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DYNAMICS OF COLLABORATIVE NAVIGATION AND APPLYING DATA DRIVEN METHODS TO IMPROVE PEDESTRIAN NAVIGATION INSTRUCTIONS AT DECISION POINTS FOR PEOPLE OF VARYING SPATIAL APTITUDES

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To the Graduate Council:

I am submitting herewith a dissertation written by Gengen He entitled "DYNAMICS OF COLLABORATIVE NAVIGATION AND APPLYING DATA DRIVEN METHODS TO IMPROVE PEDESTRIAN NAVIGATION INSTRUCTIONS AT DECISION POINTS FOR PEOPLE OF VARYING SPATIAL APTITUDES." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Geography.

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DYNAMICS OF COLLABORATIVE NAVIGATION AND APPLYING DATA DRIVEN METHODS TO IMPROVE PEDESTRIAN NAVIGATION INSTRUCTIONS AT DECISION POINTS FOR PEOPLE OF VARYING SPATIAL APTITUDES

A Dissertation Presented for the

Doctor of Philosophy

Degree

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DEDICATION

I dedicate this dissertation work to my parents, Paul Friday, Francis Ho, Yanyan Song, who inspired, supported me and encourage me through this long process. My grandparents would also have been very proud.

I dedicate this dissertation work to my wife, Keyla G. Ward, who always believed in me, stood by my side and merged her own journey of growth and self-discovery with mine.

I dedicate this dissertation to my daughter Valeria He, may this be a foundation and inspiration for her future endeavors. If she ever reads this dissertation in the future, I hope she realizes that the key to accomplishing difficult tasks is through creative thinking, resourcefulness and persistence.

I also dedicate this dissertation to my advisor, Prof. Shih-Lung Shaw, for his guidance, patience and encouragement through this whole process. Dr. Shaw took a chance on me and launched my career in this field. I am truly grateful for this opportunity. As the Chinese saying goes: “One day your teacher, forever your father. ” 一日为师，终身为父

Finally, I dedicate this dissertation to the late Professor Georges Guiochon, who brought me to UT Knoxville on his research grant. I am happy to finally complete this for you, may you rest in peace.

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I will look back at my years in Knoxville with great fondness.

ABSTRACT

Cognitive Geography seeks to understand individual decision-making variations based on fundamental cognitive differences between people of varying spatial aptitudes. Understanding fundamental behavioral discrepancies among individuals is an important step to improve navigation algorithms and the overall travel experience. Contemporary navigation aids, although helpful in providing turn-by-turn directions, lack important capabilities to distinguish decision points for their features and importance. Existing systems lack the ability to generate landmark or decision point based instructions using real-time or crowd sourced data. Systems cannot customize personalized instructions for individuals based on inherent spatial ability, travel history, or situations.

This dissertation presents a novel experimental setup to examine simultaneous wayfinding behavior for people of varying spatial abilities. This study reveals discrepancies in the information processing, landmark preference and spatial information communication among groups possessing differing abilities.

Empirical data is used to validate computational salience techniques that endeavor to predict the difficulty of decision point use from the structure of the routes. Outlink score and outflux score, two meta-algorithms that derive secondary scores from existing metrics of network analysis, are explored. These two algorithms approximate human cognitive variation in navigation by analyzing neighboring and directional effect properties of decision point nodes within a routing network. The results are validated by a human wayfinding experiment, results show that these metrics generally improve the prediction of errors.

In addition, a model of personalized weighting for users' characteristics is derived from a SVM^{rank} machine learning method. Such a system can effectively rank decision point difficulty based on user behavior and derive weighted models for navigators that reflect their individual tendencies. The weights reflect certain characteristics of groups. Such models can serve as personal travel profiles, and potentially be used to complement sense-of-direction surveys in classifying wayfinders.

A prototype with augmented instructions for pedestrian navigation is created and tested, with particular focus on investigating how augmented instructions at particular decision points affect spatial learning. The results demonstrate that survey knowledge acquisition is improved for people with low spatial ability while decreased for people of high spatial ability.

Finally, contributions are summarized, conclusions are provided, and future implications are discussed.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION AND ORGANIZATION OF DISSERTATION

1.1 Research Background and Research Questions

Navigation relies on knowledge of environmental features (i.e., landmarks) along networks of interconnected routes (Ishikawa & Montello 2006, Siegel & White 1975) and can be divided into two sets of interrelated processes, locomotion and wayfinding (Montello, 2005). Wayfinding involves reasoning about the environment in order to reach a navigational goal. Wayfinding relies both on transient and enduring representations of the environment (Waller and Hodgson, 2006) and is facilitated by representations that consist of memorable and distinctive places (Presson and Montello, 1988).

Human beings are spatial in nature, constantly processing and communicating spatial information. In an unfamiliar or novel environment, people break down information in their environment, create mental maps, and subsequently generate directions in natural language for themselves, and for others (Tversky et al., 1998). People attempt to derive memorable, meaningful cues from their environment, often assigning them personal significance. Imagine you are in a novel unfamiliar environment such as Tokyo Japan and you have to navigate through a neighborhood to reach your destination using maps on a GPS-equipped smartphone, using your inherent cognitive abilities. What can you do to find your way? Navigation systems are commonly used to help with wayfinding in novel environments. Figure 1.1 displays a typical contemporary navigation aid that offers directions at turning points on a route. This system can be helpful in many instances. However, typical systems offers little information about landmarks while disregarding the personal characteristics of the user.

Further imagine that scenario in Tokyo, where certain neighborhoods have no legible street signs to offer assistance. You enter a destination on your phone and a route is generated for you on the screen. During the navigation, you fail to reconcile the information on the phone's map with the environment being traversed. You continue to walk and make mistakes at a series of decision points, take subsequent wrong turns and end up being lost. Now, imagine that the navigation system you are using is able to give you directions in the context of your actual experience on the route. Directions that are timely and natural such as: "take a left turn after you reach the two story yellow building with a stop sign outside - if you see the parking garage, you have gone too far" or "reach the corner where there is a large crowd gathering, then turn right to cross the street". These instructions could be more appealing and valuable to the everyday user. Such a system would take into consideration your navigational preferences, spatial abilities, and consider your potential interaction with various landmarks on your route. To make such a scenario possible, more information is needed to understand how individuals navigate in space and how the interaction occur dynamically between people and their environment. To make these design suggestions systematically possible, one should further classify individual behavior in the real environment and derive methods to calculate the potential guidance value of landmarks at decision points.

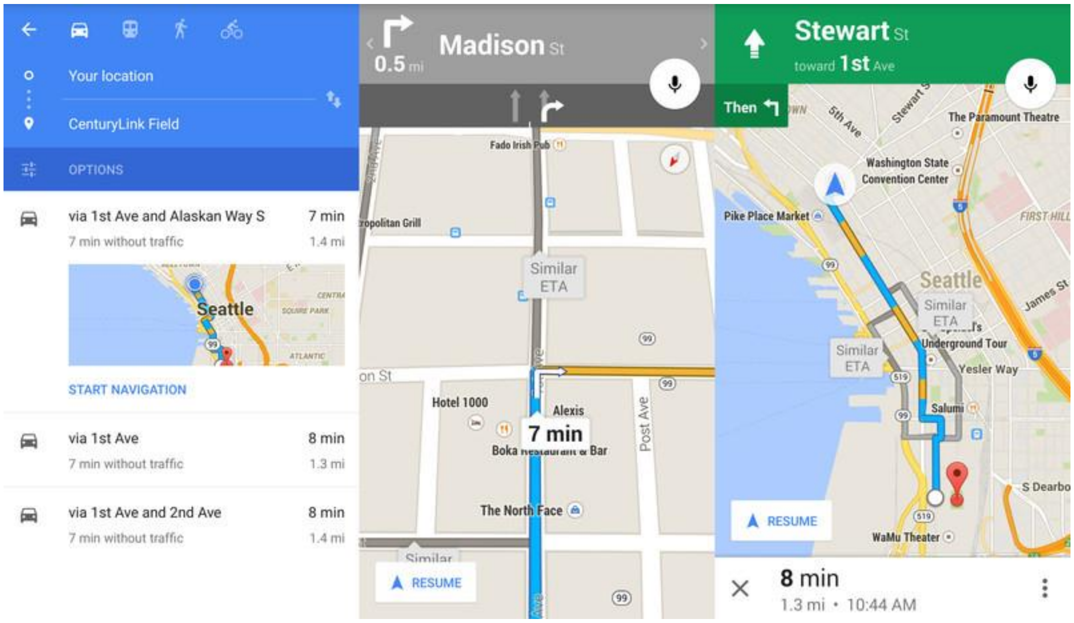

Figure 1.1 Displays an example of commonly used existing navigation systems, the middle Figure showing what pedestrians typically use – offering turn-by- turn directions at intersections. (© 2017, Google Maps)

In order to operate in space, humans must encode information about the environment and form operable mental maps. One must gather information about the environment, and the routes - and subsequently synthesize spatial knowledge from them. Spatial knowledge is classified into three types: landmark knowledge (knowledge about discrete objects or scenes), route knowledge (sequences of landmarks and associated decisions), and survey knowledge (configurational, map-like knowledge) (Siegel & White, 1975). In survey knowledge, landmarks and routes are interrelated, and the distances and directions between them are available. The acquisition of survey knowledge is considered a more sophisticated process in large-scale spaces. Layouts and routes cannot be easily grasped from a single vantage point. Therefore this typically requires more mental integration (Ittelson, 1973). Due to this difficulty, large individual differences exist in the acquisition, interpretation, and retention accuracy of survey knowledge (Ishikawa & Montello, 2006).

Individual differences exist in spatial information processing as well as wayfinding strategies. Studies have presented different wayfinding strategies employed by pedestrians such as landmark based, route based, or survey type navigation (Pazzaglia & De Beni, 2001). The theories describing the cause for the differences in spatial knowledge acquisition are insufficient (Allen et al., 1996, Hegarty et al., 2006). One theory that attempts to explain the differences is based on how information in the environment is encoded and converted to spatial information, with memory playing a vital role. People operate on what they can and choose to remember - differences in the way people remember the environment affect the way they operate in it. This theory is based on the role of working memory in spatial information acquisition. Working memory is a temporary storage system under near-conscious control that has the capability to support complex thought processing - before information is sent to long-term memory (Baddeley et al., 2003). Many wayfinding tasks operate in this domain, using the working memory system for spatial information processing.

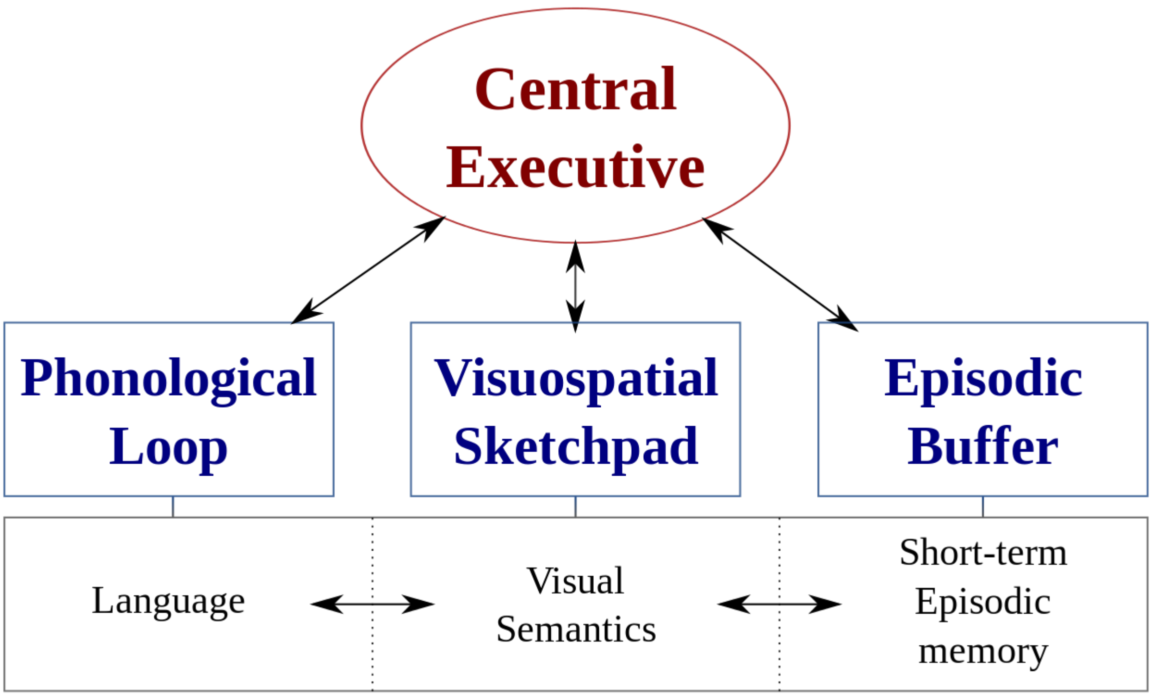

Figure 1.2 Diagram of Baddeley and Hitch working memory model (Baddeley et al., 1974) - the central executive acts as supervisory system and controls the flow of information from and to its slave systems: the phonological loop and the visuo-spatial sketchpad. The phonological loop stores verbal content, whereas the visuo-spatial sketchpad caters to visuo-spatial data. Both of the slave systems only function as short-term storage centers. In 2000, a third slave system was added to the model - the episodic buffer.
Source:https://en.wikipedia.org/wiki/Baddeley%27s_model_of_working_memory#/media/File:Working-memory-en.svg

In the model of working memory, three capacity-limited systems have been proposed: an attentional control system – the central executive, and two subsidiary storage systems – and the phonological loop and the visuospatial sketchpad (Baddeley & Hitch, 1974). The concept is illustrated in Figure 1.2. The phonological loop holds speech-based and acoustical information, the visuospatial sketchpad, on the other hand, has two subcomponents that process visual and spatial information respectively (Baeyens & Bruyer, 1999). These and other findings explore the underlying biological and cognitive differences that lead to varying spatial aptitudes resulting in differences in spatial behavior. Spatial behavior can be measured in wayfinding tasks. Humans' discussion of space can be a reflection of this internal cognitive process. Although not fully understood, spatial ability is a cumulative reflection of these internal processes. Although differences in cognitive processes is theoretical, actual measurements of spatial ability can be performed with various tests.

Variations in spatial ability and spatial cognition effectively are measured by a self-administered sense of directions (SOD) report - with demonstrated validity (Hegarty et al., 2002). The Santa Barbara Sense of Direction survey, henceforth referred to as SBSOD, is the standard survey used in cognitive geography research, particularly involving human subjects and navigation. The acronym SBSOD will be used interchangeably with SOD in this dissertation. Self-report tests, such as the SBSOD, have been shown to provide objective measures of these abilities with a high degree of reliability (Hegarty et al., 2002). The SBSOD is a self-reported test, hence can generate a classification before navigation. The SBSOD scale consists of fifteen 7-point Likert questions about spatial orientation and navigational tendencies. Seven of the questions are stated positively (e.g., "I am very good at giving directions"), while the other eight are stated negatively (e.g., "I very easily get lost in a new city"). The SBSOD score is the basis for differentiating the spatial ability of participants in this dissertation. The SBSOD questionnaire is attached in appendix A.

What is the connection between working memory models and SOD scores in research on human spatial behavior? It has been shown that people with a higher SODs tend to do better with "survey tasks" that require configurational understanding of environments (Hegarty et al., 2002). Wen, Ishikawa and Sato (2011) examined the involvement of three different components of working memory in the acquisition of three types of spatial knowledge, in relation to participants' SOD scores. The study showed that people with a good SOD encoding of landmarks and routes, retained primarily verbally and spatially, were able to integrate knowledge about them into survey knowledge with the support of all three components of working memory. In contrast, people with a poor SOD encoded landmarks, retained only verbally, tended to rely on the visual component of working memory in the processing of route knowledge, thus failing to acquire comprehensive survey knowledge. Figure 1.3 shows the proposed model for the acquisition of spatial information for people of good SOD and poor SOD. It should be noted that people with poor SOD do not process landmark knowledge spatially, hence lacking the ability to form complete survey knowledge with accurate spatial information. Note that the acquisition of survey knowledge can be measured with participants performing sketch tests at the conclusion of targeted wayfinding tasks.

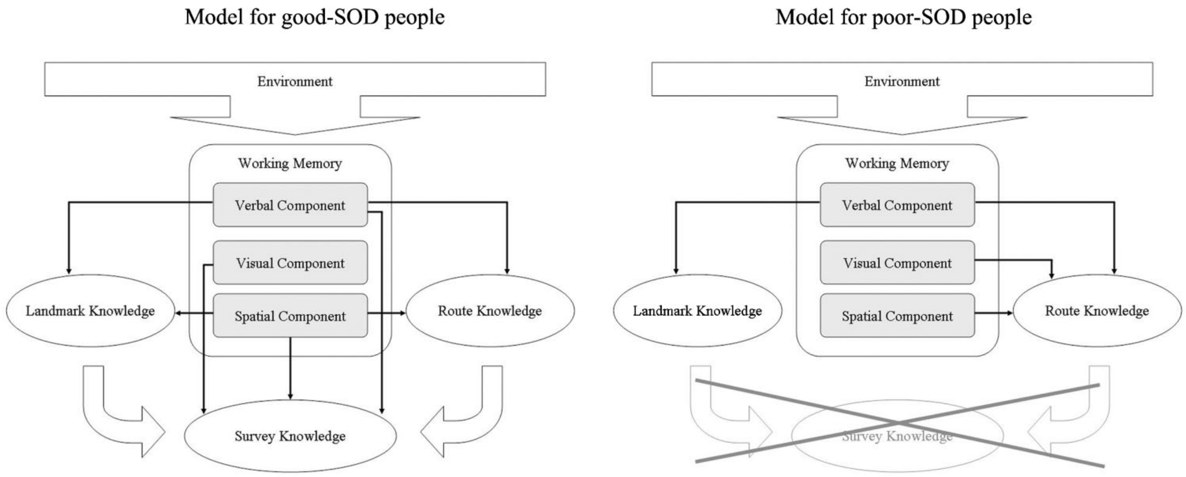

Figure 1.3 Model for spatial knowledge acquisition. Black arrows indicate the encoding processes for the three types of spatial knowledge; white arrows indicate the integration of landmark and route knowledge into survey knowledge. For good-SOD people, information about landmarks and routes is processed in the verbal and spatial components of working memory. Knowledge thus acquired is integrated into survey knowledge being processed in all three components of working memory. In contrast, for poor-SOD people, landmark knowledge is not spatially processed and route knowledge is visually processed. Source: (Wen et al., 2011).

Since people of varying spatial aptitude fundamentally differ in the processing of spatial information, many researchers strive to understand and quantify the actual differences in spatial experience, wayfinding, and spatial learning in the environment. Urban settings are particularly useful for these studies. Many investigators employ empirical studies to measure the effects of environment on navigators. For example, Garden et al. asked participants to learn two routes in a European city, with concurrent articulatory-suppression and spatial-disrupting tasks, and then to follow the learned route again. Results showed that survey-type participants' performances were disrupted by spatially concurrent tasks, whereas non-survey participants' performance was disrupted by verbal tasks (Garden et al., 2002). This in turn leads to varied results for people of differing spatial abilities. Ishikawa et al. have shown that people with varying spatial abilities tend to select different landmarks during navigation (Ishikawa et al., 2008). Höelscher, Tenbrink, and Wiener studied routes planned by participants who were familiar with an environment. They found that the routes planned by individuals for themselves to follow, the routes planned for others, and the routes actually traversed through the environment were significantly different from each other. This finding suggests that cogitation about wayfinding tasks is vitally linked to the context of the activity being carried out (Höelscher et al., 2011). Many studies attempt to classify user behavior and establish a relationship between spatial ability and wayfinding performance. As each person and environment is inherently distinct, varying experimental design can often reveal novel aspects and insight about the human wayfinding process.

Building upon previous idea and methods in the field of cognitive geography and environmental psychology, the first research question in this dissertation is:

- **What are the differences in the perception of the environment and the communication of spatial information by people of varying spatial abilities? What differences are there during navigation between people of high and low spatial abilities? What additional difficulties may be encountered by wayfinders if people of varying spatial abilities simultaneously collaborate on a spatial wayfinding task?**

Answering this question requires closely examining the behavior of individuals in real world navigation. It will be particularly revealing to have people of varying spatial abilities perform wayfinding tasks simultaneously. Spatial information is communicated through natural languages (Tversky et al., 1996), reflecting the internal cognitive process. If participants are required to exchange and communicate spatial information with someone that perhaps processes the environment differently, such differences can be revealed. When forced to process spatial information originating from a dissimilar cognitive process, adjustments and adaptions will be required. A side-by-side comparison of behavior, as well as mistakes and discrepancies, will generate a useful dataset for analysis that can highlight these intrinsic differences.

While many studies have examined behavior of individual users, the challenging nature of a simultaneous pedestrian setup has made it difficult to carry out, thus insufficiently presented in literature. One reason is that researchers are still trying to elucidate the individual processes that affect wayfinding performance - which is not yet fully understood. The second reason is that an experimental design involving multiple simultaneous wayfinders is logistically difficult to setup and implement. In order to cognitively challenge an individual, it is ideal to place them in a culturally unfamiliar setting, with novel landmarks, and perhaps with a lack of understandable signs. This setup can challenge the wayfinders and reveal more about the cognitive process and patterns that otherwise would have been revealed in a familiar setting. This dissertation describes experiments that attempt to meet these challenges by creating an experimental setup in an unfamiliar environment that is non-trivial for users.

The phenomenon of navigation and wayfinding is a constant interaction between people and environment. It is important therefore to further classify the environment traversed. Unlike robots that make an instant decision to make a turn, humans have to process the environment at decision points before making a logical and deliberate choice for a spatial action (Klippel et al., 2011). Action at decision points tends to alter the course and effectiveness of navigation tasks (Richter et al., 2012). Decision points are points in an environment, such as intersections, where navigators have to make a choice about whether to change direction or continue without deviation. Decision point salience can be broken down into *computational* and *cognitive* salience. Cognitive salience is related to the personal significance for humans during a navigation task. Cognitive salience has been studied in relation to landmarks, structures of intersections, and graph connectivity (Claramunt et al. 2007). Computational salience, on the other hand, is a method of classifying the importance of decision points for wayfinders with respect to individual differences and ability (Takemiya et al., 2013). These saliences represent the difficulties in an environment. The application for such calculations is in determining where people are likely to make mistakes.

Mistakes are revealing relative to the navigation task, to the environment, and to the user. In an experimental setup where wayfinders are expected to follow certain routes, it is possible to measure the location, nature, and severity of mistakes made. Subsequent analysis can often lead to insights. The second central research question of this dissertation involves classification of the traversed environment in the framework of wayfinder errors:

- **What features of the environment can help predict where people are likely to make mistakes? Can difficulty of certain decision points be pre-determined, before navigation takes place, purely from analysis of topological features? What computational methods can be applied to predict difficult-to-navigate decision points? How useful are the predictive capacity of these metrics in the real world?**

Due to the dynamic and complex nature of the environment, answering these questions requires a data-driven analytical approach that mirrors actual human behavior. Many computational methods have been established in the past. Using computational methods, it is possible to generate arbitrary data, such as thousands of routes and possible deviations, to test predictions. Many of these predictions could be validated with actual human behavior-based data. A meaningful contribution to the field is thus being able to establish links between computational methods and actual wayfinding performance.

There are many useful metrics used in network analysis. One prominently used computational method is PageRank, the foundational algorithm that powers the world's most popular search engines. PageRank is an algorithm for calculating the stationary probability distribution of an ergodic Markov chain (Langville et al., 2006). It was developed originally for ranking web pages in Google search results, but has also been successfully applied to word-sense disambiguation (Aguire et al., 2009), as well as ranking popular locations in a spatial environment (Jiang et al., 2009). In PageRank, the importance of a node in a graph is related to the importance of nodes that point to it (Page et al., 1999). The algorithm uses direction information about which nodes point to each other. In the context of wayfinding, nodes are decision points and the connecting nodes are streets. The direction of the edges is determined by movement from a starting decision point to a goal decision point. In iterative implementations of PageRank, all nodes are first initialized with the probability that a node is randomly chosen; that is, 1, divided by the number of decision points in the graph, $|G|$:

$$PageRank^0(i) = \frac{1}{|G|} \forall i \in G$$

PageRank applications show that decision points are not isolated, that their importance is related to the network. This is an important implication for environmental psychology. Many of the patterns are invisible to the human observer but can be illustrated through various computational methods. Imagine traversing through different neighborhoods in a large city, given that there are variations in one's spatial cognitive process. Walking quickly through a street with many successively changing landmarks and different directions also has a pronounced effect on one's navigation decisions. Many subtle processes of wayfinding are not quantitatively represented. Computational methods that take into account these subtleties will be useful in determining potential mistakes in navigation. It is a significant contribution to the field of cognitive geography to test existing methods, and to establish algorithms specific to pedestrian wayfinding that take into consideration both the graphical nature of the routes and uniqueness of decision points.

