

SLAM ALGORITHMS BASED ON PLACE AND GRID CELLS MODELS

ADVANCED SEMINAR

submitted by
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A D V A N C E D S E M I N A R

SLAM Algorithms based on Place and Grid Cells Models

Problem description:

Robotic systems can perform well-defined tasks with exquisite precision at high speeds, but they have much more difficulty when operating in unstructured environments. Improved spatial navigation skills would increase autonomy of robots and would extend the range of tasks they could potentially address. Standard solutions integrate different sensory signals to localize a robots position with reference to external objects. However, such localization algorithms only work well in static surroundings. On the contrary, animals such as rats and humans effortlessly adapt to new environments and learn to orient themselves even in dynamical situations. With the discovery of place cells and grid cells [1], neuroscientists are starting to disclose the mechanisms underlying spatial navigation skills in animals. At the same time, engineers are trying to take inspiration from biology to make spatial navigation of mobile robots more flexible and robust [2, 3]. In this advanced study the student shall evaluate the state-of-the-art of Simultaneous Localization and Mapping (SLAM) algorithms that take into account the latest neurophysiological findings about place cells and grid cells.

In particular the student shall compare existing SLAM algorithms based on:

- biological realism
- computational load
- system performance

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Abstract

Regular SLAM algorithms suffer from several problems that make real world scenarios to an objective far from feasibility. They are only capable of performing in static environments with only few landmarks, and if used in real world environments soon exceed available hardware power.

However in everyday life we can observe many examples of systems performing SLAM pretty accurate without intensive computation. These systems are capable of solving navigational objectives in an effortless, robust and general approach. They can use it in marine, aerial or wide open landscapes and also urban environments are only a minor issue. These apparently powerful systems are called humans, birds, fish or in short animals. Millions of years of evolution formed an astonishing navigation system in the brain of mammals. Humans as well as other animals such as rodents have to face navigation problems in large, non-static environments with non-Gaussian noise and as we know we are quite capable of mastering such problems as well as rodents are. They fulfill the task of mapping the environment even better than we do.

Consequently researchers started to investigate brain functionalities of rodents and soon built a first model of those. Nowadays, there exist several models for spatial navigation and the purpose of this review is to compare each of them to regular SLAM approaches in terms of computational cost and performance. We also assess the biological realism of the models based on recently findings from neuroscience.

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Chapter 1

Introduction

Since the beginning of investigation of autonomous robots in the 70s, researchers have been confronted with the problem of how to localize a robot in an environment and building a map of it simultaneously. The task of localisation using all given sensors and a static map of the environment was relatively obvious and therefore solved early. The same happened to the problem of mapping where a robot is set in the world without a map but knowing its exact global location. The dilemma started when researchers tried to do both at the same time, meaning they set a robot in an unknown environment without knowing its global position. This case represents the typical **chicken or egg causality dilemma**: the the robot neither knows the map nor its location and needs to approximate both simultaneously. Research referred to this problem as **SLAM**, simultaneous localisation and mapping problem. This became a "fundamental challenge in robotics" Aulinas et al. [2008] and is crucial when building completely autonomous acting robots in different and prior unknown environments. Not only researchers of the field of robotics were eager to come up with an algorithm for that. Researchers from other fields, e.g. computer vision Engelhard et al. [2011] also started to search methods to solve the SLAM problem. Cheeseman et al. [1987] came up with a first approach, and most methods today are built on that.

Since then, the application fields of SLAM algorithms have grown and thereby the challenges as well. Whereas researchers focused on ground robots in artificial environments at the beginning they now expanded their investigations to aerial Kim and Sukkarieh [2003] and marine robots Aulinas et al. [2008] in order to compete with real world problems. With these new application areas researchers were also confronted with new problems. Using SLAM in marine environment means to face unstructured 3-dimensional sensor data with a lot of noise. None of the today's known algorithms are capable of fulfilling the task of localisation and mapping in such an environment. One new and promising approach to face such problems is the use of bio-inspired SLAM based on **Grid** and/or **Place Cells**. These cells were discovered in rodents' brain and are thought to be responsible for localisation in mammals Hafting et al. [2005]. In this way researchers try to imitate mammals'

brain functions to get a more stable, reliable and general system. SLAM algorithms are widely used in research, some scenarios are for instance:

- autonomous driving Levinson and Thrun [2010]
- autonomous flying Kim and Sukkarieh [2003]
- autonomous underwater localisation Williams et al. [2000]
- robot navigation Thrun and Liu [2005]

Each scenario has its own problems to face and can occur in several variations. Nevertheless the basic problem is the same and if an algorithm can be found which is robust, fast and reliable, it can be used in every scenario. We think that bio-inspired SLAM has the chance to become that algorithm.

This work is organized as follows :

- Chapter 1 : **Introduction** describes the SLAM problem and its drawbacks. Also it gives a small introduction to neuroscience.
- Chapter 2 : **Review of bio-based SLAM algorithms** explains some recent place/grid cell-inspired SLAM algorithms.
- Chapter 3 : **Conclusions** gives a summary and outlook for further work.

1.1 How do SLAM algorithms work

One key point in solving the SLAM problem is that the robot needs to be aware of its kinematic model. Leonard and Durrant-Whyte [1991] This is necessary to deduce its new location after moving from one point to another. However the kinematic model and therefore the calculated locations have some uncertainties. That means with every motion the estimation error of its position propagates. To correct and update this error the robot is equipped with a sensorial system, that makes measurements of the environment i.e. landmarks. Equipped with this sensor information and the kinematic model, the robot tries to deduce an appropriate representation for both of them and to find correlations between them. Given uncertainties (noise) in all the measurements and therefore the location as well as the map can only be approximated, a good solution was found in probabilistic techniques such as **Particle Filters**, **Kalman Filters** or **Expectation-Maximization (EM)**. These techniques were explicitly built to encounter noises of several sources. Aulinas et al. [2008]

As an example we are going to describe the principle of SLAM on the basis of **Kalman Filter** in the following.

