With this a regime of stable and unstable propagation can be seen with direction of vectors either going left-up or down-right on the phase plane. Nullclines are also present which show how 'a' and 'sigma' change with changes made to the network model. Coloration of grid is done based on the following results from simulation run at each point:

a. Spike count increase (Blue).
b. Decrease in tempral spread (Red).
c. Both a,b (Green)
d. Neither a nor b (Black).

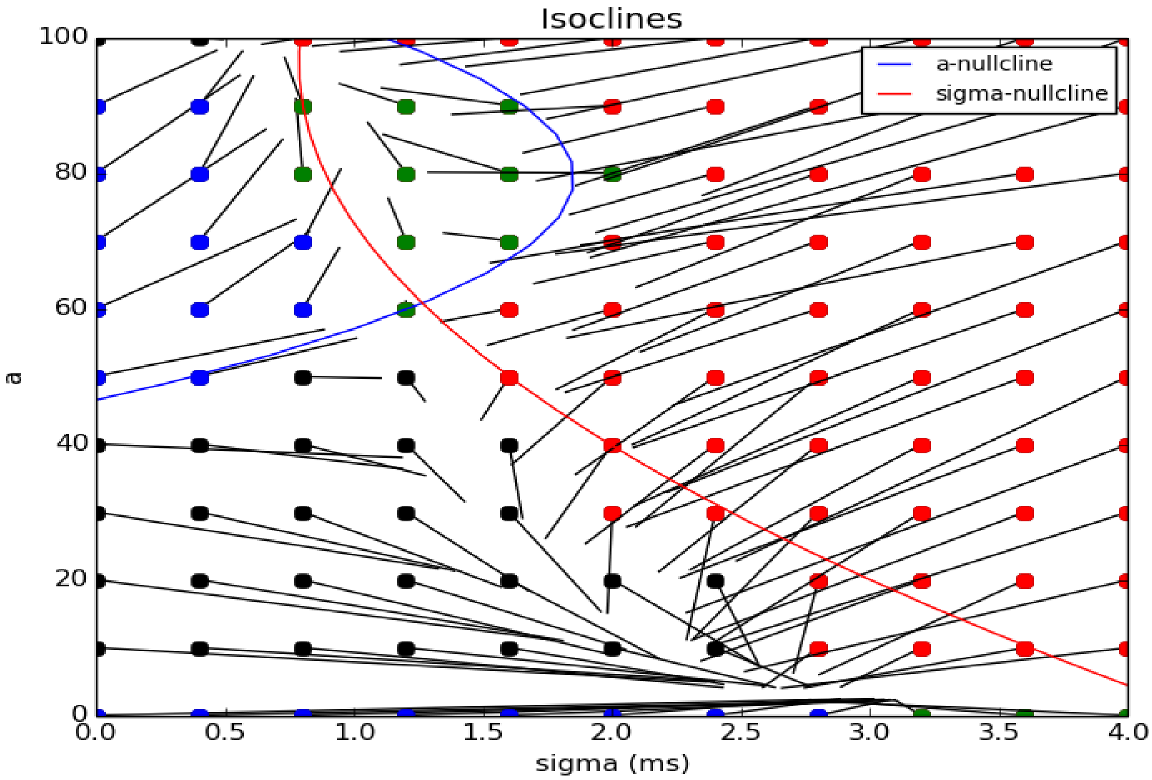


Illustration 8: Phase portrait with number of neurons per layer, 100. The green overlap shows that two fixed points exist at the intersections of blue and red nullclines.

2.8 Finding the stable and saddle fixed points:

Stable fixed point is point where all the stabily propagating signal converges to. The two fixed points in the phase portrait are present only when the 'a' nullcline (Blue) intersects with the sigma-nullcline (Red) as seen in Illustration 8. To study the movement of fixed points while changing the network model parameters and noise we pick out the points of intersections from the overlap (Green region) where the one on the top-left is stable and the bottom-right is saddle. A 3D plot is done to observe the change in nature with respect to any network parameter. In the below figure Illustration 9 we can see the various fixed points present.

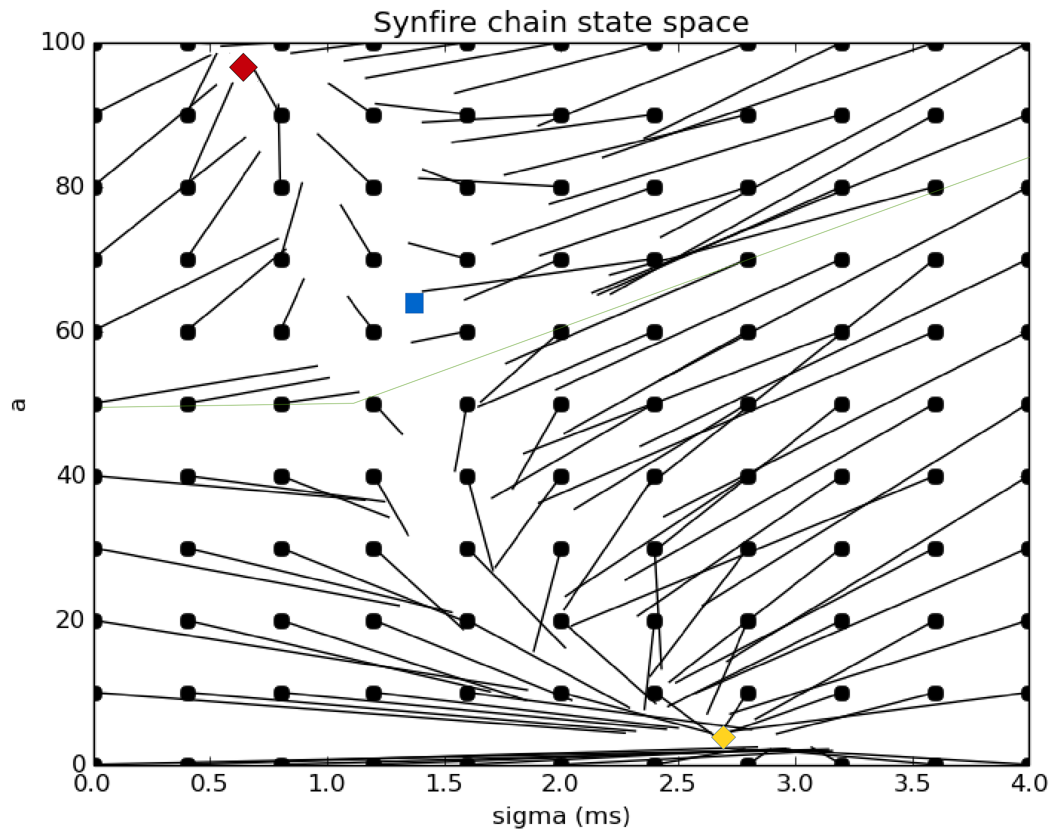


Illustration 9: Activity propagation phase diagram. a, spike count and sigma is the variation in spike time. stable fixed point ,Red,(95,0.75) and Blue,(62,1.375) stable fixed point. Green line separates the stable and unstable propagation regimes. Yellow is the point corresponding to the form of basal noise activity in the network.

Chapter 3

Results:

A feed-forward network (FFN) is a simple network configuration which is used to address the spike activity propagation across layers of brain. Neurons form weak synapses but many with neurons across the group. A propagating pulse (spike activity) needs to attend certain amount of synchrony to elicit an action potential in the receiving neuron. The amount of synchronisation is depending on the firing rates of neuron and the membrane potential of the receiving neurons. The background activity present in the network facilitates in increasing the sensitivity of membrane potential to incomming pulse by lowering the firing threshold for the neuron.

3.1 Average membrane potential and activity propagation for various neuron pool sizes:

In the below figure the membrane potential average is at -62 mV with the firing threshold at -50 mV.

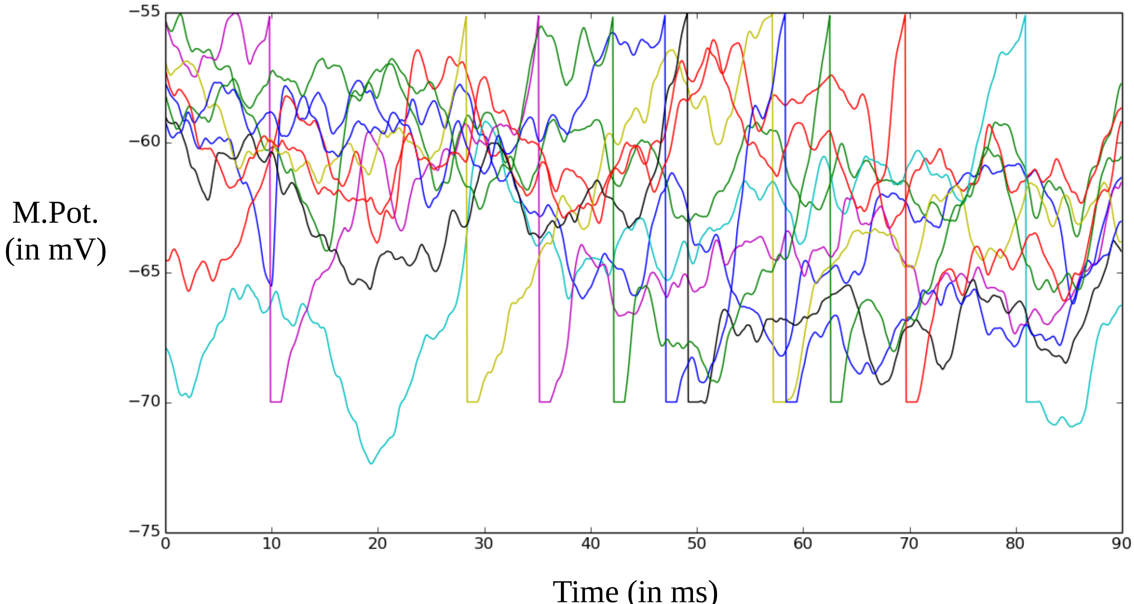


Illustration 10: Form of the action potential is shown in the figure for some neurons from all the 10 layers of excitatory feed-forward network. Average membrane potential is found to be -62 mV.

