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Grid Neuron Model for Spatial Navigation

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Abstract: Cognitive robots are required to work in dangerous areas since humans are unable to due to health-related restrictions. Robot interaction with the working environment is hampered by the fact that a robot cannot learn the spatial semantics of the environment or an object. In this work, a computational agent is created to address this issue. This agent learns cognitive maps from input spatial data of an environment or an item by simulating the behaviour of place neurons and grids. It is suggested that a novel quadrant-based modelling strategy be used to simulate the behaviour of the grid neuron, which, like the real grid neuron, can produce periodic hexagonal grid-like output patterns from the input body movement.

1. INTRODUCTION

Modern society is faced with a number of new difficult jobs that are difficult for humans to handle. Some of these include constant surveillance, investigation of far-off planets, satellite repair, caring for elderly family members at home, serving in the military at risky locations, carrying out challenging rescue operations involving deft decision-making and complex manoeuvres, etc. Some of the duties stated are stressful and time-consuming, some are dangerous to one's health, and some are impossible to complete due to a lack of time. Robotic machines are considerably faster and more powerful than people, yet they lack the intelligence to take their place. Since the human memory process produces intelligent human behaviour, the memory process must be computationally imitated in order for robotic machines to take the place of humans in the aforementioned jobs. Humans makes use of grid neuron for spatial learning. A grid neuron divides an environment into a hexagonal grid pattern. A grid neuron possess several grid neurons where each is having own orientation and spacing in firing locations. When we overlap the hexagonal grids of several different grid neurons then we get unique pattern for each location, the overlapping pattern is like a grid code of the agent to memorize the spatial location. To provide the spatial learning in AI agent, in this article a quadrants-based method is proposed that may generate a periodic hexagonal-shaped grid pattern can imitate the functionality of grid neurons. The model takes the motor input and generates the hexagonal pattern.

2. LITERATURE SURVEY

If we talk about physical tasks in robots, the robust localisation on an object is particularly dramatic. In particular, the localization and path merging in navigation is a highly contentious issue for which several efforts have been made for more than 20 years [1,2,3]. The extended kalman filter (EKF) was the first method proposed for the localisation of an agent [4]. Since the complexity of EKF is quadratic in relation to the number of landmarks, it cannot be used effectively in a big environment [5]. The localization is also crucial for tasks involving object manipulation, because body movement must be coordinated with a mental image of the object. Other cognitive tasks, such as taking in an object, physically or physically recognising an object, can be completed using bodily movement together. The job is undoubtedly inappropriate if we're speaking about object-handling operations. It is well known from examinations of human brain that the collaborative network of place cell neurons and grid is in charge of comprehending the spatial semantics of a location or object. Additionally, the network combines body movement with the observed semantics to aid in localization of a human within a place or item. A human performs numerous bodily tasks with such localization. The general concept of a grid cell neuron has been employed in quite a few published bio-inspired modelling studies on localization. The least experienced of all is RatSLAM (Simultaneous Localization and Mapping) [17]. Through the use of a 3D continuous attractor network of pose cells, the model has demonstrated localization. Since the model's network size depends on the size of the environment, it is essentially unusable for large localities.

Since 2005, many computer models of grid neurons, including the continuous attractor [18], oscillatory intercession model [18], and hybrid oscillatory attractor network [19, 20], have been developed. These models all contribute to the hexagonal grid patterns. The models did not, however, address the problem of ambivalence in the intercession of various grid layouts. An agent may localise in the incorrect location or direction as a result of ambivalence. A new robotic architecture has merged the visual place cell with the grid cell to cap the angular drift of the route integration in the direction of modelling a place neuron. Despite the existence of numerous theoretical models, none of them have implemented the object-handling functions of the grid neuron and place cell. Additionally, the grid and place cell neurons are essential for episodic memory. A place cell neuron is used by episodic memory to understand the

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mechanisms for producing and recalling, predicting the future, and planning. Even while the robots of today use sophisticated sensors and cutting-edge visual systems to carry out their tasks, their methods are still quite flawed. We require body object integration somewhere, combined with sophisticated vision and sensors, for smooth operation. This technology may have various uses in machine learning, smart grids, and the energy industry.

3. COMPUTATIONAL SPATIAL MEMORY ARCHITECTURE

Tasks that call for combining physical movements with a mental map of an object. Other cognitive tasks, such as picking up or holding an object, recognising an object by touch or by holding it, etc., can be performed via body motion amalgamation. When it comes to activities involving object manipulation, the work is unquestionably improper. In real life, a human performs a variety of tasks that call for comprehension of a cognitive map of an object's and working environment. The combination of body part movement with the recognised cognitive map of an object is necessary to execute localization, planning, and predictions when performing tasks like cleaning with an object, maintaining a machine on a space mission, or navigating in the dark, among others. Numerous efforts have been made in the areas of localization and path intercession for more than twenty years. The earliest or initial mechanism suggested for the localisation of agents is the Kalman filter. Since the complexity of EKF is quadratic in relation to the number of landmarks, it behaves incorrectly or improperly in a large environment. The object handling also depends on the localization.

