

# Investigating Human Learning and Decision-Making in Navigation of Unknown Environments

Abhishek Verma\* Berenice Mettler†

\* *Ph.D. Student, University of Minnesota Minneapolis, MN 55455  
USA (e-mail: verma043@umn.edu).*

† *Associate Professor, University of Minnesota Minneapolis, MN 55455  
USA (e-mail: mettler@umn.edu).*

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**Abstract:** Humans often navigate in unknown and complex environments. As they gain experience, they can eventually determine near-optimal (e.g., minimum-time) paths between two locations from memory. The goal of this research is to understand the heuristics that humans use to solve path-planning problems in unknown environments. This paper presents a modeling and analysis framework to investigate and evaluate human learning and decision-making while learning to navigate unknown environments. This approach emphasizes the agent (a vehicle with a human driver on board) dynamics, which is not typical in navigation studies. The framework is based on subgoals that are defined as intrinsic patterns in interactions between agent dynamics and task environment. Subgoals represent nodes in a graph representation of the task space. The evaluation framework uses Dijkstra's algorithm to find minimum-time paths in the subgoal graph. To account for limited working memory in humans, the shortest-path search in the graph is terminated at a specified maximum depth. The cost beyond the maximum depth is approximated using learned cost-to-go values at subgoals. The graph framework is applied to evaluate human data from simulated guidance experiments in which subjects were asked to find minimum-time routes from pre-specified start to goal states, over multiple trials.

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## 1. INTRODUCTION

Humans are capable of learning complex unknown environments and use the knowledge to determine near-optimal routes. This capability is not unique to spatial environment navigation but is also essential to other spatial tasks such as pertaining to surgery. The goal of this research is to understand humans' environment learning and path-planning capabilities. Such understanding can help to design planning algorithms that are computationally efficient as well as better understand how to improve human-machine interfaces in particular between operators and autonomous agents.

### 1.1 Spatial Representation: Cognitive Map

Tolman (1948) introduced the concept of the cognitive map, a mental representation of a spatial environment, as an alternative to stimulus-response based explanation for rats' behavior. Cognitive mapping focuses on "the knowledge problems": what people remember most when they visit new places and how they organize spatial information to form knowledge of their environment (Jefferies and Yeap (2008)). For example, Stevens and Coupe (1978) experimented with human subjects to explore distortions in subjects' judgements of relative geographical locations. Based on observations, they presented a model that stores spatial relationships hierarchically and is governed by storage-computation trade-off. Spatial relationships that are not stored are inferred by extrapolating from the stored spatial relations. Such studies have shown that humans or animals

most probably use a graph representation which captures topology as opposed to a metric map, for a task space.

### 1.2 Cognitive Robotics

Cognitive robotics is inspired from human/animal spatial cognition (Christaller (1999)). For example, Vasudevan et. al (2007) proposed a hierarchical probabilistic representation of space, based on high-level environment features such as household objects and doors. Such object-based representation of a spatial environment is comprehensible to humans.

### 1.3 Spatial Navigation and Wayfinding

Human spatial navigation and wayfinding has been studied in the past (e.g., Golledge (1995); Gillner and Mallot (1998); Waller et. al (2000); Raubal (2001); Meilinger et. al (2008); Christova et. al (2012); Vilar et. al (2014); Sakellaridi et. al (2015)). Golledge (1995) experimentally investigated what selection criteria, other than traditional ones such as minimum time, humans use to select a route in a map. Gillner and Mallot (1998) studied the effect of local visual information on human environment learning, using movement data from experiments in a virtual maze. The results indicated that humans learn a maze as a view graph, i.e., sequence of local views and movements. Information at a node includes a recognized position, movement decisions, and expected next views for different decisions. Waller et. al (2000) showed that for learning their location, humans may rely more on distance information than bearing information, and suggested to account for

this finding in modeling human place learning. Vilar et al (2014) experimentally showed that horizontal signage prove more helpful than vertical signage in improving wayfinding performance of humans.

#### 1.4 Guidance Engineering vs Spatial Cognition

The above studies in general focused on pedestrians or simple movements. In agile guidance tasks, such as a pilot operating a high-speed vehicle in a complex environment or surgeons under time pressure, the interactions between vehicle dynamics and task environment play a role in determining what elements of the environment are more relevant than others.

Mettler (2011) discussed the gap between engineering methods of guidance and spatial cognition. As stated by the author, “simple forms of navigation, or way finding, have been the main focus of spatial cognition but without accounting for the effects of dynamics”. The author proposed the idea that skilled human pilots possess a system to conceptualize spatial behavior that preserves the interrelation between movement dynamics and geometry and topology of the environment. In subsequent studies, Kong and Mettler (2013) studied the guidance behavior in complex environments focusing on the agent-environment interactions. They found that skilled operators organize their behavior according to interaction patterns. These sensory-motor patterns represent units of behavior which satisfy the various system constraints and exploit the equivalences in the problem space. Furthermore, the interaction patterns make it possible to abstract a task environment as a graph of subgoals. Such graph framework can be elaborated to build a cognitive map to model and investigate human learning and decision-making in complex task environments. This paper uses the subgoal graph to investigate human environment learning and spatial navigation in guidance tasks where human subjects navigate using a complex dynamic vehicle.