The synchronisation and the number of incomming spikes play an important role in determining the nature of propagation which can be either stable (i.e, synchronously propagating) or unstable (i.e, propagation with decreasing activity and synchrony). The number of neurons present in a layer or the neuron pool also determines the nature. For bigger neuron pool the activity is found to stable and is unstable when small. In the figures below are for w(neuron per group) 90,100 & 110.

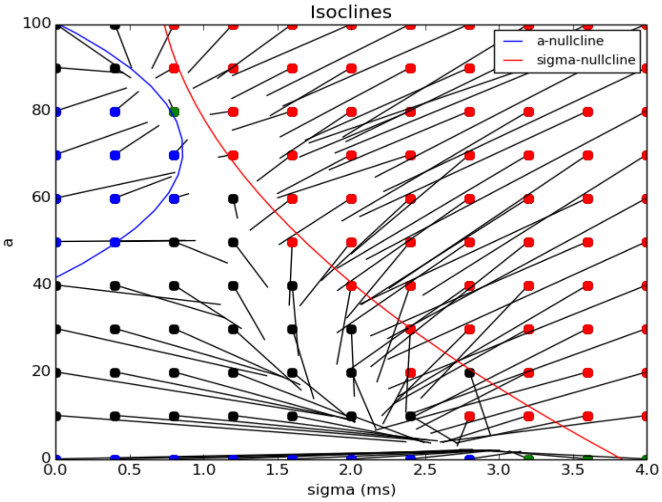


Illustration 12: Neuron per group, 90

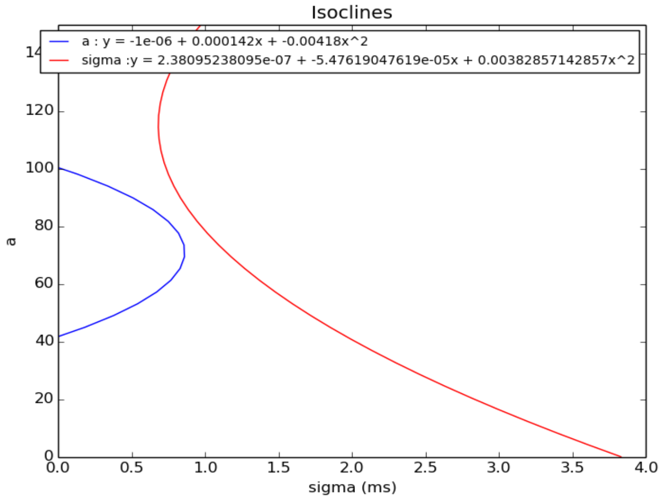


Illustration 11: Isoclines for w 90

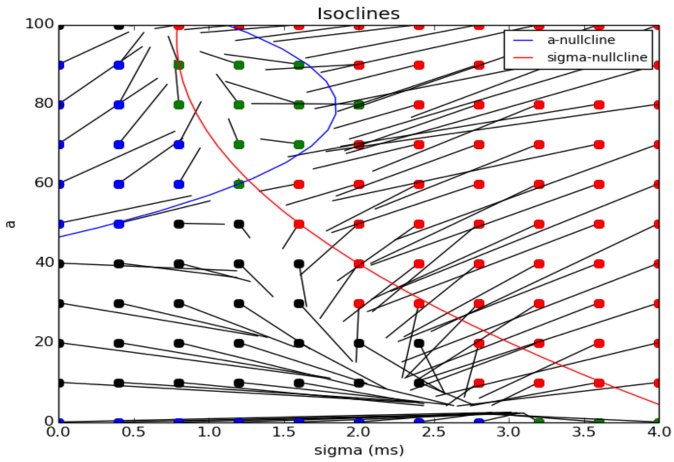


Illustration 13: Neurons per group,100

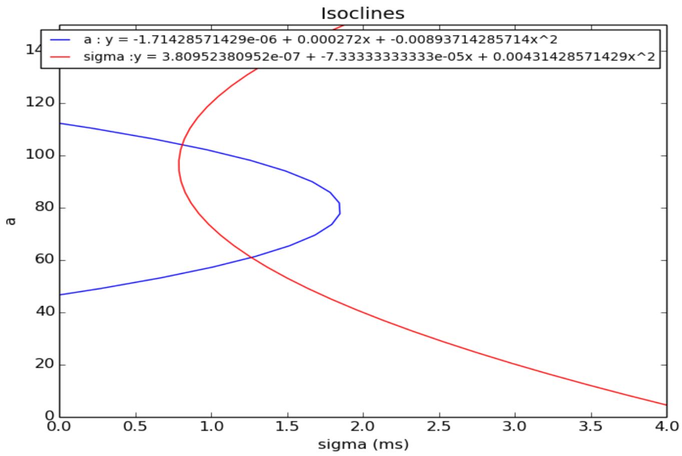


Illustration 14: Isoclines for w 100

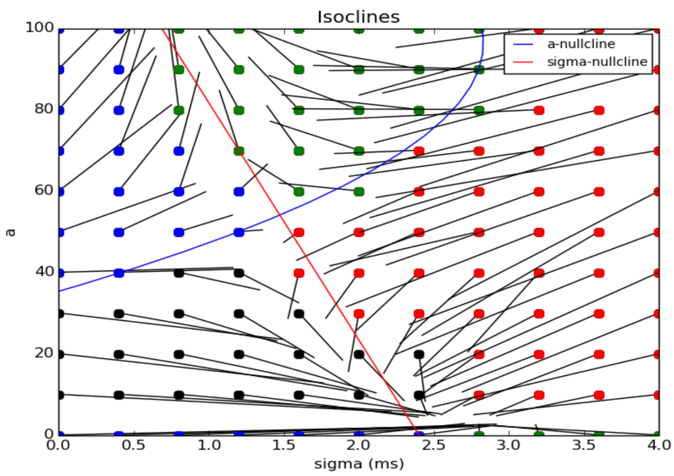


Illustration 16: Neurons per group, 110

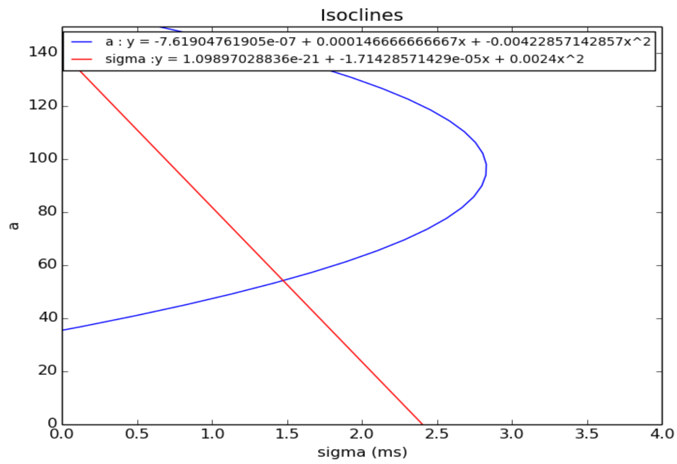


Illustration 15: Isoclines for w 110

3.2 Spike response probability :

The size of neuron pool affects the spike response probability which is a sigmoid function of number of incomming spikes.

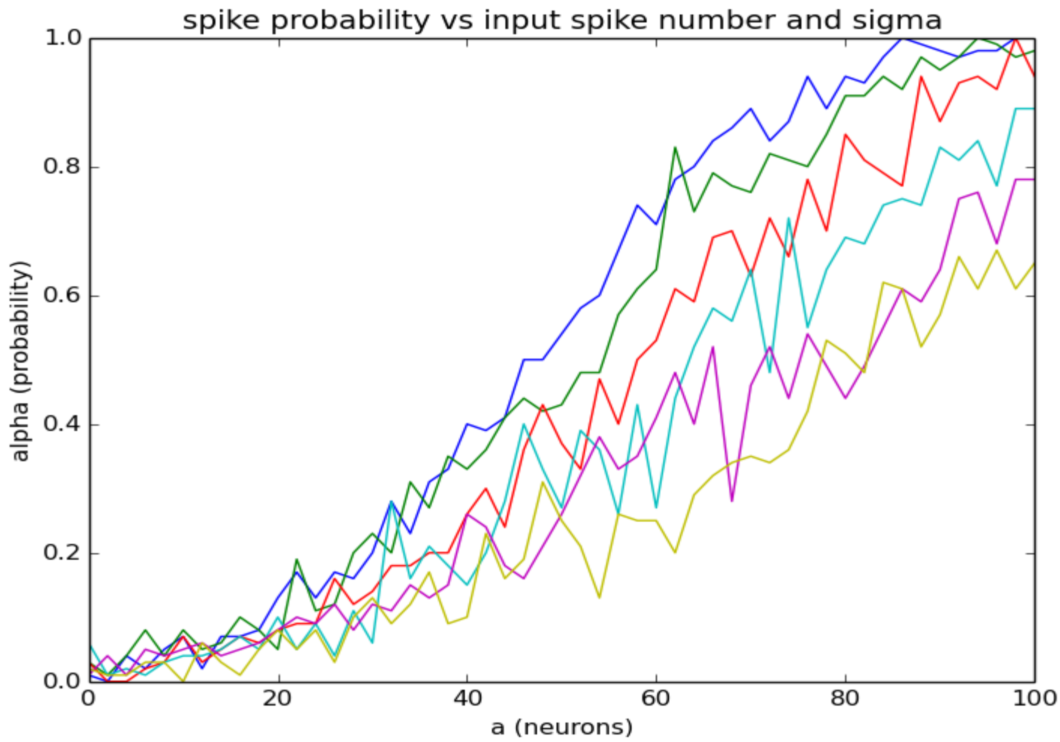


Illustration 17: 'Alpha' is the probability of spikes in the last layer and 'a' is number of spikes present in the input to the first layer of FFN. It is seen that the response saturates and trend is a sigmoid.

