EVOLUTION OF REPRESENTATION OF TEMPORAL SEQUENCES WITH RESPECT TO INDIAN MUSIC

A THESIS

submitted by

SUSWARAM ANIRUDH

in partial fulfillment of requriements

for the award of degree

of

BACHELOR OF TECHNOLOGY

MASTER OF TECHNOLOGY

DEPARTMENT OF ELECTRICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY MADRAS.

MAY 2017

THESIS CERTIFICATE

This is to certify that the thesis titled **EVOLUTION OF REPRESENTATION OF TEMPORAL SEQUENCES WITH RESPECT TO INDIAN MUSIC**,submitted by **Suswaram Anirudh**, to the Indian Institute of Technology Madras, Chennai for the award of the degrees, **Bachelor of Technology and Master of Technology**, is a bona fide record of the research work done by him under our supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

Prof. Srinivasa Chakravarthy
Research Guide
Professor
Dept. of Biotechnology
IIT-Madras, 600 036

Prof.Aravind R
Research Co-Guide
Professor
Dept. of Electrical Engineering
IIT-Madras, 600 036

Place:Chennai

Date:

ACKNOWLEDGEMENTS

I would like to thank IIT- Madras for giving me the opportunity to work on a project and my guide Prof.Srinivasa Chakravarthy , for allowing me to work with him and his invaluable help throughout the project , right from identification of project topic , to helping mould approaches and identifying new directions to work in when a line of thought had to be abandoned.

I would also like to thank my co-guide , Prof.Aravind S , for his support provided .

I am deeply indebted to Vignesh Muralidharan and Karthik Soman (PhD scholars) who supported and helped me at various stages during my project . Their inputs on the approach to the problem helped me in doing lot of my research work quickly.

I would also thank the all the members of Prof.Srinivas sir's lab for many helpful suggestions during my project work .

.

ABSTRACT

KEYWORDS: Ragas, Music ,Jeeva Swarams, Spatial cells

The spatial cells in the hippocampus play a pivotal role in the navigation of an animal.There is a comprehensive , unifying model that shows emergence of not one but a variety of spatial cells, without special symmetry assumptions. Unlike most existing models, this model uses locomotor inputs to extract information regarding the head direction. Path integration is performed by a layer of oscillatory neurons whose frequency is modulated by the head direction outputs. In subsequent unsupervised layers of anti-hebbian lateral connections, this model resulted in the emergence of grid cells (square and hexagonal) and border cells; place cell responses are found at a higher level. The grid and place cells in the model exhibit phase precession in both 1D and 2D spaces. Similarly ,we were keen in analyzing the functioning of spatial cells on music .We actually used 2 approaches during path integration .Since the input was frequencies of notes , we initially felt that the integration of frequency for the calculation of frequency of oscillatory neurons is not necessary because our input itself was frequency .This approach gave interesting results as the cell's activity was peaking at jeeva swarams of that raga (important notes of that raga.) which were defined in our Indian music since ancient times . Our second approach was to consider the frequency inputs as mexican hat functions and giving it to the model and treat it in the same way as the above mentioned model. This approach gave us interesting results which will be mentioned in detail in results section .Briefly speaking , this approach same as above resulted in emergence of place cells and border cells .

TABLE OF CONTENTS

LIST OF FIGURES

TABLE OF CONTENTS

1 INTRODUCTION

The discovery of place cells in the CA1 field of hippocampus is perhaps the first step in our understanding of how space is represented in the temporal lobe structures of the brain. Place cells fire whenever the animal visits a certain location in the ambient space. This discovery had led to subsequent discovery of a larger class of hippocampal cells that represent space, collectively known as the 'spatial cells'. Ranck *et al* (1990) discovered a group of neurons from the postsubiculum region that fired only when the animal's head is in a particular direction in the horizontal plane (yaw plane)[4, 5]. These so-called 'head direction cells' are thought to constitute an "internal compass" that gives a sense of direction to the animal [6].Moser and colleagues[2] described a group of neurons in medial Entorhinal Cortex (mEC) that had a firing field with an astonishingly geometric regularity: multiple firing fields of a single neuron of this type roughly formed the vertices of a hexagon. Since the firing field tessellates the ambient space into a hexagonal grid-like pattern, they were named the grid cells. Further recordings from other regions of mEC showed that grid fields varied in characteristics such as grid scale and grid width, that increased along the dorsal-ventral axis of mEC[7, 8]. Moser *et al* also reported border cells, neurons from mEC that fired when the animal was close to the borders of the environment [3]. Firing of the border cells persisted even when the size and shape of the environment was altered. These border cells or Boundary Vector Cells (BVC) were also reported to be located in the subiculum region of the hippocampal formation. Thus the aforementioned types of spatial cells such as the head direction cells, grid cells, border cells and place cells seem to be the building blocks of a comprehensive hippocampal network for representing and negotiating space.

Efforts have been made to gain insight into spatial cell responses using computational models. Specifically, among the spatial cells, modelling grid cells seem to pose the greatest challenge to the modeller. Existing models of grid cells fall into two broad categories: oscillatory interference models and attractor network models. In the Oscillatory Interference model, originally proposed for place cells by O'Keefe and Recce[10], interference between two sub-threshold membrane potential oscillations (MPO) with slightly different frequencies results in an interference pattern that gives rise to spiking over spatially periodic locations. Burgess *et al*[11] extended this interference model in such a way that it can explain grid field formation in a two dimensional space. The model assumes that sub-threshold MPOs of multiple dendrites of a grid cell in mEC are modulated by the velocity of the animal such that the velocity is projected to those dendritic directions that are multiples of 60^0. In other words, the model is based on an unrealistic constraint that the preferred head directions are sharply concentrated around integral multiples of 60^0.