Kalman Filter These algorithms usually consists of two separable consecutive steps. In the first one the algorithm tries to approximate the state of the system (e.g. the robot's position and orientation in a state-vector) given its motion model and the last executed action. Unfortunately this information includes some noises. The noises are represented by a covariance matrix of Gaussian distribution. It is important to note that the regular Kalman Filter is only able to process unimodal, white, Gaussian noise (for further information, see Julier and Uhlmann [1997]. Combining the state-vector and the covariance matrix we obtain an approximation of the state. If we only executed this step the noise and thereby the error would propagate over time. To avoid that, we introduce the *correction step*. With this second step we use measurements of landmarks or external cues to correct the covariance matrix accordingly. By now the reader should have identified the similarities to the previous described SLAM algorithms. Kalman Filters incorporate all of the presented measurements and provide an estimate of the state. This is exactly what a SLAM algorithm should be able to do. Maybeck [1982]

1.2 Drawbacks of regular SLAM

The research community around SLAM algorithms has made big progresses in the past. Algorithms that are used by today's robots are quite efficient and flexible, especially in structured (artificial landmarks given) and bounded regions of smaller size. However the common SLAM algorithms have still huge drawbacks that make real world scenarios to an objective that seems still far away from feasibility. If we want to use SLAM algorithms in large or even increasing areas, the computational cost would soon exceed available hardware power. All previous described scenarios use the assumption that the environment is static and doesn't change during execution. Based on that the robot is asked to perform an exploration step, in which it is mapping the environment. Not until then, the robot is able to perform its actual task, that can be: finding a reward or transport an object to a given area.

Nevertheless this is uncommon for real world environments since they are seldom static, actually they are changing very fast and often. Another drawback is that almost every SLAM algorithm assumes that the noise is gaussian, which cannot be guaranteed in real world scenarios.

Humans as well as other animals such as rodents have to face navigation problems in large, non-static environments with non-Gaussian noise. As we know from our own experience, we are more or less capable of mastering such problems as well as rodents are O'keefe and Nadel [1978]. This group of animals is even better performing localisation in a complete unknown environment, since it was shown in experiments that for example rats can navigate even without external cues. Moser et al. [2008] How they do this and what we can learn from that will be the discussion of following sections.

1.3 Place & Grid cells

In order to understand the working mechanism of cells responsible for navigation in rodents, we are first going to give a brief introduction to neuroscience and the nervous system.

In the last years neuroscience became an interdisciplinary science that involves many fields like medicine, biology, chemistry, engineering, computer science and lot more. It is the science of the nervous system, its construction and advancement. Neuroscience is promised to provide an explanation to the fundamental question of 'how our brain works?'. To answer this, most researchers agreed that a bottom-up approach is adequate and they are eager to find fitting models.

We are especially interested in these models in order to transfer the results to bio-inspired systems and get an overall surge of performance and ease of building those systems.

The single Neuron According to the bottom-up approach we first have a look at the smallest part of the nervous system: the neuron. The neuron is the basic and elementary entity of the nervous system in the body of mammals. It has several inputs (dendrites) and usually one output (axon), see figure 1.1

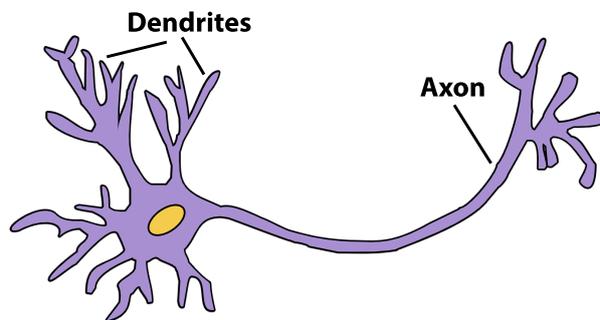


Figure 1.1: A typical neuron. Information flows from the dendrites to the axon.

As depicted, the dendrites are tiny branches connected with axons of other cells and ending near to the soma of the neuron. Starting from the soma, the axon in turn connects to other dendrites. Depending on the neuron, the length of axons varies between some micrometers up to one meter. Friede et al. [1984]

Imagine a cell, that receives a signal at its dendrites which can induce a change of the potential inside the cell. It is possible and common that several dendrites receive a signal at the same time. All those signals are summed up in the soma of the cell. If this sum exceeds a defined threshold the cell fires an action signal along its axon(s). At the very end of the axon where it is usually connected to some dendrites, molecules (so called neuro-transmitter) are released which excite the dendrite and may result in the next action potential.

Due to leaking in neurons membrane there are big uncertainties in this system that lead to a transmission probability of only 40% Tsodyks and Markram [1997]. We need to keep that in mind for later purpose.

Millions of single neurons are connected to form a biological neural network called brain. Thanks to early works of Angelo Mosso, who started with neuro-imaging Sandrone et al. [2012], we know that the brain can be divided in different areas that are responsible for different tasks. It was found out by O'keefe and Nadel [1978] that some parts of the hippocampus and its surroundings are involved in navigation. He called the neurons in this part **place cells**. The surrounding areas were assumed to feed the place cells with information necessary for this task. 2005 Hafting et al. [2005] proposed that **grid cells** in the medial entorhinal cortex (MEC) perform *path integration* and feed this information to the hippocampus and the place cells.

Path integration or the so called processes of *dead reckoning* is widely used in navigation and describes the calculation of the current location by incorporating a previously known position and the motion model (speed, orientation of itself).

In the following we will describe those two cell types and how they are artificially modelled.

Grid Cells One synapse upstream of the hippocampus locates the medial entorhinal cortex in where grid cells are located. These are "place selective cells that fire at multiple discrete and regularly spaced locations" Hafting et al. [2005]. This means that a grid cell stretches a field of firing locations over the environment. Typically those firing patterns are of hexagonal shape. Due to the variety of grid cells, they represent a map of the animals relative position. The different spacing of grid cells allows to uniquely associate combinations of them to locations in the environment. It is assumed that they derive this map from information of speed cells (providing information about the change in position) and head direction cells (providing information about the relative direction of the head), see Taube et al. [1990] for further information. With this behaviour grid cells perform path integration and as a consequence are almost independent of external cues. This can be seen in an experiment of Hafting et al. [2005] when a rat is placed in a maze without any external stimuli and the grid cells firing continuous. However it is believed that they regularly use such stimuli to correct their approximation of the location. In 1.2 we can identify the hexagonal firing pattern of a cell while a rodent moves in the environment.

