Guide Me through Somewhere Important: Decision-Point Salience and Collaborative Navigation

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ABSTRACT

People often work together to collaboratively navigate environments. Unfortunately, people make mistakes when giving directions to others, which can be especially troublesome when giving directions via a cell phone to a partner that cannot be physically seen. To facilitate collaborative navigation between spatially separated partners, contemporary navigational aids provide information about important landmarks and decision points in an environment. To learn more about what kinds of mistakes people make in navigating and the problems they have in giving and receiving route directions, this article presents an empirical study on dynamic, collaborative wayfinding, which looked at decision points where wayfinders made navigational errors. We found metrics rating the salience of decision points in an environment that correlate with where people tended to make mistakes in navigation, and argue that navigational aids could highlight these points to wayfinders so that they can pay special attention when giving directions traversing these points. We finish by outlining how the lessons learned in this study can be applied to real-time navigational aids.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; I.2.1 [**Applications and Expert Systems**]: Cartography

General Terms

Algorithms, Spatial Cognition, Wayfinding

Keywords

navigational aids, location-based services, geospatial information, human spatial cognition, real-time applications

1. INTRODUCTION

"Where are you now? Tell me when you get to the T-shaped intersection and I'll tell you where to go." Utterances such as these are frequently heard as people traverse environments with help from others. Despite (or because of) assistance from others, however, people make mistakes when navigating environments. If decision points where people are likely to make mistakes could be elucidated via computational means and wayfinders could be warned while traversing an environment, then many mistakes may be preventable.

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The present study analyzes where mistakes were made in a collaborative wayfinding task where participants simultaneously directed each other through pre-learned routes, while communicating remotely via cell phones. Although some of the participants were able to complete their traversals without error, many participants took wrong turns at decision points, thus deviating from their pre-determined routes. We outline several methods for calculating the salience of decision points. The concept of computational salience is applied to data from an empirical study that we conducted. Implications from linking computational salience to decision points in an environment where wayfinders made mistakes are then discussed in the context of improving navigational aids, and a plan for future work is presented.

1.1 Wayfinding and Decision Points

Wayfinding is a motivated activity to reach a destination that requires both locomotive and cognitive skills. Therefore, studying wayfinding can provide insights into many aspects of human spatial cognition. To traverse an environment to a goal location, external representations of the space, such as maps, are often used. People are thought to develop mental representations of space, often conceptualized as comprising the identify of landmarks (landmark knowledge), sequential order of landmarks along a route (route knowledge), and spatial configuration of landmarks and objects in an environment (survey knowledge) [9].

Contemporary GPS and location-aware smartphones can assist people with wayfinding by providing turn-by-turn directions. Over-reliance on such devices, however, can make it difficult for wayfinders to cope with situations where navigational aids cannot be used [8]. Ishikawa et al. [4], also demonstrated that contemporary GPS devices decreased wayfinders' configurational knowledge of travelled routes, while increasing the time and distance required to traverse. Thus contemporary navigational aids might actually make it harder for wayfinders to learn about the environment they are traversing and to recover from mistakes.

Decision points are locations in an environment, such as intersections, where navigators have to make a decision about whether to change direction or continue straight. Takemiya and Ishikawa showed that by using information about decision points traversed, the performance of wayfinders could be classified in real-time [10] and future decision points that they would traverse could be predicted [12]. The efficacy of the classification and prediction demonstrates that the structure of an environment is closely related to the efficiency of wayfinding and determining where wayfinders will go, and that decision points are a useful conceptualization of an environment. To find possible ways to assist wayfinders, the present work considers mistakes that people make in route following at decision points in an unfamiliar environment, and focuses on the salience of decision points, to come up with a computational method of eliciting points where wayfinders will be likely to make mistakes.

1.2 Decision-Point Salience

The salience, or importance, of decision points can be conceptualized as consisting of various facets, among which are *cognitive salience* and *computational salience*. Cognitive salience is the importance of decision points to humans undertaking a wayfinding task, and it has been studied in relation to landmarks. The structure of intersections [6] and graph theoretic measures of street connectivity were also found to be related to cognitive salience [1].

Computational salience was first defined by Takemiya and Ishikawa [11] as the importance of a decision point for classifying wayfinders with respect to their abilities (individual differences). In other words, this is the importance of a decision point for discriminating between good and poor performing wayfinders. In [11], many potential algorithms for calculating computational salience were tested, using computationally generated routes as training input. Computational salience was found to not necessarily be related to cognitive salience, although some measures of computational salience put forth by Takemiya and Ishikawa were found to correlate with the occurrence of decision points in cognitively ergonomic route directions [13]. Computational salience can be a useful concept for discriminating between good and poor performing wayfinders, so the present work applies it to finding decision points where collaborative wayfinders are likely to make mistakes.

