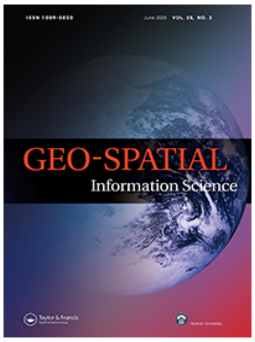

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Geospatial brain-inspired navigation: a neurocognitive approach for autonomous systems in complex environments

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ABSTRACT
Autonomous navigation plays a crucial role in cutting-edge scientific and technological domains, such as autonomous driving and space exploration. Current models often rely on knowledge of the discharge patterns of navigation cells in living organisms (e.g. place/grid cells) to encode spatial information, which works well in ideal environments. However, real-world autonomous navigation presents greater challenges due to complex and dynamic geospatial information, leading to issues such as low robustness, poor interpretability, and high energy consumption for existing models. To address these challenges, it is essential to explore the roles and functional connectivity of distinct brain regions involved in processing real-world geospatial information and integrate these insights into autonomous navigation algorithms. This paper reviews empirical studies using neuroscientific techniques to investigate how the human brain processes geographical information during navigation. In particular, we discuss opportunities and challenges associated with three critical aspects: (1) expanding the understanding of cognitive mechanisms from isolated regional functions to integrated functional connectivity and large-scale brain networks, (2) refining neurocognitive experiments to provide ecologically valid evidence in complex and dynamic contexts and (3) developing efficient approaches to computationally mimic and implement spatial cognition mechanisms of human brain in navigation algorithms. Addressing these difficulties would not only enable machines to navigate autonomously and effectively in complex real-world and extreme environments (e.g. space and the deep sea) but also pave the way for the development of future intelligent systems (e.g. GeoAI) with human-like cognitive capabilities.

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Brain-inspired navigation; geospatial cognition; mechanisms; cognitive experiment; computational model

1. Introduction

Navigation is critical for the long-term autonomous survival of human beings in large-scale and complex natural environments and is also a basic spatial activity that is indispensable in daily life. Successful navigation requires a range of geospatial information to form an internal representation (i.e. mental map/cognitive map) of the surrounding area (Gold and Saarinen 1995; Tolman 1948). Through continuous interaction with the environment, navigators acquire spatial knowledge by learning landmarks and routes, and gradually develop their cognitive maps of the environment, which support self- and goal-localization, landmark anchoring, route planning, and adaptive navigation strategies in navigation processes. While existing models of spatial knowledge acquisition offer valuable insights into autonomous navigation (Hegarty et al. 2006; Siegel and White 1975). These models do not clarify how spatial information is perceived, processed and then used by navigators, i.e. how spatial information is efficiently processed by the brain into spatial knowledge, thereby offering limited support for the development of navigation systems that are robust, energy-efficient, and interpretable. The human brain, a generalized intelligence system that has evolved naturally over hundreds of millions of years, is essential for perceiving, memorizing, processing and applying geospatial information, as well as for integrating this information to construct, update, store, and retrieve mental maps (Butler, Hardcastle, and Giocomo 2019; Peer and Epstein 2021; Raichle 2009). For this reason, state-of-the-art autonomous navigation systems have been initially developed based on cognitive computational models inspired by the firing patterns and mechanisms of navigation-related cells in the animal and human brain, particularly place cells and grid cells, which have been extensively studied in the field of neuroscience. By mimicking the geospatial information processing

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(e.g. spatial coding, landmark anchoring and route planning) observed in biological systems, these models achieve improved navigation performance (Burgess et al. 1997; Mulas, Waniek, and Conradt 2016; Samu et al. 2009). However, these models rely on simplified representation of spatial information, by encoding isolated navigation-related neurons or brain regions, while overlooking the involvement of advanced cognitive functions that are essential for real-world navigation processes. As a result, these models struggle to navigate effectively in complex and dynamic real-world environments (Bellmund et al. 2018; Ismakov et al. 2017).

Existing autonomous navigation algorithms learn animal/human cognitive mechanisms in highly controlled and simplified laboratory environments (Liu et al. 2022; Tang, Yan, and Tan 2018; Yu et al. 2019; Zhou, Weber, and Wermter 2018). However, unlike navigation in the strict control setting, real-world navigation involves substantial geospatial information, such as urban elements (i.e. paths, edges, districts, nodes, and landmarks (Lynch 1964)), terrain types, weather conditions, and fluctuating light conditions. These factors collectively contribute to the complex spatial information encountered during real-world navigation, with each playing a distinct role. For example, real-world environments are often cluttered with ambiguous or incomplete landmarks, requiring navigators to rely on imperfect or partial information to make decisions (Prescott 1996; Strickrodt, O'Malley, and Wiener 2015). Beyond landmark clarity, the geometric structures of the environment, such as two-dimensional layouts (e.g. grid vs. non-grid road networks) and three-dimensional vertical arrangements (e.g. low-rise vs. high-rise buildings), also affect how navigators acquire spatial knowledge and construct mental maps (Gardony and Taylor 2011; Montello and Pick 1993; Ruddle et al. 2011). These factors, combined with the need to process and adapt to unexpected changes in dynamic contexts (e.g. moving vehicles and pedestrians), demand additional navigation processes such as obstacle avoidance and path replanning. All these factors significantly increase the navigators' cognitive load, as well as the complexity of navigation tasks and computational modeling in real-world settings (Armougum et al. 2019; Richardson, Montello, and Hegarty 1999), thereby decreasing the accuracy and applicability of existing autonomous navigation methods (Michael M. Milford and Schulz 2014).