Place Cells It was figured out early that place cells in the hippocampus build a neural map - cognitive map - of the environment by means of change in the firing patterns. However this is not an easy task and we describe this profoundly in the following. Every place cell correlates with one place field, that is an area in the environment where the firing activity of the corresponding cell increases rapidly. However if this area is not in vicinity, the place cell decreases its firing rate until it stops. O'keefe and Nadel [1978] found this principle while experimenting with rats, where they are placed in a maze and decoyed by food. Every time they move to

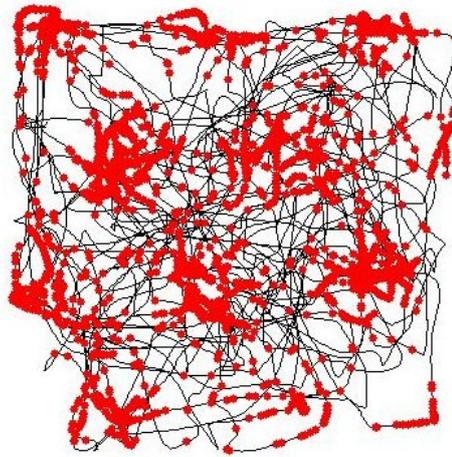


Figure 1.2: Black path is trajectory of rat. Red dots are firing locations of a grid cell. Moser et al. [2008]

a certain place a specific cell in the hippocampus becomes active, whereas in the neighbouring place a complete different cell shows activity. He concluded that place cells are allocentric and behave individualistically, this means that neighbouring cells are as likely to fire for neighbouring fields as they are for distant fields. Allocentric indicates that those cells are defined with respect to the outside world rather than the body.

In another experiment the authors place rats in a maze in complete darkness to prevent them from identifying landmarks or any external cue. The place cells do not work very accurately any more, what led to the conclusions that they are fed with information by visual cortex and rely thereby on external cues. However the cells still work and O’Keefe [1999] were convinced that place cells use also idiothetic information for navigation or to correct the position in the cognitive map. It was figured out later that this information is most likely to come from grid cells. Jeffery et al. [2004]

1.3.1 Models of Grid and Place Cells

In the last thirty years several approaches were made to describe the navigation system in rodents. In 1971, O’Keefe and Dostrovsky [1971] found the first representative of this system: the place cells. After that many researchers focused on the hippocampal region and its surroundings, especially the entorhinal cortex, since it was thought that most of the information that flows into the hippocampus origins in that area. In 2005, after 34 years of research, Hafting et al. [2005] came up with the approach of grid cells in the medial entorhinal cortex that form a grid like structure and are strongly connected to the hippocampus. We are now confident that these two areas are responsible for navigation in rodents and we refer to this as the hippocampal-entorhinal spatial representation system Moser et al. [2008]. In order

to understand this system we first describe **Attractor Neural Networks** and then continue with two major models, one for grid cells and one for place cells. After that we explain how those models are connected.

Attractor Neural Networks (ANN) We know that a biological network of neurons describes a dynamical system in which memory is referred to as stable states and in which input can change these stable states smoothly. To model and evaluate this behaviour and thus brain functions, Amit [1992] describes a structure called **Attractor Neural Network**.

ANN is a special designed neural network, whose neurons are connected recurrently and "whose time dynamics settle to a stable pattern" Wills et al. [2005]. Those patterns are in fact stable states within the state space of the system and are called *attractors*. When exciting such a network with an input - this can vary on the purpose, but we usually use sensorial inputs - the global firing pattern will form a stable state which is typically for the given input. This stable state is not a concrete output of the network, but rather a global firing pattern that can have stationary, cyclic or stochastic looking. Therefore we do not receive a direct output of the network. However we can receive a signal that reports that an attractor has been reached. Subsequently we can identify this attractor and interpret it.

Usually several inputs are related to the same attractor. The ANN can form different types of attractors: point, continuous, plane, or competitive. Using point attractors, the network has only a few stable states that are not directly connected to each other. Whereas if continuous attractors are used, the network has infinity point attractors that are condensed to a line in the state space and we can move on this line smoothly. These attractors are the best structure to describe cognitive processes for what we know so far Amit [1992]. However some models use competitive attractors that are described briefly in the following.

Competitive attractor networks work similarly to continuous attractor networks but with the feature that the neurons in this network are arranged so that they excite other neurons nearby and inhibit those in a bigger distance. This principle leads to the so called **activity packets** Samsonovich and McNaughton [1997]. These are regions where a conglomeration of neurons are active. Exciting neurons in vicinity to such a packet moves the whole activity in direction towards it, whereas exciting neurons far away establishes a new activity packet. For example, head direction and place cells are often represented with that.

ANNs are also known to be capable of performing pattern completion and pattern separation. As we will show later this comes in handy for modelling place-/grid-cells. To use ANNs in an appropriate way, we need to be able to control the attractors, that means move them to desired locations in the state space or even change the type of attractor from point to continuous. For a comprehensive understanding we recommend Amit [1992].

Theoretical Models of Grid Cells As suggested by Hafting et al. [2005], grid cells in the MEC develop a map that supports navigation. How this map is constructed and maintained is still a topic of current research.

However it is unanimously agreed that external stimuli is used to initialize the grid map, subsequently idiothetic information is processed to change the grid. Therefore path integration is seen as the major data source for the grid map. We want to give a brief overview of two promising models for grid cells, the **interference model** and the **continuous attractor model**.

The former one was proposed by O'Keefe and Recce [1993]. According to this model the idiothetic information is retrieved from a single cell level and is associated to the phase precession of grid cells. This precession describes the relation of spike timing in grid cells to the theta phase at the time a rat is moving through a firing field. When modelling those phase precession, O'Keefe and Recce [1993] uses two oscillatory signals retrieved from the theta rhythm that slightly differs proportional to the speed of the rats movement. With this interference pattern it is possible to approximate the speed of the rat, integrate it and consequently obtain its position along the track. In Burgess et al. [2007], they extend the model by adding another dimension to the interference in a way that a map can be established with a differ of 60° in directions, that results in the typical hexagonal grid map.

The latter model uses ANN with continuous attractors. For it was shown by Hafting et al. [2005] that in the grid phase exists no topographically structure of neighbouring grid cells, the approach of McNaughton et al. [2006] describes a model where a topographical arranged network only exists in early stages of the postnatal development. This serves then as a tutor to learn randomly distributed Hebbian connections among different packages of grid cells. As a result of this training, continuous attractors establish in the network. After the training is completed the topography starts to vanish. In order to represent a complete grid map, the model proposes that a layer of other neurons, whose firing patterns depend of external stimuli, connects to the grid cells. By receiving signals from one firing grid cell, neurons in this layer start to send signals to other grid cells representing the next location along the trajectory. This depends obviously on the speed and direction of the rat, hence this layer consists of head-direction and speed cells Samsonovich and McNaughton [1997]. We can transfer this principle to the continuous attractor network, such that the layer of head and speed cells excites the attractor on the continuous attractor line according to the speed and direction.

