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Chapter

Role of the Hippocampal Formation in Navigation from a Simultaneous Location and Mapping Perspective

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Abstract

The research of the brain has led to many questions, with most of them still not having a definitive answer. One of those questions is about how the brain acts when we navigate a new space. Inside the Temporal Lobe's Hippocampal structure, specific types of neurons and neuronal structures are responsible to identify spatial elements. To recognize spaces, these cells require data, which is obtained from the subject's senses. It is important to understand how these features are captured, processed, encoded and how the Hippocampus, and its neighboring elements, use the information to help in the navigation and mapping of a place. A specific type of neurons seems to support an animals location and spatial mapping, on other areas of research, discrete global grid systems are used to increase the independence of the autonomous vehicles, allowing the indexing of assets across the globe by partitioning the earth into grids that take into account the heterogeneity of the scales of the associated geospatial data. In this context, the main objective of this chapter is to make an analysis about the biological and technical aspects of navigation by establishing a bridge between the Hippocampus and Simultaneous Localization and Mapping (SLAM) methods.

Keywords: hippocampus, entorhinal cortex, SLAM, Grid Cells, robotics, spatial navigation, sensory processing

1. Introduction

The brain is a complex structure that somehow is able to make associations between different inputs from different areas. The information used for these associations results from the body senses, including the Visual, Olfactory, Auditory, Gustatory, Somatosensory and Self-Motion. This process is done without labeling the data entries. It is believed that most of these associations occur in the Hippocampus. The Hippocampus is a Temporal Lobe element and its functions are related to the creation of new memories [1], control of emotions [2] and spatial navigation [3]. There are several conceptual models about the functioning of the Hippocampus, one of them is the memory index theory where the Hippocampus plays the role in creating an index of neocortical pattern associations related to a context or situation [4]. Since the discovery of the Place Cells in the Hippocampus and their connection of spatial

processing elements of the Entorhinal Cortex (EC), it is believed that the Hippocampus can identify places and the contextual situations associated with those areas [5]. The information about the state of the senses enters the Hippocampus through the EC, that in turn receives inputs directly from the senses or through supporting elements like the Parahippocampal gyrus and Peririhinal Cortex [5]. The EC area is divided into two different parts, the Lateral Entorhinal Cortex (LEC), that is responsible for the handling of data not related with spatial navigation, and the Medial Entorhinal Cortex (MEC). The Grid Cells are a set of cells located in the MEC, with the assumed ability to identify positions inside a spatial environment. Such behavior is possible due to its hexagonal firing pattern [5]. Also, according with [6], the Grid Cells are organized in a multi layer format. Such organization allows those cells to give the necessary precision in the determination of a spatial position. The information produced by the Grid Cells is sent to the Hippocampus, specially affecting the Place Cells, where the data is used to encode and to create representations of the known places, by adapting to new environmental changes with a mechanism called global remapping [7]. Is important to understand how the senses gather information from the environment and how such data is processed, because a coherent understanding of the space depends in the acquisition of such information. The Vision, the Audition and other senses are crucial for the navigational calculations because those elements are used to determine the environmental landmarks, essential in the creation of a mental map [7]. In this scope, the purpose of this book chapter is to describe the work done until now in this area, focusing in how the obtained sensory information can be used for spatial navigation and how the Hippocampal Formation elements are used to solve navigational problems. This book chapter is composed of five sections. The first section, contains an analysis about the importance of navigation and how these questions are handled with the available computational resources, followed by a second and a third sections about how the brain elements gather, interpret, prepare and encode the sensory information used in spatial navigation applications. The fourth section, focuses in the bridge between the knowledge obtained from neuroscience trials and experiments using the available computational tools to simulate/recreate some of the Hippocampal Formation characteristics, based in computer models dedicated to the Hippocampus and to EC. It ends with a section dedicated to the discussion of the extracted scientific information.

2. The importance of navigation

The ability to navigate is an important function, common to animals. Navigation is useful to avoid dangerous areas and to find the necessary resources for survival, including food and resting places [8].

Complementary to their intrinsic abilities for navigation, Humans initially had few, external, tools to solve navigation problems. Most of the times the stars in the sky were the only reliable reference to determine our position [9]. However, such navigation method is fully dependent from the stars or the sun, which can only be seen during the day, or in a clear night sky, not to mentioned the fact that our perception of the stars change duo to the Earth rotation [10]. To answer such questions several instruments were created, like the Geographical Representation Systems, that map the entire world with a relative good precision or physical tools that helped solving possible errors in the calculation of the position. Also, the navigation task can be seen has a pure mathematical problem [11]. The Simultaneous Localization and Mapping

(SLAM) approach, has the challenge to map unknown environments, supported by different types of algorithms for spatial mapping of a space, contributing to the increase of autonomy in virtual and physical agents.

The following sequence of sub-chapters start with an analysis about the past and present of the Geographical Representation Systems, followed by a perspective about the SLAM characteristics, ending with an in depth analysis about the available methods and strategies used to solve navigational problems.

2.1 Geographical representation systems

As mentioned previously, the initial navigation methods made by humans relied on the observation of the stars like the North Star, the Southern Cross, or using Planets like Jupiter or Saturn [12]. Back in that time, there were several charts with the position of the Stars and Planets in the different hours of the day. The stars were a complementary element of a navigation method called dead reckoning. The Dead Reckoning is a method which allows the calculation of a heading without using heading calculation instruments like the compass. It uses the distance, the known positions recorded in a time period and the estimated drift to determine the direction of travel [13].

In the 1500 a.c, a certain type of instruments such as the Quadrant and the Astrolabio were used to get a better position from the stars, and with them it was possible to discover a sea route from Europe to Brazil [14]. Later, the navigational tasks become easier with the help of another instrument called the Gyroscope, that had the function to determine the horizon line [15].

