A Multi-Strategy Spatial Navigation Model in a Text-Based Environment

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ABSTRACT: *Cognitive maps have been used to explain the cognitive processes underlying human spatial memory for several decades. Numerous theories have offered explanations regarding the structure of cognitive maps from the perspectives of spatial cognition, visual perception, and neuroscience. Within this literature, two representations of cognitive maps (map-like representations and route-based representations) have generally been used to model the learning of spatial information. Map-like representations involve spatial geometries, with landmarks acting as strong references. Alternatively, route-based representations consist of sequences of positions, orientations, and landmarks. Studies suggest that humans use both of these representations, and that the representation (and thus the strategy) used is often a function of the agent's familiarity with the environment. In this paper, we propose an ACT-R model that integrates both these representations and their associated strategies, using a route-based representation when learning new environments and a map-based representation to refine the agent's understanding. The results show that the map-based representation could improve an agent's route-following abilities in at least two cases: (1) searching the route when the agent is in an off-route position, and (2) for taking novel shortcuts in the route. Our model's behavioral output is consistent with the literature (Foo, Duchon, Warren, & Tarr, 2005; Foo, Warren, Duchon, & Tarr, 2007), in that our agents like human beings rely primarily on route-based memory when navigating while using map-based memory as a secondary reference.*

1. Introduction

Spatial memory refers to that aspect of human cognition responsible for the storing and processing of environmental clues and spatial orientations. This type of memory is necessary for humans to navigate their surroundings, and is essential for related tasks like returning home or locating food.

In attempting to understand the formation of spatial memory, Tolman (1948) studied the food finding and navigating behavior of rats in a series of maze studies. To explain the novel shortcutting behavior he observed, he concluded that rats and creatures more generally, including humans, generate what he termed *cognitive maps*. The notion of cognitive maps has since gained general acceptance, as has the role of hippocampus in storing these representations (O'Keefe & Nadel, 1978).

Subsequent work regarding cognitive maps has, however, varied in several important ways including: the representation structures necessary to construct them, the kinds of data contained by them, and the strategies used to generate them. After providing a general overview of spatial memory, we will briefly address each of these topics before introducing our model.

1.1 Types of spatial memory

With the development of cognitive map theory, two general representations of cognitive maps have become widely accepted by researchers in this area, that is, the cartographic (or map-like) representations and route-based representations.

Cartographic representations involve a Euclidean map of the space in question, including landmarks, exocentric orientations, and relative directions. Gallistel (1990) states that a cognitive map can constitute a position vector with the positions and attributes of the key points, as well as geometric relations between these points encoded in memory. Position vectors provide a promising representation of spatial knowledge for two reasons: first, they can theoretically represent all types of spatial knowledge as vectors by accurately encoding the geometric relations between a given set of points; second, they can help humans to make novel shortcuts or detours efficiently by retrieving and processing position vectors. Some researchers (Poucet, 1993; Tversky, 2003) have argued that cartographic representations are also scalable and hierarchically organized, similar to a roadmap that displays the boundaries of various political units (i.e., states, counties, and townships).

Alternatively, route-based representations are sequences that consist of landmarks, egocentric orientations, distances, and locations. Compared with map-based representations, route-based representations are a weaker form of spatial memory because they are easily disturbed by changes to the environment such as the loss of key landmarks or other spatial clues (Bennett, 1996). Although route-based spatial memory is more contextually dependent and thus not sufficient for guiding navigation, it is, nevertheless, an essential form of spatial memory because it is the primary method used by humans when encountering new environments (Foo, Duchon, Warren, & Tarr, 2007; Foo, Warren, Duchon, & Tarr, 2005). With several route-based memories, humans can gradually establish a cartographic memory of the environment by recognizing landmarks, connecting positions, and changing egocentric coordinates (Hart & Moore, 1973).

1.2 Navigation strategy

Based on numerous studies of human navigation behavior (Wehner & Menzel, 1990; Cartwright & Collett, 1982; Gallistel, 1990), researchers have proposed three basic navigation mechanisms: path integration, route-based navigation, and map-based navigation.

Path integration can be found in insect navigation, as well as in other creatures. Path integration is mostly associated with a "home vector", or a representation in working memory that stores egocentric orientations and distances from home. When they leave home, insects keep updating their "home vector", enabling them to find the right path home (Wehner & Menzel, 1990). As the home vector is a working memory element, it is believed that path-integration does not involve any type of spatial memory.

