Acquisition of Survey Knowledge using Walking in Place and Resetting Methods in Immersive Virtual Environments

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ABSTRACT

Locomotion in large virtual environments is currently unsupported in smartphone-powered virtual reality headsets, particularly within the confines of limited physical space. While motion controllers are a workaround for this issue, they exhibit known problems: they occupy the subject's hands, and they cause poor navigation performance. In this paper, we investigate three hands-free methods for navigating large virtual environments. The first method is resetting, a reorientation technique that allows for both translation and rotation body-based cues. The other two methods are walking in place techniques that use only rotation-based cues. In the first walking in place technique, we make use of the inertial measurement unit of the smartphone embedded in a Samsung Gear VR to detect when subjects are stepping. The second technique uses the Kinect's skeletal tracking for step detection. In this paper, we measure the survey component of spatial knowledge to assess three navigation conditions. Our metrics examine how well subjects gather and retain information from their environment, as well as how well they integrate it into a single model. We find that resetting leads to the strongest acquisition of survey knowledge, which we believe is due to the vestibular cues provided by this method.

CCS CONCEPTS

• **Human-centered computing → Virtual reality**;

KEYWORDS

Virtual reality, navigation, redirected walking, walking in place

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1 INTRODUCTION

Virtual reality (VR) provides engaging experiences and allows for training and simulation in a controllable environment. Virtual worlds, as with the real world, can differ vastly in size and scale. Large virtual environments, then, are necessary to provide analogs to large real-world environments. Exploring these large environments in smartphone-based VR systems (e.g., the Samsung Gear VR) introduces a difficult challenge. There is no native position tracking for these devices, which is disappointing, given the freedom they provide. The rendering and display systems of smartphone-based VR are entirely on-board, making the system tetherless. With the broad adoption of smartphones and the ease of acquiring a cheap housing unit (e.g., the Google cardboard [Google 2017]), smartphones provide an enticing platform for VR. In this paper we explore three naturalistic methods of navigating in large environments using smartphone-based VR systems: resetting [Williams et al. 2007] and two types of walking in place [Slater et al. 1995; Tregillus and Folmer 2016; Williams et al. 2011]. Resetting utilizes real walking and allows for unbounded space by reorienting subjects towards the center of the room when a boundary is encountered, all the while maintaining virtual heading. Walking in place induces translation based on a subject's stationary motion. This is, to our knowledge, the first evaluative study for spatial cognition using mobile VR and the first to utilize a real walking metaphor in mobile VR.

While many methods have been developed for navigation in large virtual environments [Engel et al. 2008; Interrante et al. 2007; Razzaque et al. 2001; Williams et al. 2007], the best method of doing so depends on many factors. These factors include room size and layout [Azmandian et al. 2017], technology, the virtual environment [Langbehn et al. 2017], performance metrics, etc. For example, if the room size is sufficiently large, then a redirected walking technique might be employed [Steinicke et al. 2008, 2010]; if the room size is small, however, some of these techniques can induce simulator sickness or require pre-computed trajectories, e.g., the methods of Langbehn et al. [2017]. If the environment is very large, then some method of locomotion beyond normal bipedal locomotion may be appropriate, e.g., the methods of Williams et al. [2007] or Interrante et al. [2007]. In this paper, we will consider some of these factors and make assumptions about others. In particular, for resetting, we assume a reasonably sized open room (roughly 4m x 4m) is available for the real world enclosing space, and that the virtual environment is easily navigable by ordinary locomotion. Walking in place methods, of course, do not have any space requirements beyond standing space.

There are various performance metrics used to judge the success of locomotion methods [Whitton et al. 2005], such as breaks in presence [Peck et al. 2009], simulator sickness [Freitag et al. 2014; Grechkin et al. 2016; Neth et al. 2011], and judgments of relative direction [Williams et al. 2007], etc. Because we are interested in training and simulation, we believe the acquisition of spatial knowledge to be a valuable metric. Navigation methods have been linked to the acquisition of spatial knowledge [Ruddle et al. 2011, 2013; Wilson et al. 2016, 2014] with walking methods outperforming other methods, e.g., joystick, teleportation, and flying. In this paper we compare how well three methods of navigation afford the acquisition of spatial knowledge, specifically survey knowledge [Chrastil 2013; Ishikawa and Montello 2006].

