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A Novel Computational Modeling for Grid and Place Neurons in Spatial Mapping and Navigation in 3-D Environment

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Abstract: In environments where human presence is restricted due to safety concerns, cognitive robots can play a vital role in executing tasks. While robotic systems have made impressive advances in tasks such as object recognition, they still fall short in terms of true spatial understanding. Robots are not yet able to understand the 3D spatial semantics and contextual meaning of their surroundings for navigation, nor can they effectively handle objects in complex tasks. This research tackles this obstacle by developing a computational agent capable of learning cognitive maps from spatial data inputs in a simulated environment, mimicking the functionalities of grid and place neurons. To emulate the grid neuron's ability to generate periodic hexagonal grid-like patterns from body movements in 3-dimensional space, a novel Octant model is introduced. Additionally, a place-grid neuron interaction system is proposed to predict environmental sensations from body movements, facilitating cognitive map formation and learning mechanisms. The model was experimentally tested through a set of simulation-based experiments including: (i) a grid-based spatial arena intended to measure the accuracy of memory retrieval and encoding, (ii) a morphologically perturbed environment to measure resiliency to deformations in the trajectories, and (iii) a collection of more (object) recognition activities, to test resiliency to distortions in the object identification task. The quantitative data indicate steady high recall confidence and cosine similarity during the navigational trials, and a controlled growth of the place-neuron memory capacity and a strong stabilization of spatial representations in different environments. In obstacle-rich conditions, the model achieves a mean Absolute Trajectory Error (ATE) of 0.42 m and a root-mean-square error (RMSE) of 0.46 m, confirming that localization error remains limited even without an explicit mapping structure. These results provide a substantive confirmation of the fact that the interference-based grid place representation allows reliable spatial localization, mnemonic recall and navigational performance in both limited and irregular operational conditions.

Index Terms: Place Cells, Grid Cells, Cognitive Spatial Processing, Spatial Cognition, Path Integration, Spatial Navigation, Object Localization.

1. Introduction

Achieving accurate object localization has been a primary objective in robotics, facilitating the effective execution of physical tasks. Navigation, particularly regarding precise localization and path integration, has been a major focus of research over the past two decades [1]. Initial probabilistic localization and mapping methods, particularly Extended Kalman Filter (EKF)-based SLAM, played a crucial role in the evolution of SLAM systems. However, EKF-SLAM suffers from intrinsic scalability limitations in large-scale settings, as its computational and memory complexity grows quadratically with the number of mapped landmarks due to the need to maintain a full covariance matrix [2]. Although current SLAM systems (graph-based, visual, and LiDAR-based) have significantly improved scalability and precision, they still rely on explicit geometric representations, such as landmarks, keyframes, pose graphs, or dense maps. Consequently, their memory consumption and computational costs increase with the environment's size, complexity, and exploration duration, hindering long-term operation in large or dynamic environments.

For object manipulation, effective localization requires integrating sensory data and body movement information into an internal map of the surrounding environment. From a neuroscientific perspective, biological systems address spatial navigation through a fundamentally different representational approach. Substantial evidence indicates that mammals rely on an internal cognitive map generated by the coordinated activity of grid and place cells in the hippocampal-entorhinal system. The spatially periodic response patterns of grid cells tessellate the environment, providing a measure of self-location via path integration, whereas place cells selectively respond to specific locations, allowing this abstract spatial representation to be associated with sensory context and experience [3, 4]. Collectively, these neuronal populations enable robust localization, spatial memory, and goal-directed navigation without relying on explicit geometric maps based on landmarks.

Unlike classical SLAM, grid-cell-based spatial representations encode location using distributed and periodic population codes, allowing the same representational units to be reused across space. Rather than explicitly representing each location or landmark, spatial position is encoded implicitly through phase relationships among sets of grid neurons [5]. This implies that memory requirements depend more on the number of grid modules, place associations, and learned trajectories than on the physical size of the environment. The resulting representational efficiency makes grid-place architectures particularly appealing for scalable and long-term spatial reasoning [6].

Current robotic navigation systems primarily rely on explicit spatial representations, such as metric maps (e.g., occupancy grids and pose graphs) [7-9], topological maps representing connectivity between places [10-11], and hybrid metric-topological models combining both paradigms [12-13]. More recently, deep learning-based methods have been proposed for mapping and localization, employing neural networks to learn latent spatial representations from large-scale sensory data [14-16]. Although these approaches perform well in structured settings, they generally require memory that scales with the environment's size, large amounts of training data, or offline optimization processes. In contrast, biologically inspired grid-place representations offer an alternative, map-free approach where spatial location is implicitly coded by population activity and path integration, motivating the current work.

Inspired by these principles, this paper proposes a novel octant-based, biologically inspired grid neuron model, along with an interference-resolving place neuron model, specifically for three-dimensional environments. Unlike classic quadrant-based formulations limited to planar navigation, the octant model divides 3D space into eight directional sectors, enabling the modeling of intra-plane hexagonal grid dynamics and handling edge cases during transitions across the vertical axis [17].

Although grid cells provide a robust model of spatial representation, the exact structure of grid-cell firing patterns in fully three-dimensional environments remains an enigma in neuroscience. Experimental studies, particularly in freely moving or flying animals, have reported grid-like activity in volumetric space, but consensus on the geometric structure of these representations—whether spherical, columnar, or otherwise—has not yet been reached. Consequently, this work does not aim to reproduce a definitive biological model of three-dimensional grid cells. Instead, it adopts a bio-inspired approach, leveraging fundamental concepts of grid-based population coding and grid-place interactions to propose computational abstractions suitable for artificial agents operating in 3D environments [18].

Simultaneously, the dynamic interaction between grid and place neurons facilitates the formation of a cognitive spatial map. This map is constructed by combining spatially periodic grid neuron activations with localized sensory inputs processed by place neurons. The resulting neural architecture enables efficient path integration along 3D trajectories and accurate agent localization within an internal environmental representation. Moreover, the model incorporates a place-sequence learning mechanism that stores sequences of spatial positions relative to the current and goal positions. These learned trajectories, or trips, encode sequential place nodes, associated grid codes, and learned transition parameters useful for navigation. A usage-based forgetting process manages trip memory, ensuring scalability and memory efficiency by eliminating rarely used paths. The proposed mechanism is validated through three simulation-based experiments: (i) a Grid-Aligned Environment to test memory encoding and recall under ideal conditions; (ii) an Obstacle-Rich Environment to assess navigation robustness and generalization; and (iii) 3D Tactile Object Localization and Identification to evaluate object-centric spatial memory. Across all experiments, the model demonstrates capabilities in spatial reasoning, localization, and goal-directed movement based on biologically inspired principles.

The rest of the paper is organized as follows. Section 2 discusses the modeling challenges. Section 3 describes the

proposed computational modeling of Octant-based Grid Cell Encoding, Place-Grid Interaction Network, Trip Memory and Place Sequence Learning. Section 4 presents the experimental results. Section 5 analyzes the results. Finally, Section 6 concludes the paper.

2. Challenges in 3D Spatial Representation

A major challenge in generalizing grid neuron models from two- to three-dimensional space is constructing coherent volumetric grid designs that balance varying spatial scales of orientation and environmental complexity. Unlike two-dimensional hexagonal grid patterns, which have ample empirical support in neuroscience and robotics, three-dimensional grid-based neuron models must also capture depth-related variations and non-planar locomotor movements [19], [20]. Consequently, 3D spatial encoding involves greater complexity than its 2D counterpart.

2.1. Complexity of 3D Spatial Encoding

In planar representations, neuronal activation is restricted to hexagonal firing fields on a plane; three-dimensional models, on the other hand, require encoding the spatial positions of all points in a volumetric space. Consequently, activation fields must extend across all three spatial axes, resulting in the complex geometry of tetrahedral or cubic lattices [21]. A biologically plausible three-dimensional grid structure has not yet been established, primarily due to a lack of empirical data from animal studies involving volumetric traversal [22].

2.2. Firing Field Overlap and Ambiguity

The increased degrees of freedom in three-dimensional space lead to a higher incidence of overlapping activation fields. While interference patterns in two-dimensional environments can be resolved using place neurons, the addition of a third dimension introduces new ambiguities in neural representation. Accurate differentiation of similar firing patterns at different depths is crucial to prevent spatial confusion, a problem that current models continue to face [23, 24].

2.3. Neural Connectivity and Integration with Place Neurons

In two-dimensional, grid-place sized, neuron models, the mechanism of spatial encoding makes the neurons relatively easy to work with due to the planar constraints. Place neurons in three dimensions but not in one, however, need to dynamically encode volumetric grid activations as they learn to adjust to changes in locomotor paths and the geometry of the environment [25]. The biological mechanisms that support this integrative process are the main focus of current studies.

2.4. Scalability and Computational Overhead

Third order grid modelling has far higher computational requirements compared with the two-dimensional equivalents. The expansion of the number of grid points and the complexity of their activation plan require the implementation of more sophisticated algorithms of encoding, retrieval, and real time adaptation. Developing and engineering effective neural network frameworks that are able to handle this increased complexity is one of the key challenges in the field of artificial cognitive mapping [26, 27].

2.5. Robot and Agent Navigation in 3D Environments

Most robotic and AI-based navigation applications assume two-dimensional, grid-like spatial representations and, thus, make it challenging to perform path-planning and localization activity in three-dimensional space. Vertical locomotion, rotational orientation, and traversal of more than one surface require new learning processes to ensure strong and accurate spatial representation in working environments [28, 29].