It is well known from researches on human brain that the cooperative network cell of place and grid neurons is what combines bodily movements with learnt semantics to aid with localization within an environment or item. The generic logic of grid cell neurons has been employed in several published bio-inspired modelling projects on localization. Of all of them, RatSLAM [121] is the most well-liked. The model uses a 3D continuous attractor network of posture cells to describe localisation. As the model's network size depends on the size of the environment, large environments make the concept utterly unworkable. Since 2005, a large number of computer models of grid neurons have been published. These models include continuous attractor, oscillatory interference model, and hybrid oscillatory attractor network, which have produced hexagonal form grid patterns. Despite this, the models have not been able to resolve the ambivalence in many grid patterns' intercession. An agent may mistakenly identify with the wrong location and direction as a result of ambivalence. In order to minimise the angular drift of the path amalgamation, a novel robotic design has integrated the visual place cell with the grid cell in the direction of modelling a place neuron. Despite the fact that there are a tonne of theoretical models, none of them have utilised the grid neuron and place cell actions to carry out object handling duties. The grid and place cell neurons also play a significant role in episodic memory. In order to comprehend the mechanism for remembering, generating predictions, and planning, episodic memory makes use of place cell neurons. Although the robots in the current situations use sophisticated sensors and sophisticated visualisation processes to perform actions, the methodologies are still very flawed. We require bodily object amalgamation somewhere, coupled with cutting-edge eyesight and sensors, for simple working. In this chapter, a computational grid place neuron model is introduced to address the previously described difficulties of earlier tasks.

3.1 Preliminaries of Grid and the Place Neuron

Understanding the suggested computational work on the grid and the place neuron requires knowledge of some hypotheses, findings from scientific study, and architectural specifics pertaining to both the grid and the place neuron. John O'Keefe et al discovered the place cell in the CA3 region of the hippocampus in 1971 while conducting experiments on the rat brain. He discovered that the neuron only gives a spike when the rat enters a specific area of the environment, which is why the neuron a name was given "Place Neurons" [89]. Any Place neuron that is activated indicates that a person is in a specific location in the environment. The place field [40] (see Figure3) is the size and shape of the field in which a place neuron can become activated, and that place field may be influenced by the environment's dimensions and shape.

The scientific world was unsure how a neuron acquired information about a position in the environment prior to the discovery of grid neurons. This conundrum was made worse when it was discovered that the place neuron activates earlier in the theta rhythm during traversal toward the site where it is located [90], demonstrating that the place neuron can anticipate their future positions. Since the place neuron produced the same behaviour even in complete darkness (without any visual input), having been hypothesised that the place neuron learns the cognitive map of an environments, or internal environmental representation. However, with the discovery of grid neurons in rodents' entorhinal cortex [90] and humans [91], the picture becomes clearer to the researchers because they have discovered a neuron that is among the major sources of contribution to place neurons [65] that can generate the periodic activation pattern that resembles a hexagonal grid while navigating in an environment (i.e. activation derives from the self-motion) as reported in. The grid neuron functions like a light bulb that only illuminates when an agent enters the firing range of any grid point on the hexagonal grid; depending on the bulb's speed on how far away It is the agent from the nearby grid point. The grid point is the centre of a circular shooting range that surrounds each grid point and that we have dubbed the ring of grid in our

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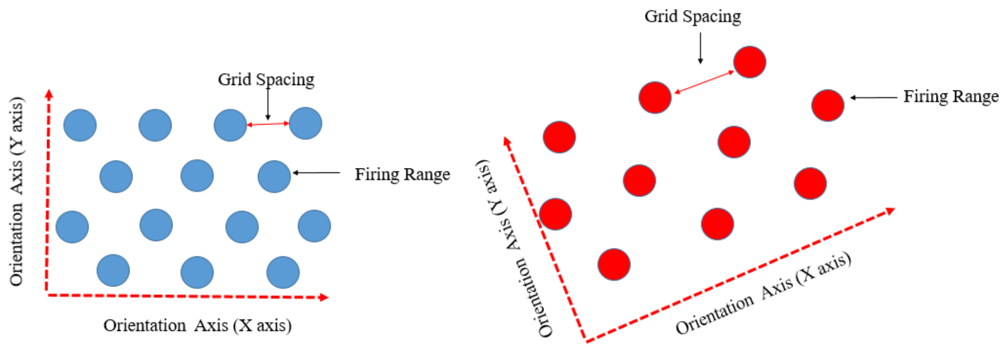
essay. Additionally, the brightness of the bulb, or the grid neuron, will be high when the distance between the agent and the centre is less or vice versa. The grid or bulb becomes active if the agent enters the ring of grid of a grid point; otherwise, it will remain lightened down or inactive. Figure 4.1(a) shows how the location of an agent affects the activation of a grid neuron. At time t = 2, the grid neuron in red represents that is the agent at any grid point of the hexagonal-shaped grid, and at time t = 0, the grid neurons is represented by the colour blue, which indicates that is the agent not in range firing of any grid point, and the grid neuron is inactive.

