Proceedings of the 2019 Winter Simulation Conference
Y. Shi, J. Du; C. Szabo, P. Haas, and Y-J. Son, eds.

SIMULATION OF SPATIAL MEMORY FOR HUMAN NAVIGATION BASED ON VISUAL ATTENTION IN FLOORPLAN REVIEW

Yangming Shi

Department of Civil and Coastal Engineering
University of Florida
1949 Stadium Road Weil Hall 454
Gainesville, FL 32611, USA

Jing Du, Ph.D.

Department of Civil and Coastal Engineering
University of Florida
1949 Stadium Road Weil Hall 460F
Gainesville, FL 32611, USA

ABSTRACT

Human navigation simulation is critical to many civil engineering tasks and is of central interest to the simulation community. Most human navigation simulation approaches focus on the classic psychology evidence, or assumptions that still need further proofs. The overly simplified and generalized assumption of navigation behaviors does not highlight the need of capturing individual differences in spatial cognition and navigation decision-making, or the impacts of diverse ways of spatial information display. This study proposes the visual attention patterns in floorplan review to be a stronger predictor of human navigation behaviors. To set the theoretical foundation, a Virtual Reality (VR) experiment was performed to test if visual attention patterns during spatial information review can predict the quality of spatial memory, and how the relationship is affected by the diverse ways of information display, including 2D, 3D and VR. The results set a basis for future prediction model developments.

1 INTRODUCTION

Understanding and modeling human navigation behaviors, i.e., the cognitive process of monitoring the surrounding environment and making decisions to move from one point to the destination (Loomis et al. 1999), is critical to many civil engineering tasks, such as building inspection (Shi, Du, Tang, et al. 2018), construction worker logistics (Feng et al. 2013), jobsite management and emergency wayfinding in hazardous situations (Du et al. 2019). The Agent-based Modeling (ABM) literature has also presented a long-lasting interest in simulating human navigation (Lamarche and Donikian 2004; Bohannon 2005; Guy et al. 2010; Vemula et al. 2017). Nonetheless, most existing methods of human navigation simulation are based on limited evidence from early psychology literature, or assumptions that still need further proofs. Representative assumptions include shortest path assumption (i.e., assuming that humans always select the shortest path) (Helic et al. 2013), collider assumption (i.e., modeling human agents as repulsive particles) (Zarrinmehr et al. 2013), and hazard avoidance (i.e., assuming that human agents know and can avoid hazards) (Gelenbe and Wu 2012). Although effective, this simplified approach of human navigation behavioral modeling brings two potential problems. First, it does not highlight the need of capturing individual differences in wayfinding and navigation decision-making. Humans rely on different types of spatial knowledge (e.g., frames of reference, route knowledge and survey knowledge or cognitive map) in navigation tasks, and the strategy of encoding and decoding spatial knowledge is significantly different across different people. For example, evidence shows that females tend to focus on landmarks in navigation while males tend to build an overall cognitive map of the entire space (Sandstrom et al. 1998). Second, a generalized assumption of human navigation behaviors does not take the task context into account. When assigned with different tasks, it is reasonable that the specific navigation behavior demonstrated by a person will be changing. For example, in a building inspection task, test subjects may focus more on points of interest (POIs) since they are related to identifying discrepancies between design and as-built structures (Shi, Du, Tang, et al. 2018); while in an emergency wayfinding task, test subjects may focus more on route knowledge since finding ways in retract in critical to the success of the task (Vilar et al. 2013). As a result, there is a remaining need to explore a data-driven, evidence-based prediction model of human navigation behaviors for relevant simulation studies.

In this study, we propose that the visual attention patterns in building floorplan review, is a stronger predictor of human navigation behaviors. We also recognize the need of testing various building information display methods that are popular in today's practice, including 2D drawing (a more traditional one), 3D interactive models (such as Building Information Modeling), and emerging Virtual Reality (VR). It is admitted that given the complexity of human cognition and behaviors, it is difficult to solve all the prediction problems in a single study. As a result, this study will only focus on the foundational mechanisms in which visual attention data (encoding information) is translated into the key cognitive process of navigation, including memorizing the frames of references. As a result, we will test two important hypotheses:

> *H1: Visual attention patterns in building floorplan review is a strong predictor of the likelihood of correctly memorizing frames of reference.*
>
> *H2: Information display methods affects the relationship between visual patterns and spatial memory.*

In the remainder of this paper we will introduce a VR experiment we performed to test the hypotheses.

