Bio-inspired Robot Localization

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By

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ABSTRACT

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This report describes neuromorphic implementations of neuroscience principles and explains how a bio-inspired inertial navigation system would facilitate in robot path planning. Robot path planning has already been implemented in various ways. However, this research will describe biology inspired methods for robot path planning that imitate the processes of the inertial navigation system in the brain. The brain performs high level computing at low power. If the same processes could be replicated on electronic circuits, then these circuits could possibly perform higher level computations at low power as well.

CHAPTER ONE

Path Planning in the Brain

Neurons

In order to carry and transmit information throughout the brain, the brain depends on the spike in voltage of cells in the brain called neurons. (See Fig. 1). The three main parts of a neuron are the cell body, the dendrites, and the axon. The action potential describes a sudden change in electrical potential across the cell membrane.

Neurons transmit information by attaching to the dendrites of other neurons and inducing a current through chemical processes. This current then produces a spike in voltage within the cell nucleus. The spike in voltage allows one neuron to transmit a chemical signal to another. An action potential, or spike, describes the moving of information down an axon, away from the cell body [6]. This only occurs when the neuron achieves a threshold of -55 mV. In its resting state, the electrical potential across the membrane is about -60mV. The membrane potential can be as high as 50mV at the height of the action potential [5].

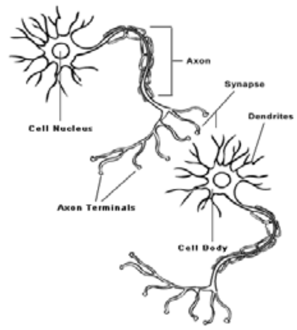

Figure 1: Neurons [12].

Grid Cells and Place Cells

In order for one to localize oneself and move in space, the brain relies on the spiking of neurons in the brain called grid cells and place cells. Place cells were first discovered in the hippocampus of the brain of rats during the 1970s. Certain place cells would fire or exhibit a spike in voltage depending on a rat's location in space. In a two-dimensional space, for example, a certain place cell would fire depending on one location and another would fire based on another location. Figure 2 shows the firing fields of place cells and grid cells as a rat traverses a two-dimensional plane. The different circles represent firing fields or the points at which the corresponding neuron will fire. The plane on the left shows the single firing field of a place cell located in the hippocampus. The right hand plane shows the firing fields of a grid cell that make up the vertices of a hexagonal grid. As a rat transverses across a path, place cells will fire depending on a particular location. Grid cells, on the other hand, will have multiple firing fields that make up a hexagonal grid; neurons will fire on the external vertices and center of its respective grid [6].

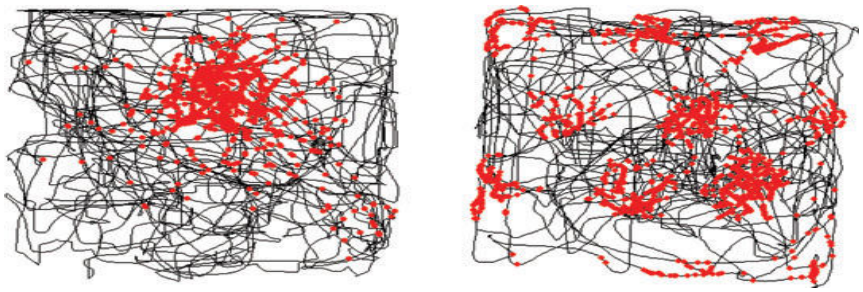

Figure 2: Place Cell and Grid Cell Firing Fields [6].

Figure 3 shows a more simplified representation of grid cells. Unlike Figure 2, this figure displays the various aspects of firing fields that differentiate grid cells. Each grid is characterized by spacing (distance between fields), orientation (tilt relative to an external reference axis), and phase (xy displacement relative to an external reference point) [6]. Neuron 1 has a spacing that is greater than that of Neuron 3, for example. However, they do share the same phase. The firing of different neurons as the rat traverses across multiple grids narrows down its location in space.

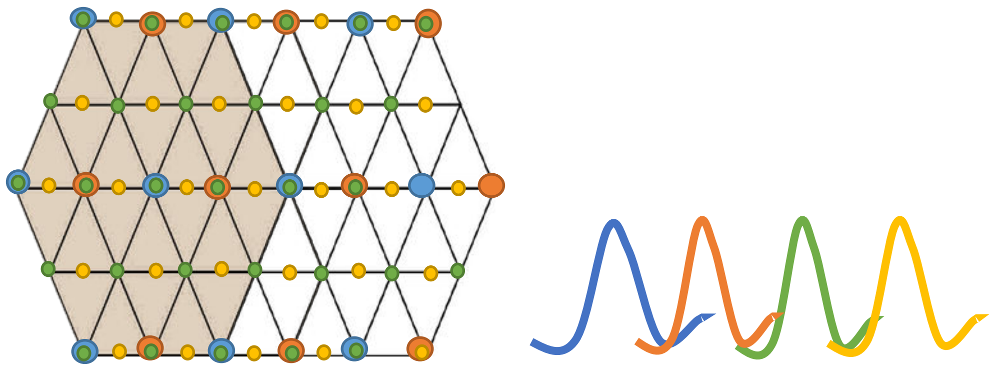

Figure 1: Grid Cell Representations.