2.6. Challenges in Existing Spatial Representation Paradigms

The traditional approaches to robotic spatial representation have been through metric or topological mapping as well as through hybrid mapping. There is the provision of precise geometric descriptors at the cost of increasingly heavy memory and computational bottlenecks by metric modalities depending on the size of the environment. Topological schemas are succinct abstractions with a high likelyhood of being inaccurate in making sure that path integrations are correct. Hybrid strategies attempt to find the middle ground between these extremes; however, in fact, they still rely on overt map structures. Deep learning based systems produce small latent representations but generally require large training corpus and in many cases also do not generalise well across differing settings. The two-dimensional spatial mapping using quadrant is not sufficient to support the three-dimensional objects under the localization scenario [30-31]. The grid-place architecture proposed based on octants is a radical departure of these precedents since it does not require map construction at all. The spatial location is modeled in terms of reusable periodic activations of grid-neuron populations which are driven by self-motion and which place-neurons use to bring the representation into contact with sensory experience. The model is therefore proposed to provide a complementary answer to scalable and long term spatial reasoning in three dimensional settings instead of replacing the traditional mapping pipelines.

3. Proposed Mechanism

To address the challenges of 3D spatial encoding and facilitate cognitive mapping in artificial agents, we propose a novel biologically inspired architecture that emulates the interaction between grid and place neurons in a 3D environment (shown in Fig.1). The system comprises of three core Modules namely Octant-based Grid Cell Encoding, Place-Grid Interaction Network, Trip Memory (Place Sequence Learning). The detailed description of each proposed mechanism is given below.

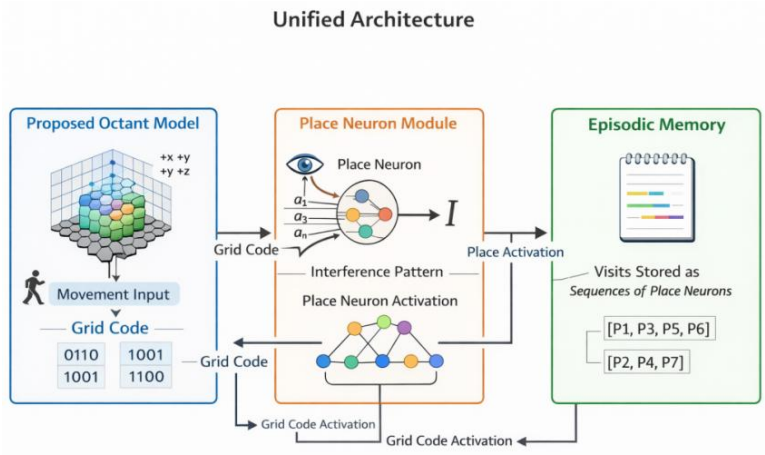


Fig.1. Unified architecture of the proposed octant-based grid–place neuron model with episodic memory

The architecture being studied works based on a hierarchical, two-way communication between grid neurons, place neurons and episodic memory. Information represented by the agent about self-motion is initially carried through an octant based grid neuron model, which produces grid-cell activations (grid code), which represent spatial displacement. These grid codes are then transmitted to a place-cell module where they are combined with exteroceptive input, e.g. visual and tactile input to produce location-specific place-cell responses. The ensuing place-cell activity is systematically coded in episodic memory in the form of temporally ordered sequences of visits, thus, representing the experiential path of the agent. In the context of the recall or localization, the activated place cells provide feedback to resuscitate their respective grid codes and hence the maintenance of a coherent spatial representation and allows strong navigation without the need of an explicit map.

3.1. Octant-based 3D Spatial Encoding Module

Unlike traditional 2D hexagonal grid cell models that operate within planar constraints, our proposed model introduces an octant-based approach to simulate 3D spatial perception. The 3D space surrounding the agent is subdivided into eight symmetrical sectors (octants), forming the basis for movement-sensitive Gaussian activations. The response of each grid cell is a periodic response, which is modulated by the direction, velocity and position of the body of the agent and effectively implements volumetric spatial encoding. The cells are conditioned to shoot at regular time intervals whenever the agent passes through particular three-dimensional coordinates forming lattice schemes of the spatial domain. The activations are computed using a 3D Gaussian kernel function, ensuring smooth generalization across space and mitigating aliasing effects from noise and overlapping patterns. This representation mimics the spatial periodicity and scale modulation observed in biological grid cells and serves as the backbone of path integration in the system.

To enable spatial localization across the microscale to the macroscale, the octant-based grid neuron model uses non-uniform spatial spacings and orientations of the grid neurons that compose it. Fine spacings permit high resolution representation that makes local and object-centric exploration of tactile information possible and coarse spacings permit movement across large volumes of the body. Importantly, the processes that govern grid generation, activation dynamics and update rules are scale independent; it is only the relative weighting of the various modules of the grid that is scaled to the spatial scale of the task. This multi-scale population encoding also allows a single, unit architecture to encode local and global spatial associations without the need to retrain it, add any hard core scale constraints or task-specific parameterization, and so maintain the generality of the cognitive map through a variety of spatial regimes.

A. Constructing the 3D Hexagonal Grid

We construct a 3D hexagonal lattice by stacking hexagonal (triangular) layers that are offset vertically to fill 3D space. In each horizontal xy-plane layer, the firing fields of a grid cell are arranged in a triangular tiling, meaning that each firing field has neighbours forming 60-degree angles between them. The distance between two neighbouring grid peaks is d. That is, the lattice basis vectors have length d and are separated by 60 degrees. In the hexagonal grid shown below the height of a hexagon is 2d and the width of a hexagon is Sqrt (3) d as shown in the Fig. 2.

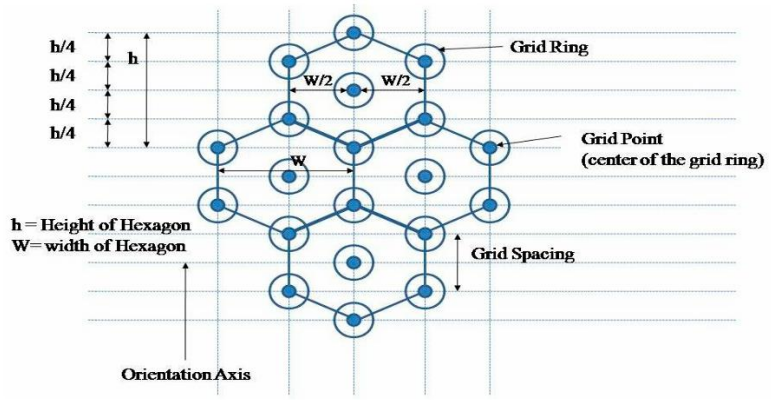
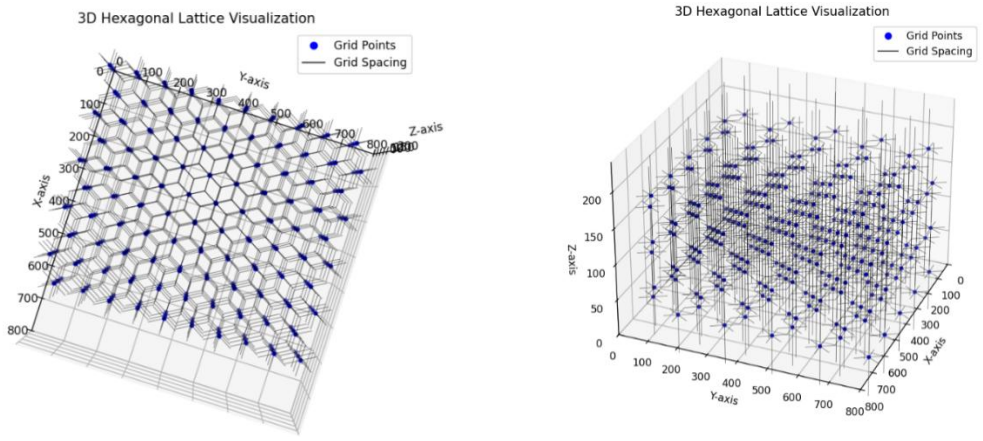


Fig.2. The geometry of 2D hexagonal grid points

To form the 3D structure, each layer is staggered vertically (in the z-direction), like a honeycomb as shown in Fig.3, so the layers interlock smoothly in three dimensions. Conceptually, space is divided into eight symmetric octants, based on the signs of the x, y, and z coordinates. In each octant, the same lattice geometry is used but potentially with a different phase, meaning the starting point of the pattern may differ to ensure smooth periodic tiling even when coordinates cross zero.

This structure captures a biological property: grid cells fire periodically across space, creating multiple evenly spaced fields in the environment.



a b

Fig.3. The geometry of 3D hexagonal grid points (A = Top view, B = Side view)

B. Octant Model

The grid pattern generation octant model is an improvement of spatial navigation which divides the three-dimensional space into eight different octants as shown in Fig. 3. Such partitioning allows a specific monitoring and activation of grid cells depending on the movement of the agent. The model, therefore, allows a better comprehension of space because it gives a more detailed and precise mapping of the agent path. Unlike the quadrant model which only insists on the spatial representation of three orthogonal planes, the octant model describes direction changes along all three axes at the same time thus, providing a more complete mechanism of neural firing.