Beyond environmental complexity, limitations within existing autonomous navigation algorithms further compromise their real-world applicability. These systems predominantly rely on high-precision sensors to continuously collect and process large volumes of spatial information (Vivacqua, Vassallo, and Martins 2017; Zecca, Marks, and Smith 2019), leading to substantial computational demands and elevated energy consumption. Additionally, these algorithms often employ artificial neural networks and deep learning methods to enhance performance, while reduce the interpretability of the model. Consequently, achieving an optimal trade-off among energy efficiency, robustness, and transparency remains a persistent challenge. In contrast, the human brain performs complex navigation tasks with remarkably low power consumption by different functional regions and intricate neural network connections (Balasubramanian 2021). Therefore, it is necessary to understand and integrate the cognitive functions and connectivity mechanisms the human brain employs for processing geospatial information, and to address the existing challenges in power consumption, robustness, and interpretability of autonomous navigation models through the learning and modeling of these mechanisms. By modeling these mechanisms, we aim to develop geospatial brain-inspired navigation systems that can efficiently perceive, memorize, process, and apply geospatial information in complicated real-world environments or even in extreme environments.

In this review, we focus on research on the cognitive mechanisms underlying information processing during navigation. In addition to studies involving humans, we select some related studies based on rodents, as invasive experiments on humans are not ethically justifiable. The central functional areas of navigation are anatomically preserved in mammals, suggesting functional homology between humans and rodents (Clark and Squire 2013). The empirical evidence offers suggestions for future research, from experimental design in real-world geospatial environments to the development of geospatial brain-inspired navigation models that are highly robust, energy efficient and interpretable. Therefore, we suggest that researchers in the GIScience community revisit human brain cognitive mechanisms for processing complex, dynamic, multidimensional, real-time, and interactive geographic information during real-world navigation, with the aim of understanding these cognitive mechanisms and developing geospatial brain-inspired navigation models for novel autonomous navigation systems.

2. The cognitive mechanisms underlying geospatial information processing

2.1. *What are the cognitive mechanisms?*

The essential nature of cognitive mechanisms for processing geospatial information during navigation should be clarified. Specifically, each cognitive process of spatial navigation, such as spatial coding, landmark anchoring and route planning (Epstein

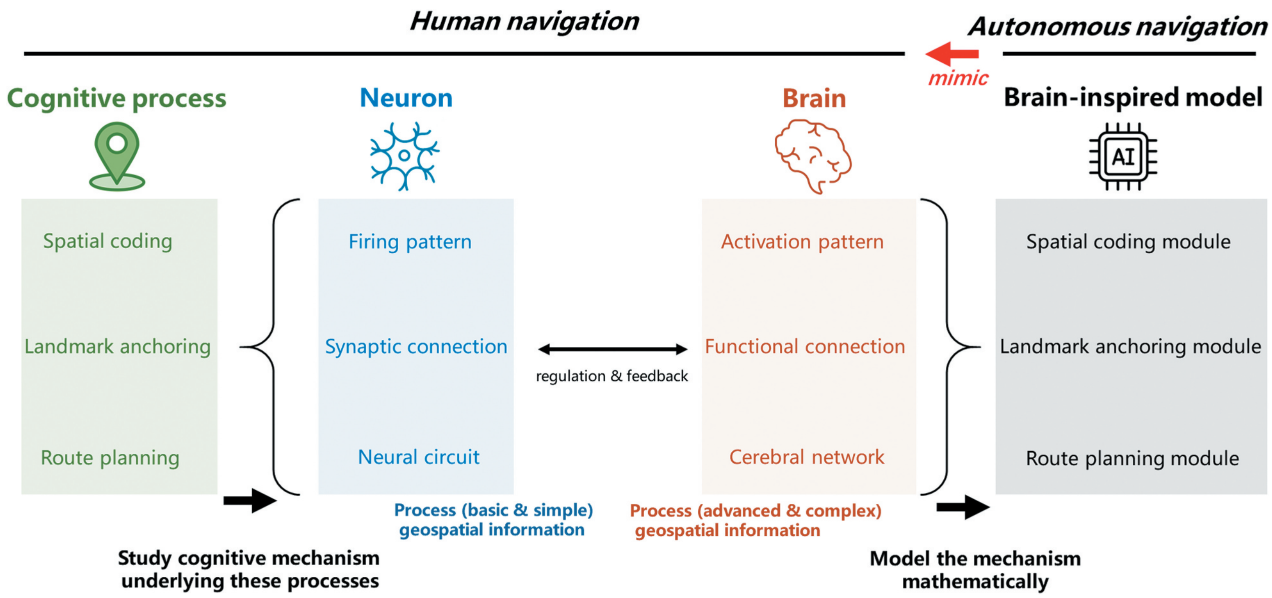

Figure 1. Framework of geospatial brain-inspired navigation.

et al. 2017) engages unique cognitive mechanisms. The cognitive mechanisms underlying these processes involve how geospatial information is perceived, memorized, processed, and integrated at multiple levels, from microscopic neuron firing pattern and macroscopic brain regional activities to localized neurons/brain regions to entire neuronal circuits/brain networks to reveal unified/unique patterns. Understanding cognitive mechanisms at the neuronal and brain-region levels separately, as well as the regulation and feedback processes performed across these two levels, can provide valuable insights for developing models and algorithms to simulate and reproduce human-like intelligent behavior (Figure 1).