Neuron 1
Neuron 2
Neuron 3
Neuron 4

Moser explains that distal sensory cues and geometric boundaries strongly influence the firing location of place cells. In previous experiments, rats walking in a circle caused rotation of the place fields. Furthermore, “extending the sides of a rectangular recording box stretched or split the fields in the extended direction.” While geometric boundaries primarily influence the firing fields of place cells, landmarks do influence place and grid cells to an extent. However, often times the removal of landmarks do not change firing patterns. The firing of grid cells is primarily influenced by path integration or the integration of linear and angular self-motion [6].

There are two main models that describe the firing behavior of grid cells and place cells: the attractor network and the oscillatory interference model. The attractor network describes the synaptic connection between neurons that makes up a sort of network of nodes [3]. According to Moser, an attractor describes a "stable firing state." When traversing a path, a network can store and recall several of these attractor states associated with different locations when prompted by sensory or path integration cues [6]. Phase precession takes effect in the oscillatory interference model as the oscillatory inputs induced from various firing fields superimpose. Oscillatory interference deals with the background theta rhythm in the rat brain at 4-12 Hz and the spatially specific firing of place cells and grid cells. A decrease in distance and an increase in velocity towards a certain location results in the phase of the theta cycle increasing as the rat passes through the place field [1].

CHAPTER TWO

Robot Path Planning

This research is a part of a greater goal to achieve a method for bio-inspired path planning in robotics. Implementation of neuromorphic inspired path planning has proved advantageous in robot localization in other research. In simultaneous localization and mapping (SLAM), a robot obtains a map of its environment and localizes itself within this map. With previous methods of robot path planning, there are issues with data association and perceptual ambiguity. Data association describes the comparison of two features observed at different times and whether or not they correspond to the same object. Perceptual ambiguity involves distinguishing between areas in an environment with similar visual patterns. Bio-inspired SLAM could possibly offer solutions to these predicaments. For example, presentations encoded by place cells in the rat brain integrate visual cues with kinesthetic feedback information in order to recognize places already visited thus distinguishing among perceptually similar places. Ramirez and Ridel improve the data association process by integrating kinesthetic and visual information derived from artificial landmarks. A rat inspired method for robot localization is simulated where sensory input to the model include information from affordances, motivation, kinesthesia, and landmarks. Similar to head direction cells in rats, affordances deal with the turns a rat can execute at any given time. Similar to neural processes in the rat brain, a path integration module is also simulated that takes kinesthetic inputs of magnitude and direction to update the position of the rat's point of departure. Neurons in the place cell module behave much like those in the hippocampus of the rat and activate dependent on kinesthetic and landmark information [8].

Our research also proposes a method for achieving bio-inspired localization in an IRobot (Fig. 4). While currently most of the controller and math model is simulated in Matlab, the goal is to have this control model implemented in hardware. Figure 6 details a robot localization system that imitates the navigation process of the brain. Multiple neuron circuits like the one in Figure 5 are connected on a printed circuit board in Figure 4. The motion sensors will estimate where the robot is located in space. Signals from the sensors will induce firing patterns in each of the four neuron circuits like the firing patterns presented in Figure 3. These firing signals will then enter the Analog to Digital Converter (ADC) of a microprocessor. A Matlab simulation will then combine the firing signals and decode the robot's location to a unique place.

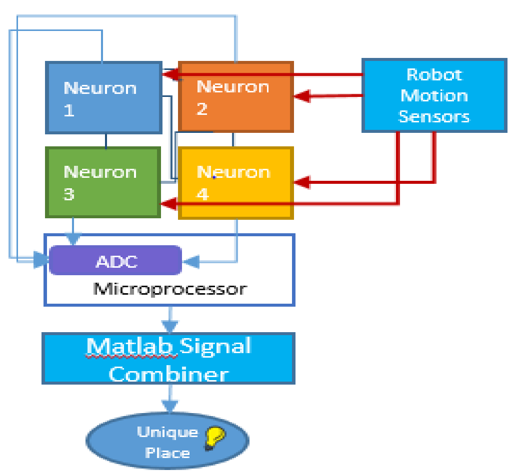

Figure 4: Generic Reconfigurable Neuron Board.

