Investigating the Role of Memory in Navigating Unseen Environments using Cognitive Maps

Socially Interactive Agents Track

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1 INTRODUCTION

Our goal is to simulate agent navigation in an unknown or partially known environment. Our approach stands in contrast to models of agent simulation that have been built upon the assumption of omniscient knowledge [5] of the surrounding environment.

The wayfinding procedure we present in this paper is modeled after human cognitive processes, including landmark navigation, path integration, and memory. We consider landmarks as salient objects or locations captured by the visual attention [9]. In memory, the interactions between landmarks during memory decay are modeled by a spring-mass system, which is an intuitive model that accurately parallels recent accounts of cognitive maps [1] [20]. An agent relies on a complex cognitive architecture comprised of distinct memory layers [22] that maintain its cognitive map of explored areas of the environment.

2 RELATED WORK

Navigation. Which navigational method is used by animals and humans? while some researchers believe not only that animals and humans form a cognitive map, but also that it is perfectly Euclidean [4], others claim that the famous experiment conducted by Tolman on cognitive maps in rats has never been replicated [17] and that evidence of the existence of a cognitive map in bees is inconclusive [2]. The latest research shows that while some animals rely strongly on path integration [2], humans are not particularly adept at it. Even though it is possible for them to orient themselves in the absence of landmarks [18], their preferred navigation method is landmark navigation. Overall, human beings can adopt different strategies based on their needs [9].

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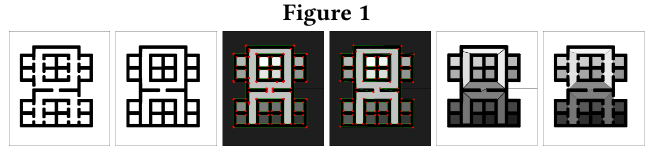
Computational Models of Wayfinding. How can wayfinding be correctly simulated as a *human navigation process* that incorporates a cognitive map of the environment? In 1978, Kuipers published the first comprehensive computational account of wayfinding, the TOUR model [12]. TOUR tries to model a cognitive map of a large-scale space through a hierarchical system that integrates a network of links between locations with a catalog of routes (defined as sequences of actions). Overarching regions delimited by dividing boundaries present an additional level of abstraction. Other models followed.

ELMER [14] also hierarchically integrates navigation plans and knowledge base routes. *The Traveler* [13] presents a cognitive agents that tries to build feasible paths to a location by connecting nodes in a network. SPAM [15] implements a fuzzy map in which the spatial values are not fixed, varying within a certain range. NAVIGATOR [6] does not rely on a complete model of the spatial layout but more on route knowledge and on a city-block metric. All of these methods, while trying to model a cognitive map, refrain from a purely allocentric, Euclidean view.

Memory Decay. Several models of spatial distortion in memory have been proposed [20], like the Nelson-Chaiklin model, in which the distance between the target and the landmark is underestimated according to a power function. According to the Huttenlocher model, the recollection will be influenced not only by the location of the target but also by the spatial category to which the target belongs [10]. Schmidt et al. propose a partition model according to which the space is subdivided into zones dominated by single landmarks; the midpoints between landmarks may function as additional attraction points [20].

Figure 1



(a) (b) (c) (d) (e) (f)

3 GEOMETRIC ANALYSIS OF BUILDING ENVIRONMENTS FOR NAVIGATION

The virtual environment (VE) is assumed to be a one-story building that is composed of rectangular rooms adjoined to connected rectangular hallways. The entrance of a room is assumed to be smaller than the length of any of its walls (Assumption R), and the entrance of a hallway is assumed to be as wide as the inner width of the hallway (Assumption H). A binary floor plan image can be generated from the navigation mesh [11] of a VE (Fig. 1.a).

3.1 Floor Plan Segmentation

The floor plan image is segmented in two phases. In the first phase, a morphological closing operation [21] is applied to the image to separate rooms from hallways (Fig. 1.b). Based on Assumption R, a closing operation can be parameterized to close the entrance of a room without filling its entirety. Assumption H makes this approach inapplicable to hallways. This phase leaves the hallways as one connected component (HCC), which the second phase segments coherently.