The presence or absence of synchrony in incomming spikes linearly affects the spike response probability as the window for integration of spikes gets affected.

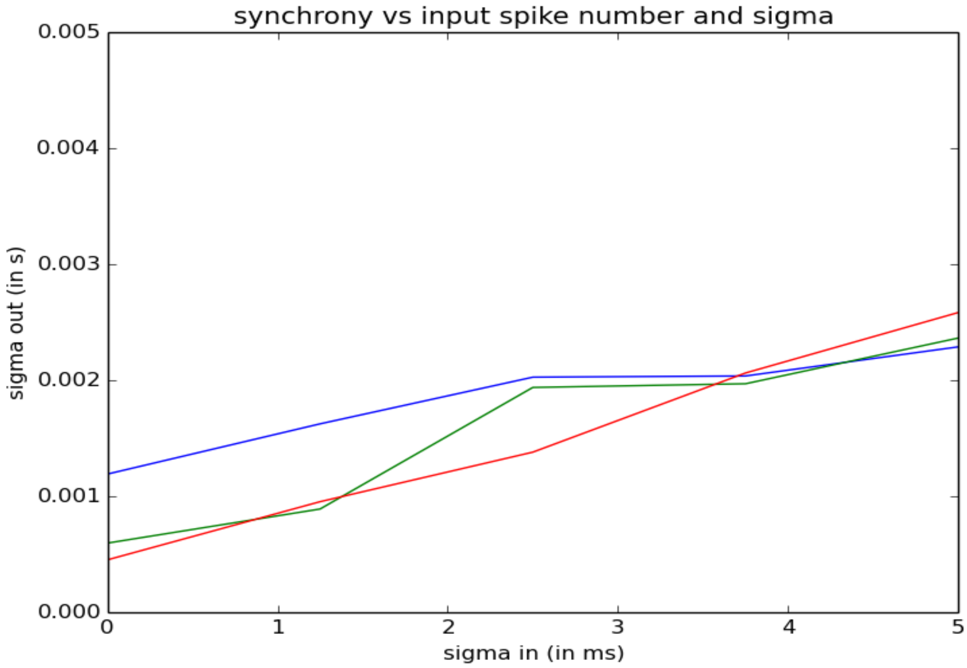


Illustration 18: 'Sigma' is the spread of spikes in time. Spread in output versus the spread in input is plotted. The trend is linear indicating that spread alone is not sufficient for synchronisation.

3.3 Spike activity propagation in an Excitatory-Inhibitory Feed-Forward Network :

Cortex is found to contain both excitatory and inhibitory neurons roughly in ratio of 88:12. Earlier FFN created was of only excitatory nature and lacked inhibitory connections.

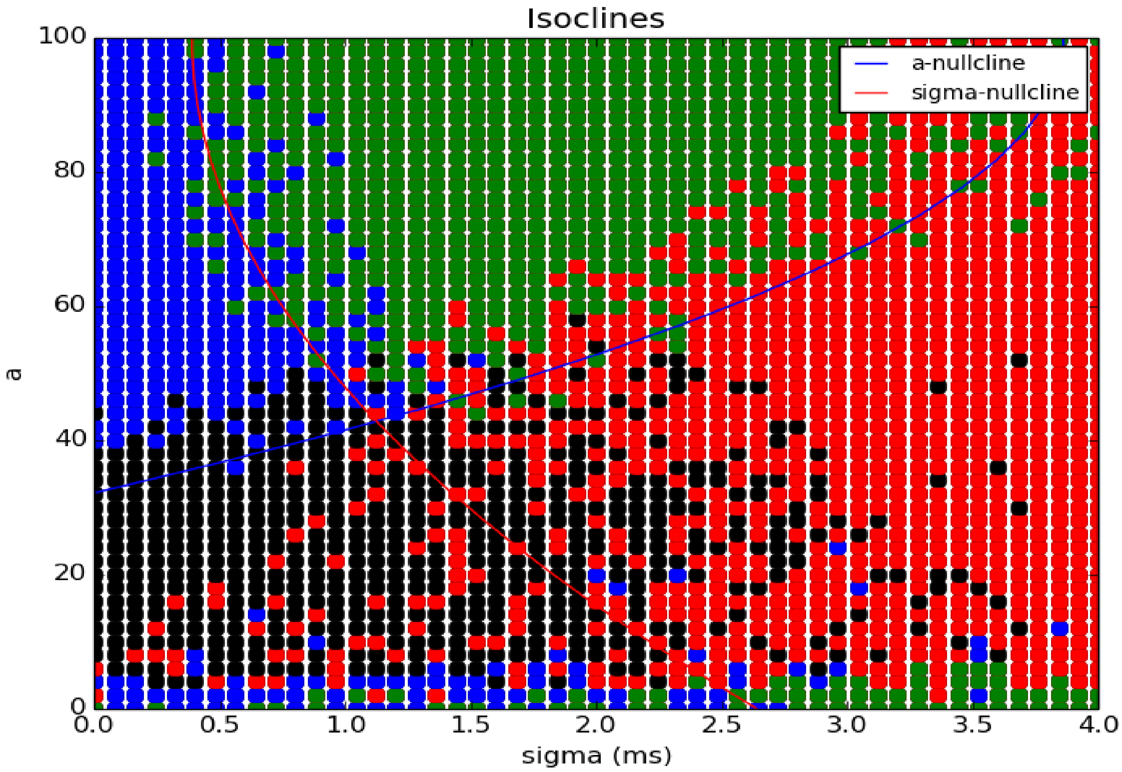


Illustration 19: Without inhibition: w = 125, grid 30x30

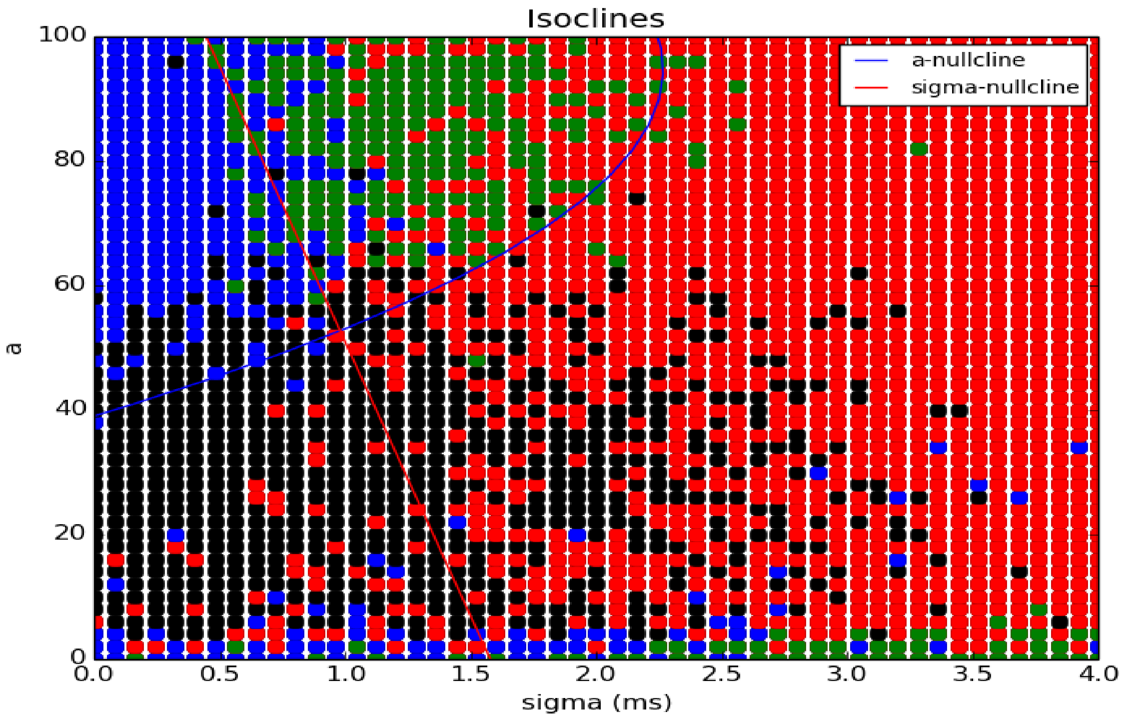


Illustration 20: With Inhibition: w = 125, weight of inhibition = -69.4, grid 30x30,

Inhibition in a network is found to determine a window for spike integration and hence is required to attain synchronisation. A new FFN was created containing both inhibitory and excitatory neurons differing only in the nature of synapses they formed. The excitatory and inhibitory neurons synapsed with all the neurons of the subsequent group. Parameters like the weight of inhibition & compostion (E-to-I ratio) were varied. Both the parameters affected the strength of inhibition. It is found that as the strength of inhibition was increased the fixed points started to disappear for the EI-FFN containing 125 neurons (Illustration 19 & 20). The disappearence of fixed point is similar to that observed by varying the number of neurons present per group for an E-FFN (Illustration 12,13,16).