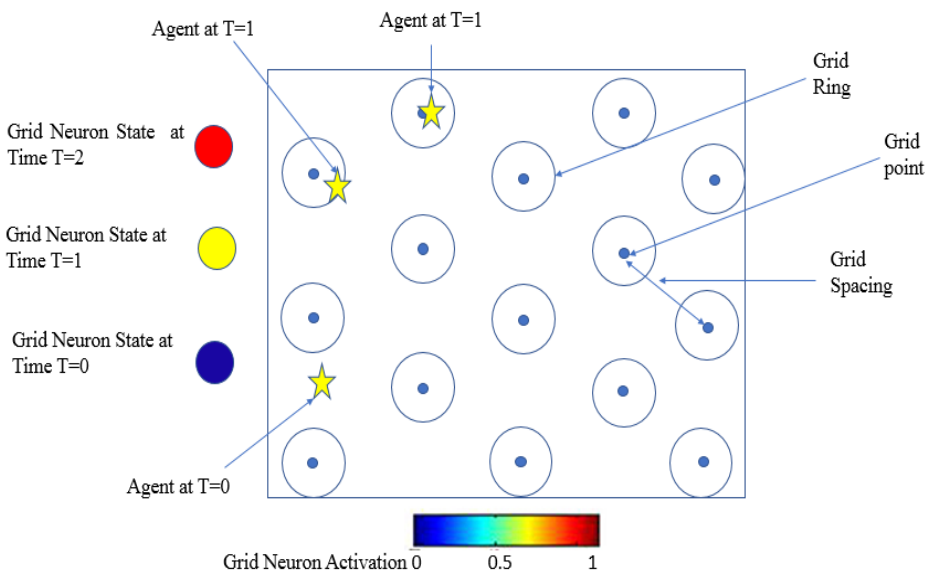
A grid neuron's grid pattern could differ from that of the other grid neurons in terms of spacing and orientation. Figure 1(b) depicts three distinct grid neurons with various spacing and orientation. These patterns are stacked to form a singular compact code known as the grid code (grid neuron activation), which corresponds to the current sensory input [93] or the agent location (as shown in Figure 2). The code can be associated with the current sensory input, such as the visual input of place considering an environment, and creates a cognitive an environment map. Since grid activation is a periodic pattern, each grid neuron's activation is predicable based on the integration of a person's movement (their own motion) and the grid's present state of activation. Rodents and humans may navigate to their objective position in the dark (when visual inputs absent) [94] thanks to the prediction of grid code, which entails the prediction of associated information's the self-motion input that helps to locate itself in the working environment [39].

3.1.1 Grid Code

The grid pattern of each grid neuron changes in spacing or orientation, which has already been proven through research on grid neurons [94, 95, 96], as seen in Figure 1(b). since a grid neuron can fire at various places throughout its environment, the activation of a single grid neuron cannot be used to determine where an agent is firing. Each site will produce a different interference pattern from several grid activations if we take the grid activation pattern of many grid neurons into consideration (shown in Figure 2).



(a)



(b)

Figure 1: Grid neuron: (a) Various spacings and orientations of grid patterns, (b) Activation of grid neurons

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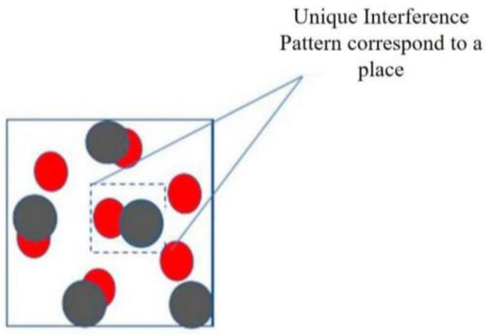

Figure 2: Using grid patterns that overlap to produce localization

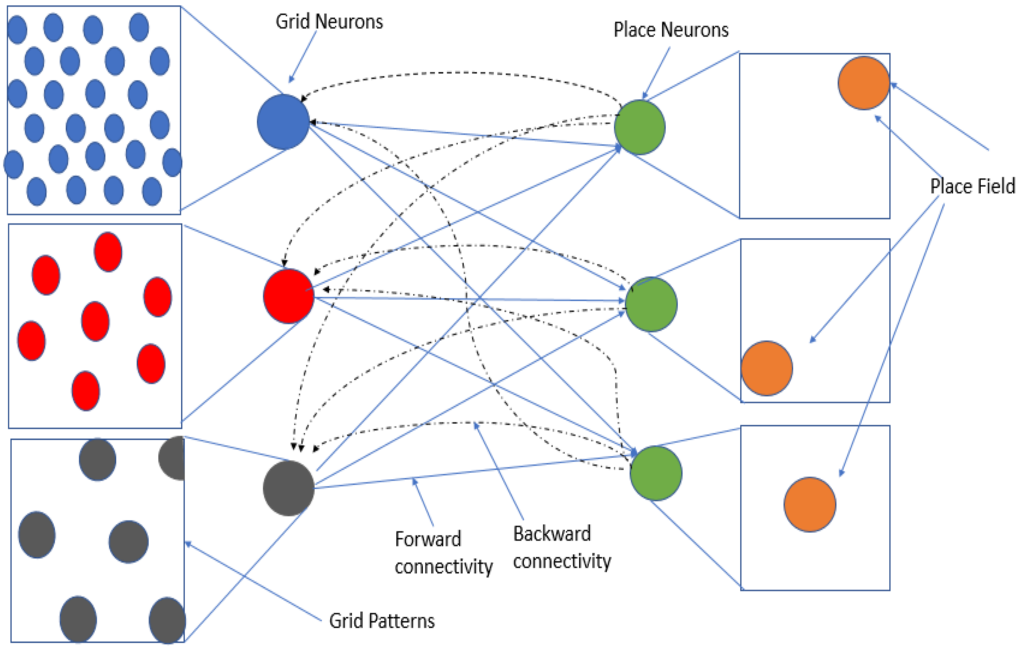

Figure 3: Grid and place neurons are biologically interconnected.