At that time, it became clear the necessity to have a system which could represent with a certain precision all the regions of the globe. The Mercator projection divides the world into a squared grid, and its basis are still used in our days, despite the fact that this representation method was developed in the XVI century [16]. Nowadays, there are new forms to find and represent spatial information. The Global Positioning System (GPS), that uses the trilateration method where the distance between a device to a set of three or more satellites is used to calculate the position, as demonstrated in **Figure 1** [16], and the Web Mercator projection, that allows the implementation of Mercator projection characteristics in digital platforms. Also, the Equal Earth projection is used to represent the geographical surface using the continent area proportions. The combination between a Polynomial Equation with the Robinson projection, are the basis of the method that has an easy implementation and it is a good attempt to represent the Earth in the fairest possible way [18].

Also, there are other types of systems with the capability to represent the surface of the Earth. The Discrete Global Grid Systems (DGGS) are a digital geographic representation form where the projections are formed using geometrical forms, called cells, in a hierarchical structure. The main function of DGGS consists in creating maps of information providing a digital framework used in Geographical Information Systems [19]. The implementations of this approach can be found in Hexagonal Hierarchical Geospatial Indexing System (H3), developed by the Uber Tecnologies Inc., and the Open Equal Area Global Grid (OpenEAGGR) where the cells have the same size, and it has the possibility to convert from latitude and longitude references, to cell elements [20]. Although, the DGGS systems seem to be used in the representation of geographical information, they appear to have difficulties in the aggregation of similar information. According, with [21], the best methods to index spatial data are the ones that use the triangle from has a base, where its edges are bisected, forming sub-triangles, allowing the increase of precision.
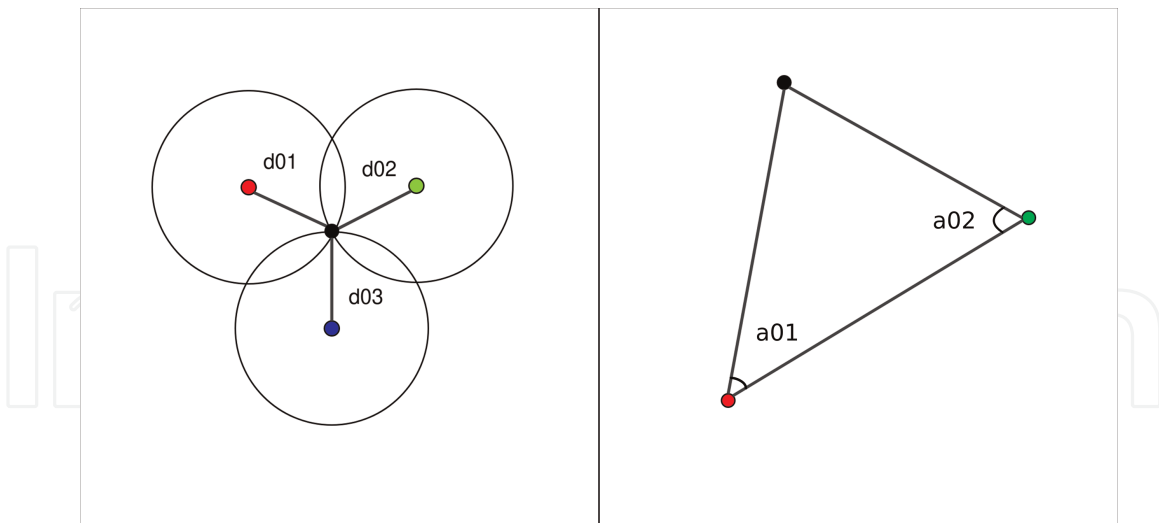
Figure 1.
Demonstration of the difference between trilateration and triangulation, adapted from [17]. The left image is the trilateration method where the distances are used to determine a location. The image on the right is the triangulation method, where the position of the objective (black dot) is determined by the angles a01 and a02 that connect the reference points to the objective.

2.2 Simultaneous localization and mapping

The SLAM problem involves creating a map of an unknown environment while simultaneously determining the location of a mobile agent, virtual or physical, within that environment, without any previous information about the space [11]. The solution to the SLAM problem increases the autonomy of the agents, but it is necessary to take into account the environment of the agent, namely if it is indoor, outdoor, underwater or in the air. At first, the SLAM question was approached using a probabilistic mindset, taking into account that is problem has a chicken and egg situation. The robot needs a position has a reference to start the mapping, but how it is possible to give such position where there is no map references [22, 23].

During the mapping process, the agent extract landmark information from its sensors as long as it stays inside the designated area. Depending of the SLAM method, the mapping procedure can be made with statistical strategies or using Machine Learning procedures, like the Deep Learning Neural Networks, where those structures are used to recognize environmental references [24]. To better characterize the behavior of the SLAM methods, the steps can be divided into four parts: (i) the input of the data, which consists in the extraction of environmental information, (ii) the mapping of place based in the acquired data, (iii) the determination of the location using navigation planning strategies and (iv) the output based on the results obtained from the previous steps [25].

Nowadays, the SLAM methods are more accurate and precise because of the development of new types of sensors like the Lidar, that sends light beams which reflects in the objects creating a good map of the space and the Visual SLAM which captures information from the agent's video resources, making the definition of the landmarks less probabilistic and more dependent of the surrounding space. Also, the SLAM approaches can be applied in 3D spaces, allowing vehicles, or agents, to keep track of their position and to map areas while they are navigating in it [26] and they can be seen as a complement to the existing navigational technologies, like the GPS

[27], where the SLAM can complement the other navigational methods, by correcting the drifts and inaccuracies caused by the navigational instruments [28].

2.2.1 Methods and implementations of SLAM

At first, some SLAM solutions used various types of Kalman Filter methods, fusing the sensory data to determine the position based in the location of the landmarks. However, as mentioned in Section 2.2, with the increase of the computational resources and the appearance of new sensors, it was possible to develop new methods that took into account these new technological improvements.