2 THEORETICAL BACKGROUND ABOUT HUMAN NAVIGATION

2.1 Spatial Memory and Navigation

In this research we focus on the navigation scenarios based on spatial memory, i.e., navigating in an unfamiliar space based on the memorized information about the space. Numerous studies have been done to investigate the development of spatial memory in built environments. Topics include gender difference (Duff and Hampson 2001; Tlauka et al. 2005), age difference (Reuter-Lorenz et al. 2000; Nagel et al. 2009), relationship between wayfinding and navigation performance (Werner et al. 1997; Richardson et al. 1999), and wayfinding training (Bliss et al. 1997; Waller et al. 1998). Meanwhile, many scholars, such as Goldin and Thorndyke (1982); Werner et al. (1997); van Asselen et al. (2006) found that humans usually rely on different spatial cues to develop an effective spatial memory, such as landmarks, moving routes, and survey knowledge or cognitive map of a space (Siegel and White 1975). These ways of spatial memory development ultimately affect navigation performance, which are measured as distance and orientations (Thorndyke and Hayes-Roth 1982; Richardson et al. 1999; Ishikawa and Montello 2006; Verghote et al. 2019), hand-draw sketch maps (Devlin 1976; Golledge et al. 1985; Jansen et al. 2009), and quantitative deviation metrics such as Santa Barbara Sense-of-Direction (SBSOD) (Hegarty et al. 2002). Although the previous works have set a solid theoretical foundation about contributing factors (gender, age, environmental cues Etc.) to spatial memory, and further, to the final navigation performance, it still remains unclear if an effective prediction model of navigation performance can be achieved; and if so, what the predictors are. Furthermore, with the fast development of computing and visualization techniques, emerging visualization techniques such as BIM, and Virtual Reality (VR) and Augmented Reality (AR) are popular in current practices into the buildings and construction projects. It requires more direct evidence about how humans acquire spatial information/knowledge, and how it is affected by the review of spatial information.

2.2 Information Format and Spatial Memory

Amid the fast development of information technologies, diverse ways of spatial information display are introduced to instruct navigation activities, such as verbal instructions, traditional 2D maps, 3D models, and advanced VR/AR technologies. However, the impact of these visual representations on human spatial cognition is still not fully understood, and as a result, literature tends to present conflicting findings. Some researchers found that the emerging visualization technologies improve navigation performance (Dadi, Goodrum, Taylor, and Carswell 2014; Dadi, Goodrum, Taylor, and Maloney 2014; Sweany et al. 2016), possibly due to the additional information captured by the semantically-rich presentations. Dünser et al.

(2006) conducted a large-scale study (215 students) to investigate the potential of VR/AR applications to improve spatial ability. They found that VR/AR techniques were effective to improve spatial ability. Meanwhile, the addition of visual display features such as stereoscopic visuals and head-tracked viewing have been shown to significantly improve people's ability to identify gaps or follow connection of visual geometry (Bacim et al. 2013; Ragan et al. 2013). Evidence has also shown that VR displays can improve the memory of steps in arranging 3D objects in spatial layout (Ragan et al. 2010) or remembering spatially distributed information (Ragan et al. 2012), suggesting that VR can reduce the strain on spatial memory to improve navigation performance on spatial tasks. Verghote et al. (2019) compared the impact of 2D drawing and 3D model on in-door wayfinding performance. They found 3D models have a beneficial impact on individual's wayfinding performance compared to the traditional 2D drawings. In contrast, increasing evidence also indicates that 3D or VR visual representations are not better than traditional 2D drawings in certain situations, due to the cognitive burden to process additional information such as texture, color, orientations to the users that may overburden their brain (Bawden et al. 1999; Richardson et al. 1999; Eppler and Mengis 2004). For instance, Bliss et al. (1997) compared three different methods for navigation task in an unfamiliar building using 2D blueprint, VR, and no-training (control group). They found that subjects trained with VR and 2D blueprints performed better than those without training. However, there was no significant difference between VR and blueprint groups in the speed and accuracy of the navigation performance.