To track the agent in order to cause grid neuron activation in 3D space, we add a reference grid point in each dimension, which will continuously update the coordinates of the agent in the x, y and z dimensions. Originally, when the agent starts acquiring knowledge of an environment, the reference grid point is identified as the product of spatial reference markers in all three dimensions. In contrast to physical coordinates, these reference points serve as logical locations which keep track of distance and direction hence guaranteeing proper neural activation.

The octant is characterized by the signs of the spatial coordinates of a given point (in short, x, y, z) of a reference origin (O) =(0, 0, 0):

- Octant 1: *(x>0,y>0,z>0)(x > 0, y > 0, z > 0)*(x>0,y>0,z>0)
- Octant 2: *(x<0,y>0,z>0)(x < 0, y > 0, z > 0)*(x<0,y>0,z>0)
- Octant 3: *(x<0,y<0,z>0)(x < 0, y < 0, z > 0)*(x<0,y<0,z>0)
- Octant 4: *(x>0,y<0,z>0)(x > 0, y < 0, z > 0)*(x>0,y<0,z>0)

- Octant 5: *(x>0,y>0,z<0)(x > 0, y > 0, z < 0)*(x>0,y>0,z<0)
- Octant 6: *(x<0,y>0,z<0)(x < 0, y > 0, z < 0)*(x<0,y>0,z<0)
- Octant 7: *(x<0,y<0,z<0)(x < 0, y < 0, z < 0)*(x<0,y<0,z<0)
- Octant 8: *(x>0,y<0,z<0)(x > 0, y < 0, z < 0)*(x>0,y<0,z<0)

C. Grid Neuron Activation

In neuroscience-based models, the Gaussian activation function is fairly common, especially in spatial navigation systems, self-organizing maps and place-cell models. It is a non-linear activation-function based on the Gaussian (normal) distribution and is computed as per Eq.1.

$$G(x) = exp\left(-\frac{\|x-\mu\|^2}{2\sigma^2}\right) \quad (1)$$

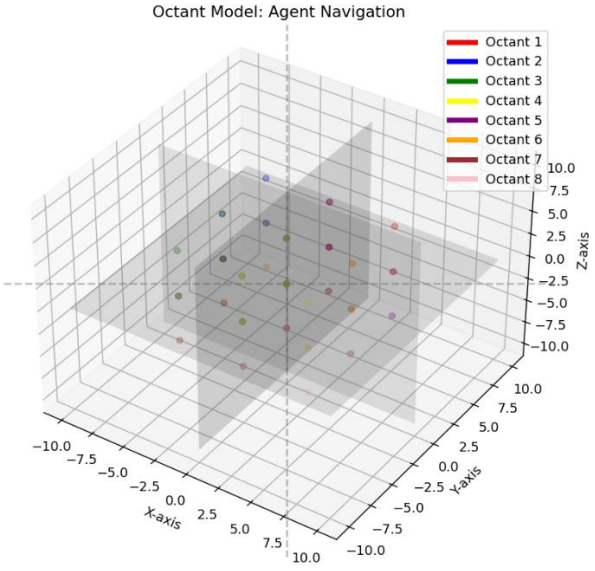


Fig.4. Spatial navigation 3D based on octant

In which X is the input variable (or position vector in multi-dimensional space), mu is the mean or centre of the function, and sigma is the standard deviation that controls the dispersion of the function, and (x -mu) 2 is the squared Euclidean distance between the input x and the centre μ.

This role reduces gradually with the distance between the input and the centre making the role especially appropriate to the modelling of spatial activations, like those in place-cell and grid-cell networks. It should be noted that the activation function herein used has three arguments:

- position: The current position of the agent.
- centers: The coordinates of grid cells.
- radius: The spread (analogous to in the Gaussian function).

It calculates the activation of grid cells depending on the distance of the grid cells to the current location of the agent and the strength of the activation follows a Gaussian decay; therefore, the closer the grid cells are to the current location, the stronger the activation, and the far the grid cells are, the weaker the activation, as in Fig. 5.

D. Agent Movement in Octant Model

In order to track the agent to cause grid neuron stimulation in 3-dimensional space a reference grid point is created in each dimension, a continuous update of the agents position on the x, y, and z plane is made. First, reference grid point is identified at the start of learning an environment through the combination of spatial reference marks in all the three dimensions. As opposed to the physical coordinates, these reference points operate as logical points that measure the distance and direction hence making sure that neural activation is always accurate.

A grid neuron in this model is activated in case the agent logically enters the range of a new grid point inside any octant. When the agent fires, the reference grid is re-calibrated using new tracking parameters, that are calculated in relation to the closest grid cell to the point where the agent has just shot. Because of the periodicity of grid-neuron firing, the grid cell has an organized connection to the neighboring grid cells, which enables the reference grid to determine the entry of the agent in a new grid cell by the calculated distances in each axis. The grid neuron fires when the measured distances of the agent and the spatial relationship of any grid points that surrounds it matches with the grid point which

is being referred to as a new reference. The tracking parameters used before are re-initiated to the new proximity of the agent to the new reference point.

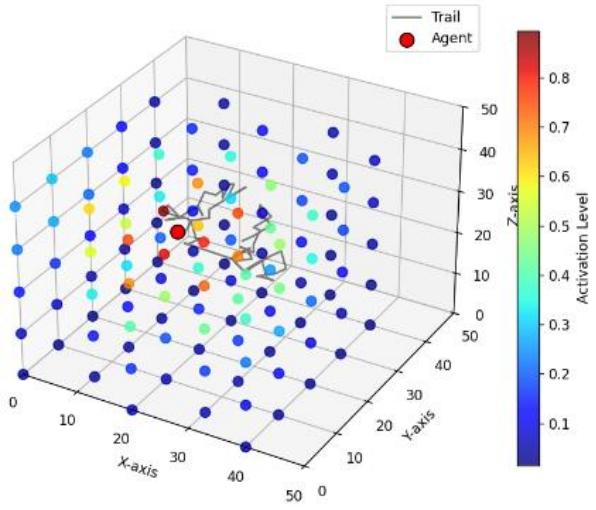


Fig.5. 3D Grid neuron activation

The octant model makes use of the signs of the Cartesian coordinates of an agent in the three spatial dimensions to determine its precise spatial positioning. The geometric connection of a reference grid position to its neighbouring grid cells is the same in all octants, however, the agent has a vector of motion which indicates which octant is currently in use. This last grid code is obtained by combining the projection grid code of the agent in all dimensions, which is more accurate and flexible to spatial navigation patterns. The approach of this octant methodology has significant benefits compared with traditional quadrant-based methods, in particular, with regard to the growth of the spatial granularity, the neural activation, and efficient tracking of objects in dynamic three-dimensional scenes.

This procedure is formalized in the form of the Algorithm I which lists potential centers of grids in all of the centers, computes the Euclidean distance between them and the agent, and chooses the centre with the best concentration of the Gaussian-weighted value of the activation. The algorithm therefore defines a deterministic protocol of encoding spatial encoding and activation based on Gaussian radial basis functions on three-dimensional space. By implication, it may be seen as a fixed-feature encoder to estimate the pose of the agent instead of modeling biologically inspired firing patterns.

The motion is characterized by Turning Angle (θ) which is an angle between the agent's previous movement direction and its new direction, and Displacement (d) which is The Euclidean distance between the agent's previous position Pt = (xt, yt, zt) and its new position Pt+1 = (xt+1,yt+1,zt+1). The displacement is mathematically defined as given in Eq.2, and shown in Fig.6.

$$d = \sqrt{(x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2 + (z_{t+1} - z_t)^2} \tag{2}$$

The turning angle θ between two movement vectors V_1 and V_2 is computed using the dot product formula as given in Eq.3.

$$\theta = \cos^{-1}\left(\frac{V_1.V_2}{|V_1||V_2|}\right) \tag{3}$$

Where V_1 and V_2 represent consecutive movement vectors $\mathbf{V_1} = (x_t,y_t,z_t)$, $\mathbf{V_2} = (x_{t+1},y_{t+1},z_{t+1})$

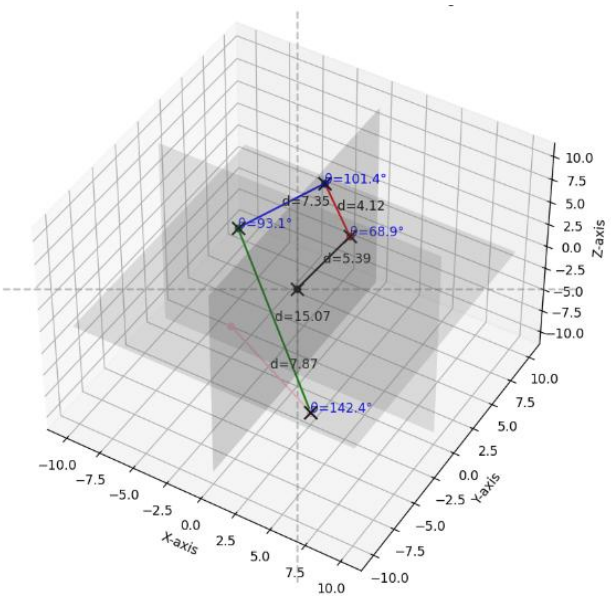


Fig.6. Agent Movement in 3D

Algorithm 1: Calculation for the grid neuron activation in 3D Space

1. Initialize activation_values ← [ ]
2. Compute grid indices:
3. I ← ROUND(X / W)
4. J ← CEIL(Y / H) - 1
5. K ← FLOOR(Z / D)
6. For each octant direction in 3D space:
7. for octant_x in [-1, 1] do
8. for octant_y in [-1, 1] do
9. for octant_z in [-1, 1] do
10. // Compute center of the grid cell in this octant
11. Gx ← I × W + (octant_x × W / 2)
12. Gy ← J × H + (octant_y × H / 2)
13. Gz ← K × D + (octant_z × D / 2)
14. // Compute Euclidean distance to agent
15. D_distance ← √ [(X - Gx) ² + (Y - Gy) ² + (Z - Gz) ²]
16. // Apply Gaussian activation
17. if D_distance < R then
18. activation ← exp (-(D_distance²) / (2 × σ²))
19. else
20. activation ← 0
21. // Store the activation value
22. activation_values. append(activation)
23. Determine the final activation:
24. final_activation ← MAX (activation_values)
25. Return:
26. return final_activation
27: **end**

