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Hippocampus Neurons and Place Cells/Place Field Representation to Provide Path Navigation

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Abstract—**The hippocampus region may help in the design of a neuro-controller used for path navigation of a robot. The spatial representation of the hippocampus can help provide a spatial mapping of the environment. The representation used is the place cell/place field representation. Place cell represents a population of neurons and place fields provide the spatial mapping of the environment. A place cell fires if the agent is believed to be in the environment for which its respective place field is representing. The hippocampus-inspired neural network model is not only spatially motivated but is also directionally driven. This model will be fully implemented onto an FPGA device to provide autonomy.**

Index Terms—**Neural network architecture, neural network hardware**

I. Introduction

THE hippocampus is often described in term of place cells and place fields. A place cell fires in accordance to its respective place field. A place field corresponds to one section in the environment. Therefore, the arrangement of place fields can provide a complete representation of the environment to the hippocampus [1]. An animal relies on this ensemble of place cell activity to achieve self-localization. The spike frequency of a place cell encodes a specific location or the centre of a place field. Activity is recorded and identified in the hippocampus based on this spike frequency. If an agent responds significantly to a section in the environment, the place cell that corresponds to that place field shows an increase in the mean firing rate [1].

This paper describes the place cell and place field representation, and the methods involved in the design of a hippocampus-inspired neural network model, designed to provide path navigation. Section 2 describes the place cells, place fields and head direction cells. Section 3 describes the hippocampus-inspired neural network model and Section 4 indicates the learning algorithms that govern the functionality of the neural network model. Section 5 describes the success of the neural network and finally, the paper concludes with the motivation towards the full implementation of the neural network model onto a Field Programmable Gate Array (FPGA) device.

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II. Place Cells, Place Fields and Head direction cells

Place fields provide the representation of the external environment to the animal. The place cell refers to the hippocampus neurons that respond when the animal is located at the point in the environment which the place field represents. Therefore, the place cell/place field representation conveys information on both the temporal information and spatial aspects of the animal's navigation. Head direction cells provide the information with regards to the animal's head direction.

A. Temporal Information: Spiking Neurons

Temporal information about the place cell is determined by the spiking dynamics of the neurons of the place cell. The spiking dynamics of the neurons are governed by the strength of its excitation. If a neuron is excited, the spike frequency of the neuron is high. If the neuron is inhibited, there will be a decrease in spike frequency. This spiking dynamics are defined by weights of the neuron synapses. The weights in the model are updated according to the Hebbian Timing-based Learning Rule, Spike Timing Dependant Plasticity (STDP). STDP is dependent on the time of spikes between the presynaptic (sending) neurons and the postsynaptic (receiving) neuron. If the presynaptic spike precedes the postsynaptic spike within the time constant, there will be a significant increase in weight. Otherwise, the weight is depleted [2].

B. Spatial Information: Place Cells/Place Fields

Spatial information is determined by appropriately averaging or fitting the activity of an ensemble of the place cells with respect to the place field it represents [2]. The firing properties of a single-cell in the CA3-CA1 region of the biological hippocampus proper offer limited clues about the computational advantages of the hippocampus (see section III), thus, spatial representation of the CA3 and CA1 may offer some additional information to the network, for example, to augment differences between input patterns, without interference to the stored information [3].

Hippocampus place fields in rats are able to encode a region a few times the animal's size. The spatial relationship between place cells and the place fields is not preserved across different environments. One representation of place cells in one environment (its place field) can represent a completely different place field in another. Therefore, a given place cell can have many different place field representations in different environments, resulting in a dense population of highly overlapping place fields [4]. It was also pointed out in [4], that the rat's hippocampus CA3-CA1 place cells are not topologically organized. There is no relationship between the physical place field topology and the anatomical place cell arrangement. Two place cells coding for neighboring location are not necessarily adjacent anatomically.

The biological hippocampus can also develop more than one place field representation for the same environment. The remapping of the environment can take place whenever the current spatial representation of the environment becomes inconsistent with respect to the rat's perceptual context. A change can also occur without any change in the environment [4].