CHAPTER THREE

Neuron Circuit

Neural systems have been proposed for use in robot path planning. Murray and Corso propose a method for very large scale integrated (VLSI) neural networks using pulse encoding. This method produces advantages as parallel analogue computation allows for improvements in speed and efficiency.

Wijekoon and Dudek propose a silicon neuron circuit that imitates the firing behavior of a biological neuron (See Fig. 5). Neural firing behavior can be represented by slow fast dynamical system of equations. The firing behavior of the neuron circuit is modeled by a dynamical system of equations similar to that for biological neurons. The two state variables correspond to the voltages across two capacitors that serve as the “membrane potential” (U) and the “slow variable” (V).

$$\dot{V} = \begin{cases} l_1 V^2 - l_2 V - l_3 U^2 + l_4 U + l_5 & \text{when } V \geq U - V_T; \\ m_1 V^2 - m_2 V - m_3 UV + m_4 & \text{otherwise} \end{cases}$$
$$\dot{U} = k_1 V^2 - k_2 V - k_3 U^2 + k_4 U + k_5$$

Equation 1. System of equations for firing behavior of neuron circuit [11]

$$v' = 0.04v^2 + 5v + 140 - u + I$$
$$u' = a(bv - u)$$

Equation 2. System of equations for firing behavior of biological neurons [4]

Like an actual neuron, a spike is induced by a current input. The circuit also takes on various input voltages that can be changed in order to alter the firing to certain bursting and chattering patterns found in the brain [10, 11]. The neuron circuit was simulated in Pspice. Changing voltage parameters can alter the nature of the spike. In our case, we would like to alter the spike to imitate the increasing and decreasing firing behavior of a neuron as a rat approaches and leaves a firing field.

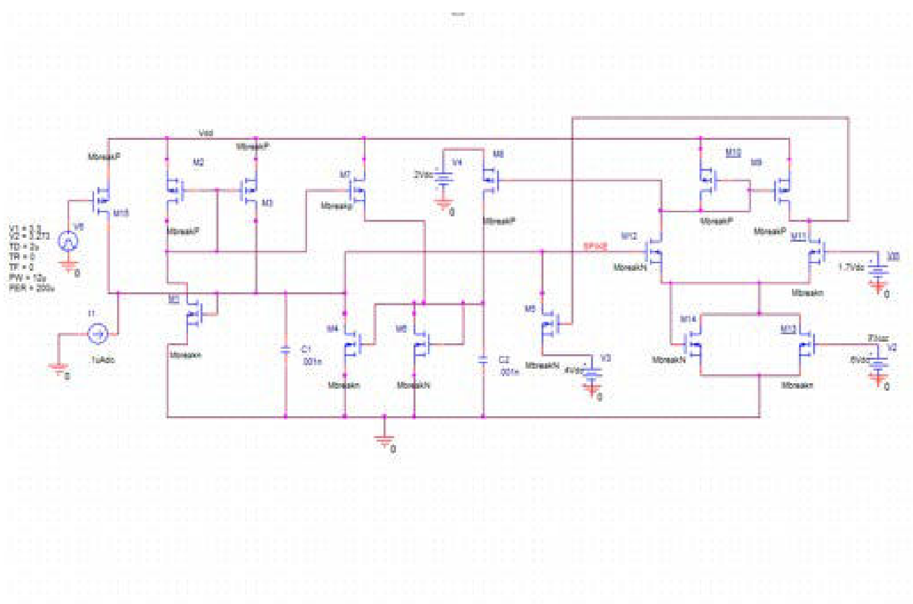

Figure 2: Neuron Circuit.

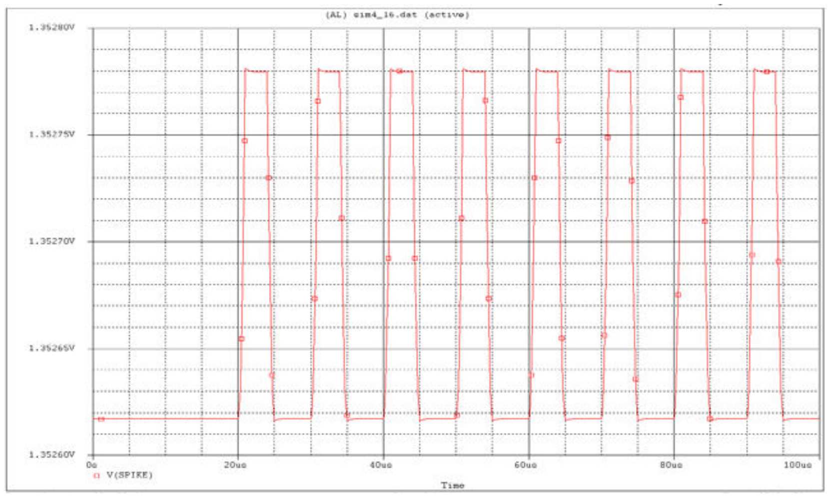

Figure 6. Simulation of Neuron Circuit.