2. METHODS: COMPUTATIONAL SALIENCE

The present work focuses on modeling the computational salience of decision points with the goal of eliciting points where people who engage in collaborative wayfinding are more likely to make mistakes. The goal of this is to enable future work to develop navigational aids that can prevent these mistakes, by calling attention to computationally salient points for human navigators. The algorithms used for calculating computational salience in the present work are described in the following subsections. Traversal probability, PageRank, and the outflux scores are from [11], whereas entropy difference, degree centrality, closeness centrality, betweenness centrality, and outlink scores are being studied here for the first time in the context of computational salience.

2.1 Traversal Probability

Decision points that are frequently traversed by wayfinders in an environment between a start and a goal are likely to be crucial to the wayfinding task. For navigational aids to be practically implemented for any arbitrary environment, the traversal probability of decision points cannot be determined by empirically observing humans and recording the traversal probability. Rather, the probability must be elucidated via computational means, without using empirically observed training data.

As in [10, 11, 12, 13], routes were computationally generated using a modified A* heuristic search algorithm. 1,000 routes were generated from the start to the goal location, for each of two routes through a real environment (described in section 3). 10% of the time the search heuristic search randomly chose between two decision points when determining which point to use for the next iteration of the search. This had the effect of creating reasonable, yet imperfect routes between the start and goal locations. From the computationally generated routes, the traversal probability for a decision point was computed as the fraction of generated routes that contained that point.

2.2 Entropy Difference

The routes generated as described in section 2.1 were used to calculate traversal probabilities for all decision points in the environment (see section 3) modeled in this study. These probabilities define a probability distribution over all decision points that can be assigned an information-theoretic entropy. Entropy was calculated for the entire graph of all decision points, so to relate this to an individual decision point, a new probability distribution over all decision points was created where an individual point's probability was set to zero. This distribution was normalized to sum to unity and the entropy was calculated. The absolute value of the difference between the entropies between the two distributions was then defined as the *entropy difference*. This was done in turn for each decision point, and the differences in entropies were taken as a measure of how important decision points were to the diversity of traversals through an environment.

2.3 PageRank

PageRank is an algorithm for calculating the stationary probability distribution of an ergodic Markov chain [7] and was originally developed for ranking Web pages in Google search results. It has also been successfully applied to studying navigation by ranking popular locations in a spatial environment [5]. In PageRank, the importance of a decision point is related to the importance of decision points that lead to it. All decision points are initialized with the probability that a point would be randomly chosen, and then PageRanks are calculated via the power iteration method. Decision points with higher PageRank values were considered more important.

2.4 Centrality Measures

We examined degree, closeness, and betweenness centrality measures to elucidate decision-point importance. Degree centrality is a measure of the fraction of decision points that a decision point is connected to. In this article, the undirected form of degree centrality was used. Decision points with a high degree centrality are important to the connectivity of the street network.

Closeness centrality measures the inverse sum of the distances to all other decision points. This intuitively shows how close a decision point is to other points.

Betweenness centrality for a decision point is the fraction of all-pairs shortest paths that pass through the decision point. This measures the importance of a decision point for enabling paths between other points.

2.5 Outflux Scores

Outflux scores were introduced by Takemiya and Ishikawa [11], as a meta-algorithm that takes computational salience scores and computes a set of scores that are derivatives of the original scores. The outflux score is calculated for a metric by summing up all the scores for decision points reachable from the current decision point via outlinks. The absolute value of the difference between this sum and the score for the current point is then calculated and that is the outflux score.

2.6 Outlink Scores

The present work aims to to find a way to computationally elicit decision points where wayfinders make errors. Because navigational errors entail leaving a decision point along an efficient route, the decision points following a given point can be seen as determining the importance of the point. To model this, outlink scores were calculated for each decision point by summing the scores for each outlink decision point. As with outflux scores, outlink scores are a meta-algorithm and requires the output of one of the other algorithms as the input.

3. METHODS: EMPIRICAL EXPERIMENT

We conducted an empirical study to analyze how people work together to guide each other through an environment in real-time (see [2]), involving two pre-defined routes through a residential neighborhood in Tokyo with no visible street names and winding, narrow streets. Route 1 was more complex than Route 2, but the two routes took comparable times to traverse (mean 6 minutes 30 seconds for Route 1, and 7 minutes 21 seconds for Route 2).