3.2 Agent's Movement Representation

The entire body of the agent has been treated as a single entity for the purposes of navigation in an environment; other cases are defined in the experimental section. According to Figure 4, the agent movement is represented by the angle of turning and the displacement, where the angle of turning is the angle between the previous movement's direction and the current movement's direction, and the displacement is the distance between the current position and the previous position.

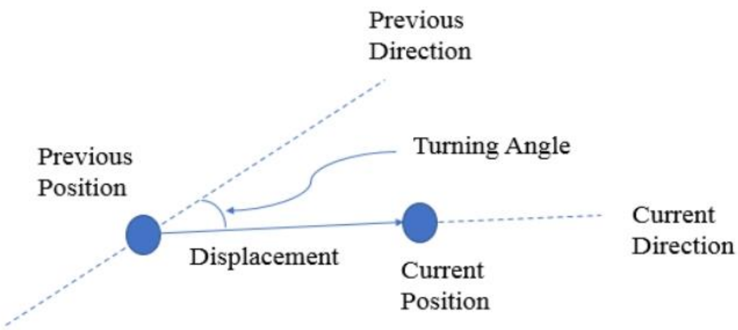

Figure 4: Movement of the agent

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3.2.1 Quadrant Model for Grid Pattern Creation using Amalgamation of Body Movement

We employed a grid point instance that continuously traced the agent coordinate in the x and y axes as well order to trace the agent for firing a grid neuron. The instance points of all grid neurons will be in their initial positions when we start to comprehend the surroundings. The grid point instance lacks any actual coordinates; all it has is a logical concept that continuously tracks the agent's location and motion until the grid neuron fires. Only when the agent enters the vicinity of another grid point or a grid neuron's ring of grids will the grid neuron fire. The reference grid is reset to the new the values of agent tracing parameters when the grid neuron fires, and the new value is calculated in relation to grid point whose grid ring the agent's entering.

The centre of grid ring, or the grid point, has a clear relationship with its nearby grid points because of the periodicity when firing pattern. Based on an association between the measured distances along both dimensions (i.e., the x and the y-axis) from the instance of grid point, any reference grid point can use this association to determine whether an agent has been entered into the locality of any of its surrounding grid points or grid rings or not. When an agent's location in reference to the instance point begins to resemble any of the nearby grid points, the grid neuron fires. The grid-point having an equivalent association to the agent will be considered a new instance point. Since the recently updated instance point, the principles of the tracing parameters (parameters like the agent's distance from the instance point) will be updated. The same action will be carried out repeatedly until the agent stops.

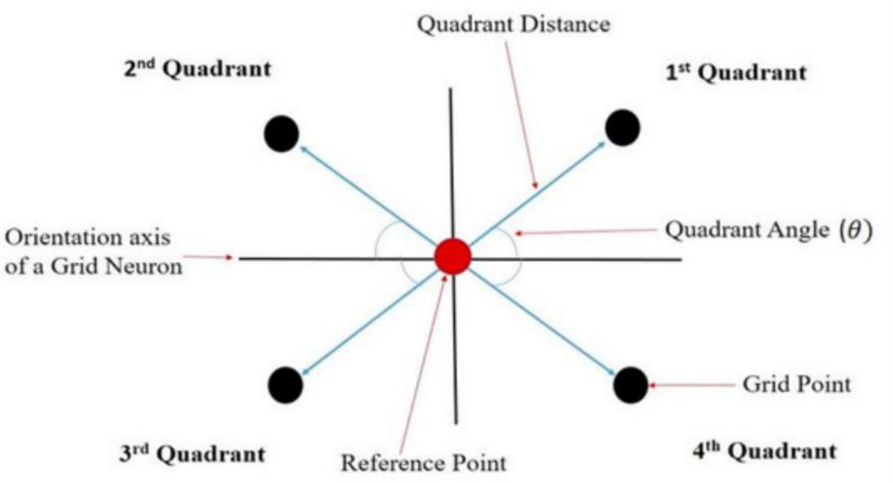

Figure 5: A grid point's quadrants with respect to it

The agent can travel across any of the instance ring's four quadrants because the instance ring is not always the origin. As illustrated in Figure 5, each grid ring has a corresponding grid ring in each of the other quadrants that is separated by the same distances along both dimensions. This uniformity causes the association of the instance ring with the nearby grid rings being the same in all four quadrants. The signs of the agent's location will indicate the current quadrant number, but even though they are equivalent to the nearby grid rings, the signs won't be taken into consideration because the associations are the same in all quadrants.

3.2.2 Agent's Coordinate Calculation

$$\theta 1 = \begin{cases} \theta 1 + \theta 3 \; if \; (Direction == LEFT) \\ \theta 1 - \theta 3 else \end{cases} \quad (1)$$

$$X\_cordinate = X\_cordinate + (magnitude * cos(\theta 1)) \quad (2)$$

$$Y\_cordinate = Y\_cordinate + (magnitude * sin(\theta 1)) \quad (3)$$

The aforementioned equations determine the new the coordinates of agent w.r.t the reference grid point based on the angle of movement (measured in degrees), the direction of movement, which can be either left or right, the magnitude of the movement, and the agent's previous coordinates. Figure 4.7 depicts all of the equations' used parameters (Eqs. 4.1, 4.2, and 4.3).