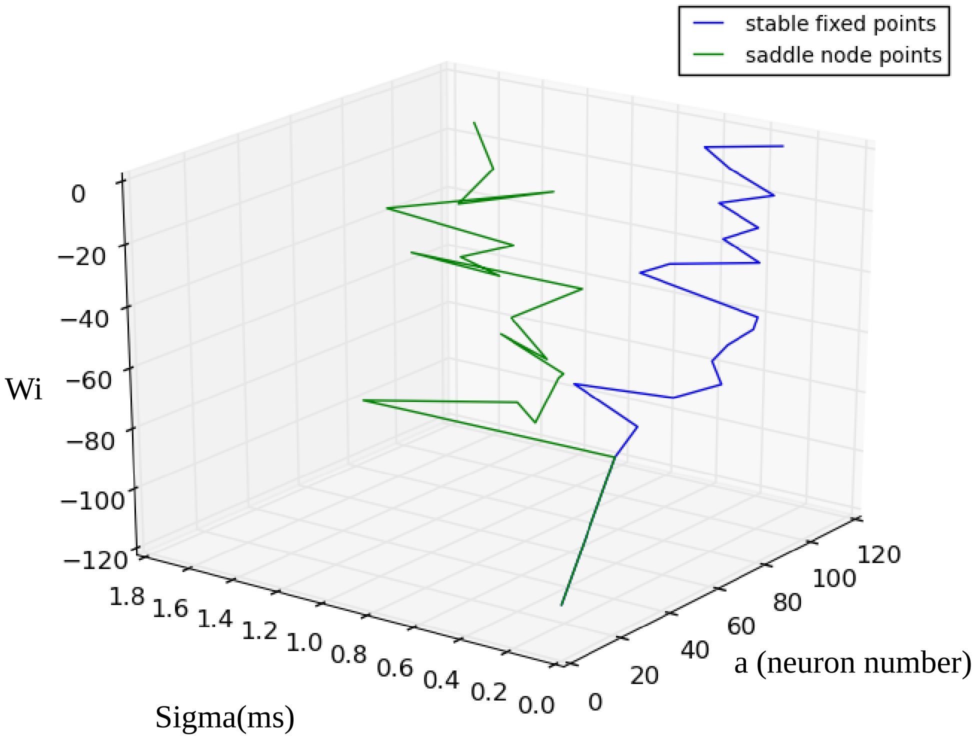


Illustration 21: A 3D plot with positive X & Y axis being sigma and neuron number. Z-axis is the weight of inhibition

The timescale of inhibition and excitation were same hence the resultant effect was just a decrease in strength of excitation to the subsequent group. The speculation that inhibition in the FFN affected synchrony was ruled out.

3.4 Rate of inhibition and its effect on propagation :

The background activity was the key determinant of nature of propagation which affected the membrane potential of the neurons in the groups. Background activity comprised of 20000 synspses feeding to every neuron in the FFN with 88%% being excitatory and 12 inhibitory. The excitation by noise is delivered at 2 Hz and inhibition at 12.5 Hz. The 2 Hz excitation is constantly present due to the large number of excitatory noise neurons firing whereas inhibition comes in short time interval. This short time interval of incomming noisey inhibition in FFN defines the window of integration for spikes. It is found that as the frequency of inhibition was decreased the synchrony in spiking activity decreases.