Forty-four non-Japanese participants (27 men and 17 women, mean age 25.9 years) from 15 countries participated in the study and were randomly assigned to either Route 1 or Route 2. Participants were paired into 22 groups, based on their scores on the Santa Barbara Sense-of-Direction scale (see [3]). They were guided along the assigned routes by an experimenter, while vocalizing their thoughts into a voice recorder. Participants then returned along the same route to the common starting point, switched routes, and used cell phones to guide each other along the routes they had previously been guided along. During the collaborative guiding, the experimenters followed behind each participant, recording their time, path, and behavior, and guided them back to the route if they wandered too far from it. From the 44 route traversals in our study, we collected all decision points where participants deviated from the predefined routes.

4. RESULTS

To find a computational method for determining decision points where navigational errors are likely to occur in collaborative navigation, we performed an empirical study (section 3) and then compiled a list of decision points where participants made errors. We then used the computational metrics from section 2, to calculate the salience of decision points in the environment.

4.1 Navigational Errors and Computational Salience

Figure 1 shows Hinton diagrams of correlations (Pearson r) between computational salience measures and navigational errors at decision points. The area of each square represents the magnitude of the correlation, with darkness representing either positive correlation (white squares) or negative correlation (black).

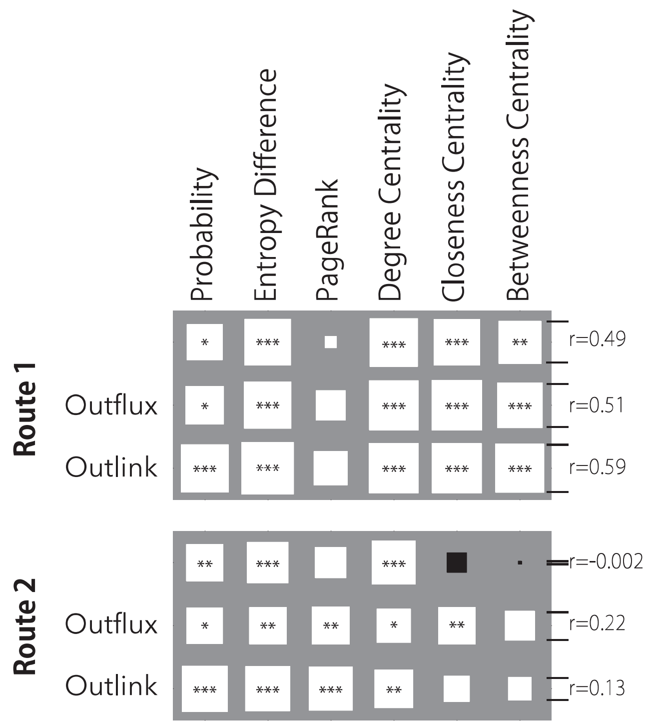

Figure 1: Correlations between decision-point computational salience measures and the incidence of navigational errors at decision points ($*$ denotes $p < .05$, $p < .01$ with **, and *** denotes $p < .001$) for Route 1 (top) and Route 2 (bottom). The area of each square denotes the correlation magnitude. r values for correlations along the right-hand side are shown for scale.

As Figure 1 shows, *outlink entropy difference* scores for decision points correlated most strongly with the incidence of navigational errors for both Routes 1 and 2 made by the participants in our empirical study ($r = .68$ for Route 1 and $r = .50$ for Route 2, p's$< .001$). *Outlink probability* also strongly correlated with where wayfinders made errors ($r = .56$ for Route 1 and $r = .53$ for Route 2; p's$< .001$). Overall, outflux scores did not correlate as strongly as outlink scores with navigational errors.

Disregarding the outflux and outlink scores, *degree centrality* of decision points was the most strongly correlated metric with navigational errors ($r = .58$ for Route 1 and $r = .47$ for Route 2, p's$< .001$), followed by *entropy difference* ($r = .53$ for Route 1 and $r = .42$ for Route 2, p's$< .001$). Other measures of computational salience did not correlate as strongly.

5. DISCUSSION

5.1 Relating Environmental Structure and Navigational Errors

Outlink entropy difference and outlink probability both strongly correlated with mistakes that collaborative wayfinders made at decision points. For Route 1, many participants made a mistake at the decision point where a hospital was located. Participants often mentioned the hospital as a salient landmark, suggesting that the hospital was perceived as important to understanding the environment. The decision point where the hospital was located had the third-highest outlink entropy difference and the highest degree centrality score for Route 1, showing that the computational salience measures were able to capture the structural importance of this decision point in the graph. Namely, wayfinders made many mistakes at that decision point because of the structure of the street network, and not only because of a failure to recognize the hospital as a landmark.

