The Role of Motivation and Complexity on Wayfinding Performance

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1 Introduction

Imagine a scenario where you are on a leisurely stroll through a familiar neighborhood park. Imagine a second scenario, where you are frantically running late to catch your flight in an unfamiliar airport. The wayfinding tasks represented in these two scenarios are performed under varying conditions. The parameters of these conditions include motivation, time constraints, and familiarity. This research attempts to explore the performance of wayfinding tasks of varying degrees of familiarity and route complexity, which are performed under varying task conditions.

A virtual reality (VR) desktop display was used to simulate the interior of a building to create a test environment. Participants were asked to perform a variety of navigation tasks under motivated and not-motivated (control) conditions. In order to test the effect of past knowledge on performance, participants first explored the environment with the goal of learning several paths, both simple and complex, between different pairs of landmarks. They were then tested on both the previously learned routes and new set of routes, which could be implicitly derived from the previously established spatial knowledge. The performance of the tasks across the two groups (motivated and control) was compared to understand the role of motivation on wayfinding.

2 Knowledge Based Wayfinding

The research builds on a number of recent efforts in modeling a wayfinder's knowledge with the goal of tailoring output of route directions or maps to the user's mental representations, or prior route or survey knowledge (Patel, Chen, Smith, & Landay, 2006; Schmid, 2008; Schmid & Richter, 2006; Tomko & Winter, 2006). In particular, Srinivas and Hirtle (2007) developed a theoretical model that represent known and unknown sections along the same route. They refer to these routes as *k-routes*.

This empirical study extends the original k-route theory to include the situation where one learns certain routes in an area, but then needs to navigate by putting the known links in a new order, possibly reversing some of the links. For example, you might learn the route ABC and the route ECD, but now have to travel DCBA. From past knowledge, you can deduce the new route, but it would not reach the same level of ease as the known route.

To account for this situation, we introduce the concept of *deducedK* as an extension of the k-route theory. As part of this experiment, deducedK routes consist of routes to locations that the participant has incidentally viewed as part of the training phase. The task of navigating a deducedK route was expected to be more complex than a corresponding K route with equal number of turns and decision points.

3 Method

Forty participants, half male and half female, ranging in age from 18 to 36, with a mean of 23 years, participated in the experiment. The layout of the VR environment was asymmetric and consisted of corridors and rooms with ten unique locations (Figure 1). Each location was made up of a unique shape and color; the white arrow in Figure 2 corresponds to location ‘B’ in Figure 1. The environment was altered for each trial by the inclusion of invisible walls. During training, invisible walls were placed in a manner that allowed the participant to take no more than one wrong turn away from the shortest route. In the test environment, the invisible walls were placed in a manner that allowed the participant to take at most two wrong turns.

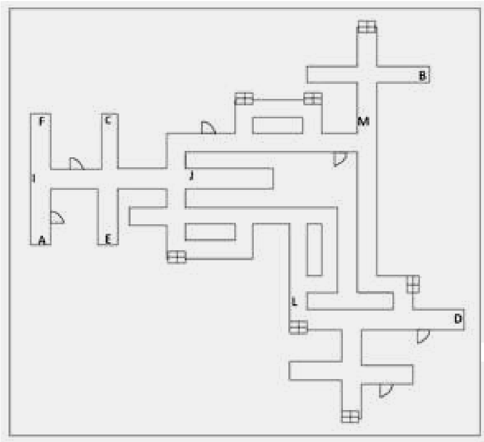

Figure 1. Layout of VR Environment.

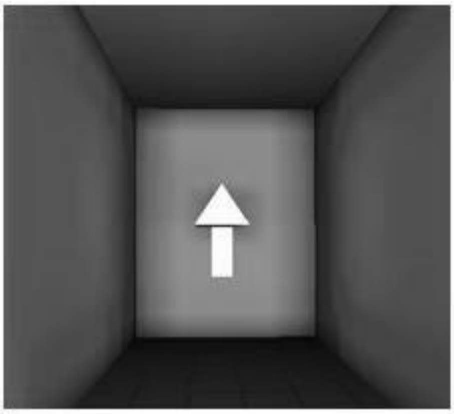

Figure 2. Snapshot of VR Environment.

Participants were assigned to either the motivated (experimental) group or the not-motivated (control) group. A randomized block design was used with gender as the blocking criteria. Four routes (two simple and two complex) were learned in the training phase, with the order of routes counterbalanced across participants.

In the test phase, subjects were instructed to find the shortest path to destinations in the test environment, some of which they were trained on in the training phase. In the control group, participants were asked to find their destination without any time constraint and were not offered a reward for completion in quick time. In contrast, participants in the motivated group were offered a reward for quick completion and were informed that their tasks were timed (details in the following subsection).