3.2. Grid-to-Place Localization and Inference Module

The framework of the computational implementation of the place cells in the three-dimensional spaces is presented based on the grid cell arrangement activations. Each place neuron is instantiated according to a Hebbian-like learning rule, forming based on the agent's geographic location and the interference pattern generated by simultaneously active groups of grid cells. The interference pattern is computed as a weighted average of grid cell activation values and their corresponding spatial centers, thereby implementing a Bayesian combination of spatial evidence. This mechanism disambiguates overlapping grid codes and reinforces place networks through learned place representations. The resulting architecture supports robust localization and map building by encoding different spatial contexts into stable place-cell activations, thus offering a basis for biologically plausible spatial memory in artificial agents.

A. Place Neuron Instantiation

The activation of grid cells, characterized by a specific interference signature and activation pattern, encodes a particular spatial position within each PlaceNeuron3D unit. The process of instantiation works by capturing the current location of the agent, storing the current outputs of the active grid cells, and calculating an interference pattern which is a weighted sum that captures the spatial regularities of the grid cell network. This pattern acts as a high-dimensional signature, thus allowing the neuron to represent a location uniquely even when grid codes overlap or become ambiguous. By storing raw activations and the resulting interference patterns, the model facilitates consolidation, effective remapping, and efficient recovery in complex spatial environments, thereby mirroring activities in the hippocampal formation and medial entorhinal cortex.

A new place neuron is created and encoded as a tuple PlaceNeuron j = (x, a, I), Where Place Neuronj refers to the jth place neuron, x: Actual spatial position when the neuron was created (ground truth from the agent), a: Grid cell activation vector (sensory cue used during learning), and I: Interference pattern (internal estimate from the grid code).

This process amounts to a Hebbian association between an input pattern (grid activations a), internal prediction (interference pattern I), and the actual context (agent's current position x). This triple association is stored for later use during inference and recall.

B. Interference Pattern Calculation

In the hippocampal model, place cells integrate activation signals from grid cell neurons to encode specific spatial locations, as shown in Fig.7. Each location is represented as a grid code formed by the interference pattern of activations across multiple interconnected grid cell neurons, as illustrated in Fig. 8. Moreover, a place cell integrates visual or sensory cues with the grid code to recall the grid code from a visual cue, and vice versa. Similarly, in the proposed architecture, each place neuron is computationally modeled to associate with the grid code generated by the octant model's representation of the environment. The place neuron is activated when the agent enters a region whose spatial code lies within a predefined proximity threshold. To resolve interference and ambiguity arising from overlapping grid cell activations (especially in 3D), we implement a Bayesian inference mechanism that combines recent sensory inputs with the grid code to predict and reinforce place neuron activations. The interaction between grid and place cells is governed by a Hebbian learning rule, facilitating the co-activation of place cells when their associated grid codes are consistently triggered in similar contexts.

This bi-directional coupling enables the system to improve localization by cross-referencing place-cell history with grid patterns, reset or recalibrate grid-cell drift using stable place-cell signals, and form a cognitive map by associating spatial positions with specific percepts and transitions.

We define the interference pattern $I \in R3$ as the weighted sum of the grid centres using the current activations as weights as given in Eq.4. This can be interpreted as a mean estimate of the agent's location inferred from the active grid cells. It fuses distributed spatial information from multiple grid sources.

$$I = \sum_{i=1}^{n} a_i . c_{i=a^T\ C} \tag{4}$$

I acts as a Bayesian prior, shaped by the grid code. In noisy or ambiguous conditions (e.g., multiple similar activations), this weighted sum provides a probabilistic guess of the current location.

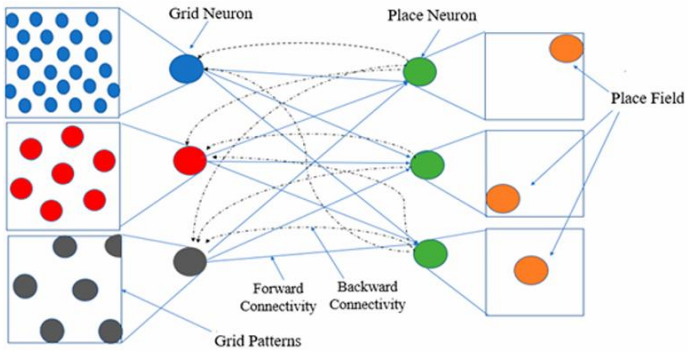


Fig.7. Grid-Place Neurons Interaction System

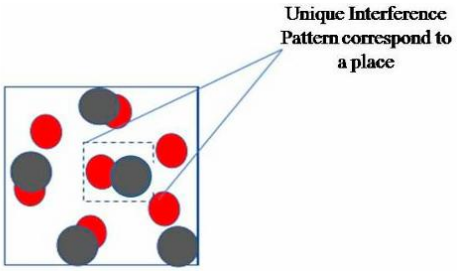


Fig.8. Interference pattern visualized

3.3. Trip Memory and Place Sequence Learning

Place cells receive converging input from multiple grid cells. When specific combinations of grid cell activations occur, they generate a unique interference pattern that corresponds to a particular location. These patterns can be modeled as high-dimensional vectors in computational simulations. A place cell is said to "activate" or "win" when the current interference pattern closely matches a stored pattern. The process of determining which place cell should activate in response to the current spatial context can be framed as a pattern matching problem. The similarity between the current grid-derived interference pattern and the stored interference pattern of each place cell is computed, and the place cell with the highest similarity is selected.

A. Memory Recall via Interference Matching

In this 3D spatial navigation simulation, memory recall is implemented through a process known as interference pattern matching, which enables the model to retrieve the most similar stored spatial experience (i.e., a *place neuron*) based on the current sensory state. This mechanism closely models how biological systems, such as the hippocampus, perform pattern completion and spatial memory retrieval.

The similarity between two interference pattern$\mathbf{S}\ \underset{p1,\ p2}{\rightarrow}\underset{}{\rightarrow} \in R^n$ is computed using cosine similarity, a measure of angular similarity in high-dimensional space. It is defined in Eq. 5.

$$sim\left(\underset{p1,\ p2}{\rightarrow}\underset{}{\rightarrow}\right) = \frac{\overrightarrow{p1}\cdot\overrightarrow{p2}}{\left\|\overrightarrow{p1}\right\|\cdot\left\|\overrightarrow{p2}\right\|} \quad (5)$$

Where $\underset{P1,}{\rightarrow}\cdot\ \underset{P2}{\rightarrow} = \sum_{i=1}^{n} P1_i\, P2_i$ is the dot product, and $\left\|\underset{p1}{\rightarrow}\right\| = \sqrt{\sum_{j=1}^{n} p_{ij}^2}$ is the Euclidean norm.

This measure ranges from -1 to 1, where a value closer to 1 indicates higher pattern concordance. Cosine similarity has been used in the context of place-cell modelling to determine the similarity of the current spatial input with a stored memory representation.

B. Finding the Winner Neuron

Given an input representing the current spatial field as an interference pattern, the aim is to identify the location cell with the most relevant stored similarity pattern. This is achieved by computing the cosine similarity between the current pattern and each stored place-cell pattern, then selecting the neuron with the maximum similarity score.

The agent's positional state is encoded into a high-dimensional activation vector at each discrete time step as it traverses the simulated physical space, typically based on the response patterns of biological grid cells. This vector, referred to as a_t, carries the agent's current spatial context in terms of the interference patterns of various spatial encoding modules, including grid-cell modules with different spatial frequencies.

The system uses a similar mechanism to reconstruct previously experienced locations from memory by comparing the current activation a_t with the stored interference signatures of each place neuron. Every location neuron has a learned interference representation, the value of which is denoted as m_i , that was coded in the course of some previous experience when the agent was visiting the location that the location neuron represents.