Route-based strategy is closely related to route-based spatial memory; both involve sequences of landmarks, turns, and locations. Based on this form of sequential memory, agents can navigate a given environment by approaching a recognized position or landmark (Cartwright & Collett, 1982). This behavioral sequence corresponds to recognizing a position or landmark, approaching it, recalling the next position, recognizing that position, and repeating this process. Route-based navigation, however, is considered an elementary strategy because it is context dependent (i.e., changes to or removal of landmarks can compromise the strategy).

Finally, map-like representations are similar to a Euclidean map, with landmarks acting as strong references. As introduced above, map-like representations provide a set of accurate references (positions, directions, and distances) that enable an agent to perceive a goal position within the environment. Gallistel (1990) states that a cognitive map can constitute a position vector that stores geometric relations. Consequently, any navigation path can be predicted by computing a position vector. Foo, Warren, Duchon, and Tarr (2005, 2007) theorize that landmarks or remarkable references also play an important role in map-based navigation because they help human to localize themselves in an environment, and to be aware of relative locations to the goal position.

1.3 Modeling Navigation behavior in ACT-R

Although many theories have been developed to understand human spatial memory and reasoning, we are still far from fully explaining all of these behaviors. One interesting approach for better understanding spatial reasoning and navigation is to develop cognitive models that seek to replicate the navigation behaviors observed in humans and animals (Harrison, & Schunn, 2002; Johnson, Wang, & Zhang, 2003; Lathrop,2008; Kurup, & Chandrasekaran, 2009). ACT-R provides a way to explore these theories.

ACT-R is a cognitive architecture as well as a unified theory of cognition. It uses a production system to implement rule-based rationality, and numerous buffers to simulate human perception. Specifically, ACT-R relies on a set of mechanisms (e.g., the utility mechanism and activation mechanisms) to simulate human memory, information processing, and reasoning. Gunzelmann and Lyon (2007) discuss the applicability of integrating a module for human spatial memory into ACT-R from both a theoretical and empirical perspective. They conclude that ACT-R can support modeling spatial cognition by providing mechanisms for learning and information processing. Gunzelman and Anderson (2002, 2004) proposed a series of ACT-R models to execute a self-orientation task with multiple strategies. These models matched human data for this task. Based on these models, they then extended the perception module of ACT-R in multiple directions including object buffer, location buffer, and imagery buffer.

Researchers using ACT-R have not only modeled fairly localized tasks but also larger tasks such as navigating a maze, a community, or even a country. Fu (2003) developed a navigation model based on a 2D map representation implemented in ACT-R. By using a simple grid map as a testing environment and coding the map representation into declarative memory, the model supported two basic navigation strategies: hill-climbing and a simple planning strategy. More recently, Reitter and Lebiere (2010) presented a path-planning model that emulates the navigation strategies observed in humans using two components: a visual attention component and a spatial experience (memory) component. The visual attention component simulates the heuristics applied by human beings when performing a visual search in an unfamiliar environment. These heuristics include three basic tasks: straight-line extraction, visual search, and goal recognition. The spatial experience component encodes into declarative memory the spatial information gained by the agent's perceptual-motor module, generating a path or route representation. The agent then follows the path by activating declarative memory chunks sequentially. When there are existing paths available in declarative memory, the model will tend to navigate using the experience component. Otherwise, the agent tends to use the visual attention component.

In this paper, we discuss an ACT-R model using two representations of a cognitive map to implement both a route-based and a map-based strategy in MEDAS: a text-based multi-agent environment. Comparing to Reitter and Lebiere's (2010) work, there are three innovations to their basic approach: (1) theoretically, we propose a more complete approach for modeling spatial memory that draws upon previous literature (O'Keefe & Nadel, 1978; Bennett, 1996; Gallistel, 1990) by adding a map-based memory; (2) our model enhances the agent's performance by applying navigational shortcuts and route-searching strategies from a map-based memory; (3) this model can be easily extended to model social and network behaviors as it is implemented in a multi-agent environment.

2. MEDAS

Kitchin (1994) suggests that cognitive maps are applicable to non-spatial environments if the task in question involves using spatial memory (e.g., a text-based maze). For this experiment, we create such an environment, MEDAS or Multiple Environment Dynamic Agent Simulation. MEDAS is a text-based simulation capable of supporting simulation experiments at various levels of abstraction. Developed in C with additional scripting features implemented in Python, the simulation runs as a telnet client listener, transmitting string information using the telnet socket protocol. We also create a socket connection in Lisp to enable ACT-R agent to communicate with MEDAS.