C. Head Direction Signaling System: Head Direction Cells

There is another representation that is used in the study of the hippocampus [1], [4], [5] and is implemented in the present hippocampus-inspired neural network. This representation is known as the head direction cell. This cell representation differs from the place cells. Rather than signaling the rat's location in space, the cell signals the animal's head direction. Each cell fires only when the animal's head faces one particular direction, regardless of the animal's behavioral state. The cell activity is also independent of the position of the animal's head relative to its body or any particular individual environmental stimulus. Each cell has its own unique preferred direction, so that each possible directional heading is represented by activity in a particular subset of head direction cells [1]. Head direction cells may also incorporate information about the current directional heading, along with movement-related information indicating changes in head direction in order to predict future directional headings.

III. Hippocampus Neural Network Model

The hippocampus neural network model is inspired by the structure of the hippocampus proper region. The model in this study includes the superficial entorhinal cortex region (layer II/III), EC_IN, the CA3 region, the CA1 region and the medial entorhinal cortex region (layer IV/V), EC_OUT. The behavioral description of neurons in each region is modeled using the Izhikevich bifurcation neuron algorithm [6], [7].

The hippocampus-inspired neural network model is arranged similarly to the arrangement identified in the rat hippocampus. The arrangement is displayed in Fig. 1 and is referred to as a neuron assembly (NA). The other significant motivation for the neural network arrangement is from the

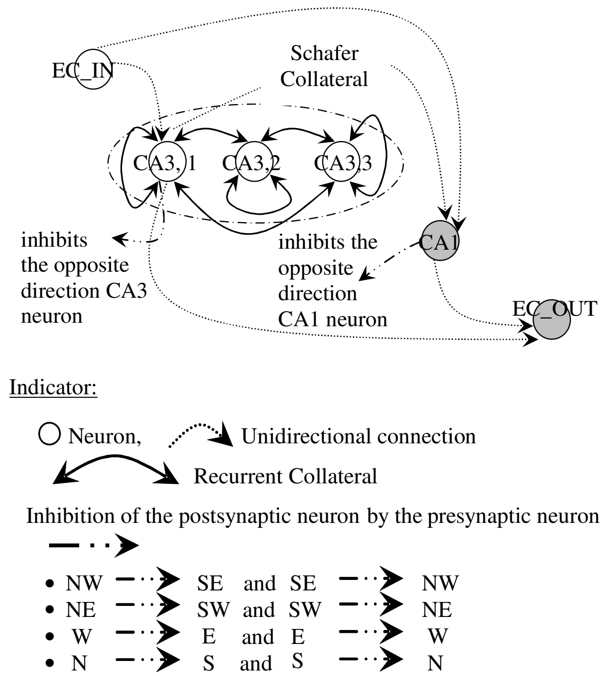

Fig. 1. Synaptic connections between the neurons in the Neuron Assembly (NA). This figure also describes how one NA connects to its opposite direction NA. Summation of the firing rate of the output neurons, CA1 and EC_OUT neuron (shaded neurons) helps indicate the next desired move (From Fig. 1 [7])

theory of the head-direction signaling system [1]. There will be 8 NAs in the neural network, where each NA represents one direction of the compass.

A. The Neural Network Model

There are two hierarchical levels in the neural network model

1) First hierarchy: Single cell firing model designed with properties similar to head direction cells. This model indicates the directional information to the neural network.

2) Second hierarchy: Place cell and place field representation. This representation is used to provide the spatial mapping to the hippocampus, a characteristic for which the hippocampus is famous for. This spatial mapping provides the location information input to the neural network.

The firing rates of the CA1 and ECOUT neurons in Fig. 1 are used to determine the preferred direction of the agent. The neurons with the maximum firing rate indicate the next preferred direction to be chosen. This is the first hierarchy of the model which uses temporal information of the neurons to indicate direction of movement.