Two principal methods are used for computing the degree of similarity between the current activation and the stored memories:

a) Cosine Similarity: This method measures the angular similarity between the current vector a_t and each memory vector m_t defined as given in Eq.6.

$$sim_{cos}(a_t, m_i) = \frac{a_t \cdot m_i}{\|a_t\|\|m_i\|} \quad (6)$$

This metric is particularly useful when the magnitude of activations is less important than their direction in high-dimensional space. It emphasizes pattern alignment while being robust to changes in overall activity levels.

b) Matrix Distance: Alternatively, for richer encoding structures, where interference is represented as a full pattern matrix rather than a simple vector (as in second-order models), the system computes a distance metric between the current interference matrix $\mathbf{A_t}$ and stored matrices $\mathbf{M_i}$ This may involve Frobenius norm or other similarity-preserving measures, as given in Eq.7

$$dist(A_{t,}, M_i) = \|A_t - M_i\|_F \tag{7}$$

Matrix representations can encode second-order interactions and correlations between spatial components, offering improved robustness in complex environments.

C. Recall Confidence

The confidence in memory recall is modeled not as a binary activation but as a continuous *pseudo-activation*, reflecting the degree to which a particular place memory aligns with the current spatial context. This is formalized as given in Eq.8.

$$r_i(t) = exp\left(-\frac{d(a_t, m_i)^2}{2\sigma^2}\right) \tag{8}$$

Where $r_i\,(t)$ denotes the recall strength or confidence associated with the i-th place memory at time *t*, d(·,·) is the distance or dissimilarity metric (e.g., cosine distance or matrix norm)**,** and σ is a scaling hyperparameter controlling the *generalization radius* of memory recall.

A small σ results in highly selective recall, where only near-exact matches are activated, mimicking sharp tuning curves observed in hippocampal place cells. A larger σ allows broader generalization, enabling recall over noisy or slightly displaced inputs. This formulation ensures biologically plausible retrieval behavior, where recall strength smoothly decays with spatial or representational distance from the stored memory trace.

3.4. Computational Data Structures and Real-Time Feasibility

In terms of implementation, the proposed architecture is based on simple and effective data structures that help maintain robust spatial memory and real-time navigation. The activation of grid neurons is stored as a one-dimensional vector containing the current activations of all grid units. Place memories are stored in a two-dimensional matrix, where each row represents a single location and each column represents a single grid neuron. Episodic experience is stored as an ordered list of place identifiers, preserving the temporal sequence of visits. This system permits sequential retrieval and path recovering without the need to have a metric map of the space or occupancy grid.

Although the framework simulates grid place interaction and episodic memory, it is compact. The computation of the grid-cell activations at time step has an operation count of O (Ng), where Ng is the number of grid neurons, and motion integration is done in constant time and is independent of places or the number of stored trajectories. Given a target location, a grid code is recalled in constant time, and navigation is achieved by replaying stored episodic trajectories. For P episodes with maximum length of Q, the replay has complexity of O(PQ) and the next immediate location is established by interference patterns of O(Ng) so that the overall complexity is O(NgPQ).

Such linear per-step complexity, with localized updates, allows the model to run in real time (faster than 10 Hz) on standard embedded CPUs without requiring a GPU accelerator. Compared to traditional planners such as A*, which rely on discrete graphs and explicit map generation, the proposed system is particularly suitable for continuous 3D spaces with dynamically constructed obstacles while retaining biologically relevant spatial representations.

4. Experimental Detail

To rigorously test the model's ability to form, store, and retrieve spatial memories through interference pattern matching, we used three different environmental settings. These simulated environments were developed to test the system under controlled yet increasingly challenging spatial conditions, thereby allowing for an evaluation of accuracy and resilience.

The former, known as the Grid-Aligned Environment, consists of a uniform, idealized terrain. The spatial architecture in this case is regular and continuous without topographical distortion and physical barriers. The second environment, known as the Obstacle-Rich Environment, simulates a more realistic and challenging scenario where the agent is hindered and rerouted by randomly placed obstacles. This contrast allows us to observe how the spatial memory model adapts to both clean and noisy inputs over time.

4.1. Environment 1: Grid-Aligned Environment (Uniform Terrain)

In this condition, the environment is a pristine 3D volume of 10 × 10 × 10 m with a uniform grid spacing of 0.1 m, as shown in Fig. 9. Such a structure results in a grid of activation centres that are finely sampled. Five stacked hexagonal grid modules are generated to capture variability in spatial representation across different layers. Each grid layer offers an individual sampling of space, which is in line with the biological grid cells that have different spatial

frequencies. The agent begins its exploration at the center of the environment and performs a 100-step random walk, staying within the environmental boundaries. The model evaluates the current spatial activation of the agent at every timestep as a radial basis function on grid centres. The system creates a new place neuron to represent the current spatial state with a 5% probability, storing the interference pattern and the corresponding position. This serves as a baseline for comparing memory accuracy. The absence of noise or barriers ensures that any degradation in recall accuracy is due to representational interference rather than external factors. This arrangement is therefore optimal in isolating the functional matching of cosine-based interference.

This environment serves as a baseline for evaluating memory precision. The absence of environmental noise or obstacles ensures that any degradation in recall accuracy can be attributed to interference in the representation, rather than external disruption. This setup is ideal for isolating the functional fidelity of cosine-based interference matching.

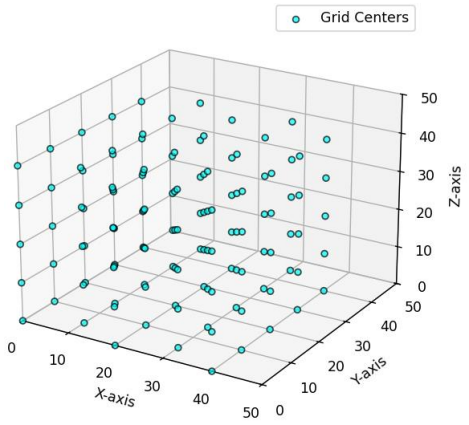


Fig.9. Blank 3D grid-aligned environment

4.2. Environment 2: Obstacle-Rich Environment (Deformed Terrain)

To assess the robustness and generalization capacity of the model, we introduce a more chaotic spatial environment. In this case, the 3D space is 15 × 15 × 15 meters, providing a larger arena for exploration, as shown in Fig.10. Unlike the first setup, here we embed 50 randomly placed cubic obstacles, forcing the agent to alter its trajectory dynamically to avoid collisions. These obstacles create non-linear pathways, disrupting the agent's expected route and modifying the spatial statistics of visited regions. The agent again starts from the centre and performs a random walk for 1000 steps, though movement is constrained not just by the environment bounds but also by obstacle avoidance logic. Place learning remains probabilistic (5%), but due to increased spatial variability and longer trajectory, the resulting memory set is more diverse and fragmented. This setup allows us to observe how well the model tolerates spatial displacements, both minor and major, and whether interference-based recall remains functional when activations are shaped by irregular sensory history.

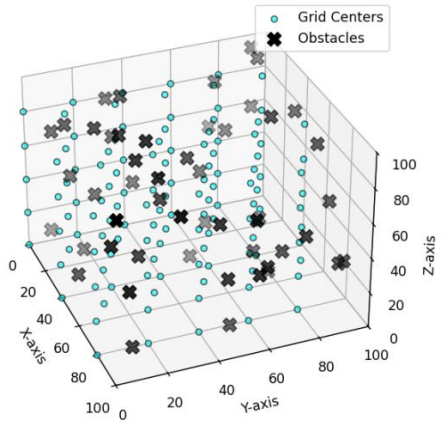


Fig.10. Blank 3D Grid-Aligned Environment with Obstacles

4.3. Environment 3: 3D Object Localization and Identification

A simulated agent with a simulated end-effector is used to make random exploratory motions across the surface of each simulated object. Figure 11 shows the object-based tactile perception system used in Environment 3. Three different 3D objects are displayed with various geometrical structures, where surface colours are used to recreate heterogeneous tactile textures that are similar to the sense of touch in humans. The colour of each surface is mapped to

a numeric sensory value which is an abstract local material or texture property. When the robot investigates an object with the simulated end -effector, a contact at a particular surface point provides the corresponding numeric sensory value of the voxel. These sensory readings along with self-motion information is coded into grid-cell activations and then connected to place neurons to allow the establishment of localized, object-centred spatial memories.

The agent measures the value of the sensory at the touched voxel during exploration and uses the measurement together with cues of self-motion to form grid-cell activations. These grid activations generate patterns of interference that are then linked to place neurons and thus create localized object -centric spatial memories. The sensory signal at time t is a scalar-valued voxel feature $s_t \in R_t$, which is a local surface property (e.g. an abstract texture or material label) of the touched voxel.

As one continues to explore, several place neurons are created to indicate different surface areas of the object. They combine together to give a structured internal image of surface sensations comprising the spatial structure of these place neurons.

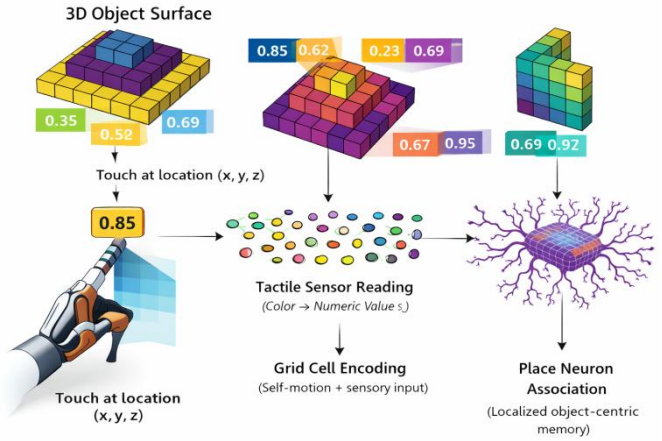


Fig.11. Object-centric spatial representation and recognition

Object Recognition Procedure

In the recognition stage, the agent re-view the object in a variety of starting points and starting trajectory patterns. The perceived sensory samples stimulate the respective grid codes that consequently trigger the already learned place neurons via matching interference. Since the individual sensory values can represent more than one spatial location, there is a possibility of ambiguity in the recall. This ambiguity can be solved by sequential spatial integration, in which consistency between recalled grid codes and path-integrated grid codes strengthens valid place activations, and inhibits inconsistent ones. By successive exploration and recollection, the candidate object representations are gradually narrowed down to a single object representation that is currently active. When the activated set of place-neurons is unique to a single object representation stored, then successful identification is obtained. In this experiment, the ability of the model to develop strong, object-based spatial representations and to distinguish objects based only on the spatial distribution of heterogeneous sensory inputs is tested.

