Identifying Mental Models of Search in a Simulated Flight Task Using a Pathmapping Approach

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Aerial assets are often used for missions such as intelligence, surveillance, target acquisition and reconnaissance. The pilot's search decisions reflect a mental model for the search space, including characteristics such as target prioritization, distance-reward evaluations, and path optimization criteria. To investigate differences in these mental models, we examined 23 participants' paths flown in a synthetic task environment in which they piloted a simulated aircraft to search for targets representing missing persons. Determining similarity among flight paths is a challenge. To accomplish this, we used a new tool (Pathmapping, a package in the R statistical computing language; Mueller, Perelman, & Veinott, 2015) to determine area-based path similarities among the test subjects' flight paths, and mixture modeling to analyze those similarities. The results indicate that an area-based measure of path similarity can be used to infer mental models from flight paths produced during a simulated search task.

Search for targets using aerial assets is common across many domains. For example, military pilots and unmanned aerial vehicle (UAV) operators must search for targets during the course of intelligence, surveillance, target acquisition, and reconnaissance operations. In the civilian sector, search and rescue personnel must search multiple locations for missing persons, often with the aid of volunteer pilots. These search operations are conducted by routing search paths through probability maps that indicate locations where the operators expect to find their targets.

Routing a flight path through a probability space is functionally similar to the Euclidean Traveling Salesman Problem (TSP) task, a NP-hard combinatorial optimization problem in which subjects must plot the shortest tour through a Euclidean problem space (e.g., MacGregor & Ormerod, 1996). Applied (e.g., Evers, Dollevoet, Barros, & Mansuur, 2011) and naturalistic (Perelman & Mueller, 2013; Ragni & Wiener, 2012; Tenbrink & Seifert, 2011) versions of this task must often incorporate optimization criteria beyond shortest overall path length which constitute constraints in the problem space, and are sometimes referred to as a Discounted-Reward Traveling Salesman problem (Blum et al., 2007). In addition to the optimization criteria, a particular problem may contain additional constraints. For example, military pilots may want to avoid certain areas due to enemy anti-air assets.

Mental Model Theory (Johnson-Laird & Byrne, 1991) proposes that, in spatial tasks, operators transform all of the constraints into a mental model of the problem space. Empirical explorations of Mental Model Theory (and similar theories, e.g. Preferred Mental Model Theory; Rauh et al., 2005) in naturalistic search tasks are sparse, but a novel experiment by Ragni and Wiener (2012) investigated constraint-based reasoning in a TSP-like problem. Ragni and Wiener presented participants with four types of problems designed to test effects of congruency with participants' mental models of the problem space and the shortest-path solution (which was not always the optimal solution in this constrained paradigm). Methodologically, the authors' problems were relatively simple, consisting of only several nodes, and so determining the number of optimal solutions for each problem was computationally tractable, allowing the authors to use percent correct as an outcome variable. However, it might be useful to make inferences about mental models in more complex environments using a continuous measure of path similarity.

Inferring psychological phenomena from path information is analytically difficult. Existing area-based solutions for comparing two paths (e.g., Asundi & Wensen, 1998; Yanagisawa, Akahani, & Satoh, 2003) are not robust to characteristics such as intersections between the two paths, loops between them, incomplete routes, and self-intersections that may be fairly common in flight paths, especially when pilots orbit a specific area to examine it further. In the present study, we use the Algorithm for finding the Least-Cost Areal Mapping between Paths (ALCAMP; Mueller, Perelman, & Veinott, 2015) to determine correspondence and similarity between participant-generated flight paths to infer their mental models for the search spaces in a naturalistic TSP.

Preferred Mental Model Theory (Rauh et al., 2005) suggests that participants would use the instructions to constrain their optimization criteria used to solve the problem. These mental models would be reflected in the routes they planned through the problem spaces. Based on the routes participants draw, it should be possible to make inferences about their mental models using the pathmapping approach.

