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Human Planning and Coordination in Spatial Search Problems ⋆

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Abstract: Search is an essential technology for rescue and other mobile robot applications. Many robotic search and rescue systems rely on teleoperation. How to cover the search space efficiently is one of the key problems in search tasks. Search is also central to humans' daily activities. Analyzing human search behavior through teleoperation could help improve understanding of human search strategies as well as autonomous search algorithms. This research proposes a novel framework to model and analyze humans' search behavior. The framework is based on structure learning and K-means clustering. The analysis of the experimental data demonstrates that (1) humans are able to solve the complex search task by breaking it up into smaller tasks; and (2) humans consider both coverage and motion cost while searching. The results are used to design near optimal subgoals to guide humans in searching. Experiments showed that the humans' search performance is improved with the subgoals assistance.

Keywords: Telerobotics, Human-machine interface, Information analysis, Machine learning, Autonomous mobile robots.

1. INTRODUCTION

Hide-and-seek is seen as a primary example of cognitive abilities in early child development (Wellman (1985)). Prior studies largely assume that targets are hidden in certain boxes or places and therefore don't consider the coverage of the entire space. Although there is no related work for human performance on coverage problems, search problems share similarities to navigation and guidance problems, which are also NP-hard. In motion guidance the task is to find the optimal path toward a goal, while in search problems the task is to find the optimal path to search for the target. Hence, the research findings in human guidance could represent a useful starting point for studying human search strategy.

Questions about how humans navigate space have engaged scientists for over 100 years. John O'Keefe found that when a rat passes a certain place while moving about in a space,, a particular neuron, called the place cell, is activated in the hippocampus (O'Keefe and Dostrovsky (1971)). More recently, May-Britt and Edvard Moser found another type of neuron, the grid cell, activates in the entorhinal cortex at regular intervals as the rat moves in space. This result suggests that these neurons serve as a coordinate system (Fyhn et al. (2004); Sargolini and Moser (2006)). They point to the existence of a system for processing spatial information. Similar systems have been found in human brains. These finding, however, don't explain how humans plan and organize their spatial behavior.

Since optimal solutions of most planning problems are computationally intractable, humans, similarly to robots, have to employ approximation methods. An important class of approximation techniques is hierarchical optimization. The general principle in human information processing is chunking. Classic studies of human information processing, highlighting the role of hierarchic organization of information and behavior, include the telegraphic language (Bryan (1899)), perception in chess (Chase and Simon (1973)) and the acquisition of hierarchical control in the temporal organization of skill (Pew (1966)). While these findings provide strong evidence for the role of hierarchical organization in information processing and control behavior, little work has been dedicated to explaining how humans plan and organize spatial behavior. To explore how humans break down a task into smaller subtasks, an analysis framework is necessary.

Kong and Mettler proposed a framework to analyze human guidance behavior (Kong and Mettler (2013)). In their experiments, the pilots had to remotely control a miniature helicopter to a fixed goal in an obstacle field from different starting points. The trajectories were collected and then analyzed using machine learning techniques. The research shows two important results. First, human guidance behavior is organized in terms of subgoals. The subgoals explain how humans break down the guidance problem into smaller tractable ones. Second, sub-problems and their associated trajectories are dictated by symmetrical properties found in relations between the agent motion and environmental constraints. The results suggest that humans exploit symmetries to decompose a guidance problem into smaller problems and that these properties can be described through subgoals. Since search is also cen-

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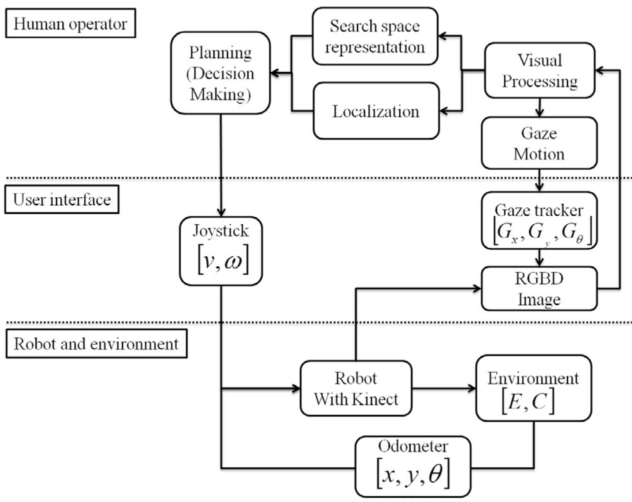


Fig. 1. Block diagram of the human search process. The backward arrows represent the feedback of gaze and remote control. The sensors in user interface and robot give ten dimensional data.