The first hierarchal level of the model or the single-cell firing model is insufficient to provide the spatial representation that the biological hippocampus is notable for. The spiking behavior of a single neuron will not have the capability to provide any useful information to its agent, with respect to where the agent is and where it wishes to navigate to. Place cells-fields representation is added on top of the single-cell firing model to help provide this spatial representation, thus the second hierarchical level to the design. The co-relationship of place cell with respect to the neuron assembly is shown in Fig. 2. The hierarchy level of the hippocampus-inspired neural network model is depicted in Fig. 3.

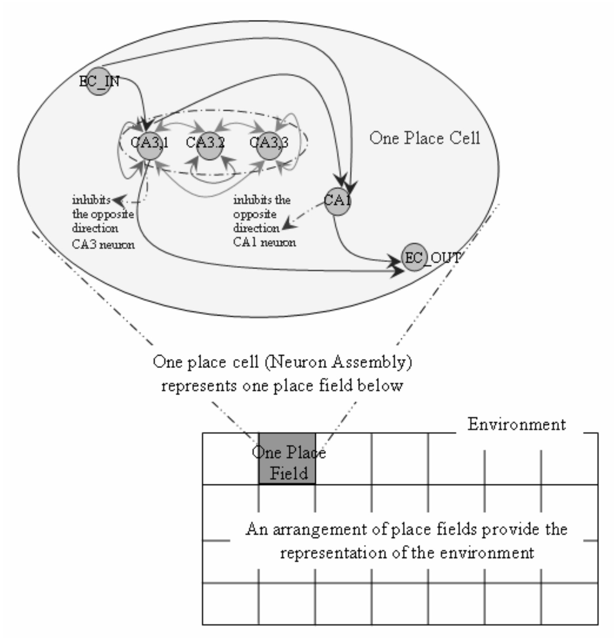

Fig. 2. Place cell and place field representation in the hippocampus-inspired neural network.

Rate based representation used in some neural network models, [1] and [2], ignores the dynamics of single neuron behavior of the hippocampus pyramidal neuron. This was incorporated in the present model so that the firing rate of a particular place field is determined from the spiking behavior of the neuron instead of its average firing rate. A novel aspect of this study is to combine temporal information with spatial information, which may provide additional information towards the functionality of the neural network and its behavior.

The arrangement of the neural network is based upon the head-direction cell representation; one NA or place cell represents a possible direction from a place field. Fig. 3 shows that when an agent is in a particular place field, indicated by (5) in Fig. 3, the first hierarchical level of the neural network or the arrangements of NAs (place cells) can help predict the next preferred direction from a particular place field. Coordinates are used to identify place fields. The next preferred direction to the neighboring place field is identified by its neighboring place cell or NA which has the maximum firing rate.

The firing rate of a place cell is the summation of rates of the spikes of the CA1 and the EC_OUT spiking neurons from the NA in the first heirarchy. The input information via excitation of the EC_IN determines which NA should be excited when there is a valid path and which will not be excited when there is not (wall). The propagation of spikes

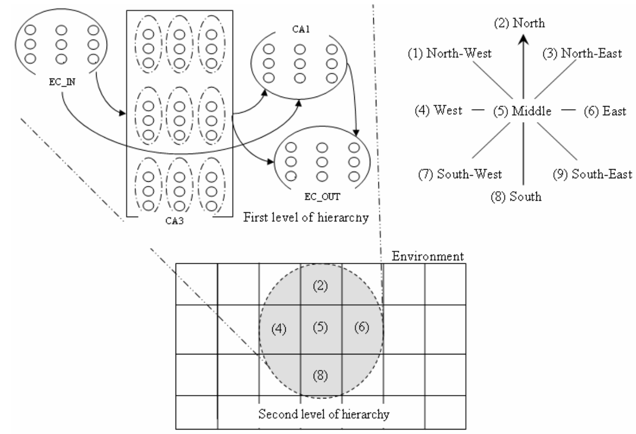

Fig. 3. The hierarchy in the hippocampus-inspired neural network model. The number (x) on each pointer indicates which direction of the compass the place cell is representing.

within the NA shows the current neuron excitability is based on its prior moves and the information provided by the input neuron, EC_IN. The firing rates of 8 NAs CA1 and EC_OUT neuron are passed to the second hierarchal level and are considered as the firing rates of the neighboring place fields.