In this paper, we will explore and test methods for using model-based clustering to identify clusters of similar paths within unlabeled exemplars. The goal of this approach is to identify the underlying goals and mental models of a search path from a bottom-up perspective. Success of this method has potential applications in aviation training, monitoring, and analysis.

Method

Participants & Apparatus

We recruited 23 participants from the Michigan Technological University undergraduate participant pool who completed 18 naturalistic TSP problems according to two different sets of instructions. In one set of instructions (TSP), participants were told that they were planning the route for a food delivery UAV, and that they should draw a route that minimizes path length in order to minimize fuel usage. In the second set of instructions (Search), participants were told that they would be repurposing the UAV to search for a missing child, and to plan a route that allowed them to minimize the time it would take to find the missing child. Problems were designed so that optimal solutions to these two different problems were qualitatively different. Instruction presentation order was counterbalanced across all subjects, and problem presentation was randomized within instruction conditions. Of the 18 routing problems, one was used as a tutorial, and 11 tested preference for probability regions of different densities, and were designed to test hypothesis that are not pertinent to the present study. Of the six remaining routing problems, two were very similar to the tutorial and thus generated near-perfect performance. For these reasons, four of the problems were selected for analysis in the present study.

Procedure

Participants completed the naturalistic TSP coded in the Psychology Experiment Building Language (PEBL; Mueller & Piper, 2014) which roughly approximated flight path planning through a probability map (see Figure 1). The experimental task differed from traditional TSP in that (1) there was no requirement for the participant to return to the starting location, and (2) the starting location was fixed for each trial. Starting locations were indicated by a green dot. Participants plotted a route through the problem space by clicking on each node in sequence, which resulted in a red line segment being drawn between the previously visited and current nodes. Each trial ended when participants had plotted a route through all of the nodes. As with real navigation tasks, participants could not undo their current route and re-plan dynamically.

Results

Preliminary Analysis

The experiment data from the four selected problems resulted in 194 flight paths (23 participants x 4 problems x 2 instructions). First, within each problem, we generated pair-wise divergence measures between all participant-generated paths using the R pathmapping package (Mueller et al., 2015), an implementation of the ALCAMP algorithm in the R Statistical Computing Language (R Core Team, 2013). The package is available for download from https://sites.google.com/a/mtu.edu/mapping/tasks, and via the Comprehensive R Archive Network (CRAN). For a comprehensive description of the ALCAMP algorithm, see Mueller et al. (2015). The divergence measure can typically be interpreted as a distance, such that a divergence of 0 indicates the paths are identical and the deviation is symmetric ($D(a,b)=D(b,a)$). However, we have not assessed whether the measure satisfies the triangle inequality (either psychologically or logically; see Tversky, 1977), so that it is likely to be possible that three paths can be found such that the $D(a,b) + D(b,c) < D(a,c)$.

Because of the potential non-metric aspects of this deviation measure, we wanted to project the deviations into a metric space for more direct analysis. To do this, we used Kruskal's Non-metric Multidimensional Scaling (via the isoMDS function of the MASS package; Venables & Ripley, 2002). We examined solutions of several different dimensionalities, but settled on two-dimensional solutions for ease of visualization, as higher-dimensional solutions typically produced similar results. Finally, we then performed a model-based clustering using a custom mixture-of-gaussians driver implemented via the flexmix package for R (Leisch, 2004; Gruen & Leisch, 2007; 2008). Stepwise flexible mixture modeling iteratively fits points to Gaussian clusters using the expectation-maximization (E-M) algorithm, and does so using a range of cluster numbers specified by the user. The ideal model (i.e., number of clusters) for each space was determined to be the number which produced the lowest Bayesian Information Criterion value. E-M is a deterministic process, but it is not guaranteed to find the global optimum. Consequently, we computed each solution from 500 randomly-chosen starting configurations and chose solutions with maximum likelihoods from each run.