3. Tasks

In MEDAS, we create a 5*5 grid map with unique names for every room; the structure of grid map is shown in Fig. 1. The task includes two steps, a learning step followed by a navigating step. The learning step corresponds to the agent's exploration of the environment while the navigating step allows the agent to recall and apply spatial memories.

In the learning task, agents randomly wander in the grid map. Each agent travels from a starting point to a goal point. When agents encounter new rooms, the server displays the room name {room name=room1} and available travelling directions {directions: north, south, and east}. The agent then chooses the next travelling direction by typing "north", "south", "east", or "west" in the command line. In the navigation task, the agent seeks to reach a goal point that it has visited in the previous learning task. The goal point's assignment is random, and the agent navigates to the goal point by retrieving memories generated during the learning task.

11	12	13 GOAL	14	15
21	22	23	24	25
31	32	33	34	35
41	42	43	44	45
51 START	52	53	54	55

Fig.1. The grid map for the task

4. The ACT-R Model

Based on our review of the spatial reasoning literature, we have implemented our model with three basic features. First, our model stores spatial memory chunks in declarative memory; and like other types of long-term memory, these chunks decay with disuse. Second, our model uses basic navigation strategies (corresponding with those observed in humans) that can be elaborated upon, increasing the agent's adaptability; but there is no visual attention component involved. Third, we include a selection mechanism that can choose navigation strategies based on different environmental factors. In the following section, we will present the structure and details of our model.

4.1 Spatial Memory in ACT-R

As noted above, our ACT-R model stores spatial memories in declarative memory, more specifically in a pre-coded declarative memory array. In this section, we will discuss in more detail the agent's declarative memory structure. Our agent generates spatial representation using three chunk types: one general goal chunk and two spatial memory representation chunk types.

1) *Goal* chunks include the goal room, current location, and the next location. These chunks are stored and manipulated in ACT-R's goal buffer.

2) *Map-room* chunks define the topological connections between rooms. They contain a current-room slot to store the current location and four direction slots to store the names of the connecting rooms.

3) *Route* chunks define the transitions between one room and the next. They contain a current-room slot to record the current room's name, as well as a next-room slot to point to the next location on the route.

4.2 The *Navigation-Agent* Model

In this section, we describe our *Navigation-Agent* model. We then introduce three basic navigation strategies employed by our model: a route-following strategy, a shortcut strategy, and a route-searching strategy.

The *Navigation*-Agent selects between navigation strategies based on its assessment of the environment. Fig. 2 and bullets 1-3 provide an overview of the *Navigation-Agent's* assessment and decision-making process, while Fig. 3 describes in more detail the shortcut strategy (the model's most important strategy).

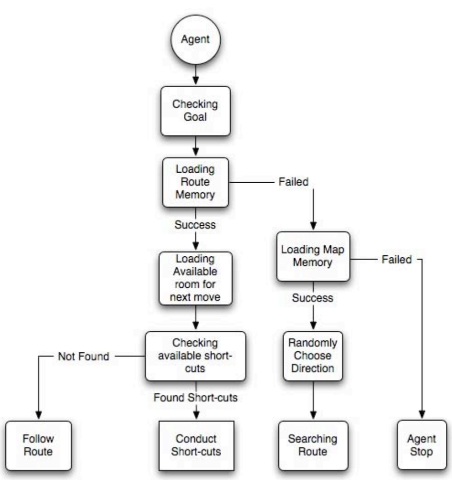

Fig. 2 The *Navigate-Agent* model's assessment and decision-making process.

1) When confronted with a new room, the agent first verifies if the room is the goal room. If not, the agent attempts to retrieve the room from its route-memory. If successful, the agent then checks if all the possible connecting rooms are also in route memory. If it finds in its memory one or more connecting rooms (with the exception of the rooms immediately adjoining its location), the agent proceeds to that room, thus executing a shortcut. If unable to identify a shortcut, the agent continues to follow the route to the next location. For example, if the route consists of the sequence 1->2->3->4->5->6->7 and the current location is 3, the agent will search for all the connecting rooms expect 2 and 4. If the searching result is 1 and 6, the agent will walk directly to room 6. If the model only retrieves room 1 from memory, the model will ignore it (as room 1 is before room 3) and proceed to room 4.

