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Understanding Human High-level Spatial Memory: An ACT-R Model to Integrate Multi-level Spatial Cues and Strategies

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Abstract

The ability to process and use spatial knowledge is a basic cognitive ability. Two human navigation strategy types (map-based and route-based) relying on two different knowledge representations have been frequently observed. These studies suggest that the first strategy uses a sequential representation and the second uses a hierarchical cluster-based representation. These studies also suggest that humans also routinely use hybrid strategies, and that the ratio between cognitive load and relative utility mediated by situational factors influences, and when modeled, could successfully predict strategy choice. We created an ACT-R model to test these hypotheses by simulating navigation strategies, strategy choices, and strategy switches. This model deepens the empirical findings by defining more clearly the memory mechanisms involved in generating the basic representation types, and by positing a theory of interaction between these types based on ACT-R's associative declarative memory. We believe that such a work provides a concrete example on principles of these biological theories can be implemented and used in cognitive architectures.

Introduction

How do spatial navigation and cognitive load interact? We start to explore this topic with a model. Researchers studying navigation behaviors have been particularly interested in two related aspects of spatial cognition: spatial knowledge, and navigation strategies that use these representations. Spatial knowledge refers to a basic understanding of spatial geometry, relations between objects, spatial cues, and event sequences relating to the passage through space. Whereas, spatial navigation strategies refer to the decision patterns based on evolving representations of this knowledge (Foo, Warren, & Tarr, 2005). It is widely accepted that spatial knowledge plays a key role in human navigation, and the representations of this knowledge can influence strategy choices and strategy switching.

Historically, Tolman (1948) conducted one of the first studies on this topic and he coined the term "cognitive maps" and was among the first to study how humans and animals organize spatial knowledge. Tolman studied the navigation behaviors of rats; he argued that cognitive maps correspond to sets of associations in the long-term memory of both humans and other mammals. Tolman also illustrated that these associations exist in long-term memory for both humans and rats because both species are capable of exhibiting novel shortcutting behavior. O'Keefe and Nadel (1978) grounded Tolman's cognitive maps in a functional analysis of the brain, arguing that cognitive maps are in essence sets of position vectors stored in the hippocampus. Further, they elaborated on the notion of cognitive maps by linking the formation of spatial representations to situational factors, arguing that cognitive maps most likely arise during "unrewarded situations". Recent neuroscience studies (Hafting, Fyhn, Molden, Moser, & Mose, 2005) have found that the entorhinal cortex contains a neuron map of the environment , which provides further support for the theory of cognitive maps.

In contrast to Tolman's cognitive map consisting of a single representation type, Montello (2001) and Siegel and White (1975) suggest a layered representation consisting of three levels and associated landmarks. The ordered trees algorithm was developed to represent regularities of verbal organizations. Hirtle and Jonides (1985) then applied this algorithm to the study of cognitive maps. Using 32 landmarks in a sample space, their subjects' responses indicated a hierarchical structure anchored by landmark clusters. These results also suggested that humans might ascribe shorter distances to within-cluster landmark pairs than across-cluster pairs, even when this is not necessarily true.

In contrast to topological or map-based representations, researchers have also observed route-based representations. These representation types rely on sequential memory and consist of landmarks, egocentric orientations, distances, and locations. Bennet (1996) and O'Keefe and Nadel (1978) argue that route-based representations are a weaker form of spatial memory, chiefly because these strategies rely on order and are vulnerable to shifts in the environment (e.g., the loss of an important landmark like a house, sign, or tree). Foo et al. (2005), however, dispute this claim, observing that humans primarily use route-based navigation along established paths. They argue that this indicates that route-based representations are not a secondary form, but rather a strong and sufficient representation. Further, Hart and Moore (1973) observed that route-based learning often takes place first upon encountering an unfamiliar place. As humans consolidate route-based representations, they argue that they also gradually begin constructing map-based representations of the environment by recognizing landmarks, connecting positions, and changing egocentric coordinates.

Both representation types are abstractions that rely on visual cues to create, but are in themselves to at least some extent tied to declarative memory. We can infer this from both O'Keefe and Nadel's (1978) and Hirtle and Jonides's (1985) work—the ability to verbalize spatial relationships indicates declarative memory retrievals. Consequently, it is widely accepted that these two types of high-level spatial representations, in contrast to visual cues, are an aspect of long-term memory that we can represent using declarative memory elements.

In this work, we propose a model that uses ACT-R's declarative memory to represent two types of spatial knowledge. We also begin to model how strategy selection depends on the spatial memory retention and cognitive load of the decision-maker.