We developed a custom mixture-of-gaussians model for this application. Because the axes in the metric solution produced by MDS are not meaningful, we estimated bivariate gaussian distributions with equal variance along both dimensions, and no covariance. Variance for each cluster was assessed independently, so that a tight cluster of solutions might be represented by a gaussian having very small variance (and thus high likelihood). As such, it is typical for solutions to produce several small gaussian clusters and one larger catch-all that captures outliers and other atypical solutions. Finally, there are often occasions in which a set of identical solutions is produced on different trials. These solutions are located at the same MDS coordinates, and if there are many such trials, E-M will tend to remove even close outliers from this cluster and retain only the identical set. This produces a cluster having variance 0, which leads to an undefined likelihood. Consequently, we restricted the minimum standard deviation of any group to be scaled to be 2% of the maximum range of the data in either direction.

To visualize the results of the above analysis, Figure 2 plots the paths belonging to each cluster separately over the points in each problem space. For Problem 2, the shortest-path solution is the one produced by all participants in group 5, which comprised 21/28 of the solutions for that instruction. The solutions to the search instructions produced three distinct sub-groups, each of which handled the bottom ten points differently. Problem 4 produced three groups: one large group (3) mapping onto a shortest-path solution (which was produced by most participants in the shortest-path instruction and about 1/2 of the participants in the search instructions) and two alternatives, both of which skipped some early locations in order to search higher-density legs earlier. Problem 5 produced three tightly-clustered groups: Group 1 was followed primarily on trials using shortest-path instructions, Group 2 and 5 which both were followed on trials using the search instructions, and one catch-all group. Finally, Problem 7 produced one group (3) that solved the two topmost clusters first (followed under the search instructions), two groups (1 and 2) that solved the problem along the linear sequence (one left and one right), followed primarily under the shortest-path instructions, and one catch-all group (4).

This analysis illustrates that in response to different instructions, participants change their search strategies in order to be sensitive to different constraints. However, it also shows that the execution of these problems is not always sensitive to instructions, and that even within a given instruction there are typically several distinct solutions. We infer that these solution map onto different mental models of the search process.

Discussion

The method described here provides an application in using the pathmapping techniques described by Mueller et al. (2015) in discovering underlying mental models of search. This demonstrates that the basic pathmapping technique can be used to assess path similarity and identify sets of similar paths. We suggest several applications of this method within the aviation community.

UAV Tracking and Analysis. Commercial adoption of UAVs has been limited because of FAA's cautious stance on permitting use by amateurs and outside of line-of-sight. One of the problems is that, unlike commercial aviation, where there is strong oversight, predictable and restricted flight routes, and relatively few air vehicles to monitor, commercial UAV applications will decrease oversight and predictability while increasing the number of vehicles by an order of magnitude. Methods such as the one we adopted here may prove useful for analyzing proposed flight routes to against a database of past flights, to better assess the likelihood of other air vehicles being in use in the planned area.

Pilot training. US Navy pilots must be capable of operating aircraft under harsh and uncertain conditions, executing landings on moving aircraft carriers and flying in formation under limited visibility conditions. In a 2011

Edge interview, Gary Klein relates a story in which a Navy pilot used to flying F4s is unable to adjust his mental model to allow him to safely land the newer A6. The pilot's mental model was reflected in an angle misjudgment arising from each plane's seating configuration (i.e., tandem vs. side-by-side, respectively). By measuring divergence between the optimal vs. actual landing or flight trajectories, the present approach would allow trainers to diagnose pilots' errors in landing and formation flying.

Search and Rescue Planning. In search and rescue operations, search operators generate probability maps that incorporate characteristics of the terrain, weather, and the missing person. Modeling missing person behavior is an art unto itself, and these efforts often include factors such as physical fitness, wilderness experience, and clues left in the environment. Systematic deviations from the optimal path out of a wilderness area may give search operators insight into the missing person's psychological state, the state of his equipment, or state of health. Based up testimony from prior recovered missing persons, and their reported trajectories, search operators will have a better picture of where a lost person may travel, given a particular mental model of the environment.