Some of these methods are the Gmapping method [29], which uses the Partical Filters to estimate the position, or the LagoSLAM [30] that works as a graph-based SLAM, where the cost function is a non-linear and non-convex formula. There are also several models that were applied to three dimensional (3D) environments such as the Loam [31], which uses a 3D Lidar sensor to scan the space and the IMLS-SLAM [32] that has a drift reduction algorithm to optimize the results obtained from the three dimensional Lidar. With the appearance of deep learning methods, it was possible to fuse the Artificial Intelligence neural networks into SLAM methods, as in the VoxelNet [24] that uses 3D networks to help in the extraction of features and the SqueezeSeg [33] which uses Convolutional Neural Networks to perform a real-time data segmentation [23].

In terms of the Visual SLAM algorithms there are some approaches like: (i) the ORB-SLAM [34] that uses the ORB computer vision method [35] to define the environmental landmarks, (ii) the OpenVSLam [36] which can be used with different types of cameras and it has algorithms that handle the features in a sparse form and (iii) the VINS [37, 38] that is a SLAM system, with the ability to work in real-time, which can be used in robots running ROS. The VINS can work in mobile platforms like the iOS and it can receive information from different types of sensors like the GPS, to correct some of the method drifts. Deep Learning approaches are also present in Visual SLAM methods, like in the: (i) DeepSLAM [39] that handles some of the noise present in the gathered images; (ii) the ScanComplete [40] model which calculates the position even with incomplete three dimensional scans and (iii) the DA-RNN [41] that has a Recurrent Neural Network to label the spatial data captured by RGB-D cameras [23].

In all of the possible approaches to solve SLAM, there is one that enhances the brain's ability to navigate through different types of spaces and environments. Biological based SLAM, started to appear when the scientific community have found different types of brain cells, using the Hippocampal Formation elements, with the ability to solve navigational tasks [42]. Some of these methods use special types of neural networks such as the Spiking Neural Networks (SNN) to mimic the brain behaviors in the processing of sensory data to map environments and spaces. The details of these types of models will be further discussed in Section 5.

3. The hippocampus and navigation

As mentioned in Section 1, the Hippocampus is a brain element that is present in humans and other animals. It is located in the Temporal Lobe area and is composed of a left and right Hippocampus. Inside it there are several sub-structures essential to the creation of short-term memories, to the recognition of data patterns and to identify

spatial areas [4, 43]. With that in mind, it is important to understand how the different sub-structures handle the information, what are the functions of their neural elements and how they work with the data sent though the EC.

In the following sub-chapters are dedicated to the biological analysis of the substructures of the Hippocampal loop, starting with the Dentate Gyrus and ending at the Subiculum, as demonstrated in **Figure 2**, maintaining a constant bridge between the Hippocampus functions with their ability to solve navigational problems.

3.1 Dentate gyrus

The Dentate Gyrus (DG) receives information from the layer II of the LEC and MEC. It is considered a sensory data pattern separator element, that removes the disambiguity obtained from the sensory data [45]. The DG seems to allow the discrimination of elements, like the difference of two objects in the same space [45]. The DG is composed by the Granule Cells and Mossy Cells. They are specialized in the processing of sensory information, to make some associations and to detect misplaced
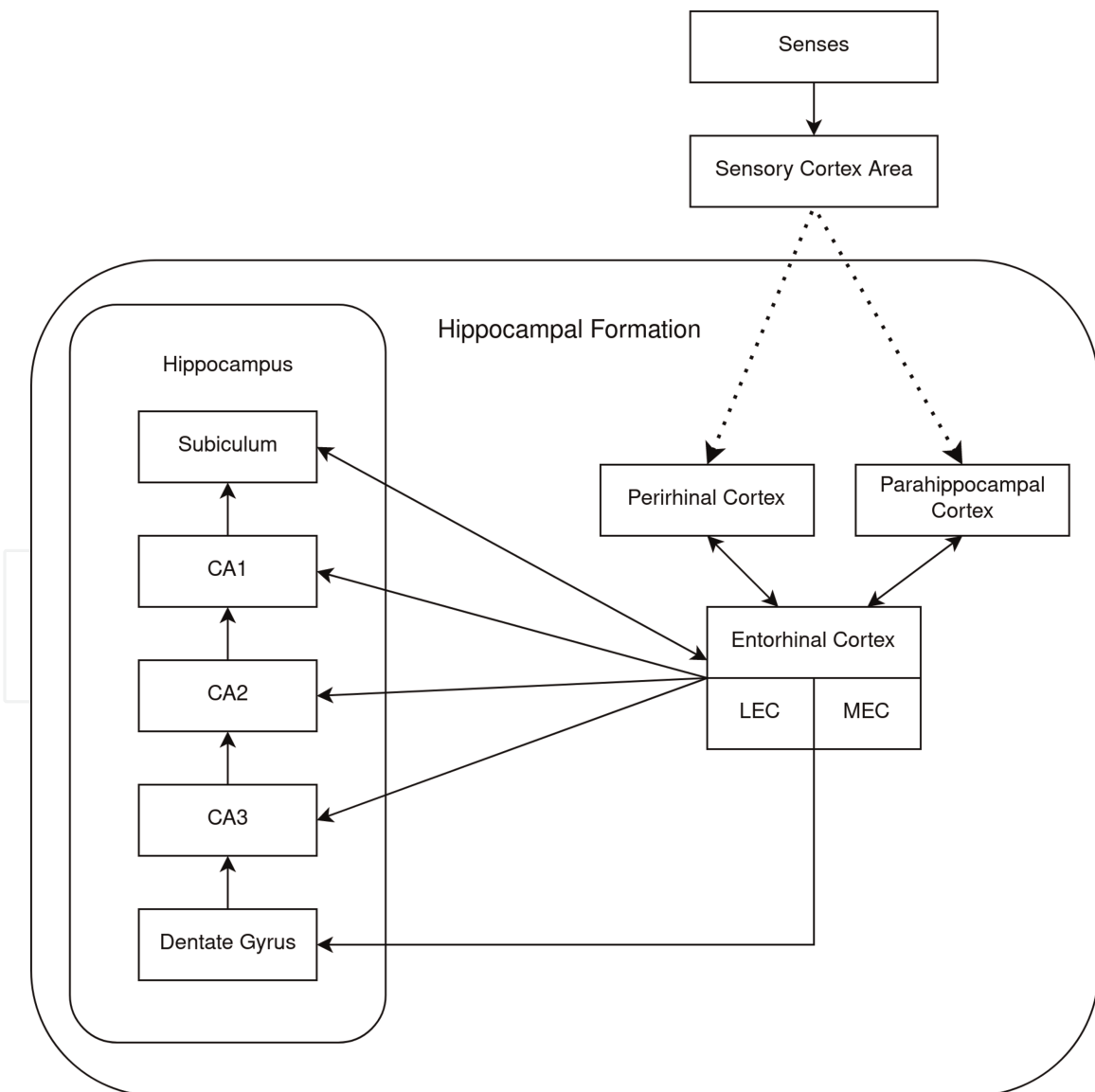