Theoretical Model of Place Cells Researchers have studied the hippocampus since O'Keefe and Dostrovsky [1971] proposed that it has a major influence on the navigation task of mammals. They developed several models of how the hippocampus may represent navigational information. An emphasis lays on place cells since it is thought that they have a major contribution to this task. The reader may find an incomplete list of proposed models in the following:

- "Spatial cognition and neuro-mimetic navigation: a model of hippocampal place cell activity" - Arleo and Gerstner [2000]
- "Cognitive maps beyond the hippocampus" - Redish and Touretzky [1997]
- "Biologically-inspired robot spatial cognition based on rat neurophysiological studies" - Barrera and Weitzenfeld [2008]
- "Robustness of visual place cells in dynamic indoor and outdoor environment" - Giovannangeli et al. [2006]
- "Robust self-localisation and navigation based on hippocampal place cells" - Strösslín et al. [2005]

However we only describe the model of Milford and Wyeth [2003] in the following. The network of the model is based on a competitive ANN whose activity packets represent the pose of the robot. The system is built on the assumption that the network of place cells is fed with visual sensory input, idiothetic information and signals from head-direction cells. All those inputs excite the network to establish one or more activity packets. New input data may smoothly shift those packets in desired directions so that they represent the current pose correctly. While smoothly shifting the activity packets along the continuous attractor, the trajectory of the robot can be derived and a map including external landmarks can be constructed. In this model the head cells provide information about orientation, whereas idiothetic information determines the location. Visual input is to "calibrate the robot's idea of pose" Milford and Wyeth [2003]. This means that for every scene the robot stores the corresponding pose. If it then encounters the same scene again, it can compare the pose of both and correct its pose idea accordingly.

1.4 Bio-Inspired SLAM algorithms

The regular SLAM algorithms that are described in section 1.1 suffer from several problems. Besides the restriction of performing only in static environments, the exceeding computational cost is another major objective.

However in everyday life we can observe many systems performing SLAM pretty accurate without intensive computation. These systems are capable of solving navigational objectives in an effortless, robust and general approach. They can use it in marine, aerial or wide open landscapes and also urban environments are considered a minor issue.

The apparently powerful systems are called humans, birds, fish or shortly animals. Million years of evolution have formed a navigation system in the brain of mammals, researcher can nowadays barely think about. What we know by now is that if

we really want to establish a model of the brain's navigation system, we have to continuously investigate the functionality of several types of cells (e.g. head-direction cells Taube et al. [1990], border cells Solstad et al. [2008], grid cells Hafting et al. [2005], place cells O'Keefe and Dostrovsky [1971]). Of course this list is not complete and there might be other cells that are responsible for navigation but have not yet been discovered.

There are some obvious advantages in using bio-inspired SLAM algorithms: First of all they are capable of real time mapping and are much cheaper in computation than for example EM-algorithms, especially if one is interested in fine maps. Furthermore, vision (i.e. regular camera) can be used to retrieve information necessary to build a map. This can be crucial since camera systems are typically cheaper than laser-based systems like LIDAR, furthermore they give us access to contextual information about the landscape.

However to completely integrate those types of algorithms in robotics we have still a long way to go. Actually, in terms of scientific time scale, we have just started investigating the brain functions responsible for spatial representation. Therefore most of the works in the field of bio-inspired SLAM are focused on how precise the systems model brain functionality and not how well it performs in an actual environment Sünderhauf and Protzel [2010]. Nevertheless some researchers have already started transferring those models to robotics and achieved astonishing results compared to regular SLAM algorithms(e.g. RatSLAM accomplished to map 66 km of urban road in real time Milford and Wyeth [2008]).

In the following we briefly describe most important models and compare them to regular SLAM approaches with the emphasis on biological realism, computational load and system performance.

Chapter 2

Review of grid/place cell-based SLAM algorithms

In this section we introduce several models of bio-inspired SLAM algorithms that are based on grid and/or place cells. For every model we briefly describe its mechanisms and then analyse it in terms of biological realism. Moreover we compare them to standard SLAM approaches (i.e. (Extended-) Kalman Filter and Particle Filter) in terms of computational load and system performance. In order to do this we first describe the performance of these regular SLAM algorithms and their drawbacks.

Kalman Filter & Extended Kalman Filter (EKF) The regular Kalman Filter is based on Bayesian Filters and represents an unimodal Gaussian distribution that estimates the state of the vehicle. Together with a covariance matrix, that estimates the error of the system, they build the core of this SLAM algorithm. It is assumed that the internal functions (state transition and measurement) are linear and the confronted noises are white Gaussian noises. Due to these restrictions the filter is not capable of performing in real-time environments.

To conquer real time requirements the **Extended Kalman Filter** was introduced. It can also handle non-linear functions by means of approximating them by linear functions. However this leads to a drastic performance loss, since every new measurement influences all the parameters of the Gaussian distribution for that they need to be recalculated Aulinas et al. [2008].

The performance of the Kalman Filters also suffers when increasing the number of landmarks. With every new added landmark all previous landmark estimations are affected. Therefore we need additional computational resources to maintain real-time processing. This can be difficult or even infeasible for long term task, where to robot faces a huge amount of landmarks. It is shown in Guivant and Nebot [2001] that the cost for maintaining a good estimate of the pose is $\mathcal{O}(N^2)$, where N is the number of landmarks. The overall computational cost is $\mathcal{O}(N^3)$

Particle Filter In contrast to the algorithms above the **Particle Filter** is capable of processing non-linear sensor data with non-Gaussian noise. This would make it to a perfect candidate to solve the SLAM problem in an adequate way. However its computational complexity also increases drastically when new landmarks are added. This makes it not suitable for real-time problems. Therefore no serious approach exists using only Particle Filters for SLAM. The most common and successful approaches like FastSLAM Montemerlo and Thrun [2007] uses Particle Filters for localisation and other techniques for mapping. However with this constellation they achieved satisfying results. They use the benchmark of the Victoria Park data set to test their vehicle. It has a path length of 3.5 km. In this test FastSLAM even outperforms EKF in memory usage and computational time Aulinas et al. [2008].