It must be admitted that the theoretical disagreement can make navigation behavioral simulation questionable. If a modeler considers simulating the navigation behaviors under different information stimuli (which is a common need in civil engineering research), the lack of widely accepted model will invalidate the simulation results. As an effort to resolve the disagreement, this study will test how the visual attention – spatial memory relationship (and further the spatial memory – navigation behavior relationship) is affected by the diverse ways of information display.

3 EXPERIMENT DESIGN

3.1 Eye Tracking as Visual Attention Analysis Instrument

In this study, we used eye tracking as the instrument for visual attention analysis. To realize eye tracking in 2D and 3D spatial information review, the Tobii eye tracker 4C mounted to the monitor was used. The accuracy of the Tobii eye tracker 4C is within a radius of 0.5 inches from the gaze positions recorded on the monitor (Bojko 2011) and the operating distance is 20 to 37 inch from the monitor (Tobii 2017). All gaze position and camera position data was recorded by the system at the frequency of 90 Hz. At the end of each experiment trial, the system automatically generated a CSV file with all data. A visualization function was also developed to playback users' gaze movements by reading the CSV file. This visualization function greatly helped us perform a holistic spatial statistical analysis. The data writing and playback functions were coded with the software developer's kit (SDK) provided by Tobii (Tobii 2018). For eye tracking in VR, an eye tracker embedded with the VR headset and the Raycast technique (Unity 2018) were utilized to record the three-axis gaze position data and camera position data. Raycast refers to an invisible ray shoots from the center of the eyeball and return three-axis vector value when it collides with the objects in the virtual environment (Craighead et al. 2008). This technique is widely implemented in the computer graphic area to study camera direction or rending path. It was realized with the application programming interface (API) provided by Unity. The Head-Mounted Display (HMD) of VR used in the experiment was Oculus Rift Consumer Version 1 (CV1) (Oculus 2016). The Field of View (FOV) of this HMD is 110 degrees in horizontal direction and 90 degrees in the vertical direction with the resolution of 2160 x 1200 pixels per eye for the dual displays (Hunt 2016). The eye tracking system was developed in the Unity 3D-5.6.3f1 version. The model used was the first floor of Francis Hall at Texas A&M University. The 2D floorplan was extracted from the original design document, and 3D and VR models were generated based on the building information model (BIM) of Francis Hall. The eye tracking system ran on a workstation that the CUP is Intel Xeon at 2.60GHz with a 64GB of RAM. The graphic card of the workstation is NVIDIA GTX 1080. Figure 1 shows the eye tracking system in different visual conditions.

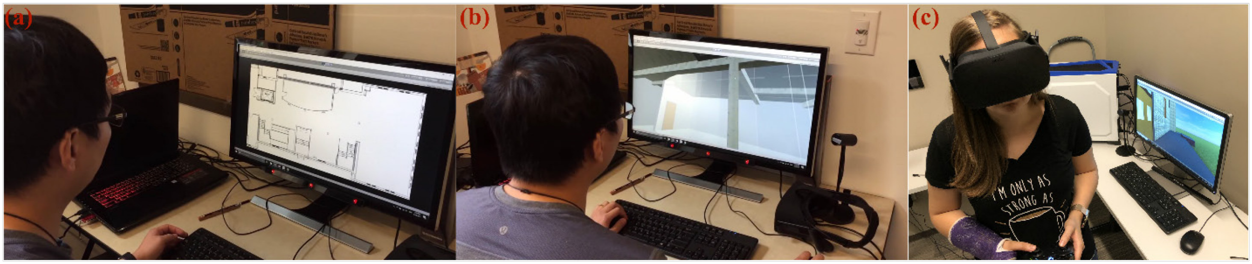

Figure 1. The eye tracking in different groups. (a) 2D eye tracking; (b) 3D eye tracking; (c) VR eye tracking