Figure 2.
Simple structure of the hippocampal formation, with the hippocampus closure adapted from [44].

items. It sends the information to the CA3 area. These cells have a low firing rate and they seem to represent the information using a sparse codification [46]. Also, the Mossy Cells act as a data hub which connects the DG to the Mossy Fibers. The Mossy Fibers are connected from the DG into the CA3 area. The Mossy Fibers could act as a conditional detonator or discriminator, because they discharge their energy potential only on special occasions and such discharge inhibits the Cornu Ammontis 3 (CA3) ability to receive information from the layer II of LEC and MEC [47].

3.2 Cornu Ammontis 3

The CA3 region is responsible for the association of episodic events and identification of information patterns, essential in the transformation of sensory events into short-term memories [45]. This area receives input from the DG, via Mossy Fibers, and the layer II of the LEC and MEC. It was discovered that inside the Hippocampus of a rat, the CA3 area has a set of recurrent connections which allows the CA3 to store information required for the pattern completion and memory association process [48]. The CA3 element is mostly composed of Pyramidal Neurons which are the elements responsible for the differentiation and the detection of overlapped memories [49]. The CA3 structure is divided into 3 different parts: the CA3a and CA3b areas seem to be dedicated to the encoding of information, while the CA3c connects to the Mossy Fibers and seems to help in the separation of occurred events [50]. Also, it is believed that the CA3 element could be important to the prediction of future steps and together with DG they could play a role in the correction of path integration calculations [51].

3.3 Cornu Ammontis 2

The Cornu Ammontis 2 (CA2) region acts as a hub between the CA3 and CA1. It is composed of Pyramidal Neurons and they seem to characterize the patterns related to social habits [52]. The CA2 has cells that discharge their energy in different locations of a space. These elements are similar to Place Cells, however their place field, which is the spatial area associated to the neuron, is more suitable to time factor changes, meaning that such elements can change their state in a matter of hours or days. This means that CA2 could create associations between time and place [53].

Also, it appears that CA2 could help in the organization of information in CA1, according with their periods and time characteristics because the information inside the CA1 is more stable to changes [54].

3.4 Cornu Ammontis 1

The Cornu Ammontis 1 (CA1) seems to be responsible for the retrieval of memory elements permitting the recognition of known episodic events, giving the "where" context on those elements [7]. The CA1 component is divided into two different parts, the distal part that is responsible to extract information from the sensory data and the proximal area which isolates the spatial information to allow the recognition of events. The CA1 could discriminate ambiguous information gathered from the MEC and CA3 areas [55]. The data stored in CA1 maintains its stability for long periods of time. Also the CA1 receives projections from the other Hippocampus, via a set of fibers called Hippocampal Comissure Fibers [56].

The CA1 could be used for Navigation purposes, because it has a special group of cells called Place Cells and their task consists in representing a specific spatial area, with the ability to adapt to environmental changes [7]. The area represent by each Place Cells is called place field and when a person or animal passes such area, the correspondent Place Cell discharges its energy [57]. The deepest part of the CA1 area has a link with the Landmark Vector Cells, because their firing is stronger when the agent is in a position of a particular landmark [58].

3.5 Subiculum

The Subiculum is located after the CA areas and it divides into different sections: (1) A section which receives the projections from the CA1 module, (2) a section dedicated to the reinforcement of the learned data and (3) a section that connects to the EC, closing the Hippocampal Loop. Also, the Subiculum can provide information regarding the boundaries of a spatial area [59]. Border Cells fire when a subject is facing a border in their allocentric direction [60]. These cells are present in other areas like the Parasubiculum and the MEC [61].

According to [62], the Subiculum may have the necessary structures to represent the memory of events with more precision and robustness. The data is converted from a sparse format to a denser one and then the processed data is sent to another brain element called Nucleus Accumbens, to decide which step to take at a given time. This could mean that the Hippocampus forms a map of possible decisions valid for a time period.

Also, inside the Subiculum there are cells called Head Direction Cells (HD), that are capable of indicating the direction which a person or animal is facing at a given moment [63]. The HD cells have a dual-axis system used to represent complex spaces and it could process 3D environments due to the possibility to calculate the azimuth using visual data as referential landmarks [64].

4. The connection between hippocampus and senses

The Hippocampus relies on the information gathered from the senses to understand the animal's surroundings. The sensory information is sent to the Hippocampus via the EC. The EC is located in the Temporal Lobe area and it can process the spatial and non-spatial information before it is sent to the Hippocampus. Giving the importance of the EC, it is necessary to understand how the data is encoded in a format, understandable by and Hippocampus and how small changes in the acquired information affect the spatial characterization.

In the following sub-section we start to mention some of the properties of the EC and how they receive and interpret the data from the senses. Then, the focus is directed in how the Vision and Audition are used for navigational purposes. This chapter ends with an analysis about how the brain elements encode the sensory information.

4.1 Entorhinal cortex

The EC area is divided into two distinct parts, the LEC and MEC, each one with different types of neurons.