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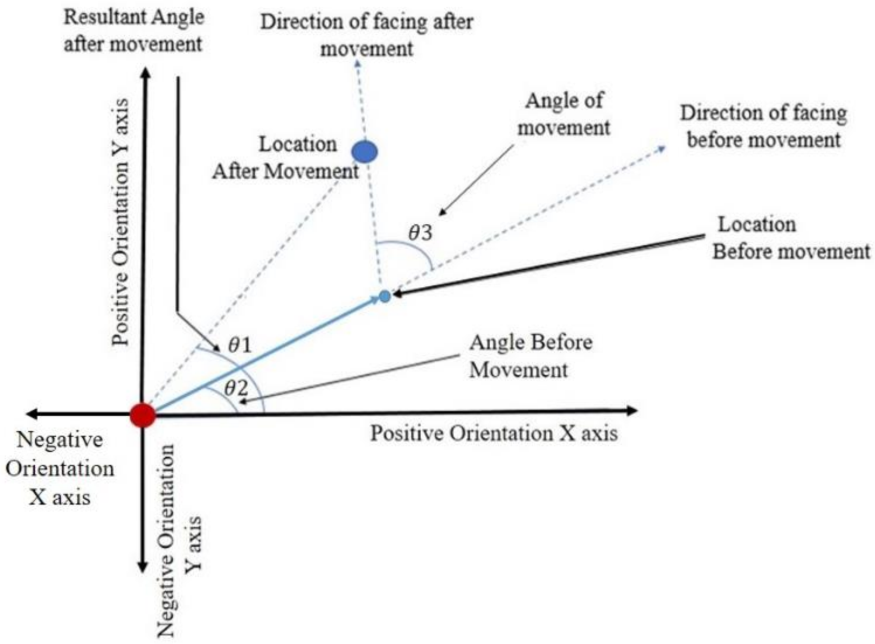

Figure 6: Coordinates for the agent w.r.t a reference grid point are calculated

The hexagon shape's geometry, as displayed below in Figure 4.8, must be understood to establish an activation pattern that resembles a hexagonal shape grid. Any two grid points in the diagram that divide the same edge are separated by a similar length of space, or the hexagon's grid spacing. The height and breadth, which are determined by figure. 6 and figure 7, are two or more additional parameters that trace the hexagonal shape.

3.2.3 Involvement of the grid neuron

Each grid point has a specific relationship to each of the different grid values in the grid pattern. If we take one of the grid points as an example point and calculate how far the other grid points are apart from it along the x and y axes, we can divide them into two groups. The first group includes grid points whose separation along the X axis is an integer multiple of the hexagon's width and whose separation along the Y axis is zero. The second category consists of those whose separation along the X-axis is the (odd number/2) multiple of breadth and separation along the Y-axis is the (odd number/4) multiple of height. The grid neuron will fire or be activated with a value of activation of 1 if the computed separation of the agent from the instance point falls into any of the aforementioned grid point categories. The agent is at one of the grid locations, as indicated by this. However, the value of activation will be less than one and inversely proportional to the separation from the centre of the grid ring, which is equivalent to the (1-s/r), where s is the distance from the grid point under whose range of firing the agent is present and the firing range's radius is r. The grid neuron will still fire even if the agent’s is present at some distance from grid point within the grid point's firing distance. There won't be any activation if the distance d is greater than the radius r.

Height of a hexagon:

$$H = 2*s \tag{4.4}$$

Breadth of a Hexagon:

$$B = \text{Sqrt}(3) * s \tag{4.5}$$

Where H is the height, B is the breadth and s is the grid spacing of a hexagon.

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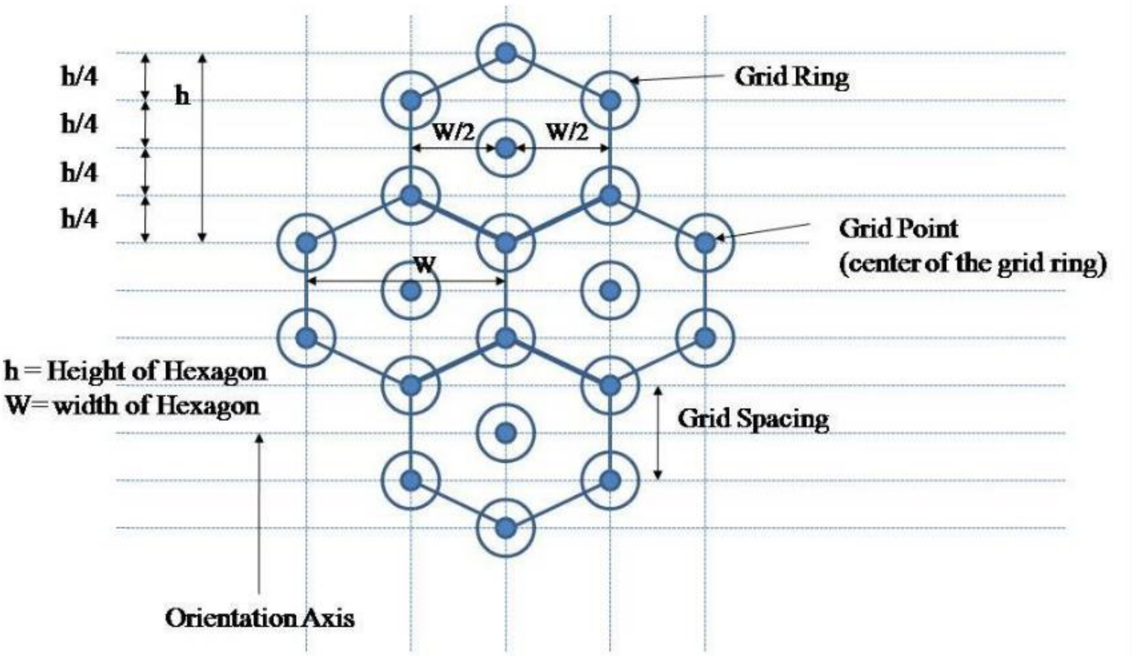