The four components of spatial knowledge are landmark, route, graph, and survey knowledge [Chrastil 2013; Ishikawa and Montello 2006]. Of most interest is survey knowledge, the acquisition of which provides subjects with knowledge of the straight-line distances and directions between places defined in a common frame of reference. To test the acquisition of survey knowledge we employ three metrics: initial angular error [Chrastil and Warren 2013; Rieser 1989], estimated path length [Chrastil and Warren 2013], and orientation time, a measure of how quickly subjects recall the relative direction of objects. These measurements are collected to determine how well spatial knowledge is acquired in the three modes of navigation. The VR interfaces, because they either have interventions in real walking or simulated walking, should differentiate themselves in their ability to allow users to acquire spatial knowledge. We find that resetting leads to the strongest acquisition of survey knowledge and is the only method in which subjects reliably encode interpoint distance information.

2 BACKGROUND

2.1 Walking in Virtual Environments

The idea of exploring large virtual environments within a limited physical space has a rich history, e.g., [Razzaque et al. 2001; Interrante et al. 2007; Williams et al. 2007; Engel et al. 2008]. Suma et al. [2012] has a succinct review of this area. These systems of navigation, however, all require a positional tracking system. When lacking a tracking system, one must employ other methods of navigation. Many methods of walking in place have been presented [Feasel et al. 2008; Leeb et al. 2006; Slater et al. 1995; Swapp et al. 2010; Tregillus and Folmer 2016; Williams et al. 2011; Wilson et al. 2014; Zheng et al. 2012] that permit users to emulate walking without physically translating. Standard techniques for walking in place [Slater et al. 1995] have been found to be better than joystick based motion, but not as good as actual walking [Chance et al. 1998; Ruddle and Lessels 2006; Ruddle et al. 2011; Wilson et al. 2016].

2.2 Body-Based Cues

The body-based cues generated from natural walking can be divided into two functions, cues that inform rotation or translation. Rotation-based cues are provided naturally in smartphone based VR systems. Smartphones have built in orientation tracking using gyroscopes and compasses. Rotational-based cues inform people of the angles they have turned, and therefore are useful for keeping oneself oriented in the environment. Providing a translational based cue for a smartphone interface requires some external tool, e.g., a tracking system. Translational cues inform people of the distance they have traversed, and are therefore useful for estimating the distances between objects and gauging the scale of the environment. In our work we provide translational cues in two ways. Resetting provides translational cues by allowing participants to access information from the movements of their muscles and the speed changes of their head. Walking in place techniques are body-active surrogates [Usoh et al. 1999] and therefore provide translational cues only from the movements of their muscles. Work from Ruddle et al. [2011] and Riecke et al. [2010] together suggest that rotation cues facilitate spatial learning in small-scale environments, whereas translational cues facilitate spatial learning in large-scale environments (for a review, see Ruddle [2013]).

2.3 Spatial Microgenesis

There are two aspects of spatial knowledge that we must acquire to build an accurate map of an environment: relative direction and interpoint distances. A abundance of research has been conducted to ascertain how this map-like model is both acquired [Ishikawa and Montello 2006; Montello 2009; Montello et al. 2004; Schiller et al. 2015] and represented [Chrastil and Warren 2013, 2015; Mou et al. 2007; Roskos-Ewoldsen et al. 1998; Shelton and McNamara 2001; Xiao et al. 2009]. To determine how this knowledge is acquired Siegel and White [1975] proposed three stages of spatial knowledge acquisition: landmark, route, and survey knowledge. Chrastil [2013] argued for a fourth type of spatial knowledge, namely the graph knowledge, to be added to this spatial knowledge framework. The stage of most interest for this work is survey knowledge. Survey knowledge is the highest and most complete form of knowledge and includes metric information and configural knowledge of non-landmark objects [Ishikawa and Montello 2006; Siegel and White 1975].

