I Feel More Engaged When I Move!: Deep Learning-based Backward Movement Detection and its Application

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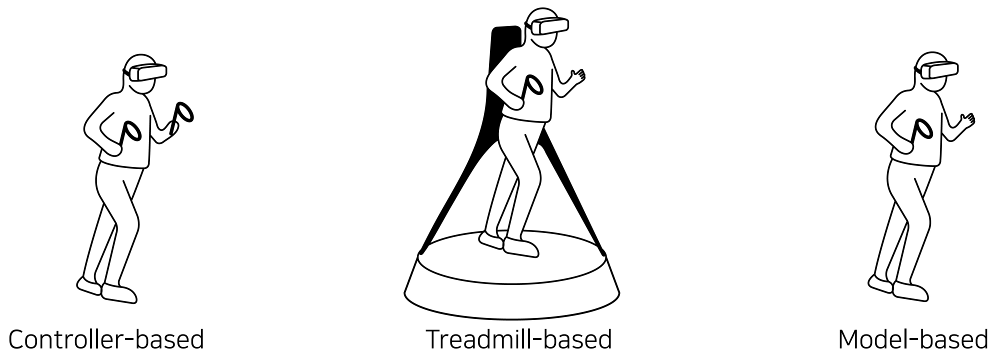

Figure 1: Three conditions of movement applied in the user study. We proposed a model designed to detect backward movement.

ABSTRACT

Movement is one of the key elements in virtual reality (VR) and significantly influences user experience. In particular, walking-in-place is a method of supporting movement in a limited space, and many studies are being conducted on its effective support. However, most studies have focused on forward movement despite many situations in which backward movement is needed. In this paper, we present the development of a prediction model for forward/backward movement while considering a user's orientation and the verification of the model's effectiveness. We built a deep learning-based model by collecting sensor data on the movement of the user's head, waist, and feet. We developed three realistic VR scenarios that involve backward movement, set three conditions (controller-based, treadmill-based, and model-based) for movement, and evaluated user experience in each condition through a study of 36 participants. As a result, the model-based condition showed the highest sensory sensitivity, effectiveness, and satisfaction and similar cognitive burden compared with the other two conditions. The results of our study demonstrated that movement support through modeling is possible, suggesting its potential for use in many VR applications.

Index Terms: Human-centered computing—Human computer interaction (HCI)—; Human-centered computing—Virtual reality—; Computing methodologies—Machine learning approaches—

1 INTRODUCTION

Virtual reality (VR) aims to provide immersive experiences to its users [50]. VR research has focused on creating realistic graphics or movements, improving user and environment interactions, experimenting with controllers that have a higher degree of freedom in a variety of situations [2, 51, 53, 67–69], and enhancing sensory support through additional sensor devices [4, 7, 10, 16, 52, 65]. Among the factors that influence immersive experiences, movement is a fundamental element that allows users to navigate and interact with the VR environment [11, 14, 24, 37, 42, 54]. Users generally expect to move analogously to what they do in the real world, and if their movement does not synchronize and map properly in VR, their user experience decreases significantly (e.g., they could feel dizzy or experience cybersickness). Research on movement in VR is largely categorized into full gait (real walking), partial gait (stepping in place without making any physical displacements), and gait negation (using treadmill or step-based devices). Walking-in-place (WIP) is a partial gait technique in which a user navigates a virtual space using leg motions while remaining stationary [59]. It has been adopted in many VR systems because the VR environment typically covers a virtual area that is much larger than what can be reasonably tracked by the limited corresponding physical space.

Despite much research on VR locomotion, studies have mostly focused on forward movement, and little focus has been placed on backward movement. According to a survey paper [1], only 20% of studies have focused on backward movement. Backward movement is a basic movement expected by the user, and many VR scenarios require it. Examples include when an object that a user wants to pick up is located too close to the user, when the user suddenly encounters a wall or a person while walking, and when the user makes a mistake in movement. Regardless of the user intention, he or she needs to be able to move backward. When the user wants to take a few steps back but is not able to, cybersickness is highly likely to occur. Supporting backward movement increases the freedom and flexibility of user control and navigation in a VR environment, and this is essential for an immersive and realistic VR experience. If these basic elements are not properly supported, the overall user experience will likely be diminished [49]. Research also highlights a strong relationship between movement and VR sickness [62]. In addition, the aforementioned 20% of prior studies have investigated backward movement using classic input devices (e.g., gamepads, mouse devices) [35] and gesture- and motion-based input (e.g., finger or body motions) [25, 35]. Backward movement with actual footsteps provides a more immersive VR experience than these earlier methods, but this has not been systematically explored in research.

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To address this research gap, this paper introduces the results of two user studies on backward movement. The first user study involved the development of a backward movement prediction model based on sensor data. We considered three sensor data sources (i.e., head, waist, and foot movements) and collected the corresponding sensor data from 20 participants. We developed forward/backward movement prediction models using deep learning from the collected sensor data. The study results confirmed that a deep learning-based, individualized model yielded the best performance (96% F1-score). The second user study involved the verification of model effectiveness through case studies. We designed three scenarios (elevator, library, and bus) that each included three moments that required backward movement. Through the evaluation of user experiences in these different scenarios, we attempted to increase the comprehensiveness of our study results. We applied three movement modalities: standard VR controller, gait negation (i.e., treadmill-based), and model-based WIP (i.e., supported by our custom head, waist, and foot sensors and deep learning prediction model). We conducted a user study with 36 participants. The results indicated that the model-based condition showed the highest sensory sensitivity, effectiveness, and satisfaction and exhibited a similar level of cognitive load on the users, compared with other conditions.

Our study results complement and expand existing VR locomotion research by presenting new methods, results, and insights on supporting naturalistic backward movement in VR. Our research also contributes not only to the application of artificial intelligence technology to VR but also to the demonstration of its effectiveness in VR scenarios. Our study methods and results can be applied to other VR systems that involve backward movement.

2 RELATED WORK

2.1 Supporting immersive experience in VR

Many studies have been conducted on providing an immersive experience in a VR environment. Here, we briefly summarize VR research that improves immersive experiences by providing environmental realism, naturalistic input, multi-user support, and movement tracking. For environmental realism, increasing the sense of reality can be achieved by creating an environment similar to a real one [13, 31, 33, 40, 61]. A realistic VR controller that simulate real tools can support realistic movement by allowing the users to directly interact with the VR environment through the user's hand [68, 69]. Computer vision technology has also been adopted to provide users with realistic experiences without a physical controller [5].

VR research has also focused on supporting multiple users [13]. Many collaborative scenarios require interactions from two or more agents. For example, social VR allows people to establish and maintain social relationships in an online space and to work together through collaboration. Several social VR applications, such as Rec Room [1], BigScreen [2], and VRChat [3], have all seen an increase in traffic. Also, through team-level VR training, users can learn how to cope with situations through collaboration required in actual training and to gain training experience [19]. Lastly, which is a focus of our study, the ability to track movement gives a strong sense of reality by making it possible to move in a VR environment analogous to movement in reality. We discuss the details of each locomotion technique in the following section.

2.2 Locomotion research in VR

Research on VR locomotion can be broadly classified into the walking-, steering-, selection-, and manipulation-based techniques [1, 32, 38]. Among them, the walking-based technique, which includes movements based on full gait, partial gait, and gait negation, has been extensively studied.

Full gait techniques include real walking, which considers the walking space in the real and virtual environments to be the same. With the full gait technique, the movement reflected when a user explores the virtual space is the same movement as walking in the real world. However, due to the nature of the infinite VR space, making the size of the real space and the VR space exactly the same is one of the biggest challenges and often times impossible to be realized [38].