For the hippocampus-inspired neural network model, the firing rates of a place cell associated with a place field and its neighboring place cells are stored in a memory matrix at the end of each episode. At the start of an initial path navigation simulation of an environment, the memory matrix only knows its starting location. The matrix builds up as the agent navigates within the environment. When the agent transverses the complete environment, the agent will then have a representation of the environment based on the arrangement of the place fields stored in the matrix. This representation thus provides the spatial representation to the neural network. For this neural network model, the arrangement stored in the memory matrix consists of the coordinate of the place field, the weight of the place field and its firing rate at its latest episode. Therefore, when a place field is revisited, the memory map provides the weight and the firing rate of the place field at its prior encounter in the environment.

A place cell firing rate is calculated base on the summation of firing rates of the CA1 and EC_OUT neurons and the previous firing rate of the place field for which the place cell corresponds to. This helps keep a record of the significance or the importance of the place fields in leading to a goal. If the place field is on the path that leads further from the goal, the weight of the place field is reduced. Otherwise the weight is increased. If the place field was not previously encountered, a new place field value is then stored in the memory matrix.

B. Stimulus representation

There are two stimulus representations in the biological hippocampus. They are allothetic and idiothetic representation of stimulus [1]. Allothetic representation provides the external stimulus to the neural network. Allothetic represents the environmental cue whose mutual relationships code for the current location of the animal. Idiothetic representation is assumed to be an environment-independent stimuli [1], [4].

These two stimulus representation are implemented in the hippocampus-inspired neural network model. The idiothetic representation is provided by the 8 NAs of the first hierarchy of the model. For the second hierarchy of the model, the summation of the firing rates of CA1 and EC_OUT neurons in the NA is considered to be the firing rate of a place cell. A place cell corresponds to one place field. When an agent is in an environment, past information (if available) is provided by the memory matrix which consists of the place fields that represents its environment. The memory matrix therefore provides the allothetic representation of stimulus.

IV. Learning in the Neural Network

The hippocampus-inspired neural network model provides navigation for an agent going through a maze. The learning rule that governs its behavior is described below:

A. Single Cell or the Place Cell Representation

The excitation and inhibition of all the synaptic weights between the neurons in NA is governed by the Hebbian timing based learning rule, STDP. The timing rule implemented onto the design is a modification of the STDP rule in [8]. The modification of the rule is that the weights will be updated in accordance with the covariance rule defined in [9] instead. If the two neurons have similar activity, the synapse between the neuron will be strengthened; else, the synapse will be inhibited [9]. The rule for weight update of the neural network model is dependent on the difference in the time the presynaptic spike precedes the postsynaptic spikes. If the time difference between the two spikes is small, the weight is increased (3). If the difference is large, the weight is either depleted or remains unchanged (4).

This STDP learning rule provides the temporal learning mechanism that is used to adjust the weights during one episode in the environment. This modified learning rule was implemented because it was found to implement the objective of the maze navigation successfully, without crossing over walls. The choice of path is determined entirely by the agent. The only external input stimulus provided to the neural network is via the excitation of the EC_IN neurons. Therefore, there is a possibility that the agent chooses an invalid path (wall). This modified learning rule prevents this from occurring.

The weights are adjusted according to the propagation of spikes between each region in the NA. If the propagation of spikes is consistent, the weights are consistently increased, resulting in an increase in excitation of the NA. If the propagation of spike is weak, the weights will be inhibited, reducing the excitation of the NA. The mean firing rate for each NA or place cell is calculated at the end of the episode. Weight, w of the neuron synapses (1) in the neural network is updated according to the modified STDP learning rule (3) and (4).

$$w(t+1) = w(t) + \Delta w \tag{1}$$

The difference between the pre- and postsynaptic spikes is denoted by Δt.

$$\Delta t = t_{post} - t_{pre} \tag{2}$$

If $0 \le \Delta t \le 50ms$, the synapses will be potentiated by

$$\Delta w = \frac{\exp\left(-\Delta t / \tau_{post}\right)}{t_{post} \times 10} \tag{3}$$

Otherwise, if $\Delta t > 50ms$, the synaptic is depressed by

$$\Delta w = -\frac{\exp\left(\Delta t / \tau_{dep}\right)}{t_{post} \times 10} \tag{4}$$

Time constant, τ_{post} = 200ms and τ_{dep} = 50ms.