3 RESEARCH DESIGN

3.1 Techniques of Walking

We implemented three techniques for locomotion in this work: the reorientation method called resetting [Williams et al. 2007], which uses real locomotion with interventions at the boundaries of the tracked space, and two techniques of walking in place, which require only the space to stand up.

3.1.1 Resetting. Our implementation of resetting was originally developed by Williams et al. [2007] and Xie et al. [2010], involves real walking, and grants full idiothetic cues to self motion. Resetting consists of two phases, the traditional walking phase in which no modification is done to either the orientation or position of the subject, and a reorientaion phase that occurs when a collision with the boundary of the tracked space occurs. During the first phase resetting is functionally equivalent to real walking. When a subject reaches a boundary of the tracked space the system initiates the second phase of resetting. During this phase the actual reset takes place and the rotational gain of the system is modified so that a virtual turn of 360 degrees is equivalent to a real world turn towards the exact center of the room. Thus, subjects believe themselves to have turned completely around and maintained their headings, while they have actually been reset away from the boundary. In the original Williams et al. [2007] work, the gain was modified by a factor of 2, but, consistent with later work, our implementation dynamically adjusts the gain to point subjects to center of the room. This manipulation results in fewer resets. Resetting provides full translational and idiothetic cues to self-motion, but the process may cause some degradation in the acquisition of rotational information because of the body rotations inserted into the path.

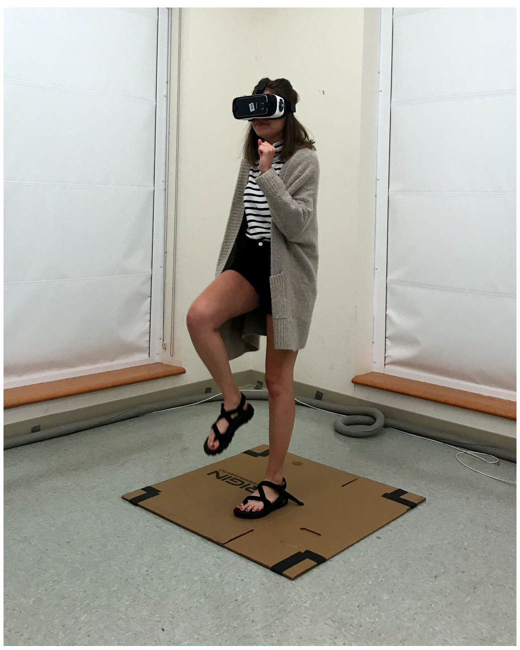

Figure 1: A demonstration of walking in place. Cardboard is placed on the floor to prevent subjects drifting as they walk in place.

3.1.2 Walking in Place. Our walking in place techniques are body-based turning methods, with turning indicated by head rotation. This means that all linear motion is in the direction of a subject's gaze which prevents looking around when walking. The first walking in place technique (Gear Only) we use takes inertial measurement unit (IMU) data directly from the smartphone of a Gear VR to determine head motion. This method is similar to how pedometers in smartphones and smartwatches work. Pedometers use pattern analysis techniques to search for repeating motions that are assumed to be steps. The repetition requirement of pedometers leads to either unreliability when the number of repetitions is low or severe lag when the number of repetitions is high. For this reason, we chose not to implement a standard pedometer. Instead, we extract the up and down acceleration of the head to impart motion in the direction of a user's gaze.

For our method walking is divided into two repeating states. We say the subject is stepping when the magnitude of the upward acceleration is greater than 0.1 m/s/s and not stepping otherwise. We assume an average walking pace of 3 m/s with each step taking 0.5s. The true target velocity in the system is the ratio of the the average rate to a user's rate of stepping multiplied by the average walking speed in the direction of the gaze. When a step begins we exponentially decay in an increasing form, (i.e., $1 - e^{-kt}$) to that maximum speed and remain there until we detect the current step has stopped, at which time we decay to half of the maximum speed. This decay upward and downward repeats for as long as the user is considered to be walking. A user is no longer considered walking if enough time (50% of a user's rate of stepping) has passed since the end of the previous step. If this cessation is detected we decay to a speed of zero. The time constant for each of these decays is 0.2 seconds to make the change in speed subtle but noticeable. Note that while optic flow and motion do not stop immediately, they do stop within roughly 0.5 seconds of a user stopping.

