Biologically Inspired Cognitive Architectures (2013) 5, 94–111

Available at www.sciencedirect.com

SciVerse ScienceDirect

journal homepage: www.elsevier.com/locate/bica

RESEARCH ARTICLE

# Pathfinding in the cognitive map: Network models of mechanisms for search and planning

Shane T. Mueller [a,b,*], Brandon S. Perelman [b,a], Benjamin G. Simpkins [b]

[a] Michigan Technological University, Dept. of Cognitive and Learning Sciences, United States
[b] Applied Research Associates, Cognitive Solutions Division, Fairborn OH, United States

Received 16 February 2013; received in revised form 17 May 2013; accepted 17 May 2013

**KEYWORDS**
Pathfinding;
Hippocampus

**Abstract**
The hippocampus has long been thought to be critical in learning and representing the cognitive map, and thus support functions such as search, pathfinding and route planning. This work aims to demonstrate the utility of hippocampus-based neural networks in modeling human search task behavior. Human solutions to pathfinding problems are generally fast but approximate, in contrast to traditional AI approaches. In this paper, we report data on a human search task, and then examine a set of models, based upon the structure of the hippocampus, which use a goal scent mechanism similar to the optimal pathfinding algorithms used in artificial intelligence systems. We compare five distinct search models, and conclude that a goal scent model driven by multiple goals spread throughout the search space provides the best and most accurate account of the human data. This research suggests a convergence in traditional AI and biologically-inspired approaches to pathfinding that may be mutually beneficial.


## 1. Introduction

The hippocampus is known to play an important functional role as a cognitive map (Burgess, 2002; McNaughton et al., 1996; O'Keefe & Nadel, 1978), while also being important for episodic memory formation and the fast binding of feature conjunctions (e.g., McClelland, McNaughton, & O'Reilly, 1995; see Norman, Detre, & Polyn, 2008, for a comprehensive review). Importantly, Samsonovich and Ascoli (2005) provided an account that united these two fairly distinct areas of research by showing how the hippocampus can provide a general capability across spatial and cognitive tasks to bind contexts together, forming (in the spatial domain) spatial maps, and (in a non-spatial domain) problem spaces. This provides a unified architecture for representing problem-based knowledge within the brain, and it is analogous to how network representations play a common

* Corresponding author at: Michigan Technological University, Dept. of Cognitive and Learning Sciences, 1400 Townsend Drive, Houghton, MI, USA.
E-mail address: shanem@mtu.edu (S.T. Mueller).

2212-683X/$ - see front matter © 2013 Published by Elsevier B.V.
http://dx.doi.org/10.1016/j.bica.2013.05.002

role in representing problems in computational optimization and Artificial Intelligence (AI), regardless of whether the problem is spatial.

Our goal in this paper is to examine how a spatial map inspired by the neural architecture of the hippocampus, as an alternative to classic AI approaches, can support and implement pathfinding algorithms. We will examine a set of neurocomputational models that use basic network activation dynamics to plan and execute a search task. The simulated paths will be compared to human-generated paths with respect to search effectiveness and efficiency, and we will examine the extent to which humans search with similar dynamics.

### 1.1. Pathfinding as optimization in artificial intelligence

The term pathfinding is commonly used in computer science and AI to describe a means for determining shortest, cheapest, or fastest routes between nodes in a network or space. For this task, a number of network flow algorithms have been proposed (cf. Ahuja, Magnanti, & Orlin, 1993) that use optimization, dynamic programming, and related methods to solve routing problems and compute network dynamics. For both humans and computers, pathfinding is a classic planning problem, as it typically involves some sort of simulation or analysis of the environment (e.g., a network) to determine a plan or a path prior to moving through the environment.