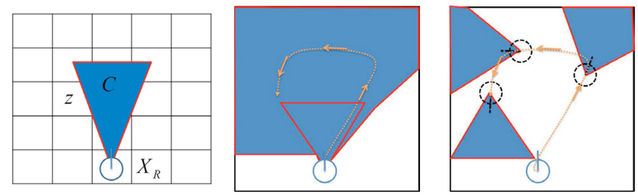
tral to humans daily behaviors, analyzing human search behavior could help design a human-machine interface for teleoperation search and improve search algorithms.

When humans remotely control a robot to search for a target in an unknown environment, they have to plan a trajectory and incrementally update the plan based on new information. Solving the decision-making problem involves a combination of visual information processing, motor control and planning processes. Figure 1 shows a main block diagram of the processes and their interaction. The operator processes information from the robot's video[1] feed to build a mental representation of the environment and localize the robot position. The operator moves his/her gaze to find the target in the images from the video stream. The map and robot pose are combined to create a map of the search space. This information is then used to determine a plan of action for the robot. Finally the plan is used to implement the control actions. This process is repeated as the robot moves through the environment until the target is found.

Three aspects of human search are investigated in this paper: Do humans break down search problems into smaller sub problems (so-called subgoal hypothesis)? What principles dictate how humans coordinate visual search and motion control? Can humans outperform robots on search problems? To explore these questions, an analysis method based on graphical models and K-means clustering was designed to determine patterns in behavior captured by the experimental data. The analysis performed in this study indicates that (1) humans break the search problem into smaller problems; (2) humans consider both coverage and motion cost while searching; (3) human performance on search problems cannot outperform robots.

The paper is organized as follows. Section 2 describes the teleoperation search experiment setup and analysis methodology. Section 3 introduces the approach used for data analysis. Section 4 describes the human experiments used to demonstrate subgoal performance. Finally, Section 5 reports the conclusions and outlines future work.

[1] The Kinect sensor supports RGB and depth images (called RGBD data)



(a) coverage (b) search path (c) subgoals

Fig. 2. Illustration of the subgoal concept. (a) The blue circle and blue area represent the current robot position and corresponding covered area, respectively. (b) Coverage and search path for continuous motion. The orange arrow represents the search path. (c) Coverage and search path based on subgoals shown (black circles).

2. HUMAN EXPERIMENT AND ANALYSIS METHODS

This section describes the key definitions and concepts used in the proposed analysis framework and human search experiments.

Definition 1: Coverage
As Fig. 2(a) shows, the robot locates at X_R and gets the sensing measurements $z = \{r_i, \theta_i\}$, where $i = 1, ..., N_z$. r, θ and N_z are the range, angle and number of sensor scans, respectively. Assume there are N_g unoccupied cells in a grid map. The robot's sensor covers N_c cells. The coverage $F_C(X_R)$ is defined as N_c/N_g.

According to X_R and z, the covered area is computed. There are 25 cells and 8 cells are covered by the robot. Hence, $F_C(X_R)$ is 32%.

Definition 2: Subgoal hypothesis
The subgoal hypothesis is that continuous search motion can be represented by finite subgoals. The robot trajectory ($X_i = \{x_i, y_i, \theta_i\}$) and the measurement data (z_i) are recorded during the search task, where $i \in \tau = \{1, .., T\}$. The coverage at the corresponding position is $F_C(X_i)$. The subgoals index is τ_s, where $\tau_s \subseteq \tau$. The subgoals of a search trajectory need to satisfy the following requirement: The total coverage $F_C(X_{\tau_{s1:sk}})$ is over 80% [2] *.*

The general idea of the subgoal hypothesis as illustrated, in Fig. 2(b)(c), is that search with a mobile robot platform can be decomposed into a sequence of smaller problems that are represented by finite subgoals. Since the subgoals are the subset of the continuous motion, the coverage of the continuous motion is always greater than the coverage of the subgoals (the polygon area in Fig. 2(b) is bigger than the three triangles area in Fig. 2(c)). Hence, the coverage based on the discrete subgoals is a lower bound of the coverage achieved through the continuous motion. As Fig. 2(b) shows, the robot moves along the search path. As Fig. 2(c) shows, 3 subgoals ($\tau_{s1:s3}$) are extracted from the search path. The corresponding coverage is $C_{\tau_{s1:s3}}$.

[2] 80% is a coverage threshold. If it is higher, the number of needed subgoals is higher. In this grid map, humans need 10∼15 subgoals to cover 80%.