Grid cell models based on continuous attractor neural network models [16-19] consist of 2D layers of neurons in which, each neuron has circularly symmetric ON-centre, OFF-surround lateral connectivity [17, 18]. Such models exhibit a hexagonal pattern in the neural space by Turing instability[20], which is unrealistic since hexagonal symmetry is seen only when the neural firing is superimposed on the ambient space; there is no evidence of such hexagonal symmetry within the neural space itself. Furthermore, to simulate path integration by the grid cells, the models assume that the animal's velocity is coupled to grid cell activity in complex ways: velocity is thought to modulate neighbourhood connectivity by introducing transient asymmetry that depends both on the speed and direction of motion, another unrealistic assumption. These models also assume a toroidal neural network topology – another unrealistic micro-anatomical constraint - to avoid the edge effect [16, 19].

These ideas, along with the underlying unrealistic assumptions, have been carried over to modelling head direction cell networks also[21-24]. Furthermore, the aforementioned modelling approaches address one spatial cell type at a time and do not offer a comprehensive theory that describes simultaneous emergence of multiple types of spatial cells.

Paper written by Prof.Srinivasa Chakravarthy, Karthik and Vignesh[25] propose a comprehensive model of spatial cell formation, that includes place cells, grid cells, border cells and head direction cells, without resorting to some of the unrealistic assumptions of the earlier models .

Using this model as basis , in this paper we will see how temporal sequence is represented in the temporal lobe structures of the brain. We will be seeing the neuronal activity in the hippocampus part of the brain for the input of which is temporal sequence.

Any musical piece can be considered as a sequence with respect to time.So , we will be using few compositions of Indian Music in our experiments in order to observe results.

1. THEORY

1.1. Brief Introduction to Indian Classical Music

Indian Classical Music is a genre of South Asian Music . It has two major traditions. The North Indian classical music tradition is called Hindustani, while the South Indian expression is called Carnatic. Our research work is mostly based on Carnatic Music.

The Indian classical music has two foundational elements, raga and tala. The raga forms the fabric of a melodic structure, the tala measures the time cycle.The raga gives an artist the ingredients palette to build the melody from sounds, while the tala provides him with a creative framework for rhythmic improvisation using time. Carnatic Music has most emphasis on tala compared to it’s counterpart Hindustani Music. Carnatic music, from South India, tends to be more rhythmically intensive and structured than Hindustani music. Examples of this are the logical classification of ragas into melakarthas, and the use of fixed compositions similar to Western classical music. Carnatic raga elaborations are generally much faster in tempo and shorter than their equivalents in Hindustani music.

Carnatic Music System

Carnatic music is a system of music commonly associated with the Southern India. The main emphasis in Carnatic music is on vocal music; most compositions are written to be sung, and even when played on instruments, they are meant to be performed in singing style. Carnatic music is mainly sung through compositions, especially the kriti (or kirtanam) – a form developed between the 14th and 20th centuries by composers such as Purandara Dasa and the Trinity of Carnatic music. Carnatic music is also usually taught and learned through compositions.

1.2. Important elements of Carnatic Music

1) Sruti

Sruti commonly refers to musical pitch. It is the approximate equivalent of a tonic (or less precisely a key) in Western music. It is the note from which all the others are derived. It is also used in the sense of graded pitches in an octave. While there are an infinite number of sounds falling within a scale (or raga) in Carnatic music, the number that can be distinguished by auditory perception is twenty-two (although over the years, several of them have converged and resulted in only twelve). In this sense, while sruti is determined by auditory perception, it is also an expression in the listener's mind.

2)Swara

Swara refers to a type of musical sound that is a single note, which defines a relative (higher or lower) position of a note, rather than a defined frequency. Swaras also refer to the solfege of Carnatic music, which consist of seven notes,"sa-ri-ga-ma-pa-da-ni" (compare with the Western do-re-mi-fa-so-la-ti). These names are abbrevations of longer terms shadja, rishabha, gandhara, madhyama , panchama ,dhaivatha,nishadha. Unlike other music systems, every member of the solfege (called a swara) has three variants. The exceptions are the drone notes, shadja and panchama (also known as the tonic and the dominant), which have only one form; and madhyama (the subdominant), which has *two forms.*

3)Raga system

A raga in Carnatic music prescribes a set of rules for building a melody – very similar to the Western concept of mode.It specifies rules for movements up (aarohanam) and down (avarohanam), the scale of which notes should figure more and which notes should be used more sparingly, which notes may be sung with gamaka (ornamentation), which phrases should be used or avoided, and so on. In effect, it is a series of obligatory musical events which must be observed, either absolutely or with a particular frequency.

Ragas can be divided into two classes: janaka ragas (i.e. melakarta or parent ragas) and janya ragas (descendant ragas of a particular janaka raga). Janya ragas are themselves sub classified into various categories. In Carnatic music, the sampoorna ragas (those with all seven notes in their scales) are classified into a system called the melakarta, which groups them according to the kinds of notes that they have. There are seventy-two melakarta ragas, thirty six of whose madhyama (subdominant) is shuddha (perfect fourth from the tonic), the remaining thirty-six of whose madhyama (subdominant) is prati (an augmented fourth from the tonic). The ragas are grouped into sets of six, called chakras ("wheels", though actually segments in the conventional representation) grouped according to the supertonic and mediant scale degrees. There is a system known as the katapayadi sankhya to determine the names of melakarta ragas.

This research work has made use of melakartha ragas for the experiements done.

4)Tala system

Tala refers to a fixed time cycle or metre, set for a particular composition, which is built from groupings of beats .Talas have cycles of a defined number of beats and rarely change within a song. They have specific components, which in combinations can give rise to the variety to exist (over 108), allowing different compositions to have different rhythms

1.3. Few more important information in Carnatic Music to be known for understanding of the work done:

Sarali Varisai:

SaraliVarisai is used to learn the swarams in the octave, usually in Mayamalavagowla ragam. It is learnt in simple straight ascending and descending fashion and a few variations. It is also learnt in multiple speeds (kalams).This is the set which beginners who start to learn Carnatic Music initially learn. The great composer Purandara Dasa, hailed as the Father of Carnatic music, created this set of fundamental exercises nearly 500 years ago, which are widely followed even today. It can also be practiced in different ragams.