To overcome these limitations, the redirected walk (RDW) method was proposed [46]. It enables actual walking in a limited space by visually manipulating the user's virtual environment and calculating gait movement to avoid collision in a limited space [18, 28, 63]. RDW can be one of the most complete VR locomotion methods if it is applied correctly in practice, but also has limitations. Sometimes RDW requires high gains of rotations and repositions that causes VR sicknesses [23].

Partial gait techniques support movement through steps in a fixed posture. WIP is a partial gait technique that detects the time when the movement occurs through data collected from the movement of the leg or body and moves the user in the direction of the head-mounted display (HMD). WIP is the most representative method when taking an action to move the foot in a stationary state. It is a convenient and inexpensive technique [21] to provide some of the proprioceptive feedback inherent in real walking [1, 43]. However, several evaluations of WIP techniques have indicated less naturalness of WIP, compared with natural walking [1].

Research has also been conducted to detect the start of movement through a pressure sensor from a stepping platform [8]. Gait negation techniques refer to supporting a full gait cycle while a person is stationary and equipment for measuring steps or wiping gestures or a treadmill is required [1]. All of these methods depend heavily on dedicated mechanical devices, which include treadmills, step-based devices, and low friction surfaces [38]. There are two types of treadmills: active and passive repositioning [43]. The active repositioning method relies on elaborate mechanical setups like the traditional linear treadmill, which supports only forward movement [20, 34, 44]. In the case of the active repositioning omnidirectional treadmill [17, 29, 55], there are potential limitations that may cause the user to lose his or her balance during turns, and sidesteps problems may occur [38]. Passive repositioning treadmills provide movement in a friction-free manner [3, 12, 58] (e.g., KAT Walk [4], Cyberith Virtualizer Elite [5], Virtuix Omni [6]). Moreover, research has attempted to compare locomotion methods through user experience perspectives. Traditional (e.g., teleport, joystick) and newly proposed methods (e.g., WIP, body motion, virtual sphere) were compared with several user experience elements including perceived presence, usability, and sickness [9, 11, 39]. In this paper, we considered backward movement and present a study of comparing user experience in controller-based, treadmill-based, and WIP-based movement.

2.3 Learning and predicting movement in VR

Considering people's different gait patterns, research has employed machine/deep learning techniques to model one's movement based on sensor data from VR devices. Examples include using a feed-forward neural network to extract patterns from the position sensor data of the HMD [54], developing a neural network to classify walking and flying patterns in WIP [60], using the same neural network using head sensor data to determine when the participant was walking [47]. Some studies used a Convolutional Neural Network (CNN) algorithm to reliably recognize human's physical activities [66] or

[1] https://recroom.com/
[2] https://www.bigscreenvr.com/
[3] https://hello.vrchat.com/
[4] https://www.kat-vr.com/
[5] https://www.cyberith.com/virtualizer-elite/
[6] https://www.virtuix.com/

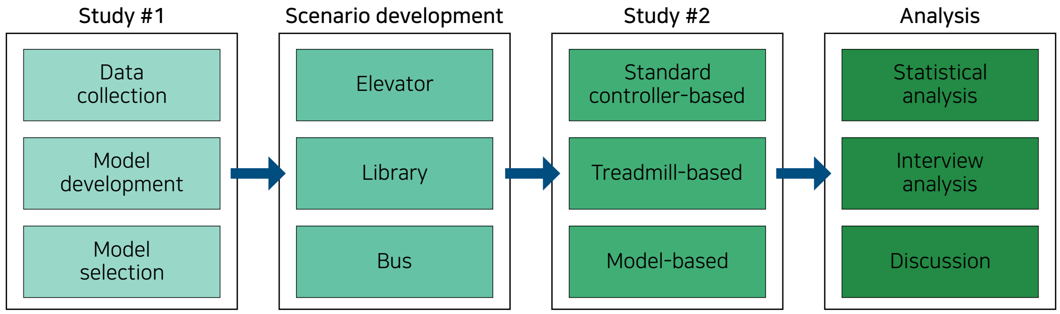


Figure 2: The study procedure. In user study #1, we developed the model that detects forward/backward movements, and in user study #2, we applied the model to three scenarios that require forward/backward movements in a natural fashion. We verified the effectiveness of our model application in terms of perceived presence, cognitive load, effectiveness, and satisfaction.

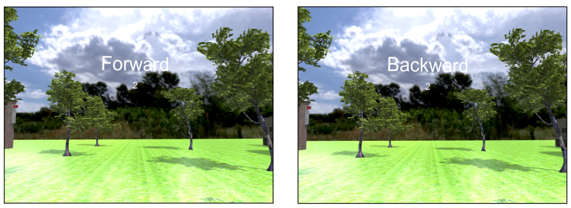


Figure 3: Data collection in Study #1. By pressing the trigger button on the controller, the participants were instructed to move forward, and by releasing the button, the participants were instructed to move backward. The participant moved forward and backward for 10 seconds each, and this was repeated six times (a total of 120 seconds). Data from the sensors of HMD, waist, and feet were collected.

to improve WIP using sensor data from HMD [26]. Furthermore, attempts have been made to promote user experience by providing a user-specific interface that reflects personal movement patterns [22, 30, 45].

As we highlighted before, only 20% of studies have focused on backward movement. We realized that aforementioned machine/deep learning-based studies did not consider backward movement specifically; thus, despite the importance of backward movement to user experience in VR, there is a lack of understanding on the detection of backward movement through computational modeling and on the feasibility of model application in real VR scenarios. Although prior research has been considered sequential patterns of movement in modeling, deep-learning algorithms, designed to learn such patterns (e.g., Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM)), have not been applied in VR locomotion research yet. This study deals with modeling the partial gait of WIP. In particular, we investigate the salient factors (i.e., sensor modality, learning algorithm, and personalization) to be considered for the development of a movement detection model.

In summary, our study contributes to the literature in the following ways. In order to support a realistic VR experience, we (1) develop models that learn temporal sequences of body motions from the head, waist, and feet, (2) apply the model to three scenarios that users can encounter in a real VR environment, (3) measure the effectiveness of the model, and (4) discuss important points for better developing and applying models to support VR locomotion.

3 Study Procedure

Figure 2 shows the overall research procedure. It is largely composed of two studies, and in the first study (Study #1), we developed models for detecting backward movement and examined the performance of the models. In the second study (Study #2), we applied the developed model with the best performance to three VR scenarios (i.e., elevator, library, and bus) in which a user encounters moments to move backward. Especially, we included two additional conditions for movement (i.e., standard controller-based and treadmill-based) to compare the effectiveness and user experience of the model-based movement.

Our research was approved by the Institutional Review Board (IRB) at our university. We used the HTC VIVE PRO HMD, and the study was conducted based on Unity 3D in a Windows 10 system equipped with Intel Core i7, RAM 16GB, and GeForce RTX 2070.

4 Study #1: Backward Movement Detection

4.1 Study procedure

The primary goal of Study #1 was to investigate the possibility of detecting forward and backward movements. First, we measured the influence of sensor types and their combinations on the performance of the machine/deep learning model. This gave us information about the utilization of the sensors to maximize the model performance while also considering computation complexity. Second, we investigated the feasibility of the use of the general model that was developed from all participants' data. By comparing the performance of the individual models for each participant and the general model for all participants, we were able to discuss the direction of model development.