The LEC receives inputs from the Perirhinal and Parahippocampal corteces. Those elements process data gathered from the olfactory and somatosensory senses [65]. Also, the LEC appears to encode temporal information across different periods of time [66], using a set of cells called Ramping Cells. They act as a supporting element in the acquisition of a time reference because they discharge the energy in a periodic format. The data is further sent to the Hippocampus to a group of cells called Time Cells and they useful for organizing the memory according with their time reference [67].

The MEC is divided into 6 different layers, each one with specific types of neurons and neuronal structures. The first layer is related to the transfer of information between the second and third layers. The elements responsible for such behavior are the Chandelier Cells because they regulate the inhibition response to the Pyramidal Neurons [68]. The second layer is composed of Stellate Cells that support Grid Cells with the ability to transmit the necessary information for the path-integration calculations [69]. The third layer is a mixture of Pyramidal Neurons and Stellate Cells [70]. The fourth, fifth and sixth layers are dedicated to the association of spatial and non-spatial features because they are essentially composed of Pyramidal Neurons and Horizontal Chandelier Cells and they can send information directly to the Hippocampus [65]. The Grid Cells appear to create an internal map structure of a spatial environment, where each point in the map is displayed in an hexagonal form when applied to a 2D environment [5]. The display of the points and the firing of these cells is determined by the velocity and the head direction of the individual, where the hexagonal shape is maintained at all times as it can be observed in **Figure 3**. The **Figure 3** has images that enhances the hexagonal shape of the Grid Cells and the results that proved its properties.

The velocity and direction, are represented by the Speed Cells and HD cells [5]. The Speed Cells and HD cells are supported by the Conjunctive Cells that discharge their energy potential when a subject is facing a specific direction of movement. Also, it is possible that the Conjunctive Cells are responsible for the encoding of data combinations between Speed Cells, Place Cells and HD cells, allowing them to act as an information integrator [72]. The Grid Cells firing displacement, have a spacing value close to and they are organized an multi-layered form. Each layer represents a different spatial precision of the environment, allowing the increase of certainty, relative to the position of the agent [73].

4.2 Importance of vision and audition in space characterization

As mentioned in Section 1, all the senses have a relative importance in the gathering of the spatial data. For this chapter we will focus on the Vision and Audition.

The Vision and Audition send their information in two different pathways, the Dorsal stream which can indicate the information related to high-level information like the where and how, and the Ventral stream that has low-level data such as the recognizing and identification of objects [74].

Yet, as mentioned in the previous sections, the visual elements are used by the HD cells as inputs used in the determination of the heading. On the other hand, the audition contributes to the spatial characterization because some of the landmarks and spatial identifications are obtained using the auditory system [75]. Also, it is necessary to understand how the sensory cues are converted from the physical element to the neural language and how such data is interpreted by other brain structures [76].
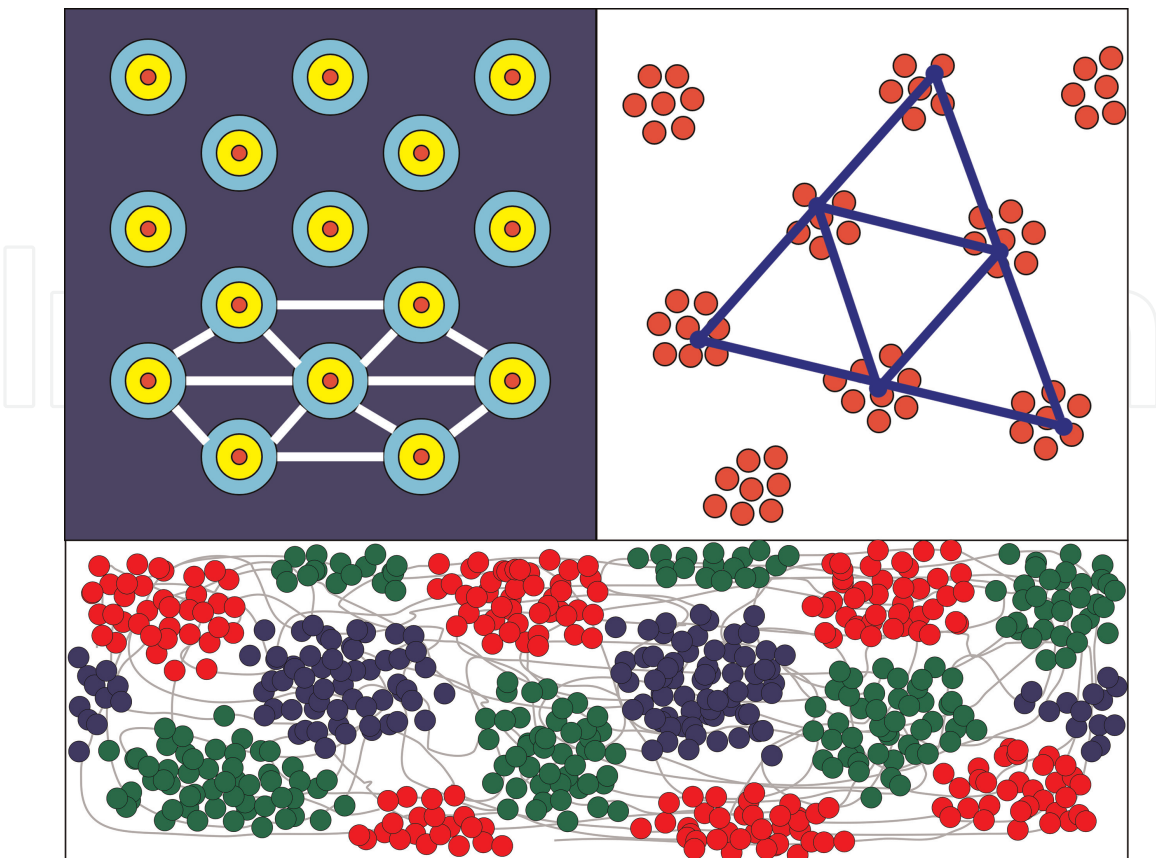
Figure 3.
The Grid Cells main characteristics adapted from [3, 5, 71]. The left image shows the hexagonal shape of the Grid Cells, the right enhances the possible triangle properties. The bottom image is an adaptation of the obtained scientific results from [71].