Speeds in Carnatic Music:

In carnatic music, speed is relative. It is measured as the number of notes per beat of the tala, rather than the number of notes per second or minute. The first speed is rendering one note per unit of the tala. The 2nd speed is exactly double of this, i.e. two notes per unit. The 3rd speed is four notes per unit.

Speed of the tala is rarely varied; only the speed of the music is. But even this is not accomplished in an arbitrary manner. There is a mathematical precision to it. For instance, the 2nd speed is exactly twice as fast and the third is exactly twice as fast as the second and so forth. First 3 speeds are the ones in which musicians generally practice and perform.

Varnam:

Varṇam is a form of song in the Carnatic music repertoire consisting of short metric pieces which encapsulate the main features and requirements of a raga. The features and rules of the raga (also known as the sanchaaraas of a raga) include how each note of the raga should be stressed, the scale of the raga, and so on. Varnams are also practised as vocal exercises by performers of Carnatic music, to help develop voice culture, and maintain proper pitch and control of rhythm. It is the most complex of vocal exercises. In modern carnatic concerts, it is usually sung as a first song and is supposed to help warm-up.So varnam clearly represents a raga and it's characteristics.

Vadi Swara:

Vadi, in both HindustaniMusic and CarnaticMusic, is the tonic (root) swara (musical note) of a given raga (musical scale). "Vadi is the most sonant or most important note of a Raga. It does not refer to the most played note but it rather refers to a note of special significance. It is usually the swara which is repeated the greatest number of times, and often it is the swara on which the singer can pause for a significant time. Vadi swara in a raga is like a king in a kingdom. Specialty of any raga depends on vadi swara and because of this, the vadi swara is also called the Jeeva swara.

Samvadi Swara:

The samavadi is the second-most prominent (though not necessarily second-most played) note of a raga in Indian classical music. The vadi and samvadi are in most cases a fourth or fifth apart.

In any raga, there is 'Poorvaanga' & 'Uttaranga'. Poorvaanga is usually first half section of raga, say 'Sa' to 'Pa' and Uttaraanga is'Pa' to 'Sa' (taara shadjamam). Vadi is important note in Poorvaanga and Samwadi is important note in Uttaraanga. The two notes also define how poorvaanga interacts with uttaranga while transiting from one section to other.

Vadi and Samvadi swaras discussion and significance comes from the times of ancient India where Sage Bharatha mentions about it in his book called NatyaSastra.

2. EXPERIMENT METHODS

2.1. Input Encoding :

Our input through out the experiments will be a one dimensional sequence (vector) which has frequency of the each note. It can be assumed as the samples of music taken with respect to time .Ideal case would be a person singing and then taking samples of frequency with respect to time. But since the area of pitch detection itself is in its initial stages and no proper algorithm is in place for it, we have considered the samples taken as if the music is being played on keyboard(piano) . Since it is well known that each note on keyboard has a particular frequency. It is easy to capture the frequency of each note as it is when played on keyboard.

Table 2.1

C(C_4)	Sa	261.626
C#	Ri_1	277.183
D	Ri_2	293.665
D#	Ga_1 or Ri_3	311.127
E	Ga_2	329.628
F	Ma_1	349.228
F#	Ma_2	369.994
G	Pa	391.995
G#	Dha_1	415.305
A	Dha_2	440.000
A#	Ni_1or Dha_3	466.164
B	Ni_2	493.883
C	Sa(Top one)	523.251

For our experiments we were stick to only one octave that is C_4 to C_5. So the frequency range will be from 261.626 to 523.251.

Since it is already said that we will be considering the compositions from Carnatic Music, when we play it on keyboard it is difficult to represent or play the small nuances which we call gamakams in Carnatic Music . So for the simplicity purpose we neglect the representation of these gamakams and consider it as a plain note.

One more interesting thing we can observe from the table is that , the frequencies are logarthamically equally spaced .Each note is $(2)^{1/2}$ of the previous note in that table . So this gives us some flexibility for us to change to logarthamic scale when ever it is requried.

To capture the speed of the note which it is presented or played, we represented it as number of times that note has been sent . We have considered varnams and sarali varisai in our experiments and it is actually sung in 2 and 3 kalams (speeds) respectively and it is also known that in 1st speed each note is represented(sung) for approximately 1 sec , we have sent each note for 800 continuous times such that the model receives the note for 1 second . Similarly for 2nd and 3rd kalams(speeds) each note is sent 400 and 200 times respectively.

This is the way in which we get our raw initial input which will be used in each of our experiments.

2.2. MODEL 1

Gaussian Layers:

For our first part of the experiment we developed gaussians for each of the inputs(frequencies) which centers on that frequency i.e peaking at that frequency and slowly dying out . The range considered for the gaussians is from 255hertz to to 530 hertz which covers every note's frequency that is from Sa to Sa(Top One) .So for example , if the note sent is Pa then gaussian will be centered around 391.995hertz and slowly dies out on either side .

The picture of Gaussian centered around Pa is shown below.

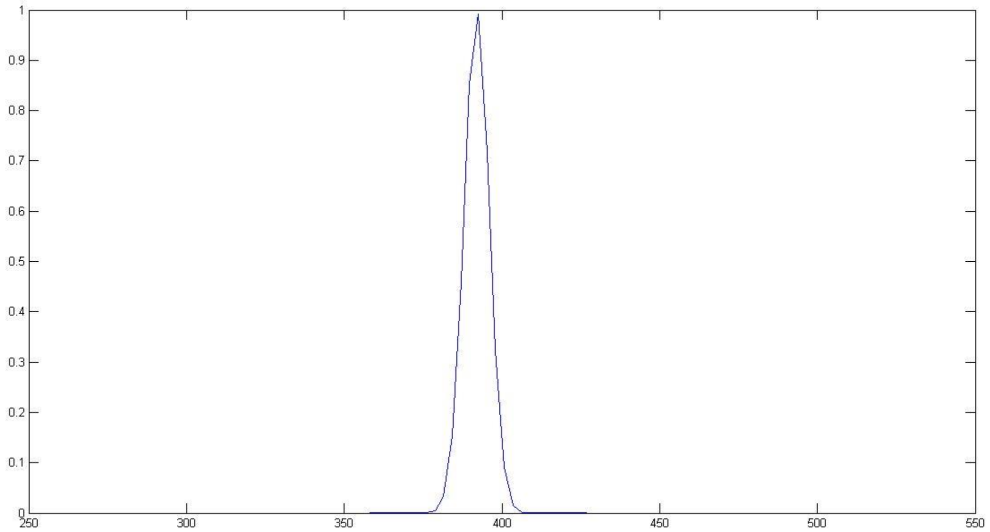

Figure 2.1

This is just to convert our discrete samples into continuous over the range of frequencies used . Now this Gaussian input of each note can be given to the Path Integration layer.