We recruited 20 participants for the user study via a university bulletin board or word-of-mouth. The participants were invited to a university laboratory and instructed how to use the VR devices and what to do in the VR environment. All participants are undergraduate students (mean age: 24.3, SD: 2.6), and 12 of them have casual VR experience. Figure 3 illustrates a virtual environment that we organized for data collection. Participants were asked to wear a HMD, and a VIVE tracker was attached to the feet and waist. We asked the participants to hold the VIVE controller and follow the message ("move forward or backward") on the screen. If the participant holds the trigger button of the controller, the participant is asked to move forward. If the button is released, the participant is asked to move backward. Through this, we were able to collect sensor data that corresponded to forward or backward movements. Participants were asked to walk back and forth for 10 seconds each as naturally as possible (walking-in-place). This was repeated for six times, and we collected each movement for 60 seconds (120 seconds in total) per participant.

4.2 Model feature engineering

We collected position data (three degrees of freedom: $\pm$x, $\pm$y, $\pm$z) in the user's virtual environment from the HMD and the VIVE trackers on a participant's waist and feet every 0.1 second, same as the prior study [26].

WIP in a VR environment is based on the condition in which the movement is reflected in the virtual space when a user's legs are

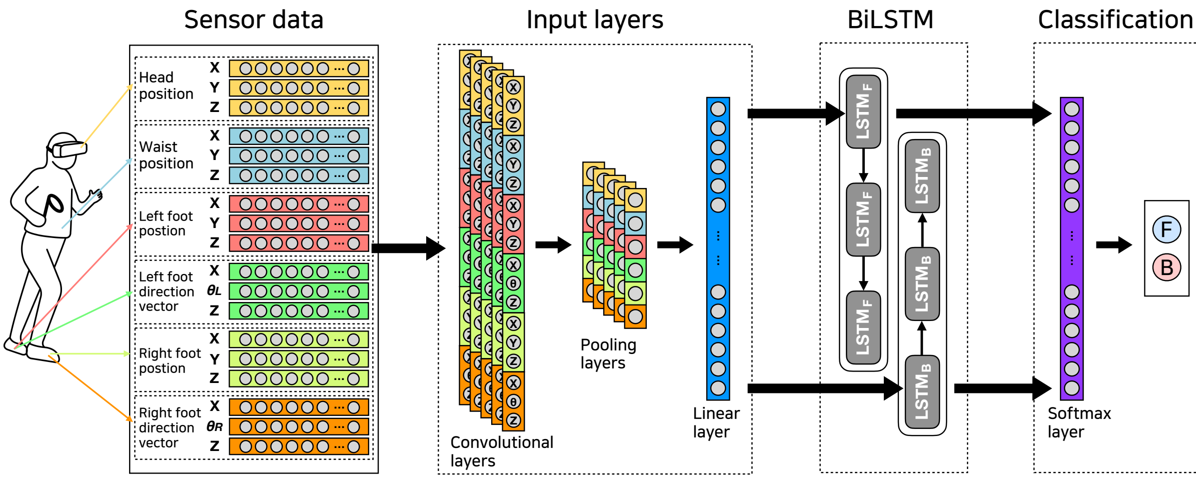


Figure 4: Architecture of the BiLSTM model that was designed to learn temporal sequence of sensor data.

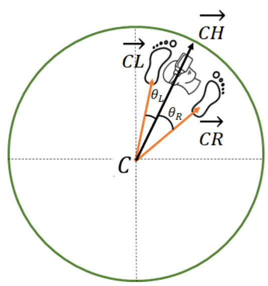


Figure 5: Additional features used for tracking a user's forward and backward movement within an area defined by a virtual circle (C: center, R: right foot, L: left foot, H: head forward). A user's position needs to be readjusted to the center when the user's actual position is not on the center.

moving in motion while the user's location displacement is fixed and unchanged. However, during WIP, it often happens that a user physically moves forward or backward. In this work, we placed a virtual circle with one meter radius (Figure 5), allowing the user to move within a certain range. However, if the user accidentally moves out of the circle, he or she receives an alert from the system to go back to the inside of the circle. We wanted to make sure that the position change in the real space caused by movement in the virtual space to be minimized.

Based on these conditions, we extracted features that can aid in identifying the user's forward/backward movement even when the user's location from the center of the virtual circle changes. One important point is that we need to readjust a user's position to the center when the user's actual position is not on the center. We thus considered the components of the vector representing the direction from the center of the virtual circle to the position where both feet are located ($\overrightarrow{CL}$: left foot, $\overrightarrow{CR}$: right foot). We used the x and z coordinates of the user, excluding the y coordinate (height). We calculated the theta formed by the vector of each foot and the vector of the head orientation ($\overrightarrow{CH}$) and derived the dot product value. We added these six features (i.e., $\overrightarrow{CL}_x$, $\overrightarrow{CL}_z$, $\overrightarrow{CR}_x$, $\overrightarrow{CL}_z$, $\overrightarrow{CL} \cdot \overrightarrow{CH}$, and $\overrightarrow{CR} \cdot \overrightarrow{CH}$) in modeling.

4.3 Model development

For modeling, we used machine learning—Decision Trees (DT) and Random Forest (RF)—and a deep learning algorithms—Bi-Long

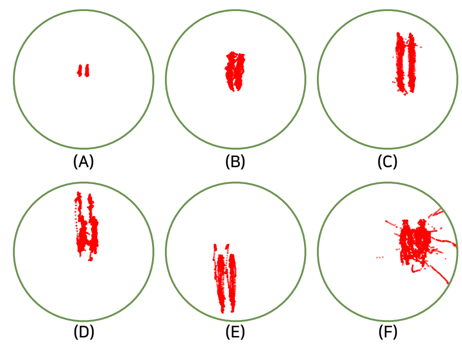


Figure 6: Different patterns of movement by participants. Users of (A) and (B) maintained their position at the center of the circle, those of (C), (D), (E) deviated from the center, and those of (F) exhibited more complex movement patterns. This relates to a higher performance of individual models than one integrated model using all participants data.

Short-Term Memory models (BiLSTM). We chose the tree-based machine learning algorithms because they generally show good and reliable performance in classification tasks. Long short-term memory (LSTM) is a recurrent neural network (RNN) architecture and introduces long-term memory into RNN. It mitigates the vanishing gradient problem, which is where the neural network stops learning because the updates to the various weights within a given neural network become smaller [48]. We used LSTM to learn temporal characteristics of the movement and developed BiLSTM [27] because we were interested in the forward and backward sequences of the utilization of sensing data.

For BiLSTM (Figure 4), since we collected samples for 120 seconds at 0.1 second rate, our input tensor was set to 1200×18(features)$\times 10$(window size) as a sequence length of 1.0 second. The hidden size and the number of layers were set to 256 and 2, respectively. We set the batch size to 100, the learning rate to 0.001, and the embed dimension to 18. The model was trained by 200 epochs to achieve the best performance. We used five-fold cross validation (i.e., 80% for training and 20% for testing).

4.4 Results

Table 1 summarizes the performance of three models. All models yielded good performance over 90% F1-score. The BiLSTM model

	Decision Tree	Random Forest	BiLSTM
Average of individiual models with each participant	0.92	0.94	0.96
Integrated model with all participants	0.90	0.93	0.94

Table 1: Performance of three models (F1-score). BiLSTM yielded the best performance, highlighting the importance of temporal factors in modeling movement.

showed the highest result (96% F1-score) compared with the machine learning-based models. Regarding the difference between the average of the individual models and the integrated model using all participants' data, all models yielded higher performance (1-2% increase). We believe that individualized models worked better due to different patterns of WIP. Figure 6 illustrates such different patterns of movement (based on the coordinates of x and z), which were manually clustered by the authors of this paper.