Wayfinding is a complex task that employs intricate mental processes. Technology often attempts to mimic complex natural processes. Navigation systems can follow a similar principle to mirror human cognitive and communication processes, which hitherto has been a challenge. There are many ways to improve navigation system design. When giving instructions to one another, humans tend to predominantly use landmarks, by which we understand distinctive objects in the environment (Lynch 1960; Denis et al., 1999). It has been shown that the inclusion of landmarks into system-generated pedestrian routing instructions raises the user's confidence in the system - when compared to a system that only gives relative direction instructions (Ross et al., 2004). Traditional map-based navigation data models currently cannot effectively integrate landmarks into pedestrian navigation instructions - therefore they often lead to inconsistent or incorrect spatial cognitive processing (i.e., wayfinding errors) in pedestrian navigation scenarios (Lin and Chien 2010). This in turn could cause confusion to pedestrians and lead to less efficient routes than the route instructions provided by landmark-based navigation systems (Elias and Paelke 2008, Hile et al. 2008, Ishikawa et al. 2008). In addition, humans tend to choose objects in the environment that are *salient* in certain situations, i.e., that are prominent in a way that makes them easily recognizable. Many researchers have proposed computing salience values for landmarks (Raubal and Winter, 2002; Duckham et al., 2010; Nothegger et al., 2004). However, in many of these cases, salience is determined arbitrarily and not universally applicable for the large population of landmarks, limiting their effectiveness and value to the individual.

Contemporary systems do not quantify or rank decision points by their respective difficulty to individual users. As a result, existing systems lack an effective way to determine which decision points can best benefit the user with additional information. Previous classification of landmarks and decision points predominantly have been heuristically and manually generated, not tuned or determined by the actual users. A navigation system should aim to maximize its usefulness for the individual and mirror the individual's thought process when interacting with the environment. It is thus important to quantify individual behavior during navigation, leading to the next research question:

- **What is an effective way to create individual models for navigation that can elucidate the tendencies of each individual navigator? How to create weights that measure the significance of various features of an environment to benefit an individual user? How to effectively determine decision point difficulty of a route based on the behavior of an individual wayfinder?**

This issue has not been sufficiently addressed in past research. There are significant challenges to overcome in order to sufficiently answer the question. The first problem is obtaining a useful dataset that reflects actual human behavior, including sufficient aspects of the environment to be simultaneously analyzed. Such a dataset should not just contain the performance of the users, but also information about the environment, and perhaps the cognitive ability and preferences of the users themselves. A second problem is to establish a standard to measure errors. Errors give insight to the human cognitive process. Previous research has not adequately addressed how to define mistakes and use methods such as machine learning to connect mistakes with human behavior - that is: using information about mistakes in navigation as a method to model individual spatial behavior. A third problem is to find an effective method to derive weights to differentiate effects of various environmental features on the wayfinder. Navigation is complex and a robust quantitative method that can take into account all the factors during the wayfinding task has not been established.

With the availability of a useful dataset, theoretically one can find a way to determine the effects (weights) of each parameter that represent a wayfinding profile of a wayfinder. In a route with *n* decision points, if a person has difficulty at one decision point over another, some characteristics of the decision should possess predictive qualities for future as yet unseen decision points. Interactive salience can be determined for each user relative to decision points - defining how relatively difficult a decision point is for an individual. Since people vary greatly in respect to their cognitive process, this is not a problem of *absolute salience* but relative salience ranking. Approaches such as SVM Ranking described by (Joachim 2002) holds potential for both creating ranks and weights to help differentiate decision points and wayfinders. Ranking decision points on a route can help a system determine where to best provide additional information on the route, making navigation guidance more efficient and personal.

After quantifying user behavior and the environment, the next step is to incorporate these insights into more effective system design. The first step is to preliminarily test the effects of additional information on the users and measure their individual response. Since a problem with navigation systems is their effect on spatial learning, it would be useful also to test how new features might affect an individual's ability to acquire survey knowledge during wayfinding tasks. The final major question of this dissertation is:

- **What new features can be added to the design of pedestrian navigation aids? Will the improvement benefit everyone equally? What effects will these improvements have on the wayfinding performance and spatial learning of individuals of varying spatial aptitudes?**

Augmented instruction at specific decision points is an established way to improve user experience in wayfinding (Hara et al., 2010). The challenges of augmented instructions at decision points in GIS involve the design of an underlying representational database structure, as well as the effects of augmentation on users. Although not the focus of this dissertation, it is important to discuss existing work undertaken in data structure design that is the foundation for improvement in GIS. Most existing database models for GIS and navigation systems focus on the organization of navigation routes and navigation instructions while ignoring the cognitive load in the process of finding routes. Navigation data models such as Kiwi, SDAL, and GDF focus on route-specific guidance data (e.g., point of interest (POI), road networks, and public transportation systems) and navigation instructions (e.g., distance, turn direction, and voice instruction). Richter (2008) developed the generation of unambiguous, adapted route directions (GUARD) to generate context-specific route instructions using landmarks in which the route instructions adapt to route properties and environmental characteristics. For example, GUARD generates route instructions by considering "the circular order that the branches of a decision point form and the order of events in route following that are induced by the directedness of a route". Fang et al introduced (LPNDM) to support the modeling of landmarks and use of landmark-based route instructions augmented on photographs for pedestrian navigation services (Fang et al., 2011).

These models attempt to offer additional information for the user during wayfinding, but the additional information should come with consideration of the user. The challenge therefore is to understand what decision points and for whom the added instructions can most benefit. Such a prototype can use augmented instructions at decision points and measure the improvement of users or groups. While improvement in wayfinding efficiency is expected from these new capabilities, it would be important to see how such improvement might vary for people of high versus low spatial aptitudes. In addition, it would be insightful to measure the effects on spatial learning by the use of the new features, and whether it is consistent for people of varying spatial aptitudes.

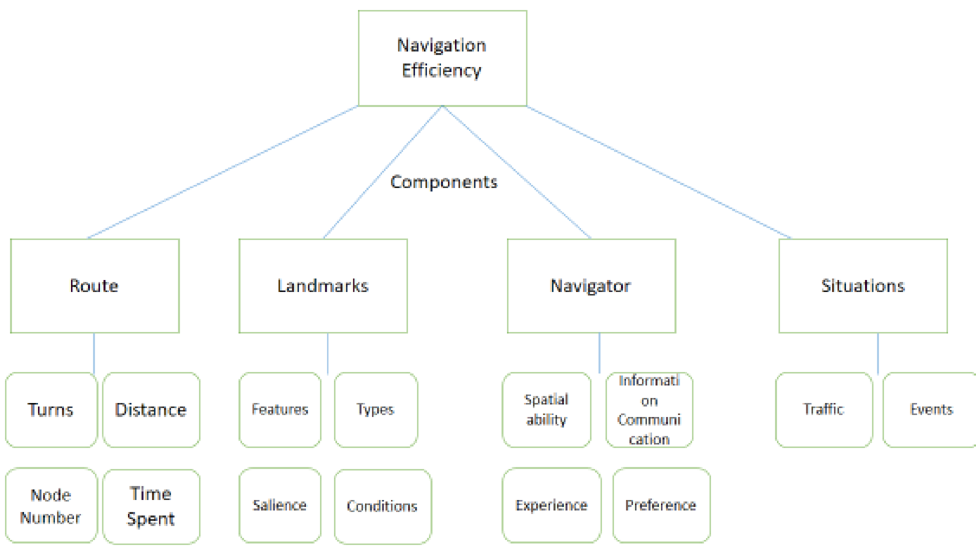

Figure 1.4. Components of Navigational efficiency. Navigation is a complex process that can be affected by, but not limited to, those described above. Many of these components have not been sufficiently addressed in the past in terms of understanding human behavior in navigation space. This dissertation will attempt to address these issues and potentially quantify them in classifying the environment and individual behavior.

To organize the research questions proposed for this dissertation, the following diagrams are provided. Figure 1.4 shows the components that may affect navigational efficiency, many of which will be actively addressed in this dissertation. Attempts will be made to differentiate these features and calculate their weighted effects on each individual users. The flow chart in figure 1.5 describes the research methodology and flow of the dissertation, the chart demonstrates that cognitive studies is a dynamic and imperfect process - instead of arriving at the right answer, there are often unknown factors that affect the outcome. The purpose is to arrive closer to an understanding while quantifying as many factors as possible regarding the human spatial experience.

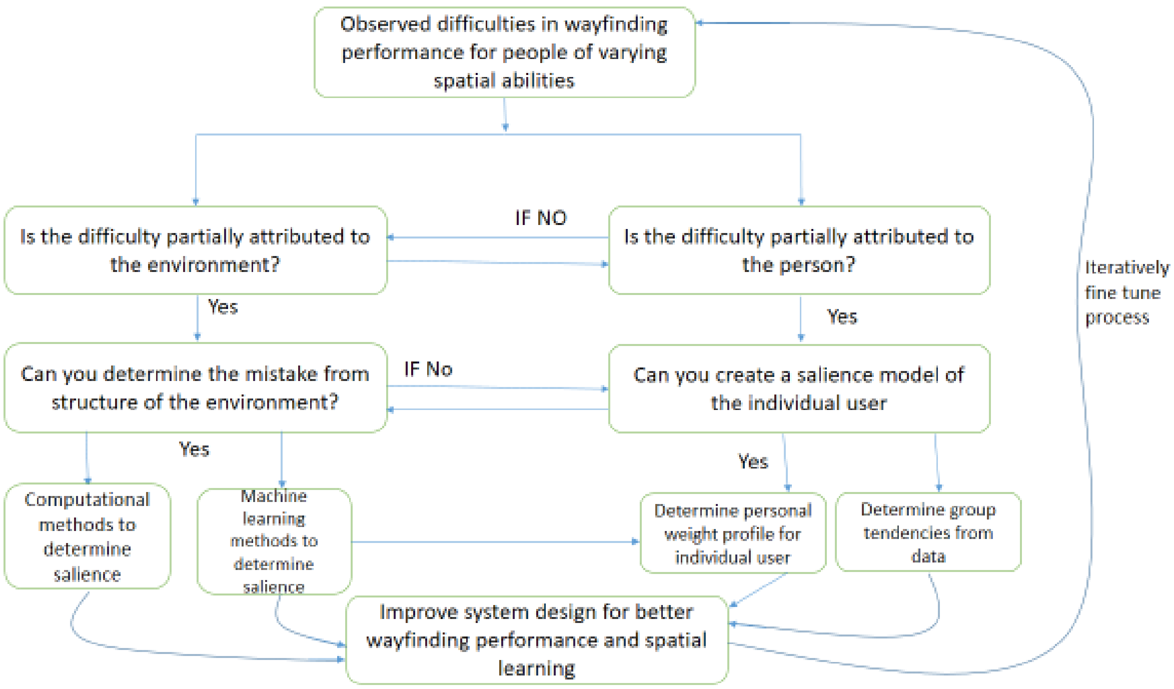

Figure 1.5 shows the logical flow of this dissertation and how research questions will be addressed. It should be noted that it is an iterative process – a purpose driven pursuit to further understand individual behavior and finding features that could improve usefulness and efficiency of navigation systems.

The dissertation will attempt to examine the previously presented questions in a various steps. The dissertation centers on the understanding and analyzing of difficult decision points in navigation - and using various analysis techniques to classify the environment and wayfinders. The organization of this dissertation is presented in the following section.

1.2 Organization of Dissertation

This dissertation includes modified versions of three manuscripts targeted for various peer-reviewed journals.

Chapter two presents an empirical study that derives a rich and diverse dataset that will serve as the foundation of three chapters. A novel collaborative navigation study design is carried out with two people simultaneously navigating and communicating in a culturally unfamiliar environment in Tokyo. The setup includes 44 participants with varying spatial abilities divided into 22 pairs. Subsequent analysis will reveal their ability patterns. Communication, in terms of direction given and direction received, between the users will be closely examined. This study endeavors to gain insight into the way people of varying spatial abilities communicate spatial information - particularly highlighting the difficulties faced when the pairing is far apart in spatial aptitude. This experimental setup allows for the discovery of incongruence between users. This incongruence can mirror the reality faced in contemporary navigation systems, where a system does not distinguish between users nor optimize direction generation. This study also is designed to discover tendencies of people of varying spatial ability groups. This study also can reveal gender specific peculiarities in wayfinding, if any, but this complex topic is not the focus of this dissertation.

Chapter three searches for ways to effectively determine decision point salience using computational methods. The primary computational means of this study is to combine meta-algorithms (outlink score and outflux score) with various established methods of social network analysis while validating them against actual human behavior. A goal of this study is to measure the effects of these algorithms on existing metrics and to find ways to further classify the environment. Another purpose of this study is to determine if there are network effects in a route description beyond the obvious characteristics of decision point descriptions. This study will determine whether these two computational metrics are more specific to navigation because they take into consideration certain human cognitive processes not inherent in the measurement of other computational metrics.

The ability to distinguish decision points is important from a system perspective, and is a key step for improved navigational instructions by allowing the system to highlight potential difficult spots for navigation. Computing decision point characteristics generally is the first step in generating a wayfinding description. Highlighting these points can allow a system to more efficiently provide additional instructions. After decision points are classified in a topological sense, the next step is to attempt to find personalized profiles for individual users from real world data.

Chapter four consists of two parts. This study takes the empirical dataset of real world wayfinder behavior and attempts to derive ranking of decision points and personal weight models of the users. Chapter four proposes to apply machine learning methods, particularly ***RankingSVM***, concurrently known as ***SVM^{Rank}*** for this purpose. SVM^{rank} method can automatically derive a mathematical model to rank the difficulty of a decision point on a route from a combination of topological and descriptive features of the environment. If this method is effective, this ranking can have many potential applications, from aggregating group behaviors to determining specifically difficult decision points for users of certain characteristics in an urban environment.

The second part of chapter four tests a prototype of an augmented decision system. The primary purpose of this prototype is to test the effects of added instructions on spatial learning. If findings from this dissertation are eventually applied to navigation systems, will such systems actually compensate for decreased spatial learning abilities? A post-experiment sketch test is used to assess the survey knowledge acquisition of the users. The results will attest to the usefulness and effectiveness of augmented navigation technology and whether it affects people differently. What subset population can benefit more from an augmented navigation decision system, and what other improvements are suggested by this study?

Chapter five summarizes the major contributions of this dissertation research. The contributions to the field of navigation, system design, spatial cognition, spatial ability, pedestrian navigation, decision point salience, machine learning methods, and personalization in GIS are re-iterated. Implications for improved model-building, GIS based navigation system design, and city planning will be presented. This dissertation ends with a discussion of future research directions.

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CHAPTER 2

COLLABORATIVE NAVIGATION IN AN UNFAMILIAR ENVIRONMENT WITH PEOPLE HAVING DIFFERENT SPATIAL APTITUDES

This chapter is a slightly modified version of a paper published by Spatial Cognition & Computation Volume 15 - Issue 4 in August 2015. Co-Authors: Toru Ishikawa & Makoto Takemiya.

2.1 Abstract

This study addressed the issue of collaborative navigation, by examining the types of information communicated in the processes of direction giving and receiving between people who guided each other simultaneously to a destination over the cell phone in a novel environment. When paired with a partner whose sense of direction differed greatly from their own, people found the collaboration difficult and took a longer time to verbally direct the partner to the destination. Landmarks that people used in giving navigational instructions differed depending on sense of direction. People with a good sense of direction adjusted route directions to their partners' wayfinding ability. Results from a detailed qualitative analysis of participants' verbal protocols and implications for personalized navigation tools are discussed.

Keywords: collaboration; landmarks; navigational instructions; route directions; sense of direction; wayfinding

2.2 Introduction

Imagine a situation in which you and your partner are at different locations in an unfamiliar environment and desire to meet at a certain place. You do not know how to get to the place from your current location but your partner does, or vice versa. In such a case, in a modern setting, people can assist each other in finding their way in real time over the mobile phone, with one person describing what is seen in their surroundings so that the partner can direct them. In providing navigational directions, then, would a subject select different landmarks or instructional strategies depending on whether the partner is a child, an older person, a foreigner, or a poor wayfinder? Most likely your instructions would be dependent on your perception of both the environment and the partner's wayfinding ability. Contemporary navigational aids, however, take a generalized approach, primarily providing turn-by-turn route directions with little consideration of a user's spatial aptitudes.

Such a collaboration in navigation is often encountered in daily life and constitutes an important part of everyday spatial cognition. To our knowledge, however, no empirical research exists regarding how people tackle such a common but challenging task of *collaborative navigation* - requiring having to know where they are and informing other people how to proceed. In the existing literature of human wayfinding, the experimental task of navigation is set as an *individual* activity, and its *simultaneous*, *interactive* aspect has not been sufficiently investigated.

One exception is the study by Forlizzi, Barley, and Seder (2010), which looked at how a person in the passenger seat interacted with a driver in providing navigational directions toward a destination. In the study, the passenger consulted a map and other pieces of information for as long as desired beforehand to generate navigational directions. Maps are a powerful tool to help the viewer comprehend spatial relations between places in a bird's-eye view, and the knowledge acquired from maps differs from knowledge acquired from direct navigational experience in the environment (Thorndyke & Hayes-Roth, 1982). This study rather focuses on the acquisition and communication of route information in direct, real-time navigation.

Another exception is the study by Reilly et al. (2009). It looked at how pairs of travelers together collaborate in navigating toward destinations, by sharing a single cellphone and consulting information displayed on it. Strategies employed by paired travelers changed dynamically with their roles (i.e., a leader or a follower) and the phases of navigation. Although the study did not deal with the type of collaboration that the present research endeavors to examine (i.e., how people find the way together using a shared navigation tool vs. how people guide the partner remotely through verbal directions), it points to variations in navigational roles and strategies when two people interact with each other.

There are some variations in the forms of collaborative navigation. One is simply finding the way to a destination in a pair (or group) traveling together. In such a case, a person who is deficient in wayfinding abilities (or a person with a poor sense of direction) could simply follow the partner and leave the wayfinding or route-planning task to the partner completely. This is not an ideal setting for an experiment that is examining cognitive interactions and processes of collaborative navigation. Another form is one person providing navigational directions, in advance, to another person who is to visit a new place. This type of information provision has been examined in terms of route descriptions generated by individual participants from memory (e.g., Denis et al., 1999), but lacks in the simultaneous and collaborative aspect which this study focuses on.

A third form of collaborative navigation is where two people travelling and assisting each other in real space in real time, which is the target for the present research. Specifically, this study examines peoples' collaborative navigation behavior, particularly by focusing on the difficulties that people have understanding the navigational directions provided by the partner and giving directions that are understandable to the partner. Importantly, it takes the effects of navigators' spatial aptitudes into account, and looks at the types of information communicated, and the efficiency of navigation by people with different levels in sense of direction.

2.3 Background and Objectives

2.3.1 Navigation and wayfinding

The goal of navigation, which is defined as consisting of wayfinding and locomotion, is to move through space to reach a specific destination. Wayfinding differs from locomotion in that it involves purposeful cognitive processes beyond simple local movements or obstacle avoidance.

In successful navigation, people need to orient themselves in space and know which direction they are headed, and then plan a route and execute the planned route toward the destination (Montello, 2005). In these three stages, people will access stored knowledge about the surrounding environments (mental representations) or use navigational aid information (external representations). In particular in a new environment, people may rely heavily on navigational aids, as well as their cognitive spatial abilities, to find their way. Recently, modern communication technologies such as GPS-enabled devices and location-aware smartphones have been developed to assist people in navigation. These technologies, however, are often found to be non-optimal - for example increasing travel time and distance compared to traditional paper maps or decreasing the accuracy of the users' configuration knowledge of the traveled routes (Ishikawa et al., 2008). Thus there is room for improvement for such advanced systems in the design and format of information presentation.

2.3.2 Spatial ability and sense of direction

Spatial abilities are important for the daily activities of spatial learning and behavior in the environment, such as wayfinding, layout learning, or map reading (e.g., Hegarty et al., 2006; Liben & Downs, 1993; Newcombe, 2010). Self-report tests, such as the Santa Barbara Sense-of-Direction (SBSOD) scale, have been shown to provide objective measures of these abilities with a high degree of reliability (Hegarty et al., 2002). The SBSOD scale consists of fifteen 7-point Likert questions about spatial orientation and navigational tendencies. Seven of the questions are stated positively (e.g., "I am very good at giving directions"), while the other eight are stated negatively (e.g., "I very easily get lost in a new city"). Hegarty et al. (2006) showed that sense of direction related more strongly with learning about large-scale spaces from direct experience than with learning from visual media such as a video or a virtual environment. Ishikawa and Nakamura (2012) found differences in landmark selection between people with a good and poor sense of direction, with the former selecting fewer landmarks and focusing on commonly recognized landmarks. Therefore in this research, SBSOD scores are used as a potential correlate with collaborative navigation performance.

2.3.3 Landmarks and navigational directions

Successful wayfinding requires accurate encoding of landmarks, and good mental representations and navigational instructions typically contain landmarks placed in a correct sequence (Lee & Tversky, 2005). Although a landmark remains a somewhat elusive concept with a range of definitions (Presson & Montello, 1988), its major characteristic is singularity, which leads to its uniqueness or memorability in the environment (Lynch, 1960), typically in terms of visual., semantic, or structural salience (Sorrows & Hirtle, 1999). Thus, introducing judiciously selected landmarks into route directions can help navigators to envision the environment during, or in advance of, actual traversal (e.g., Klippel & Winter, 2005; Raubal & Winter, 2002; Tom & Denis, 2003). In the present study, particular focus is placed on the types of landmarks selected by collaborating navigators and the effectiveness of those landmarks for route directions in dynamic and interactive situations.

2.3.4 Research objectives

With these background issues in mind, we conducted an empirical study in which people guided each other in pairs to a destination over the cellular phone, while each person was trying to reach the destination on the basis of the other person's navigational directions. This allowed us to study the dynamics of spatial communication in a real-time setting, beyond a static analysis of route descriptions generated by individual participants from memory (Lovelace, Hegarty, & Montello, 1999). Also, to examine the effects of spatial ability, we divided participants into two groups (high and low sense-of-direction groups) based on their SBSOD scores, and looked at how they select and communicate information about the routes interacting with each other. In particular, as pointed out by Reilly et al. (2009), behaviors and instructions during collaborative navigation may dynamically change, and this flexibility could relate to the travelers’ perceptions of the partner’s ability, as well as to their own spatial abilities. These considerations motivate the present study. In light of past studies that discussed differences in landmark selection between familiar and unfamiliar people (Lovelace et al., 1999) and between recall from memory and identification during travel (Ishikawa & Nakamura, 2012), this research focused on landmark selection in situ by people unfamiliar with the environment. This study also considered gender-related differences in route descriptions and navigational strategies that have been reported in the literature. Specifically, since men and women tend to differ in configurational understanding of environments (Ishikawa & Montello, 2006) and the use of concrete objects versus cardinal directions as landmarks (Ward, Newcombe, & Overton, 1986; Allen, 2000), it might be the case that male-male or female-female pairs find navigational communication easier than male-female pairs. Thus, the present study examines navigation performance by pairs of the same and different sex, as a possible effect of similarities in wayfinding tendencies.

2.4 Method

2.4.1 Participants

Forty-four adults (27 male and 17 female) participated in the experiment in return for monetary compensation. The mean age of the participants was 25.9 years. They were non-Japanese English speakers who had been in Japan for varying lengths of time (1 week to 2 years), and none of them had been to the study area before the experiment. Based on their scores on the SBSOD scale, which they took prior to the experiment, participants were labeled as either high or low through a median split at the score of 4.3 out of 7 (the larger the better). They were then grouped into 22 pairs with respect to high- and low-SOD combinations: 6 high-high (H-H) pairs, 10 high low (H-L) pairs, and 6 low-low (L-L) pairs. Concerning sex composition, 9 pairs were of the same sex (7 male pairs and 2 female pairs) and 13 pairs were of different sex.