We use this kind of input in one of our model which will be mentioned below.

Oscillatory Layer:

Once each input comes out of Gaussian layer G_i we will give it to oscillatory layer. It represents the input as oscillations.The oscillatory response of i^{th} Gaussian layer i.e i^{th} input is

$O_i=\sin[\int 2\pi f_o\, dt + \beta G_i]$

where β is the spatial scaling parameter, f_o is base frequency of the oscillators .

The oscillatory layer has the above mentioned dynamics.This actually encodes time varying input onto periodic oscillations.

The oscillatory cell responses of i^{th} oscillatory neuron, (O_i) are then thresholded by the following rule,

$O_i^{Thr}=H\,(O_i - \varepsilon_o)\,.\,O$

where , H is Heaviside function and ε_o is the threshold value.

This oscillations are being used in order to capture any inherent periodicity or patterns in the input .In order to do that we will be doing PCA.The O_i^{Thr} are projected via a linear weight stage (W^O) to a subsequent layer, the SC layer. Weight (W_{ij}^O) from i^{th} O^{Thr} to j^{th} SC layer neuron is computed by performing Principal Component Analysis (PCA) over O^{Thr}. The response of i^{th} neuron in the SC layer is given as,

$SC_i = \sum H[\,(W_{ij}^O * O_j^{Thr}) - \varepsilon_{SC}\,]$

where, H is Heaviside function, N is the number of PI neurons, and ε_{SC} is the threshold value.

The top few components of the computed principal components (PC) responses with respect to time (input sequence) are plotted on the graph and it's responses are analysed .

RESULTS

This experiment has been done using sarali-varisai of Carnatic music in 10 different ragas in different speed i.e 1st speed 2nd speed and 3rd speed.Speeds are controlled by number of times we send each note in our input It has been observed that the activity of neurons was same when ever a particular note occurs irrespective of sequence.This is because since we were not integrating the input sequence anywhere it is independent of it's predecessor or successor. Most importantly it has been observed that the activity of neurons was peaking at Vadi and Samvadi swarams of that particular ragam . It is also observed that the Poorvanga part and Uttharanga part responses for the raga were complementary to each other i.e if poorvanga part was positive then uttharanga part was negative and viceversa.

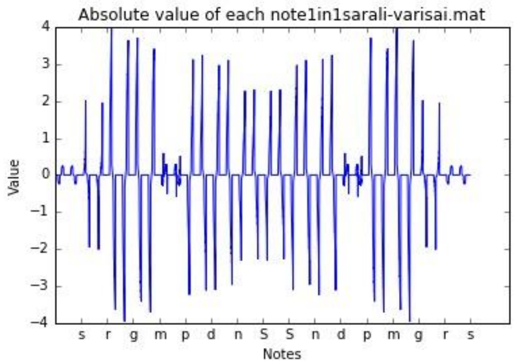

Figure 2.2

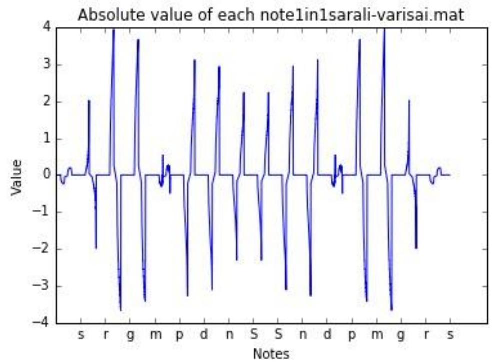

Figure 2.3

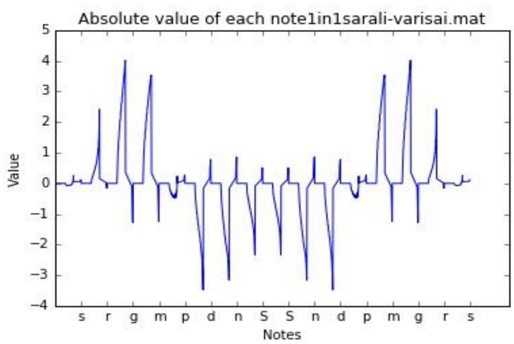

Figure 2.4

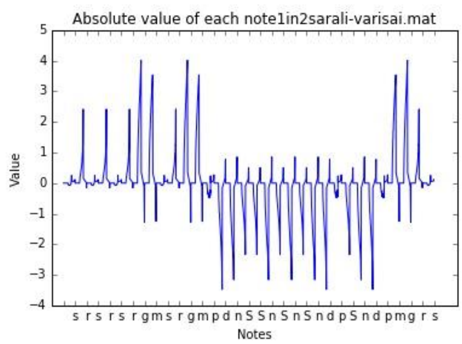

Figure 2.5

The above 4 pictures shows the responses for Shankarabharam ragam with the notation of Sarali Varisai. Fig 1 is 1st sarali varisai in first speed .Fig 2 is 1st sarali varisai in second speed .Fig 3 is 1st sarali varisai in third speed. Fig 4 is 2nd sarali varisai in third speed.

We can clearly observe that the activity as the speed increases is becoming more centered and centered around the note .We will be showing results for other ragas only in 3rd kalam as it itself gives us complete picture . Fig 3 and Fig 4 shows that the activity of neuron for a particular note is same independent of the sequence.