All participants were asked to find the previous set of four (Simple and Complex) K routes, followed by a new set of four (Simple and Complex) deducedK routes. The deducedK routes could be derived from the explicitly established route knowledge, but had not been directly traversed during the training phase.

4 Results

4.1 Time

Figure 3 displays the time participants took to complete each route in the test phase. A longer task completion time indicates that participants either lost their way more often,

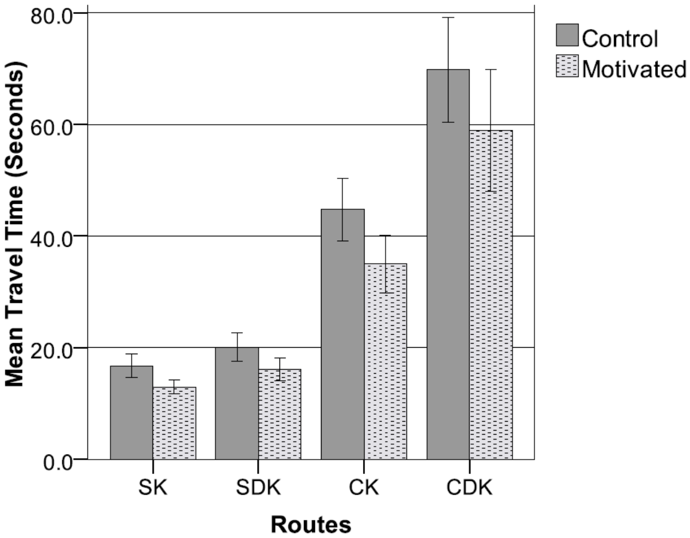

Figure 3. Plot of mean travel times (seconds) of SimpleK (SK), SimpleDeducedK (SDK), ComplexK (CK), and ComplexDeducedK (CDK) routes.

took their time in making decisions, or both. Participants in the motivated group travelled the SimpleK, $t(37) = -3.11$, $p < .01$, SimpleDeducedK, $t(37) = -2.43$, $p < .05$, and ComplexK, $t(38) = -2.58$, $p < .05$, routes significantly faster than participants in the control group. In contrast, no significant difference in mean travel time for ComplexDeducedK routes was found between the two groups.

4.2 Wrong Turns

Figure 4 displays the average number of wrong turns for each of the four types of routes across the two groups. While there were no overall differences between the motivated and control groups, there was a difference in the pattern of responses. In particular, strong positive correlations were found between wrong turns and time for the motivated group travelling the complex routes, ComplexK, $r(20) = .89$, $p < .01$, and ComplexDeducedK, $r(20) = .85$, $p < .01$, but not for the control group. This suggests that participants in the motivated group spent less time making decisions, as that longer travel times were the direct result of an increased number of wrong turns. In contrast, participants in the control group spent more time making decisions and less time moving, so longer travel times were often just the result of careful consideration of the next step and not necessarily indicative of an travel error. Additional analyses show other interesting trends in the data.

5 Discussion

This research was an attempt to explore the nature of the interaction between affect and wayfinding. Specifically, the study was designed to explore the interaction between motivation and the performance on variably complex routes. The results indicate that route complexity does in fact interact with motivation. Motivation improved time related performance of simple and moderately complex tasks. However, motivation failed to improve time related performance on the most complex tasks.

The results of our study gain relevance as they form the basis for future work that would investigate possible performance degradation on very complex tasks, under highly motivated or rushed conditions. This suggests that future automated route

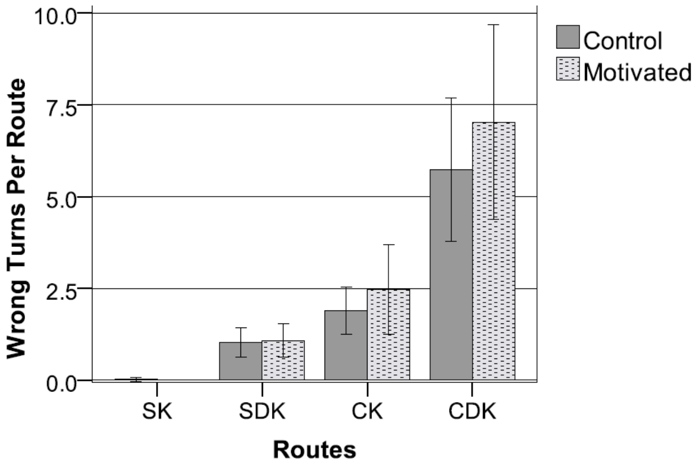

Figure 4. Plot of average number of wrong turns for each of the four types of routes—SimpleK (SK), SimpleDeducedK (SDK), ComplexK (CK) and ComplexDeducedK (CDK).

guidance systems may need to tailor their personalized route directions in accordance to not only a wayfinder's prior knowledge, but also their emotional state.

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