At the neuron level, cognitive mechanisms are primarily reflected in the neural firing activity of spatially tuned cells – such as place cells, grid cells, and head direction cells – as well as their coordinated interactions during spatial information encoding, typically recorded using invasive or implantable electrode techniques. At the brain-region level, cognitive mechanisms refer to the distinct functional roles of specific brain areas and their inter-regional connectivity, which together facilitate the integration and processing of geospatial information. This coordinated activity forms the basis for decision-making in navigational contexts. To investigate these processes at the brain-region level, neuroimaging techniques such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET), electroencephalography (EEG), and magnetoencephalography (MEG) are commonly used to examine the functional roles of brain regions, their connectivity, the overall organization of functional networks, and the dynamic changes in these networks during the execution of complex behaviors or cognitive tasks.

2.2. How are cognitive mechanisms integrated into autonomous navigation models?

The current core functions and modules of autonomous navigation models include mapping, localization and route planning (Ling and Shen 2017; Noh, Park, and Park 2020; Siagian, Chang, and Itti 2014). The traditional way for machines to accomplish these three tasks is to apply traversal ideas and algorithms to use relevant information in the environment and create fine-grained internal representation maps including the position of the machine in the environment; then, the optimal path is planned according to special rules (Cadena et al. 2016). Obviously, this method of mapping and planning is very different from how the human brain performs such tasks because a traversal-like mapping/planning process is not feasible owing to the memory capacity and energy consumption of the human brain. Thus, the critical limitations of existing autonomous navigation algorithms are low robustness, poor interpretability, and high energy consumption. If cognitive mechanisms can be learned and modeled by machines, machines may be able to process geospatial information as efficiently and cost-effectively as the human brain. In addition, the interpretability of the model may be significantly improved if the model mimics the cognitive processes of the human brain.

Autonomous navigation models are typically structured into functional submodules (e.g. mapping, localization, and planning modules) for distinct computational tasks. Similarly, human navigation also involves a series of cognitive subprocesses in human brain, including spatial coding, landmark anchoring, and route planning (Epstein et al. 2017). Therefore, submodules in navigation systems may need to be explicitly assigned to the cognitive mechanisms of specific cognitive subprocesses, enabling more biologically inspired system designs. Cognitive mechanisms of human brain could be mathematically abstracted in the model through cognitive computational modeling. Similar to cognitive mechanisms, mechanisms can be abstracted and expressed at different levels to develop brain-inspired navigation models with different applications. The representation of spatial relationships via neurons is currently the predominant approach. For example, cognitive map models have been constructed on the basis of the firing mechanisms of different neurons, such as place cells and grid cells, and their connections (Klukas, Lewis, and Fiete 2020; Zilli 2012). This approach focuses on modeling the activity of individual neurons and neural networks, emphasizing neuronal firing patterns, synaptic connections, and the dynamics of local networks. Such models are generally suitable for navigation tasks in simple environments, which include simple visual information, clear routes and obvious landmarks (Milford and Schulz 2014).

At the brain function and connectivity level, information flow and functional connectivity between brain regions are used in the construction of cognitive maps, with the aim of capturing global functional patterns rather than the fine-grained activity of individual neurons. However, there is no easy way to express these cognitive mechanisms abstractly in existing autonomous navigation models. A major reason for this difficulty is that brain regions are usually not clearly responsible for only one function, and the synergy and cooperation of different brain regions are extremely complex. Owing to the ambiguity of cognitive mechanisms, abstracting such mechanisms in models for learning is very difficult. In the future, if the cognitive mechanisms at the level of brain function and connectivity are clarified, another major challenge will lie in how to effectively abstract and incorporate these brain-region level cognitive mechanisms into computational models. Neurodynamic approaches, such as attractor networks and oscillatory models, may offer promising solution, especially for simulating the flow and integration of information across brain regions (Barry and Burgess 2014; Burgess, Barry, and O'Keefe 2007).

Finally, the model should integrate information across multiple levels to adapt to environmental changes and achieve precise navigation in dynamic geographic spaces. A hierarchical model, which includes microlevel neuron modeling and macrolevel brain region activity modeling, can be considered in such cases. In hierarchical models, neural activity is translated into brain region activation, and feedback connections are used to adjust neuronal excitability or inhibition. Dynamical modeling and simulations can be used to capture the dynamic interactions between these levels, and differential equations or large-scale neural network simulations can be employed to observe the mutual influences of neural activities at the cell and whole brain levels (Breakspear 2017).