Anomaly Detection. Real-time trajectory-based anomaly detection algorithms have been previously applied to detect illicit activity among taxi cab drivers (Chen et al., 2012). While the intent in that domain was to catch fraudulent taxi cab drivers, in the aviation domain anomalous activity might represent failure in instruments or communications devices, or more sinister activity such as a hijacking. Computing a plane's divergence from its planned flight route would permit anomaly detection in real-time as the ALCAMP algorithm is robust to differences in path length (i.e., incomplete routes).

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Tables and Figures

Table 1.

Mean pairwise areas computer between optimal and participant-generated paths, given TSP and Search instructions. (TSP – Search) indicates M, (SD) divergence (pixels / 1000) between the optimal route, given TSP instructions, and the participant-generated routes, given Search instructions. Results of one-sample t-tests, difference scores for the area comparisons with each optimal trajectory, shown below each problem's descriptive statistics.

Problem	**TSP Instructions**			**Search Instructions**		
	TSP Optimal	**Search Optimal**	**Proportion Correct**	**TSP Optimal**	**Search Optimal**	**Proportion Correct**
V with Clusters	96.12 (86.04)	126.94 (62.95)	15/28	100.89 (54.93)	58.71 (59.31)	20/28
	$t(27) = 0.18$, $p = .857$			$t(27) = -3.05$, $p = .005$		
Z	0 (0)	39.07 (59.78)	28/28	46.41 (3.33)	40.18 (33.10)	15/28
	$t(27) = 73.67$, $p < .001$			$t(27) = 0.12$, $p = .905$		
Loop	77.84 (137.33)	155.32 (134.79)	21/28	91.40 (115.60)	142.17 (132.50)	24/28
	$t(27) = 3.30$, $p = .003$			$t(27) = -4.89$, $p < .001$		
Z with Clusters	14.87 (27.33)	178.70 (73.74)	27/28	213.92 (28.52)	91.79 (87.59)	17/28
	$t(27) = 19.71$, $p < .001$			$t(27) = -3.07$, $p = .005$		

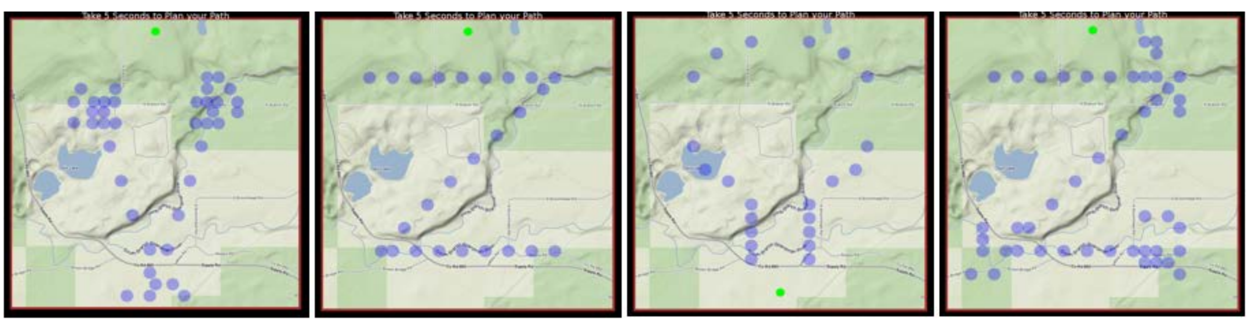

Figure 1. Selected problems from the study. Nodes are shown in blue, while the starting location is shown in green.

The distributions were mathematically validated for two solutions – one optimizing for path length (i.e., the shortest path solution) and the other for estimated time to find (i.e., the shortest average distance between nodes). Path length optimization solutions for these distributions exclude crossovers, whereas optimizing for estimated time to find permits solutions with crossovers while prioritizing clusters of nodes early in the flight path.