The biological hippocampus exhibits gamma oscillations (40-100 Hz) modulated by slower theta oscillations (4-12Hz) [10]. The value of τ_{post} = 200ms was chosen because during motion, hippocampal processing is thought to operate within a sinusoidal EEG theta frequency [1]. Therefore, if two neurons spike within its theta period, (83-250ms), the weight between of the synapse will be increased. Furthermore [2] stated that, NMDA-dependent long-term potentiation, LTP in hippocampus only occurs if the presynaptic activity precedes postsynaptic activity by less than approximately 200ms. The depletion of weights will occur only if $\Delta t > 50ms$, therefore the value τ_{dep} = 50ms was chosen.

When there are increases in weights in an NA, there will be inhibition in weights of its opposite direction NA (see Fig. 1). The change of weights is defined by

$$\Delta w = -\frac{\exp\left(-\Delta t / \tau_{post}\right)}{t_{post} \times 10} \tag{5}$$

where w is the weight of the opposite direction NA.

B. Place Cell/Field Learning

For this model, the firing rate of the CA1 and EC_OUT neurons of the NA is considered to provide the current firing rate of the place cell with respect to a particular place field. To provide an updated spatial representation of the environment, the recalculation of the firing rate is as follows:

The temporal information of the NA provides short term memory, whereby the weights are adjusted with respect to its movements. The weight of the NA CA1-EC_OUT synapse will be considered in the second hierarchy level as the weight of the current place cell. This value of the weight, w_i is then compared against the previous weight value of the place field for which the current place cell represents, w_j. If there is a significant change in the weight, Δw_{ij}, a new value, w_{new} of the weight for the place cell is calculated. The weight changes according to the directional damping weight change rule (6) taken from [8].

$$\Delta w_{ij} \rightarrow (w_{ij})\Delta w_{ij}, \text{ if } \Delta w_{ij} < 0; \text{ else} \quad \Delta w_{ij} \rightarrow (1 - w_{ij})\Delta w_{ij} \tag{6}$$

where i and j in [8] is defined as post- and presynaptic neuron. For our neural network model, i represents the weight of NA CA1-EC_OUT synapse or the *current* value of the place cell. j is the weight of the place field for which the current place cell represents but the weight value is taken from the *previous* place cell (or NA) representation of this place field when the agent came across this same place field previously.

Directional damping was originally used to maintain synaptic weights within a specific range, typically [0,1]. Directional damping occurs if a weight is near a boundary, changes that push this value towards the boundary are slowed down; changes that push it away from the boundary are not [8]. Directional damping was included as it is believed to be suitable for providing spatial representation of the neural network. The new weight of a place field is calculated as such:

$$\Delta w_{ij} = w_{previous} - w_{current} \tag{7}$$

$$\Delta w_{ij} \rightarrow (w_{previous})\Delta w_{ij} \tag{8}$$

$$w_{new} \rightarrow (w_{current}) + \Delta w_{ij} \tag{9}$$

The difference in the weights, Δw_{ij} identify that there might be a change to the way the agent perceive the environment (7), for example, a path will no longer lead to the goal. The new firing rate of the place field will differ significantly from the firing rate of its place cell when a change is indicated (9). When the two weights are similar (Δw_{ij} is small), this can justify that the agent perception of its environment still has similar attributes to when the place field was previously encountered. Therefore, the new firing rate of the place field is similar to its previous value.

The new firing rate of a place field, r_i is given by the average activity of the current firing rate of the place field (*current*) and the firing rate of that same place field at its previous encounter *(previous).*

$$r_i = \frac{w_{current} r_{current} + w_{previous} r_{previous}}{w_{current} + w_{previous}} \tag{10}$$

When a new place field is found, $w_{previous}$ and $r_{previous}$ are equal to zero and current values are stored. When the new representation of the environment is complete, the weights and the firing rate of the place fields are then stored to the memory matrix.