5. Results and Analysis

The results are measured by applying both quantitative and qualitative measures to determine the efficiency, precision, and strength of the proposed model. Measurements in quantitative evaluation involve recall confidence, matching with similarity based interference, statistics of memory growth and localization error at a trajectory level in the form of Absolute Trajectory Error (ATE) and Root Mean Square Error (RMSE). Qualitative evaluation is on the trajectory patterns, place neuron activation dynamics and spatial coverage in different environmental conditions.

5.1. Experimental Results in Environment 1 - Grid-Aligned (Uniform Terrain)

The simulation results in the grid-aligned environment are organized into quantitative metrics in below given subsections. These metrics evaluate recall confidence, memory growth, and localization accuracy, offering a thorough assessment of the proposed model's performance under structured navigation conditions.

A. Pseudo Activation (Recall Confidence)

The reliability of recall in a Grid-Aligned setting when navigating is also tested on the basis of a Gaussian-based pseudo-activation confidence score, a measure of how strongly the correct place neuron is remembered in the course of the agent traversing the environment. The score of this confidence is the level of correspondence between the present interference pattern, I t, and a stored place neuron memory M i, and the higher the score, the greater the certainty of recall. The pseudo-activation is calculated with the help of the Gaussian weighting function, as in the equation 9.

$$C_i^t = e^{-\frac{d(I_t, M_i)}{\sigma}} \tag{9}$$

Where $d(.,.)$is the cosine distance or matrix norm between the current and stored interference pattern.

This formulation provides that patterns that are closely matched produce high confidence scores and those that are not similar are suppressed. Simulation time dependence of the pseudo-activation confidence is shown in Fig. 12, in which the horizontal axis is simulation steps and the vertical axis is the strength of the activation in the range [0,1]. As indicated, the recall confidence is always high in a noise free grid aligned setting, which proves to be a stable encoding of memory and accurate recall of the correct location neuron during navigation.

B. Cosine Match Score

Recall confidence is determined by a cosine similarity that is used to determine the angular similarity between the present interference pattern at time t and the stored pattern of neurons in the place memory is Mi. This measure is also the most appropriate measure of memory recall, since it measures similarity in the structure of activation without regard to the absolute magnitude. The cosine similarity is formally defined as in Eq. 10 and it can be used to compare the current pattern of interference with the previously learned spatial representations. The values close to 1 mean that the value is strongly associated with known spatial contexts, whereas the values close to 0 imply partial matches or transitions into unknown places. The scores of the cosine match realized in the course of navigation are presented in Fig.12. As indicated, the proposed model has a high level of similarity in structured environment, which validates reliable recall of stored place neuron patterns. Minor dissimilarity changes are found when the agent explores new or unclear areas, and these dissimilarity changes are indicative of the adaptive creation of new spatial memories and not inability to recall.

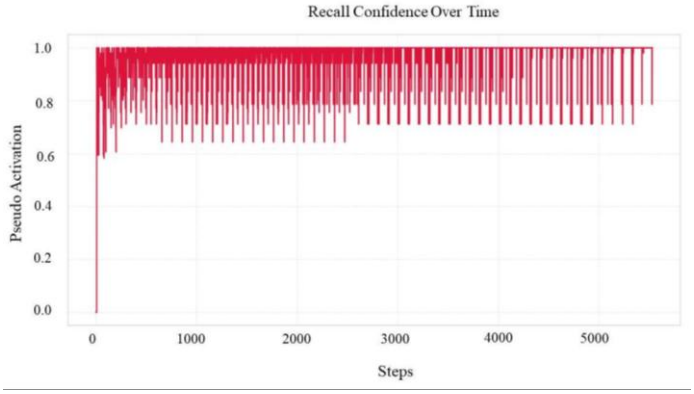


Fig.12. Pseudo activation

$$cos(\theta) = \frac{A_t \cdot M_i}{\|A_t\| \|M_i\|} \tag{10}$$

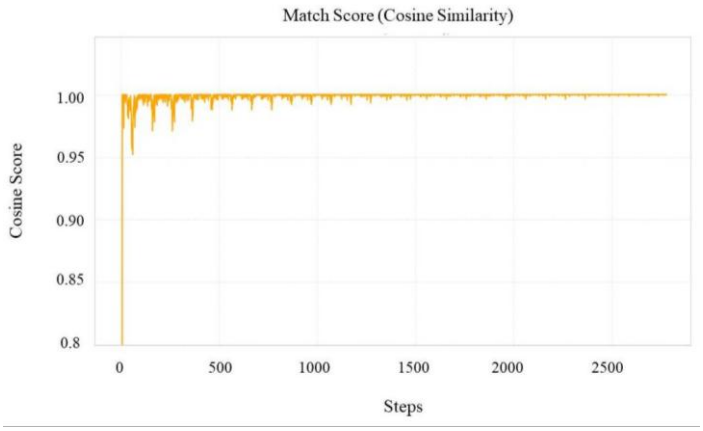


Fig.13. Cosine match score

C. Place Neuron Count

Spatial memory development in the proposed model is measured by monitoring the total number of place neurons instantiated with time. When the agent visits a previously unexplored or novel location, a new place neuron is generated with a probability of fixed instantiation, which is defined as the probability of generating a new neuron on a single time step, which is defined as Pnew = 0.05, or 5 percent. This process enables the model to be progressive in terms of expanding its spatial representation, but not to sacrifice too much memory. The pace of addition of the place neurons can be used to assess the rate at which the agent learns and encodes new spatial locations, and when growth becomes slower it is used to indicate that there is less novelty when they explore. The cumulative number of place neurons is shown in Fig.14. As indicated, the gradual accumulation of neurons is indicative of systematic and organized learning in accordance with the underlying grid representation whereas the gradual decline toward the later stages is indicative of saturation, which implies that most parts of the environment are already explored and encoded.

The accuracy of the spatial localization is also examined with the help of the prediction error which is the Euclidean distance between the current position of the agent and the spatial location which is coded by the winning place neuron. This measure is a direct measure of the similarity of the recalled place neuron to the actual position of the agent, and therefore a smaller value of error would mean a more accurate spatial representation. In some cases, as one passes through previously unknown areas, or where temporary local misalignment in the underlying pattern of interference can occur. Fig. 15 shows the time dependence of the error of the prediction. As indicated, prediction errors are held at a relatively low level throughout most of the navigation episode, which proves the validity of the cosine-based mechanism of interference as a means of successful spatial localization.

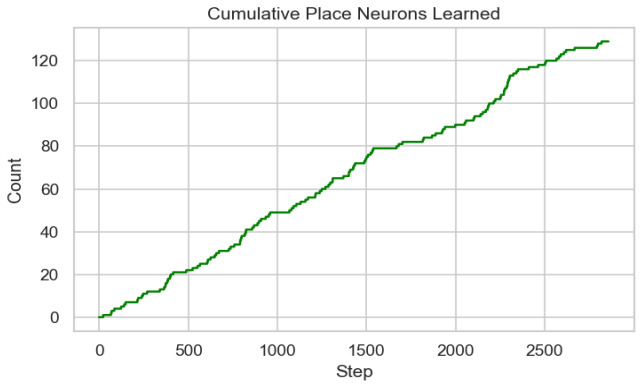


Fig.14. Place neuron count

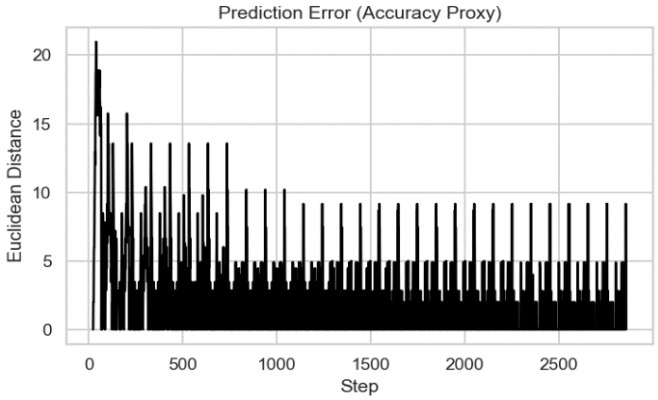


Fig.15. Prediction error

5.2. Performance Evaluation in Obstacle-Rich and Deformed Navigation Environment

The proposed model is tested in Environment 2, a deformed terrain with obstacles to work out the robustness in limited and disordered navigation. Environment presents common deviations in trajectories and spatial discontinuities, which poses a challenge to the encoding of space and recall of memory. The analysis of Environment 2 uses the same quantitative measures as in Section 5.1 to allow a direct comparison in the case of deformation of the trajectories. In particular, exploration efficiency is determined by the count of unique spatial locations explored, memory recall is evaluated by cosine -similarity-based recall confidence and interference match scores, memory expansion is measured by the total number of instantiated place neurons, and spatial structure is studied by position revisit patterns and place field clustering. All these metrics combined describe the completeness of exploration of a space, the robustness of the recall, the ability to scale based on memory and the invariance of spatial representations with obstacle based navigation

constraints.