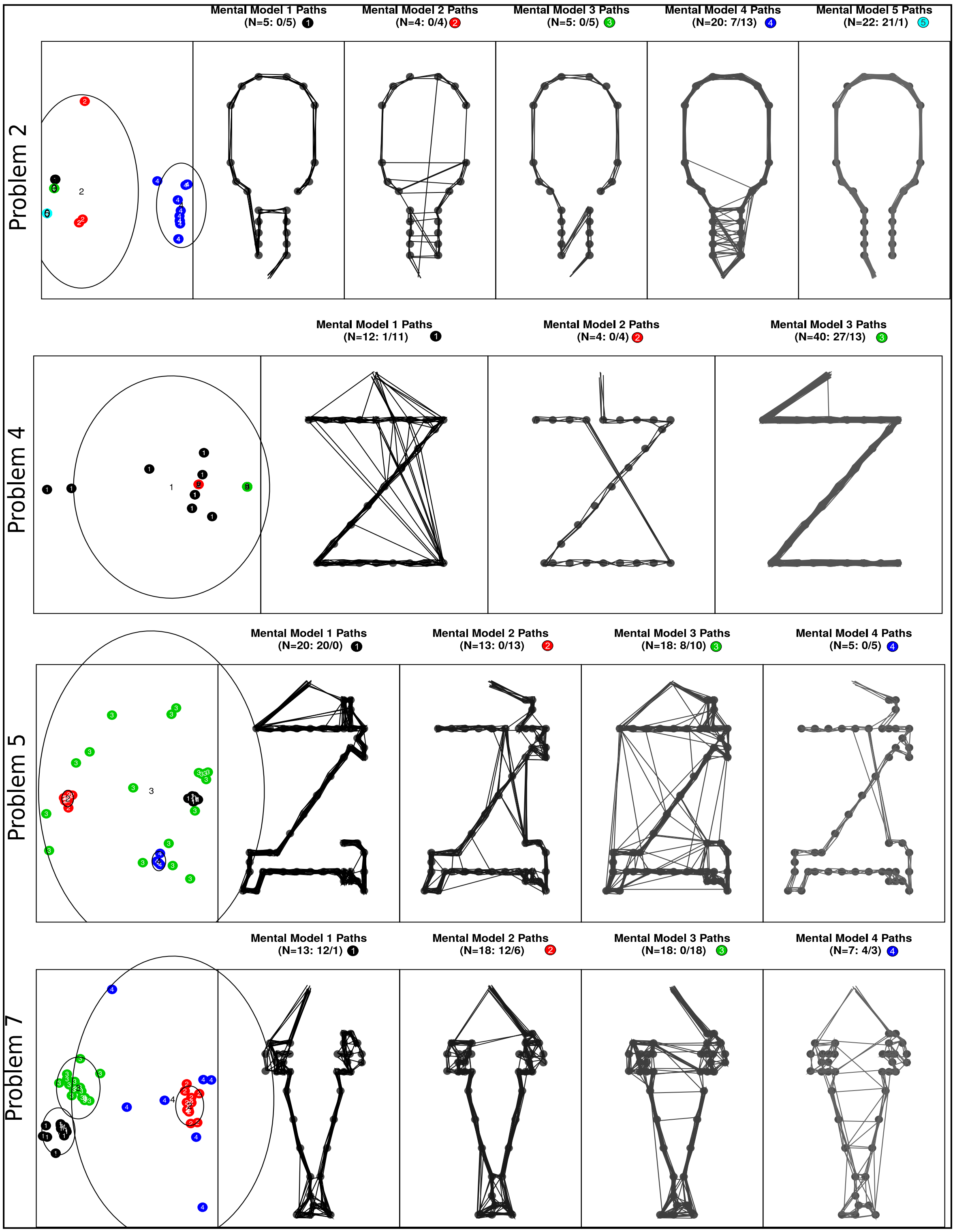

Figure 2. Mixture modeling results for four candidate problems. Leftmost panel in each row shows the isoMDS solution, and remaining panels show clusters of solutions (plotted with jitter). Title indicates the number of solutions in cluster, along with the breakdown between the two instructions. Details of each solution are discussed in the text.