The Kinect v2.0, which directly tracks users' feet and legs, offers a more direct method of measuring walking in place. This second walking in place technique utilizes the Microsoft Kinect v2.0 to track the angle formed (for both the left and right leg) by the hip, the knee, and the ankle joint. We assume the user is currently stepping if the angle formed is less than 145 degrees. We add an additional modification to the algorithm to allow for quicker detection of cessation of steps. We assume that if both leg angles are over 165 degrees for 0.1 seconds then stepping has stopped. The Kinect produced errors with step detection in certain orientations. Tracking was most stable when users faced either towards or directly away from the Kinect. When facing to the side and obscuring the back leg from the camera the system was prone to missing steps and causing unintended slow downs. This occurred primarily during the initial practice phase as subjects learned to adjust rapidly and controlled their motion effectively. In both methods we placed a 1m x 1m piece of cardboard on the ground and instructed subjects to walk in place, only on the cardboard; the cardboard, in effect, prevented drift.

3.2 Metrics

Since we are interested in how well our tested methods of walking facilitate the acquisition of spatial knowledge, in particular survey knowledge, we employ two metrics that allow us to measure how well survey knowledge has been acquired. As stated in Section 2.3 there are two important aspects of survey knowledge: interpoint distance information and direction information. Another important aspect in any of the types of spatial knowledge is recall time, and for this reason we look at orientation time, the time a subject takes to determine the direction of the target object and begin walking.

3.2.1 Initial Angular Error. To measure how well a subject is able to judge relative direction we employ a task similar to the classic pointing task [Loomis et al. 1999; Rieser 1989]. The task we use is to have a subject walk from a temporarily visible object to an instructed invisible, unseen target object [Chrastil and Warren 2013]. Subjects are instructed to walk directly (in a straight line) to the target object as if there were no walls (noting that the walls were actually gone at this point) and the direction they walk measures the strength of their configural knowledge without respect to scale. Specifically, we measure the difference in angle between the direction of the actual target and the direction of walking after 1 meter [Chrastil and Warren 2013].

3.2.2 Estimated Path Length. The other component of survey knowledge is interpoint distance information, which is typically acquired slowly. We test how well subjects have acquired this metric information by employing a simple walking task. By controlling for the amount of time spent searching through the environment we can analyze how quickly survey knowledge is obtained, in particular its metric component. Note that metric information in this experiment is gained primarily through path integration and is therefore not likely subject to biases in perception that have generated a significant body of work in the virtual environments community (see Creem-Regehr et al. [2015] for a recent review).

3.2.3 Recall time. We can also measure the strength of subjects' survey knowledge by testing their recall time in determining the relative direction. Before subjects can begin walking they must know in what direction the target object is. By measuring the time the starting object is presented to the time subjects begins walking we can measure how well subjects can recall the relative direction of objects and orient themselves in the the maze.

3.3 Hypotheses

Given the fundamental differences in the proposed locomotion methods we developed two hypotheses for this experiment. First, given that the subjects are only actually translating during the resetting condition, we expect users in the resetting condition to exhibit better performance on the path length metric than users employing the other methods to walk. Our hypotheses derives from prior literature (Ruddle et al. [2011]; Chrastil and Warren [2013]) that demonstrates the importance of locomotion in acquiring spatial knowledge.

Regarding initial angular error, we have two walking in place methods which do not manipulate rotation-based cues, and resetting, which does. We hypothesize that resetting's rotational manipulation will result in degraded performance for initial angular error.