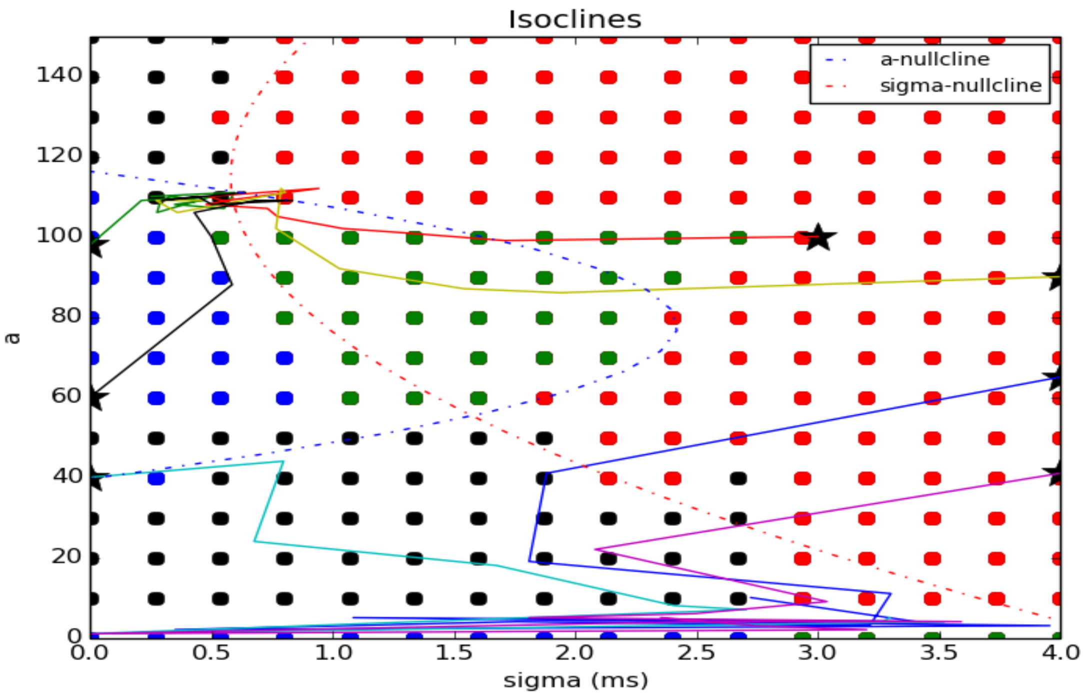


Illustration 22: Wi = -34, w = 125, Inhibition rate = 2Hz

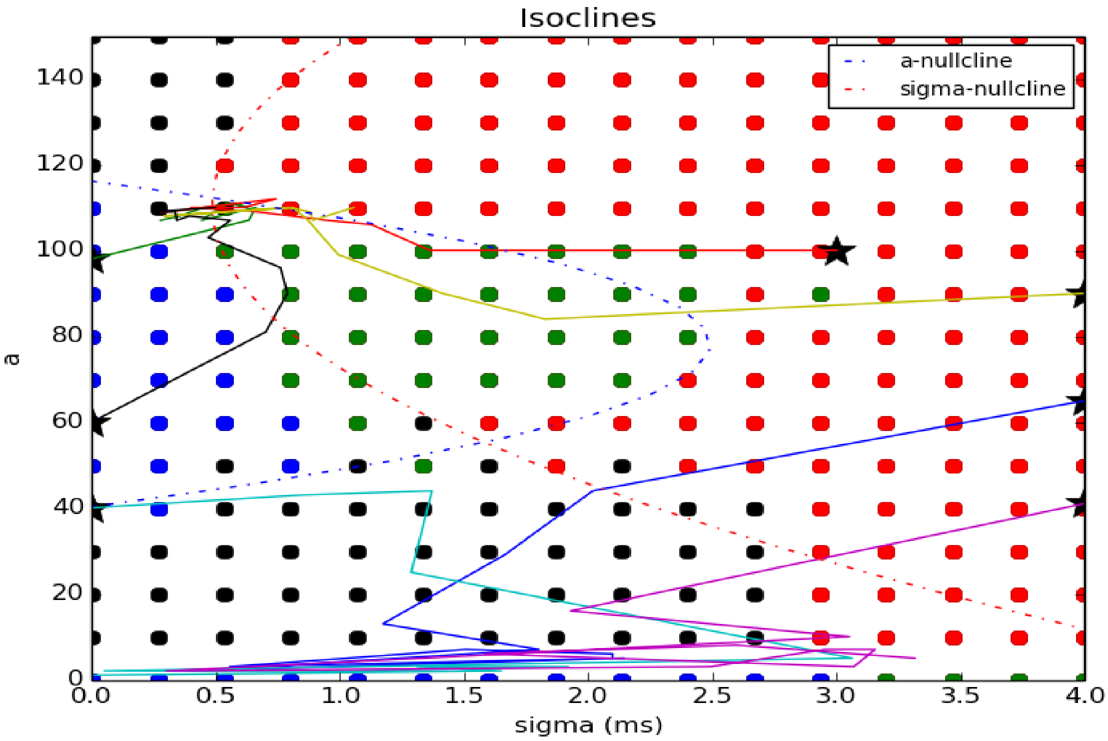


Illustration 23: Wi = -34, w = 125, Inhibition rate = 4.6Hz

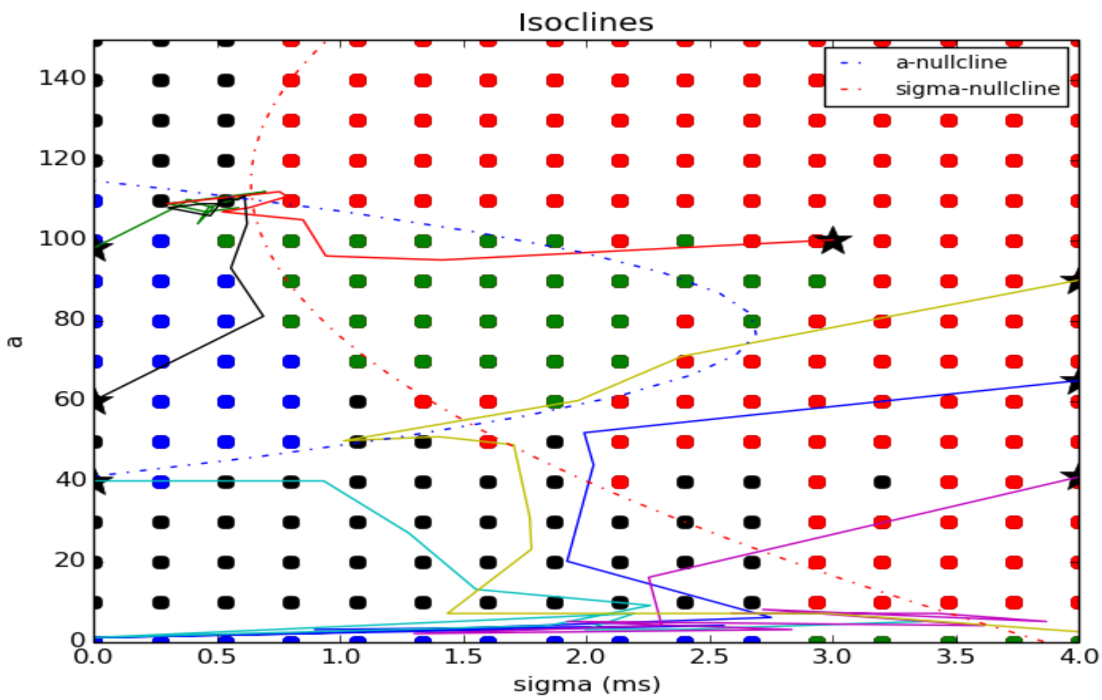


Illustration 24: Wi = -34, w = 125, Inhibition rate = 19Hz,

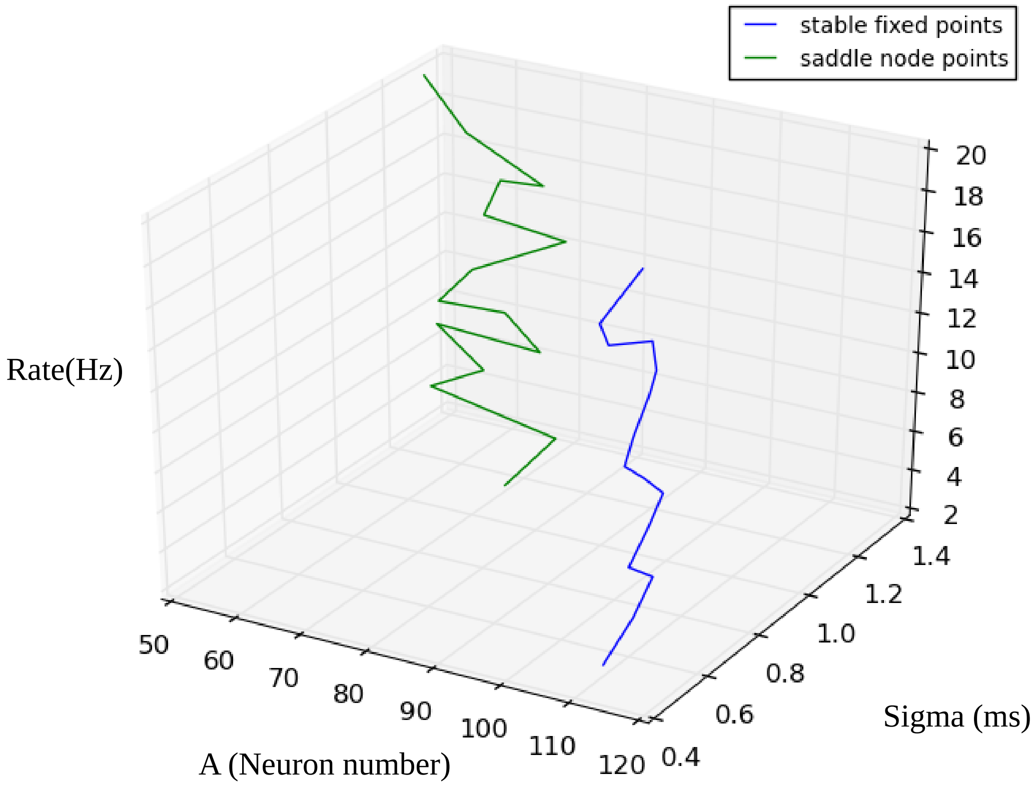


Illustration 25: A 3D plot with positive X & Y axis being neuron number & sigma. Z-axis is the rate of inhibition

Another interesting discovery was that as the frequency of inhibtion was increased to very high number the synchrony attained in the spiking activity decreased due to the fact that the window of integration of spikes became extremely small.

3.5 Introduction of connection probability in EI-FFN :

To make EI-FFN more realistic probabilistic connections were made across subsequent groups.