3. A review of current empirical studies on cognitive mechanisms

3.1. Cognitive mechanisms at the neuron level

Cognitive neuroscience research has demonstrated that spatial coding, landmark anchoring, and route planning are closely related to a variety of spatial information encoding cells in the brain, including place cells, grid cells, head direction cells, and boundary cells (Ekstrom et al. 2003; Epstein et al. 2017; Jacobs et al. 2013; Kim and Maguire 2019). These cells are located primarily in the hippocampus and entorhinal cortex within the limbic system of the brain and encode diverse types of spatial information. Place cells, which are located in the hippocampus, encode information about an animal's location as it moves through an environment (O'Keefe and Dostrovs 1971), which is essential for the formation of cognitive maps. Grid cells, which are located primarily in the medial entorhinal cortex, provide a coordinate system for encoding spatial location information from place cells and integrating velocity and self-motion information, serving as a potential basis for path integration (Hafting et al. 2005; Whitlock et al. 2008). Owing to the functional characteristics of place cells and grid cells, these cells are believed to collectively encode allocentric spatial location information.

Successful navigation requires not only a clear sense of one's own position but also a sense of non-allocentric information. Head direction cells encode the orientation of an animal's head and were initially discovered in the presubiculum of rats, but subsequent research revealed their distribution in the entorhinal cortex and retrosplenial cortex (Sargolini et al. 2006; Taube, Muller, and Ranck 1990), and such cells are widely distributed throughout the entire limbic system. Additionally, other types of cells have been found, such as border cells (encoding the distance between themselves and the boundary) (O'Keefe and Burgess 1996), speed cells (encoding velocity information) (Kropff et al. 2015) and time cells (encoding time information) (MacDonald et al. 2011). Cells that encode spatial information constitute the intrinsic spatial localization system of the brain (Epstein et al. 2017). Neural circuits in the entorhinal cortex and hippocampus constitute the core of the navigation and localization systems (Frank, Brown, and Wilson

2000; Tang, Li, and Yan 2010); these circuits support map-like spatial encoding, including the encoding of spatial representations (Epstein and Kanwisher 1998; Spiers and Gilbert 2015; Spiers and Maguire 2006), spatial distances (Deuker et al. 2016; Morgan et al. 2011; Nielson et al. 2015), spatial memory (Epstein, Parker, and Feiler 2007; Kolarik et al. 2016; Maguire, Nannery, and Spiers 2006; Teng and Squire 1999), and spatial scale Evensmoen et al. (2015); Salgado-Pineda et al. (2017); Peer et al. (2019), as well as the implementation of navigation strategies (Hartley et al. 2003; Iaria et al. 2003; Marchette, Bakker, and Shelton 2011).

In general, humans and animals encode their own position through population discharge vectors formed by many place cells in the hippocampus. When the same element is encountered again during navigation, specific place cells are activated, encoding the position within the environment by representing the spatial relationships between elements. Place cells also receive directional information from head direction cells and path integration (dead reckoning) information from grid cells in the entorhinal cortex. Grid cells integrate motion information from the vestibular system and represent the distance and directional information between different positions in the environment by integrating motion speed and direction information, which is passed to place cells for encoding. This process enables the creation of a representation of the spatial structure of the environment, leading to the generation of cognitive maps that represent spatial relationships. The cognitive mechanisms at the neuron level are primarily related to the encoding of spatial information, while the mechanisms underlying landmark anchoring and route planning remain unknown. These processes are more advanced and complex and may require the collaboration of many intraneuronal/neuronal circuits, and invasive experiments with normal human participants are difficult to perform.

3.2. *Cognitive mechanisms at the brain region level*

At the brain region level, the hippocampus and entorhinal cortex are the core brain regions responsible for constructing cognitive maps (Cholvin, Hainmueller, and Bartos 2021; Epstein et al. 2017; Park et al. 2020). They are highly organized structures, and their interregional communication is a key component of spatial navigation (Jeffery 2007; Poulter, Hartley, and Lever 2018). In addition to the encoding of spatial information and the construction of cognitive maps, the cognitive map must be anchored to the real world by matching real-world locations with those on the map, which generally involves perceiving and recognizing landmarks and scenes in the environment. This process is associated with the occipital place area (OPA) (Julian et al. 2016; Kamps, Lall, and Dilks 2016) and the parahippocampal place area (PPA) (Epstein and Kanwisher 1998; Persichetti and Dilks 2019). Moreover, determining one's position and orientation on the basis of perceived information is linked to the function of the retrosplenial cortex (RSC), which coordinates egocentric local scenes with broader allocentric maps (Marchette, Ryan, and Epstein 2017; Meilinger 2008). Next, knowing the locations of other potential navigation points is crucial. While this information can be obtained from cognitive maps, studies have shown that long-term spatial knowledge is also encoded in the RSC (Vass and Epstein 2013). Unlike the cognitive maps encoded in the medial temporal lobe (MTL), the RSC may encode vectors representing only the most prominent or frequently traveled locations (Kuipers, Tecuci, and Stankiewicz 2003; Schinazi and Epstein 2010), facilitating rapid path planning between familiar places. Finally, effective route planning between different locations is essential. Route planning is closely associated with the prefrontal cortex, and the neural circuits between the prefrontal cortex and the medial temporal lobe support route planning (Chadwick et al. 2015; Howard et al. 2014) and the selection of optimal paths (Balaguer et al. 2016; Javadi et al. 2017; Kaplan et al. 2017).