3.2 Experiment Procedure

The inclusion criteria of the experiment recruitment was that participants had never been to Francis Hall and they had basic knowledge of buildings. Participants were asked to review the floorplan or models provided by us at our lab. Then they were invited to the real building to identify and speak out the frames of reference (FORs, aka, Points of Interest, POIs) they remembered. We focus on FORs memory as the spatial memory indicator as literature shows FORs to be critical to human navigation behaviors (Nardini et al. 2008). With that said, we designed 28 FORs evenly distributed in the building (Figure 2). We collected participants' gaze movement data when they reviewed the building in 2D, 3D and VR formats, and their identification of memorized FORs later.

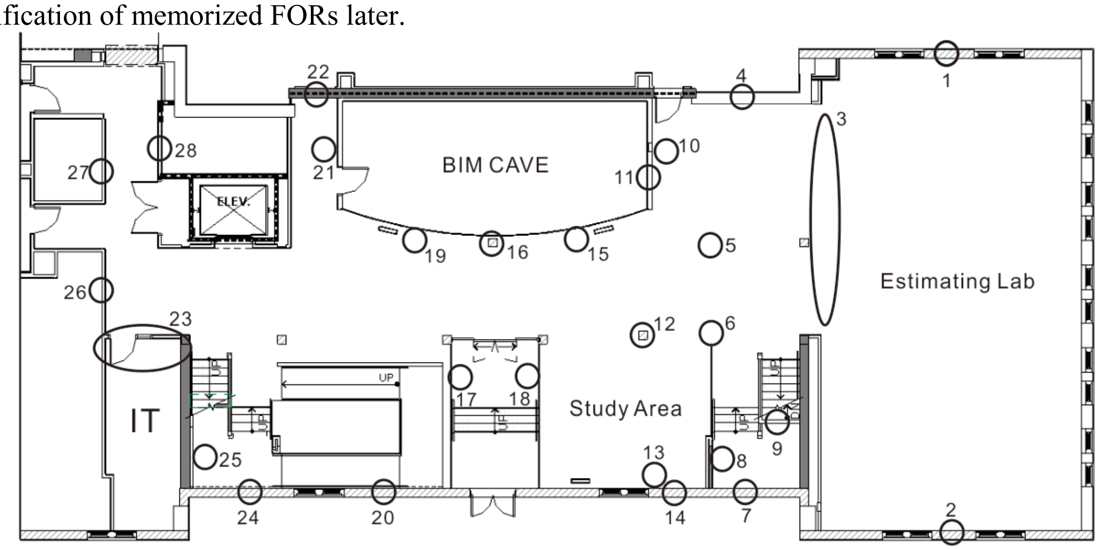

Figure 2. FORs (n=28) in the building

The experiment consisted of seven sessions: (1) pre-questionnaire, (2) cube test (spatial cognition ability test), (3) training session (to familiarize with the eye tracking systems), (4) review session, (5) plotting session (sketch memorized floorplans and details, will be reported in another paper), (6) real world navigation session, and (7) post-questionnaire and interview session. The pre-questionnaire session (5 to 10 minutes) was designed to collect participants' basic demographical information such as age, gender, major, degree level, and previous game and VR experience. The cube test (5 to 10 minutes) was used to evaluate participants' spatial cognition abilities and set a baseline of their navigation performance. Cube test is widely used in previous spatial cognition studies (Sweany et al. 2016; Verghote et al. 2019). The training session (5 to 10 minutes) was designed for participants to familiarize with the review devices, navigation functions, and the virtual environment. For the 3D group, participants were instructed to use a keyboard and mouse to navigate and change their field of view (FOV) when they interacted with the 3D model. For the VR group, participants were taught to utilize an Xbox game controller to control their navigation and use their physical body rotation to control their movement directions in the virtual environment. The review session (5 minutes) was used for participants to review and memorize the layout and details of the building. Participants were randomly assigned to one of the three groups depending on what information they were given (2D, 3D, and VR). Five minutes was limited for the review session as some participants may feel sickness (nausea, headache, dizziness, and light headed) for 10 minutes or more in the VR environment based on our previous studies (Du et al. 2016; Shi et al. 2016; Du, Shi, et al. 2017; Du, Zou, et al. 2017; Du et al. 2018; Shi, Du, Ragan, et al. 2018). The plotting session (5 minutes) was designed to evaluate how much the participants remembered based on their review in the general perspective. The participants were given a sheet with the outline of the building to plot the layout of the building. This is an effective way of testing the cognitive map of the test subjects, i.e., the mental model of the memorized space. After the plotting session, participants were immediately asked to navigate in the real building (15 minutes). The starting point of the inspection was the entrance of the building to be consistent with the experience in the 3D and VR reviews. During the experiment, we accompanied the participants to record the identifications of FORs so they can focus on their navigation task. At the end, participants were asked to fill out a post-questionnaire and provide comments and feedbacks. The post-questionnaire was designed to collect participants' feedbacks of using the system including ease of control, fun, presence, sickness, and attention. The entire experiment procedure took approximately 60 to 90 minutes for each participant. Figure 3 shows participants in different groups utilizing the system to review the building.