We know that vadi and samvadi swarams for the shankarabharanam is ga and dha and clearly the activity of neurons is peaking at those notes which is quite interesting .This actually means that the neurons are actually picking the important notes of the raga and their emphasis is mostly on those notes . And we can also observe that the poorvanga part in shankarabharanam is positive and uttharanga part is negative and poorvanga peak gave us vadi and uttharanga part gave us samvadi , which are jeeva swarams of that raga .

Similarly below we will be showing the results where it gave vadi and samvadi swarams for few more raagas.We will be showing the neuron responses only in 3rd speed as it gives entire information.

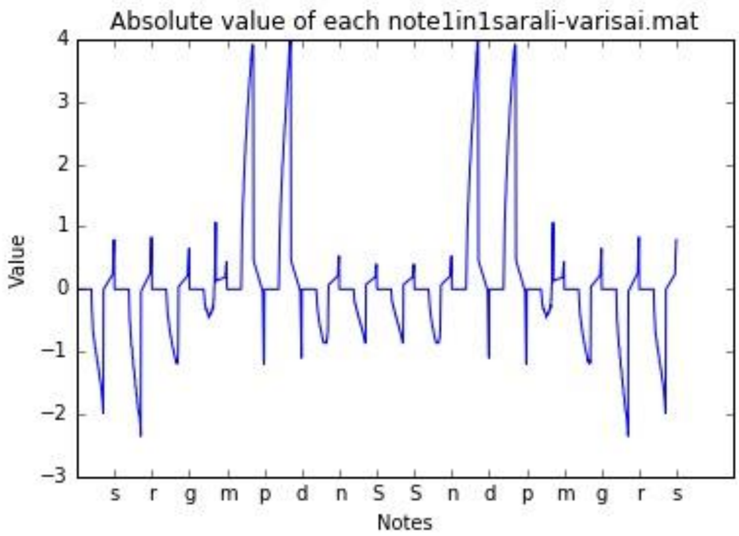

Figure 2.6

Rishabham and Dhaivatham are the important notes in the above mentioned raga which is Mayamalavagowla.And you can clearly see that vaadi swara has negative response which samvadi has positive response.

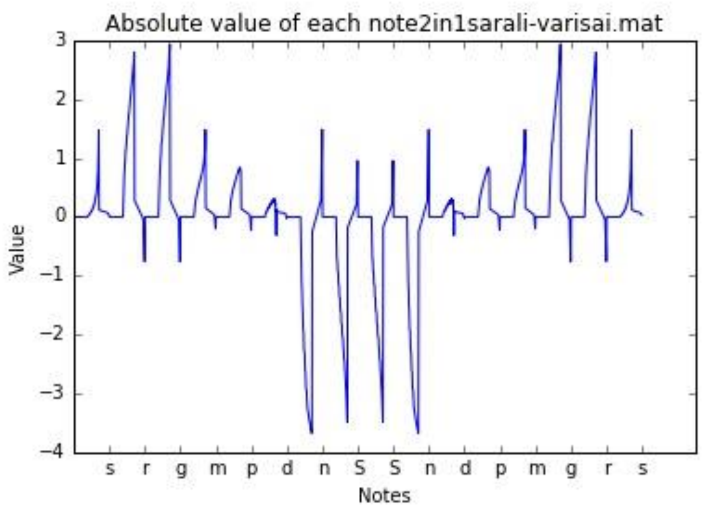

Figure 2.7

So the above raga corresponds to Simhendra Madhyamam and the vadi and samvaadi swarams are gandharam and nishadham .We can clearly see the above mentioned quality here as well .

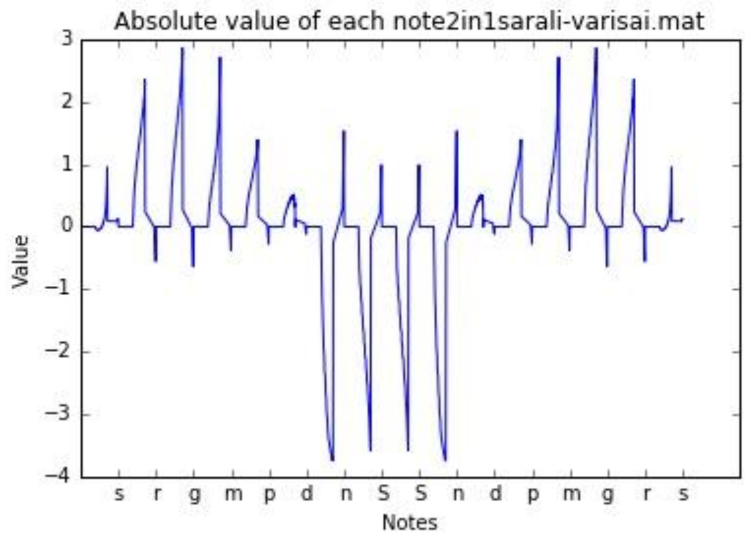

Figure 2.8

Again for Raga Keeravani Ga and Ni are vaadi and samvaadi which can be seen from above figure .

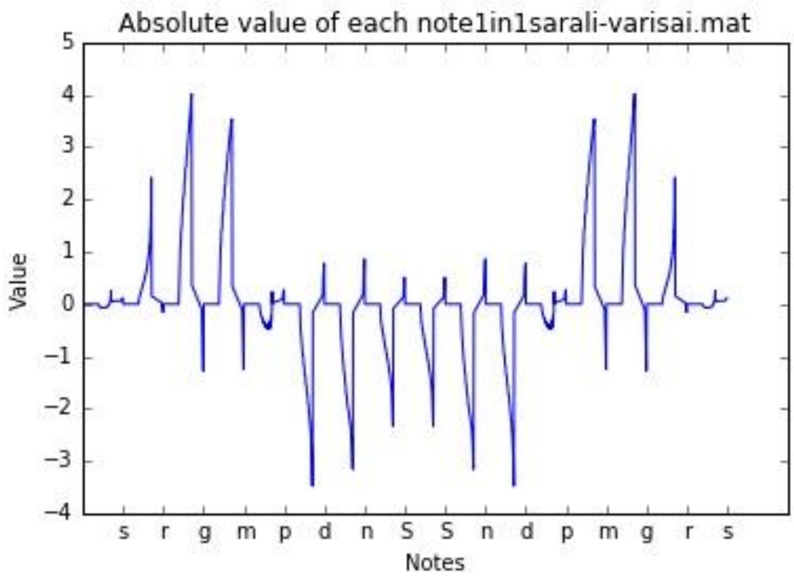

Figure 2.9

For Harikhamboji its equivalent in hindusthani is Khamaj raag and its vadi and samvadi notes are Ga and Dha respectively. So that is also clearly observed from the above figure.