Regarding the mechanisms at the brain region level, the functions of individual brain regions are better understood, but the functional connectivity between brain regions and the brain networks involved in geospatial information processing are less studied. Furthermore, while the prefrontal lobes have been shown to be critical for spatial decision making (e.g. route planning), the functions of the prefrontal lobes are extremely complex, and specific mechanisms in this region remain elusive; thus, further research is needed to determine how geospatial information is used for decision-making in brain networks.

4. Opportunities and challenges for future related research

4.1. *Expanding cognitive mechanisms: from individual functions to functional connectivity and networks of brain regions*

The cognitive mechanisms underlying geographic spatial navigation include mechanisms at both the neuron and brain region levels. Research on neuron-level cognitive mechanisms typically involves understanding how individual neurons represent spatial information and how multiple neurons work together to form functional circuits or networks. Researchers can explore how individual neurons process spatial information and communicate with other neurons through synapses, as well as the connectivity patterns between neurons, the functions of local circuits, and how these circuits accomplish complex cognitive functions. These studies are often conducted via techniques such as optogenetics and connectomics and electrophysiological experiments (Kim, Adhikari, and Deisseroth 2017). While neuron-level cognitive mechanisms provide the foundation for brain region functions, isolated studies at the neuronal level cannot fully explain complex cognitive phenomena. For these reasons, as well as the difficulty of conducting this type of research with healthy people, future research in this area is not the focus of this study.

The interaction and coordination between various brain regions are essential for achieving the overall cognitive processes underlying geographic spatial navigation. Research on brain region-level cognitive mechanisms requires neurocognitive navigation experiments with high ecological validity to explore brain region responses, interregional connections, functional network organization, and dynamic changes in these networks during the execution of complex behaviors or cognitive tasks. First, it is necessary to identify the brain regions related to geographic spatial navigation, such as the hippocampus, entorhinal cortex, parietal cortex, prefrontal cortex, and their subregions, and their functions during navigation. On this basis, the activity and interactions of the functional connectivity networks between these regions can be investigated. However, the flow of information and interactions between these regions are highly complex, making it a significant challenge to fully capture and understand their dynamic connectivity. Different brain regions may be involved in multiple cognitive processes simultaneously, making it difficult for researchers to isolate the independent roles of each region in specific cognitive tasks through single experiments or techniques. The study of brain region-level cognitive mechanisms requires recording and analyzing large-scale brain activity, yet current noninvasive brain imaging techniques (such as fMRI and EEG) have limitations in terms of both temporal and spatial resolution. A lower temporal resolution restricts the observation of rapid changes in brain activity, whereas complex connectivity within the brain cannot be captured with insufficient spatial resolution. Additionally, understanding the collaboration and connectivity between multiple brain regions, integrating neuronal activity to create macroscale brain region activities, and clarifying the complex coupling and feedback mechanisms across different levels pose substantial challenges.

4.2. Refining neurocognitive experiments to provide specialized evidence in complex and dynamic contexts

Integrating multiple experimental techniques to design geospatial brain-inspired navigation experiments with high ecological validity facilitates the exploration of cognitive mechanisms. Geospatial brain-inspired navigation experiments should evolve from survey-based assessments of behavioral performance, such as interviews and questionnaires (Hegarty et al. 2002; Vandenberg and Kuse 1978), to the use of neuroscientific experimental techniques to investigate the cognitive mechanisms underlying navigation behavior. Recent noninvasive neuroimaging experimental techniques in neuroscience and psychology, such as fMRI, EEG, functional near-infrared spectroscopy (fNIRS), MEG and eye tracking, have significantly contributed to geospatial navigation research (Andersen et al. 2012; Liljeström et al. 2009; Lin, Chiu, and Gramann 2015; Mononen et al. 2025). Researchers can investigate the cognitive mechanisms involved in the navigation process in a targeted manner by using the adaptability of various technical approaches (Table 1). However, owing to the requirements for ecological validity, geospatial navigation experiments still need to be adapted and adjusted from traditional neuroscience experiments. The specific challenges and suggestions are related to two key aspects: complex environments and mobile properties for navigation. First, navigation behavior occurs in complex real-world environments; thus, the stimuli used in experiments should closely mimic those encountered in actual geospatial settings (Bülthoff and Veen 2001; Matusz et al. 2019). Second, the mobile nature of navigation should be considered in the design of experiments and the selection of experimental techniques (Park, Dudchenko, and Donaldson

Table 1. The applicability and characteristics of different technological approaches.

Technique	Applicability	Temporal Resolution	Spatial Resolution
fMRI	Suitable for studying deep brain structures (e.g. hippocampus, entorhinal cortex) by measuring blood oxygenation changes linked to neuronal activity	Second-level (1 s-3 s)	Millimeter-level (1 mm-3 mm)
EEG	Suitable for capturing electrical signals from neuronal activity to analyze cortical dynamics	Millisecond-level (0.1 ms-10 ms)	Centimeter-level (1 cm-10 cm)
fNIRS	Suitable for inferring localized neural activity by measuring blood oxygenation changes	Subsecond to second-level (0.1 s-1 s)	Centimeter-level (2 cm-3 cm)
MEG	Suitable for detecting weak magnetic fields from neuronal activity to analyze cortical dynamics	Millisecond-level (1 ms-10 ms)	Millimeter to centimeter-level (3 mm-10 mm)
Eye tracking	Suitable for analyzing spatial cognitive processes via direct eye movement responses to external stimuli	Millisecond-level (0.5 ms to 33 ms)	Angular resolution (0.5°-2° visual angle)

2018). Therefore, a single experimental method is insufficient for accurately studying spatial information processing during navigation.