Model implementation in ACT-R

Our model is different from previous navigation models (Gunzelmann & Anderson, 2004; Lathrop, 2008; Reitter & Lebiere, 2010; Zhao, Hiam, Morgan, & Ritter, 2011). It implements spatial knowledge with multi-level structures and proposes three navigation strategies with different cognitive costs that are dynamically selected.

Implementing spatial knowledge

To implement spatial knowledge in declarative memory, we first define the basic *location* chunk that represents an individual waypoint in the environment with identification information such as objects, landmarks, and topological connections. Out model uses this chunk to construct both route knowledge and map knowledge.

Sequential knowledge

We use *route* chunks to represent sequential transitions between the start location and the end location. Different from the conventional route, the *route* chunk of this model only consists of 4 *locations*, and we implement a longer path as a linked list of several *route* chunks. This approach is developed to match the limitations of human attention. When navigating along a long path, humans can only focus on a subset of the route because of the limitations of their working memory. According to Luck and Vogel's study (1997), the average number of visual items that a human can hold in visual short-term memory ranges from 3 to 5. Consequently, we take the mid-number 4 as the size of a *route* chunk. We expect we will examine and adjust this number in the future. Finally, implementing a route with a list of subset route chunks enables the model to integrate two long routes and also to discover shortcuts in the routes.

Figure 1 explains how to implement a long route with the route chunks. In this figure, we use 3 route chunks to implement a route consisting of 10-locations. The first route chunk contains the first 4 locations and an associative slot that points to the next route chunk.

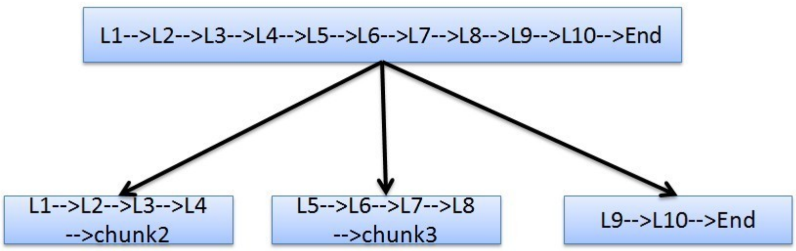

Figure 1. An example of route chunk

Configurational knowledge

We use a *map* chunk to represent the configuration of the whole environment in a hierarchical structure. In this model, we create two chunk types to implement topological knowledge: (a) the *map* chunk to represent topological relations between locations; and (b) the *zone* chunk to implement hierarchical relations between locations. We create the *zone* chunk because humans use clustering to organize large amounts of map knowledge again because of working memory limitations. Thus, humans cannot without some external aid process all the spatial information of a large environment such as a skyscraper or town. The node chunks of a *zone* chunk could be either *location* chunks or *zone* chunks, and we use an ordered tree algorithm (Hirtle & Jonides, 1985) to build up a hierarchical structure of the environment. Figure 2 shows an example of map chunk within a hierarchical structure. In this example, the highest chunk is the *Zone1* chunk that contains 5 sub zone chunks with topological relations between them. In the secondary level, the *Zone6* consists of 4 locations chunks, and these locations chunks could also be contained by other zone chunks such as *Zone2* and *Zone4*.

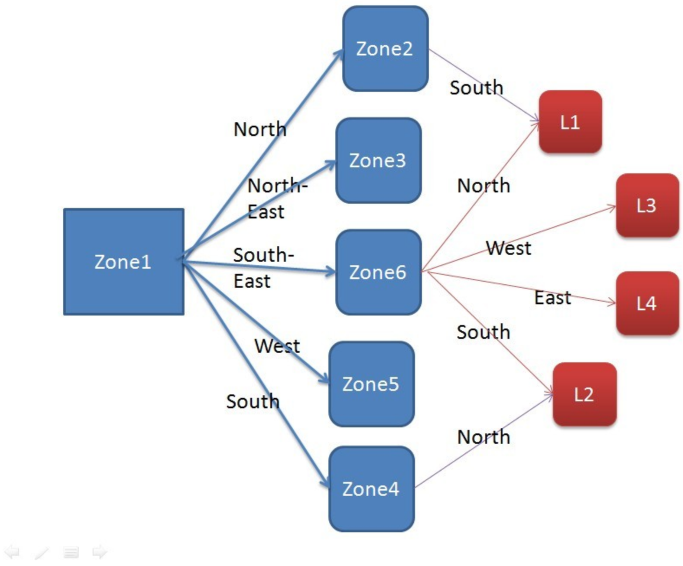

Figure 2. An example of map chunk

Navigation strategies on based on spatial knowledge

Humans use multiple navigation strategies based on different types of spatial knowledge (Bennet, 1996; O'Keefe & Nadel, 1978). In our model, we implement three navigation strategies:

(a) The route following strategy (or route-based strategy) is the most basic strategy. Based on sequential knowledge, humans will conduct sequential actions to follow landmarks in order. This strategy is considered weaker in the sense that referents depend on sequence, which if broken leaves no other cues. Humans even when primarily using this strategy, generally supplement this learned order with other knowledge.