Based on these results, we confirmed a potential of modeling a user's forward/backward movement. Our next goal was to evaluate and validate the effectiveness of the model through its application to more realistic VR scenarios. This also allowed us to investigate user experience associated with VR locomotion supported by artificial intelligence. In the next section, we describe Study #2.

5 Study #2: Effectiveness of backward movement detection model

5.1 VR scenarios

VR is a medium that has many elements of a computer game. In general, representation, interaction, conflict, and safety define computer games [15]. Conflict is a naturally occurring process during interactions in the game, interfering with a player's goal achievement. Conflict is also an intrinsic element of all games, and its form can be direct or indirect. In this study, we designed a scenario that requires a moment of backward movement in consideration of the characteristics of the virtual space and the direct/indirect form of conflict. Direct conflict in VR includes confronting obstacles, and indirect conflict includes one's failure to hold an object due to a wrong distance from the user and the object (too close or far).

Three VR scenarios contain both direct and indirect conflicts. Each scenario takes about three minutes and has three events where backward movement is required. Figure 7 illustrates each scenario, and Table 2 describes a scenario detail.

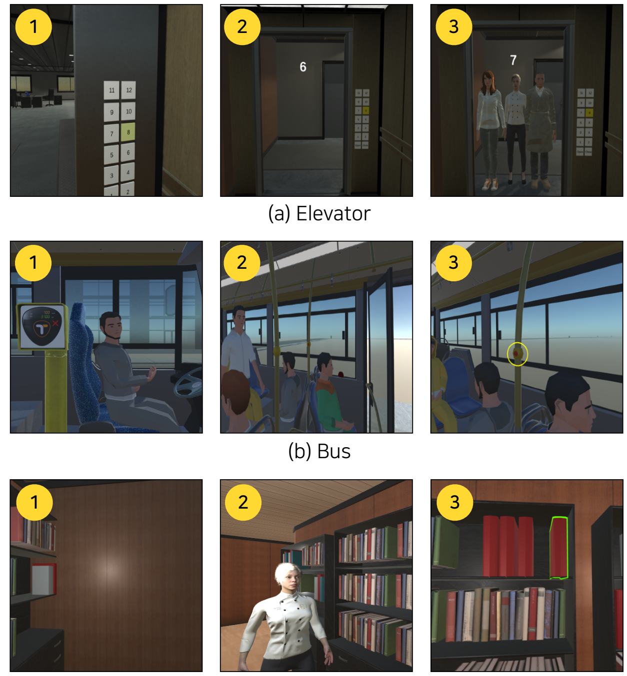
5.2 Methods

5.2.1 Independent variables

The purpose of the user study is to compare and analyze the effectiveness of the model for predicting backward movements with other methods (i.e., controller-based and treadmill-based). These three conditions were independent variables (Figure 8).

- **Control (Standard VR controller-based movement)**: In this condition, a participant was given two VR standard controllers. One controller was to move, and the other controller was to pick up and hold an object. A participant could move in any directions using the trackpad of the movement controller.
- **Experimental #1 (Treadmill-based movement)**: We used Kat Walk mini [7], an off-the-shelf device that supports VR locomotion. It secures a user's body while s/he engages in VR (including walking) and supports friction-free movement in the form of sweeping, which is the same method supported by most passive repositioning treadmill-based devices on the market (e.g., Virtuix Omni, Cyberith Elite). Kat Walk mini does not officially support backward movement by a natural walking form; instead, it can be done by placing one foot in the center of the treadmill and fixing the other foot back (Other devices are quite similar to the KAT Walk mini in requiring a specific condition (e.g., leaning backward) to support backward movement). To pick up and hold an object, a participant used one VR standard controller.
- **Experimental #2 (Model-based movement)**: We used the BiLSTM model that had shown the best performance in Study #1. To pick up and hold an object, a participant used one VR standard controller. Participants wore a waist band and shoes attached with VIVE trackers as used in Study #1.

[7]https://www.kat-vr.com/products/kat-walk-mini-vr-treadmill



(a) Elevator (b) Bus (c) Library

Figure 7: Three scenarios used in Study #2. Each scenario has three moments that need backward movement.

5.2.2 Dependent variables

We used evaluation metrics in two categories (i.e., system logs and user experience responses) as dependent variables.

- **System logs**: We measured the amount of time taken from the point where the participant received the prompt of moving backward to the point when s/he actually moved back. We set the distance to one meter (approximately two steps backward, equivalent to 39.3 inches). It is clear that the more time it takes to move back successfully, the higher difficulty (or less intuitive movement) that the participant would experience.
- **User experience**: We employed presence and cognitive load metrics and developed user perceived satisfaction and effectiveness of movement. The questionnaire for presence consists of 18 questions (Table 3) [57]. Cognitive load refers to the amount of information that working memory can hold at one time. It is the individual's cognitive capacity for learning a task, solving a problem, etc. The primary idea is that, if the cognitive load exceeds an individual's processing capacity, s/he will struggle to successfully complete the task and his/her user experience will diminish. We used Students' Mental Load and Mental Effort in Biology Education-Questionnaire (StuMMBe-Q) [36]. This questionnaire considers two aspects (i.e., mental load and mental effort), and each aspect is measured by six questions. The

Scenario	Tasks
Elevator	1. Failure to adjust the position while trying to press an elevator button (indirect; step back to see the button) 2. A player tries to get off the elevator on the wrong floor (direct; step back to the elevator again) 3. Several people enter the elevator (direct; step back to give room)
Bus	1. A driver asks a user to step back for a moment (direct; step back and wait for the driver's okay-sign) 2. A passenger gets off the bus (direct; step back to give room) 3. Failure to adjust the position while trying to press a stop button (indirect; step back to see the button)
Library	1. Suddenly encounter a wall while looking for a book (direct; step back and move on to the direction indicated by the system) 2. While looking at books, someone is coming through (direct; step back to give room) 3. Failure to adjust the position while trying to pick up a book (indirect; step back to see the book)

Table 2: Detailed description of the VR scenarios. Each scenario has three events that need backward movement (Refer to Figure 7).

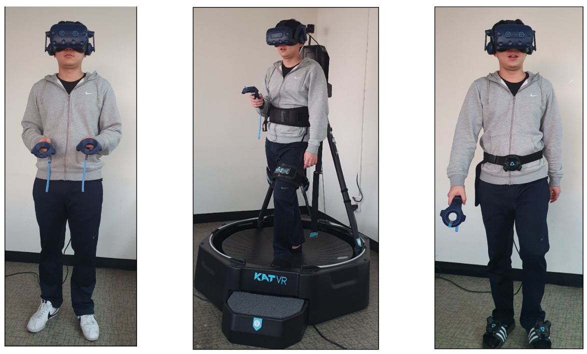


Figure 8: Three conditions used in Study #2.

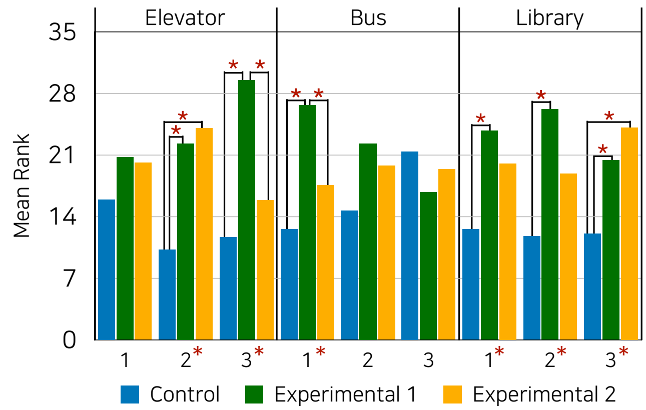


Figure 9: Differences in the completion time of backward movement among three conditions ($^*p < 0.05$). The model-based condition generally showed higher results than the controller-based condition but lower results than the treadmill-based condition. Note that we separately measured the differences for each event in each scenario due to their contextual difference that entails backward movement.

responses to all aforementioned questionnaire items consisted of a 7-point Likert scale (1: strongly disagree; 7: strongly agree). The evaluation metrics of presence and cognitive load have been used in many VR studies [6, 41, 56, 64], showing their validity. For perceived satisfaction and effectiveness of movement, we used the following questions: "Moving in VR was satisfactory" and "Moving in VR was effective."