4 METHODS

4.1 Participants

For this study we recruited college age students from our institution between the ages of 18 and 25 (mean=20.7, median=21). Twenty subjects participated (9 male, 11 female), gave written consent, and were compensated $10 for participating in the experiment, which was approximately one hour in duration. Subjects were informed of their method of walking and the metrics we would collect (initial angular error and path length). Two subjects were excluded from data analysis due to system malfunctions, and therefore six subjects remained in each of the three conditions.

4.2 Equipment

The environment was developed in Unity and based on the maze developed by Chrastil and Warren [2013]. A Samsung Gear VR head-mounted display (HMD) provided visual information to subjects. Subjects used either a Samsung S6 or S7 phone as the rendering device. The resolution in each eye is 1280x1440. The field of view of the Gear VR varies somewhat depending on the phone used; we did not measure this, but Samsung reports it as 96°; however, online reports place it at about 90°. Subjects' motion was tracked in one of three ways. The first was using a Vicon Motion Capture system in which body data were transmitted directly to the phone. Our system used 8 MX40 cameras to track the position of 6 optical markers and reconstruct the orientation and position of each subject's head. The physical space used was roughly 6x5 meters; the available tracked space was 5x4 meters. The second utilized the built-in IMU of the Gear VR to detect steps and the final method used a Microsoft Kinect v2.0, which used KinectVR [KinectVR 2017] to transmit data using a Node JS server to the phone. All data were transmitted over a LAN using a NETGEAR WNR3500 router. Subjects provided input using the Gear VR's touchpad.

4.3 Environment

Figure 2: Top-down view of the environment used in the practice phase of Experiment 1. There are four objects for the subject to find and four landmarks (paintings).

In this experiment each subject was presented with three distinct environments. The first was a training maze shown in Figure 2. Subjects were placed in a practice maze in order to train in their assigned technique of walking. The second was the learning maze shown in Figure 3; subjects were instructed to learn the spatial relations among the eight objects contained in this maze. Four landmarks were present to aid in learning the overall layout. A first person view of the learning maze is shown in Figure 4, with one of the eight objects. Due to the geometry of the maze, a subject could

Figure 3: Top-down view of the environment used in the learning phase of Experiment 1. There are eight objects for the subject to find and four landmarks (paintings) to facilitate learning.

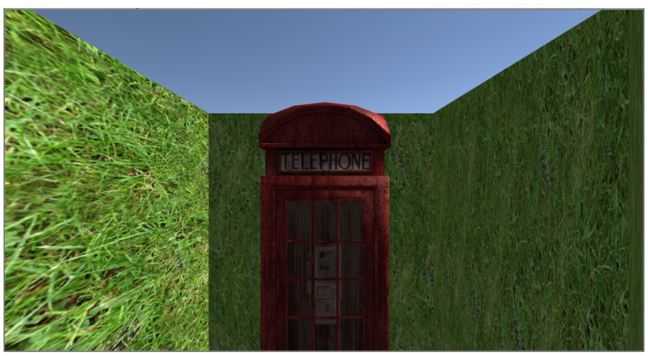

Figure 4: This figure shows the telephone booth as would be seen by subjects during the orientation phases of the experiment.

not see any two objects at the same time. The final environment is presented during the actual testing phase. Figure 5 shows a first person view while the subject is in a sparse environment with a Voronoi textured ground plane to give the subject some ocular flow for feedback on distance traveled.

4.4 Procedure

Subjects were first given instructions on how to move in their technique of walking. The first phase of the experiment was to place the subject in the training maze (Figure 2) and give them five minutes to freely explore the maze to learn how to walk around in their condition. Subjects were required to complete the full five minutes of this phase to ensure they were confident and competent at navigating. After this phase subjects were taken out of the headset and given instructions on what to do in the next maze. Subjects

Figure 5: At the beginning of the testing phase subjects are informed of the target object via a heads up display. This disappears shortly so as not to distract the subject during walking.

were also told to try and remember relative locations of objects as they would be tested later on them.

Next they were placed in the learning maze (Figure 3) and given 10 minutes to freely explore and learn the layout. They were not able to walk through the walls. At the end of 10 minutes subjects began the assessment phase and were placed in the Voronoi textured environment where they were given their next set of instructions.