CHAPTER FOUR

Discussion and Conclusions

Fiete presents a 1-D math model that describes neuron firing behavior in the rat brain (Fiete et al., 2005) and is detailed in Figure 7 below. The modulo operation evaluates the remainder after division of x by λ_α. The lattice period λ_α describes the spatial period specific to each neuron while x is an internal estimate of what the rat's position is. If there are sensory cues, x is a pretty good estimate of the rat's location, but in a landmark free environment, x may be a poor estimate. A collection of phases χ_α will specify a location x in space [12]. The model below presents the firing behavior of two neurons below. With a greater value of λ_α, the red neuron produces a larger spacing than the blue neuron.

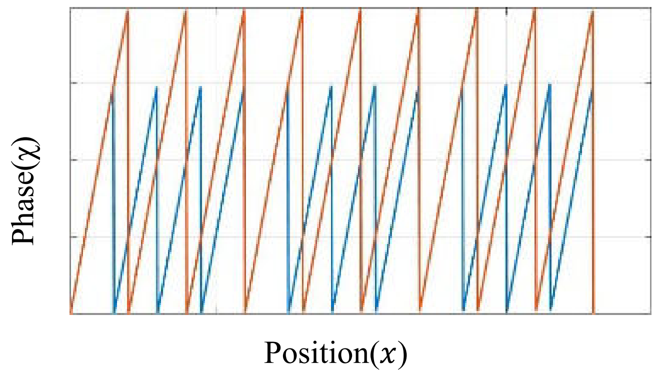

Figure 7: Modulo Firing Behavior

$$\chi_\alpha = x \bmod \lambda_\alpha$$

Equation 3: Modulo Operation

Another model that we have proposed, that might better represent firing behavior, uses a Gaussian distribution and is presented below. The Gaussian distribution models the firing behavior of a rat as it crosses through a certain firing field. As a rat approaches a firing field, the spiking of a neuron will fire with increasing frequency. As it passes a firing field, the neuron's frequency of firing will subside. The smaller spikes represent the firing of a single neuron at different points in space; their spacing is differentiated by different values of μ. The large spike represents the firing of a different neuron. Its spikes will be differentiated from that of other neurons by different values of σ. Note that the larger neuron fires at a greater frequency for a longer time, indicating the firing behavior of a neuron with a coarser grid resolution.

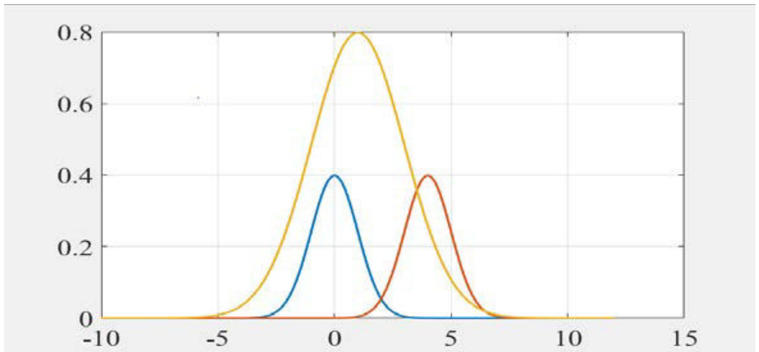

Figure 8: Gaussian Distribution

$$y = f(x|\mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

Equation 4: Probability Density Function

If we can somehow find the inverses of the models, than we can locate a position based on a set of firing frequencies. Another goal is to get the neuron circuit simulation in Fig. 6 to produce the same increasing and decreasing firing behavior presented in the Gaussian distribution model. In Fig.6, the circuit produces a rise in voltage. By changing input voltage parameters, the firing behavior could be altered to produce the same increasing and decreasing firing behavior.

Bio-inspired path planning with neuromorphic implementations offer a number of advantages to traditional path planning. Not only does it attempt to address the issues of data association and perceptual ambiguity with the bio-inspired methods, it also addresses the issue of high computation as the use of transistors on analog circuits lead to greater power efficiency. Through neuromorphic research, we expand our knowledge and understanding of the brain's ability to compute, which might, in turn, aid us in future tasks [9].

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