(b) The goal-directed strategy (or map-based strategy) is usually applied when the goal is visible or they are quite familiar with nearby environments. We implement the goal-directed strategy based on the configuration knowledge of the environment because map knowledge could provide sufficient information for orientation and finding a direct path to the goal. As we implement map knowledge in a hierarchical structure, the goal-directed strategy also plans a path hierarchically from the highest level to the lowest level. For example, if a person tries to navigate from NY to LA with the goal-directed strategy, we expect the traveler would plan starting from the state level and ending at the street level.

(c) The hybrid strategy implies some proceduralized skills that allow agents to identify regularities that then allow them to make predictions about the environment. Further, the prediction should be built based on a strong understanding of the environment configuration. More specifically, this strategy allows humans to achieve two high-level spatial behaviors: 1) route integration and 2) taking shortcuts. For route integration, it enables finding a path between the end point of one route and the beginning point of another route; for shortcuts, it enables finding shortcuts.

As we noted earlier, humans show a general preference to select the cognitively least expensive strategies (Foo et al., 2005). More specifically, we interpret this strategy preferences in the following order: route-based strategy, the hybrid strategy, and map-based strategy. This preference, however, could be altered by individual difference and previous experience with successful shortcuts. Our navigation model implements this preference as proceduralized skills, and it could be changed by ACT-R's reinforcement learning with each navigation strategy.

Result and discussion

We use a text-based environment named VIPER (Kaulakis et al., 2012) to conduct our preliminary experiment, because our model currently focuses on spatial behavior based on memory representation, and it has not used ACT-R's visual buffer. In VIPER, we create a 5-by-5 map configuration with 3 routes from a start location to the goal location. We ran each strategy 20 times to navigate from the start to the goal, and our initial results suggest that these strategies could navigate the agent successfully when there was no noise added to the process. We also applied mental noise by adjusting the activation noise parameters from 0.0 to 1.4 in ACT-R. Adding noise allows us to explore the effects of mental workload and other moderators, because a process with higher workload is more likely to be disturbed by mental noise.

Figure 3 shows an illustration of the 5-by-5 map configuration. For the map-based memory, we encoded 25 locations with 4 basic zones. For the route-bsed memory, we encoded 3 routes into the declarative memory.

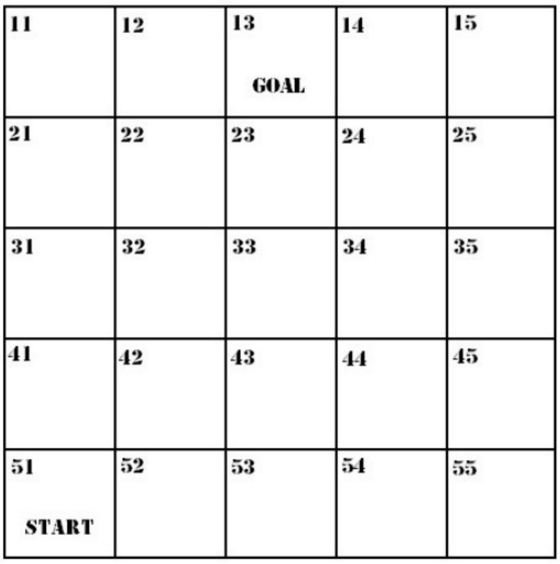

Figure 3. The 5-by-5 grid map for the task.

Figure 4 shows the effect of adding noise to the process. Consequently, we can find that all the curves increase as noise increases, meaning that activation noise disturbs the navigation process. The times for the hybrid strategy and map-based strategy are higher than the route-based strategy, suggesting that they are more cognitively expensive.