2) If the model fails to retrieve the room from route-memory, it will try to retrieve the current room from its map-memory. If successful, the agent randomly picks one visited room as the next stop. The model will continue using this partial random walk strategy until the agent finds a room along its route.

3) In the event that the agent fails to retrieve any chunks from map-based memory, the agent will be unable to use any memory-based navigation. In other words, the agent has no memory of either this room or its adjacent rooms, so it stops.

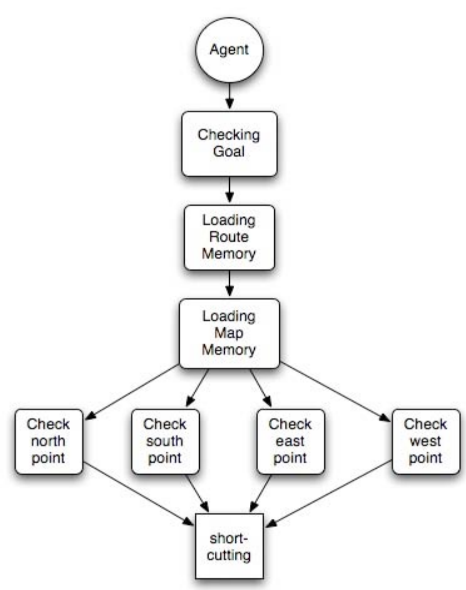

Fig. 3. The shortcut strategy.

5. The Experiment

In our experiment, we tested a *Navigation-Agent* for which we hand-coded a declarative memory structure. In this section, we review the details of our experiment and its results for both the shortcut and combined strategies.

5.1 Some features of the experiment

For our experiment, we used a *Navigation-Agent* consisting of 45 productions and using three basic navigation strategies. These strategies correspond to two major phases (learning and navigating), and two memory types (map-memory and route-memory). We used ACT-R's default parameters throughout the experiment. The experiment environment was a 5*5 grid graph with a name for each room (e.g., 42). We hand-coded 11 route chunks; these chunks formed a route between designated start and goal points. In addition, we created 15 map-room chunks to represent the known spaces in the maze. These spaces enabled the agent to take shortcuts or to search for possible routes when the agent wandered to an off-route location. Fig. 4 shows the room names, as well as the agent's initial map-memory and route-memory. In the figure, each room has a designated identifier. The red (solid) line indicates the topological relations coded into the agent's declarative memory; the green (dashed) line indicates the coded route.

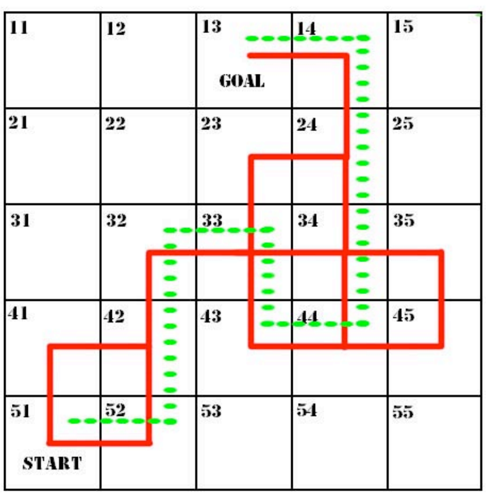

Fig. 4 The structure of testing environment and pre-coded declarative memory

5.2 Testing the Shortcuts Strategy

To test the shortcut strategy's effectiveness, we designated room 51 to be the start point and room 13 to be the goal point. The result trajectory is indicated by the blue ("x--x") line. We can see from Fig. 5 that the agent used the route-following strategy to navigate to room 33 (moving through four rooms). At room 33, the agent checked each connecting room (rooms 32, 23, 34 and 43). Because rooms 32 and 43 are adjacent to room 33, the agent only checked whether rooms 23 and 34 were en route. In this instance, the agent successfully retrieved room 34, the 8th room on the route. Successfully finding a shortcut, the agent proceeded directly to room 34. The agent then resumed using the route-following strategy to navigate to its goal point.

In this instance, the agent only used one shortcut (moving from room 33 to room 34), and it did not head north to move directly from room 33 through 23, to 13. This finding matches those of Foo, Warren, Duchon and Tarr (2005, 2007) that human prefer following route to navigate. Also, it echoes the human tendency to rely primarily on route/landmark-based strategies to find shortcuts (using map-based knowledge as supplement) as opposed to primarily using cartographic representations.