In this phase subjects experienced a series of trials to find objects from various locations within the maze. To begin, subjects pressed the touchpad on the Gear VR and were placed back in the learning maze directly in front of an object, which allowed subjects to orient themselves. They were instructed not to walk around to prevent seeing any more of the maze. When oriented, subjects pressed the touchpad again placing them back in the Voronoi environment. The time taken to orient themselves in the environment was recorded as orientation time. Upon being placed in the Voronoi environment subjects were given another object in the maze to walk to via a heads up display (see Figure 5). Subjects were instructed to walk directly to the target object in a straight line. A second measurement of time (target acquisition time) was taken here to denote the time taken to recall the direction of the target object. This straight line condition ensured their walked path was a novel shortcut. The position in the maze, time, acceleration (for the Gear only condition), and orientation of the headset were recorded at every frame for potential reconstruction. Subjects indicated the conclusion of a trial by pressing the touchpad a final time. Each subject completed forty trials in total. Beginning and end objects were randomly selected for each subject.

5 RESULTS

To simplify analysis and remove the variability we divide our 40 trials into four blocks of 10 trials each. We present three measures of how well subjects have acquired spatial knowledge and, in particular, survey knowledge. All ANOVAs were performed using SPSS and the tests for normality and homogeneity of variances were met. Error bars in all figures denote standard errors of the mean.

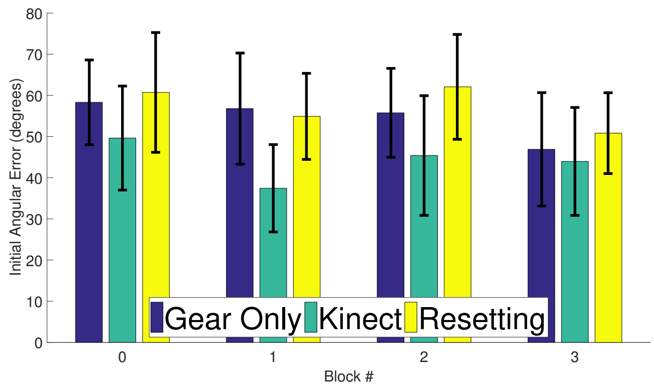

Figure 6: This figure shows the mean initial angular error of subjects by condition and blocks of 10 trials.

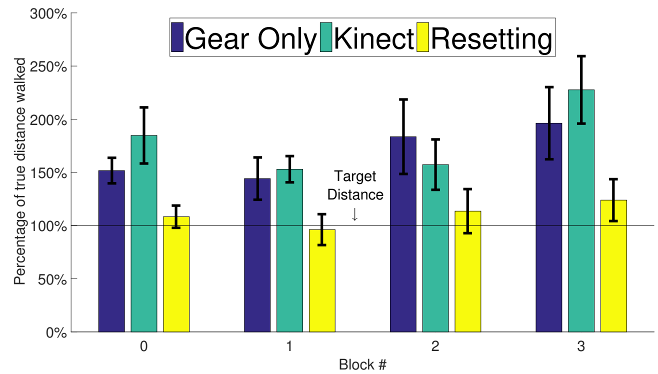

Figure 7: This figure shows the mean distance subjects walked as a percentage of true distance by condition and blocks of 10 trials.

5.1 Initial Angular Error

Figure 6 shows the initial angular error by condition and four blocks of 10 trials. A 3 (navigation method) x 4 (block) repeated measures ANOVA on absolute angular error found no effect of condition (F(2,15) = .338, p = .718) or block (F(3,45) = 1.171, p = .331). The lack of a significant effect differs from our second hypothesis, a surprising result given that the walking in place conditions do not manipulate orientation whereas resetting does. In all conditions, the mean absolute angular errors are in line with those found by Chrastil and Warren [2013].