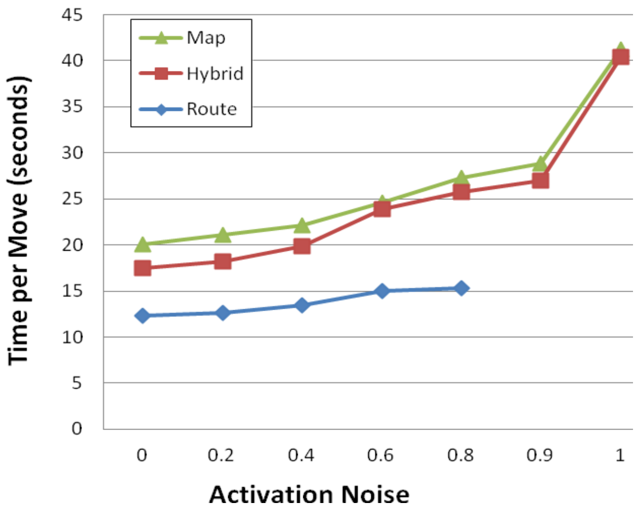

Figure 4. The influence of activation noise on the strategy running time (the route line ends at 0.8 because all runs above that point fail).

Comparing map-based strategy and the hybrid strategy, we notice that the map-based strategy curve is higher than the hybrid strategy initially, but the difference disappears as noise increases. This is because the hybrid strategy uses route knowledge initially, and it gradually relies on map knowledge when the route-based strategy is not reliable under high cognitive noise. From this, we can conclude that, in terms of the retrieval cognitive load (equivalent to the complexity of the cognitive process) each strategy imposes:

map-based strategy ≥ the hybrid strategy > route-based strategy

Figure 5 shows the influence of activation noise on the strategy's success rate. Increasing the activation noise decreases the success rate of the route following strategy most rapidly because some waypionts on the route could not be retrieved, and the route following strategy fails. This result matches empircal data (Bennet, 1996; O'Keefe & Nadel, 1978), i.e., that the route knowledge is a weaker representation and the navigation strategy based on the route knowledge is easily disturbed.

Figure 5 also shows that map-based strategy and hybrid strategy can be disturbed by acitivation noise, but their failure rate is less sensative. Finally, we could draw a conclusion that, in term of rubustness of the strategy to noise in cognition:

The hybrid strategy > map-based strategy > route-based strategy

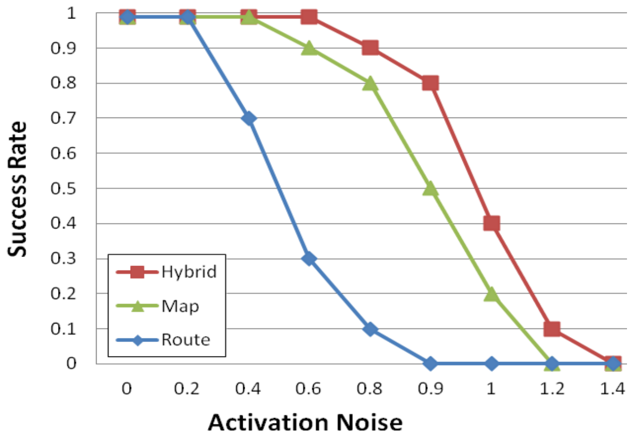

Figure 5. The influence of the activation noise on the running success rate of three strategies.

Conclusion and future work

In this work, we are trying to show how principles of these biological theories can be implemented and used in cognitive architecture rather than testing the model itself by data fitting. To achieve this, we introduced a multi-strategy navigation model in ACT-R by building two spatial representations in ACT-R's declarative memory. We used a linked list of sub-routes to represent route knowledge, and a hierarchical structure of individual locations to represent map knowledge. Based on the two representations and empirical studies, we proposed and implemented three navigation strategies: route-following, goal-directed, and the hybrid.

In our preliminary experiment, we compared the running time and navigation success rate of three strategies, and we found that the order of cognitive complexity is map-based ≥the hybrid > route-based strategy, and the order of their robustness is the hybrid > map-based > route-based strategy. Our findings reflect the internal process of human navigation, and they also match previous theories (Bennet, 1996; O'Keefe & Nadel, 1978) and empirical studies (Foo, Warren, & Tarr, 2005). We believe that such work could not only implement biological theories with a cognitive architecture but also provides a solid step for creating a computational equivalent of mind.

In the future, we plan to extend this model with a spatial learning module rather than encoding spatial knowledge in declarative memory, because the learning sequence of special objects is an important factor that may influence the initial activation values of location chunks. In addition, we should test this model in a more realistic environment by using ACT-R's visual buffer. This may provides us some more accurate predictions of human spatial behavior since vision is the primary spatial resource of human beings. This work might also be very useful for social cognitive simulation as spatial behavior can be a key factor of social network(Morgan, Morgan, & Ritter, 2010).

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