2.4.2 Study Area and Routes

The study area was a residential neighborhood in the proximity of a railway station in western Tokyo (Nakano-Sakaue). As in many typical Japanese residential neighborhoods, there were no visible street-name signs in the area.

Thus, instead of using street names as landmarks, participants needed to identify landmarks based on their perceptions, particularly under the constraints of environmental and cultural unfamiliarity, and the pressure of processing spatial information in real time while providing navigational information to the partner. In the area, two routes were selected that shared a common starting point and had respective goal locations (Figure 2.1). It took on average 6 minutes and 30 seconds to travel Route 1, and 7 minutes and 21 seconds to travel Route 2. Examples of major landmarks that participants identified along the routes are shown in Figure 2.2.

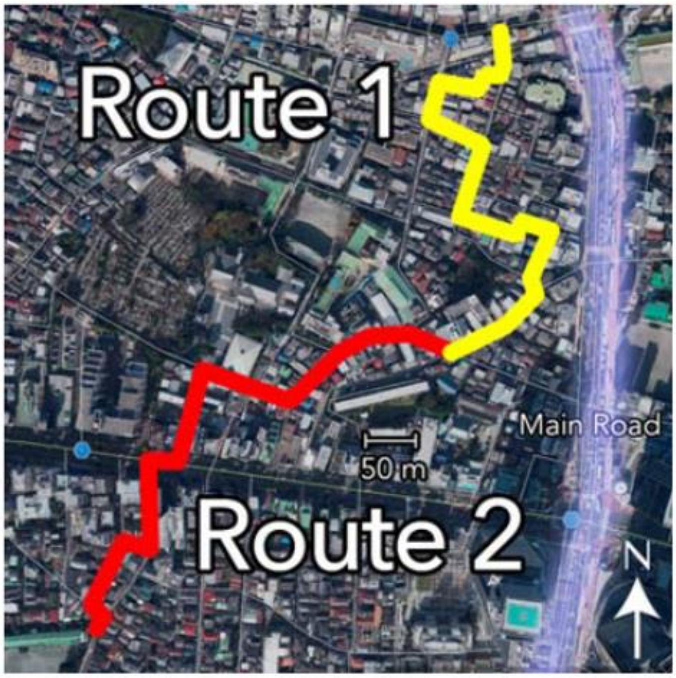

Figure 2.1: A map of the study area. The two routes, Routes 1 and 2, share the same starting point and have respective goal locations. Map data © 2013 Google, ZENRIN.

Figure 2.2: Examples of major landmarks along the routes: a hospital building on Route 1 (left) and a temple on Route 2 (right). Photographs taken by author.

2.4.3 Procedure

Participants were taken to the study area in pairs (which were formed based on their SBSOD scores as described in section 2.1), one pair at a time, and each member was randomly assigned to either Route 1 or Route 2. At the starting point, the cardinal direction of north was pointed out to participants, so that they could use the information if they wanted later.

Then each member of the pair started to walk along the assigned route to the destination, being guided by a research assistant. During the initial guided walk, participants verbalized their thoughts about the route into a voice recorder; they were asked to mention anything in the environment that they noticed and thought important in describing the route or guiding an unfamiliar person along the route.

When reaching the destination, they retraced the traveled route to the starting point. They then switched routes and started to navigate the other route, now being directed by the partner rather than by a research assistant. This was done by the participants helping each other navigate through a conversation over their mobile phones. Namely, a person who had first traveled Route 1 (or Route 2) traveled Route 2 (or Route 1) being guided by the other person and also guiding the other person along Route 1 (or Route 2). This concurrence of traveling and guiding may have posed an extra cognitive load, but did not make the task too difficult, as all pairs somehow reached their goal destination.

The navigational directions communicated between the two members over the mobile phone were recorded. In giving navigational directions to the partner, participants had to rely on memory from the initial guided walk. They were asked to instruct the partner to traverse the same route that they had been guided along, rather than finding a short cut to the destination. In communicating navigational directions participants used English, in which we had previously verified their fluency.

The research assistants walked behind the participants to record their travel behavior, and guided them back to the assigned route if they deviated from the route by more than 40 meters or wandered onto the main road (which makes an edge of the study area, shown in Figure 2.1) (there were six such instances observed among the 22 pairs). In doing so, we had identified possible locations in the study area beforehand beyond which participants wandered off the route more than 40 meters. The research assistants recorded the travel time and the route that the participants took. Distance of the route was measured on a map afterward, to give travel distance, inclusive of the distance traveled off-route if the participant deviated from the route and were taken back[1]. Upon completion of the navigation tasks, the participants were interviewed about their experience and then debriefed about their activity.

2.4.4 Coding of Verbal Protocols

Audio recordings from the initial guided walk and the subsequent collaborative navigation were transcribed and content analyzed (or coded), with respect to the contents mentioned and the confidence of utterances (cf. Hsieh & Shannon, 2005).

The contents mentioned were classified into the categories of landmarks (roads, permanent landmarks, ephemeral landmarks, and signs), additional descriptions (colors, written letters, and other), and navigational directions ("to go straight", "to make a turn" or turn sequences, cardinal directions, distance based directions, and time-based directions). To assess the reliability of coding, we asked two independent people, who did not know about the experiment, to classify the contents of the 22 pairs' verbal statements, and found that their classifications of landmarks, descriptions, and directions into the above categories showed no discrepancy.

Based on the recordings from the collaborative navigation, each statement of direction given was classified into four categories: (a) giving determinate directions (e.g., "Go straight for 100 feet and turn left at the hospital"); (b) giving less determinate and exploratory directions (e.g., "I think you should turn at the sign and there should be a white building afterwards"); (c) asking for cooperation (e.g., "Where are you right now? I think there is a staircase around there somewhere, so tell me when you find it"); and (d) being lost (e.g., "Where are you right now? I don't know where you are").

Each statement of direction received was also classified into four categories: (a) following determinately the exact directions given by the partner (e.g., "Yeah I see that, I'm going there now"); (b) following directions in an exploratory way interacting with the partner (e.g., "I'm at the street corner. I see a stop sign to my left. What do I do now?"); (c) trying to find a place in

[1] *1. It was possible to set the place shared by the two routes (the starting point in the current experimental design) to be the goal for collaborative navigation. In that case, after the initial walk, participants need to walk an extra distance, probably along a circuitous path outside of the study area, so that they are not exposed to the other route when switching routes. Also in that case, participants may stop navigating each other when they see their partners around the goal location, rather than directing them specifically up to the goal. Thus, to keep the experimental design concise and to examine how participants initiate and terminate collaborative navigation processes, the current design was employed.

response to a request of cooperation (e.g., “I will go look for a parking lot. Where should I turn after that?”); and (d) being lost (e.g., “I don’t know where I am. I don’t understand what you want me to do”).

For both direction giving and receiving, the categories (a) to (d) are in the decreasing order of the degree of confidence; that is, they show the degree to which the directions are given concisely and directly or received as they are without requiring additional interactions. So, as a measure of the level of confidence, we gave four points to the statement classified into category (a), three points to category (b), two points to category (c), and one point to category (d).

To assess the reliability of the coding of direction giving and receiving, three people (the first author and two independent people, who did not know about the experiment) were asked to score the confidence levels for all utterances by the 22 pairs. Figure 2.3 shows the correspondence between the three independent raters’ classifications in terms of Cohen’s kappa coefficients. Cohen's kappa coefficient is a statistic which measures inter-rater agreement for qualitative (categorical) items. It is generally thought to be a more robust measure than simple percent agreement calculation, since κ takes into account the possibility of the agreement occurring by chance. Of the 66 kappa values, one value was below .60 (specifically .59), 45 values were between .60 and .80, and 20 values were above .80. As a rule of thumb, Landis and Koch (1977) discussed that kappa values .41–.60 indicate a moderate fit, .61–.80 represents a substantial fit and .81–1.00 is an almost perfect fit.

According to this interpretation, the three raters’ classifications show a good agreement. For the protocols with a lower inter-rater agreement, conversations were exchanged in quick succession, back and forth, and statements such as “I think I know where I am” or “I think I found the building you were talking about” were observed, which the raters sometimes found difficult to classify. In the analysis below, a mean of the three raters’ scores is used as the measure of confidence level.

	Correspondence Between Raters		
Pair No.	Raters 1 and 2	Raters 2 and 3	Raters 1 and 3
1	0.73	0.71	0.83
2	0.85	0.84	0.95
3	0.85	0.82	0.90
4	0.70	0.69	0.72
5	0.74	0.70	0.70
6	0.74	0.78	0.84
7	0.73	0.72	0.80
8	0.89	0.91	0.96
9	0.75	0.64	0.62
10	0.66	0.67	0.71
11	0.74	0.66	0.72
12	0.97	0.97	0.99
13	0.77	0.73	0.70
14	0.68	0.63	0.60
15	0.62	0.59	0.72
16	0.71	0.74	0.76
17	0.70	0.70	0.74
18	0.74	0.72	0.75
19	0.69	0.69	0.73
20	0.97	0.97	0.99
21	0.75	0.74	0.80
22	0.72	0.78	0.81

Note: The 22 pairs are in no particular order.

Figure 2.3: Cohen's kappa coefficients for the classifications of confidence level by three independent raters.

2.5 Results

2.5.1 Mean Navigation Performance

We first compared travel distance and time among the H-H, H-L, and L-L pairs, considering that a longer distance indicates more navigational errors and a longer time indicates more frequent stops for re-orientation and repeated communications (Figure 2.4).

An analysis of variance (ANOVA) showed that the difference in travel distance among the three groups of pairs was not statistically significant, $F(2,19) = 0.68$, $p = .519$. The difference in travel time was not significant but marginal, $F(2, 19) = 3.21$, $p = .063$, implying a tendency that pairs with different SBSOD scores (the H-L pairs) took a longer time than pairs with similar SBSOD scores (the H-H and L-L pairs). Concerning the effects of sex composition on travel distance and time, pairs of the same and different sex showed no significant differences, $t(20) = 0.52$, $p = .61$; and $t(20) = 1.11$, $p = .28$, respectively.

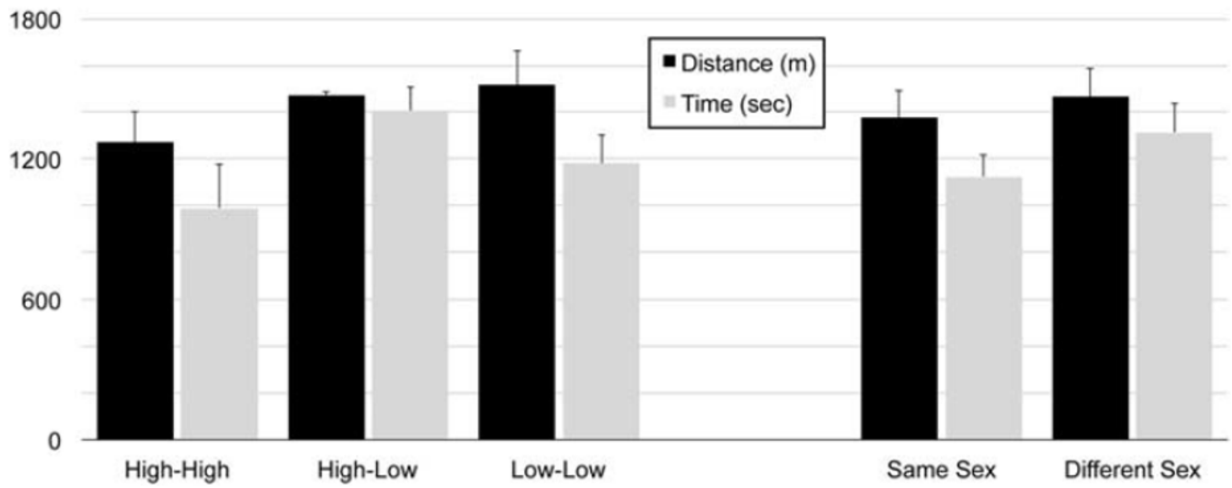

Figure 2.4 Mean travel distance and time for the H-H, H-L, and L-L pairs (left) and for pairs with the same and different sex (right). Vertical lines depict standard errors of the means.

2.5.2 *Types of Navigational Instructions by Efficient and Inefficient Groups*

To look at the overall navigation performance by the 22 pairs, we computed a composite performance score for each pair, by combining the z-scores (standardized values in terms of the mean and standard deviation across the 22 pairs) of the pair's travel distance and travel time (lower values indicate better performance). The 11 pairs with the smaller scores were labeled as the top-half (or efficient) group, and the 11 pairs with the larger scores were labeled as the bottom-half (or inefficient) group. The utterances made by the two groups were counted and classified into the types of contents described in section 2.4 (landmarks, additional descriptions, and navigational directions). Figure 2.5 shows that both groups of participants mentioned roads, permanent landmarks (such as buildings), and turn sequences frequently.

To compare the distributions for the two groups shown in Figure 2.5, since participants mentioned multiple categories, we conducted a mixed analysis of variance with the group (top- vs. bottom-half) as a between-subject variable and the content category as a within-subject variable. The analysis yielded significant main effects, $F(1, 20) = 19.18$ and $F(11, 220) = 327.40$, and a significant interaction, $F(11, 220) = 15.38$, $p < .001$.

The bottom-half group gave larger numbers of instructions, suggesting the inefficiency of their instructions and difficulties with guiding their partners (see the qualitative analysis in section 2.5.4 for more detail). In the instructions roads, permanent landmarks, and turn sequences were mentioned frequently, while cardinal directions, distance, and time were rarely mentioned. Post-hoc t-tests with a Bonferroni correction revealed a significant difference between the top and bottom-half groups for roads, permanent landmarks, ephemeral landmarks, colors, and turn sequences, $t(20) = 4.48$, 4.18, 3.72, 4.28, and 4.60, respectively. Although the difference was marginally significant, the top-half group mentioned cardinal directions more frequently than the bottom-half group, $t(20) = 2.01$, $p = .058$. Utterances of the other types of instructions did not differ between the two groups.

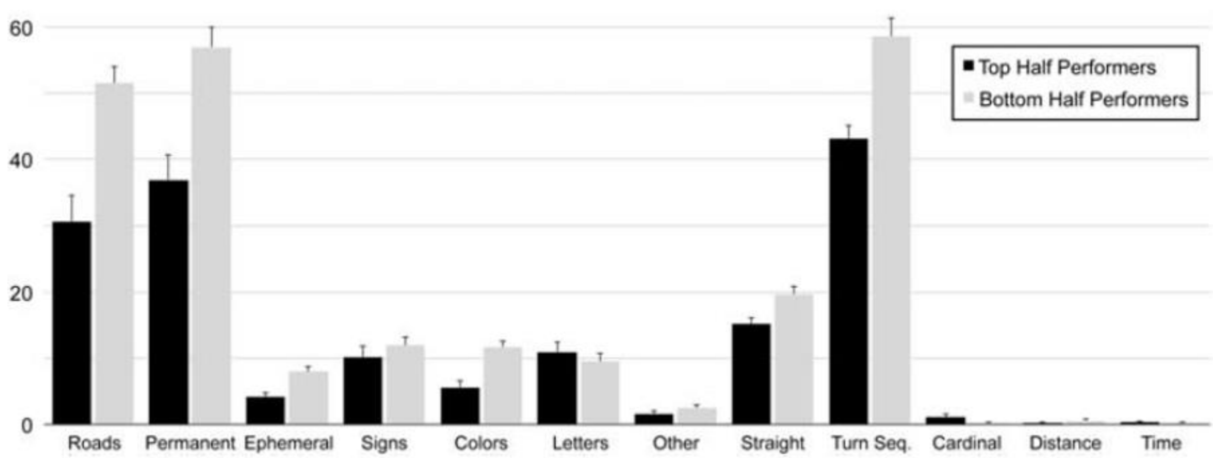

Figure 2.5. Frequency distributions of the types of navigational instructions uttered by the top- and bottom-half groups. Bars indicate mean numbers for each group and vertical lines depict standard errors of the means.

2.5.3 Relationships Between Navigation Performance and SBSOD Scores

The two performance measures, travel distance and time, were not significantly correlated with the SBSOD scores when the raw scores were examined (that is, when each participant's SBSOD score and travel time and distance for the second walk were examined). When the differences in

SBSOD scores between the pair members were examined, however, travel time was found to be significantly correlated, r = .42, p = .049 (Figure 2.6). This indicates that as the difference in sense of direction between the members within a pair increased, communication of navigational information became more difficult and required a longer time, thus increasing travel time. In fact, travel time was significantly correlated negatively with confidence levels, r = 2.77, p < .001.

2.5.4 Qualitative Analysis of Verbal Protocols and Conversation Dynamics

To identify the types of information that the navigators communicated and to characterize the problem-solving processes underlying collaborative navigation, we conducted a qualitative analysis of the 22 pairs' verbal protocols, by classifying the pairs in terms of the combination of high- and low-SOD pairing (the H-H, H-L, and L-L pairs) and composite performance scores (efficient and inefficient groups).

Tables 2.1-2.5 illustrate the contents and processes of the dialogues between navigators from three selected pairs, showing the frequency with which each type of utterance was made with an identification of the level of confidence (see section 2.4) for every minute during navigation. These qualitative case analyses are important because they provide information that was not revealed in the quantitative analysis due to the complexity of information dynamics in real-time collaborative navigation and provide insights about individual differences in cognitive mapping discussed in the literature (Ishikawa & Montello, 2006).

Efficient H-H Pairs

Mean confidence level for these pairs (n = 5) was high, with a score of 3.6 for direction giving and 3.3 for direction receiving (on a 4-point scale, with a larger value indicating higher confidence as described in section 2.5). Their conversations consisted predominantly of statements similar to "yeah I see that," and only minimal feedback requests and interruptions were needed (see the example in Table 2.1).

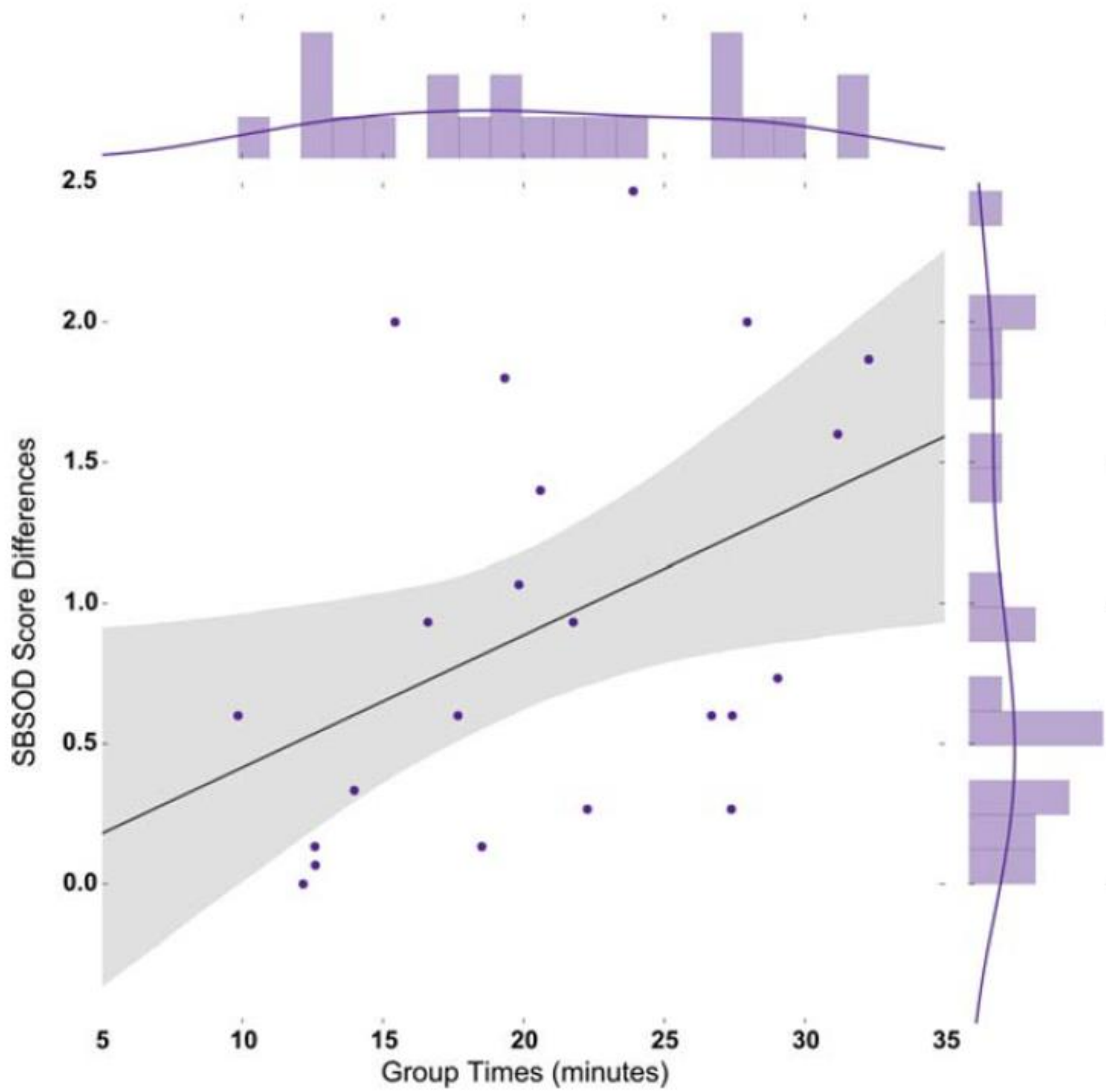

Figure 2.6: Relationship between travel time and the difference in SBSOD scores between pair members. The bars represent aggregate numbers in different segments. Shading denotes a 95% confidence interval for the linear regression line.

Table 2.1: Minute-by-minute breakdown of the types of navigational information communicated between members of one of the efficient H-H pairs. This shows the frequency with which each type of utterance was made for each route (rows), and for every minute during navigation (columns). Darker shades indicate larger numbers of utterances (the same in Tables 2.2 and 2.3 below).

Route 1	***Min***	***0***	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***Total***
Landmarks	Roads				2	1		1	1						5
	Permanent			1				1		2	2	2			8
	Ephemeral		1												1
	Signs		1												1
Descriptions	Colors														0
	Letters														0
	Other					1									1
Directions	Straight			2	1			1							4
	Turn		2	1	4	1	1	2	2	1	1	1			16
	Cardinal														0
	Distance														0
	Time														0
Direction giving	Determinate		1	1	1	1	3		1	2	1	1			12
	Exploratory					1		1	1						3
	Cooperative														0
	Lost														0
Direction receiving	Determinate			1	1				2		2	3	1		10
	Exploratory			1	2	4	1		2	3	2	1			16
	Cooperative														0
	Lost														0

Table 2.1 continued:

Route 2	*Min*	*0*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*Total*
Landmarks	Roads	0	2	1			1		2		1				7
	Permanent						3	1	1		2		1		8
	Ephemeral														0
	Signs														0
Descriptions	Colors										2				2
	Letters							2							2
	Other								1						1
Directions	Straight		1				1				1	1			4
	Turn		2	1	1		3	3	2		3		1		16
	Cardinal														0
	Distance														0
	Time														0
Direction giving	Determinate		1	1			3	2	2		3				12
	Exploratory				1	4	1		1			2	1		10
	Cooperative														0
	Lost														0
Direction receiving	Determinate		2	2	1			2	1	2					10
	Exploratory			2	1	1	1	3	2		1	3			14
	Cooperative														0
	Lost														0

The H-H pairs performed best in terms of travel distance and time (Table 2.2), making the fewest navigational errors and maximizing the time that both members were continuously walking. As seen in Table 2.1, the landmarks that they selected were salient and meaningful to both members, mostly roads and buildings. Furthermore, their statements were minimal, efficient, and evenly distributed (compared to other pairs' protocols shown in Table 2.2 and Table 2.3). All instructions were given with high confidence, either "determinate" or "exploratory," rather than "cooperative" or "lost."

Table 2.2: Minute-by-minute breakdown of the types of navigational information communicated between members of one of the inefficient H-L groups.

