Neuroscience Research in Spatial Navigation Using Robotic Animals

Nate Sutton
Department of Bioengineering
George Mason University
nsutton2@gmu.edu

1. Abstract

1.1 Introduction
The focus of this review is neuroscience research using robots programmed to navigate spatial environments using methods based on animal cognition. The use of cognition-based methods in robot navigation has multiple translational applications such as self-driving cars, and robots that handle hostile, dull, dangerous, and dirty activities [1]. The use of robots for testing spatial cognition neural theories can provide advantages in accumulating real-world environment data, obtaining a diversity of test environments, and being able to directly reuse test environments where animal neural recordings were captured.

1.2 Methods and Results
Multiple types of neurons encode separate properties of space that are used in navigation activities, e.g., using information around one's body to determine position while comparing that to a goal path (path integration). Research producing better knowledge of brain spatial processing mechanisms with those cell types helps inform the design of algorithms for navigation in robots. A type of advance that has been made in neural algorithm design was the inclusion of conjunctive cells modeling. The cells combine and compress sensory information in cells, e.g., visual landmarks, odors, sounds, touch, for neural computational efficiency gains [2]. A type of challenge in navigation is simultaneous localization and mapping (SLAM), which is a problem that has attracted widespread attention in the field of computer vision. An innovative approach toward SLAM that is based on rodent cognition is named RatSLAM [3]. It uses an attractor network algorithm to process spatial information cues to understand environments, allowing the navigation to be robust to ambiguous spatial landmark information and path integration errors. RatSLAM has been expanded on with features such as merging information between robot rats toward their common objective of understanding spatial environments [1]. Integration of advanced forms of neuromorphic hardware, for instance, International Business Machines' (IBM) Neurosynaptic System, into robots designed for navigation enables computational efficiency gains [4].

1.3 Conclusion
Research with robots designed with navigation algorithms based on neural cognition has been advanced by studies investigating multiple factors involved in the activity of navigation. Several research projects have used discoveries learned from the fields of robotic navigation and neuroscience to create new investigations that improved the state of spatial navigation science.

Keywords: Review, Spatial Memory, Navigation, Robotics, Animals, Grid Cells, Place Cells, Neural Network Algorithms

2. Introduction

Robotic animals offer distinct advantages that make them an integral part of researching the neuroscience of spatial navigation. The robots can help bridge the gap between theory and practice by testing programmed neuroscience models in environments that can be less constrained than virtual ones. For example, putting a robot in a previously unexplored environment that may contain obstacles never introduced to its brain model when it was constructed can reveal how it adapts to a novel setting. Rodents are a highly popular type of animal that are engineered as robot recreations for research. One reason for their popularity is the frequent use of rodents in neuroscience research exploring spatial navigation, and using the same subjects in the form of robots creates a direct connection to that existing research.

Notable challenges also exist in the use of the robots. A difficulty that can be encountered is needing to deploy a machine into environments where they only have the computing power that is built into them as opposed to a large scale computer that only needs to stay in one place during virtual simulation. Hybrid solutions exist including wireless communication between a robot and large computers but issues can come up involving latency and transmission signal blockages. Other challenges include the ability of robots to successfully transport themselves across uneven and difficult terrains.

Significant areas of work that have advanced robotic navigation are simultaneous localization and mapping (SLAM) and light detection and ranging (LiDAR). In SLAM, a robot must locate itself within a map of an environment while simultaneously updating its map over time [5]. Realigning itself within the map is therefore repeatedly needed. LiDAR sends laser lights onto objects and measures the reflected light with sensors [6]. The reflected light can accumulate into what is known as data point clouds which approximate object shapes. Robotic systems can use an alternative to LiDAR to recognize visual objects in their field of view, including standard cameras that stream visual input to robots, and LiDAR can additionally be used in combination with such cameras.

In addition to visual input sensors, there are multiple hardware components that can be found on the research robots. Light detectors can be used for measuring ambient light, odometers can be used to track self-motion, compasses are used to understand head directions, whisker sensors can evaluate textures, the tracking of actuators and other mechanical motions can be used to develop internal records of positions [6]. Wheels are often used for locomotion, wired or wireless information connections can be present, and other components are optional. While the hardware can be different in physical design to body parts, algorithms can map the components to simulated internal neuroscience processes to adapt the input to be interpreted as analogous animal sensory stimulation. Multiple computer hardware architecture choices are available for constructing robot systems. Some types of hardware architectures are Von Neumann, graphics processing units (GPUs), field-programmable gate arrays (FPGAs), and neuromorphic designs [7]. Von Neumann is a traditional form of computer processor design and neuromorphic systems mimic neural processing approaches in their circuitry.