Figure 7: Grid point relationships

Since there are an infinite number of grid points, a method is required to select only those grid points that are close to the agent's location. This allows the Euclidean distance to be calculated to determine if the agent is near the chosen grid point's firing field or not. The association of the grid points has been covered before, therefore choosing the grid points is rather simple.

Here, we can choose from two sets of grid points: the first is made up of grid points with X coordinates equal to (breadth * round(Bx/breadth)) and Y coordinates falling between (height*(ceil(By/height)-1)) and (height*(ceil*(By/height)), where Bx and By are the coordinates of the agent along the X and Y axes, respectively, and ceil is the ceiling function.

The second category includes those contains the grid point coordinates for X and Y are respectively in the ranges of (floor (By/height) + 0.25 and (floor (By/height) + 0.75 and round (Bx/breadth)-0.5 and round (Bx /breadth)+0.5. The following procedure contains the entire pseudocode to measure the onset or activation of a grid neuron.

3.3 Pseudocode to Calculate the Activation of a Grid Neuron

Algorithm 4.1: Calculation for the Grid Neuron activation

```
I □ round (X coordinate /width)      // round is the round off function
J □ ceil (Y coordinate/ Height) -1   // ceil is ceiling function
while  J< ceil (Y coordinate/ Height) do
        J □J +0.5;
        Gx□ I * width// Gx is the x coordinate of the chosen grid point;
        Gy□J * Height// Gy is the y coosrdinate of the chosen grid point;
        D □Euclidean ((X,Y), (Gx, Gy));
        // Euclidean to find the gap between agent and the chosen grid point
        if D < Radius then
            Activation □ 1- (D/ Radius);
        else
            Activation □0;
        end
        if Y is the 0.5 multiple of the height (h) then
            Activation □1;
        else if X is the 0.5 multiple of the W (width) then
                If Y is the 0.25 multiple of the height (h) then
                    Activation □1;
                else
                    Activation □0;
```