Route 1	***Min***	*0*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*	*27*	*28*	*29*	*30*	*31*	*32*	***Total***
Landmarks	Roads	1		1	1		1	1				1	2	1	1	1			2	1	2	1	1	1		1	1		1		1		1		24
	Permanent		1									1			1		1						1	3									1	1	10
	Ephemeral							2											2					1											5
	Signs																																		0
Descriptions	Colors				1			3	1																										5
	Letters				1			1	1																										3
	Other												1													2									3
Directions	Straight	1	1	1			1								1	2			2	1				2							1				13
	Turn	1	1	1	1		1	1				1	1	1	1	1			2	1	3	2	1	2	2	2	1		1				2		30
	Cardinal																																		0
	Distance																																		0
	Time																																		0
Direction giving	Determinate	1	1	1	1			1				1	1						1		1			2		1					1		1		14
	Exploratory						2	1				1		1		1	1		1	1		1	2	2	1		1		1			1	1	1	20
	Cooperative						2	2					1	1		3	2	1				1		1	2	1						1	1		19
	Lost							1									1																		1
Direction receiving	Determinate	2		1	1		1			2	1	2								1															11
	Exploratory		2	2	2	2	3		3	3	2	3	4	3	2	1				1	1	3	2			1	2	1	1	1	1	1			47
	Cooperative					2	2		2	1	2	2		2	4	2	2	2									1		1	1					26
	Lost					1	2		1	2	1		2	1	1	2	2												1	1					17
Route 2	***Min***	*0*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*	*27*	*28*	*29*	*30*	*31*	*32*	***Total***
Landmarks	Roads	2	1	1	1	3			2	1			2			1	1		2	1					1	1			2						22
	Permanent	1		2	1	2	1		2	2	1		1	1			2		1	1	2	1			2	2	1	2		1	1				30
	Ephemeral																																		0
	Signs	1	2			1	1		1	1	2				1		1												1						12
Descriptions	Colors					1				1	1				1	1									1										6
	Letters	1	1			2				1					1	2			1									1		1	1				12
	Other		2						1	1																			1						5
Directions	Straight	1	2	1	1	1			1	1							1			1	1				1		1								13
	Turn	4	2	2	2	1	1		1	2			1	1	1		2		1			1	2		2	1	1		2	1					31
	Cardinal																																		0
	Distance																																		0
	Time			1																															1
Direction giving	Determinate	1	1	2	1	1			2	2	1						1		1	1	2	1	1								1				19
	Exploratory		1			2	1		1	2	1		1	1		2	1		2		1		1		2	2		1		2	1				25
	Cooperative					2	1		1	2	2		2	1		2						1			1			1	2	2					20
	Lost																																		0
Direction receiving	Determinate			1									1		1		1	1	1	2						1					1		2	1	13
	Exploratory		1	2	3		2	3				3	1		1			4	2	3	2	3	2	3	2	1	2	2				1	2	1	46
	Cooperative							2				2				1		2							1					1		1	2		12
	Lost											1						1				1													3

Table 2.3: Minute-by-minute breakdown of the types of navigational information communicated between members of one of the inefficient L-L groups.

Route 1	Min	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	Total
Landmarks	Roads		1			1		1	1	1				2	2		1	1	1	1	13
	Permanent		4	2	1			1		1	1			1	1		1		1	1	15
	Ephemeral		1		1	1		1						1							5
	Signs		1			1													1	1	4
Descriptions	Colors		3																		3
	Letters					1				1							1		1		4
	Other		1	1				1						1	2		1				7
Directions	Straight		1	1				1						1			1	1	1	1	8
	Turn		1		2	2		2	1	1	1			2	1		1		1	1	16
	Cardinal																				0
	Distance																				0
	Time																				0
Direction giving	Determinate		1	1				1			1				2					1	7
	Exploratory				2			1		1				1							5
	Cooperative				1	1		1		1	1			1	1		1	1		1	10
	Lost																				0
Direction receiving	Determinate			1	1		2		1	2	1	1	1					1	1	1	13
	Exploratory			2	3	2	3	1	2	3	1	1	2		1	3	1	2	3	1	31
	Cooperative											1	2			1	1	1	1		7
	Lost																				0
Route 2	***Min***	***0***	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	***17***	***18***	***Total***
Landmarks	Roads	1	1	1				1	1	2	2	1			1		1		1	1	14
	Permanent		1	2	1	2	4	3	3	3	2	2	4		3	4		1	1	2	38
	Ephemeral		1					1	1			1	1								5
	Signs			1	1	1					1	2									6
Descriptions	Colors		1	2	1	2	1					1	4			1					13
	Letters			2	1	1	1	2	1	1		1	2			1		1			14
	Other					1		1	2		1	1	2			1			1		10
Directions	Straight	1		1	1			1	1		2	1				1		1			10
	Turn		2	1		2	2	2	2	1	1	2	1		1	4		3		1	25
	Cardinal	1																			1
	Distance																				0
	Time																				0
Direction giving	Determinate	1	1	2		1	2	1			1	2	2			1				1	15
	Exploratory		1		1			1	1	2		1	1			2					10
	Cooperative			2	2	1	1			1			1		2	1	1	1	3	1	17
	Lost					1	2											1	1		5
Direction receiving	Determinate		1	1	1	1		1		1	1									1	8
	Exploratory		1		1	1		2	2	1	1			2	2		3	2	2	1	21
	Cooperative					1		1			1			3	1		2				9
	Lost													1			1				2

The following are examples of verbal navigational directions for the six groups of pairs, broken down by SOD combinations and navigation performance.

(A) Efficient H-H pair (clear instructions with cardinal directions and landmarks):
"You want to go left there, so your next thing after that is another left, so it should be basically to a point where you have to turn. You went down the stairs, take a right, heading north, then you hit a T, then you went left. It should not be toward the stairs."
"OK."
"Have you crossed the street? Take the first left, on the first right, take the pedestrian pathway to the right around the parking lot. When you get to the other side of the parking lot, make the first left, you are going in the exact same direction you were going, you zigzaged the same way around the parking lot, you are just one street over."
"I have crossed the street, I am standing at the corner of the large black building 'Leopalace.' So I'm looking for the parking."

(B) Inefficient H-H pair (one person giving clear directions with references to a major landmark and the surrounding area but the partner not finding it):
"Go toward the main road, got it. Did you see two motorcycles, should be on your left. What's around you? Pink houses? I don't remember that. Wait, on that road, if you keep walking, what's in front of you? A parking lot? If you see the car parked, is it green? Turn left there, facing that. Did you see a clinic? Tomoyama Clinic? Turn left at the corner of the hospital. There is a small road there."
"A clinic? I don't see a clinic. From the position of the poster, turn right? Turn left at the hospital? I'm not at the hospital yet."
"From there to the red car, is it far? Go back there once, close to there should be a clinic. Close to that red car, there is a small red traffic cone too."
"Now I can't still see the sign for the clinic, I should look for the clinic, right?"
"Can you still see the clinic? Are there any pink posters close to you? No? Liberal Democratic Party, on your left. Can you repeat that?"
"Now I'm looking for the clinic. I haven't seen it yet. I saw a poster, some political

poster, says hope."

(C) Efficient H-L pair (able to adjust and tell the partner to go backward):
"Alright, you should be on the right path, there should be a small road coming up ahead, go straight then take a right."
"I think I'm lost, I probably took a turn too early. I took two rights and a left as you described, after the house with the staircases on the outside and the Mercedes parked in the front."
"Did you see a stop sign? No? Where are you now, near a parking lot? I think you might have walked past it, go back a few blocks and tell me when you see a red sign with kanjis written on it . . . . What do you see now? Are there any lamps in front of you? Go there, is a small road, follow that way. Is like an S thing."

(D) Inefficient H-L pair (describing different things):
"Look for a nice looking house with flowers hanging outside. You will see a gravel road right next to the house."
"I don't see the house with a nice look and flowers hanging outside. The houses all look the same, but I did walk past a four-way crossing after turning left from where you last told me."
"OK, go back to the crossing and describe to me again what you see. I remember there was a left turn there, and another left should bring you to the house. Just go back."
"Here is a poster with some kanji on it, I think it is something political., is that the one?"
"I can't read kanji. I'm not too sure, but look for a cone close to there."

(E) Efficient L-L pair (a rare case using cardinal directions and time-based instructions):
"If you are at the clinic, go straight, there is a red upside-down triangle. The clinic is where you turn left, heading west, and the other side of the street should be a sign

with a bicycle. Head north from there.”

“Got it.”

“You are going to be looking for, the easiest thing is a building faintly painted pink or purple, also a green car, but you are going to turn right in between the house and the car.”

“I see Hossen Hall. I’m going left, so I’ll stay on the main road for a minute or two.”

(F) Inefficient L-L pair (simply telling the partner to search for the next visible landmark):

“I think you should be coming up on a turn and you should be able to see a building from there, pinkish. Then there is like a turn after that, I can’t remember. Tell me what you see right now.”

“What do I see now? I’m coming to another junction now, is like a pinkish building. There is like a notice board, I turn right at the notice board. I think you lost me. A park? There is a what?”

“You should just try to find the main road again, just walk until you see the main road, the main road. Once you get there, you want to turn left toward the Chinese restaurant, toward the main road. I don’t remember the turns before that, but if you find the main road and the Chinese restaurant, then you are good.”

“OK, I’ll just try to find the main road. I’ll tell you when I get there.”

Inefficient H-H Pair

There was one pair in the inefficient H-H category, which is worth a detailed description because of its poor performance despite the members’ high sense of direction. This pair consisted of a woman and a man with SBSOD scores of 4.7 and 6.3, respectively. The woman received directions from the man for Route 1, and performed in the lowest 10% of all participants for that route, whereas the man completed Route 2 efficiently through her directions.

Examinations of their verbal protocols revealed that the man gave directions that he thought were clear and precise for Route 1 using a hospital as a landmark, but the woman did not recognize the hospital even though she was right next to it. As a result, she spent much time searching for it, consequently confusing the partner (Table 2.2). During the conversations, the man consistently referred to the hospital as an important landmark, instructing correct turn sequences, and even mentioned less salient or ephemeral landmarks around the area to help her look for it. In the follow-up interview, she responded that she did not find the hospital because the hospital sign was hanging above eye-level. This example points to the inefficiency of sticking to a specific type of information and failing to adjust navigational directions to the partner's wayfinding ability. Showing the difficulty that this pair had communicating with each other, the pair's mean confidence level was low, with a score of 2.9 for direction giving and 2.7 for direction receiving.

In light of this finding, we further examined the possibility that the recipient misunderstood directions even when the directions were given correctly. Results showed that a majority of high-SOD participants (15 of 22) gave directions that were executed correctly at more than 75% of decision points (e.g., intersections), but it holds only for a minority of low-SOD participants (7 of 22). This difference did not reach significance but showed a marginal trend, X^2 (1, N =44) = 3.30, p = .069, implying a tendency that low-SOD participants misunderstood correctly given directions. Chi square method was used to investigate whether distributions of categorical variables differ from one another.

Efficient H-L Pairs

Despite the good performance by the efficient H-L pairs (n = 4), their mean confidence level was not as high as that for the efficient H-H pairs (or the efficient L-L pairs, see later), and was low similar to other inefficient pairs, with a score of 3.0 for direction giving and 2.8 for direction receiving. It indicates the difficulty of interacting with partners with different levels of sense of direction. Verbal protocols of one of the efficient H-L pairs demonstrated a dynamic adjustment of navigational directions during the course of conversations.

The dialogue began with the high-SOD member mentioning less-salient or ephemeral landmarks, cardinal directions, and written marks or letters. When the low-SOD member replied that he could not identify the landmarks or understand the cardinal directions, the high-SOD member shifted to using predominantly color-based, permanent landmarks to instruct turn sequences (Table 2.2). This phenomenon is particularly interesting because it indicates that high-SOD people were able not only to identify commonly recognizable landmarks (as shown by Ishikawa and Nakamura, 2012), but also to select from a larger repertoire of different types of landmarks adjusting to the partner and situation.

Inefficient H-L Pairs

The H-L pairs generally found the task of communicating route information in collaborative navigation to be challenging. Their mean confidence level (n = 6) was low, with a score of 2.9 for direction giving and 2.7 for direction receiving.

These pairs are of particular interest because their performance reveals how people with different levels of sense of direction interact with each other. Five of the 10 H-L pairs performed above average among all the 22 pairs in terms of travel distance, and only three pairs performed above average in terms of travel time. They took the longest time (Figure 2.2), possibly because the high-SOD members needed extra time to re-examine their mental maps and adjust their navigational directions upon feedback requests from their low-SOD partners. Common examples of their conversations include two members referring to different things.

One inefficient H-L pair consisted of a man and a woman with SBSOD scores of 5.2 and 3.3, respectively. The woman directed a turn too early at one landmark, which caused the man to miss the landmark and thus to explore the area for as long as 5 min. She was unable to backtrack her directions and simply insisted that the partner find it. This misdirection caused the man to give many faulty directions eventually. It exemplifies how interactions with a partner can affect the quality of one's own navigational directions. This pair's communication dynamics are shown in the example conversations. In comparison, it shows that their conversations took much longer with many inaccurate and repetitive statements being uttered, and a large percentage of directions were communicated with low confidence.

Efficient L-L Pairs

The efficient L-L pairs (n = 2) showed high confidence, comparable to the efficient H-H pairs, with a score of 3.5 for direction giving and 3.4 for direction receiving. This contrasts with the low confidence level for the efficient H-L pairs. There was one particularly efficient group among the L-L pairs. This pair was in the top 5% of all the 22 pairs in terms of travel distance and time, making no navigational errors throughout the process. The members were both male, with SBSOD scores of 3.3 and 3.4. Their performance resembled that of a typical H-H pair and their conversations were minimal and efficient (Table 2.3).

In this particular case, both members used cardinal directions, which was the only case among the six L-L pairs. It points to the difference of its spatial information processing from other L-L pairs and the existence of variations in navigational behavior even among the L-L pairs.

<u>Inefficient L-L Pairs</u>

Showing the overall difficulty that the inefficient L-L pairs had in communicating with each other, their mean confidence level (n = 4) was low, with a score of 2.9 for direction giving and 3.0 for direction receiving. The mean value for direction receiving was comparatively higher than that for the inefficient H-H pair or the efficient and inefficient H-L pairs, suggesting the inefficient L-L pairs' insensitivity to the lack of understanding in receiving navigational directions.

The L-L pairs in general traveled the longest distance, indicating that they made the most navigational errors. They did not take the longest travel time, however (Table 2.3). This can possibly be explained by the exploratory actions taken by the pairs, since many people with lower SBSOD scores were unable to give clear directions, even in terms of turn sequences.

This phenomenon can be seen in the dialogue chart for one of the inefficient L-L pairs. Although many landmarks seemed to stand out in the minds of the navigators, they were not placed in the correct spatial context. For example, many landmarks were repeatedly mentioned, sometimes in an incorrect order. Backtracking was uncommon for the L-L pairs, and they typically instructed their partner to skip ahead to the next landmark with such directions as "look for it, tell me when you see it". It resulted in reduced conversation; they simply walked randomly, with a higher average speed in the hope of finding the next landmark. Consequently, some of the L-L pairs walked faster, without taking the time to properly re-orient themselves physically and cognitively.

2.6 Discussion

This article examined the important and challenging, but yet insufficiently investigated, daily phenomenon of collaborative navigation, through quantitative and qualitative analyses of the navigational information communicated between partners of different spatial aptitudes.

Concerning the effects of sense of direction, no significant correlations were observed between navigation performance (travel distance and time) and raw SBSOD scores, but there was a significant correlation between travel time and the difference in SBSOD scores between paired members. That is, when people are paired with partners whose sense of direction is greatly different, they find it harder to communicate navigational information efficiently and take a longer time to guide the partners to the destination. Such inefficient communications were observed when poor-SOD people misunderstood correctly given directions or confused the good-SOD partners by incorrect directions. Stated differently, it can be easier when two people with a poor sense of direction help each other (see section 2.4.5), compared to when a person with a good sense of direction helps someone with a poor sense of direction (section 2.4.4). This difficulty is reflected by the lower level of confidence for the H-L pairs, even when they showed efficient navigation performance (section 2.4.3).

Although having difficulty interacting with partners with a poor sense of direction, people with a good sense of direction are flexible in giving navigational directions and able to adjust the types of information to the partner. For example, successful navigators tended to use the least amount of extra descriptions such as colors, and elaborated on the initial descriptions focusing on salient landmarks. At the same time, many people with a good sense of direction added extra descriptions when prompted by their partners for more information. They also tended to tell their partners to return to a previous spot (seven such instances were observed), while people with a poor sense of direction tended to tell the partners to proceed to the next landmark (nine instances observed). Furthermore, good-SOD people referred to new landmarks not mentioned in their initial guided navigation, while poor-SOD people failed to mention the same landmarks.

These results show that good-SOD people collect and store various information about the traversed environment (some of which could be redundant), and adjust their instructions to the needs of their partners. In contrast, poor-SOD people know that particular landmarks exist but do not place them in the correct spatial setting or are unable to convey the information in a flexible manner tailored to their partners.

People with a poor sense of direction tended to select ephemeral landmarks such as vehicles and pedestrians, as well as semi-permanent landmarks such as posters and signs. This is in line with the finding by Ishikawa and Nakamura (2012) that people with a better sense of direction tended to select fewer landmarks, focusing on common and easily recognizable ones.

Environmental perception may be fundamentally different for people with a poor sense of direction, to whom non-permanent things stand out cognitively in an unfamiliar environment. It potentially causes a problem for successful navigation because of the ephemeral nature of those landmarks, but at the same time it may be useful as “special” landmarks targeted to poor navigators on real-time navigation tools.

Therefore, the efficiency of collaborative navigation relates to sense of direction: Generally, the H-H pairs collaboratively navigate efficiently and the L-L pairs do so inefficiently. As indicated by the significant correlation between travel time and the difference in pair members’ SOD scores, the H-L pairs tend to navigate inefficiently; but when the high-SOD member is able to adjust instructions to the low-SOD partner, they travel efficiently. However, there are contributing factors other than sense of direction for collaborative navigation, as suggested by the observations of the inefficient H-H and efficient L-L pairs.

It points to the fact that SOD taps into the ability to learn about and orient oneself in the environment, but not necessarily the ability to communicate route directions to other people. An examination of these issues from the wayfinding and collaboration perspectives is an important research question for a further study.

In the present research, the two persons in a pair navigated toward the goal simultaneously guiding each other through the mobile phone. A comparison of H-L and L-H pairs in an experiment in which the pair members would once take the role of either the instructor or the recipient and then switch the roles (i.e., the giving and receiving of navigational directions would not occur simultaneously), would be interesting, particularly to examine the mental processes in detail in the context of different roles in collaborative navigation. It is as an experimental design and analysis desirable for future research.

In summary, people with different levels of sense of direction perceive the environment differently and prefer different types of landmarks, which they communicate to other people with different frequencies. People with a better sense of direction better organize acquired spatial information and subsequently construct more concise and intelligible instructions based on it.

The relationship between collaborative navigation performance and the difference in sense of direction between pair members, and the efficacy and flexibility of good-SOD peoples' navigational directions clarify the dynamic nature of wayfinding in collaboration. Importantly, the findings corroborate and expound the existing research into individual differences (Ishikawa & Montello, 2006), sense of direction (Hegarty et al., 2006), route descriptions (Denis et al., 1999), landmark selection (Ishikawa & Nakamura, 2012), and wayfinding collaboration (Reilly et al., 2009).

This distinction can be applied to the development of navigational aids for people with lower spatial abilities, who comprise a significant portion of the population. Personalized landmark-based pedestrian navigation tools capable of selecting viable landmarks tailored to the user should be developed in the future. Application devices that assist in the wayfinding in unfamiliar environments, and training and improving navigational habits and abilities, should also be considered.

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CHAPTER 3

DETERMINE COMPUTATIONAL SALIENCE USING VARIOUS COMPUTATIONAL METHODS TO IDENTIFY POTENTIAL DIFFICULT DECISION POINTS AND WHERE WAYFINDERS ARE LIKELY TO MAKE MISTAKES

This chapter is a modified version of a conference paper published in the Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems Article:

Guide me through somewhere important: decision-point salience and collaborative Navigation. SIGSPATIAL/GIS 2015: 71:1-71:4 co-authors: Toru Ishikawa, Makoto Takemiya

3.1 Abstract

People often work together to collaboratively navigate in daily life. However, people often make mistakes when giving directions to others, which can be especially difficult when giving directions via a cell phone to a distant partner. Contemporary navigational aids could provide information about important landmarks and decision points in an environment. To learn more about what kinds of mistakes people make in navigating and problems with route directions, the present study presents an empirical study on dynamic, collaborative wayfinding with emphasis on decision points where wayfinders made navigational errors. Using the concept of computational salience, various network analysis metrics are tested to determine the importance of decision points in an environment to correlate with where people made mistakes in navigation. Outlink and outflux scores, meta-algorithms that derive a secondary score on existing metrics, is validated to be an effective predictor of navigational errors. It can be argued that navigational aids could highlight identified points to wayfinders, so they can pay special attention when giving directions traversing these points, thus eliminating errors and troublesome spots. This chapter conclude by outlining how the lessons learned in this study can be applied to real-time navigational aids.

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

3.2 Introduction

"Where are you now? Tell me when you get to the T-shaped intersection with the green sign and I'll tell you where to go from there." Utterances such as these are frequently used as people traverse environments with help from others. Despite assistance and guidance, people still make mistakes when navigating unfamiliar environments. If decision points where people are likely to make mistakes could be elucidated via computational means and highlighted pre-navigation, wayfinders could be warned while traversing an environment, thus preventing many mistakes from occurring.

The present study analyzes decision points where mistakes were made in a collaborative wayfinding task. Focus was placed on collaborative wayfinding because it is a common yet under studied activity. Collaborative navigation is in some ways more difficulty than individual wayfinding due to the fact that not only the person giving directions has to understand the environment, but the person receiving directions has to understand the directions and reconcile them with the environment they are in. In our wayfinding task, 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. Being able to predict where wayfinders will make wrong turns by finding a computational method that is correlated with navigational errors at decision points.

In this article, several methods for calculating the salience of decision points are outlined. The concept of computational salience is applied to data from an empirical study that was conducted. Implications from linking computational salience to decision points in an environment where wayfinders made mistakes are then discussed in the context of cognitive variations among the wayfinders, the effects of environmental structure on navigation and improving navigational aid design. Finally, a plan for future work is presented.

3.2.1 Wayfinding and Decision Points

Wayfinding is a directed activity to reach a destination. Wayfinding requires both locomotive and cognitive skills. Studying wayfinding can provide insights into many aspects of human spatial cognition. Successful wayfinding requires that people orient themselves in an environment, plan a route, and execute such a route (Montello, 2005). To traverse an environment to a goal location, representations of the space, such as maps, are often used. People develop analogous mental representations of space, often conceptualized as comprising the identity 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) (Siegel & White, 1975). Traversing an environment requires that landmarks and the spatial relations between them be properly encoded into a mental representation of the space (Lee et al., 2005).

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 (Parush et al., 2002, Richter et al., 2007). Contemporary GPS devices also has been shown to decrease 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 recover from mistakes. Decision points are points in an environment, such as intersections, where navigators have to make a decision about whether to change direction or continue without deviation. Takemiya and

Ishikawa showed that using information about decision points traversed, the performance of wayfinders could be classified in real-time (Takemiya and Ishikawa, 2011) and future decision point difficulty that they would traverse could be predicted (Takemiya et al., 2013).

The efficacy of 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. Additionally, decision points have been shown to be important for route following and providing information about what routes to follow (Allen et al., 2000, Daniel & Denis, 1998, Lovelace et al., 1999). Decision points are often featured when providing route directions (Allen et al., 2000, Denis 1997, Lovelace et al., 1999) and previous work has shown that residents of Venice, Italy, for example, tended to select landmarks at or near decision points (Denis et al., 1999). Decision points can also be important for communicating overview information on a route (Richter et al., 2007) and they have been shown to play an important role in mental processing during route following (Janzen et al., 2004). To find 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 generate a computational method of defining points where wayfinders will be likely to make mistakes.

3.2.2 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. Visual, cognitive, and structural qualities that make a landmark and objects in an environment salient to humans were discussed by Sorrows and Hirtle (1999). Previous work also calculated the cognitive salience of landmarks (Raubal et al., 2002) and buildings as landmarks (Nothegger et al., 2004), with the goal of using this information in automatically generated route directions, and validated the fact that this approach was capable of extracting landmarks deemed important by human participants. This method was then expanded to include environmental features such as visibility (Winter et al., 2003) and landmarks at decision points (Klippel & Winter, 2005). The structure of intersections (Klippel et al., 2005) and graph theoretic measures of street connectivity were also found to be related to cognitive salience (Claramunt & Winter 2007, Tomko et al., 2008).