Similarly experiments on Todi , Kharaharapriya , Pantuvarali ,Kalyani also gave it's vadi and samvadi swarams respectively.

These are the results obtained from the first model where it is not sequence dependent because we are not integrating the input in the oscillatory layer and hence it gave the importance of notes in that particular raga .

2.3. MODEL 2

In this our approach was exactly same as the approach in the paper written by Prof.Srinivas, Karthik and Vignesh . The only thing we were worrying was about the representation of the temporal sequence input in such a way that it some how similar to the navigation of animal in 2d space. So we came up with the representation like when current note X_i is being sung or given to the model , on the 2 dimensional graph we are currently on (X_i , X_{i-1}) point . 2 dimensional graph where x and y axis corresponds to the frequency range of the notes i.e from 250 to 530 .

So we will be having trajectory i.e each point (X_i , X_{i-1}) in an sequence forms a trajectory on the 2 dimensional frequency space . Similar to the calculation of speed of animal we will calculate the speed here also which will be proportional to simple euclidian distance between adjacent points as the time here which is duriation for which a note is sung is constant.Since we know trajectory, we can also calculate the direction at each instance on the trajectory . For the randomness in the trajectory we choose varnam in carnatic music because it kind gives us whole picture of raga (it contains entire information about raga's behavior) and that's why the trajectory will be closely random in nature.

So after getting these speed and direction we implement it in the following way to see how representation of temporal sequence(here music) is done in the brain .

2.4. Approach 1

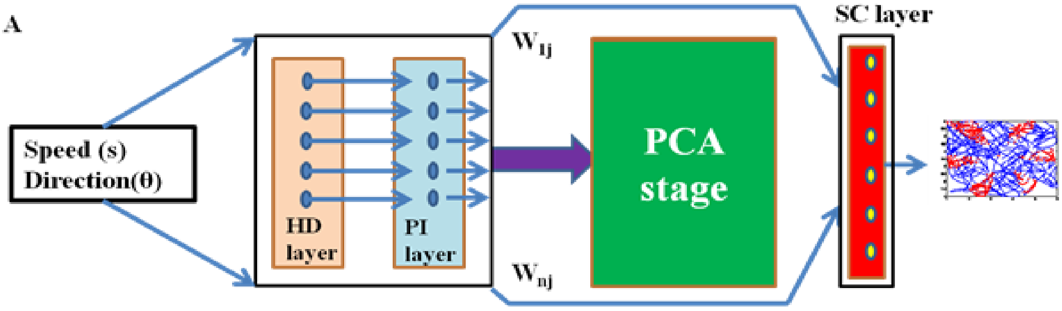

Figure 2.10

The proposed model has three layers, HD layer, Path Integration (PI) layer and an output SC layer that represents the region of Entorhinal Cortex (EC) to which the PI response vector converges as input (Fig. 1A). The response of i^{th} HD cell is computed as the projection of the current note's direction onto the i^{th} preferred direction, given as,

$$HD_i = \cos(\theta - \theta_i)$$

θ is the current note direction and θ_i is the preferred direction of i^{th} HD cell. The outputs of HD layer project to the subsequent PI layer, via one-to-one connections of unity strength. PI neurons are modelled as oscillatory neurons whose phases encode the result of path integration performed on HD cell responses. Each HD cell modulates the corresponding PI neuron's dendritic frequency from its base frequency f_0 thereby changing the phase of the PI neuron. The response of the i^{th} PI cell is given as,

$$PI_i = \sin[\int 2\pi(f_0 + \beta s HD_i)dt]$$

where β is the spatial scaling parameter, and s is speed i.e proportional to euclidian distance between two adjacents points in trajectory.

The PI cell responses of i^{th} PI neuron, (PI_i) are then thresholded by the following rule,

$$PI_i^{Thr} = \mathrm{H}(PI_i - \varepsilon_{PI}).PI_i$$

where, H is the Heaviside function, and ε_{PI} is the threshold value.

The thresholded PI values are projected via a linear weight stage (W^{PC}) to a subsequent layer, the SC layer. Weight (W_{ij}^{PC}) from i^{th} PI^{Thr} to j^{th} SC layer neuron is computed by performing Principal Component Analysis (PCA) over PI^{Thr}. The response of i^{th} neuron in the SC layer is given as,

$$SC_i = \sum_{j=1}^{N} \mathrm{H}[(W_{ij}^{PC}.PI_j^{Thr}) - \varepsilon_{SC}] \qquad (2.1.4)$$

where, H is Heaviside function, N is the number of PI neurons, and ε_{SC} is the threshold value.

The top few components of the computed principal components (PC) will be shown to reveal a variety of spatial cell-like responses like place cells, border cells , and corner cells (whose firing fields are at the corners of the space) as shown below. The emergence of spatially periodic firing field is due to the inherent periodicity in the PC weights.The firing field of each neuron is depicted by placing red dots on those positions of the trajectory where the respective neuron in the SC layer is active (crosses the threshold value) .