V. Results

To test the hippocampus-inspired neural network, the neural network was used to control an agent going though a maze, Fig. 4. The agent's EC_IN neuron will activate and fire if there is a possible path for the agent. The EC_IN neuron will be quiescent if there is a wall ahead. The connectivity within the CA3-CA1 network will remind the agent of its prior moves. The reminder of the prior moves is provided by the residual activity from synaptic weight adjustments within the NA. This provides the first responses of the neural network. The place cell/place field representation of the network, from the memory matrix, will then remind the agent of the crossroads that it had previously encountered and which path on that crossroad it had chosen. With this, the agent can then make a better path decision for that position.

In one test, Fig. 4(a) when the neural network was only implemented with the first hierarchal level, the single-cell representation, the agent successfully managed to go through the maze i.e. from the start to the exit of the maze and was never stuck in a loop (the agent going through the same path again and again without trying other possible paths). Most importantly, the agent remembers to stick on a path and never try to cross over walls or the direction which are considered to be illegal. Learning in this test was believed to be successful but the efficiency of learning is poor. This is because the agent took quite a significant amount of time to complete the maze. The implementation of the second hierarchical level of design has allowed the efficiency of learning to increase. This was measured by the significant reduction of time for the agent to complete the maze, Fig 4(b)-(c).

The winning time indicates the time that the agent took to complete the maze from start (at the top left corner of the maze) to the exit (the bottom right corner of the maze). The timer function used is the Matlab® timer function. The maze function was taken from Matlab® Central File Exchange, modified so that a hippocampus-inspired neural network can be implemented to control an agent navigating its way through the maze (Fig. 4).

Grey squares in Fig. 4 show the points in the maze that an agent has previously encountered. The agent is identified as the black square. Fig. 4 (a) is simulated without the implementation of the second hierarchical level or the place cells and place field representation, and Fig. 4 (b) or test (b)

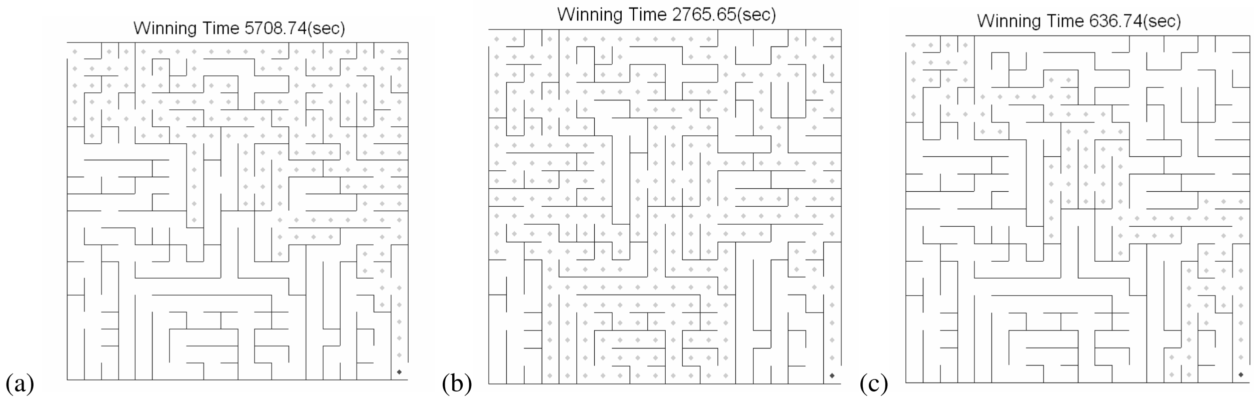

Fig. 4. How the agent (black square) navigates it way through the same 20x20 maze. In all three mazes, the agent is at the exit of the maze or the bottom right corner of the maze.

includes this level. At the start of the maze all weights of the synapses are set to 0. Fig. 4 (c) or test (c) is when the agent goes through the maze again after it completes the maze in test (b). At the start of test (c), the weight of the synapses at the end of the previous test, test (b) and the memory matrix of test (b) are retained at the start of test (c). The significant drop in the completion time of test (c) indicates that the agent has an established arrangement of place fields and is familiar with the environment. One episode (one gray square) requires 2s to simulate in Matlab®.