2.1 RatSLAM

The first model we review is **RatSLAM**. It is the oldest bio-inspired SLAM algorithm but was development over time so that several versions have been published Milford and Wyeth [2003, 2008, 2010]. Many institutes and researchers use this platform to investigate the possibility of bio-inspired algorithms or brain functionalities Glover et al. [2010]; Tian et al. [2013]; Wiles et al. [2012]. The complete model is based on laboratory experiments with rats where the neural activity of the hippocampus and its surroundings were recorded. O’keefe and Nadel [1978]. RatSLAM started using a model of the early discovered place and head direction cells Milford and Wyeth [2003]. In 2010 Milford and Wyeth [2010] published a new version of RatSLAM that included a model of the newly discovered grid cells. Since it is the most recent approach we describe this version of RatSLAM.

Architecture The continuous attractor model builds the basis for the complete architecture, see 2.1. The network is formed by a cluster of so called "pose cells", with inhibitory or excitatory connections. Activity in this cluster is encapsulated to activity packets, that represent the position and orientation of the robot (similar to grid cells). If the robot moves, the dynamic of the network changes due to new input information and therefore updates the pose estimation (red arrows). It is possible that more than one activity packet develops in the network. They represent different beliefs of the robot’s location. The probability for one location can be calculated by the firing rate of active cells in that packet. The model also consists of an episodic spatial representation that imitates the functions of the hippocampus (i.e. place and head-direction cells). This representation is used to correct the estimate of the CAN (orange arrows). Excitatory connections from internal place cells to pose cells help to correct the path integration error by means that a place cell recognizes previously seen landmarks and consequently sends a signal to corresponding cells in the CAN. If the signal is strong enough the activity packet shifts into this direction or if necessary the complete internal estimation recalibrates (left activity packet). The

spatial representation in RatSLAM is partly topographical and partly grid based.

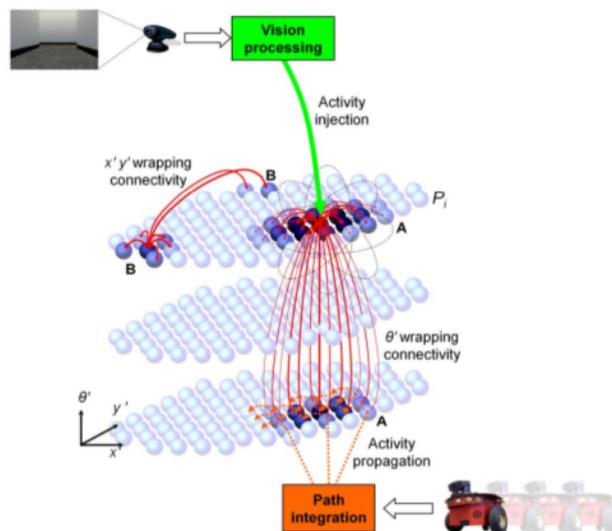


Figure 2.1: The three layers of RatSLAM architecture. Dark blue dots in the upper layer form the activity packet. Red arrows represent excitatory connections. Orange arrows show the update of the estimated pose during path integration Milford and Wyeth [2010]

Biological realism Most of the discovered cells that are thought to be responsible for navigation in rats are incorporated by the RatSLAM approach. Like Grid cells in a rat's brain the agent is endowed with a multiple beliefs representation system. Like a biological grid cell, it uses visual as well as idiothetic information to estimate the pose and throughout that constructs a grid like map. The RatSLAM approach incorporates models of head-direction, place and grid cells in an adequate manner. The place cells and their response to external cues conduce to correct the pose estimated by the CAN. Overall we can conclude that Milford and Wyeth [2010] tries to reflect the biological system as explicitly as possible. However there are some drawbacks. The connections between the grid cells and place cells are predefined and cannot be altered during execution. This is biologically not correct since we know from Giocomo et al. [2011] that place and grid cells strengthen their connections via Hebbian Learning. Another point where the model differs from biology is the predefined number of cells. That means it is not possible to add new cells if the robot encounters a new environment. Old cells can be recruited to different environments, though. It was shown in Hafting et al. [2005] that the grid structure and firing behaviour maintained after removing all external cues, that is complete darkness, for over 30 min. In Milford and Wyeth [2010] they tried the same with the robot however with little success only. The estimation error started to increase constantly

right after all cues have been removed.

Performance & computational cost With the experiment in Milford and Wyeth [2010], the authors show that the RatSLAM system is able of moving autonomously in a dynamic environment. Over a period of 37 hours the robot travels a distance of 40 km and performs its task (deliver packages to predefined goals) with an accuracy of over 98%. It learns the environment online while performing. Even after replacing objects in the environment the robot is able to perform its task. Since this experiment is not a common benchmark test, we can only estimate the performance of regular SLAM algorithms. SLAM with extended Kalman Filter could not achieve this performance due to its difficulties with increasing numbers of landmarks would . At the end the RatSLAM robot has learned over 2500 experiences what would exceed the possibilities of EKF SLAM. In the Victoria Park benchmark FastSLAM proves to be able to perform in an outdoor environment over a length of 3.5 km, therefore it could be able achieve an equivalent performance as RatSLAM in the office bench mark test. However as we know no similar test has been performed so far.

2.2 Model of T. Strösslin & D. Sheynikhovich

This model was first published in 2000 Arleo and Gerstner [2000] and further developed (Chavarriaga et al. [2005a,b]) until 2008 when the project ended. The last publication is from 2009 Sheynikhovich et al. [2009] where they added the recently discovered grid cells to their model. The goal of the project was to investigate spatial representation, goal-oriented navigation and the underlying learning rules. They constructed a model of the rat's navigation structures in the brain and implemented that on a Khepera Robot for test purpose. The major emphasis of the project is on the biological realism and not on the performance of the system.

Architecture The precisely modelled architecture of the system is directly transferred from recent findings in the field of biology and can be separated in several tasks. To separate the different tasks of the model, Strösslin et al. [2005] constructs populations of 'rate-coded neurons' and divides them into input-, intermediate- and an output-layer. Each can be divided into several modules that are responsible for different tasks but are highly interconnected. The input layer processes all kind of input data (basically visual images and odometric information). The layer consists of different cell types like step- and rotation cells combined in the local view module. For our purpose it is sufficient to remember that rotation cells are responsible for determining the heading regardless of the position, whereas the step cells do it vice versa. They are encapsulated to the visual cell (VC) module where they process data of the visual input and feed it forward to the intermediate layer.