Navigation in real-world and ecologically valid settings involves rich, dynamic, and context-dependent environments. These environments contain complex spatial cues, diverse visual features, and task-relevant changes that place higher cognitive demands on perception, attention, and memory systems. However, many existing neuroscience experiments that often rely on highly controlled and simplify environmental settings, resulting in relatively straightforward perceptual processing (Kay et al. 2008; Sadr 2011) but limiting the understanding of how human brain interacts with real-world scenarios. A series of studies examined the neurocognitive mechanisms involved in various navigation processes (Arajo, Baffa, and Wakai 2002; Cornwell et al. 2008; Liu, Dong, and Zhu 2019; Wirth et al. 2020; Miyakoshi et al. 2021), or in different groups such as sex (Kober and Neuper 2011), education level (Erkan 2018), and age (Lithfous et al. 2018) using noninvasive neuroimaging technique (e.g. fMRI, EEG and EEG). These studies typically require participants to remain stationary while viewing images or videos, and stimulus materials can be presented only through 2D monitors, which may cause neuroimaging results to diverge from actual neural activity (Taube, Valerio, and Yoder 2013).

In addition, the impact of mobile properties on ecological validity cannot be overlooked. Head movements are strictly limited when using static neuroimaging methods such as fMRI; however, these movements are involved in actual navigation. While static imaging methods can elucidate the cognitive mechanisms associated with navigation, the lack of idiothetic information may compromise the accuracy of the identified navigation mechanisms (Chance et al. 1998; Waller, Loomis, and Haun 2004). For example, stationary navigation tasks can result in sensory conflicts and impaired performance because subjects must compensate for missing idiothetic information with alternative navigation strategies (Gramann 2013; Ladouce et al. 2017). Therefore, mobile brain/body imaging (Jungnickel et al. 2019) has the great potential to facilitate real-world navigation experimental setting with high ecological validity. Mobile EEG and fNIRS are valuable mobile imaging techniques that effectively accounts for sensory input resulting from body movement and can be used to measure neural activity while subjects move freely (Atsumori et al. 2010; Piper et al. 2014). Innovative data analysis methods for mobile EEG devices have been developed to overcome the control issues associated with stimulus presentation with traditional brain imaging techniques in real-world settings, providing high ecological validity (Wunderlich and Gramann 2021). Mobile eye tracking has been widely employed to investigate visual attention behavior (Dong, Liao, and Zhan 2019; Liao et al. 2019; Dong et al. 2022) during wayfinding processes in real-world or virtual environments. Considering motion devices integrated with virtual reality (VR), including VirtuSphere and CyberWalk, have been developed to provide a more natural sense of movement in immersive environments (Hardiess, Mallot, and Meilinger 2015), integrate these VR setting with mobile brain/body imaging techniques could provide a more controlled but high ecological validity setting for navigation experiment.

Building on the potential of mobile brain/body imaging and VR-integrated settings, researchers have begun combining techniques such as EEG and eye tracking to investigate navigation-related cognitive processes with greater ecological validity. For instance, studies have utilized these methods to assess cognitive loads during map-reading tasks (Keskin et al. 2020), evaluate the effectiveness of navigational aids (Ying, Dong, and Fabrikant 2024), and identify activities performed on maps (Qin et al. 2024). These approaches capture dynamic neural and visual attention data in real-world or simulated environments, offering insights into spatial cognition that static methods cannot provide. However, each technique has limitations, such as constrained temporal or spatial resolution and varying suitability for mobile tasks (Friedrich et al. 2016). To comprehensively explore the neural mechanisms underlying geospatial information processing during navigation, integrating multiple experimental methods through carefully designed studies is essential. For instance, fMRI serves as the primary noninvasive technique for imaging deep brain structures, such as the entorhinal cortex and hippocampus, enabling the recording of neural activity within the entorhinal-hippocampal loop. However, its low temporal resolution and the necessity for participants to remain stationary during scanning restrict its utility in mobile tasks. Despite the absence of idiothetic information, the memory and planning systems contribute to the formation of cognitive maps, and fMRI remains the predominant method for studying these cognitive maps and their neural representations (Epstein et al. 2017). Therefore, different techniques can be used in conjunction with fMRI to explore the mechanisms of processing representations of perceptual information in deep brain structures. Integrating synchronized eye-tracking data with fMRI enhances spatiotemporal resolution and aids in uncovering the relationships between complex cognitive processes and brain functions (Peitek et al. 2018). This approach is particularly valuable for tasks such as reading, visual search, and scene comprehension, as simultaneous recording of eye-tracking trajectories and brain responses enables a more comprehensive understanding of cognition (Richlan et al. 2013). Combining fMRI and EEG enables brain activity to be recorded with high spatial and temporal resolution (Cichy and Oliva 2020). This combination has been shown to be useful for a variety of studies, including the localization of psychiatric disorder foci, the involvement of different brain cellular discharges, and insights into how the brain functions in different states or responds to various stimuli (Gotman and Pittau 2011; Laufs et al. 2003; Ritter and Villringer 2006).