Figure 3. The participants were utilizing the system to review the building (2D, 3D, and VR groups respectively).

4 RESULTS AND DISCUSSIONS

A total of 63 participants (35 males, 28 females) took part in the study, including 10 undergraduate students and 53 graduate students. All the participants were recruited via the university emailing list. Participants' age ranged from 19 to 39, and the median age was 26. Their previous game and VR experience were also collected since these experiences could affect people's VR task performance (Enochsson et al. 2004). The participants reported their previous game and VR experiences on an 11-point Likert scale (0- no experience, 10-a lot of experience). The average game experience was 4.68, and the average VR experience was 2.79. The results indicate that most participants have similar level of game and VR experience, which should not affect our following analysis.

Based on the experiment data, we analyzed the relationship between visual fixation time on the FORs in the review session and the effectiveness of spatial memory. According to the previous eye-tracking studies, fixation is defined as a stale eye-in-head position within two-degree dispersion tolerance over 100 to 200 millisecond staring duration and fixation time is defined as the cumulative duration of fixation within a point of interest (Jacob and Karn 2003). It is a critical eye tracking metric that widely used in driving simulation (Shinoda et al. 2001; Caird et al. 2008), reviewing web pages (Buscher et al. 2009), and marketing (Khushaba et al. 2013). The review fixation time represents participants' visual attention on the each FOR. An algorithm of calculating gaze fixation for each FOR was developed to record the fixation time of each gaze point visit in the array. The Spearman correlation test indicates that there is a significant positive correlation between the review fixation time and the likelihood of participants correctly memorized that POI, as shown in Fig.4 (a) (rho=0.778, $p<0.001$)). It indicates that as a participant spends longer time in reviewing a certain FOR, the likelihood of correctly memorized it increases. It supports hypothesis 1.

This finding is also supported by existing cognition literature (Awh et al. 2000; Awh et al. 2006; Gazzaley and Nobre 2012). A prediction model was developed as:

$$M_{combined} = 0.000675t^2 + 0.03819t + 0.4514 \quad \ldots\text{Eq(1)}$$

Where $M_{combined}$ is the overall spatial memory indicator (percent memorized FORs), t is the fixation time. We then analyzed if the visual attention-spatial memory relationship is the same across the three visual conditions. We found that although in general spatial memory improved as review fixation time increased, the increasing rate was different across the three groups, suggesting that the visual format of display affects the visual attention-spatial memory development relationship. Hypothesis 2 is also supported. Figure 4 (b) shows the relationships between fixation time and the likelihoods of participants correctly memorized the FORs (or POIs) across three groups. The 2D group demonstrated the lowest learning efficiency (measured as the increasing rate), indicating that prolonging review time with 2D drawings has the least impact on the development of better spatial working memory. In contrast, the VR group showed the highest learning efficiency. As the review fixation time increased in the VR review, participants tended to develop better spatial working memory and the likelihood of memorizing the building components was significantly increased. While the 3D group was somewhere between the 2D and VR groups. Based on the experiment data, three models were developed for 2D, 3D and VR displays respectively:

$$M_{2D} = -0.000217t^2 + 0.02171t + 0.416 \quad \ldots\text{Eq(2)}$$
$$M_{3D} = -0.001655t^2 + 0.04143t + 0.5264 \quad \ldots\text{Eq(3)}$$
$$M_{VR} = -0.005234t^2 + 0.08825t + 0.4726 \quad \ldots\text{Eq(4)}$$

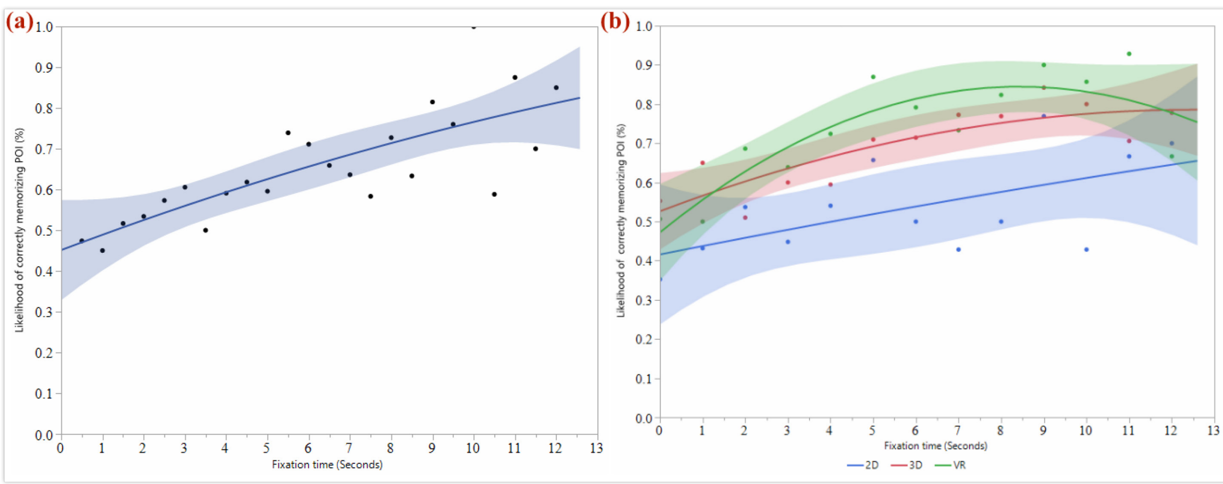

Figure 4. (a) The relationship between review fixation time and likelihood of correctly memorizing POIs (b) The relationships across three groups

We further found that the spatial memory has a direct impact on the navigation patterns of test subjects. Figure 5 (a) shows the aggregated view of the navigation trajectories of 63 participants (red lines indicate navigation trajectories; blue dots show gaze focus points). Figure 5 (b) and (c) are the navigation trajectory of two subjects with distinct spatial memory performance. Specifically, the subject shown in Figure 5(b) memorized 82.14% of FORs, while the one shown in Figure 5(c) memorized 28.57% of FORs. A spatial statistics (PDMs, see Roduit et al. (2007) confirms that the two navigation trajectories are significantly different in space ($p<0.01$). We are currently working on a prediction model to describe the relationship between spatial memory and the spatial statistical features of the navigation patterns that will be reported later.