Overall, these measures attempt to propose a method to determine the cognitive salience of features in an environment for people navigating. While cognitive salience measures decision points that are important to humans, computational salience measures points that are important for computational models of wayfinders. Computational salience was first defined by Takemiya and Ishikawa (Takemiya & Ishikawa, 2012) as the importance of a decision point for classifying wayfinders with respect to their differences in their individual abilities. In other words, this is the importance of a decision point for discriminating between good and poor performing wayfinders. This is an important step in determine the type of instructions to offer for the individual wayfinder. 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 (Takemiya et al., 2012). Computational salience can be a useful concept for discriminating between good and poor performing wayfinders, the present work applies computational salience to finding decision points where collaborative wayfinders are likely to make mistakes.

3.3 Methods: Various Computational Salience Metrics

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 **salience** (also called **saliency**) of an item is the state or quality by which it stands out relative to its neighbors. Saliency detection is considered to key attentional mechanism that facilitates learning and survival by allowing organisms to focus their limited perceptual and cognitive resources on the most pertinent subset of available sensory data. In navigation, salience help certain features stand out and can act as anchors for people finding their way. The goal of this study is to enable future work to develop navigational aids that can prevent mistakes at salient decision points 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. The metrics include: traversal probability, PageRank, outflux scores, entropy difference, degree centrality, closeness centrality, betweenness centrality, and outlink scores.

3.3.1 Traversal Probability

The probability that wayfinders will traverse a decision point has meaning because 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. Routes in this study were computationally generated using a modified A* heuristic search algorithm. In the present work, 1000 routes were generated from the starting location to the goal location, for each of two routes through a real environment (Figure 3.1). To introduce randomness to simulate human wayfinders taking wrong turns, 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 can be calculated. It is determined to be the fraction of generated routes that contained that point.

3.3.2 Entropy Difference

The routes generated (Figure 3.1) were used to calculate traversal probabilities for all decision points in the environment modeled in this study. With respect to analyzing route traversals, information gain measures the amount by which a decision point decreases entropy (i.e., increases the homogeneity) of good and poor sets of routes, bounded by whether or not they contain the decision point being considered. The approach of computationally generating routes as a prior for classifying wayfinders allows computing the entropy of each decision point with respect to performance classes. These probabilities define a probability distribution over all decision points that can be assigned an information-theoretic entropy. Equation 1 shows the calculation of entropy, H, for a set of decision points $d \in D$ in the environment, where P(d) is the probability of a decision point being traversed in the computationally generated routes, with all probabilities being normalized to sum to unity.

$$H = -\sum_{d} P(d)\log_2 P(d) \qquad (1)$$

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 then 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.

3.3.3 PageRank

PageRank is an algorithm for calculating the stationary probability distribution of an ergodic Markov chain (Langville et al., 2006) 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 (Jiang et al., 2009). PageRank is a well-established algorithm in the field.

In PageRank, the importance of a decision point is related to the importance of decision points that lead to it. To calculate PageRank, all decision points are first initialized with the probability that a point is randomly chosen, that is, 1 divided by the number of decision points in the graph, |G|. PageRanks are then calculated via the power iteration method. For each iteration, r, of the algorithm, the score from the previous iteration, r−1, is combined with a weight d = 0.99, corresponding to a 1% chance of randomly jumping to another point (this stochasticity correction is required to guarantee convergence of the algorithm; see (Bryan and Leise, 2006). This is shown in Equation 2:

$$\text{PageRank}^{r}(i) = (1-d)\times\frac{1}{|G|}+d\times\sum_{k=1}^{s}\frac{1}{|O_{jk}|}\times\text{PageRank}^{r-1}(j_k) \tag{2}$$

where |Ojk| is the number of outlinks from the current decision point k to other points. Direction of edges linking decision points was determined based on the net directionality in the computationally generated routes. The algorithm continues until the change in PageRank between iterations is less than some small value, ε. Decision points with higher PageRank values were considered to be more computationally salient.

3.3.4 Degree Centrality

Degree centrality is a measure of the fraction of decision points that a decision point is connected to. A node’s in and out degree measure the number of in and out nodes that comes out of each link. Degree Centrality Measures the number of direct neighbors at each decision point, it is useful in assessing which nodes are central in the spread of information.

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 and were thus taken to be more computationally salient.

3.3.5 Closeness Centrality

Closeness centrality measures the inverse sum of the distances to all other decision points (Freeman, 1978). Closeness Centrality measures the average length of the shortest path between the node and all other nodes in the graph. From a social network perspective, it is a measure of reach – how fast information can reach other nodes from existing nodes. This algorithm intuitively shows how close a decision point is to other points. Therefore decision points with higher closeness centralities were considered more computationally salient.

3.3.6 Betweenness Centrality

Betweenness centrality for a decision point is the fraction of all-pairs shortest paths that pass through the decision point (Brandes 2001). Betweenness centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes. This measures the importance of a decision point for enabling paths between other points. Decision points with higher betweenness centrality were taken to be more computationally salient.

3.3.7 Outflux Scores

Outflux scores were introduced by Takemiya and Ishikawa 2012 as a meta-algorithm that takes computational salience scores and computes a set of scores that are derivatives of the original scores. The theory behind outflux scores is that regions of similarly scored decision points are often clustered together; so decision points leading into a region with very different scores may be important to wayfinding because these points lead to areas that are qualitatively different with respect to the metric being analyzed. Outflux scores are calculated as in Equation 3:

$$outflux = \left| \left(\sum_{out} \omega_{out} \right) - \omega_{curr} \right| \qquad (3)$$

where ω_{out} is the score for an outlink decision point and ω curr is the score for the current decision point. The heuristic sums up all the scores for the decision points pointed to by the current decision point via its outlink, and calculates the salience of the current decision point as the absolute value of the difference between the summed scores and the current score. The outfluxscore 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 this sum and the score for the current point is then calculated.

For outflux scores, the scores being considered must be calculated with one of the previously defined metrics. For example, "outflux PageRank" was calculated by first calculating the PageRanks for all the decision points in a graph. Then the outflux PageRank scores were calculated for each decision point by considering the PageRank score for the current point and the scores of decision points pointed to by the current point.

Ouflux score may be difficult to intuitively understand, one can use the following scenario for comparison. Imagine you are walking from a farm to the edge of a city, or from a sparsely populated neighborhood to a densely populated one, there is a change of scenery, emotion and information processing associated with the change. Existing metrics do not take that into consideration, however outflux score attempts to identify similar neighborhoods or clusters in a pre-determined route, thus taking into account human variability on the same navigational route that would have otherwise been unaccounted for.

3.3.8 Outlink Scores

The present work aim to find a way to computationally elicit decision points where wayfinders will 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.

$$outlink = \sum_{out} \omega_{out} \qquad (4)$$

As with outflux scores, outlink scoring is a meta-algorithm and requires the output of one of the other algorithms as the input. As a concrete example, "outlink PageRank" was calculated by calculating PageRanks for all decision points and then summing up the PageRank scores for outlinking points, for each decision point in the environment. Outlink scores are thus calculated similarly to outflux scores, with the only exception that the score for the current point is disregarded.

The concept of outlink and outflux score may not be intuitive to understand. In less technical terms: Metrics such as PageRank, betweenness centrality, traversal probability, entropy, and closeness centrality give information about the decision points themselves - these metrics show something about each targeted decision point A, such as the probability of traversing through point A. However, during navigation, the next point from the decision point is also important in influencing the outcome of the wayfinding. During pedestrian navigation, one often does not realize reaching a decision point until he/she has already passed it, which means that the subsequent decision points (B,C,D,E…) beyond the current decision are important for the users as well as the present decision point (A).

Outlink and outflux meta-algorithms derive secondary scores in combination with established methods. The Outflux score sets <u>boundaries</u> for regions of similar salience, while the derived score is based on the idea that similar regions have similar salience scores, and that clustered salience values change spatially. Outlink scores on the other hand are meaningful for decision points that have multiple links. The derived score considers a series of actions leading to a decision point. Outlink scores have an important implication for the direction of travel through a decision point. These two concepts will be explained in context in the results and discussion sections of this chapter.

3.4 Methods: Empirical Collaborative Navigation Exercise

The relationship between computational salience and collaborative wayfinding tasks has not been studied previously. Due to the importance and ubiquity of collaborative wayfinding activities, we carried out an empirical study to analyze how people work together to guide each other through an environment in real-time. The participants were divided into different groups based on their scores on the Santa Barbara Sense-of-Direction (SBSOD) scale. We guided pairs of participants along predetermined routes, then switched the routes and had the participants guide each other along the route previously learned. The decision points where wayfinders made mistakes in following the predetermined routes can provide insights about the environment, the perception of the environment by people of differing spatial abilities, as well as how people of varying spatial abilities communicate spatial information at various decision points.

3.4.1 Study Area

The study took place near Nakano-Sakaue Station in western Tokyo. This is a typical Japanese residential neighborhood, with no visible street names and winding, narrow streets. Participants needed to distinguish landmarks visually and cognitively, place them in the correct spatial setting, and relay the information to their partner. Figure 3.1 shows the two routes defined in the study area. 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).

3.4.2 Participants

Forty-four non-Japanese participants (27 men and 17 women, mean age 25.9 years) from 15 countries participated in our study. All of the participants were English speaking non-native Japanese and had been in Japan from 1 week to 2 years. None of the participants had been to the study area before. All participants were given equal monetary compensation for participating in the experiment.

Figure 3.1. *Map of the two routes used in our empirical study (© 2013 Google, ZENRIN).*

3.4.3 Procedures

Participants were paired into 22 groups, based on their scores on the SBSOD scale (see (Hegarty et al., 2002). The groups were divided along the median score of 4.3 into high-score and low-score groups. The participants were then paired into 6 high-high pairs, 10 high-low pairs, and 6 low-low pairs. Each pair was taken to the study site on different occasions, accompanied by two experimenters to manage the task. Participants were randomly assigned to either Route 1 or Route 2. They were then 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 guiding them back to the route if they wandered too far from it.

3.4.4 Determining Navigational Errors

From the 44 (22 each for Routes 1 and 2) route traversals in our study, we collected all decision points where participants deviated from the predefined routes. Every point traversed outside of the predefined routes was considered an error in navigation, up until the participant returned to their assigned route. Thus the decision points where errors occurred are where the participants made mistakes in navigating, either from bad instructions from their remote partner, or from misunderstanding directions.

3.5 Results

This article intends to investigate navigational errors in collaborative wayfinding and to find an optimal computational method for determining decision points where navigational errors are likely to occur. Toward this end, an empirical study was conducted followed by a list of decision points compiled where participants made errors. The computational metrics from section 3.2 are subsequently applied to calculate the salience of decision points in the environment. Whereas previous work has studied the relationship between computational salience and patterns of people navigating unknown environments on their own (Takemiya et al., 2012), the present work does this for pairs of people navigating collaboratively, traversing a pre-determined route, rather than planning their own.

3.5.1 Navigational Errors and Computational Salience

Figure 3.3 shows a map of decision points where participants made navigational errors. From this Figure it is apparent that more decision points in the environment for Route 1 posed difficulty than for Route 2 (26 vs. 14 decision points), despite the fact that Route 2 took more time on average to traverse. Figure 3.3 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). Correlations with $p < .05$ are marked with *, $p < .01$ with **, and $p < .001$ with ***.

(a)

(b)

Figure 3.2: Often-used landmarks in the routes: a hospital in Route 1, on the left side of the photo (a), and a temple in Route 2 (b)

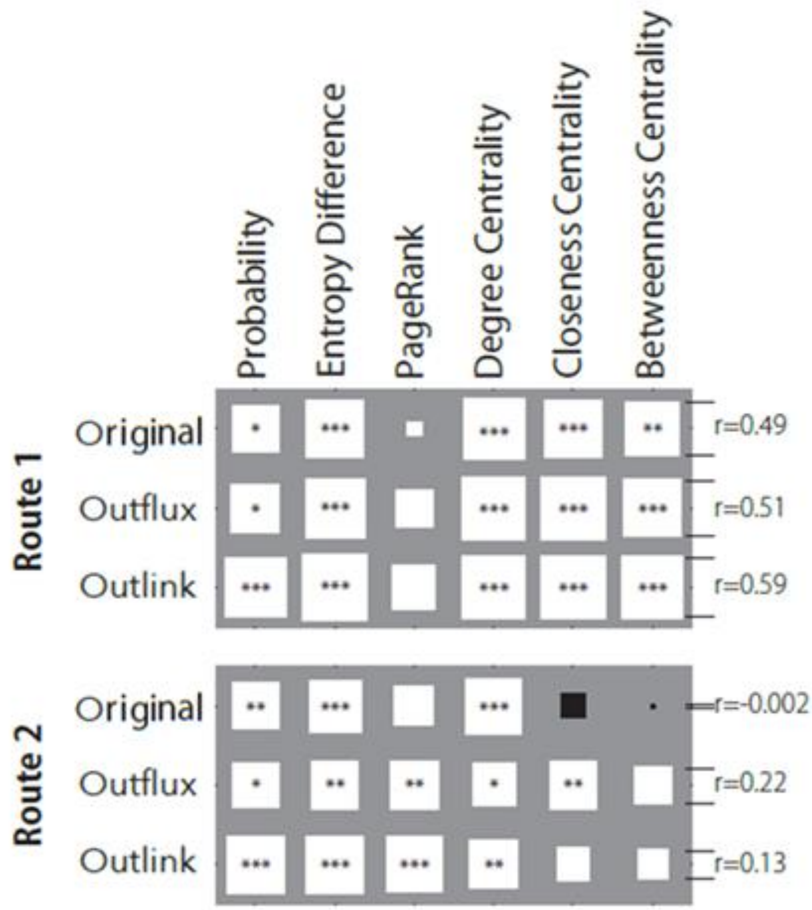

*Figure 3.3: Hinton Diagram of correlations between decision-point computational salience measures and the incidence of navigational errors at decision point (* denotes p < 0.05, p < 0.01 with **, and *** denotes p< 0.001 for Route 1 (top) and Route 2 (bottom). The area of each square denotes the correlation magnitude. R values for correlations along the right-hand side are shown for scale.*

As Figure 3.4 shows, outlink entropy difference scores for decision points were the most strongly correlated ($r = .68$ for Route 1, $r = .50$ for Route 2, $p < .001$ for both routes) with the incidence of navigational errors for both Routes 1 and 2 made by the participants in our empirical study. Outlink probability was also strongly correlated with where wayfinders made errors ($r = .56$ for Route 1, $r = .53$ for Route 2, $p < .001$ for both routes). Overall, outflux scores did not correlate as strongly as outlink scores with the navigational errors. This finding hints that these metrics are validated with actual performance and can be used to effectively predict performance on these routes.

Disregarding the outflux and outlink scores, degree centrality of decision points was the most strongly correlated ($r = .58$ for Route 1, $r = .47$ for Route 2, $p < .001$ for both routes) metric with navigational errors, followed by entropy difference ($r = .53$ for Route 1, $r = .42$ for Route 2, $p < .001$ for both routes). Other measures of computational salience were not as strongly correlated. One interesting pattern, however, was that for PageRank, closeness centrality, and betweenness centrality, the outflux and outlink measures were more strongly correlated with navigational errors than the original metrics, and outlink probability was more strongly correlated with errors than the probability metric.

In addition, outlink scores correlated strongly with navigational errors for both Routes 1 and 2, whereas other metrics did not correlate as strongly for Route 2, compared with Route 1. This can partially be explained by the structural difference between the two routes.

3.6 Discussion

3.6.1 Relating Environmental Structure and Navigational Errors

Detailed analysis of Route 1 revealed that many participants made a mistake at the decision point where a hospital was located. Because participants often mentioned the hospital as a salient landmark, it can be inferred that the hospital was 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. This suggests that wayfinders made many mistakes at that decision point because of the structure of the street network (not only because of a failure to recognize the hospital as a landmark).

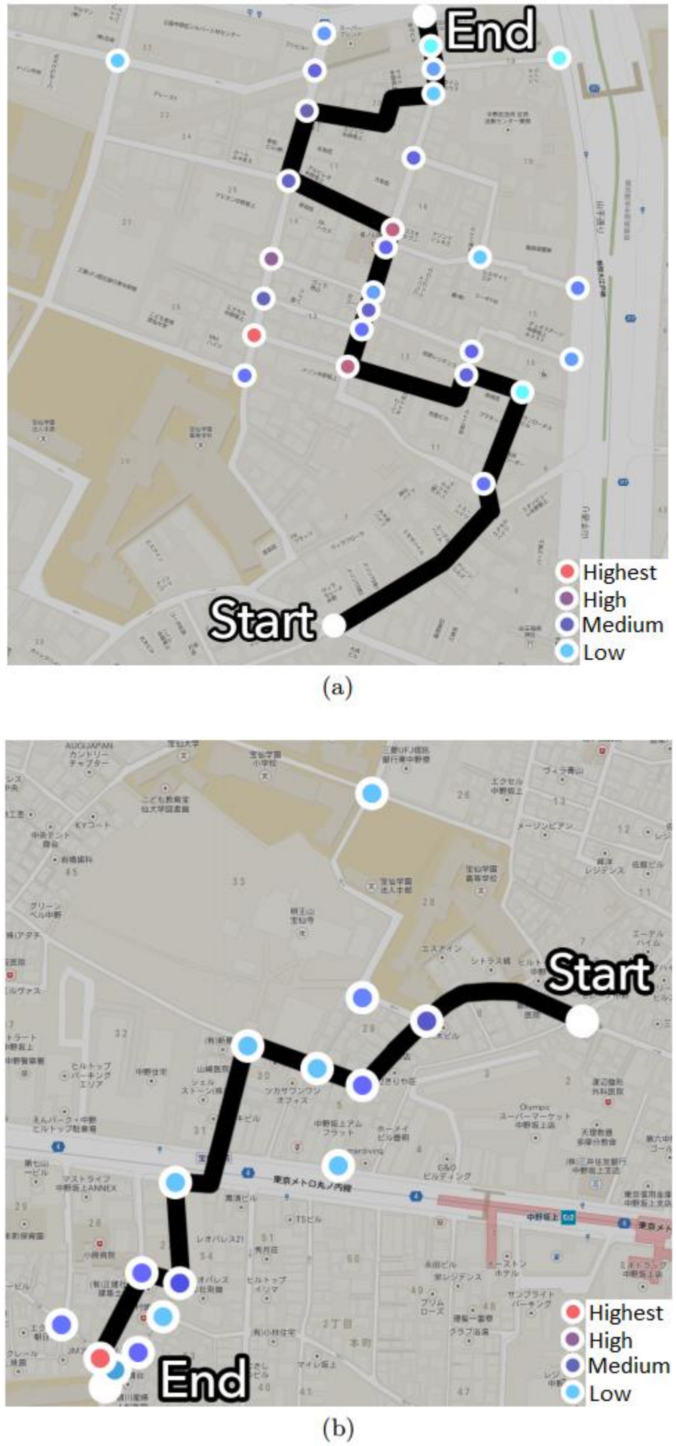

Figure 3.4: Map showing decision points and frequencies where participants made errors for Route 1 (a) and Route 2 (b). Redder circles denote more mistakes and more blue circles denote fewer mistakes, black lines show the predetermined routes, and white circles denote the start and goal locations.

The finding that outlink entropy difference and outlink probability were 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 based on the probability that a decision point will be traversed. If a person is travelling in space, their attention span, cognitive ability, walking speed and other factors will invariably fluctuate, as a result, there will be a fluctuations and variability in the way each person navigates. The concepts of outlink and ouflux takes into consideration these often subtle variabilities on a route in terms of proximity and direction that continued travel may have on a wayfinder. When you travel from one neighborhood to another there might be slight differences in perception and cognitive processing of the environment. When one changes direction or chooses one decision point over another, such an effect can also occur. These are subtle yet important factors in determining the outcome of a navigation, this dissertation attempts to elucidate this process, setting up a foundation for further investigation in future research.

This article validates the importance of using probabilities that decision points occur in generated routes to correlate with human behavior. In addition, when attempting to predict where navigational errors will occur, one should consider the probabilities of outlinking decision points. Outlinking decision points approximates the effects of direction and subsequent decision points on an existing decision point. This method reveals quantities otherwise indistinguishable with traditional analysis. Given the nature of navigational errors, that they stem from deviating from an efficient path, the efficacy of the outlink metrics is unsurprising. When considering where people will make mistakes, it is important to consider the properties of decision points that are outlinks from the current point. Future work should expand using probabilities and entropy to consider mutual information between decision points to uncover information-theoretical relationships that might be useful for route prediction.

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

The computational salience measures were calculated using only knowledge of the connectivity of decision points and computationally generated routes, rather than empirically observed data - yet statistically meaningful correlations with points where wayfinders made navigational errors were found. The feasibility of using computationally generated data makes it possible to calculate computational salience scores for any arbitrary environment. This makes the approach outlined in this article practically implementable for real-time navigational aids, such as location-based services offered in cell phones. For remote collaborative navigation where one person is guiding another via a phone or some other medium, knowledge of decision points where wayfinders are more likely to make mistakes could help the person use extra care when giving directions at those points. Using this approach, it is likely that many navigational errors would be prevented.

Transcript analysis of the participants revealed that many of the navigational errors were made at, and not between, decision points. The errors consisted of people either failing to mention necessary landmarks, mentioning landmarks in an incorrect spatial context, or the partner who was receiving directions not being able to recognize the landmarks despite being directed to the correct place. These mistakes potentially might be avoided if a priori decision-point salience can point out potential places of deviation for wayfinders.

Failing to mention landmarks was the most common error observed in the study and was made 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 the hospital, 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.

Although not studied directly in this paper, a similar approach should 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. Future work should investigate implementing an approach such as this and testing it with individual wayfinders.

3.7 Conclusion and Future Work

This article outlined a method for linking the computational salience of decision points and navigational errors made by empirically observed wayfinders. Using salience metrics calculated from the probability that a decision point was traversed in computationally generated routes, points that are statistically correlated with navigational errors made by wayfinders were elicited. 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. It was found that outlink entropy difference and outlink probability, both metrics for computational salience that are original to this study, were strongly correlated with the incidence of navigational errors.

These metrics are both tractably calculable, given a graph of the street network of an environment, as well as start and goal locations. 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. The next step should be the creation of ranking systems based on actual individual wayfinder behavior. Combining a priori prediction of route information with real time data of actual users can lead to the creation of a more robust, responsive and accurate decision system for pedestrian navigation. Improved classification of decision points and wayfinders is an important step in designing more efficient navigation systems.

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CHAPTER 4

RANKING DECISION POINT SALIENCE AND CREATING INDIVIDUAL NAVIGATION PROFILES FOR USERS OF VARIOUS SPATIAL ABILITIES USING SUPPORT VECTOR MACHINES

This chapter is a modified version of a manuscript planning to be submitted to a relevant journal. A separate study that tested an augmented instruction prototype is added and presented along side this chapter.

4.1 Abstract

This chapter presents two studies. The first study applies a machine learning method to derive a mathematical model to rank the difficulty of decision points on a route from a combination of topological and descriptive features given by the navigator. Each possible decision point is modeled as a feature vector of ten features. The method can rank the decision points by difficulty while at the same time derive weights for the individuals. The weights help create a preliminary wayfinding profile of individuals with varying spatial abilities. This study proposes a system for optimally identifying difficult to navigate decision points, allowing pedestrian navigation to be improved with timely and relevant personalized instructions at difficult to navigate decision points while understanding which features cause specific difficulties for individual wayfinders. The second study tests an augmented instructions prototype with emphasis on measuring its effect on spatial learning. The prototype was tested on a new group of participants. Improvements in spatial learning is measured through sketch maps. Low spatial aptitude group improved spatial learning with the use of augmented instructions while people of high spatial ability showed decreased survey knowledge acquisition. Implications for system improvement and future works are discussed.