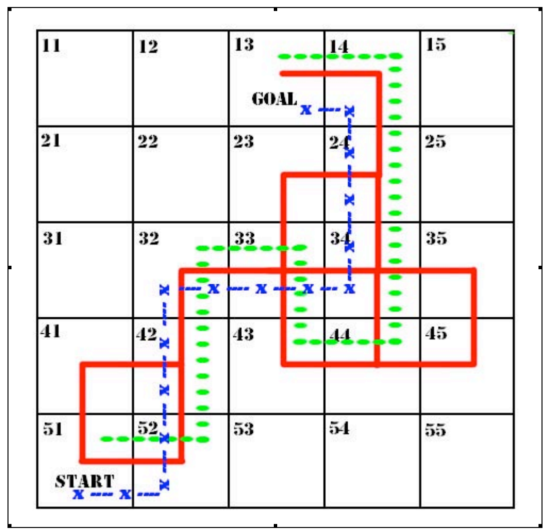

Fig. 5 The sample trajectory of the shortcut strategy

5.3 Testing the Combined Strategy

As our agent uses multiple strategies to navigate its surroundings, we tested how effectively the agent was able to combine the three strategies to reach its goal location. For this experiment, we set the start point at room 23 and goal point at room 13. The result trajectory is shown as the purple ("o--o") line in Fig 6. In Fig 6, we can see that the agent started at an off-route location. Consequently, it first used a searching strategy to randomly pick a visited direction to walk. In this instance, the agent chose to travel to room 33. Discovering that room 33 was along its route, the agent next searched for a possible shortcut. Finding one, the agent jumped to room 34 directly. The agent then applied a route-following strategy to find its goal point.

The strategy sequence illustrated in Fig. 6 consists of a route-searching strategy, shortcut strategy, and route-following strategy. As noted above, Foo, Warren, Duchon and Tarr's (2007) findings indicate that human beings generally rely on route-based strategies, but they will resort to map-based strategies when they find that key landmarks are missing. Our agent simulates this behavior by supplementing its route-based representation with map-based knowledge.

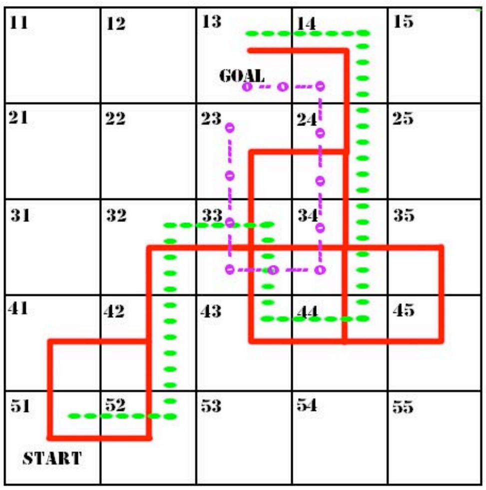

Fig. 6 The sample trajectory of the combined strategy.

5.4 Testing the Subsymbolic Parameters

Because we implement human spatial memory as declarative memory chunks, we use ACT-R's chunk activation mechanism in our model to reflect the stochastic nature of human memory. In our experiment, we tested how memory influences strategy selection and navigation performance by testing the model at various levels of activation noise. We set the activation noise from 0 to 1.2, with the base-level activation being set to -3.5. For every activation value, we run 10f replications of the agents' route from room 51 to room 13. We recorded the performance of the model using two different measures: the success rate (or the successful completion rate) and the total time for each run. We only recorded the running times for successful trials.

Fig. 7 shows that the average running time increases as we increasing the activation value. There is a sharp running time increase at the noise value of 1.0, meaning a noise of 1.0 could be a threshold for the model. Above this threshold, the robustness of the model will be heavily disturbed.

Fig. 8 displays an inverse relation between success rate and noise value. A very interesting fact shown in Fig. 8 is that the success rate also falls significantly at the noise value of 1.0. This matches the result of Fig. 7 that noise value of 1.0 is a threshold for the robustness of the model. This result also suggests that success rate and running time are related because they share the same threshold.