Multiple types of cells, circuits, and network designs are included in neural computations simulated in the robots. Robots can directly recreate neural cells in nodes of its neural network or analogous navigation algorithm, or elements of the cells' information processing can be included in similar functions. Vision authenticity can be added by including models of neural vision cells that recognize specific features of visual input and process that through filters such as Gabor filters. Some spatial cognition specific cells are place, grid, head-direction, and border cells [2]. Conjunctive cells combine disparate types of cells together, e.g., vision and place cells. Learning and memory of spatial understanding can be captured with the use of such cells in regions including the hippocampus. Motor control cells are receivers of commands from cognitive processes that direct movement instructions.

Cells involved in decision making, such as cortical cells in the prefrontal cortex, basal ganglia, and other regions, can be used in processes that aggregate information and execute choices.

Network-level spatial cognition theories can contribute to controlling the way mapping of environments are understood in the robot minds. Notable quantities of publications have been produced with the theories of continuous attractor networks, oscillatory interference, and self-organizing maps [7]. Hybrid models that combine the theories together have also been studied. Network algorithms can assist navigation by including content such as communication through neural rhythms, path integration, and specific ion channel chemical balances [8]. A large range of network scales have been used to explore the theories and the choice of network size relates specifically to the research question under investigation. Larger network sizes can incorporate features including sensor error correction by encoding related sensory input information in different network locations and comparing them [5]. Limitations can occur with having large scale networks on robots because of the cost or size of hardware needed to provide the storage capacity.

Robotic animals are able to provide a valuable resource for explorations of neural spatial navigation and wide variety of customized designs are possible. Advancements made in general robot navigation, such as SLAM, and those found through neuroscience, for instance visual object recognition with neural networks, can benefit each other through exchange of knowledge between them. An important strategic choice in experimental design is made by researchers when they choose which hardware and software components to focus their resources on when building their robots. Robots can add important advantages to neural research but understanding the variety of options and methods that are available with them can be useful for investigators deciding how to effectively include them in their work.

3. Methods

The process of SLAM includes multiple components to help guide a robot toward its goal location. Fundamental parts of the process can include (1) landmark extraction, (2) data association, (3) state estimation, (4) state update, and (5) landmark update [5]. These activities have been identified as occurring in a similar form in the hippocampus of rodents [5, 9-12]. Many animals and robots evaluate their place in an environment using allocentric and egocentric perspectives [13]. In terms of spatial understanding, allocentric perception is judging one’s place from objects external to one’s body and egocentric perception is using internal body sensations to help determine one’s place.

The fundamental parts contribute in specific ways to successful navigation. Landmark updates are an allocentric type of sensory recognition where objects, e.g., a sign with a store name, known to be associated with a location are used to track position in an environment. Landmarks are fixed objects that remain in the same place while one travels the environment. Data association is the process of connecting sensor observations with elements in a map of the environment. State estimation is the process of detecting one’s position in an environment given sensor data. States represent the location and in some cases orientation of oneself [14]. Updates of states and landmarks are done after actions such as movements are performed or time has passed.

Object recognition algorithms are commonly a part of robotic visual input collection techniques to help inform navigation choices. LiDAR can help provide data for object recognition and can work together with or separately from SLAM. Researchers can choose what level of neural vision authenticity is important to their investigations and decide which methods to include based on that. LiDAR is less similar to natural vision systems than cameras, because cameras operate more in the way eyes process sight than LiDAR’s laser sensors, but a wide variety of off-the-shelf products are available for integrating LiDAR if it is wanted.

Neuroscience processes can be recreated in robots for further study of them or to assist with robot navigation, and they involve multiple cells that can work in cooperation with each other as well as perform functions separate from each other. Grid cells create a map of the spatial environment that one experienced and stores that in memory [15]. The cells have been given the name “grid” because their physical positions in their neural region resembles a grid structure. Position changes in oneself are tracked through neural signals that transverse the grid area. Specifically, the physical movements that an animal creates are recreated as neural activity level movements along a corresponding group of neurons representing the environment area.