The experiment is performed on the Shankarabharanam varnam and firing field of first few neurons in the order were as follows

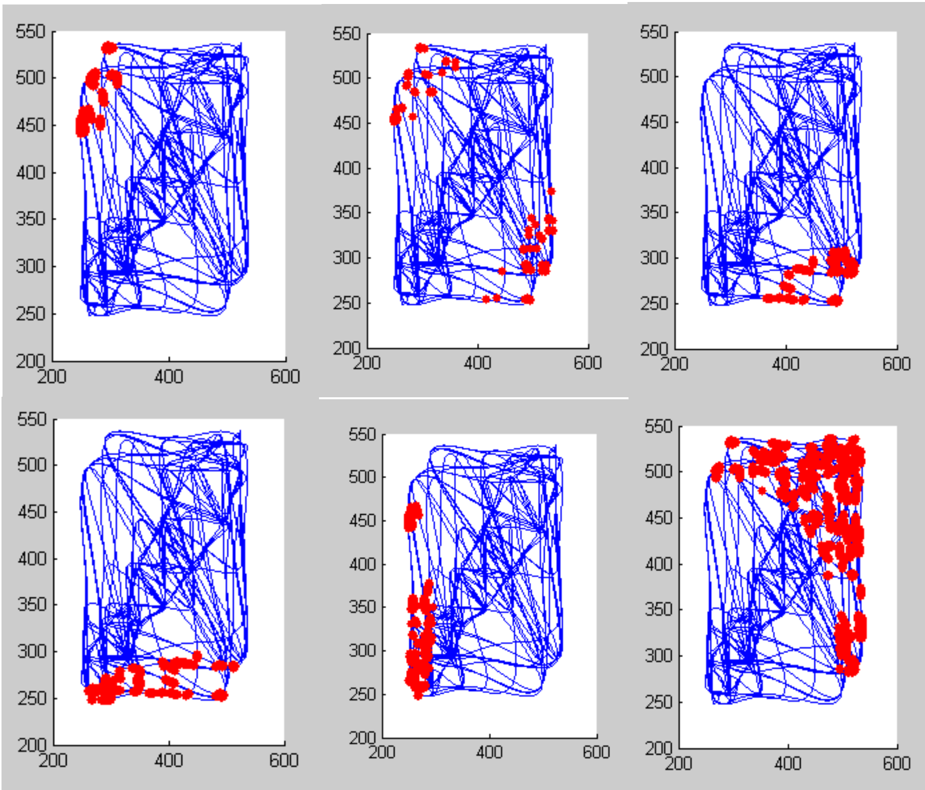

Figure 2.11

Clearly from above we can see corner cells which are firing at cornes of the trajectory and border cells which are firing at only borders and border and corner which are firing at both

2.5. Approach 2

Instead of performing Principal Component Analysis (PCA) in this approach we will be using LAHN which is biologically more plausible than the above one . Everything else remains same except that PCA is replaced by LAHN . Details of LAHN is mentioned below

Lateral Anti-Hebbian Network (LAHN)

LAHN is a neural network with Hebbian afferent connections and anti-hebbian lateral connections, known to be capable of extracting sparse features from the input patterns. LAHN response is computed as follows.

$$\xi_i(t) = \sum_{j=1}^{m} q_{ij}\chi_j(t) + \sum_{k=1}^{n} w_{ik}\xi_k(t-1) \qquad (2.2.17)$$

ξ is the output of LAHN, χ is the input PI value, q_{ij} is the forward Hebbian connection from j^{th} input to i^{th} output neuron, w_{ik} is the lateral connection between i^{th} and k^{th} output neuron, m is the input dimension, and n is the number of output neurons. The lateral and forward weight update equations are given as,

$$\Delta w_{ik} = -\eta_L \xi_i(t)\xi_k(t-1) \qquad (2.2.18)$$

$$\Delta q_{ij} = \eta_F[\chi_j(t)\xi_i(t) - q_{ij}\xi_i^2(t)] \qquad (2.2.19)$$

η_L and η_F are the learning rates for lateral and forward weights respectively. After training, the weights of the $LAHN_{SC}$ converge to the subspace of the PCs of the input vectors[36]. As described in the simulations of results section (Fig 2.B.1-2.E.1), neurons of $LAHN_{SC}$ developed unique spatial firing fields resembling place cells, border cells ,corner cells etc.

For the same varnam LAHN responses gave firing across the diagonals which is like most frequent places and most important transisitons in varnam