VI. Conclusion

This network differs significantly from the biological hippocampus network because the decision-making of the neural network is based upon the theory of head-direction cell. The hippocampus-inspired neural network is primarily directionally driven and not spatially driven like the actual hippocampus. However, addition of the spatial mapping provided by place cells/place field representation greatly improves performance.

The spatial motivation of the neural network provides a secondary stimulus to the neural network model whereby the primary output of the neural network comes from the first hierarchal level of the neural network or the NA arrangement (Fig. 1). The NA arrangement can be said to be sufficient, but the spatial representation of the neural network is added to help improve the efficiency of the neural network, as shown in the previous section.

The spatial representation of the hippocampus is described by the place cell/place field representation. Place cell represents a population of neurons in the hippocampus. Place fields are used to provide a spatial mapping in the hippocampus of the external environment. One place cell will correspond to a particular place field. A place cell fires if the agent is in the environment which the place field represents. The place cell with the maximum firing rate indicates the correct direction for the agent. The firing patterns of the place cells provide the temporal information of the neuron in the network.

The hippocampus-inspired neural network model was designed and tested on Matlab®. An ideal path navigation module is the hippocampus-inspired neural network successfully implemented to a stand alone hardware platform, or a FPGA device [7].

The success of this research project will be measured by its capability to implement a stand alone learning and memory hardware device that can independently learn its environment unsupervised. This can be achieved by a full implementation of the neural network onto an FPGA. This motivation also helps eliminate the need of an operating system used to implement the neural network functions. Such a device can provide an efficient neurocontroller module used to control the functions and the behavior of a robot.

References

[1] A. Arleo, W. and Gerstner, "Spatial cognition and neuro-mimetic navigation: a model of hippocampal place cell activity," *Biological Cybernetics,* vol. 83, pp 287-299, 2000.

[2] K. I. Blum and L. F. Abbot, "A model of spatial map formation in the hippocampus of the rat", *Neural Computation,* vol. 15, pp 85-93, 1996.

[3] S. Leutgeb, J. K. Leutgeb, A. Treves, M. Moser, and E. I. Moser, "Distinct ensemble codes in hippocampal areas CA3 and CA1," *Science, vol. 305, pp.* 1295-1298, 2004.

[4] A. Arleo, "Spatial Learning and Navigation in Neuro-Mimetic Systems: Modeling the Rat Hippocampus," P.h.D. thesis, Laboratory of Computational Neuroscience, Swiss Federal Institute of Technology of Lausanne (EPFL), Lausanne, Switzerland, 2000.

[5] P. E. Sharp, H. T. Blair, and M. Brown, "Neural Network Modeling of the Hippocampal Formation Spatial Signals and Their Possible Role in Navigation: A Modular Approach," *Hippocampus*, vol. 6, pp. 720-734, 1996.

[6] E. M. Izhikevich, "Which model to use for cortical spiking neuron?," *IEEE Trans. Neural Networks,* vol 4, pp 1063-1070, September 2004.

[7] M. Mokhtar, D.M. Halliday, A. M. Tyrell, "Autonomous Navigational Controller Inspired by the Hippocampus," in *Int. Joint Conf. on Neural Networks*, Florida, 2007.

[8] E. A. DiPaolo, "Spike-Timing Dependent Plasticity for Evolved Robots," *Adaptive Behavior*, vol. 10, no. 3-4, pp. 243-263, 2002.

[9] D. Floreano and J. Urzelai, "Evolutionary Robots with On-line Self-organization and Behavioral Fitness," *Neural Network,* vol. 13, pp 431-443, June 2000.

[10] L. Wiskott, M. J. Rosch, and G. Kempermann. (2004, December 30).. "What is the Functional Role of Adult Neurogenesis in the Hippocampus?" in *Cognitive Science EPrint Archive (CogPrints).*