Keywords: SVM, Machine Learning, Augmented Directions, Spatial Ability

4.2 Introduction and Background

Modern day Information and Communications Technology (ICT) is changing the way people interact with their environment. People are becoming increasingly dependent on navigation technologies in smart phones and GIS to find destinations and to reach their goals. Pedestrian navigation in particular has been increasingly gaining attention in the mobile phone industry (Hile et al. 2008, Roger et al. 2009). Many advances have been made that allow users easy access to points of interests and provide written or verbal turning directions to help them arrive at their destinations. Many improvements are being made in the pedestrian navigation applications, such as larger databases of points of interest, more efficient algorithms and other interactive functions. However, contemporary navigation and GIS design takes little consideration peoples' individual tendencies, spatial abilities, or fundamental cognitive processes during navigation. In order for navigation aids to work more effectively for pedestrian navigation in the urban environment, there is a need to more clearly differentiate individual abilities and features of a route.

Differences in spatial ability can translate to communication difficulties during navigation, which in turn affects wayfinding efficiency. People of varying spatial abilities choose different landmarks on a route and subsequently have difficulty guiding each other in an assigned spatial task. The study suggested the need to further classify the environment, routes, and individuals as the basis for improved navigation system design (He et al. 2015).

The previous chapter provided an approach to decide which points to consider for augmentation using various computational methods and establishing the concept of computational salience. Each decision point is inherently different and complex. How likely a person is to make a mistake at a decision point and how much that mistake can cost is often not evident by purely examining it from a topological perspective or with landmarks. Increased availability of big data can be applied to the improved modeling of individual behavior. Machine learning has gained traction in the field of navigation and has been adopted to differentiate objects in space, for example - design automated navigation for the visually impaired (Bernabie et al., 2011). Rousell et al. (2017) also applied machine learning methods, particularly image recognition for landmark detection in real time pedestrian navigation.

Machine learning, particularly binary classification methods, can be used to understand differences in individual ability, perception and experience. Support Vector Machines (SVMs) have been extensively researched in the data mining and machine learning communities and actively applied to various applications. SVMs are typically used for learning classification, regression or ranking functions. For these they are called classifying SVM, or support vector regression or ranking SVM (SVM^{rank}) respectively. Learning rank functions are distinguished from learning classification functions. Unlike classification functions, which output a distinct class for each data object, a ranking function outputs a score for each data object, for which a global ordering of data is constructed. The target function F (Xi) outputs a score such that F (Xi) > F (Xj) for any Xi > Xj.

Many researchers have proposed systems capable of providing more natural route instruction to pedestrians in the city environment (Boye et al., 2014, Rehrl et al., 2010). A pedestrian's position can now be tracked using GPS on the smartphone, and can produce real-time instructions such as "turn right here" or "go left when you see the store". A challenge for such a model is to optimize the formulation of instructions, to minimize misunderstanding, and to cater to the cognitive ability and habits of the individual. Informing navigators specifically what they should look for at a decision point can reduce misunderstanding, increase navigational efficiency and improve the overall experience.

Real-time classification, robustness and efficiency are important considerations in system design. If a navigation system gives too much information, providing user instruction at every turn, it would be counterproductive, ineffective and burdensome. Such a system would also likely increase user's reliance on the navigation aid while further hindering survey knowledge acquisition (Ishikawa et al., 2008). A system should optimally exist in the background, actively processing information, interacting with the user and providing helpful information at the right time and place. In order to find the balance from both a system and user perspective, it is therefore important to know ***which decision points*** to augment and ***for whom*** the best results can be achieved.

Salient landmarks are helpful in pedestrian navigation, imagine using the Eiffel tower as a point of reference. However, most human activities in novel urban settings do not involve particularly salient landmarks, and some are hidden or inconspicuous. Since landmarks are essential for wayfinding, many researchers have focused on automatically computing salience values for landmarks (Raubal & Winter, 2002; Duckham et al., 2010). These schemes typically involve using known features to influence salience such as size, visibility, shape and color. Weight systems are used for these scores but the weights are set manually, based on various heuristic approaches. In this study, the weight are to be determined by the interaction of the pedestrian user with the decision points, rather than preset manually. The assumption is made that salience of each decision point is *user-dependent*: different users will experience varying degrees of difficulties in a novel situation. Another novelty of this approach is the assumption that landmarks alone do not fully determine the difficulty of the decision point. Rather, the actual interactive salience of a pedestrian navigation is a combination of landmarks, the topological features, the situational context, as well as personal influences. Models can thus be created from existing data while reflecting real world tendencies of the users.

4.3 Related Approaches

Landmarks can often facilitate the communication of spatial information. Nothegger et al. (2004) extended an evaluation study in which human subjects are shown panoramic views of intersections and are asked to choose the most prominent façade. The automatically computed salience measures reflect the human choices, thus proving the suitability of the models. Sorrows and Hirtle (1999) moved away from computing salience of individual landmarks, because necessary data is often difficult to obtain. Sorrows and Hirtle proposed to measure salience on the basis of an object's category, using heuristics to determine how suitable a certain category is as a landmark: experts were asked to rate landmark categories according to a set of nine factors that are proposed to describe the salience types (Sorrows & Hirtle, 1999). Ratings were given on a five-point scale according to how suitable a specific instance of a category would be as a landmark, and how frequently such an instance occurs. The final score of a category is computed as a weighted sum of these rankings.

Sorrows and Hirtle (1999) proposed a widely used description of the characteristics of landmarks in the domain of Geographic Information Science. The authors compared commonalities between real and electronic space and proposed three different characteristics of a landmark: (1) Visual prominence, which describes the visual importance of a spatial feature, (2) Semantic salience, which describes the cultural or historical importance of the feature, and (3) Structural salience, which explains the role that feature plays in the configuration of the environment. The concept can be combined and overall salience value of a landmark can be computed according to the widely used Klippel and Winter's (2005) equation:

$$S = w_v s_v + w_s s_s + w_u s_u; \qquad w_v + w_s + w_u = 1$$

Sv, Ss, and Su are the visual salience, semantic salience, and structural salience, respectively, and Wv, Ws, and Wu are the weights assigned to the three types of saliences. These weight parameters are set by users in real-world applications. The salience measure is the sum of the weighted single characteristics defining a landmark. The approach is an attempt to generically describe the nature of landmarks in the real or virtual environment but no formalization is proposed (Caduff and Timpf, 2008).

Burnett (2000) used a system of permanence, visibility, and location in relation to a decision point, and uniqueness and brevity as the aspects of landmarks - the purpose of which was to investigate properties of landmarks for usability in car navigation. Two aspects of Burnett's proposal correlated with aspects proposed by Sorrows and Hirtle (visual salience to visibility; structural salience to location in relation to a decision point).

These proposals are among many approaches to delineate the complex nature of landmarks. These approaches are restricted to qualitative and often subjective characterizations, and often lack an answer on how to determine landmark salience for navigation. In this study, the assumption is made that what is salient about a landmark or lack thereof, can be reflected in the actual performance of wayfinders. The majority of potentially useable landmarks are not universally salient, what is salient to some may not be salient to others. Saliency is a subjective function that can be more realistically determined by the actual performance in a spatial task. This approach offers a way beyond objective landmark classification to determine the difficulty inherent in a decision point. The individual data derived ranking of decision points can subsequently lead to a better provision of resources and more timely assistance.

4.4 Ranking Decision Points and Creating Weights Profiles

4.4.1 Study Design

This study builds on the empirical study presented in chapter two of this dissertation. Figure 4.1 shows the study site and the routes traversed by the participants. 44 participants (27 male, 17 female) were divided into high and low spatial abilities groups at the SBSOD median score of 4.3. The participants traversed two separate guided routes sharing a starting point. Upon completion of the first route, the participants switched routes and guided each other using cell phones from memory. The experimenters followed the participants, recorded their actions, and guided them back to the predetermined route. If a wayfinder deviated by more than two decision points, it is counted as a mistake is recorded by the experimenter. Deviation of two decision points was determined as basis for a mistake because such a setup gives the user a chance to make an adjustment while eliminates random errors. The cell phone conversations were recorded and the conversations transcribed and analyzed.

This study attempts to construct a mathematical model that can predict salience in new unseen situations specific to a wayfinder. In the previous chapter, computational salience predicted certain mistake prone decision points. The metrics, although validated by actual user data, are not matched to individual users, but worked well as a whole. In contrast, the present study, each decision point can be modeled as a vector of features and attempt to further understand individual effects. No assumption is made about what feature will influence salience. The effects of these features is reflected in the learned weights for each individual navigator. When a person makes a mistake at a decision point, it can be an indication that the decision point poses a salience score higher than another decision point.

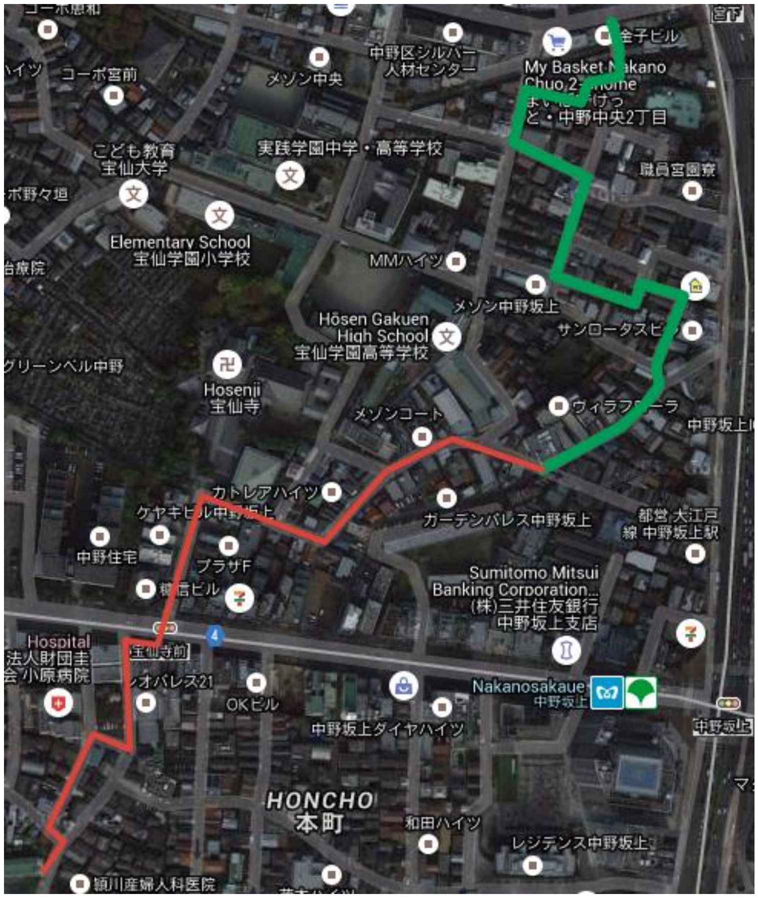

Figure 4.1. Map of the two routes used in our empirical study (c 2013 Google, ZENRIN). Green represent Route 1, red represents route 2. Both routes share the same starting point.

This study attempts to construct a mathematical model that can predict salience in new unseen situations specific to a wayfinder. In the previous chapter, computational salience predicted certain mistake prone decision points. The metrics, although validated by actual user data, are not matched to individual users, but worked well as a whole. In contrast, the present study, each decision point can be modeled as a vector of features and attempt to further understand individual effects. No assumption is made about what feature will influence salience. The effects of these features is reflected in the learned weights for each individual navigator. When a person makes a mistake at a decision point, it can be an indication that the decision point poses a salience score higher than another decision point.

4.4.2 Mistake Analysis

In this study, mistakes form the basis of the learning method. Each conversation is transcribed and the actions of the wayfinders closely examined both quantitatively and qualitatively to find mistakes. The mistakes of the participants on the assigned route and mistakes of the participants against the given verbal instructions of the route both count as errors. The following are some examples of mistakes from the actions of the wayfinders taken from the transcribed conversations.

Example 1:

Participant one Instructions: ***"When you get to the next crossroad, look for a hospital sign, when you see the hospital., make a left until you get to another crossroads."***

Participant two actions: Walks past the hospital. Takes right turn, returns to hospital after walking for two blocks.

Example 2:

Participant one Instructions: ***"When you arrive at the building with the white staircase and a small car parked in the front, keep walking one block and turn left when you see the stop sign."***

Participant two actions: Failed to see the parked car and turns one block too early.

Example 3:

Participant one Instructions: ***"When you see the building with the flower pot at the intersection, turn right."***

Participant two actions: Goes straight, passing the decision point and turn at next intersection

4.4.3 Performance inequalities represented in equations

The foundation of this mathematical model is expressed as inequalities. Whenever a person has difficulty at a decision point *A* in a route, over other decision points, i.e. (*B, C, D, E*), this indicates that *A* has a higher score according to the individual's salience model than the other decision candidate's decision points. When a person has difficulties at decision point A rather than decision point B, one can represent this as the inequality:

$$W^*(X_A - X_B) > 0$$

X_A and X_B are vectors that represent A and B respectively, the weight can be positive or negative dependent on the difference between the vectors, the product of the equation is always greater than zero. This inequality can attests to the fact that *A* is more difficult than *B* in the model *W*. All the factors involving the decision point thus generate a number of inequalities. Set M as a set of the total number of inequalities for all decision points. The function thus seek to find a weight vector *W* such that $W * (X_{li} - X_{mi}) > 0$, for $1 \leq i \leq M$. Substituting difference (di) for $(X_{li} - X_{mi})$, the goal is to find appropriate values for the weights in **W** that satisfy as maximum number of the inequalities in w*di > 0. The slack variable ξ,, accounts for the uncertainty in the modeling. This variable can be introduced into the following optimization problem as presented by (Joachim 2002). The slack inequality can be used to account for inconsistency in user performance:

$$\begin{array}{lll} \text{minimize} & \frac{1}{2}\mathbf{w}\cdot\mathbf{w} + c\sum_{i=1}^{m}\xi_i & \\ \text{where} & \mathbf{w}\cdot\mathbf{d_i} + \xi_i \geq 1, & i = 1\ldots m \\ & \xi_i \geq 0, & i = 1\ldots m \end{array}$$

This optimization problem attempts to minimize discordant pairs in the equation, *c* allows for trading off of margin size for training error. The purpose of this model is to rank the decision points from most to least difficult for the prospective user. Such a model can assign a numerical score to each available decision point indicating its salience. The weights gained for each user can be tuned and set as a profile for personalized navigation in GIS. The numerical salience scores are not very important, and should not be interpreted as absolute salience. The numbers themselves are simply a means to get to the ranking. The numbers do not represent potential difficulty in an absolute manner nor can salience scores are be meaningfully compared across different situations and circumstances. The difficult decision point might be perceived as very salient or not very salient at all, it is more appropriate to describe them in a relative manner.

4.4.4 SVM Ranking Method

SVMs were initially developed for classification (Burges, 1998) and have been extended for use in regression. Using weight techniques of SVM, a global ranking function *F* can be learned from an ordering *R*. Assume *F* is a linear ranking function such that

$$\{(x_i, x_j): y_i < y_j \; \varepsilon \; R\}: \boldsymbol{F}(x_i) > \boldsymbol{F}(x_j) <=> w \cdot xi > w \cdot x_j$$

A weight vector **w** is adjusted by a learning algorithm. The ordering *R* is linearly rankable if there exists a function *F* (represented by a weight vector **w**) that satisfies the equation for all

$$\{(x_i, x_j): y_i < y_j \; \varepsilon \; R\}.$$

There are two special properties of SVMs: 1. By maximizing margin, the system can achieve high generalization. 2. Kernel trick can support efficient learning of nonlinear functions. SVM^{rank} is a machine learning method which deploys a pairwise approach – transforming ranking to pairwise classification. Many pairwise ranking methods in machine learning have been developed in the past few years, these include:

- *Ranking SVM* (Joachim 2002), which uses a pairwise classification using SVM;
- *RankBoost* (Freund et al., 2003), which uses pairwise classification using boosting mechanisms;
- *RankNet* (Burges et al., 2005), a pairwise Classification system using Neural Net
- *FRank* (Tsai et al., 2007): a pairwise regression using Fidelity Loss and Neural Net
- *GBRANK* (Zheng et al., 2007): Pairwise Regression Using Boosting Tree
- *IR SVM* (Cao et al., 2006): Cost-sensitive pairwise classification using SVM
- *LambdaMART* (Wu et el, 2010): Using Implicit Loss Function

For the study at hand, all of the above methods were considered. SVM^{rank} was chosen for the ranking and weight generation prerogatives. SVM^{rank} uses pairwise classification on differences of feature vectors. In SVM^{rank}, corresponding positive and negative examples exist, and the hyperplane always passes through the origin. This algorithm has been used for various non-linear ranking tasks, e.g. in sentiment classification (Kennedy and Inkpen 2006), and named entity recognition (Bunescu and Pasca, 2006). SVM^{rank} is robust and implementable with the available dataset.

4.4.5 Feature Vectors

In this model, each decision point can be represented as a vector with 10 numerical features, (X = X_1, X_2, X_3, …. X_{10}), that specify scores along $\boldsymbol{n}$ dimensions. Each dimension might represent scalar attributes like time, distance, or categorical attributes (assigning 1 if prominent landmark present, 0 if not). The salience of s(x) of a decision point is a linear combination $W * X$, where W = (W_1, W_2, W_3, W_4….. W_n) is the salience model that specifies the relative importance of the different features for the user. The features are listed below. These ten features are selected as they can be derived from user data. The following feature vectors are organized by their types.

Distance

Distance between decision points capture both the structural and visual aspects of the topology

- distPrevious – Distance to previous decision point

- distNext – Distance to the next decision point
- distfrombegin – How far the decision point is from the beginning

Time

Time is an important factor that has often been overlooked in salience calculations. The amount of time spent at a decision point is an indication of potential difficulties at the location, as indicated by the people taking time to cognitively process the situation.

- Time – time spent at decision point

Landmark Types

Ephemeral landmarks have been shown to affect navigational efficiency for people of lower spatial abilities (He et al., 2015). In this study, ephemeral landmarks exist alongside salient landmarks, in many cases, simultaneously. Both salient and ephemeral landmarks are taken as feature vectors in the training.

- salientLM – if a salient landmark exists
- ephemeralLM – if an ephemeral landmark exists
- 3 arcs @node – there are three possible links at decision point
- 4 arcs @node – there are four possible links decision point
- signs – whether signs exists at decision point
- color – whether colors other than black and white exist at decision point

The 10 features aim to capture various aspects of interaction between decision point and the user. No explicit assumptions about what positive or negative influences are made. Contribution of each weight to the individual can be examined from the derived weights. Group tendencies may be evident by aggregated analysis of group weights.

4.5 Decision point ranking and individual weights profile results

For analysis purposes the users are divided into four spatial ability groups: Highest Quartile: (SOD ≥ 4.87); Middle High Quartile: (4.3≤SOD<487.); Middle Low Quartile: (3.67≤SOD≤4.3) and Lowest quartile: (SOD < 3.67). Models are assessed for training with individual users, aggregated quartile groups, users in high (SOD >4.3) and low (SOD≤4.3) ranges.

4.5.1 Ranking Results

One *instance* in this ranking problem is defined as a candidate set along with its relevant mistake-prone decision points. For evaluation purposes, the set of all instances was split into a training and test set. The training set is used to derive a salience model according to previously mentioned methods in section 4.4.3. In order to evaluate ***w,*** the salience of each member of each instance of the test set was computed. The machine learning metric of Mean Reciprocal Rank (MMR) is used to assess the effectiveness of the ranking model against actual performances. If the model ranks the n^{th} decision points in terms of difficulty, its reciprocal rank will be 1/n (Radev et al., 2002). Total reciprocal rank is the sum of the reciprocal ranks of all difficult decision points on the route selected by the users. To calculate the mean, this total number is divided by the total number of decision points.

Table 4.1 Group Training on 65% of Data

Group Training Data	*Total Mistakes*	*MRR*
Overall	237	0.49
High SOD	96	0.44
Low SOD	141	0.61
Top Quartile SOD	45	0.46
Middle High Quartile SOD	51	0.35
Middle Low Quartile SOD	64	0.58
Low Quartile SOD	77	0.6

A SVM ranking method can effectively create individual models of wayfinders. Table 4.1 and 4.2 demonstrate the evaluation measures for a training model on 2/3 of available data. How useful is this result? The purpose of this study is to propose an interactive system that can quantify the importance of each decision point to an individual and thus provide instructions in accordance with the derived rank. When examining the results it is noted that some individuals produced better results than others, and the results are unrelated to the training size.

Table 4.2 Individual Training

	MRR		*MRR*
1	0.42	***23***	$\boxed{\underline{\textbf{\textit{0.7}}}}$
2	0.6	***24***	0.38
3	0.29	***25***	0.69
4	0.35	***26***	0.56
5	0.46	***27***	0.39
6	0.52	***28***	0.43
7	0.46	***29***	0.52
8	0.34	***30***	0.42
9	0.46	***31***	0.5
10	0.44	***32***	0.42
11	0.37	***33***	0.36
12	0.6	***34***	0.46
13	0.39	***35***	0.44
14	0.42	***36***	0.32
15	0.68	***37***	0.46
16	0.35	***38***	0.61
17	0.4	***39***	0.52
18	0.46	***40***	0.38
19	0.34	***41***	0.5
20	0.5	***42***	0.46
21	0.64	***43***	0.64
22	0.6	***44***	0.6

Table 4.1 and 4.2 present results that compare training on aggregated group size versus training on individuals. The highest Mean Reciprocal Rank is bolded and boxed. When training size increases, MRR does not improve with increased training size.

When training size is increased, no additional improvement is seen. This shows the effectiveness of such a model, that the size is sufficient and that the availability of the data is enough using this method to create meaningful ranks. This also demonstrates that the model works more effectively on an individual level. The overall mean reciprocal rank for training is 0.49, a respectable number hinting at the usefulness of such an approach.

4.5.2 Individual Weights in a Salience Model

In the process of ranking decision points, weights are generated for the individual user. The weights can serve as a basis to profile individual user tendencies. Closer examination of the weights also demonstrated certain tendencies of users in various spatial ability groups, although such generalizations would be better served with additional testing and validation. Table 4.3 lists all the individual weights derived in this study. The weights are obtained when training on all instances. When aggregating by quartile groups, some patterns emerge. For people of very high spatial ability, the average time weight was the highest amongst the groups. In other words, time spent at a decision point is a good indicator of potential difficulty of people with high spatial abilities. People of high spatial aptitude employ a different mental model and possess greater capacity for spatial information processing (Wen et al., 2011). Given ample time, people of higher spatial ability have the capability to rearrange their mental map and re-orient the routes spatially. The high weights show that people of higher spatial ability have a tendency to take more time to figure out the problem, resulting in higher weights for time. People of middle high spatial ability have the highest weight in making mistakes at decision points that are *closer* to the next decision point while participants within the middle low group have the highest weight on decision points that are *farther* to the next decision points. Effects of distance on navigational performance merits closer investigation in future research. It could be explained that some people can process information faster, while distance may decay cognitive ability, the succession of decision point have been shown to pose difficulties for some participants. Chapter two discussed the effects of topological features on navigation tendencies, outlink and outflux scores were shown to improve error prediction rate due to its approximation of topological effects of wayfinding cognition. It could be prudent to combine computational metrics with weights to more clearly understand fluctuating topological effects on wayfinding behavior.

Looking at individual weights more closely, table 4.3 shows salience models of four subjects with sorted weights of the features. These selected individual profiles give an example of how weights may differ across various groups. For example, Subject 32 has a high weight at ephemeral landmarks while subject 7 had a negative weight at ephemeral landmarks. Such insights would not have been derived without the $SVM^{ranking}$ methods. The model more optimally serve the purpose of understanding individual behavior. Although SBSOD is the standard contemporary research protocol to differentiate users, it is not ideal in taking into account situational variability. In addition, SBSOD surveys are self-assessed and given pre-navigation. Sense of direction surveys such as SBSOD can be complemented with the derived weights. These weights are updated post navigation and can dynamically update each individual's profile. A post navigational reconciliation with weights can improve the accuracy and predictability of SOD surveys to better differentiate and classify individual wayfinders.