Additionally, fNIRS can easily be integrated with other methods, such as EEG (Ahn et al. 2016; Chen et al. 2015), leading to enhanced temporal and spatial resolution and improving the feasibility of mobile imaging for navigation tasks in realistic environments. Although mobile imaging devices are limited in their ability to accurately reflect neural activity in deep brain structures, their use provides a better understanding of the role of motion information in navigation, complementing the dynamically relevant data not available through fMRI alone (Park, Dudchenko, and Donaldson 2018). In particular, combining multiple techniques to obtain multimodal neural data allows researchers to obtain a more comprehensive understanding of brain activity. For example, fMRI can be used to determine activation in the entorhinal cortex and hippocampus, whereas fNIRS and EEG can be used to monitor cortical activity during actual motor tasks. Although fNIRS has centimeter-scale spatial resolution, due to the high degree of correspondence between fNIRS and fMRI data, fNIRS can provide supplementary information for exploring deep brain structures (Cui et al. 2011)

However, comprehensive experimental studies using various techniques face several challenges. In MRI environments, correcting EEG artifacts, such as gradient and pulse artifacts, is essential for accurately reflecting brain activity (Mullinger and Bowtell 2011). Effective artifact correction is crucial for accurate EEG analysis. Moreover, collecting EEG and fMRI data requires the use of MRI-compatible EEG equipment to prevent interference and ensure safety without compromising image quality. Combining EEG and fNIRS involves addressing motion artifacts and light interference issues (Makeig et al. 2009; McIntosh et al. 2010), which can be mitigated through the use of improved sensors (Khan et al. 2012) and algorithms such as principal component analysis (PCA) and independent component analysis (ICA) (Delorme, Sejnowski, and Makeig 2007; Herold et al. 2017). Integrating multimodal data necessitates the development of new analytical methods and advanced computational techniques. Furthermore, participant safety and comfort remain concerns during extended tasks. Despite these challenges, the results of comprehensive experiments continue to provide unparalleled insights into the brain mechanisms underlying navigation, driving ongoing research efforts.

4.3. Developing geospatial brain-inspired navigation algorithms that mimic cognitive mechanisms of the human brain

Existing brain-inspired navigation models are typically autonomous navigation models based on the construction of cells that encode spatial information. Researchers have improved existing autonomous navigation models by adopting the approaches through which animals encode spatial information. For example, Milford, Wyeth, and Prasser (2004) developed RatSLAM, an approximate computational model based on the hippocampal complex. RatSLAM simulates the place field function of place cells in the hippocampus (i.e. neural activity patterns correlated with spatial location) to achieve self-localization and map construction. Milford et al. further expanded RatSLAM by integrating visual features of the surrounding environment into an "experience map," which works as a hippocampal cognitive map (Milford, Prasser, and Wyeth 2005). The experience map enables a robot to reset its localization error by revisiting known areas (referred to as loop closure). The construction of this computational model is similar to the "predictive processing" paradigm proposed in Hohwy's brain function model (Hohwy 2013). This paradigm suggests that the brain processes information through continuous model refinement via the interactions between top-down predictions (from higher cognitive areas) and bottom-up sensory inputs (from sensory organs). Furthermore, in Milford's brain-inspired navigation model, an experience map is constructed by encoding spatial information from perceived landmarks and scenes and then using loop closure detection to continuously refine this map. In subsequent studies, additional mechanisms have been incorporated into models to encode spatial information, such as grid cells and head direction cells (Tang, Yan, and Tan 2018; Yu et al. 2019; Zeng and Si 2017; Zeng et al. 2020; Zhou, Weber, and Wermter 2018). Some studies, inspired by the functional connectivity between CA1 and CA3 in the hippocampus formation, have integrated this mechanism into existing autonomous navigation models (Nakashima et al. 2024). This integration has improved the self-localization performance of these models in simulated environments, further demonstrating that incorporating cognitive mechanisms can enhance autonomous navigation algorithms. However, these models demonstrate insufficient generalizability in real-world environments and struggle to adapt effectively to dynamic changes in actual geographic spaces. Behavior and cognition arise from the interplay among various brain regions; no neuron functions in isolation

(Thiebaut De Schotten and Forkel 2022). Thus, effective navigation in complex real-world environments remains challenging with existing navigation models, possibly because of their dependence on spatial metric representation mechanisms at the neuron level, without integrating higher cognitive functions.