Idiothetic and visual information is combined in the head direction (HD) module, that is one of the most important modules of this model. The HD module feeds information about the relative head direction to the path integrator (PI) module, that implements the location memory. This module also receives visual information about the location from the allothetic place code (APC) module that corresponds to the lateral entorhinal cortex. It processes this information to perform path integration. Using information about path integration from the PI module and allothetic information from the APC module the combined place code (CPC) module determines the pose of the agent. It represents the hippocampus with its corresponding place cells. The information of the CPC module enables to generate a map and perform navigation on this map. For a better understanding we depicted the architecture in 2.2

The main purpose of the later published model Sheynikhovich et al. [2009] is to investigate the behaviour of grid cells. It alters in the way that the path integrator module is replaced by the grid cell (GC) module, that models the medial entorhinal cortex and implements a biology-like path integration. It forms a continuous attractor network, whose activity packet represents the rats position. This position is approximated using speed and direction information. As in other models the activity packet is shifted according to the input data. To correct the position the module also receives visual information about the location from the visual cell module. However they neglect the head direction module and feed the grid cells directly with self-motion cues.

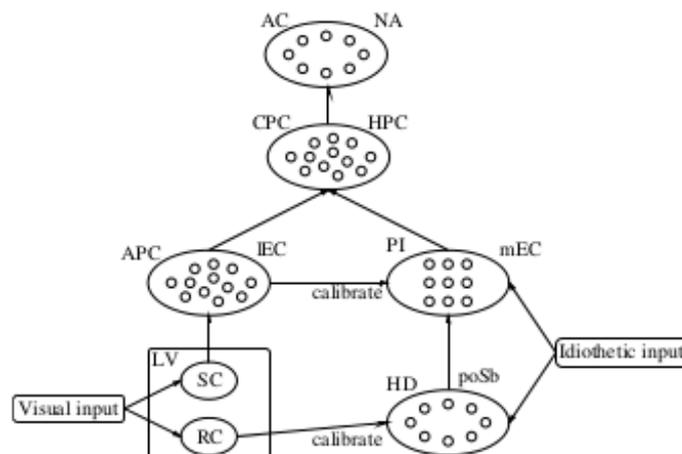


Figure 2.2: Structure of the modules. Information flows from the bottom upwards. Strösslin et al. [2005]

Biological Realism The ambition of Strösslin et al. [2005] was to build a precise model of the navigation functions of the brain. Thereby they use 'rate-coded'

neurons in their system to encode signals. Such neurons are thought to represent the biological ones the best Izhikevich et al. [2003]. These neurons are synchronized by a global clock signal in the system that corresponds to the theta rhythm detected in areas of the hippocampus in rats. It is assumed that with this rhythm the hippocampus can synchronize the data processing throughout its different areas. This is an important feature for information processing in general and especially for navigation task, since it uses time dependent information. All parts of the rodent navigational system, that were known when Strösslin et al. published their system, are modelled and transferred to the approach in an adequate manner. They try to rebuild a precise model of the spatial representation system of rodents what can be clearly seen in the architecture paragraph. There we described each model system and the counterpart in the rodent brain.

Since the discovery of grid cells in the medial entorhinal cortex was still ahead, the approach of Strösslin et al. [2005] misses this kind of cell. However they imagined correctly that the navigation system needs to perform path integration somehow, therefore they implemented a path integration module, in which each neuron fires at "a predefined preferred position [...] such that a square region of space is uniformly covered" Strösslin et al. [2005]. Coming with the discovery of Hafting et al. [2005], they changed their model Sheynikhovich et al. [2009] and used grid cells instead of the non-biological path integration module.

One major drawback is that the first presented model misses grid cells and the second - that finally implements grid cells - misses head direction cells. If both were implemented in on approach it could be a very pinpoint model of the brain's navigation system.

Performance & computational cost When talking about performance and computational cost we will always state which model we talk about, since we actually introduced two different ones.

It is shown in Sheynikhovich et al. [2009] that the virtual rat, endowed with the grid cell model, performs effortlessly in the water maze benchmark environment. It is also able to re-orientate itself again after being set out randomly in a before explored environment with false location and orientation. The orientation error for this task is similar to a real rat. A problem occurs when landmarks are being removed and the rat needs to determine whether it is looking in one direction or the direction 180° shifted. It determines the orientation confidently but is actually wrong with that. This so called rotational error in visual cells leads to a wrong estimation of the pose. This also happens to rat that rely on landmarks, though.

The experiments in Strösslin et al. [2005] are performed under a previous exploration stage, what is unwanted in real world experiments. However the agent needs 1000 time steps to facilitate the building of a cognitive map of the environment. Furthermore the agent performs in real world environments (77cmx77cm) afterwards and is very capable of that. Its performance is accurate, while moving 200 time steps it produces a rotational error less than 1° and a location error less than 1 cm.

Unfortunately the main purpose of the system is to investigate the brain functions and not to mess with existing SLAM systems. However we can have an attempt to approximate the performance of the system. The fact that the system’s emphasis is on biological realism could make it very robust to noise and flexible compared to EKF-SLAM and most likely FastSLAM as well, since the underlying (attractor) neural networks are capable of processing every kind of noise (non-Gaussian). Given that RatSLAM (see 2.1) is also based on ANNs and it performs very well in real world environments, we could expect that the model of Strösslin et al could outperform EKF-SLAM in real world scenarios as well. However the authors mention real time experiments only in Strösslin et al. [2005].

2.3 Spatial Cognition Model of Barrera & Weitzenfeld

The model presented in Barrera and Weitzenfeld [2008], builds a topological-metric map of the environment during exploration stage, using idiothetic and visual information. They investigate not only the spatial learning processes of a rat’s brain but also how reinforcement learning is realized. For our purpose it is enough to consider the spatial representation system of the architecture and analyse this without considering the actor-critic modules. In figure 2.3 the complete system is depicted. However we only describe the modules in the red circle.