5.3 Study procedure

We recruited a total of 36 participants (mean age: 25.1, SD: 3.0) through a university bulletin board or word-of-mouth. All participants were university students (24 undergraduates and 12 graduates). In this study, we employed between-subjects design. The order of the scenarios was randomly assigned and counterbalanced across the participants. We randomly assigned 12 participants to each of the three conditions. The study procedure was as follows.

- The participants provided demographic information and answered questions about their prior VR experience.
- The participants were given verbal explanations on the study procedure. They were encouraged to ask any questions.
- The participants went through a short tutorial to experience forward and backward movements.
- (Only for the experimental #2 group) The participants went through a calibration phase to collect movement data for two minutes. To build a model, we used the BiLSTM and the same parameters identified in Study #1.
- The participants used their assigned training condition for around 10 minutes (each scenario runs about three minutes). After completing the task, they answered a survey, which consisted of the questions on presence, cognitive load, satisfaction, and effectiveness, and had a brief interview.

The participants were instructed to raise their hand if they felt uncomfortable during the experiment (we did not have such a case). The study was conducted about 22 minutes on average. Upon completion of the experiment, the participants were compensated $10 for their time.

5.4 Results

As a validation check, we did not find a significant influence of participants' prior VR experience on the results.

5.4.1 System log analysis

Each scenario has three events that require backward movement; thus, we calculated the time taken for each event (a total of nine tasks per participant as described in Table 2). Because the data were not normally distributed, we used a non-parametric test (i.e., Kruskal-Wallis) for comparing the three conditions. For post-hoc comparisons, we used the Mann-Whitney test.

Figure 9 illustrates the results. Overall, the control condition (controller-based) showed the lowest mean rank score (i.e., quicker completion time for backward movement) than other two conditions. This is a somewhat reasonable result because using the trackpad on the controller to move is easy and done quickly. When we take a closer look at the significant differences among the groups, the number of significant differences between the controller-based and the treadmill-based conditions was six (two from Elevator, one from Bus, and three from Library), and that between the controller-based and the model-based conditions was two (one from Elevator and one from Library). This indicates that the model-based condition was more effective than the treadmill-based condition. Given that we identified two significant differences out of nine between the controller-based and the model-based conditions, this also indicates that the completion time of backward movement in the model-based condition was still reasonably short.

5.4.2 User experience analysis

We measured presence, cognitive load, effectiveness, and satisfaction for each condition. As the responses were normally distributed, we used the analysis of variance (ANOVA) and Tukey posthoc tests for group comparisons.

Factor	Question	C	E1	E2	F(2,33)
1. Ability to control system	How well were you able to control the system?	5.8	4.9	5.8	2.05
2. Responsiveness	How responsive was the environment to actions that you initiated (or performed)?	6.4	4.8	6.2	9.68^{**}
3. Naturalness of interaction	How natural did your interactions with the environment seem?	5.8	4.4	5.8	3.44^{*}
4. Naturalness of control	How natural was the mechanism which controlled movement through the environment?	5.0	4.4	5.5	2.22
5. Sense of object movement	How compelling was your sense of objects moving through space?	4.9	4.5	6.2	5.32^{**}
6. Real world consistency	How much did your experiences in the virtual environment seem consistent with your real world experiences?	4.7	4.6	5.8	2.86^{+}
7. Anticipate action results	Were you able to anticipate what would happen next in response to the actions that you performed?	5.4	5.5	5.6	0.05
8. Ability to search	How completely were you able to actively survey or search the environment using vision?	5.6	5.1	6.1	2.70^{+}
9. Sense of self movement	How compelling was your sense of moving around inside the virtual environment?	5.1	4.9	6.1	2.53^{+}
10. Object examination	How closely were you able to examine objects?	4.8	5.1	6.3	11.45^{**}
11. Different viewpoints	How well could you examine objects from multiple viewpoints?	5.3	4.9	6.2	5.09^{**}
12. Object manipulation	How well could you move or manipulate objects in the virtual environment?	5.1	4.8	6.1	3.52^{*}
13. Involvement	How involved were you in the virtual environment experience?	5.8	5.5	6.8	4.32^{*}
14. Action outcome delay	How much delay did you experience between your actions and expected outcomes?	2.9	3.1	2.7	0.15
15. Subject adjustment	How quickly did you adjust to the virtual environment experience?	5.8	5.7	6.5	2.55^{+}
16. Subject proficiency	How proficient in moving and interacting with the virtual environment did you feel at the end of the experience?	5.3	4.8	6.1	3.66^{**}
17. Subject involvement	Were you involved in the experimental task to the extent that you lost track of time?	5.8	5.8	6.6	1.97
18. Sense of perspective	How effective was the sense of perspective (depth of field)?	5.3	6.1	6.5	4.49^{**}

$^{+}p < 0.10, ^{*}p < 0.05, ^{**}p < 0.01$

Table 3: Questions and results of user perceived presence (C: control group, E1: experimental group 1, and E2: experimental group 2). Generally, the experimental group 2 (the model-based condition) showed the highest results in many factors.

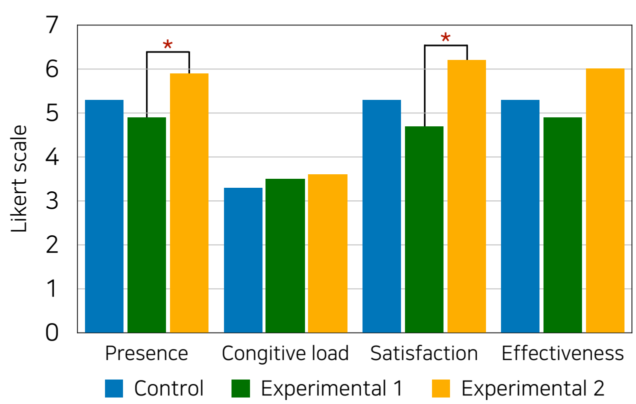


Figure 10: Difference in user experience results among three conditions. The model-based condition showed significantly higher presence and satisfaction than the treadmill-based condition ($^{*}p < 0.05$). The cognitive load results were quite identical among three groups. Although there was no significant difference in effectiveness, the model-based condition showed the highest result.

Table 3 shows the presence scores. We found significant differences in "2. responsiveness," "3. naturalness of interaction," "5. sense of object movement," "10. object examination," "11. different viewpoints," "12. object manipulation," "13. involvement," "16. subject proficiency," "18. sense of perspective" of the factors among the conditions. For responsiveness, posthoc tests showed significant differences between C and E1 ($p < 0.01$) and between E1 and E2 ($p < 0.01$). For naturalness of interaction, we also found significant difference between C and E1 ($p < 0.05$) and marginally significant difference between E1 and E2 ($p = 0.07$). For sense of object movement, E2 showed significant higher results than C ($p < 0.01$) and E1 ($p < 0.01$). For object examination, E2 showed significant higher results than C ($p < 0.01$) and E1 ($p < 0.01$). For different viewpoints, E2 showed significant higher results than E1 ($p < 0.01$). For objective manipulation, significant difference was found between E1 and E2 ($p < 0.01$). For involvement, marginally significant difference was found between C and E2 ($p = 0.07$) and significant difference between E1 and E2 ($p < 0.05$). For subject proficiency, E2 showed significant higher results than E1 ($p < 0.05$). For sense of perspective, E2 showed a significantly higher result than E1 ($p < 0.01$).