Table 4.3 presents the weights of all features for each individual participant, along with their SOD score, and group performances. The participants are sorted by their SOD score, and divided into quartiles. Average weight is calculated for each quartile group with the highest weight average among the four quartiles highlighted in bold. (MH = Middle High, ML = Middle Low)

				Performance		Derived Weights									
Participant #	Group #	SOD	Group	Group Time	Partner Distance	distPrevious	distNext	Distfrombegin	Time	salientLM	ephemeralLM	3arcs	4arcs	Signs	Color
43	22	6.33	highest	926	540	-1.565	-0.986	0.264	0.526	-1.68	-0.867	-0.37	0.248	0	0.56
23	7	6.27	highest	1870	1270	1.12	-0.87	-0.38	1.86	0.47	0.06	0.68	1.27	0.76	1.87
37	19	5.47	highest	1434	570	-1.25	0.85	-1.17	1.43	0.62	-1.06	1.56	0.07	-0.64	1.28
15	12	5.47	highest	591	490	-0.46	-0.76	-0.9	-0.26	0.05	0.04	0.87	-0.67	0	-1.78
31	16	5.40	highest	1677	630	0.67	1.13	-1.12	1.65	-1.42	1.25	1.67	0.65	0.87	0.78
6	3	5.27	highest	1236	433	0.256	1.09	0.37	1.35	-0.23	1.2	0.89	0.45	-0.45	0.06
16	8	5.27	highest	1060	490	1.17	1.22	-0.47	0.89	0.09	0.32	-0.26	1.14	0	0.76
12	6	5.27	highest	730	887.5	-0.46	0.12	1.14	0.021	-1.12	-0.54	-0.45	0.56	0.23	-1.61
11	6	5.27	highest	730	597.25	-0.86	-0.23	1.1	0.56	-1.02	-0.65	0.67	1.14	-0.36	-1.32
30	15	5.20	highest	1936	1311	1.12	1.35	1.13	1.12	0.97	0.35	0.68	1.08	-0.33	-0.15
14	12	4.87	highest	591	570	-1.34	-1.269	-0.0246	0.63	0.155	-0.37	-1.16	-1.123	0	0.56
Average		5.46		1161.91	708.068	*-0.145*	*0.150*	*-0.006*	***0.889***	*-0.283*	*-0.024*	*0.435*	*0.438*	***0.007***	*0.092*
Participant #	Group #	SOD	Group	Group Time	Partner Distance	distPrevious	distNext	Distfrombegin	Time	salientLM	ephemeralLM	3arcs	4arcs	Signs	Color
	13	4.73	MH	1306	570	0.82	1.14	-0.87	0.98	1.43	-0.78	1.32	1.43	-0.86	0.08
13	7	4.67	MH	1870	570	1.16	1.43	-1.15	1.21	1.08	-1.23	1.06	1.13	0.24	0.16
21	11	4.67	MH	1601	570	1.723	0.79	-0.72	1.13	-0.72	-0.67	1.23	0.78	0	0.24
24	8	4.67	MH	1060	570	1.156	0.36	0.27	0.35	0.65	0.72	0.45	0.45	-0.32	-0.36
40	20	4.67	MH	756	490	-0.67	-1.25	-1.92	-0.89	-0.64	-0.57	-0.52	0.34	-0.87	0.72
7	4	4.60	MH	1160	741.5	-0.74	-0.56	0.086	0.48	-0.786	0	0.346	-0.898	0.025	-0.653
39	20	4.60	MH	756	570	-1.24	-0.89	0.75	-0.48	1.43	-0.29	-0.63	0.67	0.56	-1.12
28	14	4.53	MH	1643	582	0.92	1.16	-0.84	1.24	1.32	1.15	1.43	1.54	0	-1.32
3	2	4.40	MH	1742	621.625	1.17	-0.76	-1.15	1.16	0.87	-0.58	1.255	1.62	0.43	0.24
36	18	4.40	MH	1111	570	0.97	1.17	1.12	1.08	-0.67	1.12	0.67	1.23	0.42	-0.23
44	22	4.33	MH	926	590	0.56	-1.12	0.72	0.12	0.07	0.79	0.67	0.67	-0.32	1.02
Average		4.57		1266.45	585.920	*0.530*	*0.134*	*-0.337*	*0.580*	*0.367*	*-0.031*	*0.662*	*0.815*	*-0.063*	*-0.111*
Participant #	Group #	SOD	Group	Group Time	Partner Distance	distPrevious	distNext	Distfrombegin	Time	salientLM	ephemeralLM	3arcs	4arcs	Signs	Color
27	14	4.27	ML	1643	542	1.25	1.241	0.26	1.12	1.23	-0.26	1.34	1.63	-0.32	1.23
35	18	4.27	ML	1111	653	-0.6	1.154	-0.25	0.21	1.09	1.43	0.87	1.16	-0.23	0.24
10	5	4.27	ML	996	625	-1.12	1.098	-0.76	-0.32	0.89	0.34	-0.32	-0.98	0	0.67
19	10	4.13	ML	839	716.612	0.65	0.568	1.36	-0.78	0.79	-0.67	-0.23	0.78	0.78	-1.32
22	11	4.07	ML	1601	1096	0.2	0.867	0.78	1.32	1.53	1.37	1.65	1.54	0	0.89
17	9	4.07	ML	1190	760	0.56	-0.12	-0.19	1.08	1.14	-0.56	0.87	0.98	-0.32	-0.76
41	21	3.87	ML	1645	989.35	1.12	1.254	1.28	1.23	1.52	0.23	1.43	1.64	0	-0.67
5	3	3.87	ML	1236	570	0.87	1.346	0.35	1.08	1.02	-0.08	1.65	1.24	0	1.09
25	13	3.80	ML	1306	908.2	-0.4	0.867	-0.6	0.75	0.56	-1.12	1.23	1.32	-0.32	0.45
20	10	3.80	ML	839	570	0.62	1.546	-0.92	0.79	-0.23	1.23	0.35	1.12	0.23	0.08
4	2	3.67	ML	1742	692.41	1.76	1	1.76	1.16	1.08	0.31	1.45	0.98	0	1.02
Average		4.01		1286.18	738.416	0.446	**0.984**	**0.279**	0.695	**0.965**	**0.202**	0.935	**1.037**	-0.016	**0.265**
Participant #	Group #	SOD	Group	Group Time	Partner Distance	distPrevious	distNext	Distfrombegin	Time	salientLM	ephemeralLM	3arcs	4arcs	Signs	Color
32	16	3.40	Lowest	1677	854	1.345	0.976	-0.15	0.01	1.55	1.523	0.785	1.136	0	-1.124
2	1	3.40	Lowest	755	490	0.87	0.67	-0.27	-1.13	-0.87	0.37	1.47	0.98	-0.64	0
29	15	3.33	Lowest	1936	1360	1.236	0.43	0.986	-0.156	1.568	-0.87	1.52	1.92	0.876	-0.57
9	5	3.33	Lowest	996	614	0.25	0.35	0.47	0.24	0.08	-0.87	0.65	-0.53	0	-0.67
42	21	3.27	Lowest	1645	570	-0.81	-0.89	-1.254	0.87	-0.67	-0.78	1.15	0.67	-0.3	0.09
1	1	3.27	Lowest	755	570	0.12	1.34	-1.15	-0.45	0.57	0.87	1.06	1.13	-0.32	0.24
38	19	3.00	Lowest	1434	803.6	-0.4	-1.12	1.25	1.24	1.65	-1.14	1.13	1.43	-0.87	0.45
18	9	3.00	Lowest	1190	960	1.265	1.123	0.547	0.079	-1.132	-1.13	1.116	1.536	0	1.158
8	4	2.80	Lowest	1160	1261.1	1.465	0.568	-0.152	0.053	1.25	0.589	1.254	0.89	-0.52	0.286
34	17	2.27	Lowest	1336	1020	1.52	0.78	1.43	0.87	1.45	0.05	0.52	0.92	0	1.12
33	17	2.00	Lowest	1336	793	0.76	-0.65	-0.8	0.76	1.22	-1.43	0.78	0.24	0.25	-0.03
Average		3.01		1292.73	845.064	***0.693***	*0.325*	*0.082*	*0.217*	*0.606*	*-0.256*	***1.040***	*0.938*	*-0.139*	*0.086*

Table 4.4 Comparing the feature weights for four subjects models (One from each of the four quartile groups)

Subject 14		**Subject 7**		**Subject 35**		**Subject 18**	
Highest Quartile		**Middle High Quartile**		**Middle Low Quartile**		**Lowest Quartile**	
Feature	**Weight**	**Feature**	**Weight**	**Feature**	**Weight**	**Feature**	**Weight**
Time	0.63	Time	0.48	ephemeralLM	1.43	4 arcs @node	1.54
Color	0.56	3 arcs @node	0.35	4 arcs @node	1.16	distPrevious	1.27
salientLM	0.16	Distfrombegin	0.09	distNext	1.15	Color	1.16
Signs	0	Signs	0.03	salientLM	1.09	distNext	1.12
Distfrombegin	-0.02	ephemeralLM	0	3 arcs @node	0.87	3 arcs @node	1.12
ephemeralLM	-0.37	distNext	-0.56	Color	0.21	Distfrombegin	0.55
4 arcs @node	-1.12	Color	-0.65	Time	-0.23	Time	0.08
3 arcs @node	-1.16	distPrevious	-0.74	Sign	-0.24	Signs	0
distNext	-1.27	salientLM	-0.79	Distfrombegin	-0.25	ephemeralLM	-1.13
distPrevious	-1.34	4 arcs @node	-0.9	distPrevious	-0.6	salientLM	-1.13

Table 4.4 presents four examples of sorted feature vectors, i.e. salience models. These weights were obtained when training on all instances of subjects. The different orderings of the features reflects different preferences of these subjects in various groups during navigation. This study created individual models to further understand navigation and human to environment interaction. The ultimate application of these findings is to incorporate them into a more efficient and personalized pedestrian navigation system. Targeted and timely navigation instructions such as augmented instructions at difficult decision points holds the potential to improve performance for the user. The second part of this chapter presents such a prototype that tests this concept. Given the increased reliance on navigation aids, special emphasis is placed on survey knowledge acquisition by users of this prototype.

4.6 Effects of augmented instructions on spatial learning findings

4.6.1 Study Design

In part two of this study, a prototype is designed, coded, and installed on an Android system. The prototype application offers augmented directions at decision points with photos, information about the decision point such as intersection, identifiers, signs, and façades of the buildings (Figure 4.2). A new group of 32 participants (20 male, 12 female) participated in the study, and divided along median score of 4.27 into high group (SOD > 4.27) and Low group

(SOD < 4.27) respectively. The participants were given the mobile phone device (Samsung Galaxy 5) and navigated the same route as the previous study. In the first routes, the participants navigated using a traditional map with the routes highlighted. The experimenter followed the same protocol from earlier studies to track their progress and record mistakes at each decision point. In the second route of the task the navigators used the prototype that provided augmented instructions at all possible decision points. At the end of each navigation, the participants were asked to conduct a map sketching task, which is designed to assess their survey knowledge acquisition from their recently completed wayfinding task. No time limit was imposed on the task. In the map-sketching task, participants drew sketch maps of the traveled routes in as much detail as possible from memory on a blank A4 sheet of paper (Figure 4.4), this study is designed to assess the effects of augmented instructions on participant's survey knowledge acquisition.

Figure 4.2. Screenshot of the decision point augmentation system used by the participants. This system displays information about the decision point to the users upon approach to those decision points. The information includes structural salient landmarks, non-structurally salient landmarks, events observed by participants in study one, and signs and other relevant information. The prototype is intended to give the users guidance at these decision points.

Spatial learning is an important skill for general learning and scientific reasoning (Newcombe, 2014). Increased reliance on technology is decreasing spatial learning, particularly in children. Survey knowledge acquisition can be measured by sketch tests and has been applied in many studies. For example, Meneghtti examined cognitive processes in children with Down syndrome where children listened to route or survey descriptions with or without creating a corresponding sketch map (Meneghetti et al., 2007). Sketch maps, when applied in a post navigational exercise can serve as an useful indicator of survey knowledge acquisition.

To assess the map-sketching task, the accuracy of drawn maps is examined in terms of a bi-dimensional regression coefficient (Tobler 1994). To complete this analysis, 10 locations on each route (the start, goal and 8 other decision points) were selected as “anchor” points, and the actual map and a sketch map were overlaid so that the anchor points on the two maps matched as closely as possible. The value for bi-dimensional correlation was computed, which gives the degree of correspondence between the two maps ranging in value from 0 to 1 (the larger, the better correspondence). Correlation values were are subsequently transformed through Fisher's *r*-to-*z* transformation, with the alpha level of 0.05 used for statistical purposes. (Silver & Dunlap, 1987). In addition, the overall number of correct sketch maps and proportion of correct turns are calculated.

4.6.2 Effects of augmented instructions on map learning results

Intuitively, improvement is anticipated with additional instructions at decision points. However, it is interesting to see whether everyone can benefit equally from these additional instructions. Paired t-test of two samples for means revealed a significant increase for people with lower spatial abilities when using the prototype compared with people of higher spatial abilities ($T(15)=2.13$, $p < 0.05$), showing that people of lower spatial ability benefits more from such instructions.

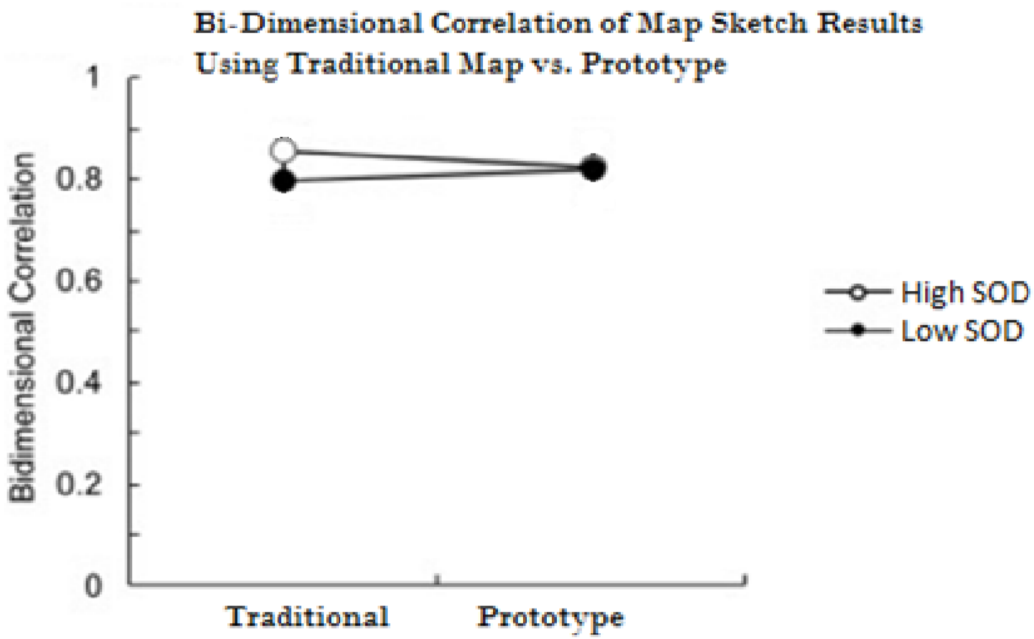

Figure 4.3 Bi-dimensional correlation map of two sessions, the first using traditional map and the second with the prototype. Improvement is seen for people of low SOD while decrease in spatial ability is seen by people of high spatial aptitude.

Table 4.6 Number of correct turns correctly recalled by the participants using the prototype. This analysis is simply counting how many turns the user recalled correctly in their exercise

	Traditional	Prototype
Proportion of correct turns		
High SOD	0.86(0.16)	0.83(0.16)
Low SOD	0.66(0.21)	0.74(0.21)*

* = p < 0.05

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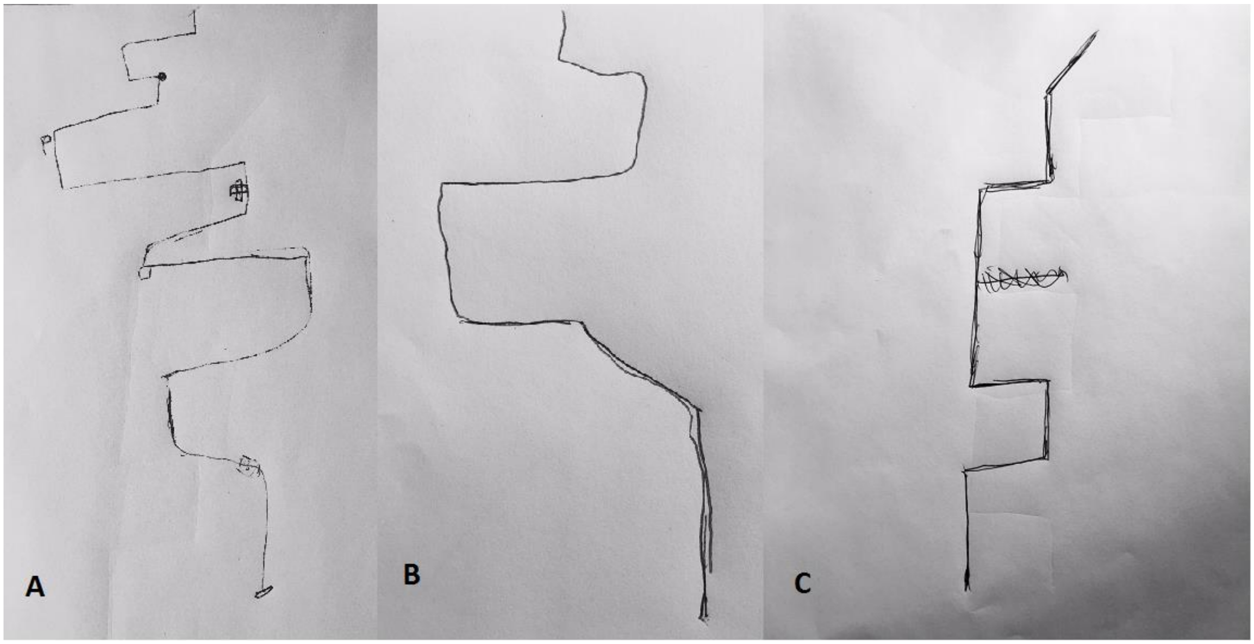

Figure 4.4. Examples of sketch map testing results for people of high and low SOD groups by method. A is done by participant 12 (middle low quartile SOD) in an augmented route, B is done by participant 7 (lowest spatial quartile SOD) in a route without prototype, and C is done by participant 21 (middle high quartile SOD) with prototype.

Bi-dimensional correlation showed that the number of correct sketch maps decreased for people using the prototype for people with high SOD. There were significant effects of augmented instructions for people of poor SOD. ($M_{low} = .82$). $F(2, 32) = 5.21$, $p < .05$. For map sketching, low SOD participants did better with augmented directions while the good SOD group did worse in the second session with augmented instructions. When examining proportion of correct turns, the results showed a slight decrease in percentage for people with higher spatial abilities. Table 4.6 shows the proportion of correct turns recalled by the participants on the sketch test, this showed similar trends as the bi-dimensional correlation analysis. Improvement in proportion of correct turns recalled is statistically significant for the low spatial ability group.

4.6.3 Discussion

Results from the sketch map tests point to an uneven benefit from augmented instructions. People of lower spatial aptitude improved in performance disproportionally than people of higher spatial ability while at the same, spatial learning actually decreased for people of higher spatial abilities. This is an interesting finding, and could be explained by people of higher spatial aptitude relying less on the directions and trusting instead their own cognitive processes. People on the other spectrum however, are more reliant on the system to complement their own cognitive processes with the additional information. This is consistent with finding from other researchers (Ishikawa et al, 2008). It is interesting to observe this pattern with the prototype. Greater sample size and machines with more advanced personalization algorithms can perhaps further validate this finding. The results of this study suggests that augmented instructions can make people with high SOD more *passive* while making people of poor SOD more *active* in their wayfinding tasks. This perhaps can affect how people view augmented instructions and hold implications for the adoption of augmented reality.

4.7 Conclusion and Future Directions

A novel approach is presented to determine difficult to navigate spots for people of varying spatial abilities while creating personalized models for individual users. This is an important step for creating efficient individualized navigation systems using landmark, topological features and behavioral data that is easily computable from readily available crowd sourced data. The weights calculated for each individual attest to our uniqueness and stresses the need to recognize our fundamental differences in wayfinding tendencies. As with all models, it is not perfect, while there is room for improvement, the proposed method will be a useful addition to existing methods to compute salience for various features. Many existing methods use heuristically or arbitrarily predetermined weights, the weights used in this study are derived from actual data, an important step for making the system more responsive and dynamic. Other data that can be incorporated into the system, including more complex data about human behavior, past travel experiences, information about landmarks, topological information, traffic, and surveillance data - all represented in the structure of a spatial database. The following is a rudimentary concept of combined data derived from these weights, a very basic information product that aggregates some of the findings of the study. This map can be used to highlight decision points that are difficult for wayfinders of certain characteristics, a similar purpose as presented in the previous chapter.

The decision point difficulty map (Figure 4.5) demonstrates the concept of aggregating the weights at each decision point. Such a map shows potential difficult spots for certain group of wayfinders. Decision point difficulty analysis can be expanded to metropolitan level with the availability of larger datasets. Potential data sources include telecom data or movement data from social media platforms such as Wechat. Finding specific difficult decision points or various hotspots in an urban environment may have particular usefulness for special groups such as the elderly, children and foreigners in their daily lives and travels. From understanding the user on a personal level to identifying difficult spot on urban sized implementation, there are many potential economic and social implications to such a design.

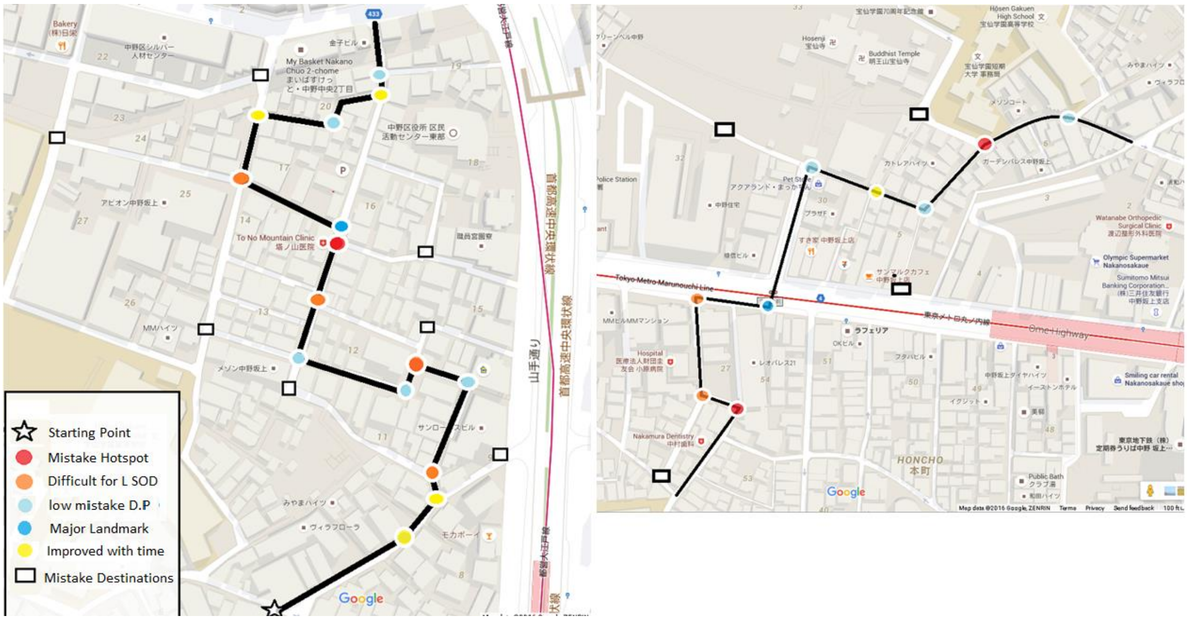

Figure 4.5. This map is an example of a decision point difficulty map that aggregates the findings of the study. The map highlights decision point with particular difficulties for certain groups. This information product can potentially give useful insights to the decision points in this study.

Constructing salience models of navigation is an important step toward personalization of GIS and adoption of its functions for individual users. There have been many suggestions in the improvement in the personalization of GIS, predominantly through additional information and profiles stored in a relational SQL database. Aoidh et al., (2012) proposed an implicit approach for personalizing mobile GIS to suit user preference and needs. The approach is based on generating an individual user profile containing information related to user movement and preferences. In this system, user preferences are extracted implicitly through interactions of the user with system. McArdle et al., (2010) proposed an approach for recommending personalized content to the user. The approach creates two types of profiles: personal profiles and region-based profiles, which are combined to personalize the content of the GIS according to the users' needs and interests. This study set the basis for personalized navigation system design by delineating the relationship between improvement in performance and personal and environmental characteristics of the user. The weights of the models can be viewed as precursor "profiles" of users that can fit into the vision of these authors. Such a profile can be integrated into existing GIS to improve its functionality while trending GIS towards a more personal direction.