During the second phase, the contour of the pixels belonging to the HCC is first smoothed, such that in sequence, no three points are collinear and no two points are closer than a threshold (Figs. 1.c,1.d). For each point on the smoothed contour, a line is drawn to the closest other point, cutting the HCC (Fig. 1.e). A final labeling of connected components will properly distinguish between coherent hallway segments (henceforth referred to as hallways). Assuming hallways are elongated and the lengths for hallways h_1 and h_2 are respectively at least $w_2 + m$ and $w_1 + m$, $m = \sqrt{w_1^2 + w_2^2}$, lengthwise along the contour(s) of a hallway, the turning point's closest other point is a non-sequential turning point for bends, T-junctions, and intersections of hallways. After the phases, a watershed transform is applied to the labelled image to determine which segments (rooms and hallways) are connected in the VE, which is used to form a cell and portal graph [8] (Fig. 1.f).

4 MEMORY-ENABLED AUTONOMOUS AGENTS

4.1 Landmarks (Visual Attention)

The visual attention (VA) of the agent captures non-occluded landmarks in the agent's visual field up to a capacity [7]. Landmarks consist of manually curated objects in the VE and procedurally generated "reference points in the environment [...] where navigational decisions have to be made" [16]. Such reference points are located at the portals of the prior cell and portal graph. Landmarks in close enough proximity are considered as the same landmark to avoid redundancy. Each landmark has an inherent salience value based on its physical properties/surroundings, which serves as its priority in the agent's VA. This salience can be increased based on the agent's navigational goals.

4.2 Route Formation (Short-Term Memory)

The purpose of the short-term memory (STM) is to convert the instantaneous perception information from the VA into temporal position information (i.e., routes travelled between landmarks by the agent). As landmarks are captured by the VA, the STM stores them with their VA priorities. While a landmark remains in the VA, its STM priority does not decay. Otherwise, its STM priority decays until at zero, it is removed from the STM. The retention of the STM is limited to a capacity that the sum of the STM priorities cannot exceed. If this capacity does not exceed that of the VA, the agent will have no memory of past landmarks, resulting in a degenerate cognitive map.

For an agent that steers forward to navigate, this temporal perception information contains surrounding landmarks, which the agent can use to accurately determine the closest landmark (i.e., its general position). When the agent nears a different landmark, the route (i.e., change in landmarks) is stored in its long-term memory (LTM).

4.3 Cognitive Map (Long-Term Memory)

The cognitive map (CM), which serves as an agent's LTM, is modeled as a spring-mass system in the plane of the VE. In the CM, the masses (henceforth referred to as CM landmarks) represent landmarks, the masses of CM landmarks represent their memorability, and the springs represent traversed routes.

When a route is first formed, its landmarks become CM landmarks connected by a spring. While a landmark remains in the VA, its position in the CM is the same as in the VE. Otherwise, its CM position decays according to the physics of the CM, which is separate from that of the VE. This changes where the agent recalls the landmark to be located. Initially, the mass of a landmark in the CM is its VA priority. While a landmark is closest to the agent, its mass in the CM does not decay. Otherwise, the agent is decreasingly able to recall that the landmark exists and the CM landmark's position is subject to accelerating decay.

The decay of the CM is based on the Nelson-Chaiklin model of memory distortion, where "distortion is [...] toward the nearest landmark because the distance between landmark and target is underestimated" [20]. Therefore, the equilibrium length of all springs is zero. Also, each time a CM landmark is revisited, its mass is reset and increased by a multiplicative factor. During this process, if a CM landmark's mass exceeds a threshold, the CM will set its mass to m_{max} and stop decaying the CM landmark's mass and position [19].

4.4 Active Perception (Wayfinding)

When an agent is tasked with a navigational goal, its behavior reflects its knowledge about the goal. If the goal is in the STM, it is directly navigated to. If the goal is unknown, the agent performs a thorough blind search. Otherwise, if intermediary goals (i.e., subgoals) are unknown, the agent will recall the goal's heading and perform an oriented search [3] in the VE (implemented as greedy best-first search where the heuristic is the difference between a local heading and the goal heading). If subgoals are known, oriented search is performed for each subgoal in sequence.

To determine whether subgoals are recalled, uniform cost search to the goal is performed on the CM, considering each route r's cost as $aE(r) + (1 - a)(1 - M(l))$, where l is r's other landmark, $E(r)$ is the normalized Euclidean distance, and $M(l)$ is the normalized CM mass. Depending on a, the cost strikes a balance between the agent's familiarity with the landmarks and its recalled lengths of routes. For $a > 0$, when all landmarks exist in the CM with mass m_{max}, the route cost becomes proportional to $E(r)$, resulting in the shortest path. The CM landmarks in the path are then probabilistically recalled based on $M(l)$.

5 CONCLUSION

This novel framework for landmark navigation in crowd simulation gives new nuances to the navigational behaviors of agents, making them more comparable to those of humans, and the framework's intuitiveness makes it accessible for exploring new crowd scenarios.

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