Dijkstra's (1959) algorithm provides the classical optimal solution to the shortest-path problem, in which one wants to find the shortest (or cheapest) way to get from one point to another within a network. Dijkstra's algorithm is relatively inefficient when computed serially, although it is guaranteed to find the shortest path, which in its worst case might require exhaustive search of the problem space. Most alternatives involve using heuristics that can help point the pathfinder in the right direction, with the $A^*$ algorithm (Hart, Nilsson, & Raphael, 1968) being the most famous and widely used, especially for game-related pathfinding and AI. The strength of $A^*$ is that it finds the optimal solution, but tends to do so, on average, in fewer steps than other algorithms. Consequently, although it uses heuristics to guide search, it still finds the optimal solution and does not need to resort to satisficing. Improvements to $A^*$ that consider both the search time and execution time, allowing better real-time performance and acceptable performance in unknown environments, remain an active are of research (e.g., Time-limited $A^*$, Korf, 1990; Time-bounded $A^*$, Björnsson, Bulitko, & Sturtevant, 2009; Real-time $D^*$; Bond, Widger, Ruml, & Xiaoxun, 2010).

In contrast to the optimal-heuristic pathfinding provided by $A^*$, human pathfinding often finds close-to-optimal solutions, and can do so with relatively little effort. For example, Pizlo and colleagues (e.g., Pizlo, Stefanov, Saalweachter, Li, & Haxhimusa, 2006) have found that human solutions to the spatial traveling salesman problem (where an efficient path to multiple locations must be planned) are typically close to optimal (often only 5–10% longer), but unlike the optimal algorithms, the time required scales linearly with the number of nodes in the path. Because the traveling salesman problem is NP-complete, no known polynomial-time algorithm exists to solve it, and the worst-case solution times are exponentially related to the number of nodes. Thus, in general, human pathfinding is not optimal, but can be very efficient ($O(N)$ rather than $O(N^p)$ or $O(p^N)$) at identifying near-optimal solutions.

### 1.2. Neurocomputational models of the hippocampus

Neuroscience research on the hippocampus, including related afferent structures, has often focused on its role beyond pathfinding, extending to its role in episodic memory formation (Norman et al., 2008; O'Reilly & Rudy, 2001) sequence prediction (Levy, 1996) and short-term memory (Jensen & Lisman, 1996). Furthermore, much research has addressed lower-level functions that support spatial reasoning such as the existence of place cells (O'Keefe & Nadel, 1978); grid cells (Burgess & O'Keefe, 2011; Hafting, Fyhn, Molden, Moser, & Moser, 2005); mechanisms of path integration (McNaughton et al., 1996), and the role of theta phase precession (Burgess & O'Keefe, 2011). Neurocomputational models of the functional role of the hippocampus in spatial reasoning have often focused on the cornu ammonis (CA; Levy, 1989; Levy, Colbert, & Desmond, 1990). By understanding the layered structure, the interconnections, and the learning mechanisms, models of CA have proven capable of a number of cognitive functions (e.g., Jensen & Lisman, 1996; Levy, 1996) with Levy's model notably describing a biologically plausible system for sequence prediction, a task used in both navigation and problem solving.

Though these models were initially explored using computation alone, other researchers have since used models of the architecture of CA to simulate animal and human behavior (Burgess, 2002; Gaffan, 1998; Trullier & Meyer, 2000), and to drive robot navigation (Arleo & Gerstner, 1999; Reece & Harris, 1996). Subsequent to early work by Levy and colleagues (1989, 1990), models are often equipped with functional modules intended to increase both their complexity and validity. For example, the model presented in Levy (1996) allowed CA3 to recall activation sequences but lacked a path integration system, hypothetically present in the hippocampus, and central to the function of other models (e.g., McNaughton et al., 1996). Despite the growing cognitive capabilities of neural models of the hippocampus, functional assessments remain relatively constrained to rat data or simple laboratory tasks, with relatively few extending to more complex behavior (e.g., Ascoli & Samsonovich, 2013; Newman et al., 2007; Samsonovich & Ascoli, 2005). Our goal is to examine the functional properties of such networks to understand how they may support more complex realistic search performed by humans. Consequently, we will first examine a data set involving complex human search, which may prove useful for guiding neurocomputational models of pathfinding. We believe that the constraints provided by a naturalistic search task will help demonstrate where models are either sufficient or underspecified.