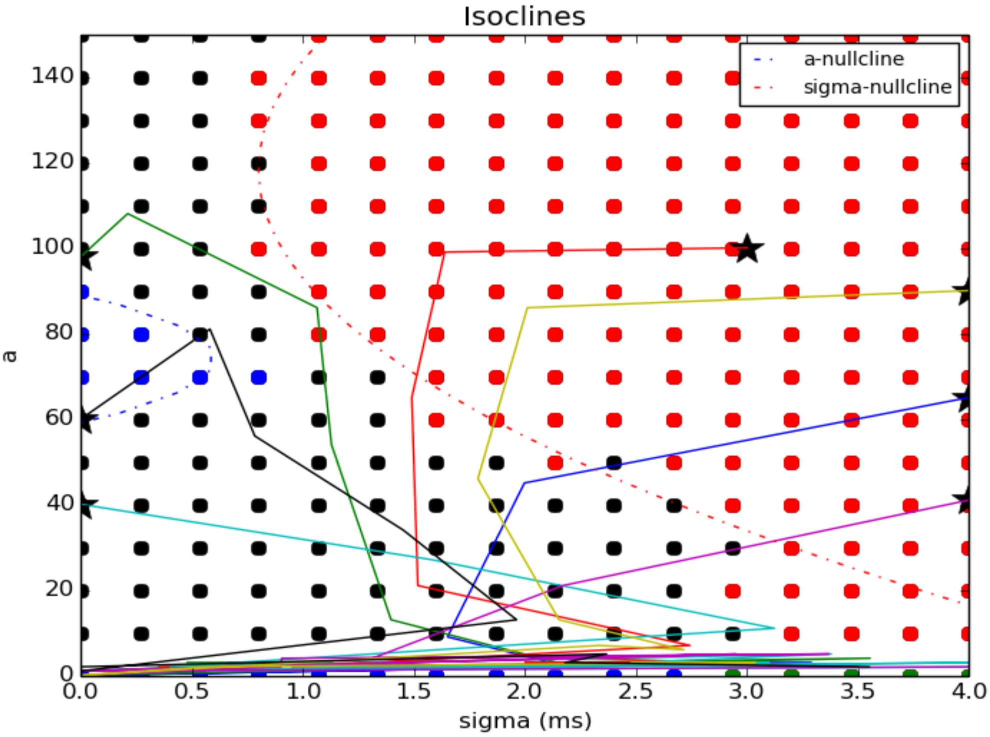


Illustration 26: Wi = -34, w = 125, Probability = 0.7

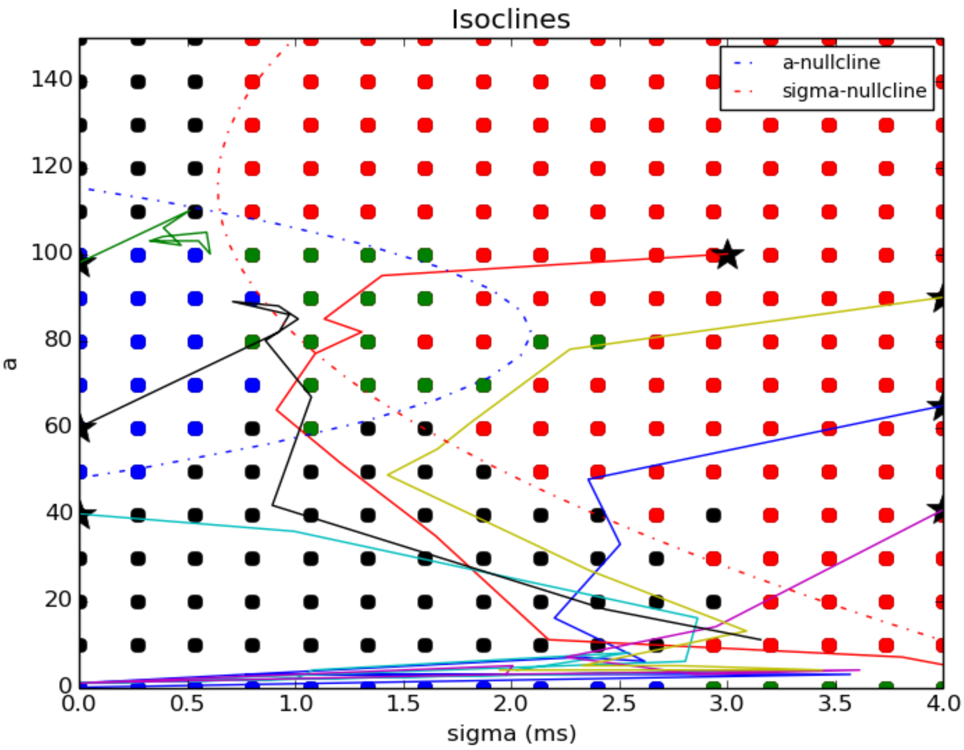


Illustration 27: Wi = -34, w = 125, Probability = 0.89

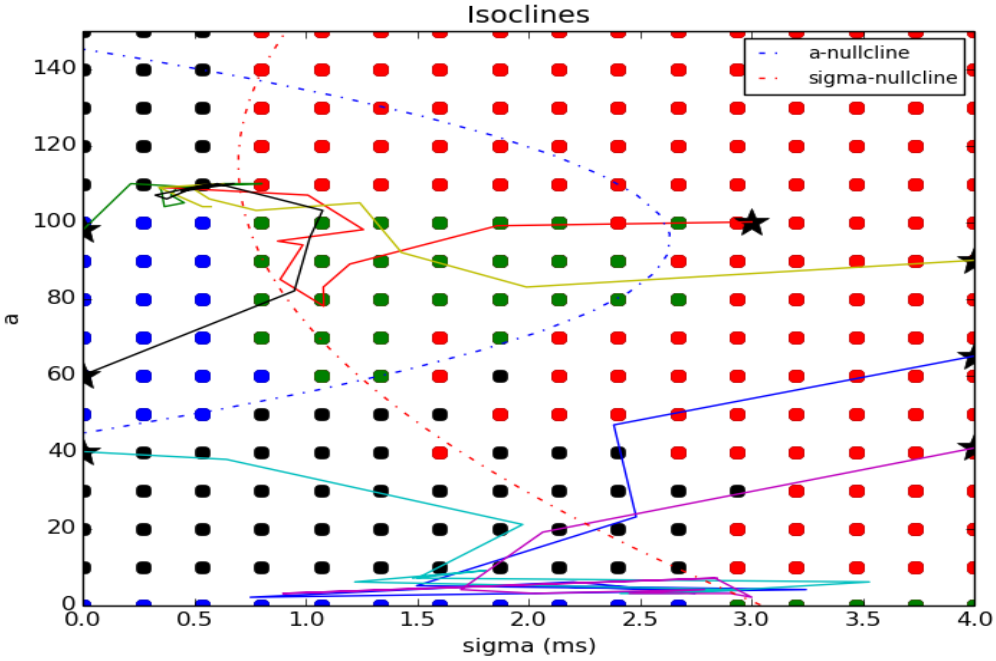


Illustration 28: Wi = -34, w = 125, Probability = 0.97

It is observed that for low probabilities of connection the propagation became unstable. Though for a higher probability of 89% most of the propagation traces entered unstable regime. For 97% connectivity the propagation is stable for most of the grid points.

3.6 Balance of Excitation and Inhibition in excitatory-inhibitory feed-forward network :

The balance of excitation and inhibition was studied in this network. Balance of excitation and inhibition (BEI) is a necessity for long distance propagation.

Figure below show movement of stable fixed point leftwards indicating a decrease in sigma as the proportion of inhibitory-noise neuron is increased.

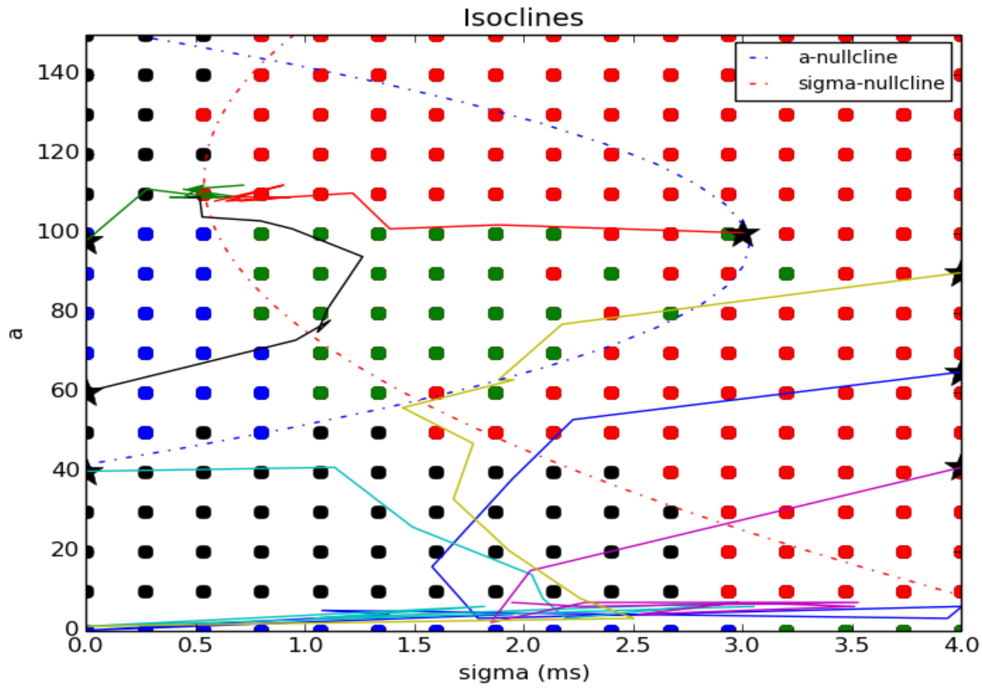


Illustration 29: Wi = -34, w = 125, Proportion = 0.17

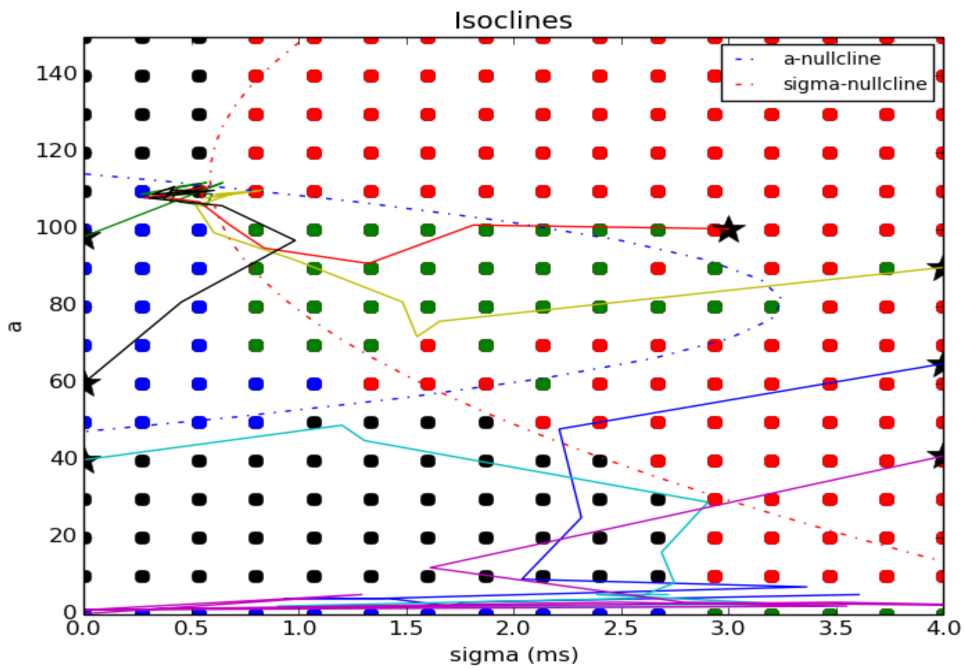


Illustration 30: Wi = -34, w = 125, Proportion = 0.64

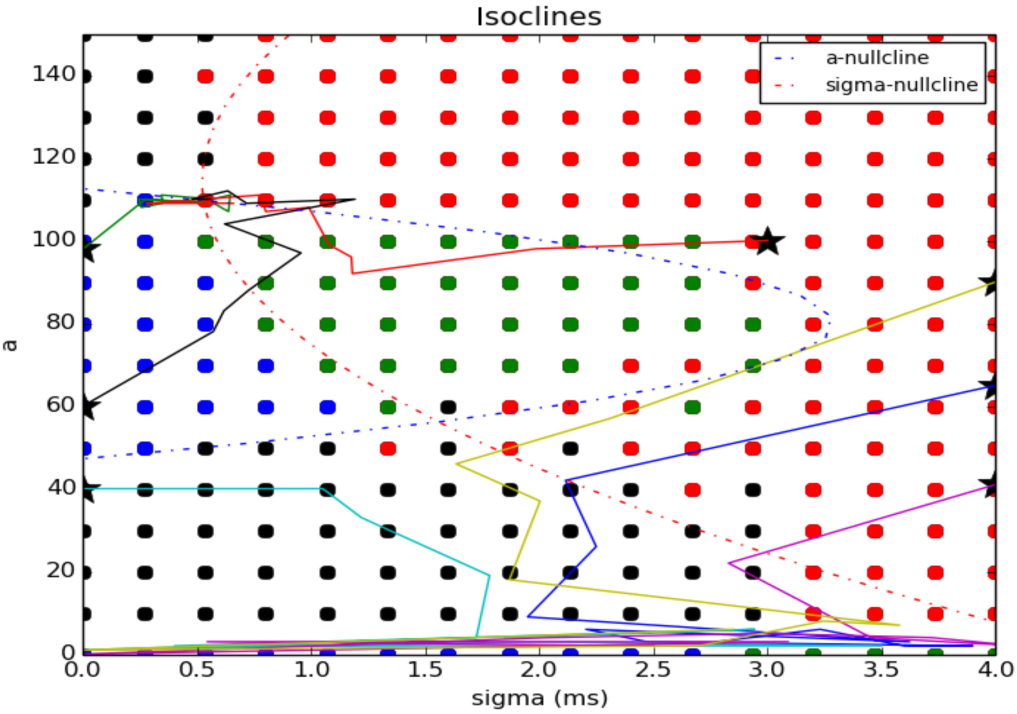


Illustration 31: Wi = -34, w = 125, Proportion = 0.85

BEI is found to vary across areas of brain and affects the spatio-temporal aspect of spike activity. For E-I ratio in noise of 0.1-0.5 , the fixed points seaparated over temporal scale and became synchronized at 0.5 ms.