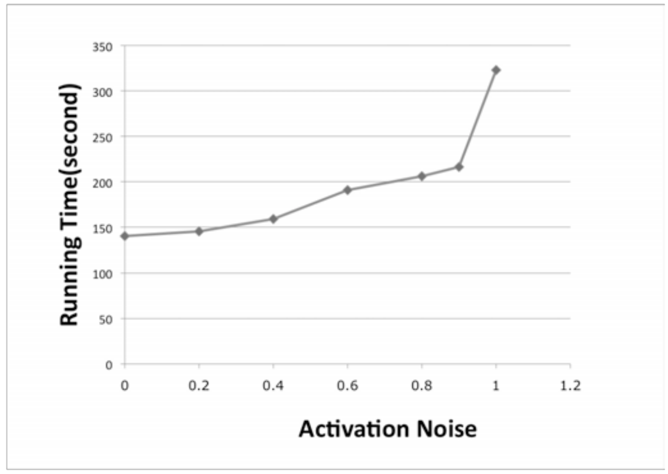

Fig. 7 The effect of activation noise on time to navigate the maze.

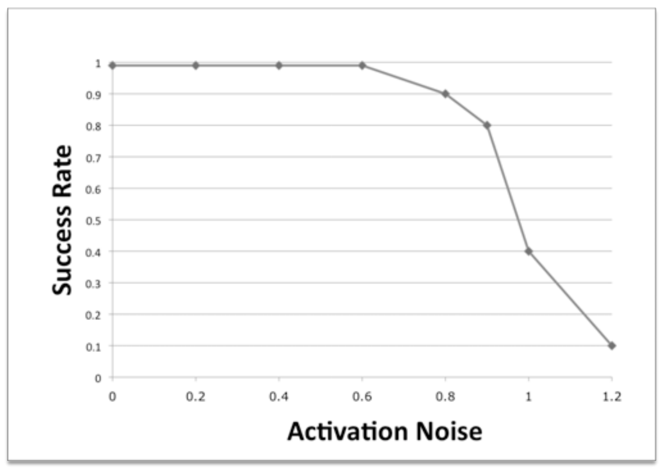

Fig. 8 The performance of model degrades with the increase of noise.

6. Conclusion and Discussion

In this paper, we discussed a memory-based model of human navigation implemented in ACT-R. The model illustrates the connection between spatial memory representations and strategy choices, as well as simulating both spatial learning and navigating. In the model, we proposed a novel approach to represent human spatial memory in ACT-R that simultaneously encodes both route-based and map-based representations into declarative memory. To enhance the model's adaptability and robustness, the model employed three basic navigation strategies: route-following, shortcut finding, and route-searching. we have three conclusions for our work.

First, we found in our experiment that map-based representations can improve an agent's route-following abilities in at least two cases: (1) searching the route when the agent is in an off-route location, and (2) for finding novel shortcuts from the route. These findings arise from two basic behaviors: (1) relying on route-based representations but supplementing those representations with map-based knowledge, and (2) switching navigation strategies when landmarks are missing.

Second, as the model involves subsymbolic information to guide navigation, we also conducted an experiment to examine the relationship between the model's subsymbolic processing and its performance. Testing the model at a range of activation noise values from 0 to 1.2, we found, as anticipated, that increases in activation noise corresponded with an increase in the model's running time and a decrease in its success rate. The result also suggests a clear threshold for the model (an activation noise level of 1.0 with a -3.5 base-level activation). If the noise exceeds this threshold, we find a precipitous drop in performance. The result also indicates that the running time and success rate of the model are highly correlated because they share the same stability threshold. This model of navigation is thus influenced by factors included in ACT-R and its extension. For example, practice will make the route following faster; one of the processes that are stress and fatigue will impede navigation. This also does match the pilot study data that we collected informally (unpublishable due to the regulation of research in Penn State).

Third, the model can be easily extended model social behavior. In the future work, we will build a functional model that could not only navigate based on existing memory but also could explore a new environment and independently record spatial information (dispensing with the hand-coded memory structure). Taking this step is necessary because human navigation behavior requires the dynamic formation of memory structures capable of supporting a wide array of navigation tasks. Also, it is in the formation of these structures that many of subsymbolic aspects of human spatial cognition come to influence the ability of human beings to navigate their surroundings. Bypassing this step seriously undermines the fidelity of these models.

We hope to leverage this work in future studies. As a group, we have been interested in modeling social and network behaviors (e.g., Morgan, Morgan, & Ritter, 2010; Qiu, Ivanova, Yen, Liu, & Ritter, in press). To model these behaviors in a town or spatial layout, we needed a more robust navigation mechanism, one capable of simulating goal directed behavior. This model now allows us to more fully explore how changes in proximity influence individual behavior (e.g., the inducement of stress and tension or the effect of leaders on subordinates), and potentially group outcomes.

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