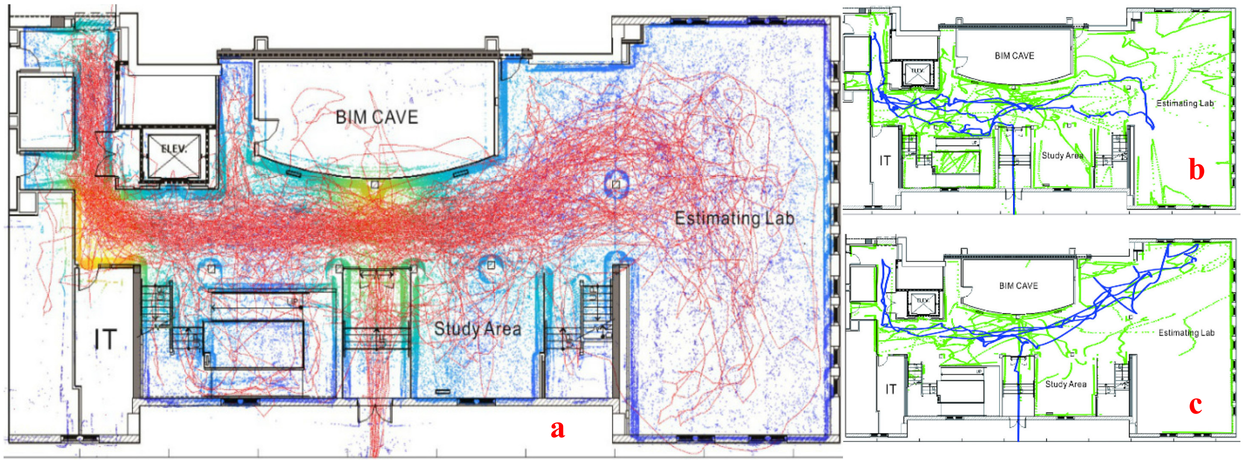

Figure 5. (a) Navigation trajectories and gaze points of test subjects (n=63); (b) navigation trajectory of a subject with more effective spatial memory (82.14%); (c) navigation trajectory of a subject with less effective spatial memory (28.57%).

5 CONCLUSIONS

Human Navigation modeling and simulation is important to the civil engineering literature, and the simulation literature in general. Understanding the fundamental cognitive process and behavioral rules of human spatial cognition, wayfinding, and navigation behaviors will help improve the validity of the relevant simulation studies. In this paper, we propose that visual attention patterns during building information review is a stronger predictor of human memory of key frames of reference, which later affects human navigation patterns in a less understood way. A VR experiment was performed to find out if the relationship between visual attention and spatial memory exists. A total of 63 students from Texas A&M University participated in the experiment, where their gaze data and movement data were collected with our system. Results indicate that there is a strong relationship between the visual fixation time on the 28 FORs and final spatial memory. The relationship was also affected by the specific spatial information they were given. We further found that there is a potential relationship between the spatial memory and the spatial statistical features of the navigation patterns, which is current under our investigation. This study is expected to contribute the navigation simulation literature by providing fundamental models and evidence about the impact if visual attention and information format on human navigation behaviors.

ACKNOWLEDGMENTS

The authors would like to acknowledge Shyam Prathish Sargunam, senior software engineer from Autodesk and Dr. Eric Ragan, Assistant Professor from the Department of Computer & Information Science & Engineering (CISE) at the University of Florida for helping us improve the system. This material is supported by the National Science Foundation (NSF) under Grants1761459 and 1761950, as well as National Institute of Standards and Technology (NIST) under Grant 60NANB18D152. Any opinions, findings, conclusions, or recommendations expressed in this article are those of the authors and do not reflect the views of the NSF and NIST.

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AUTHOR BIOGRAPHIES

YANGMING SHI is a Ph.D. student in the Department of Civil and Coastal Engineering at University of Florida. He holds an M.S. in Construction Science from Texas A&M University. His research experiences focus on the development of next generation cognitive driven Intelligent Information Systems (IIS) for civil engineers and construction workers. His email address is shiyangming@ufl.edu.

JING DU is an Associate Professor in the Department of Civil and Coastal Engineering at University of Florida. He holds an M.S. in Enterprise Management from Tianjin University and a PhD in Construction Management from Michigan State University. His research experiences focus on the development and test of the next generation Intelligent Information Systems (IIS) and Intelligent Physical Systems (IPS) for the design, engineering, construction and operations of built environments. His email address is eric.du@essie.ufl.edu. His website is https://faculty.eng.ufl.edu/ericdu/.