Several other forms of cells have unique properties. Place cells operate in a way that they associate a sensory experience to a place one has traveled. Sensations can trigger activation of place cells and in turn provide evidence about the place one is located in. Head-direction cells, indicated by their name, store information about the orientation of one’s head, and that can be useful for aligning one’s body with that individual’s mental environment map. Border cells detect when one is at the border of the environment one is in, for instance, walls in a home. Conjunctive cells are able to increase the efficiency of neural coding by combining more than one of those cell types together in individual cells. To be able to discern where one is an environment, the collective evidence of these different types of cells needs to be combined together to provide one’s brain with a convincing understanding that a location is recognized.

Multiple types of network-level theories and corresponding algorithms exist for processing spatial navigation. In continuous attractor networks (CAN) modeling of grid cells, signals traveling through grid cell structures are tracked as attractor states [16]. Movement beyond certain thresholds of locomotion cause transitions between the states, and allows oneself to internally follow one’s location. Those transitions are dependent on the basin of attraction that a state has to attract a transition from another state into it [17]. One’s current location is captured as a significant amount of neural activity in a state and that is described as a “bump” of activity. In this type of model, the network of states is continuous because it has the capability to include a infinite number of neurons that connect together in a continuous design.

Other types of network-level theories are alternative explanations to CAN but they can also be combined with CAN or each other. For example, oscillatory interference modeling of grid cells includes that influence over grid cell control is through the resulting neural rhythm activity of one theta rhythm intersecting with another in a way that interferes with its normal rhythmic movement. The theory of self-organizing maps involves mapping data points onto usually a two-dimensional grid where points similar to each other are grouped together more than points that are dissimilar [18]. In that way the information in grid cells can be stored in a self-organized way that groups related content. These theories can also be applied to place or other navigation-relevant cell neural activity organization, and some models combine one theory for place cells and another for grid cells, or different cell type combinations. Such combinations of theories can also include communication exchange between the cell types to better inform spatial understanding.

For choosing a hardware architecture to build a robot with, the Von Neumann architecture is the most conventional style of architecture. The Von Neumann architecture, compared to alternatives, is often compatible with more off-the-shelf hardware and conforms to more traditional programming methods. That architecture can be the most straightforward to work with relative to common-place computing practices. There are potential disadvantages to choosing that architecture instead of others for simulating neural activities involved in spatial navigation, for example, it can be power hungry, needing deterministic behavior, primarily serial in execution, necessarily synchronous, susceptible to physical damage, and require explicit programming for each task [19].

Neuromorphic and other alternative architectures can include the advantages of processing in nondeterministic ways, having massive parallelism of conceptually simple processing units, e.g., neurons, performing complex non-sequential calculations, and being power efficient. These advantages are some of the ways that organic brains have strengths in computing information. Therefore, alternative architectures such as that one can fit better for neural simulations in some cases because their methods of computing are more similar to natural brain processes than conventional architectures, making it easier to adapt neural systems to the computing system. Greater computing power can potentially be achieved by using non-Von Neumann hardware but challenges can also exist with implementing it. Von Neumann alternatives, compared to Von Neumann systems, can potentially be more expensive, less well established technologies, and have a smaller community of users available for support.

4. Results

An advancement that has been made in SLAM technology was described in an article by Menezes et al. and included work with the RatSLAM project [1]. A robotic rat can use stored records of movement in an environment that other robots collected, or it remembers experiencing, and combine that with new movement that it has performed to map an environment. A way that movement information is shared or recalled is through a video of its path through an environment. A comparison is made between a prerecorded and new map to arrive at a consensus about the path to take. A performance gain that has been observed in the experimentation is a reduction in time to generate a map of a spatial environment, specifically the task was performed in 174 seconds instead of 204 seconds (the time needed when the recorded movement was not combined).

An advancement in the ability to simulate of spatial memory was created by Tang & Michmizos's research on navigation of an environment without visual input [7]. The robot those researchers developed was successfully able to navigate a maze environment during no visual input without running into maze border walls. This achievement was made possible by the robot accessing a memorized map of the environment that was created when visual input was permitted. The activity of simulated place cells was recorded with and without visual input and the research qualitatively found through plotting the activity a large amount of similarity between both states. Potential applications for this technology are the ability to compensate for intrinsic hardware imperfections, for instance, partial or total loss of visual input.