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```
            end
        end
end
```

4. EXPERIMENTAL TASK OF QUADRANT MODEL

The example is implemented in two distinct applications, the experimental details of which are provided in the following sub partitions, to assess the effectiveness of the suggested procedure.

4.1 Object Identification using Quadrant Model

In the experimental task of object recognition, one hundred different 2D objects have been chosen, each of which has a unique spatial allocation of sensations, making each object a permutation and combination of sensations. The object is depicted in Figure 8, where each sensation is represented by a special colour that is shared by many objects but assigned to each object at a different position.

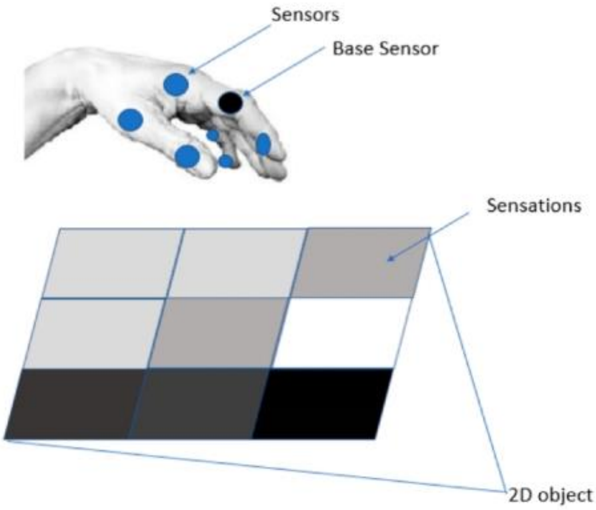

Figure 8: 2D representation of objects

By moving your fingertips over an object whose effects are displayed in the consequence area, you can complete object recognition. Three sensors are placed on each of the five fingers, while one sensor serves as the base sensor for all five fingers. Each sensor linearly generates a grid code with each movement. The base sensor's current grid code and its relative position are used by all other sensors, excluding the base sensor, to produce their grid codes. This simultaneous exploration of any environment reduces the amount of palm movements required for comprehension and recognition. If a 2D object's individual sub-regions are larger in size, multiple grid codes may be assigned to the same sensation at the time of understanding. As a result, when the sub-region is recognised by hold or touch, the measured sensation from the sub-region may recall multiple grid codes. This can create ambivalence difficulties when deciding which grid code to use for differentiation. Despite given that the following steps can be used to solve the ambivalence difficulty:

Determine the base sensor's sensation, then call back the grid code that compares to the determined sensation.

Other sensors take note of their experiences and transmit what are known as felt grid codes, which correlate to those grid codes.

As a final step, every sensor merges its relative location to the base sensor with the base sensors' grid codes to create a new grid code known as a path merged grid code.

The following comparison will be made between the detected grid codes and the path merged grid codes. To begin their placed place neurons, those felt grid codes that are similar will be chosen.

The list of active objects will only include the items that have been combined with the starting neurons; the remaining objects will be held back for activation in the future.

A similarity method will be used repeatedly until there is just one object left on the activation list.

4.2 Consequences And Discussion

Investigation tests using the artificial agent in a location of size 100 * 100 cm2 have been carried out in order, to support the quadrant model for the periodic the hexagonal design of the artificial grid neuron that has been put forth.

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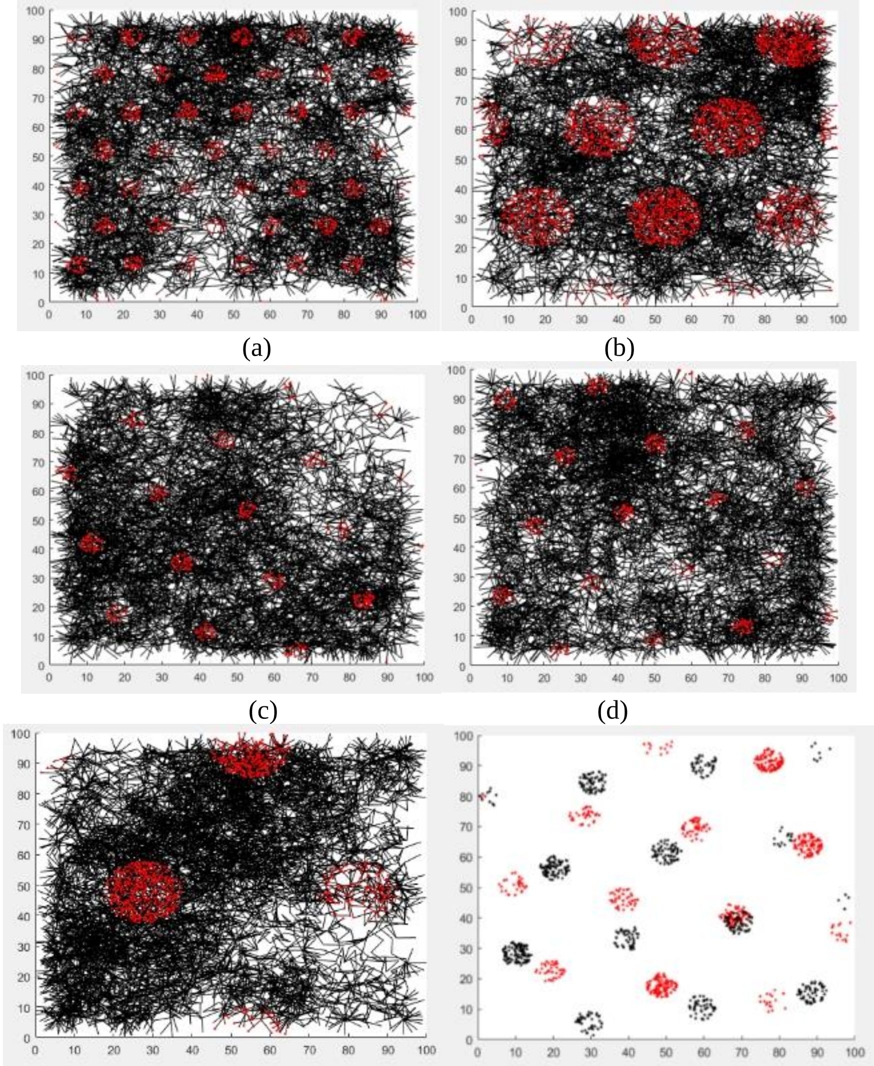
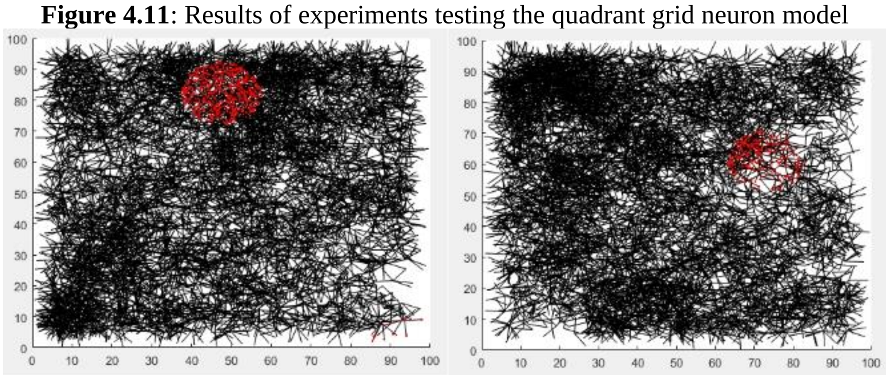
The artificial agent's step size of motion is specific, but it can move if given the chance in any direction in accordance. In Figure 4.10, which depicts the various grid patterns of various scales and orientations produced during various walks, the black colour represents the trajectory of the quadrant model agent and the red colour, the firing positions of a grid neuron. Grid patterns produce the anticipated flawless periodic hexagonal grid pattern, which is what is seen as a result.



(a) (b) (c) (d) (e) (f)

Figure 4.11: Results of experiments testing the quadrant grid neuron model



(a) (b)

Figure 9: Place neuron beginning pattern

The activation of a place neuron is actually perfect in Figure 4.11's representation of the place neuron's consequence, which is similar to what was stated above. All fields other than the place neuron's starting field have been shown to be excellently silent. The following are the methods used to examine the various grid layouts shown in Figure 9: (a) A grid