Exploring the cognitive mechanisms underlying spatial navigation and effectively integrating them with existing deep neural networks can be beneficial for addressing the challenges of power consumption, robustness, and interpretability faced by current models and algorithms. This integration can use the high interpretability of cognitive data to address the low interpretability of current navigation models. Deep learning-based neural networks have demonstrated excellent performance in object and scene recognition, with network units potentially encoding information from the mammalian visual cortex (Agrawal et al. 2014; Güçlü and Van Gerven 2015; Yamins et al. 2014). This finding indicates that cognitive data can be used to enhance model interpretability. For example, Banino et al. (2018) developed a deep reinforcement learning agent for navigation tasks on the basis of the computational functions of grid cells. The model uses hidden nodes to read motion memories stored in long short-term memory (LSTM) networks, generating firing patterns similar to those of grid cells, head direction cells, and boundary cells. This study provides evidence supporting the neuroscience theory that grid cells aid in navigating to hidden goal locations via direct routes that may traverse previously unvisited places (vector-based navigation). Moreover, some studies have used the hippocampus's potential ability to encode and predict future locations to construct a "predictive map." This map is then dimensionally reduced through grid cell modeling in the entorhinal cortex to facilitate hierarchical planning (Stachenfeld, Botvinick, and Gershman 2017). This approach not only provides an interpretation of extensive data from hippocampal research but also optimizes the reward mechanism in reinforcement learning, thereby enhancing the biological plausibility of the model. Other reinforcement learning-based navigation models have used neural mechanisms encoding spatial information to optimize reinforcement learning algorithms or enhanced the interpretability of these models by incorporating neural data from diverse sources and levels (Anggraini, Glasauer, and Wunderlich 2018; De Cothi et al. 2022; Mattar and Daw 2018). However, although this approach enhances the interpretability of computational models, their robustness remains low, and existing models remain inadequate for real-world navigation deployment.

Furthermore, brain-inspired navigation models built based on deep neural networks inherently differ from the brain in their processing of perceptual information. For example, the backpropagation (BP) algorithm lacks biological plausibility (Grossberg 1987). This discrepancy may underlie the substantial differences in robustness and energy efficiency between BP-based models and the brain. The lack of understanding of the cognitive mechanisms involved at different levels of the navigation process may also contribute to the reliance on existing artificial neural networks to approximate and optimize these mechanisms. This, in turn, may be another potential cause of inefficient use of computational resources, increased power consumption, and limited model interpretability. A feasible approach to constructing geospatial brain-inspired navigation models is to base such models on cognitive mechanisms at different levels through hierarchical modeling, cross-level information integration, dynamic modeling and simulation, and validation and refinement with experimental data (Dyhrfjeld-Johnsen et al. 2002). This approach enables interactions between neuron-level activity and brain region-level functional expression. Furthermore, such a model may capture the feedback regulation of macrolevel brain region activity on microlevel neuronal activity, providing a comprehensive framework for understanding how the brain generates complex geographic spatial navigation behaviors across different levels. Meanwhile, the development of more efficient model architectures with higher biological plausibility requires sophisticated experimental designs, with various experimental techniques integrated to improve our understanding of the cognitive mechanisms of the human brain during spatial navigation.

Finally, these mechanisms are integrated with computational hardware. For example, neuromorphic chips consume substantially less energy than do conventional computing chips (Merolla et al. 2014). The chips can simulate this perceptual encoding process, receiving environmental information through neuromorphic sensors and encoding it within spiking neural networks (SNNs). These neural networks can be designed to simulate the structure and function of brain regions related to navigation, such as the hippocampus, enabling the effective encoding of spatial information with low power consumption. For instance, neuromorphic chips incorporating cellular and neural circuit mechanisms have been successfully employed for 2D planar navigation in both virtual and laboratory environments (Fleischer et al. 2007; Zeno, Patel, and Sobh 2017). Similar to neuromorphic chips, new brain-inspired robots exhibit notable advancements in reducing both latency and power consumption across various tasks (Ma et al. 2022; Yu et al. 2023). The advancements in neuromorphic hardware and brain-inspired systems not only demonstrate practical benefits in energy efficiency and spatial navigation but also open new avenues for research in geospatial brain-inspired navigation. By leveraging human cognitive neuroscience data, such research enhances the interpretability of computational models and deep learning algorithms, while simultaneously addressing challenges related to robustness and energy consumption through the modeling of cognitive mechanisms. Consequently, the GIScience community's interest in spatial cognition should extend beyond behavioral observations to encompass the underlying neural processes. Adopting interdisciplinary approaches that integrate these neural insights with computational innovations will be critical to overcoming current limitations. Such efforts promise to propel the GIScience field forward, fostering the development of advanced intelligent systems, including GeoAI, with broader applications in spatial analysis and beyond.

5. Conclusions

The adaptability and power consumption limitations of traditional autonomous navigation models make it challenging for existing models to perform autonomous navigation tasks in complex geographic environments. This challenge necessitates the application of innovative interdisciplinary approaches to identify the neural cognitive mechanisms underlying navigation and to construct brain-inspired computational models for geospatial navigation. These new approaches require GIScience researchers to deviate from traditional paradigms and apply novel methods from other fields, which has long been difficult among GIScience researchers. The primary goal of this paper is to promote such interdisciplinary research. We believe that our proposed framework, which employs various cognitive neuroscience methods to comprehensively investigate the spatial information processing mechanisms underlying navigation, will help in the development of interdisciplinary approaches for navigation research. Finally, we hope that such an approach will improve our understanding of human navigation mechanisms and lead to the development of highly robust, low-energy-consumption, and interpretable geospatial brain-inspired navigation models that can be deployed in real-world environments.

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