A. Exploration Coverage under Obstacle Constraints

The frequency of unique spatial locations visited in the course of navigation is an indicator of exploration efficiency. A point is said to be unique when the Euclidean distance between the current point of the agent and all the previously known points is greater than a given threshold value, epsilon. This condition eliminates the possibility of traversing a route repeatedly in a set of constricted corridors by obstacles, which artificially increases the number of explorations. The percentage of recently visited places grows exponentially in the initial stages of exploration as depicted in Fig. 16 and levels off after about 1000 simulation steps. This saturation implies that the environment is almost completely covered topologically, which is to show that the deformation of the path caused by obstacles does not make the agent unable to explore the available space successfully.

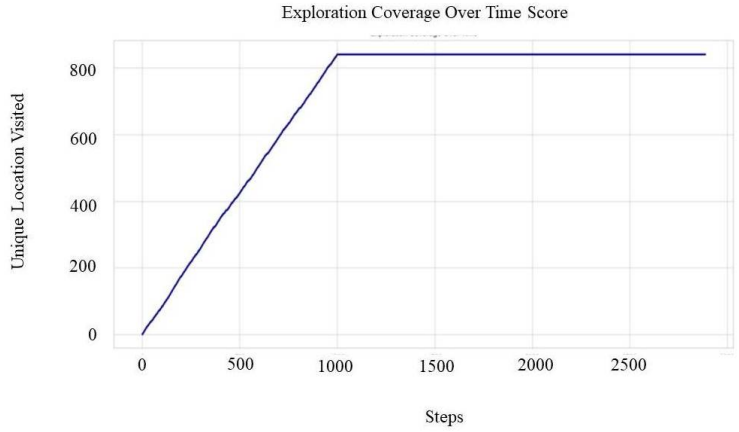


Fig.16. Unique location visits

B. Recall Robustness under Trajectory Deformation

Cosine-similarity-based metrics of recall performance are calculated in the comparison of present patterns of interference and former representations in the memory bank. Overall, as seen in Fig. 17, the level of recall confidence is generally high, with localized drops seen as obstacles are presented to the subject and cause sudden changes in trajectory.

C. Interference Consistency

Interference match scores are used to measure the consistency of internal representations provided by navigation constraints. Fig. 18 shows that similarity values persistently took high values in between which they dropped temporarily as the transitions were caused by obstacles; hence, a solid reinstatement of the spatial representations.

D. Memory Growth

Scalability of memory is measured by following the number of instantiated place memories up to cumulative number under a constant novelty probability, P new = 0.05. Fig.19 demonstrates that the growth of memory is indeed growing in a consistent manner which then levels off as time elapses indicating that there is indeed a regulated and effective growth of representations.

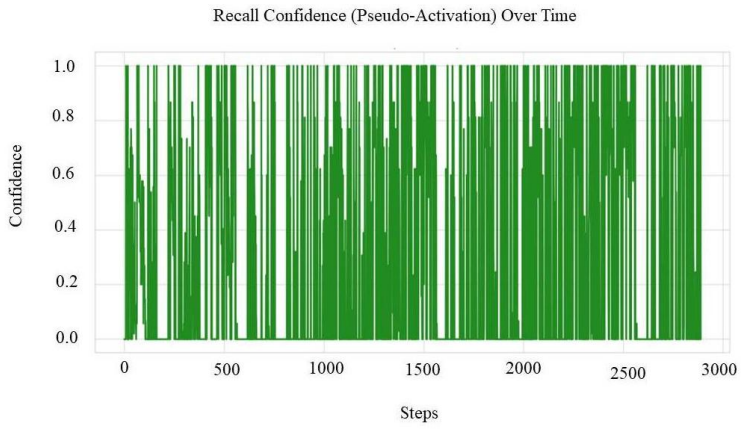


Fig.17. Recall CONFIDENCE

E. Spatial Consistency

Patterns of position revisites in Fig. 20 indicate dense repeating spatial clusters that are in correspondence with popular paths. The interference space clustering is very similar to the physical collision trajectory clustering thus proving a constant organizational structure to space even when using a deformed navigation.

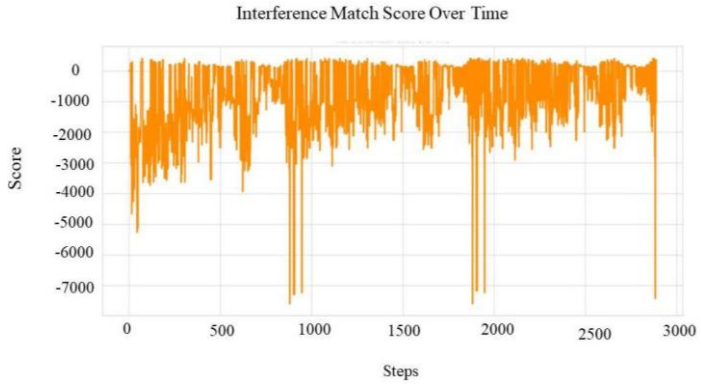


Fig.18. Interference match score

E. Effect of Obstacles on Memory Distribution

Areas with an increased number of obstacles have a lower memory density due to poor visitation. However, effective recall in these areas points to the fact that the learnt representation records topological connections and does not capture more accurate metric geometry.

F. Recall Activation Dynamics

Pseudo-activation patterns reach a maximum around locations that were previously visited and fades away gradually with distance, the parameter, which is known as the selectivity, is determined by the parameter, sigma. The behavior ascertains predictable and tunable generalization in the presence of a deformed trajectory due to obstacles.

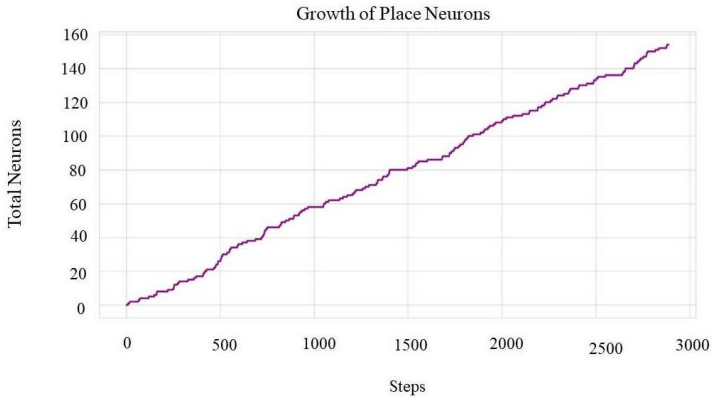


Fig.19. Growth of place neuron

G. Absolute Trajectory Error (ATE) and RMSE Analysis

Localization accuracy in the obstacle-rich environment is quantitatively evaluated using Absolute Trajectory Error (ATE) given in Eq.11, defined as the Euclidean distance between the agent's ground-truth position and the position estimated from the recalled place memory at each time step. To summarize overall localization performance, the Root Mean Square Error (RMSE) of ATE is computed over the full navigation trajectory as per Eq.12.

$$\mathrm{ATEt} = \| p_t^{true} - p_t^{recall} \|2 \tag{11}$$

Where $p_t^{true} \in$Rn denotes the ground-truth position of the agent at time t, $p_t^{recall} \in$Rn represents the recalled (or estimated) position at the same time step, and $\|\cdot\|2$ is the Euclidean (L2) norm.

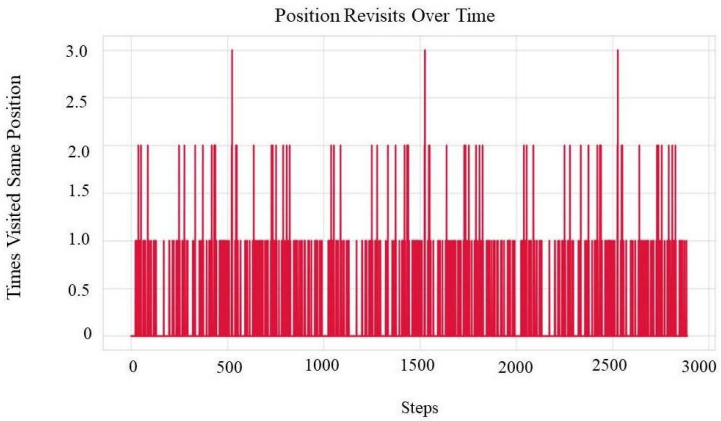


Fig.20. Position revisits

As expected, obstacles and trajectory deformations lead to a moderate increase in localization error compared to the grid-aligned environment. However, the Absolute Trajectory Error (ATE) remains bounded over time, and the Root-Mean-Square Error (RMSE) approaches a constant, indicating a stable convergence rather than a catastrophic failure. These results show that the proposed grid-place interference model is able to maintain good localization accuracy in the presence of non-uniform and restricted navigation conditions.