The fact that outlink entropy difference and outlink probability strongly correlated with errors made by wayfinders demonstrates the efficacy of using computationally generated routes to model the behavior of wayfinders and elicit decision points that are important to wayfinding. Both outlink entropy difference and outlink probability are original to the present work, and are based on the probability that a decision point will be traversed.

5.2 Incorporating Decision-Point Salience into Collaborative Wayfinding and Navigational Aids

Failing to mention landmarks was the most common error observed in the present study and was committed by all of the participants who made mistakes. The hospital was an important landmark for Route 1, so when participants guiding a partner failed to mention it, the other person was very likely to get lost. If the person giving directions had known that the decision point where the hospital was located was one of the most important in the environment, then extra care could have been taken there and fewer wayfinders would have made mistakes. A similar approach may also work for individual wayfinders navigating an environment on their own. Simply informing wayfinders about which points are riskier than others, with respect to making a wrong turn, could be enough to prevent a majority of errors.

6. CONCLUSIONS AND FUTURE WORK

We outlined a method for linking the computational salience of decision points and navigational errors made by wayfinders. The method was validated with results from our empirical study featuring wayfinders collaboratively traversing an environment by simultaneously guiding each other along pre-learned routes via cellphones. Outlink entropy difference and outlink probability, both metrics for computational salience that are original to this study, strongly correlated with navigational errors. Implications for future work are to bring awareness of decision points where wayfinders are likely to make errors to the attention of the wayfinders, via real-time location-based services.

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8. REFERENCES

[1] C. Claramunt and S. Winter. Structural Salience of Elements of the City. *Environment and Planning B*, 34:1030–1050, 2007.

[2] G. He, T. Ishikawa, and M. Takemiya. Collaborative Navigation in an Unfamiliar Environment with People Having Different Spatial Aptitudes. *Spatial Cognition and Computation*, in press, 2015.

[3] M. Hegarty, A. E. Richardson, D. R. Montello, K. Lovelace, and I. Subbiah. Development of a Self-Report Measure of Environmental Spatial Ability. *Intelligence*, 30:425–447, 2002.

[4] T. Ishikawa, H. Fujiwara, O. Imai, and A. Okabe. Wayfinding with a GPS-Based Mobile Navigation System: A Comparison with Maps and Direct Experience. *Journal of Environmental Psychology*, 28:74–82, 2008.

[5] B. Jiang. Ranking Spaces for Predicting Human Movement in an Urban Environment. *International Journal of Geographical Information Science*, 23:823–837, 2009.

[6] A. Klippel, K.-F. Richter, and S. Hansen. Structural Salience as a Landmark. In *Mobile Maps Workshop at MobileHCI '05. Salzburg, Austria*, 2005.

[7] A. N. Langville and C. D. Meyer. *Google's PageRank and Beyond: The Science of Search Engine Rankings*. Princeton University Press, Princeton, USA, 2006.

[8] A. Parush, S. Ahuvia, and I. Erev. Degradation in Spatial Knowledge Acquisition When Using Automatic Navigation Systems. In S. Winter, M. Duckham, L. Kulik, and B. Kuipers, editors, *Spatial Information Theory*, volume 4736 of *LNCS*, pages 238–254, Springer, Berlin, 2007.

[9] A. W. Siegel and S. H. White. The Development of Spatial Representations of Large-Scale Environments. *Advances in Child Development and Behavior*, 10:9–55, 1975.

[10] M. Takemiya and T. Ishikawa. I Can Tell by the Way You Use Your Walk: Real-Time Classification of Wayfinding Performance. In M. Egenhofer, N. Giudice, R. Moratz, and M. Worboys, editors, *Spatial Information Theory*, volume 6899 of *LNCS*, pages 90–109. Springer, Berlin, 2011.

[11] M. Takemiya and T. Ishikawa. Determining Decision-Point Salience for Real-Time Wayfinding Support. *Journal of Spatial Information Science*, 4:57–83, 2012.

[12] M. Takemiya and T. Ishikawa. Strategy-Based Dynamic Real-Time Route Prediction. In T. Tenbrink, J. Stell, A. Galton, and Z. Wood, editors, *Spatial Information Theory*, volume 8116 of *LNCS*, pages 149–168. Springer, 2013.

[13] M. Takemiya, K.-F. Richter, and T. Ishikawa. Linking Cognitive and Computational Saliences in Route Information. In C. Stachniss, K. Schill, and D. Uttal, editors, *Spatial Cognition VIII*, volume 7463 of *LNCS*, pages 386–404. Springer, Berlin, 2012.