We also found several marginally significant differences from ANOVA. E2 showed a marginally higher result than E1 in "1. real world consistency" ($p = 0.07$), "8. ability to search" ($p = 0.08$), "9. sense of self movement" ($p = 0.09$), and "15. subject adjustment" ($p = 0.09$).

To summarize the results of presence, the model-based condition showed the best in most factors of presence. Especially, we noted the similar or higher results of the model-based condition than the controller-based condition, even though it is much easier and more flexible to use the controller to move in our experiment. Since the only difference across the three experimental conditions was the method for movement, the naturalness of the movement is likely to be a primary factor that influences the user experience in the VR scenario, and this was well achieved in the model-based condition.

Figure 10 illustrates the results of presence (the average of 18 factors), cognitive load, satisfaction, and effectiveness. For presence, similar to what we found in the view of each factor, the model-based condition showed the highest results among the three conditions ($F(2,33) = 5.01, p < 0.01$) and significantly higher results than the treadmill-based condition ($p < 0.01$). Regarding cognitive load, we did not find significant difference among the three conditions. This indicates that the participants did not experience much mental load and effort while performing tasks. The model-based method generated a cognitive load that is similar to other methods, which shows that the participants found it to be naturalistic and easy to use. For satisfaction, the model-based condition showed the highest result ($F(2,33) = 3.01, p < 0.05$) and significantly higher result than the treadmill-based condition ($p < 0.05$). Lastly, for effectiveness, we did not find any significant differences among the three conditions but the model-based condition showed the highest result.

5.4.3 Interview analysis

After the survey, we conducted brief interviews, asking the participants about their overall feelings about the locomotion in the VR experiment. For the standard VR controller-based condition, six participants (50%) mentioned cybersickness (e.g., *"Since watching a VR screen for a while without any movement, I felt a little bit of sickness."*(P1)) and four participants (30%) indicated less immersiveness but easy control (e.g., *"Moving in VR was not that difficult* *with the controller, but it was less immersive."*(P6)). It indicates that even if backward movement through the controller's trackpad was easy and quick, many participants did not feel engaged because their feet did not actually move.

For the treadmill-based condition, five (41%) participants mentioned cybersickness (e.g., *"I felt a little bit of sickness when my movement on the treadmill was not reflected on the VR screen."*(P15)), and four (30%) mentioned less immersiveness (e.g., *"Dragging my feet for movement interrupted immersion, because it is quite different from actual walking."*(P22)). It appears that many of the participants did not feel natural to place one foot in the center of the treadmill and fixing the other foot back to move backward.

Lastly, for the model-based condition, nine participants (75%) mentioned immersiveness (e.g., *"In VR, I grabbed items using a controller and moved by actual walking. These controls are the same as those in the real world, which made me be more immersive to the VR content."*(P27)), and four (41%) mentioned less cybersickness (e.g., *"I have experienced in playing VR with the controllers. Comparing with my prior experiences, movement during the experiment was not as dizzy as I had expected."*(P31)). In summary, these results indicate that the participants' experience in the VR movement was quite positive, and compared with other two conditions, it appeared that the participants did not experience cybersickness.

6 Discussion

The role of locomotion is important in terms of user interactions with content and experience in VR. In this paper, we designed machine learning/deep learning-based models that aimed to predict backward movement using sensor data from a user's head, waist, and feet in a walking-in-place environment. We verified the effectiveness of the model by applying it to three VR scenarios. In this section, we discuss salient points and issues in model development and application. We also discuss the direction in which the future motion prediction model development research and application should proceed.

6.1 Reflection on model development and application

Regarding the model-based condition in Study #2, the model with the test data generated during the scenario experiment worked quite well for most participants. However, we experienced some cases where the performance of the model occasionally dropped (86-88% F1-score) during the scenario experiment (for two participants). We used a total of 120 seconds for collecting backward and forward movement data in Study #1 and applied the same amount of time during the calibration phase in Study #2. However, 120 seconds may not be enough for all participants, and some participants might need a longer time for data collection. Our study results confirmed that the use of an individual model was more effective than a single, generalized model (using all participants' data together). For some cases where more data use seems necessary, we could consider grouping users who exhibited similar walking patterns and using the data from the same group or conduct cluster analysis based on the existing data to identify salient groups; for example, similar to what we observed in Figure 6.

We used the basic structure of BiLSTM. Given the sequential characteristics of the step, it may be worth considering the performance of the model by applying other advanced models, such as Stacked LSTM or Convolutional LSTM (ConvLSTM). Moreover, the model will be more personalized when the test data is additionally used for model retraining. As the amount of data used for training for each user increases over time, it may take longer to retrain the model. To mitigate this issue, we could consider applying a weighted model that prefers recency, or truncating the past data and applying the most recent data for training. However, our study results indicated that a model with "reasonable" (not perfect) performance might be sufficient to support a user's VR experience. Therefore, balancing the time of model retraining, data size, model performance, and user experience seems necessary for the application of the model to VR to wider populations.

We could also consider other factors for individualized training. During the calibration phase, we could ask users to WIP at different speeds (e.g., slow walk, fast walk, light jogging) and then map it to different "default bucket" speeds in the VR environment. All detected slow walk, fast walk, and light jogging, would displace the users in VR at equal predefined pacing speed. With a model that detects these different types, we can expect a greater application of the model to many VR scenarios.

6.2 Limitations and future work

Our study has presented insights into VR locomotion. However, it has some limitations that should be addressed in future research. First, most of the participants in the user study were college students in their twenties, and because they were familiar with IT technology, it may be difficult to generalize the results. It is expected that experiments with people from a wider range of age groups and IT affinity levels, which will be conducted in the future. In addition, considering different levels of feeling discomfort when using a VR headset or being in a VR environment is important to better understand the application of model-based VR locomotion.

Second, we used three scenarios that require backward movement that can be encountered in everyday life. However, the scenarios might appear somewhat simple. VR environments are much more flexible and have a high degree of freedom compared with the real world; thus, it seems necessary to consider frequent or prolonged backward movement as well as omni-directional movement that appears a lot in first-person shooter (FPS) games and training scenarios. In addition, there might be a possible bias in participants' subjective ratings of user experience due to the less natural way of creating backward movement on the passive treadmill. In our future work, we plan to verify the effectiveness by applying the supplemented model to more diverse scenarios and walking conditions.

Lastly, there are some ambiguities in the interpretations of the results of the completion time comparison. The comparisons between the control condition and each experimental condition allowed only an indirect conclusion that Experimental 2 (our model) is more effective than Experimental 1 (treadmill). As presented in the results section, when comparing the two experimental conditions, we saw two significant differences out of nine. Thus, our interpretation of the group difference could be partially true, and more rigorous investigations are needed to verify the effectiveness of our model compared with off-the-shelf VR locomotion devices. This will be done in future studies.

7 Conclusion

In this paper, we demonstrated the effectiveness and potential of modeling a user's forward and backward movement in a VR environment. Many VR systems still suffer from users' increased cognitive load or cyber-sickness due to an absence of reliable support for or limited control to navigation and movement. As VR content is expected to be more interactive and users will expect to have more controllable or flexible experience in a VR environment, the role of movement that directly pertains to user experience will be more important. We hope our study findings give useful and applicable insights to researchers, developers, and practitioners for VR locomotion.