4.2.1 Visual cortex

The Human Vision System can be seen as two distinct parts. The first part consists in an image capturing system, where the eye and its components are used to gather visual information, and the second part is dedicated to its processing and the interpretation of the acquired data, in the so called Visual cortex.

The Human Eye is mostly formed by: (i) the cornea, which refracts light as it enters the eye, focusing the image on the retina, at the back of the eye [77], (ii) the Aquoeus Hummour that provides nutrition and oxygen to the eye's tissues, as well as maintain the shape of the eye by adjustment of the internals' eye pressure, (iii) the Iris and Pupil which are responsible for the control of the tunnel that guides the light rays [77, 78]. The conversion between the light's electromagnetic waves into neural signals, occurs in the Retina. The Retina has Photo-Receptor cells, Amacrine Cells, Bipolar Cells and Ganglion Cells. The Photo-Receptor Cells are sensitive to light. These are either Rods or Cones, respectively sensitive to the tones of gray and colors at different areas of the retina. There are 3 types of Cones, each one processes and triggers at the presence of the different electromagnetic wavelets like the red, green and blue colors [77].

The information collected from the cones is aggregated with the data from the rods using the Horizontal Cells, which are inhibitory interneurons, that balance the overall activity of the retina and improve the contrast of the visual signal that is sent to the brain. According with [79], it is possible that Horizontal Cells can have some

characteristics used in color opponency. Color opponency consists in the creating a new color by suppressing the other wavelets. Such characteristic allows the reduction of redundant information generated by the photo-receptor electrical discharges, avoiding overlap of the cone sensitivities [80].

Also, the Amacrine Cells establish links between the different layers and they could play a role in the set of contrast of the visual image. The data is sent to the Visual Cortex through the Ganglion Cells. They also have a crucial role at the regulation and synchronization of the circadian rhythm [77].

The eye and the Vision Cortex can capture and identify different image aspects, such as the edges of a shadow or a object, the motion of elements, they can distinguish from large to small objects and they have the ability to process large visual fields [81].

The information regarding the recognition of objects, processed in the Visual Cortex, is sent to the Temporal Lobe elements via the Ventral pathway where the Perirhinal Cortex acts as a hub between the Hippocampus and the visual system [82].

From the image capturing by the retina, to the data preparation made by the Visual Cortex, the usage of the Visual data in navigation can be important in the identification of spatial landmarks, the gathering of information present in a cartographic map and they can correct some of the errors made during the path-integration process. Also, the Vision data is used by the Hippocampal Place Cells to encode the specific area in the spatial environment [83].

4.2.2 Auditory cortex

A spatial environment can be characterized by the environmental sound. The Auditory mechanism has similar features with the Visual System. It can be divided into two parts: the first part is dedicated to the capturing of the sound waves and the second part for the processing and interpretation of the information gathered from the sound waves.

The sound waves are captured at the structure called external ear and the sound vibrations are extracted by the tympanic membrane which sends the vibrating rhythms into the cochlea. The cochlea has a set of elements called Hair Cells and they move with a certain vibrating frequency. Such movement causes the discharge of an energy potential, converting the sound's vibration into an neural signal. The electrical impulses are sent to the Auditory Cortex where the sound is classified according with their properties [84].

The Auditory Cortex seem to have several neural populations that react to different sound characteristics. Such statement was supported by several observations of voxels in Functional Magnetic Resonance images [85]. These elements are present in the Primary Auditory Cortex, that identifies and sorts data according to their frequency [86]. The Second Auditory Cortex identifies the sound using the pitch and melody. Also, between the Auditory Cortex and the Speech Cortex is the language processing area, necessary for the extraction of information from the voice [85].

The auditory landmarks can help in the identification and recognition of places, but according with [75] some of these landmarks are quite difficult to gather and sometimes the information acquired needs to be compared with other senses like the Vision. Also, it is stated that the ambiguous information will decrease with the amount of Visual and Auditory data. Since the audio data is stored by its frequency, it is required to locate the position of the sound source from the sound profiles received by the two ears taking into account that it is required to solve the ambiguity and sound input differences between the two ears.

The extraction of spatial features in the sound could be difficult, because of the ears position. The cues obtained using the frontal part and the back part of the head, are equal and such difficult is solved by the moving of the head to other position [87].

The difference of sound arrival can be important to the creation of a auditory spatial map which can lead to the detection of important environmental cues [88], but they need to be fused with other elements, like the Visual data, to separate the environmental data segments [75].

4.3 Encoding of sensory information

This subject lacks consensus among the scientific community. However, there are several hypothesis about how the brain handles the sensory information [89, 90].

One of the theories that has the most consensus consists in fact that the brain encodes the information in a sparse manner [89]. A sparse distributed representation can be described has a representation where not all neurons are active at a given period of time. The sparse representation together with the firing rate of the neuron can be used in the encoding of some of the sensory information like the auditory data. The generalization and pattern completion depend in the sparseness of the data and in the distributed characteristic of the neurons and the less sparse is the system the more information can be encoded and represented. A sparse codification system can be found in different areas of brain like in (i) the Auditory Cortex where the firing rate can be characterized as a binary coding, because the neuron responds to the stimulus in a fire or no fire behavior, (ii) in the Hippocampus and (iii) in the motor sensory cortex [91].

On the other hand, it is not clear how the brain enforces such codification and how this method could lead to generalization when the interactions between neurons are very low. These statements are supported by the fact that the sparse coding is not present in all the areas of the cortex and it is not clear if the brain is a discrete classifier or if it works using continuous regression, making the system totally dependent to the size of the neuronal population [92].