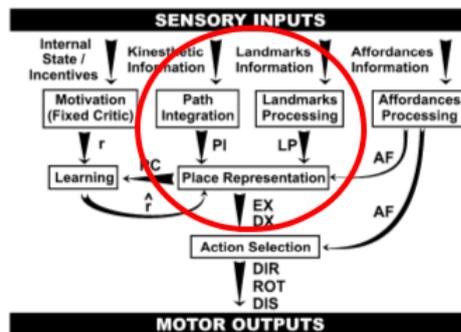


Figure 2.3: Our main emphasis lays in the path integration, landmark processing and place representation module (red circle). Information flows from the top downwards Barrera and Weitzenfeld [2008]

Architecture The spatial representation model is composed of two main modules, the landmarks processing and the path integration module. The latter one is divided into a dynamic remapping layer (DRL) and a so called path integration feature detector layer (PIFDL). The DRL uses a two dimensional array of neurons to represent the position where the agent started its movements and the path travelled

so far, according to idiothetic information. The name of the module originates in its capability of remapping the actual state of the agent according to new self motion cues. It is connected to the PIFDL via a weight matrix, where the actual learning takes place (Hebbian learning). When DRL receives a previous seen activation pattern, the weight matrix is trained in a way that the PIFDL shows the same activation pattern as before. Whereas these patterns represent kinesthetic information (in this way the PIFDL can be seen as grid cells and the path integration module as the medial entorhinal cortex). The update function of the matrix and the anchor position uses a Gaussian distribution Barrera and Weitzenfeld [2008].

The landmark recognition process takes place in the landmark processing module and works equally to the path integration module. The landmark perceptual schema (LPS), that represents distance and orientation of the landmark relative to the agent is connected to the landmark feature detector layer (LFDL) via a weight matrix. The learning processing correlates to the one of the path integration module.

The information of both is fed to the place representation module where it is integrated and used to activate a place cell layer (PCL). To integrate this information again a weight matrix is used that connects 50% of the PIFDL and 50% of the LFDL neurons to the PCL (this can be changed). The PCL activation pattern is learnt by an array of place cells that are activated only by an aggregation of activity in the PCL.

Biological Realism Like in Strösslin et al. [2005] the authors main emphasis lies on the exact representation of biological systems. Idiothetic information is processed in the path integration module that can be seen as the medial entorhinal cortex. However in this model it only receives kinesthetic information, whereas the landmark processing module only receives visual input. As far as we know from Hafting et al. [2005] the MEC also uses visual information of landmarks to correct its path integration estimation. This is obviously not the case in the model of Strösslin et al.

The weight matrices are a good choice to represent Hebbian learning, since they enable to adapt the proportion of connections from one layer to another whenever a new finding in neuroscience is made Barrera and Weitzenfeld [2008].

The place cell and the world graph layer in the place representation module models the hippocampus where allothetic and idiothetic information is collected, combined and further processed to build a topological map.

Usually the actor critic systems for goal navigation is not part of our study. However in this case it is worth to mention, since the architecture also uses a bio-inspired model for that. The hypothalamus is thought to act as an actor critic network and to evolve motivation Risold et al. [1997]. This is represented with the modules of internal incentives and affordance. This enables researchers not only to investigate the spatial navigation system of the rat but also the goal motivation scheme.

Performance & computational cost The executed experiments of Barrera and Weitzenfeld [2008] in different mazes (T-maze, 8-arm maze, multiple T-maze) show that the agents behaviour is similar to the one recorded on rats McNaughton et al. [1983]. After an exploration phase the agent is able to navigate autonomously in the environment. It executes goal-directed tasks correctly and shows thereby the ability of learning and unlearning goals.

When the agent is put in an environment without any landmarks, without any external cue indeed, it shows a remarkable ability to still navigate in this absence of cues. This could be the result of the computational expensive landmark processing module. It is mentioned by the authors that they need to improve this module. In fact the authors state that the system needs improvements in the perceptual system, that it should be placed in more challenging environments and that the computational load should be determined before it can be compared to other SLAM systems or put in a "performance scale" Barrera and Weitzenfeld [2008].

However we can try to estimate the performance. The weight matrices described in the architecture paragraph are eventually the bottleneck of the system, since they correspond to the size of the environment. They represent the complete environment as a grid map and therefore need to grow in the magnitude of the environment. The fact that every new encountered landmark needs a specific layer of neurons contributes to this assumption.

When comparing this spatial representation model with regular SLAM approaches the only indication we have is that it uses an assumption of Gaussian noise distribution for path integration and landmark processing. This could lead to a reduced flexibility and robustness compared to EKF-SLAM or FastSLAM.

2.4 Goal Directed Spatial Navigation model of Erdem & Hasselmo

A special feature in the model of Erdem and Hasselmo [2012] is the use of forward trajectory planning. They adopt head direction, persistent spiking, place and grid cells to simulate several trajectories that lead to the desired location of the rat. These cells are also involved in the mapping and localisation process of the model. Using only information about the velocity and direction of the virtual rat the authors are able to successfully perform several navigation tasks such as Morris water maze, Tolman shortcut maze or Hairpin shortcut maze.

Architecture The architecture is based on the phase interference model and uses head direction, persistent spiking, grid and place cells (where the order of information processing corresponds to the occurrence of the cells). Head direction cells generate velocity modulated spiking patterns. These patterns change their firing rate in relation to the relative direction and speed of the agent. This means they encode the direction of movement. This information is fed to persistent spiking

neurons, where it is aggregated and provided as an input signal to the grid cell layer. For a profound understanding of how persistent spiking neurons work we recommend Hasselmo and Brandon [2008]. Each grid cell is connected to several populations of persistent spiking neurons. Only if all connected neurons fire simultaneously the grid cell produces an activity pattern. The place cells aggregate these activity patterns of the presynaptic grid cells and shift their own activity pattern along the look-ahead trajectory. This facilitates the place cell layer to develop a spatial topology map of the environment.