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References

[1] M. Al Zayer, P. MacNeilage, and E. Folmer. Virtual locomotion: a survey. *IEEE transactions on visualization and computer graphics*, 2018.

[2] J. Arora, A. Saini, N. Mehra, V. Jain, S. Shrey, and A. Parnami. Virtualbricks: Exploring a scalable, modular toolkit for enabling physical manipulation in vr. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1–12, 2019.

[3] L. Avila and M. Bailey. Virtual reality for the masses. *IEEE computer graphics and applications*, 34(5):103–104, 2014.

[4] M. Azmandian, M. Hancock, H. Benko, E. Ofek, and A. D. Wilson. Haptic retargeting: Dynamic repurposing of passive haptics for enhanced virtual reality experiences. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pp. 1968–1979, 2016.

[5] E. Bastug, M. Bennis, M. Médard, and M. Debbah. Toward interconnected virtual reality: Opportunities, challenges, and enablers. *IEEE Communications Magazine*, 55(6):110–117, 2017.

[6] M. Beege, S. Schneider, S. Nebel, A. Häßler, and G. D. Rey. Mood-affect congruency. exploring the relation between learners' mood and the affective charge of educational videos. *Computers & Education*, 123:85–96, 2018.

[7] J. Blake and H. B. Gurocak. Haptic glove with mr brakes for virtual reality. *IEEE/ASME Transactions On Mechatronics*, 14(5):606–615, 2009.

[8] L. Bouguila and M. Sato. Virtual locomotion system for large-scale virtual environment. In *Proceedings IEEE Virtual Reality 2002*, pp. 291–292. IEEE, 2002.

[9] E. Bozgeyikli, A. Raij, S. Katkoori, and R. Dubey. Point & teleport locomotion technique for virtual reality. In *Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play*, pp. 205–216, 2016.

[10] G. C. Burdea. Haptic feedback for virtual reality. In *Virtual reality and prototyping workshop*, vol. 2, pp. 17–29. Citeseer, 1999.

[11] F. Buttussi and L. Chittaro. Locomotion in place in virtual reality: A comparative evaluation of joystick, teleport, and leaning. *IEEE transactions on visualization and computer graphics*, 2019.

[12] T. Cakmak and H. Hager. Cyberith virtualizer: a locomotion device for virtual reality. In *ACM SIGGRAPH 2014 Emerging Technologies*, pp. 1–1. 2014.

[13] R. M. Clifford, S. Jung, S. Hoerrnann, M. Billinqhurst, and R. W. Lindeman. Creating a stressful decision making environment for aerial firefighter training in virtual reality. In *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 181–189. IEEE, 2019.

[14] J. Clifton and S. Palmisano. Effects of steering locomotion and teleporting on cybersickness and presence in hmd-based virtual reality. *Virtual Reality*, pp. 1–16, 2019.

[15] C. Crawford. The art of computer game design. 1984.

[16] M. Dangelmaier and R. Blach. Odor in immersive environments. In *Springer Handbook of Odor*, pp. 139–140. Springer, 2017.

[17] R. P. Darken, W. R. Cockayne, and D. Carmein. The omni-directional treadmill: a locomotion device for virtual worlds. In *Proceedings of the 10th annual ACM symposium on User interface software and technology*, pp. 213–221, 1997.

[18] D. Engel, C. Curio, L. Tcheang, B. Mohler, and H. H. Bülthoff. A psychophysically calibrated controller for navigating through large environments in a limited free-walking space. In *Proceedings of the 2008 ACM symposium on Virtual reality software and technology*, pp. 157–164, 2008.

[19] Y.-C. Fan and C.-Y. Wen. A virtual reality soldier simulator with body area networks for team training. *Sensors*, 19(3):451, 2019.

[20] J. Feasel, M. C. Whitton, L. Kassler, F. P. Brooks, and M. D. Lewek. The integrated virtual environment rehabilitation treadmill system. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 19(3):290–297, 2011.

[21] J. Feasel, M. C. Whitton, and J. D. Wendt. Llcm-wip: Low-latency, continuous-motion walking-in-place. In *2008 IEEE Symposium on 3D User Interfaces*, pp. 97–104. IEEE, 2008.

[22] T. Feigl, L. Gruner, C. Mutschler, and D. Roth. Real-time gait reconstruction for virtual reality using a single sensor. In *2020 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)*, pp. 84–89. IEEE, 2020.

[23] S. Freitag, B. Weyers, and T. W. Kuhlen. Examining rotation gain in cave-like virtual environments. *IEEE transactions on visualization and computer graphics*, 22(4):1462–1471, 2016.

[24] J. Frommel, S. Sonntag, and M. Weber. Effects of controller-based locomotion on player experience in a virtual reality exploration game. In *Proceedings of the 12th international conference on the foundations of digital games*, pp. 1–6, 2017.

[25] E. Guy, P. Punpongsanon, D. Iwai, K. Sato, and T. Boubekeur. Lazynav: 3d ground navigation with non-critical body parts. In *2015 IEEE Symposium on 3D User Interfaces (3DUI)*, pp. 43–50. IEEE, 2015.

[26] S. Hanson, R. A. Paris, H. A. Adams, and B. Bodenheimer. Improving walking in place methods with individualization and deep networks. In *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 367–376. IEEE, 2019.

[27] Z. Huang, W. Xu, and K. Yu. Bidirectional lstm-crf models for sequence tagging. *arXiv preprint arXiv:1508.01991*, 2015.

[28] V. Interrante, B. Ries, and L. Anderson. Seven league boots: A new metaphor for augmented locomotion through moderately large scale immersive virtual environments. In *2007 IEEE Symposium on 3D User interfaces*. IEEE, 2007.

[29] H. Iwata. The torus treadmill: Realizing locomotion in ves. *IEEE Computer Graphics and Applications*, 19(6):30–35, 1999.

[30] O. Janeh, G. Bruder, F. Steinicke, A. Gulberti, and M. Poetter-Nerger. Analyses of gait parameters of younger and older adults during (non-) isometric virtual walking. *IEEE transactions on visualization and computer graphics*, 24(10):2663–2674, 2017.

[31] S.-G. Jeon, J. Han, Y. Jo, and K. Han. Being more focused and engaged in firefighting training: Applying user-centered design to vr system development. In *25th ACM Symposium on Virtual Reality Software and Technology*, pp. 1–11, 2019.

[32] J. Jerald. *The VR book: Human-centered design for virtual reality*. Morgan & Claypool, 2015.

[33] S. Jung, A. L. Wood, S. Hoermann, P. L. Abhayawardhana, and R. W. Lindeman. The impact of multi-sensory stimuli on confidence levels for perceptual-cognitive tasks in vr. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 463–472. IEEE, 2020.

[34] L. Kassler, J. Feasel, M. D. Lewek, F. P. Brooks Jr, and M. C. Whitton. Matching actual treadmill walking speed and visually perceived walking speed in a projection virtual environment. In *Proceedings of the 7th Symposium on Applied Perception in Graphics and Visualization*, pp. 161–161, 2010.

[35] J.-S. Kim, D. Gračanin, K. Matković, and F. Quek. Finger walking in place (fwip): A traveling technique in virtual environments. In *International Symposium on Smart Graphics*, pp. 58–69. Springer, 2008.

[36] M. Krell. Evaluating an instrument to measure mental load and mental effort considering different sources of validity evidence. *Cogent Education*, 4(1):1280256, 2017.