To further explore this result we turned to Bayes factors, an analysis method that can provide support for the null hypothesis and expresses that evidence in an odds ratio[1]. The following analyses use the methods of Rouder et al. [2009] which, because they account for sample size, adjust for power. We set the prior odds to 1 as this favors neither the null nor the alternative. We first compare the methods of Gear only and Resetting which gives us a Jeffrey-Zellner-Siow (JZS) Bayes factor of 4.47 indicating strong evidence in favor of the null hypothesis. Comparing the Gear only and Kinect conditions gives us a JZS Bayes factor of 1.45 and the Kinect vs Resetting conditions gives us .47 which are marginal and do not strongly support either the alternative nor the null.

5.2 Path Length

The second type of information needed to accurately walk to target object is interpoint distance information. Figure 7 shows how accurately subjects were able to walk the true distance. A 3 (navigation method) x 4 (block) repeated measures ANOVA on the error in relative path length shows a main effect of condition (F(2,15) = 4.923, p = 0.023). A post hoc Tukey HSD revealed that there is a significant difference between the Kinect and Resetting conditions (p = 0.022) and a marginally significant difference between Resetting and Gear only conditions. In both the Gear only and Kinect conditions subjects significantly overwalked the distance to the target (M=168% and M=181%, respectively) whereas in resetting the distance was more accurate (M=111%).

[1]Online calculators and R packages for calculating these statistics are available at http://pcl.missouri.edu/bayesfactor.

5.3 Recall Time

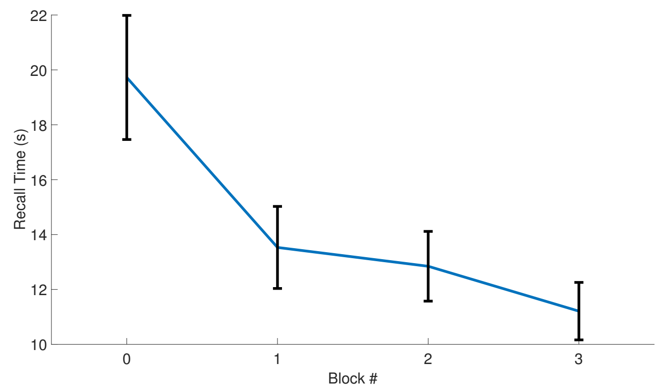

Figure 8: This figure shows the mean time subjects spent determining the relative direction of the target object. Time is plotted by blocks of 10 trials and collapsed across condition.

Finally, we analyze how quickly subjects are able to recall the maze and the target object. To do this we look at total recall time, i.e., the total time between being presented with the starting object and beginning to walk to the target object. A 3 (navigation method) x 4 (block) repeated measures ANOVA on this total recall time shows a significant main effect of block ($F(3, 45) = 21.833, p < .001$, $\eta_p^2 = 0.59$). There is also a large drop-off between the first and second block of 6.2 seconds (a 31.4% drop). Given this large dropoff and the significance of the effect we removed the first block to see if this effect continued throughout the testing procedure. We performed a 3 (navigation method) x 3 (block) repeated measures ANOVA on total recall time for the last three blocks of data and we still find a main effect of block ($F(2, 30) = 6.256, p = 0.005$, $\eta_p^2 = 0.29$).

There are two components to total recall time, the first component is the time subjects take to orient themselves within the maze (orientation time). The second component is the time subjects spend determining the direction of the target object (target acquisition time). Exploring further into which of these was the driving force in the previous result, we performed a 3 (navigation method) x 4 (block) repeated measures ANOVA on orientation time and target acquisition time and found significant main effects of block ($F(3, 45) = 16.525$, $p < 0.001$, $\eta_p^2 = 0.52$, and $F(3, 45) = 13.305$, $p < 0.001$, $\eta_p^2 = 0.47$, respectively). We also performed a 3 (navigation method) x 3 (block) repeated measures ANOVA on orientation time and target acquisition time for the final 3 blocks and again found main effects of block ($F(3, 45) = 4.424$, $p = 0.021$, $\eta_p^2 = 0.23$, and $F(3, 45) = 3.900$, $p = 0.031$, $\eta_p^2 = 0.21$, respectively). Thus, both components improve significantly by block.