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pattern designed to match the agent's 2000 pace, with a grid spacing of 15 units and a grid circle radius of 3 units; (b) A grid pattern presented next to a grid spacing of 35 units with a grid circle radius of 10 units. (c) a spacing of 25, a radius of 3, and a 30 degree orientation; (d) a spacing of 25, a radius of 3, and a 10 degree orientation; (e) spacing of 55 units, radius of 10, and 0 degree orientation, The convergence of the firing patterns of two distinct grid neurons is showing in (f). Figure 10 illustrates impact of the grid code, where a random position, whose coordinates are listed in the picture, compares to the starting point of 20 distinct grid neurons displayed using a heat map.

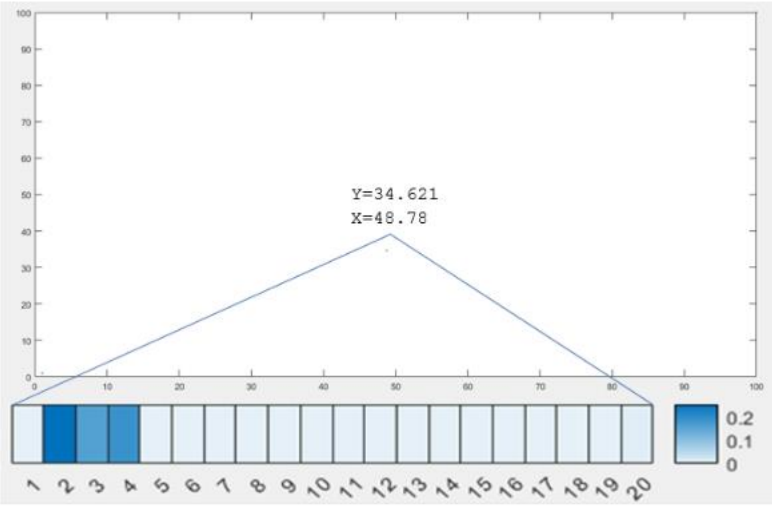

Figure 10: In a 2D environment, grid code is produced

The process is used in two different applications, object memory activity and navigation, which are briefly described in the investigation section, to evaluate the performance of the proposed place and grid neuron interaction system. The results for the activity rightness of the offered model w.r.t. the various model parameters are described in the following sub partitions.

4.3 Consequences of Object Identification

Every object will be started in the initial touch because every object is a permutation of spatial sensations. As a result, every object will be measured in the initial touch. the situation of each active object in the grid code configuration will be given the first touch, and it may even receive multiple positions in a single object where identical sensations are present in multiple locations. The upcoming touch would combine the previously remembered grid codes of each object with the hand movement, and would then anticipate the to be measured sensations. The sensation of every object will then be measured and compared to the predicted sensation. While other items become inactive, the object whose measured and anticipated sensations are identical will continue to be active. As a result, there will only be one active object left after a select few more touches, and it will be that object that has been identified. Similar to the measured consequences, the number of active objects decreases to one with an increase in touches. Figure 11 illustrates this phenomenon by showing the measured consequences for three different starting positions, each of which required a different number of touches to identify the given object.

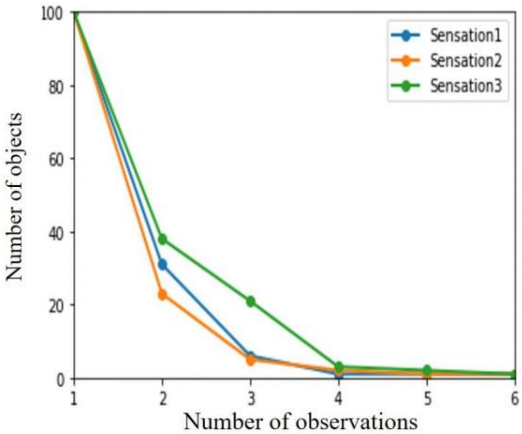

Figure 11: Object identification based on the quantity of results

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5. CONCLUSION AND FUTURE WORK

The computational modelling of spatial memory is the focus of this thesis. A unique quadrant and interference model that replicated the behaviour of a biological grid and place neuron interaction system was given in the thesis. In contrast to earlier efforts, the model does not need to learn how each site is activated, hence it does not employ filters to produce activation patterns. Instead of learning an activation type of firing locations, the proposed place interference model neurons learns the interference patterns pattern of grid neurons. The proposal is highly space-efficient and practical because there will always be a high number of firing sites in a large setting. The quadrant mode produced the ideal hexagonal grid patterns in the results section, which are very similar to the grid pattern of a biological grid neuron. A neural network-based place sequence learner that combines an episodic memory with the semantic recall of an environment adds another innovative element. As a result of frequency remember, the episodic memories are forgettable. It is sturdy in navigation and space-efficient thanks to these capabilities. In addition, compared to earlier works, a novel mechanism is provided for handling objects additionally to the navigation. The mechanism has demonstrated the application of the putative place grid neuron model in object recognition via touch at different locations of an object.

FUTURE WORK

The human brain may lock body parts onto a 3D item that simulates a biological grid neuron that can convert any object or location into a 3D grid with regular hexagonal shapes. The supplied quadrant model can only be used in a 2D setting, which limits the model's usability. The quadrant model now has four quadrants, but in the future, the number of quadrants could be increased to eight, allowing the model to produce 3D grid patterns in a 3D world.

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