#### 1.5 Paper Outline

The rest of the paper is organized as follows. Section 2 presents human guidance experiments and gives a brief overview of the system used for the experiments. Section 3 gives an overview of subgoals that are used to abstract the task environment as a graph. Section 4 describes how to extract cost-to-go information for the subgoal graph, from human guidance data. Section 5 presents a decision-making model with a discount factor and a graph pruning technique. Section 6 presents results applying the graph framework and decision-making model on human experimental data. The section also discusses the future directions based on current results.

## 2. HUMAN GUIDANCE EXPERIMENTS

This section first gives a brief overview of the experiment system used for human guidance experiments. Next, the section presents the experimental trajectories and flight-times.

#### 2.1 Experiment System

This paper uses the guidance experiment system presented by Feit and Mettler (2015), as shown in Fig. 1(a). The system consists of a monitor to display a simulated task environment, a joystick to control flight behavior and navigate in the environment, and a gaze tracking device

to record 3-D gaze location. The control inputs correspond to linear acceleration and angular rate. Maximum speed is set as 5 m/s. Angular rate is inversely proportional to the speed.

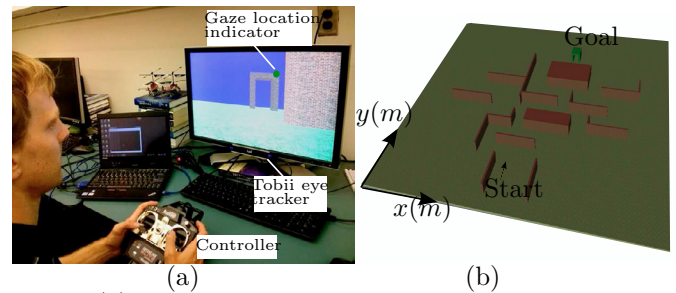


Fig. 1. (a) First-person guidance experiment system proposed by Feit and Mettler (2015) and (b) Task environment used for human guidance experiments presented in this paper.

#### 2.2 Experiments

Figure 1(b) shows the task environment for guidance experiments. The environment is quasi 3-D and made of vertical walls. Eight subjects participated in the experiments. The task objective was to find fastest (minimum-time) routes between pre-specified start and goal locations as shown in Fig. 1(b). Before the experiment, the subjects had no knowledge of the environment layout and the

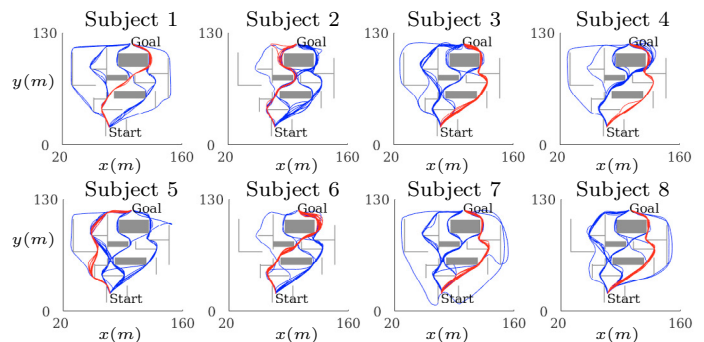


Fig. 2. Trajectories for all runs for subjects 1 to 8. Runs on the best route for each subject are shown in red.

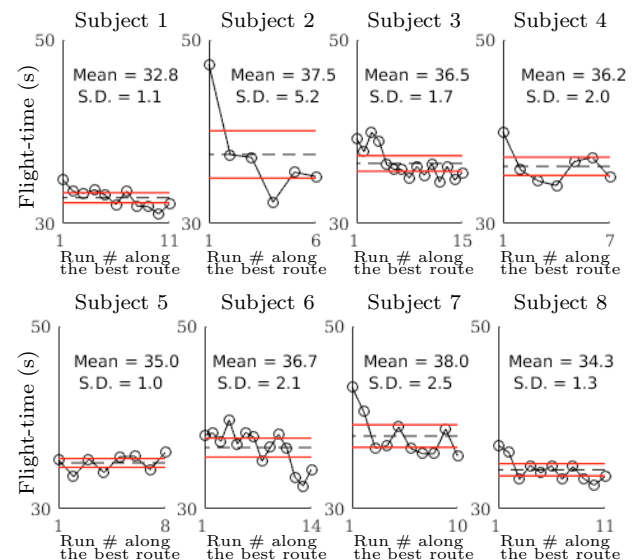


Fig. 3. Flight-times for runs on best routes for subjects 1 to 8. S.D. is the standard deviation.

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