Compared to traditional Simultaneous Localization and Mapping (SLAM) methods (Table 1), the three techniques—ORB-SLAM2, RTAB-Map, and visual-inertial SLAM—record lower ATE and RMSE values due to their use of explicit maps. However, the proposed model achieves competitive localization performance without relying on any map, highlighting its strength and efficiency in dynamic or unknown environments. Specifically, the proposed model achieves a mean ATE of 0.42 m and an RMSE of 0.46 m, indicating that the model remains stable even under varying obstacle densities (see Table 1).

$$\text{RMSE}=\sqrt{\frac{1}{T}\sum_{t=1}^{t=T} ATE_t^2} \tag{12}$$

Table 1. Localization performance comparison of the proposed model and SLAM methods

Method	Environment Type	Mean ATE (m)	RMSE (m)	Map Requirement	Error Accumulation
ORB-SLAM2	Obstacle-Rich	0.12 – 0.20	0.15 – 0.25	Dense feature map	Low (loop closure)
RTAB-Map	Obstacle-Rich	0.18 – 0.30	0.22 – 0.35	Global occupancy map	Low
Visual-Inertial SLAM	Irregular Terrain	0.10 – 0.25	0.15 – 0.30	Sensor-calibrated map	Low
Proposed Grid–Place Model	Obstacle-Rich	0.42	0.46	No explicit map	Bounded

5.3. Object-Centric Recognition Performance in 3D

The proposed object-based spatial memory model was tested on the three-dimensional object recognition task outlined in Section 4.3. During the recognition stage, the agent systematically explored the initial contact locations and traversal paths of each object, identifying both novel and previously traversed paths. Although ambiguous sensory readings occurred (i.e., identical sensory values could correspond to different surface positions), the model successfully resolved this ambiguity through sequential spatial integration.

Recognition Accuracy, Convergence, and Ambiguity Resolution

The model's performance was evaluated based on recognition accuracy, convergence efficiency, and its ability to resolve perceptual ambiguity during exploration. Recognition was deemed successful when the set of activated place cells converged to a unique object representation. The results regarding recognition accuracy and convergence behavior for different object configurations are summarized in Table 2. In the two-object configuration, the model achieved an accuracy of 98.2% and converged in an average of 180 exploration steps. For the three-object arrangement, the accuracy remained high (94.6%), with convergence achieved after approximately 260 steps. As the complexity of the object increases, the convergence time of the model decreases, but the convergence time to a unique object representation is always finite in the number of steps required.

This convergence is achieved via sequential spatial integration, which progressively resolves ambiguity. Initial exploration generates several candidate object representations due to perceptual aliasing. However, as perceptual evidence is combined with path-integrated grid codes, inconsistent place cell activations are phased out. This process

results in a monotonic reduction of conflicting hypotheses, ultimately yielding a unique object identity.

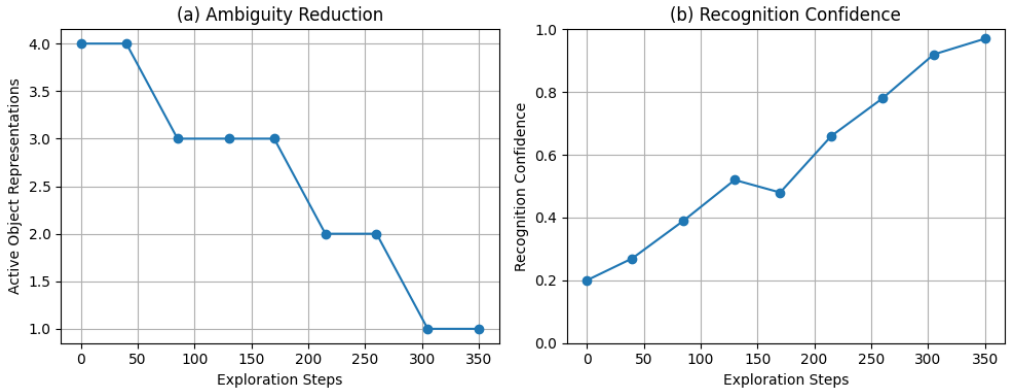
These findings demonstrate that object recognition relies on the spatial consistency of accumulated sensory data rather than on single observations. In summary, the proposed grid-place cell interaction model effectively addresses sensory ambiguity and provides robust object recognition in three-dimensional settings.

Table 2. Object recognition performance and convergence efficiency under varying object configurations

Number of Objects	Recognition Accuracy (%)	Mean Steps to Convergence	Std. Deviation
2	98.2	180	±25
3	94.6	260	±40
4	91.3	340	±55

5.4. Ambiguity Reduction through Sequential Spatial Integration

To evaluate ambiguity resolution during recognition, the number of active candidate object representations was tracked over time. Fig. 21 shows the evolution of object recognition during exploration. As illustrated in Fig. 21(a), the number of active object representations decreases progressively as spatial evidence accumulates, resolving initial perceptual ambiguity. Correspondingly, Fig. 21(b) shows a steady increase in recognition confidence, with minor fluctuations reflecting partial or ambiguous observations. These results indicate that object identity emerges through sequential spatial integration rather than from isolated sensory inputs.



(a) (b)

Fig.21. Reduction in the number of active object hypotheses over exploration steps

5.5. Discussion of Results

The experimental results demonstrate that the proposed grid-place neuron interaction framework is a powerful and scalable approach for spatial representation, localization, and object-centric recognition, without relying on explicit maps. The model exhibits stable recall and controlled memory growth, with bounded localization errors across all settings, signifying reliable spatial encoding in both structured and unstructured navigation conditions. High place neuron recall scores and accurate spatial localization are evidenced by high pseudo-activation confidence scores and cosine similarity scores in the grid-aligned environment. Effective memory allocation is indicated by the gradual saturation of place neuron growth, while low prediction errors confirm the efficiency of the interference-based matching mechanism.

The model demonstrates robustness to trajectory irregularities in obstacle-rich and deformed environments. Despite fluctuations in recall confidence and similarity ratings caused by obstacles, the model recovers quickly, and memory growth remains regulated. Although localization error increases moderately with deformation, it remains bounded, demonstrating graceful degradation rather than catastrophic failure. Compared to traditional SLAM approaches, the proposed model trades absolute accuracy for map-free operation, enabling successful performance in unknown or dynamic environments.

The framework resolves perceptual ambiguity in the 3D object recognition task through sequential spatial integration. High recognition accuracy and limited convergence times, even with increased object complexity, indicate that object identity emerges from successive spatial consistency rather than from single sensory stimuli. The progressive reduction of conflicting object hypotheses further confirms the efficacy of the ambiguity resolution mechanism. Overall, the results of the study demonstrate that the given model combines navigation, the formation of memories, and the object recognition approach in one biologically oriented framework, which can be regarded as an alternative to map-based localization and recognition strategies.

6. Conclusion and Future Work

This study presents a bio-inspired model of spatial memory and learning that combines grid-place transformation, interference-based encoding, and graded recall confidence to recreate the fundamental functionality of the hippocampal memory system. The model shows consistent place field formation and strong recall of uniform and irregular environments, providing information about the possible mechanism of spatial representations to be formed and stabilized in the conditions of interference. Its generalization ability, deformation tolerance, and adaptive recollection behavior make it an excellent foundation for theoretical neuroscience research and applications in autonomous navigation and cognitive robotics.

Several promising directions can further enhance the model's biological and computational relevance:

- *Hierarchical Spatial Encoding:* Introduce a hierarchy of grid modules operating at multiple spatial scales, enabling efficient encoding of large environments with nested place fields.
- *Egocentric Encoding Components*: Incorporate head-direction and velocity cells to enrich the model with self-motion cues, allowing path integration and orientation-aware recall.
- *Reinforcement Learning for Planning*: Integrate reinforcement learning modules that utilize place memories to optimize goal-directed trajectories and decision-making.
- *Information-Theoretic Capacity Analysis:* Quantify the model's storage and retrieval limits using entropy and mutual information measures, particularly under interference overload.
- *Online Learning with STDP:* Implement biologically plausible synaptic plasticity mechanisms, such as Spike-Timing Dependent Plasticity (STDP), to allow dynamic formation and pruning of place neurons in real-time.

All the Declarations and Statements

Author Contributions Statement

Arvind Kumar Jain: Idea of the research, conceptualization of the methodology, setting up of the algorithm and mathematical modeling framework; assisted in writing the manuscript and took part in its revision and redrafting.
Nupa Ram Chauhan: Revised and elaborated the manuscript and acted in the analytical review of the work.
Rahul Shrivastava: Co-designed and constructed the algorithm and mathematical model framework, as well as drafted the first version of the manuscript.
All Authors: Critically examined, analysed, and accepted the final draft of the manuscript.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflict of interest concerning the publication of this manuscript.

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Data Availability Statement

The datasets that were used and analysed in the current study are accessible to the related author on a reasonable requirement.

Ethical Declarations

The research is not using human subjects, human information and no animals hence ethical approval and informed consent was not needed in this research.

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Declaration of Generative AI in Scholarly Writing

No analytical and scientific interpretation was carried out using AI tools. The authors take the entire responsibility of the accuracy and integrity of the content.

Abbreviations

The following abbreviations are used in this manuscript:

PCN – Place Cell Neuron
GCN – Grid Cell Neuron
CSP – Cognitive Spatial Processing
SC – Spatial Cognition
PI – Path Integration
SN – Spatial Navigation
OL – Object Localization…

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