6 DISCUSSION

The framework of spatial microgenesis [Chrastil 2013; Chrastil and Warren 2013; Ishikawa and Montello 2006] provides a structured methodology to frame the acquisition of spatial knowledge in humans. We use this framework as the primary measure of the usability for the three methods of navigating large virtual environments presented in this paper. These three methods were resetting, walking in place using the Samsung Gear VR, and walking in place using the Microsoft Kinect. Three metrics measured the acquisition of spatial knowledge in each of these three methods. The first metric was the initial angular error, which assessed the directional component of survey knowledge. We found no significant difference between the walking methods, and a Bayes Factor analysis found high odds that the Gear only and Resetting methods had identical performance. We have no theoretical reasons for why the Kinect might differ from the other conditions, and more work would be needed to ascertain if it indeed does.

The second metric was the path length of the novel shortcuts, which measured how well subjects were able to encode distance information into their cognitive map of the environment. Confirming hypothesis one, subjects performed significantly better in the resetting condition than the walking in place conditions, where they overshot the true distance by 68% in the Gear only condition and 81% in the Kinect condition. Walking in place does not seem to permit the same level of acquisition of metric interpoint distance survey knowledge as does resetting. Subjects overwalking in the walking in place conditions might be explained by the complexity of the maze. This complexity may make the maze seem larger than it actually is, and it produced a pattern of overshooting in the absence of developed survey knowledge. It is possible, however, that this method of locomotion biases any attempt to measure the encoded metric information. Subjects were tested with only optic flow as feedback in the walking in place conditions whereas subjects in the resetting condition have full idiothetic feedback. A future study is planned to determine reasons for overwalking in the walking in place conditions.

The final aspect of spatial knowledge we examined was recall time. Across all conditions, subjects consistently improved in both measurements of map recall time. Over blocks, they were more rapidly able to localize themselves in the maze and to remember the relative direction of a target object. The steady decrease in recall time could be attributed to a strengthening of subjects' cognitive maps. Thus, while the maps did not get any more accurate, subjects recalled them faster. Since the directional component of survey knowledge is representative of direction between objects, subjects may be building a stronger but incorrect map from repeated attempts to recall their survey knowledge.

A limitation to our study may be the limited time subjects spent learning the environment. While the angular errors were consistent with the literature for this task, increased exposure may result in better survey knowledge acquisition. As previously stated, some future work is necessary to determine why subjects overwalked in the walking in place conditions. Potential avenues for this work include cross testing subjects in the various methods, or potentially assessing their metric knowledge in ways other than walking. Regardless, work needs to be done to facilitate learning metric information and expressing it accurately. One possibility is to allow subjects to see a global map to help strengthen their cognitive map or memorize the layout instead of just wandering around in it.

Determining the best locomotion method for navigating in a large virtual environment is a complicated question that depends on multiple factors such as VR equipment (e.g., whether tracking is available), and the room size [Azmandian et al. 2017]. We have not fully addressed the total question, but we have addressed pieces of it. In this paper we implemented three methods of locomotion on smartphone-based immersive virtual reality devices. This is one of the first works to look at navigation methods using mobile VR, and the first paper to investigate spatial cognition in mobile VR. Smartphone-based immersive virtual reality offers some advantages as a technology for presenting virtual reality: it is lightweight and highly portable. The resetting method that we tested in this paper required a tracking system that is not mobile, but highly portable tracking systems exist [Antilatency 2017]. Of course, limitations to smartphone-based immersive virtual reality include more limited graphical capability and more difficulty accommodating self-avatars.

We assessed the three methods for moving in a virtual environment by measuring subjects' ability to acquire survey knowledge during navigation. Two of these methods can be employed in completely mobile systems, while the other can be made somewhat mobile with additional commodity level equipment. We found that the acquisition of directional information was roughly equivalent for all conditions, but the acquisition of the scale component of survey knowledge is better in the resetting condition. This paper did not consider room size, which would potentially affect resetting, but not walking in place methods. That issue is also a topic for future work.

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