The results for first 10 neurons are as follows

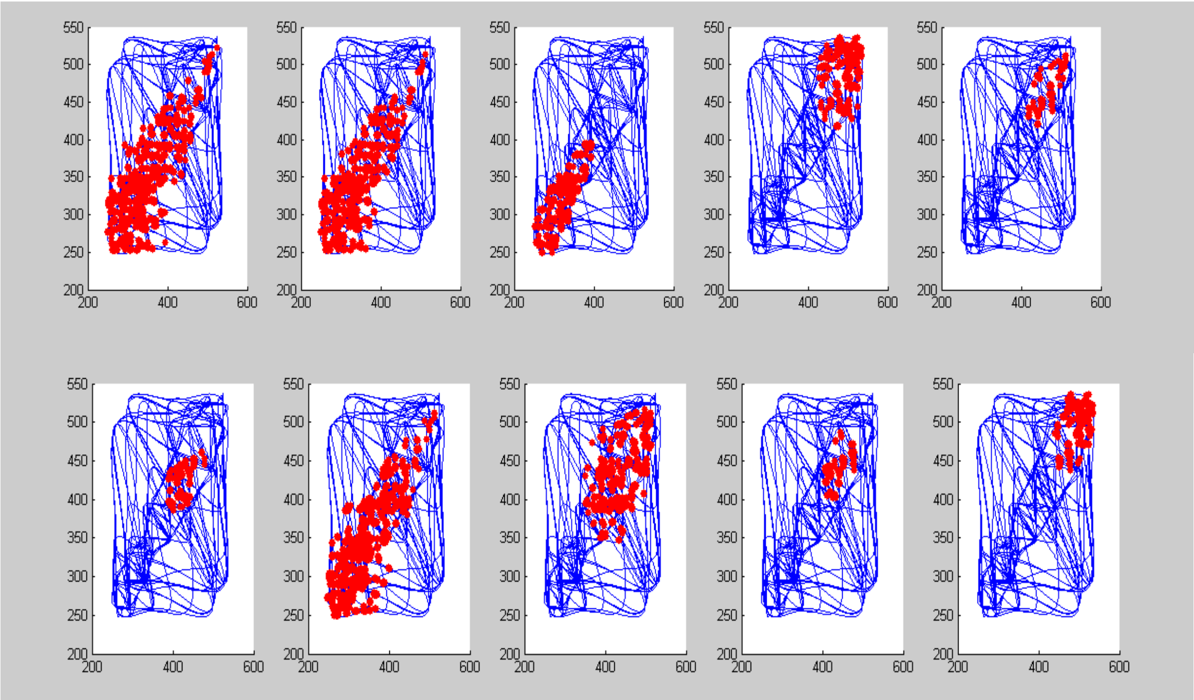

Figure 2.12

The neurons are selecting their place on the diagonal and this model gave us the place cells on the diagonal .

CONCLUSION

Our main motive when we started the project was to see the representation of temporal sequneces in the temporal lobes of brain and we actually got same results as we got for the spatial representation . Emergence of place cells , border cells and corner cells were seen . In addition to this we were also able to get jeva swarams (vadi and samvadi notes) for different ragas which were described in ancient books of India .

REFERENCES

1. O'Keefe, J. & Dostrovsky, J. The hippocampus as a spatial map. Preliminary evidence from unit activity in the freely-moving rat. *Brain research* **34**, 171-175 (1971).

2. Hafting, T., Fyhn, M., Molden, S., Moser, M.-B. & Moser, E.I. Microstructure of a spatial map in the entorhinal cortex. *Nature* **436**, 801-806 (2005).

3. Solstad, T., Boccara, C.N., Kropff, E., Moser, M.-B. & Moser, E.I. Representation of geometric borders in the entorhinal cortex. *Science* **322**, 1865-1868 (2008).

4. Taube, J.S., Muller, R.U. & Ranck, J.B. Head-direction cells recorded from the postsubiculum in freely moving rats. I. Description and quantitative analysis. *The Journal of neuroscience* **10**, 420-435 (1990).

5. Taube, J.S., Muller, R.U. & Ranck, J.B. Head-direction cells recorded from the postsubiculum in freely moving rats. II. Effects of environmental manipulations. *The Journal of neuroscience* **10**, 436-447 (1990).

6. Valerio, S. & Taube, J.S. Path integration: how the head direction signal maintains and corrects spatial orientation. *Nature neuroscience* **15**, 1445-1453 (2012).

7. Brun, V.H., *et al.* Progressive increase in grid scale from dorsal to ventral medial entorhinal cortex. *Hippocampus* **18**, 1200-1212 (2008).

8. Stensola, H., *et al.* The entorhinal grid map is discretized. *Nature* **492**, 72-78 (2012).

9. Lever, C., Burton, S., Jeewajee, A., O'Keefe, J. & Burgess, N. Boundary vector cells in the subiculum of the hippocampal formation. *The Journal of neuroscience* **29**, 9771-9777 (2009).

10. O'Keefe, J. & Recce, M.L. Phase relationship between hippocampal place units and the EEG theta rhythm. *Hippocampus* **3**, 317-330 (1993).

11. Burgess, N., Barry, C. & O'Keefe, J. An oscillatory interference model of grid cell firing. *Hippocampus* **17**, 801-812 (2007).

12. Hasselmo, M.E. Grid cell mechanisms and function: contributions of entorhinal persistent spiking and phase resetting. *Hippocampus* **18**, 1213-1229 (2008).

13. Blair, H.T., Gupta, K. & Zhang, K. Conversion of a phase-to a rate-coded position signal by a three-stage model of theta cells, grid cells, and place cells. *Hippocampus* **18**, 1239-1255 (2008).

14. Zilli, E.A. & Hasselmo, M.E. Coupled noisy spiking neurons as velocity-controlled oscillators in a model of grid cell spatial firing. *The Journal of neuroscience* **30**, 13850-13860 (2010).

15. Gaussier, P., *et al.* A model of grid cells involving extra hippocampal path integration, and the hippocampal loop. *Journal of integrative neuroscience* **6**, 447-476 (2007).

16. McNaughton, B.L., Battaglia, F.P., Jensen, O., Moser, E.I. & Moser, M.-B. Path integration and the neural basis of the'cognitive map'. *Nature Reviews Neuroscience* **7**, 663-678 (2006).

17. Fuhs, M.C. & Touretzky, D.S. A spin glass model of path integration in rat medial entorhinal cortex. *The Journal of neuroscience* **26**, 4266-4276 (2006).

18. Burak, Y. & Fiete, I.R. Accurate path integration in continuous attractor network models of grid cells. *PLoS Comput Biol* **5**, e1000291 (2009).

19. Guanella, A., Kiper, D. & Verschure, P. A model of grid cells based on a twisted torus topology. *International journal of neural systems* **17**, 231-240 (2007).

20. Turing, A.M. The chemical basis of morphogenesis. *Philosophical Transactions of the Royal Society of London B: Biological Sciences* **237**, 37-72 (1952).

21. Zhang, K. Representation of spatial orientation by the intrinsic dynamics of the head-direction cell ensemble: a theory. *The Journal of neuroscience* **16**, 2112-2126 (1996).

22. Sharp, P.E., Blair, H.T. & Cho, J. The anatomical and computational basis of the rat head-direction cell signal. *Trends in neurosciences* **24**, 289-294 (2001).

23. Redish, A.D., Elga, A.N. & Touretzky, D.S. A coupled attractor model of the rodent head direction system. *Network: Computation in Neural Systems* **7**, 671-685 (1996).

24. Knierim, W., Kudrimoti, H.S. & McNaughton, B.L. A model of the neural basis of the rat's sense of direction. *Advances in neural information processing systems* **7**, 173-180 (1995).

25.Prof Srinivas, Vignesh , Karthik A unified oscillatory network model of head direction cells, spatially periodic cells and placecells using locomotor inputs (2016)