When the agent is placed in a novel environment a specific grid cell population, that represents the starting point, is active. While moving in the environment new grid cells are recruited by tracing the path and translating the information of the previous grid cell according to self motion cues. The recruitment of place cells however is different and not so naive. We need to introduce a new place cell every time the agent encounters a place that is not represented by a place cell so far. Since this happens continuously at the exploration stage we need to define a recruitment rate. The information for one place cell is processed by exactly three unique grid cells, from which each in turn receives its input from three persistent spiking neurons. These neurons are fed with data from three head direction cells as depicted in 2.4

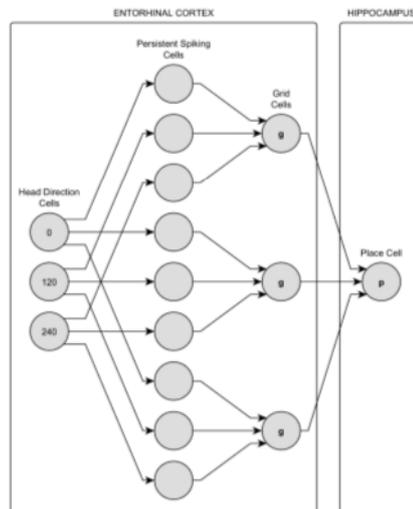


Figure 2.4: Every head direction cell is connected to three persistent spiking cells. Three of them in turn are connected to one of three grid cells and those grid cells are connected to one place cell. The information flows from the left to the right Erdem and Hasselmo [2012]

Biological Realism The model emphasizes the realization of trajectory planning throughout the look-ahead probes. Using this procedure we can get an insight in how a rodent’s brain chooses the next move to find the shortest path to a goal. They

use a phase interference model to drive the grid cell to update their spiking pattern to a specific direction and utilize them as a path integrator, what resembles the behaviour of real grid cells. The grid cell patterns allow then place cells to update their firing along the probed look-ahead trajectory what can also be seen in "the forward replay during waking seen in place cell recordings" Hasselmo and Brandon [2008]. When moving in a dynamic environment the rodent is able to recalculate its trajectory. This is a necessary feature since it can happen that the previous calculated trajectory is wrong at some point and a new one needs to be found. This is realized in the model by recalculating the trajectory as soon as the agent travelled 4 cm.

Being very accurate in modelling biological functions the model neglect the existence of different inputs. The only input that is used are self-motion cues. No visual input is provided at all.

As seen in previous models, the goal directed spatial navigation model also needs to explore the environment at the beginning, but keeps updating the map while it is in the testing stage. This reflects the behaviour of a rodent in more detail than the other models.

Performance & computational cost The proposed model is tested in several environments. As a standard benchmark test for bio-inspired models the water maze is used. The agent is able to successfully find the goal under ideal conditions Hasselmo and Brandon [2008]. However when noise is added to the head-direction cells, the agent's succeed rate decreases drastically. This illustrates a major drawback of the model, since EKF-SLAM and FastSLAM are both capable of handling noises. They have not been tested in the water maze, though.

A main result of the conducted experiments is that the agent finds shortcuts in the environment and can cross unseen regions. This results in a faster goal approaching and therefore in a increasing performance. To our best knowledge there is no experiment where the possibility of finding shortcuts is tested in EKF-SLAM or FASTSLAM, therefore we can only estimate their performance. Since both algorithms build a topological map of the environment, it should be possible for both to use common path finding strategies and thus find shortcuts also in before unseen regions.

What makes the approach of Hasselmo and Brandon [2008] cheaper in computational cost is the fact that the look ahead trajectory planning is executed by activating the head cells and "a progressive shift in spiking phase in the grid cell model" Hasselmo and Brandon [2008]. This means that the next movement is calculated by forward sampling over all possible trajectories in the environment. The performance exploration of the environment is also increased by means of this technique.

Two factors have a crucial influence on the overall performance of the system: the rate of calculating forward look-ahead probes and the rate of place cell recruitment. The latter one is a major objective in the current research of the authors. Several ideas exist to encounter the first one, for example correlate the calculation of probes

with the environment: If the agent encounters an unseen region the rate increases otherwise it decreases until a lower bound. However to fulfill tasks in a real time environment research has to be done before.

Chapter 3

Conclusions

In the previous chapter we introduced several bio-inspired SLAM algorithms used for spatial navigation. These algorithms are based on neuroscientific models of different kind of cells. For comparison reasons we also introduced regular SLAM approaches like FastSLAM and EKF-SLAM, that are the most frequent and promising algorithms. Compared to them bio-inspired models show the potential to push the limits of SLAM based robots to a new level. They are capable of acting in big, unstructured and dynamic environments. Especially the ability of acting in dynamic environments makes bio-inspired models interesting for researchers, since regular approaches are almost impotent of doing that. With this feature they don not need a previous exploration stage any more and therefore are able to deal with real world problems.

Another advantage of bio-inspired models is that they implicitly use the same sensor processing as we humans do. This makes them cost efficient since visual cameras are well developed and cheap, whereas regular SLAM approaches often need expensive sensors like LIDAR. With visual sensors the robot also receives contextual information that can be used to infer about the environment.

Bio-inspired navigation models are not only more powerful than regular ones, they also contribute to our understanding of how the spatial representation in the brain works. Neuroscientists can measure the activity of a single neuron without great effort, however to investigate a brain region or function it would be necessary to measure the activities of thousands or even millions of neurons at the same time. This is currently impossible. Therefore neuroscientists are usually forced to measure a huge bunch of cells instead, what might lead to imprecise measurements and thus to false conclusions. If such regions are modelled artificially researchers can investigate them profoundly (neuron by neuron) and adapt their Conclusion about the examined brain functions that in turn leads to more precise models. Until now, it still remains unclear whether the brain develops a truly map-like and metrical correct representation of the environment or a vague more topological representation Barrera and Weitzenfeld [2008]. Since the introduced models differ in their approaches and structures research is underway to answer this question soon.

To accelerate the development of bio-inspired algorithms and gain more attention for their field, researchers should introduce a common benchmark test (e.g. Victoria Park benchmark Montemerlo and Thrun [2007]) that can be used to compare normal SLAM approaches to bio-inspired ones so that they can show the possibilities and advantages of them. Future research will close the gap between the spatial representation in autonomous systems and the representation in the MEC or hippocampus and thus enables us to build truly intelligent and autonomous robots that can act independently in unknown environments with less computational effort than SLAM algorithms have nowadays.

Humans as they are trying to find a path in an environment tend to feel when they have chosen a wrong direction. Whether and how a rat is able to do that could be another interesting question for future work.

Bio-inspired models offer a huge opportunity not only for the field of robotic but also in other research areas. However we always need to keep in mind that nature and thereby the evolutionary process has developed optimized methods and not optimal ones.

SLAM simultaneous localization and mapping

MEC medial entorhinal cortex

ANN attractor neural network

CAN continuous attractor network

LIDAR light detection and ranging

EKF extended Kalman Filter

VC visual cell

HD head direction

PI path integrator

APC allothetic place code

CPC combined place code

GC grid cell

DRL dynamic remapping layer

PIFDL path integration feature detection layer

LPS landmark perceptual schema

LFDL landmark feature detection layer

PCL place cell layer

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