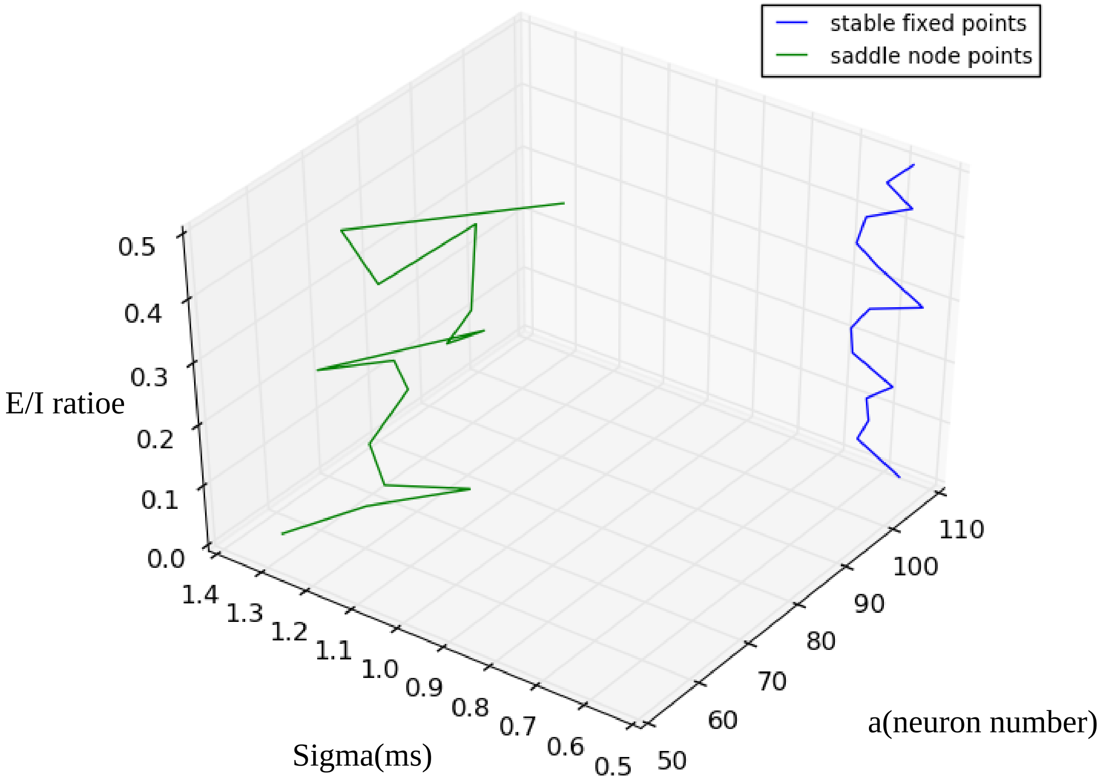


Illustration 32: A 3D plot with positive Y & X axis being neuron number & sigma. Z-axis is the proportion of noise inhibitory neuron to excitatory neuron from 0.0 to 0.5.

Whereas for higher E-I ratio the fixed points diverged on temporal scale.

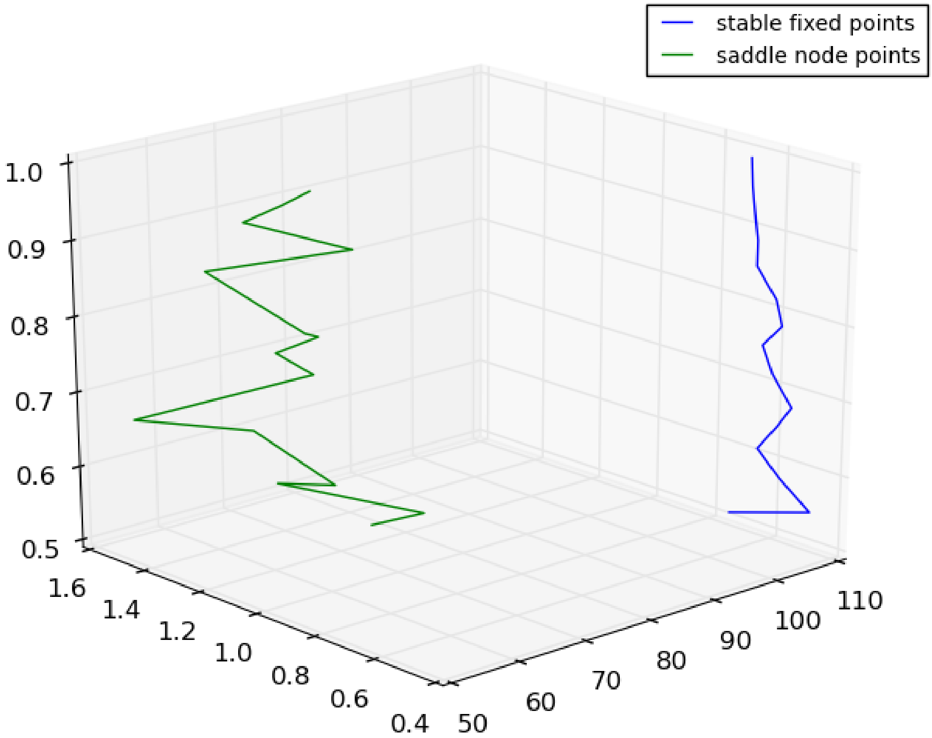


Illustration 33: A 3D plot with positive Y & X axis being neuron number & sigma. Z-axis is the proportion of noise inhibitory neuron to excitatory neuron from 0.5 to 1.0

On increasing inhibition due to noise the window for integration becomes shorter which causes less number of spikes to synchronise even though the spike numbers are high.

Chapter 4

Discussion:

It is observed that signal below 50 'a' spike number fails to propagate (Illustration 6). Noise raises the mean membrane potential to -63 mV from -70 mV (Illustration 10) thus decreasing the firing threshold in the process for signals to propagate stabily (Illustration 5).

The network is of integrate and fire neurons which have a firing threshold of -55 mV. A neuron spikes when it crosses the threshold and this spike is represented as a point in the raster plot. The Zeroth layer marked '0' is the spike volley injector which has a known spike count 'a' and a temporal dispersion 'sigma' to the first layer. This spike volley then propagates consecutively across the network in a forward direction as the network lacks back connections/synapses between two consecutive layers (Illustration 5 & 6). The spike volley propagating across the layers depending on the strength of the synapses, connectivity, temporal dispersion of spikes in a layer and the mean number of spikes in a layer either synchronizes or disperses. The propagation is coined stable when there is synchronization (Illustration 5) and is unstable when there is dispersion (Illustration 6). There is a point where the propagation shows both stable and unstable propagation with equal probability and is called the saddle node.

The spike response follows a sigmoid trend as can be seen in Illustration 17 for a excitatory feed-forward network. The sigmoidicity is due to the fact that the average membrane potential is raised which leads to saturating responses when higher number of spikes are seen by the neuron-group indicating the importance of noise for increased responsiveness. The spread of spikes increases with increasing spread in input (Illustration 18) and is linear as the strength of excitation gets distributed over a large time scale increasing the time to spike for neurons in a group.

To check the network activity behavior for different values of spike count 'a' and temporal dispersion between the spikes 'sigma',an activity phase plane is generated (Illustration 9).

The stable fixed point, red (Illustration 9), is the spike count 'a' and spike time variation where the stabily propagating signal finally converges to. The stable fixed point is point where further propagation of activity irrespective of the number of layers will remain stable and will always have the same spike count and sigma. The saddle node, blue, is the point where the propagation is both stable and unstable. The green line through the saddle node is the separatix for the stable-unstable propagation regime. There is another stable fixed point, yellow to which the unstabily propagating signal finally settles to. This fixed point is the measure of the synaptic background activity's temporal dispersion and spike count.

In excitatory feed-forward network it is observed that as the neurons per layer, w is increased the region of stable propagation expands (Illustration 12,13,15). The a-nullcline moves rightwards in the phase plane (Illustration 11,14,16). Again spike response probability due to increase in number of input spike explains this as the region where the response saturates increases. The sigma-nullcline remains unaffected though which is independent of the neuron number.

When inhibitory neurons are made a part of the network and an excitatory-inhibitory FFN is created the strength of inhibition is seen to affect the spiking activity in the subsequent groups (Illustration 19,20). The inhibition decreases the amount of excitation delivered to the subsequent group when the rate of inhibition is same as that of excitation. The synchronisation due to inhibition from neurons of FFN was ruled out.

It is found that only the background activity played an important role in bringing out the synchronisation. Interplay between inhibitory and excitatory noise not only kept the average membrane potential higher but also a time window for integration of incomming spike was present. It is seen that as the rate of inhibition due to noise is increased the extent of synchronisation increases (Illustration 22,23,24). But excess increase in inhibition rate was found to decrease the level of synchronisation as the time window for integration of incomming spikes got reduced (Illustration 25). This reduced time window can only synchronise very few spike times which are insufficient to ellicit a timed response in the subsequent group.

In a realistic scenario not all neurons from one group will synapse with the neurons of subsequent group. Connection probability was introduced and was found that for higher connection probabilities in an EI-FFN, the regime of stable propagation was large (Illustration 26-31).

Balance of excitation and inhibition is necessary for selective response to various signals. The ratio of inhibition to excitation by noise was varied by changing the proportion of noise inhibitory neurons. For a proportion of 0.5 it was found that the synchronisation increases in EI-FFN containing 125 neurons per layer (Illustration 32). But a further increase in proportion lead to a decrease in level of synchronisation as the average membrane potential of the neurons dropped (Illustration 33).