5. Computational methods about hippocampal formation and spatial navigation

Nowadays, due to the increase of technological capabilities it is possible to implement complex structures of neural networks. However, some of the used methods do not have a strong biological justification. Also, nowadays it is possible to simulate some of the current brain's neurological behaviors using certain type of networks. Those methods and strategies include neuronal simulators like Nengo [93] or The Brian Simulator [94] but also with different types of networks like the SNN. There are several models which try to simulate some of the characteristics of the EC, others focus in the Hippocampus and some even use the brain and Hippocampal features applied to navigation.

The following sub-sections start with an analysis with the EC models followed by an analysis of the Hippocampal model where it be given emphasis on their main technological characteristics.

5.1 Entorhinal cortex models

Throughout the years several computer models were developed that tried to replicate some or all elements of the EC. Some of the models focused on certain types of

cells like the Grid Cells. The Grid Cells models can be divided by their main characteristics in: (1) Oscillatory-Interference Model, (2) the Attractor Network Model, (3) the Self-Organized Model and (4) the Path-Integration Model [95].

The Oscillatory-Interference method makes use of two different oscillators and their phase difference creates the Grid Cells [95]. The oscillators can be active although it is required for them to have different frequencies. This model can respond to rapid changes in the environment and at the same time they could provide the necessary information for a rapid remapping of Place Cells [96].

The Attractor Network model uses simulated neurons, with different types of connections to represent a position in a space. The firing of the neuron is directly influenced by the behavior of the neighboring neurons. However, to recreate the functions and behaviors of the EC, this network must have a element which detects and recognizes borders/obstacles to limit the initialization of hyper-parameters, avoiding the data overfit problem [95].

A Self-Organized mechanism states that the data has to be separated by a 60-degree angle. These model makes uses of a special type of cells called Stripe Cells [97]. The Stripe Cells send to the Grid Cells, the speed information and they constrict the formation of Grid Cells by maintaining a constant hexagonal pattern displacement [95]. Those cells have different firing behaviors and the intersection of those elements create the Grid Cells. These approach is sensitive to trigonometric properties and it can represent different ranges of spatial scales [98].

The Path-Integration method states that Grid Cell's formation only depend from the velocity and direction of the agent. Also, the displacement of Grid Cells is derived by the multiplication of the previous elements with a timing factor [95].

According to [71], it is possible to recreate the EC Grid Cells using simple mathematical properties. By separating the hexagonal shape into triangles and with a specific type of Gray code, the Grid Cells are formed and characterized using a Triangular Coordinate System. This method has as its main characteristic the ability to define specific degrees of precision, because it behaves in a multi-layered form, like the real Grid Cells. Also, it assembles a property of similarity where the code of the near elements has the lowest possible difference, making this method suitable for navigation and to encode multidimensional data.

5.2 Hippocampus models

When the Hippocampus is referenced, there are several computational models which enhance some of the characteristics mentioned in the Introduction section. The NeuroSLAM [99] and RatSLAM [100] are some of the models based in the characteristics of the Hippocampal Formation.

The RatSLAM method consists in a mapping algorithm based in the characteristics of the rat's Hippocampal Formation system. This method uses the Competitive Attractor Network (CAN) to convert the Visual information to a position in a space. The CAN can have different structures and the idea consists in exciting a neuron with its neighbors, and to inhibit the distant neurons, with the ability to handle small amounts of noisy data [101]. Also, this method uses landmarks for spatial guidance and it is not dependent of a special grid system like the Cartesian method [100]. In addition, the core of the RatSLAM, had been used in the development of other neural based navigational models, like the OpenRatSLAM, that has a modular structure which is easy to implement in robots [102], and the DolphinSLAM where the properties of RatSLAM, are used in underwater environments [103].

The NeuroSLAM is a spatial neural inspired model that can be implemented in 2D and 3D environments. This method uses some of the previously mentioned biological elements like the Place Cells, HD cells and Grid Cells. The Grid Cells maintain their hexagonal displacement. They represent the position and give the metric information used in the path integration. The HD cells provide information regarding the azimuth and the heading direction of the movement. The networks for this model are made using Multidimensional Continuous Attractor Network (MD-CAN) that, with time, achieve a stable state, when the right network parameters are used [101]. Each unit has a continuous activation value between zero and one. With the simulated neurons, this model makes use of the Local View Cells which are able to resets the errors gathered during the path integration process based on the rotation data provided by the 3D visual odometry data [99].

The Neural Engineering Framework (NEF) is a model which can be applied to navigational problems. The NEF allows the simulation of biological neural models applied to cognition and other brain tasks. This can be used model visual attention, reinforcement learning and other cognitive jobs [104]. This framework allows a better understanding of the brain mechanisms using fast computational resources. The neural activity uses an tuning curve as the firing rule, which is described in Eq. (1)

$$a_i = G(a_i e_i^* x + b_i) \qquad (1)$$

where the G is a neural model, a_i is the gain parameter, b_i is the background bias and the x is the neural activity. There are several available neural models like the rate-based sigmoidal neurons, spiking Leaky-Integrate-and-Fire (LIF) neurons and other models [104]. The NEF properties can be used in programming libraries like the Nengo where the neural models are created with programming languages like Python or Java and it allows the visualization of the model behavior using Graphical User Interface tools. In terms of hardware it is possible to use FPGAs to create physical neural models, and it is also possible to convert from SNN's to Artificial Neural Networks (ANN) [105].

SNNs are a special type of network that try to recreate the neural structure of the brain. They work in a sparse manner and in a continuous time format. There are several SNN neural models like the Hodgkin-Huxley (HH) model when the discharge of sodium and potassium is simulated inside the digital neurons or the Izhikevich model which combines the characteristics of the LIF, creating a more efficient digital neuron [106]. The NEF and SNN models do not have a direct connection to the previously mentioned SLAM methods. However, with the right neural configurations, those methods can solve SLAM problems because those methods are simulations of the brain's neural dynamics [107].