[37] E. Langbehn, P. Lubos, and F. Steinicke. Evaluation of locomotion techniques for room-scale vr: Joystick, teleportation, and redirected walking. In *Proceedings of the Virtual Reality International Conference-Laval Virtual*, pp. 1–9, 2018.

[38] J. J. LaViola Jr, E. Kruijff, R. P. McMahan, D. Bowman, and I. P. Poupyrev. *3D user interfaces: theory and practice*. Addison-Wesley Professional, 2017.

[39] M. Nabiyouni, A. Saktheeswaran, D. A. Bowman, and A. Karanth. Comparing the performance of natural, semi-natural, and non-natural locomotion techniques in virtual reality. In *2015 IEEE Symposium on 3D User Interfaces (3DUI)*, pp. 3–10. IEEE, 2015.

[40] S. Nahavandi, L. Wei, J. Mullins, M. Fielding, S. Deshpande, M. Watson, S. Korany, D. Nahavandi, I. Hettiarachchi, Z. Najdovski, et al. Haptically-enabled vr-based immersive fire fighting training simulator. In *Intelligent Computing-Proceedings of the Computing Conference*, pp. 11–21. Springer, 2019.

[41] S. Nebel, M. Beege, S. Schneider, and G. D. Rey. The higher the score, the higher the learning outcome? heterogeneous impacts of leaderboards and choice within educational videogames. *Computers in*

Human Behavior, 65:391–401, 2016.
[42] N. C. Nilsson, S. Serafin, and R. Nordahl. Walking in place through virtual worlds. In *International Conference on Human-Computer Interaction*, pp. 37–48. Springer, 2016.
[43] N. C. Nilsson, S. Serafin, F. Steinicke, and R. Nordahl. Natural walking in virtual reality: A review. *Computers in Entertainment (CIE)*, 16(2):1–22, 2018.
[44] W. Powell, B. Stevens, S. Hand, and M. Simmonds. Blurring the boundaries: The perception of visual gain in treadmill-mediated virtual environments. In *3rd IEEE VR 2011 Workshop on Perceptual Illusions in Virtual Environments*, 2011.
[45] T. V. Randhavane, A. Bera, E. Kubin, K. Gray, and D. Manocha. Modeling data-driven dominance traits for virtual characters using gait analysis. *IEEE Transactions on Visualization and Computer Graphics*, 2019.
[46] S. Razzaque, Z. Kohn, and M. C. Whitton. *Redirected walking*. Citeseer, 2005.
[47] S. Razzaque, D. Swapp, M. Slater, M. C. Whitton, and A. Steed. Redirected walking in place. In *EGVE*, vol. 2, pp. 123–130, 2002.
[48] H. Sak, A. W. Senior, and F. Beaufays. Long short-term memory recurrent neural network architectures for large scale acoustic modeling. 2014.
[49] D. Saredakis, A. Szpak, B. Birckhead, H. A. Keage, A. Rizzo, and T. Loetscher. Factors associated with virtual reality sickness in head-mounted displays: a systematic review and meta-analysis. *Frontiers in Human Neuroscience*, 14, 2020.
[50] T. Schubert, F. Friedmann, and H. Regenbrecht. The experience of presence: Factor analytic insights. *Presence: Teleoperators & Virtual Environments*, 10(3):266–281, 2001.
[51] S.-W. Seo, S. Kwon, W. Hassan, A. Talhan, and S. Jeon. Interactive virtual-reality fire extinguisher with haptic feedback. In *25th ACM Symposium on Virtual Reality Software and Technology*, pp. 1–2, 2019.
[52] E. Shaw, T. Roper, T. Nilsson, G. Lawson, S. V. Cobb, and D. Miller. The heat is on: Exploring user behaviour in a multisensory virtual environment for fire evacuation. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1–13, 2019.
[53] J. Shigeyama, T. Hashimoto, S. Yoshida, T. Narumi, T. Tanikawa, and M. Hirose. Transcalibur: A weight shifting virtual reality controller for 2d shape rendering based on computational perception model. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1–11, 2019.
[54] M. Slater, M. Usoh, and A. Steed. Taking steps: the influence of a walking technique on presence in virtual reality. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 2(3):201–219, 1995.
[55] J. L. Souman, P. R. Giordano, M. Schwaiger, I. Frissen, T. Thümmel, H. Ulbrich, A. D. Luca, H. H. Bülthoff, and M. O. Ernst. Cyberwalk: Enabling unconstrained omnidirectional walking through virtual environments. *ACM Transactions on Applied Perception (TAP)*, 8(4):1–22, 2008.
[56] A. Sutcliffe. Designing for user engagement: Aesthetic and attractive user interfaces. *Synthesis lectures on human-centered informatics*, 2(1):1–55, 2009.
[57] A. Sutcliffe, B. Gault, and J.-E. Shin. Presence, memory and interaction in virtual environments. *International Journal of Human-Computer Studies*, 62(3):307–327, 2005.
[58] D. Swapp, J. Williams, and A. Steed. The implementation of a novel walking interface within an immersive display. In *2010 IEEE Symposium on 3D User Interfaces (3DUI)*, pp. 71–74. IEEE, 2010.
[59] J. N. Templeman, P. S. Denbrook, and L. E. Sibert. Virtual locomotion: Walking in place through virtual environments. *Presence*, 8(6):598–617, 1999.
[60] M. Usoh, K. Arthur, M. C. Whitton, R. Bastos, A. Steed, M. Slater, and F. P. Brooks Jr. Walking¿ walking-in-place¿ flying, in virtual environments. In *Proceedings of the 26th annual conference on Computer graphics and interactive techniques*, pp. 359–364, 1999.
[61] P. Vichitvejpaisal, N. Yamee, and P. Marsertsri. Firefighting simulation on virtual reality platform. In *2016 13th International Joint Conference on Computer Science and Software Engineering (JCSSE)*, pp. 1–5. IEEE, 2016.
[62] S. Weech, S. Kenny, and M. Barnett-Cowan. Presence and cybersickness in virtual reality are negatively related: a review. *Frontiers in psychology*, 10:158, 2019.
[63] B. Williams, G. Narasimham, B. Rump, T. P. McNamara, T. H. Carr, J. Rieser, and B. Bodenheimer. Exploring large virtual environments with an hmd when physical space is limited. In *Proceedings of the 4th symposium on Applied perception in graphics and visualization*, pp. 41–48, 2007.
[64] C. J. Wilson and A. Soranzo. The use of virtual reality in psychology: a case study in visual perception. *Computational and mathematical methods in medicine*, 2015, 2015.
[65] T. Yamada, S. Yokoyama, T. Tanikawa, K. Hirota, and M. Hirose. Wearable olfactory display: Using odor in outdoor environment. In *IEEE Virtual Reality Conference (VR 2006)*, pp. 199–206. IEEE, 2006.
[66] J. Yang, M. N. Nguyen, P. P. San, X. Li, and S. Krishnaswamy. Deep convolutional neural networks on multichannel time series for human activity recognition. In *Ijcai*, vol. 15, pp. 3995–4001. Citeseer, 2015.
[67] H. Yi, J. Hong, H. Kim, and W. Lee. Dexcontroller: Designing a vr controller with grasp-recognition for enriching natural game experience. In *25th ACM Symposium on Virtual Reality Software and Technology*, pp. 1–11, 2019.
[68] A. Zenner and A. Krüger. Drag: on: A virtual reality controller providing haptic feedback based on drag and weight shift. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1–12, 2019.
[69] K. Zhu, T. Chen, F. Han, and Y.-S. Wu. Haptwist: creating interactive haptic proxies in virtual reality using low-cost twistable artefacts. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1–13, 2019.