An accomplishment made with neuromorphic hardware is Hwu et al.'s work that for the first time embedded an IBM Neurosynaptic System (IBM TrueNorth chip) on a mobile platform under closed-loop control [4]. This system was able to achieve the creation of a robot that successfully transversed a steep mountain path in real time with only minimal intervention to make sure it stayed on the path. This was able to be done after the robot learned from itself being first manually driven by the researchers along that same path. The algorithm used for training was a deep convolutional neural network (CNN) using the IBM chip with 4096 processing cores. The robotics system was connected to an mobile phone via a wireless network hotspot to receive computing instructions with a Android-based robotics platform. The research found that good performance can be acquired through only using a fraction of the total cores available in the computing platform, and that can produce energy savings in running the system. For instance, using only one quarter of the chip's cores resulted in 85 percent accuracy in navigation.

5. Discussion

Including the performance gain that was found in Menezes et al.'s work across multiple environments can add up to significant efficiency gains. Some of the work in the study included a robot performing navigation and playing the video of that transversal back again to the robot to simulate the movement a second time. This describes the process of memory replay but the process of preplay can also be potentially used to improve the mapping of environments. Preplay is predictive path movement, that can simulate an imagined transversal through an environment, and be used to indicate the effectiveness of movement choices before they are taken. Humans and other animals use such cognition to improve the process of their navigation, and lessons learned from that neural behavior can be applied to robotic movement as well as further investigated through the use of robots.

A study by Milford et al. describes the importance of balancing biological realism and robotic system design practicality when investigating neuroscience-relevant navigation properties [20]. In the research, work involving the RatSLAM system allowed a biological simplification by creating "pose" cells that record a three-dimensional position pose of a robot rather than extracting that through more biologically complex processes. The pose cells were considered to have a low level of biological realism, but were helpful for getting the robotic navigation system working effectively. The discovery of grid cells that occurred after that research was worked on was found to have similar but not identical characteristics to the pose cells. The simplification by Milford et al. was a way that the exact current knowledge of biology was not adhered to too strictly, and produced an example of how allowing such a modification could lead to insights or predictions about biology. This general approach of balancing the amount of strict adherence to current knowledge with modifications of that knowledge can also be generalized to other disciplines. The authors state that by having a functionally driven investigation, where the new cell type was constructed to accommodate robot navigation functionality, concepts about how such novel cells could work were devised. In that way, through combining elements from both neuroscience and robotics, some contributions were able to be made to both fields.

Hwu et al.'s neuromorphic-based system can be expanded on in several ways in future work. One way that the system can be expanded is through including a sonar sensor, which can train the CNN to detect obstacles better. This could also be used to study bats or other animal behavior that use sonar for navigation [4]. In general, adding more training data to the system can potentially increase the performance of the system. That training data could either be from longer exploration sessions before testing, more sensors, or randomly varying parameters in the existing training data with approaches such as the Monte Carlo algorithm. More complex longer-term strategies for navigation can be incorporated into the system. For example, path planning and decision-making could be designed for further distance strategies. Rather than focusing on close distance locomotion obstacles, a larger scale look at the directions that would be beneficial to take for long traveling routes can help transverse extensive distances. The authors admit that a part of their success was from the basic characteristics of the landscape, for instance, the red hue of the road and bold green hue for the bordering areas. Testing the system on environments with more variety in visual and other properties can further provide evidence toward its capabilities and reveal areas of improvement that can be investigated.

6. Conclusion

Robotic animals can be a big advantage to include in spatial navigation research and a large number of options exist for ways to build them. Discoveries made in general robotics and neuroscience can help both fields by applying lessons learned from one field to the other. When building a robot for spatial navigation research, it is important to give thorough consideration to the design choices selected. Some of the choices available are inclusion of SLAM, LiDAR, accurate recreation of relevant neural cell types or alternative types of neurons, and algorithms used to process network-level computations. Other elements that can be considered are the inclusion of specific sensors, robot components suited for the physical environment they are intended for, and computer processing architectures. An in-depth understanding of the options available for constructing the robots can importantly benefit the results obtained from research with them.

Multiple instances of theoretical and technological advancements have been made using robots to aid the study spatial navigation. The ability to play back previously experienced path navigation recordings combined with new navigation experiences can accelerate the learning of spatial environment maps. Records of navigation through space can be applied to situations where minimal or no visual input is available, and offers a compensatory mechanism for finding a desired path to follow. Highly effective levels of robotic navigation operation, for example, transversing a steep mountain path, have been achieved through adding new levels of computing abilities with neuromorphic hardware. Technological improvements such as these are important steps of progress in spatial navigation research and they can be further tested, refined, and expanded to new applications, to enhance their usefulness. The improvements also improve the capabilities of robots to be used in neuroscience investigations, and in turn lessons learned from those investigations can be applied to create greater technologies in the future.

7. References

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