Finally, this data driven approach has the potential to offer a more complete and accurate classification of individual navigation behavior and cognitive process. Such a system can serve as a complementary tool to established method of Santa Barbara sense of direction survey in cognitive research. This approach can give more empirically based ratings of individuals to provide valuable insights to both research and industry.

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CHAPTER 5

CONCLUSIONS

5.1 Summary of Dissertation Research

Wayfinding research typically emphasizes either the user (Hegarty et al 2002; Schinazi & Epstein 2010) or the environment (Hillier & Hanson, 1984, Penn, 2003). User centered research focuses on the influence of individuals (such as self-reported spatial ability, well-being, experience (Hegarty et al., 2002) and group differences such as culture (Levinson 1999; Mainwaring et al., 2009), and factors on the choices made during wayfinding (Schinazi et al., 2010). Navigation is an intrinsically complex process involving constant interplay between individual cognitive functions and environmental features.

This dissertation aims to understand the dynamics of people of varying spatial ability interacting with the environment, and how specific tendencies differ between people of high versus low spatial aptitude. This dissertation offers relatable examples of difficulties in everyday life faced by pedestrian navigation. The major findings and contributions are summarized as follows:

Chapter two presented a novel experimental design to explore the dynamics of collaborative navigation, a common but under-studied phenomenon. The results from this study differ with many previous studies. Ishikawa et al. (2008) showed that people of varying spatial abilities use different landmarks during navigation. Forlizzi, Barley, & Seder (2010) looked at how a person in the passenger seat interacted with a driver in providing navigational directions collaboratively toward a destination, in an automobile. Reilly et al. (2009) looked at how pairs of travelers collaborate in navigating toward destinations together, by sharing a single cellphone and consulting information shown on it with continuous role reversals. Previous studies used similar experimental setups, revealing different aspects of wayfinding behavior.

This study combines quantitative and qualitative methods to understand the underlying cognitive and communication processes during shared navigation tasks. The difficulties demonstrated in the interaction elucidate the discrepancies between users of varying spatial aptitudes that previously has been overlooked. One prominent finding is that a pair in which both individuals had low spatial ability outperformed groups with high and low spatial ability pairing. Time increases were found to be statistically correlated with increased difference in score between group members. Through close examination of conversation and user behavior, reasons for this emerged.

People of lower spatial ability were discovered to use less salient landmarks in their navigation strategy and tended to make more mistakes at decision points that have prominent landmarks. People of lower spatial abilities not only use less salient landmarks, but also employ more ephemeral landmarks and non-conventional landmarks. In addition, people of lower spatial ability rely on the strategy of “let’s go until we find it” when faced with difficult decision points. These users tend to simply keep going when lost until they find the next recognizable decision point. These tendencies make it difficult for people of varying spatial aptitudes to effectively communicate.

People of higher spatial ability, in contrast, use more conventional landmarks plus the strategy of retracing their steps to reprocessing the environment spatially. Pairing of two high spatial ability people demonstrated the greatest efficiency and least amount of spatial communication. This is consistent with the model proposed by (Wen et al. 2011). Thoroughly examining the involvement of the three different components of working memory in the acquisition of three types of spatial knowledge, in relation to participants' SOD, showed that people with a good SOD encoded landmarks and routes primarily verbally and spatially, and were able to integrate knowledge about them into survey knowledge with the support of all three components of working memory. In contrast, people with a poor SOD encoded landmarks only verbally, not spatially and tended to rely on the visual component of working memory in the processing of route knowledge, thus failing to acquire survey knowledge. Gender differences also contributed to differences in strategy. Different partner parings demonstrated improvement in efficiency is some of the users who were able to adapt their strategy to the perceived ability of their partners.

Chapter three builds on the same empirical experiment and dataset as chapter two. This study centers around the question - how can we predict where people are likely to make mistakes on a route and offer them additional directions, in advance, in these places? Salience of decision points influence wayfinding task efficiency. Likely salience levels can be determined by computational methods. Computational salience was first defined as the importance of decision points for classifying wayfinders with respect to their and individual differences (Takemiya et al., 2012). Chapter three builds on the previous work by Takemiya & Ishikawa testing the validity of these methods using the empirical dataset from real world navigators.

Computational methods involve analyzing thousands of randomly generated routes. Some established methods are examined in this study. The methods include: traversal probability, entropy difference, PageRank, degree centrality, closeness centrality, and betweenness centrality. The concepts of outlink and outflux scores - meta-algorithms that combine the features of the previous methods with clustering and linking effects based on the graphical nature of the routes - are novel computational methods pertinent to measuring wayfinding performance. Ouflux and outlink scores are combined with each of the established methods for calculating the likelihood of mistakes prior to navigation. Meta-algorithms derived secondary scores are compared with the original metrics of computational saliences. The ouflux score measures regions of similar salience values, while outlink scoring highlights the effects of the previous decision point outcomes on the decision point in question.

PageRank has been a widely used method in network analysis, partially due to its popularity as the Google Search Engine algorithm. One important finding of the research is that the outlink entropy difference and outlink probability correlate more strongly to actual user error, and thus is a more effective measurements than original metrics such as PageRank for wayfinding applications. These two meta-algorithms, which intuitively takes into account changing user behavior during navigation in complex environments is thus an improvement over existing metrics. These two meta-algorithms take into account not just the decision points themselves, but the overall relationships to the surrounding area enclosing the overall route. In other words, decision points alone do not account for overall wayfinding performance. Successively difficult decision points, or the clustering of difficult decision points, leads to greater cognitive load on the users. Being able to identify these spots through computational means gives more information about a route not visible through human observation alone. The finding that outlink entropy difference and outlink probability were 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.

The approaches tested can be practically implementable for real-time navigational aids, such as location-based services offered in cell phone applications. Calculating the computational salience of a decision point can help navigational algorithms detect where users are most likely to make mistakes. These points of difficulty can be enhanced to a degree dictated by the performance class of wayfinders, allowing assistance to be rendered effectively. Computationally salient points can be used to improve a user's configurational knowledge of the routes traveled.

Computational methods can be used to predict navigational without actual data, but real data should also be included to rank decision points effectively. Machine learning can be used to classify and understand the structural features of an environment, and rank the decision points on a route. Chapter four applies machine learning support vector machine (SVM) ranking methods to derive individual weights for the users based on their performance while ranking the decision points. Machine learning has gained major traction in the last decade in learning human behavior and environmental cues, in applicable fields such as Robotic design (Breazeal et al., 2009), learning driving patterns (Mitrovic et al., 2001), and image recognition (Liu et al., 2012). This study applies machine learning methods to analyze spatial tasks in order to further understand the effects of various features of the environment on pedestrian navigation. SVM^{rank} method can be adopted to understand user behavior and improve direction generation. In ranking decision points on a route, pairwise method is used to determine the most difficult decision points for the user. Metrics show that such an approach works more effectively for individuals than for groups, as evidenced by the lack of improvement with increased training size. The second useful feature of SVM^{rank} is the ability to derive unique weights for individuals' characteristics that are similar to "profiles" for individual navigators. The weights can potentially be used to complement existing Santa Barbara sense of direction surveys in differentiating wayfinders. For example, the weights of user A show that he or she is more like to make mistakes at decision points with certain features such as far from previous decision point and less likely to make mistakes at decision points with another feature such as having less than 4 nodes. The weights in the models show glimpses of tendencies for some individual users in particular spatial ability groups. Time was a significant parameter for people of high spatial abilities. Decision points with characteristics of large distances to next decision point and having four nodes caused problems for middle low spatial ability individuals. People of lowest spatial ability had the highest weight at decision points with three arcs and long distance to previous decision point. These tendencies can be taken into consideration and further research with larger sample size can be conducted to validate these findings.

In addition to analysis of empirical data, this dissertation designed and tested a prototype in the same neighborhood in Tokyo Japan. The prototype offered additional instructions at decision points. The prototype demonstrated improvement in navigational efficiency and survey knowledge acquisition for certain spatial ability groups. The results from the prototype show that low spatial aptitude groups benefit more from enhanced navigation features. This is intuitive and expected. People who need assistance will naturally reach out and use more navigation aids, and having a lower baseline performance also means greater yields in improvement. What is important from the prototype testing is that people of lower spatial ability improved their spatial learning, as demonstrated by analysis of sketch tests, while high aptitude people decreased their spatial learning. The research demonstrates that augmented directions during the navigation process can influence wayfinding by making people of higher spatial ability more passive while making people of lower spatial ability more active. This study showed great promise in using augmented instructions - this is important in designing such systems to improve spatial learning. Applying these advantages to teaching spatial reasoning in children is a concept worth further investigation.

In summary, this dissertation showed that people of varying spatial abilities navigate differently in the real world. Wayfinding is not only determined by landmarks and turns, but by the structure of the environment, the density of decision points, and the proximity of difficult decision points to each other. Individual models can be created and refined to generate predictive information, creating profiles for personalized navigation systems. Using augmented instructions at decision points can improve navigation, low spatial groups can benefit while people of high spatial ability may find their abilities attenuated. There are many suggestions from this dissertation that can be applied to future research to improve navigation guidance systems.

5.2 Future Research Directions

5.2.1 Limitations

It is important to address some limitations in these studies. For the study presented in chapter two, a primary limitation is the small sample size. 44 participants were recruited and divided into 22 groups. Being an empirical study, with the nature of the study requiring simultaneous pairing of participants, and having two experimenters present - the logistics to complete such a study design in a foreign country in a limited time span required an extraordinary amount of effort and planning. Fortunately, the study yielded useful results that serve as the foundation of this dissertation. The population investigated was diverse while satisfying the English fluency and non-Japanese requirements. Future experiments should address the limitation of sample size by maintaining a similar design but with a larger and more diverse sample. Conducting experiments of this type can generate important contributions in the field of cognitive geography. The initial publication of our experiment influenced others to subsequently setup additional novel experiments.

Chapter three measures computational salience and uses outlink entropy and outlink probability to predict the prominence of decision points. Sample size is again a limitation particularly when it is used to validate large computationally generated datasets. The main limitation in chapter three is the limited number of features for n-dimensional training. Structural prominence has been shown to exhibit great influence in the performance of users on routes during navigation tasks (Frankenstein et al., 2010). If more information can be derived from physical features of landmarks, the training and modeling could be more interesting and insightful. The next step should be to incorporate the learned models in our pedestrian navigation system, and test new situations with more participants.

5.2.2 Future Research Extensions

This dissertation research serves as the starting point for investigating individual mobility habits in order to improve pedestrian navigation models. Personally, I have many follow-up questions that can be extended from this study, as I am sure readers will as well. I have listed some possible follow-up questions.

Spatial language: which aspects of spatial language lead to improved spatial performance; what types of instructions are more useful for certain groups in certain contexts?

Spatial cognition: can people of higher spatial abilities benefit from enhanced navigation systems, or are they already near the peak performance possible?

Urban geography: what road design and ordering of landmarks affects pedestrian navigation in urban environments? Can urban design be improved based on these concepts?

Database design: what is a more effective way for a machine to interactively communicate spatial information for people of lower spatial ability? How to specifically mirror the designs proposed in this dissertation, to increase the interactive nature of navigation systems.

Spatial learning: is it possible to incorporate spatial learning activities into navigation aids particularly for children using these systems?

The most natural extension of this work, in addition to more empirical studies and larger populations, is to apply the findings in the design of navigation and GIS databases. Future work should expand the use of probabilities and entropy to consider mutual information between decision points. Future implementations also should strive 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. The effect of this on both collaborative and individual wayfinding efficiency should be validated empirically on a continuing basis.

The insight and data gathered from the prototype can be aggregated for improvement in transportation, tourism and urban planning. Decision point difficulty analysis that aggregate difficult spots will identify otherwise unnoticeable difficult spots in transportation and daily activities. Gathering where people tend to linger for longer periods of time will have economic implications for store location and advertising. Better signage and understanding of the urban landscape will also result from its use.

In the process of this research, I have noticed in my daily travels that large landmarks in an urban space often do not serve an optimal purpose in guidance. For example, if the landmark is very large and prominent, it helps to guide a person in getting there, but does not always help guiding a person in a closer environment. Although the landmark can be highly visually salient, it is harder to be integrated into a mental map. Imagine trying to fit a giant puzzle piece (the landmark) to fit with a bunch of smaller ones. Large landmarks can take up multiple places at once, making it difficult to mentally orient. This study placed great emphasis on landmarks, it is worth considering that size does not necessarily mean greater salience and value for spatial knowledge acquisition, rather, specificity and context that holds greater importance. This is something worth considering in future research.

Another important issue is the actual use of navigation aids in spatial learning of humans. While navigation aids are improving navigational efficiency, an often overlooked consequence of our growing reliance on navigation technology is that it decreases environmental awareness and spatial learning for the users (Ishikawa et al., 2012). Spatial learning is not only important for navigation, but spatial thinking has been shown to helps us structure, integrate, and recall ideas. Spatial thinking is a fundamental life-long skill important in various branches of science and engineering and in everyday life (Newcombe, 2010). Active navigation is perhaps one of the best incubators of that ability. Various studies have shown negative effects on spatial learning by overreliance on technology, particularly for young children. Ishikawa et al. 2012 has demonstrated that contemporary GPS devices actually decreased wayfinders' configurational knowledge of travelled routes, while increasing the time and distance required to traverse. Other existing research agrees that guided navigation impairs spatial memory (Aporta and Higgs, 2005), and that reliance on guidance technology can make it difficult for wayfinders to be self-reliant in situations where navigational aids cannot be used (Parush et al., 2007). Girardin & Blat, (2010) cited decreased environmental engagement while other cognitive researchers implicated lack of active investment in terms of mental effort and control (Parush et al., 2007, Peruch and Wilson, 2004), and divided attention (Fenech et al., 2010), as other effects. An important step to improve spatial learning while continuing to improve navigational efficiency is an increase in engagement between system and user.

It is important to lessen our total reliance on navigation systems, which should offer help when needed. **Future research should emphasize the importance of spatial learning and acquisition of spatial ability. Geographical education should be designed not only to imbue technical skills and knowledge, but to develop spatial logic and thinking.** An optimized system catering to the individual user will have that effect and its application should be considered in the future, giving the user a chance to learn from the environment while improving spatial cognitive abilities.

Another area of focus should be navigation system design that considers not only the shortest route but the most effective route. There exists significant differences between perceived benefits and actual use of information technology. Nielsen and Levy (1994) have highlighted that the perceived usability does not always correlate with actual efficiency of an information technology. Moreover, Frøkjær et al. (2000) have found that usability has a complex dependency on efficiency, effectiveness, and satisfaction. It is common for pedestrians to select the "optimal" paths by considering multiple criteria, such as safety, traffic, weather, season, levels of noise, and accessibility, but contemporary digital maps only account for the "shortest" distance path (Armeni et al., 2013). Future research that takes human cognitive factors into consideration, that further classify human behavior, spatial ability and additional aspects of landmarks in the real environment can lend to increased criteria that will allow for human-centric "happiest", "safest", and "most useful" routes. In order for this to happen, one must determine what is ideally happy or efficient on a user level. This dissertation sets the foundation for such an approach and provides methods that can derive metrics for such a system.

I wish my findings can be applied in future development of responsive and intelligent personalized systems. This study demonstrates that available data can be applied in a relatively simple, quick and useful manner to these ends. Many approaches can be taken to improve navigational efficiency, travel experience, and spatial learning. The implementation of such concepts will be an important step in upgrading navigation systems from a general guidance system to a personalized decision system.

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APPENDIX

Appendix 1. Santa Barbara Sense of Direction Survey

Sex: F M
Age:_______

Today's Date:_______________
V. 2

This questionnaire consists of several statements about your spatial and navigational abilities, preferences, and experiences. After each statement, you should circle a number to indicate your level of agreement with the statement. Circle "1" if you strongly agree that the statement applies to you, "7" if you strongly disagree, or some number in between if your agreement is intermediate. Circle "4" if you neither agree nor disagree.

1. I am very good at giving directions.

    strongly agree 1 2 3 4 5 6 7 strongly disagree

2. I have a poor memory for where I left things.

    strongly agree 1 2 3 4 5 6 7 strongly disagree

3. I am very good at judging distances.

    strongly agree 1 2 3 4 5 6 7 strongly disagree

4. My "sense of direction" is very good.

    strongly agree 1 2 3 4 5 6 7 strongly disagree

5. I tend to think of my environment in terms of cardinal directions (N, S, E, W).

    strongly agree 1 2 3 4 5 6 7 strongly disagree

6. I very easily get lost in a new city.

    strongly agree 1 2 3 4 5 6 7 strongly disagree

7. I enjoy reading maps.

strongly agree 1 2 3 4 5 6 7 strongly disagree

8. I have trouble understanding directions.

strongly agree 1 2 3 4 5 6 7 strongly disagree

9. I am very good at reading maps.

strongly agree 1 2 3 4 5 6 7 strongly disagree

10. I don't remember routes very well while riding as a passenger in a car.

strongly agree 1 2 3 4 5 6 7 strongly disagree

11. I don't enjoy giving directions.

strongly agree 1 2 3 4 5 6 7 strongly disagree

12. It's not important to me to know where I am.

strongly agree 1 2 3 4 5 6 7 strongly disagree

13. I usually let someone else do the navigational planning for long trips.

strongly agree 1 2 3 4 5 6 7 strongly disagree

14. I can usually remember a new route after I have traveled it only once.

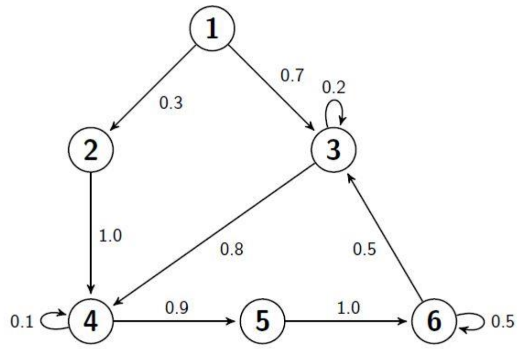
strongly agree 1 2 3 4 5 6 7 strongly disagree

15. I don't have a very good "mental map" of my environment.

strongly agree 1 2 3 4 5 6 7 strongly disagree

Appendix 2. Examples of computational methods used in Chapter 3

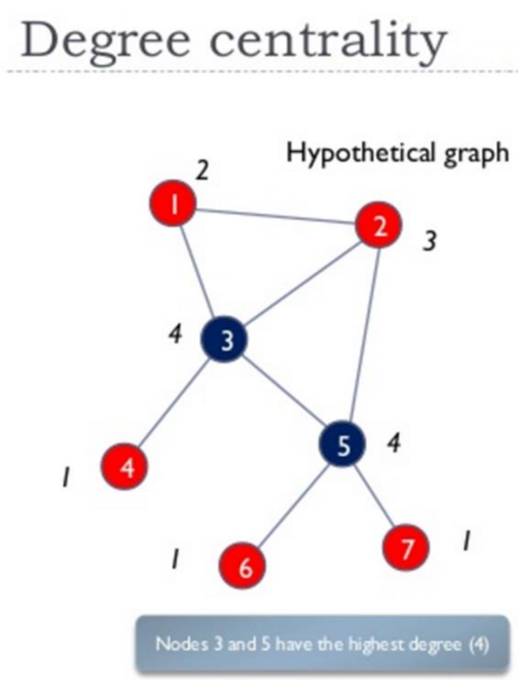
Traversal Probability: How statistically likely someone is to traverse a certain decision point on route.



Degree Centrality:

A node’s in and out degree measure the number of in and out nodes that comes out of each link.

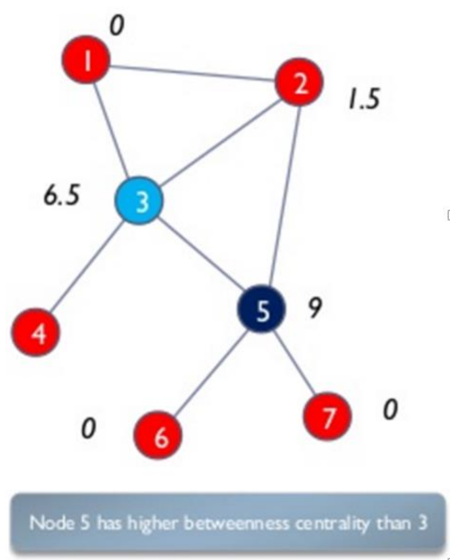
Degree Centrality Measures the number of direct neighbors at each decision point. It is useful in assessing which nodes are central in the spread of information.



Betweenness Centrality:

Betweenness centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes.

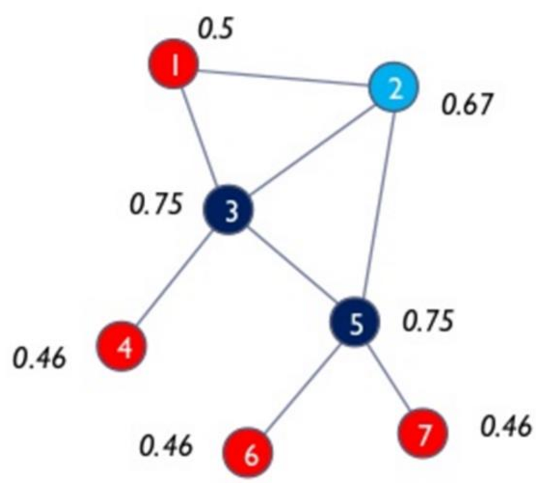
Example Betweeness Centrality graph:



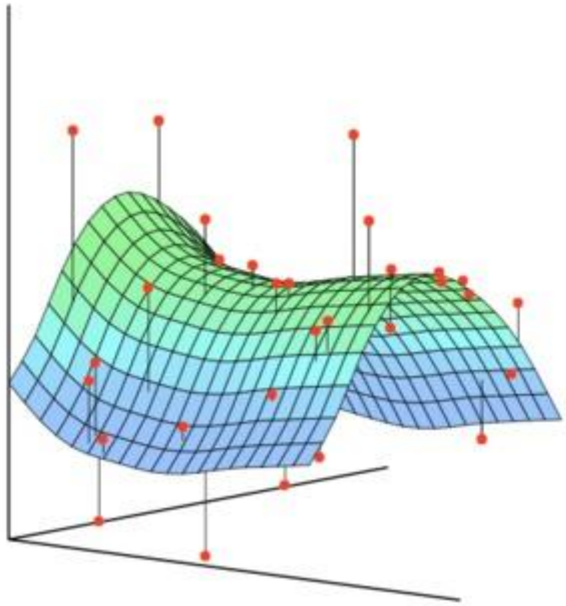
Closeness Centrality:

Closeness Centrality measures the average length of the shortest path between the node and all other nodes in the graph. It is a measure of reach – how fast information can reach other nodes from existing nodes.

Example Closeness Centrality Graph:



Appendix 3. Explanation of SVMrank algorithm



SVM*rank* learns an unbiased linear classification rule (i.e. a rule `w*x` without explicit threshold). The loss function to be optimized is selected using the '-l' option. Loss function '1' is identical to the one used in the ranking mode of SVM*light*, and it optimizes the total number of swapped pairs. Loss function '2' is a normalized version of '1'. For each query, it divides the number of swapped pairs by the maximum number of possibly swapped pairs for that query.

VITA

Gengen Friday He was born in Beijing China, grew up in Washington DC and Shanghai, China.

Mr. He graduated from Georgetown University in 2006 with Bachelors of Science in Biology and 2007 with Masters of Science in Microbiology.

Gengen has lived in China, USA, France, Peru and Japan. He received a National Science Foundation and Japan Society for the Promotion of Science EAPSI fellowship, enabling him to conduct a majority of his research at the University of Tokyo in Japan. He worked for Esri Inc. in International Sales for three years while completing this dissertation on human cognition and navigation.

He entered the Geography department at the University of Tennessee, Knoxville in 2012 where he completed his Doctoral of Philosophy degree in May 2017. He has been active in publishing papers in peer-reviewed journals (e.g., *Spatial Cognition and Computation, International Journal of Computational Biology*) and delivering presentations at professional conferences. His research interests include geographic information sciences, spatial cognition, navigation, and indoor mapping.

At the time of completion of this paper, he is employed as Assistant Professor of Geography at the University of Nottingham in Ningbo, China.