6. Discussion and conclusions

Inside the brain's Hippocampal structure there are some neurological tools that allow navigation. Their discovery led to some questions, namely: (i) what are the functions of the Hippocampal Formation and (ii) what is the correlation between the Hippocampus and Navigation?

The first studies about the Hippocampus have shown that it was essential to the formation of short-term memories, as was observed and reported for a patient that had to remove this neuronal structure to solve a problem related to seizures [1]. After

the removal, he repeated routine tasks, as if it was the first time ever. He could watch the same movie repetitively, without remembering any scene, actor, or any detail. A similar thing happened with people and places. So, the Hippocampus has shown to allow the identification of places and persons, meaning that it can give the context to a newly formed event [4]. Later studies and researches have made it clear that specific types of neurons, named Place Cells with the help of the EC Grid Cells [5], allow the identification of locations, based on environmental characteristics [7].

Even with the map, we need to have a sense of our current position, which is given by the EC [72], and to have the ability to find new or previously known areas based on the data patterns, which is the function of the Hippocampus [108]. In the Hippocampus the senses, including Vision and Audition, allow the identification of the place, like the SLAM approach which uses the spatial landmarks as a reference to determine the location and the position of a agent. Like the SLAM methods the Hippocampal Formation must have structures that can work with incomplete data. One of those structures is the CA3 area which is composed by recurrent network, that works as a memory element, which can complete some of the missing data [45]. The CA areas and the other Hippocampal elements, process the sensory data and complete the pattern that leads to the identification the current position in an environment.

The Hippocampal Formation is not the only part of the brain that is capable of processing spatial data. Recent works have discovered that the Retrosplenial Cortex, allows the processing of spatial landmarks, creating a spatial schema of the environment, with the possibility to calculate future directions [109].

The Retrosplenial Cortex has a connection to some elements of the Hippocampal Formation. The 29th and 30th areas have a higher neural density which could indicate that the Retrospleanial Cortex process hippocampal related information [110]. Its malfunction could lead to disorientation, because of the lack of ability to pair and process spatial data [109, 110].

Also, it is necessary to further analyze how other senses can contribute to the navigation tasks. "The olfactory input to the perirhinal cortex and the parahippocampal cortex, can provide information which can change the place cell mapping configuration by creating new spatial landmarks [111]. However, the landmark, starts to lose strength due to the odor habituation mechanisms that occur inside the olfactory bulb [112]. In addition, the somatosensory, receives the information from different types of senses and pathways. It passes or holds the sensory information according with the received stimulus [113].

The set of tools created by mankind to navigate in space, have only recently evolved to use non-biological Grid Cells, as defined in discrete global grid systems, that somehow approximate the latices used in the Entorhinal Cortex. Discrete global grid systems currently support the indexing of assets across the globe, allowing a more adequate partitioning and aggregation of the earth into logical structures that take into account the heterogeneity of the scales of the associated geospatial data.

With the increase of information regarding the neuronal navigation capabilities, there are some methods that bridge neuroscience and SLAM. As previously mentioned the NeuroSLAM [99], and RatSLAM [100] can be considered good approaches to solve SLAM using biological based methods. However, due to the complexity of the CAN networks, they cannot handle large quantities of noisy data. Meaning that the data has to be cleaned, which could increase the time of response. Also the MD-CAN networks reveal some instability when there are some changes in the network parameters. Such changes cause a drift in the attractor that leads to the degradation of the results [101].

Also, the RatSLAM uses some cells that have not a direct correlation with the Hippocampal Formation, like the Pose Cells that represent the location and orientation of an agent [100]. In addition, the NeuroSLAM considers an intermediary agent to facilitate the communication between the system and neuromorphic devices, which is not required when using SNNs [99].

On the other hand, the Triangular Coordinate System [71], can handle certain amounts of noise in the data using simple mathematical operations, without using any special equipment like the neuromorphic devices. Yet, this model does not address a codification for 3D environments and the hexagons seem to a have a perfect hexagonal shape, which contrasts with what is observed in some neurobiological studies.

Non-biological based SLAM approaches that were previously mentioned can already be found in some house appliances like in autonomous vacuum cleaners. So does it make sense to create a biological based artificial Hippocampal Formation structure, in robots?

The answer to this question seems to be difficult, because the SNN has a different structure and there are certain aspects that require attention. The first aspect is in the training method. It is different from the ANN because SNNs have special characteristics in the spike process, meaning that the backpropagation mechanisms cannot be directly applied. The second aspect comes from the fact that the SNNs need a computer simulated program. According with [114], it is necessary to understand how such networks could work with high performance computer elements, like the neuromorphic devices. On the other hand, the SNN would not need a large energy storage units and the robot could make difficult tasks in a more efficient way due to the network's performance capabilities [114].

As mentioned in the SLAM section, one of the steps of the SLAM approach is the navigation planning and according with [115], it seems that the Hippocampus Place Cells and the EC Grid Cells, can be used for conceptual learning, due to their capacity to organize information and to predict future states.

With the analysis of the state of the art matter, it is possible to say that the Hippocampal Formation can have the required elements for the task, because it can create a data representation of the place, based on the available environmental characteristics, allowing the understanding of the current location and which are the next available steps.

During this century, neuroscientists and engineers have been trying to close the gap between these fields with a better knowledge that could clarify some of the existing doubts about the functioning of the brain, and with new technological approaches. With the junction of the neuroscience to the robotic field, it may be possible to develop new technologies which are more adapted to the people's necessities and requirements to solve their daily challenges.

Abbreviations

ANN	Artificial Neural Networks
CA	Cornu Ammontis
CAN	Competitive Attractor Network
DG	Dentate Gyrus
GPS	Global Positioning System
HD	Head Direction
LEC	Lateral Entorhinal Cortex

LIF	Leaky-Integrate-and-Fire
MEC	Medial Entorhinal Cortex
MD-CAN	Multidimensional Continuous Attractor Network
NEF	Neural Engineering Framework
SLAM	Simultaneous Localization and Mapping
SNN	Spiking Neural Network

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