Another question of separation of signals in two excitatory-inhibitiory feed-forward networks containing a common layer between them is being investigated.

Chapter 5

Conclusion :

We observed that spiking activity has two modes of propagation. The background activity plays a key role in bringing out synchronisation which is a requirement for stable propagation of signals. Presence of inhbition in the feed-forward network containing inhibitory neurons only affected the ellicited response and is not helpful for propagation of signal. The background inhibition played a role in bringing out synchronisation while the background excitation elevated the average membrane potential thus increasing the responsiveness of neurons to weak stimulus. Balance of excitation and inhibition in the background activity plays a role in selective responses to stimuli and thus stimuli depending on the level of this balance of excitation and inhibition in different cortices ellicit response differently.

References:

Bekkers, J. M., Richerson, G. B., & Stevens, C. F. (1990). Origin of variability in quantal size in cultured hippocampal neurons and hippocampal slices. *Proceedings of the National Academy of Sciences of the United States of America*, *87*(14), 5359–62. Retrieved from http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=54323&tool=pmcentrez&rendertype=abstract

Binzegger, T., Douglas, R. J., & Martin, K. A. C. (2004). A quantitative map of the circuit of cat primary visual cortex. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *24*(39), 8441–8453. doi:10.1523/JNEUROSCI.1400-04.2004

Cossart, R., Dinocourt, C., Hirsch, J. C., Merchan-Perez, a, De Felipe, J., Ben-Ari, Y., … Bernard, C. (2001). Dendritic but not somatic GABAergic inhibition is decreased in experimental epilepsy. *Nature Neuroscience*, *4*(1), 52–62. doi:10.1038/82900

Destexhe, A., & Paré, D. (1999). Impact of network activity on the integrative properties of neocortical pyramidal neurons in vivo. *Journal of Neurophysiology*, *81*(4), 1531–47. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/10200189

Diesmann, M., Gewaltig, M. O., & Aertsen, a. (1999a). Stable propagation of synchronous spiking in cortical neural networks. *Nature*, *402*(6761), 529–533. doi:10.1038/990101

Diesmann, M., Gewaltig, M. O., & Aertsen, A. (1999b). Stable propagation of synchronous spiking in cortical neural networks. *Nature*, *402*(6761), 529–33. doi:10.1038/990101

Doupe, A. J., Solis, M. M., Kimpo, R., & Boettiger, C. A. (2004). Cellular, circuit, and synaptic mechanisms in song learning. *Annals of the New York Academy of Sciences*, *1016*, 495–523. doi:10.1196/annals.1298.035

Fabre-Thorpe, M. (2011). The characteristics and limits of rapid visual categorization. *Frontiers in Psychology*, *2*, 243. doi:10.3389/fpsyg.2011.00243

Fee, M. S., & Scharff, C. (1969). The Songbird as a Model for the Generation and Learning of Complex Sequential Behaviors, (Immelmann).

Fiacco, T. A., & McCarthy, K. D. (2004). Intracellular astrocyte calcium waves in situ increase the frequency of spontaneous AMPA receptor currents in CA1 pyramidal neurons. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *24*(3), 722–732. doi:10.1523/JNEUROSCI.2859-03.2004

GAREY, L. (1999). Cortex: Statistics and Geometry of Neuronal Connectivity, 2nd edn. *Journal of Anatomy*, *194*(Pt 1), 153–157. doi:10.1046/j.1469-7580.1999.194101535.x

Gerstein, G. L., Bedenbaugh, P., & Aertsen, A. M. H. J. (1989). Neuronal assemblies. *IEEE Transactions on Biomedical Engineering*, *36*(1), 4–14. doi:10.1109/10.16444

Gewaltig, M. O., Diesmann, M., & Aertsen, A. (2001a). Cortical synfire-activity: Configuration space and survival probability. *Neurocomputing*, *38-40*, 621–626. doi:10.1016/S0925-2312(01)00454-4

Gewaltig, M. O., Diesmann, M., & Aertsen, A. (2001b). Propagation of cortical synfire activity: Survival probability in single trials and stability in the mean. *Neural Networks*, *14*(6-7), 657–673. doi:10.1016/S0893-6080(01)00070-3

Haider, B., Duque, A., Hasenstaub, A. R., & McCormick, D. a. (2006). Neocortical network activity in vivo is generated through a dynamic balance of excitation and inhibition. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *26*(17), 4535–4545. doi:10.1523/JNEUROSCI.5297-05.2006

Hanuschkin, A., Diesmann, M., & Morrison, A. (2011). A reafferent and feed-forward model of song syntax generation in the Bengalese finch. *Journal of Computational Neuroscience*, *31*, 509–532. doi:10.1007/s10827-011-0318-z

Harris, K. D. (2005). Neural signatures of cell assembly organization. *Nature Reviews. Neuroscience*, *6*(5), 399–407. doi:10.1038/nrn1669

Häusser, M., & Clark, B. A. (1997). Tonic synaptic inhibition modulates neuronal output pattern and spatiotemporal synaptic integration. *Neuron*, *19*(3), 665–78. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/9331356

Hebb, D. O. (1949). *The Organization of Behaviour*. *Organization*. doi:citeulike-article-id:1282862

Helmchen, F., Borst, J. G., & Sakmann, B. (1997). Calcium dynamics associated with a single action potential in a CNS presynaptic terminal. *Biophysical Journal*, *72*(3), 1458–1471. doi:10.1016/S0006-3495(97)78792-7

Hô, N., & Destexhe, a. (2000a). Synaptic background activity enhances the responsiveness of neocortical pyramidal neurons. *Journal of Neurophysiology*, *84*(3), 1488–1496.

Hô, N., & Destexhe, A. (2000b). Synaptic background activity enhances the responsiveness of neocortical pyramidal neurons. *Journal of Neurophysiology*, *84*(3), 1488–96. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/10980021

Izhikevich, E. M., Gally, J. A., & Edelman, G. M. (2004). Spike-timing dynamics of neuronal groups. *Cerebral Cortex*, *14*(8), 933–944. doi:10.1093/cercor/bhh053

Kumar, A., Rotter, S., & Aertsen, A. (2010a). different perspectives on neural coding, *11*(SePTemBeR), 615–627. doi:10.1038/nrn2886

Kumar, A., Rotter, S., & Aertsen, A. (2010b). Spiking activity propagation in neuronal networks: reconciling different perspectives on neural coding. *Nature Reviews*. *Neuroscience*, *11*(9), 615–627. doi:10.1038/nrn2886

LIU, Q.-S., XU, Q., KANG, J., & NEDERGAARD, M. (2005). Astrocyte activation of presynaptic metabotropic glutamate receptors modulates hippocampal inhibitory synaptic transmission. *Neuron Glia Biology*. doi:10.1017/S1740925X05000190

Long, M. a, Jin, D. Z., & Fee, M. S. (2010). Support for a synaptic chain model of neuronal sequence generation. *Nature*, *468*(7322), 394–399. doi:10.1038/nature09514

Maass, W., & Natschläger, T. (2000). A model for fast analog computation based on unreliable synapses. *Neural Computation*, *12*(7), 1679–704. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/10935922

Mayhew, T. M. (1991). Anatomy of the Cortex: Statistics and Geometry. *Journal of Anatomy*, *179*, 203–204. doi:10.1016/0022-510X(91)90179-B

Mittmann, W., Koch, U., & Häusser, M. (2005). Feed-forward inhibition shapes the spike output of cerebellar Purkinje cells. *The Journal of Physiology*, *563*, 369–378. doi:10.1113/jphysiol.2004.075028

Overath, T., Cusack, R., Kumar, S., Von Kriegstein, K., Warren, J. D., Grube, M., … Griffiths, T. D. (2007). An information theoretic characterisation of auditory encoding. *PLoS Biology*, *5*(11), 2723–2732. doi:10.1371/journal.pbio.0050288

Rossum, M. C. W. Van, Turrigiano, G. G., & Nelson, S. B. (2002). Fast Propagation of Firing Rates through Layered Networks of Noisy Neurons, *22*(5), 1956–1966.

Steriade, M. Brainstem activation of thalamocortical systems. *Brain Research Bulletin*, *50*(5-6), 391–2. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/10643450

Teramae, J. nosuke, & Fukai, T. (2008). Complex evolution of spike patterns during burst propagation through feed-forward networks. *Biological Cybernetics*, *99*, 105–114. doi:10.1007/s00422-008-0246-9

van Vreeswijk, C., & Sompolinsky, H. (1996). Chaos in neuronal networks with balanced excitatory and inhibitory activity. *Science (New York, N.Y.)*, *274*(5293), 1724–6. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/8939866

Vogels, T. P., & Abbott, L. F. (2005). Signal propagation and logic gating in networks of integrate-and-fire neurons. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *25*(46), 10786–10795. doi:10.1523/JNEUROSCI.3508-05.2005

Volman, V., Ben-Jacob, E., & Levine, H. (2007). The astrocyte as a gatekeeper of synaptic information transfer. *Neural Computation*, *19*(2), 303–326. doi:10.1162/neco.2007.19.2.303

Wilson, H. R., & Cowan, J. D. (1972). Excitatory and inhibitory interactions in localized populations of model neurons. *Biophysical Journal*, *12*(1), 1–24. doi:10.1016/S0006-3495(72)86068-5

Zhai, R. G., & Bellen, H. J. (2004). The architecture of the active zone in the presynaptic nerve terminal. *Physiology (Bethesda, Md.)*, *19*, 262–270. doi:10.1152/physiol.00014.2004