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Velocity-Dependent Perception Threshold for Discrete Imperceptible Repositioning in a Virtual Environment During Eye Blinks

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ABSTRACT In this study, the relationship between a person's walking speed and the perception threshold for discrete implicit repositioning during eyeblinks in a virtual environment is investigated. The aim is to estimate the perception thresholds for forward and backward repositioning during forward translation following eyeblink occurrences. A psychophysical method called Staircase Transformed and Weighted up/down is utilized to quantify the perception thresholds for forward and backward repositioning. The perception thresholds for this repositioning are estimated for three different walking speeds: slow (0.58 m/s), moderate (0.86 m/s), and fast (1.1 m/s). The collected observations are then analyzed using regression analysis. The estimated perception threshold values for imperceptible forward repositioning were 0.374, 0.635, and 0.897 meters for the abovementioned walking speeds, respectively. Moreover, the respective perception threshold values for imperceptible backward repositioning were 0.287, 0.430, and 0.572 meters for the same walking speeds. The findings reveal a proportional relationship between the perception threshold values and the participant's walking speed. As such, it is possible to imperceptibly reposition a participant at a greater distance when they are walking faster relative to the same situation when the participant is walking slower. In addition, the results show that there is more tolerance in forward discrete repositioning compared to backward discrete repositioning during forward translation. These findings enable the extension of the manipulation types utilized by the Redirected Walking Technique. More specifically, this allows for implementing a sophisticated composite redirected walking controller, which utilizes continuous and discrete translation gains simultaneously; this helps not only with reducing the cognitive load, but also with reducing the amount of physical space required to support infinite free exploration in an immersive virtual environment.

INDEX TERMS Redirected walking technique, perception thresholds, eyeblinks, virtual reality, head-mounted display, discrete manipulation, stimulus intensity.

I. INTRODUCTION

Natural walking is the most intuitive approach to performing locomotion in real life. As is evident from previous research studies, utilizing real walking to perform locomotion in a virtual environment (VE) is more advantageous than other types of locomotion approaches [1], [2]. However, using natural walking to perform locomotion in a VE is also a challenging task, since the virtual world is typically much larger compared to the available physical space. The Redirected Walking Technique (RDWT) is a method that provokes imperceptible rotations of the participant's perspective in a VE, thereby creating the false impression of walking through infinite space and time in any direction within the VE, while in reality, the participant is only walking in a circle within a tracked limited physical space [3]. Since the RDWT was first introduced by Razzaque [3], several advances have been made in this research area. Classical RDWT utilizes several spatial manipulation parameters, including translation, rotation, curvature, and bending gains [4], [5], to map

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user movements in the physical space by a ratio that differs from 1:1 in the Immersive Virtual Environment (IVE). These manipulation parameters are introduced continuously and rendered at each frame to the participant's virtual perspective in the VE. However, adopting RDWT to support infinite free exploration in a VE is quite challenging, as it requires a large physical tracked walking space (40×40 meters) to produce an experience functionally equivalent to real walking in terms of proprioceptive, vestibular and visual feedback [4]. In recent years, advances have been made in reducing the spatial requirement for RDWT; for instance, limiting the virtual path in the VE to be curved only [5], or using haptic cues to modify the participant's spatial perception, such that the user is walking along a convex surface wall in the physical space (while, in a VE, the participant perceives themselves to be walking straight along the wall) [6]. However, these approaches do not support infinite exploration in an IVE. It is further evident that reducing the spatial requirement for classical RDWT while supporting infinite free exploration in an IVE has negative implications for user experience, such as spatial performance, cognitive load and task performance [2], and could even trigger simulator sickness [7]. Researchers have begun to investigate other approaches to overcome these downsides, with the idea being to utilize orthogonal concepts that can be incorporated into the RDWT without employing the same perceptual processes adopted by classical methods. Recently, the eyeblink has drawn researchers' attention owing to its potential to provide additional opportunities for discretely introducing spatial manipulation (due to the nature of eyeblink occurrence) to participants' virtual viewpoints in the VE. These spatial manipulations are rendered on the VR-headset only during eyeblinks. A study by Langbehn *et al.* [8] proposed estimating the perception threshold for translation along three different axes, namely forward "z", up "y", and right-side "x" (based on the left-handed coordinate system). The estimated thresholds ranged from 0.04 to 0.09 meters depending on the evaluated axis. The estimation process was conducted during while the observer was standing still without any translation. This implies that it is possible to imperceptibly reposition a user from between 0.04 to 0.09 meters (depending on the targeted axis) away from the previous position in VE during an eyeblink.

In this experimental study, the possibility of utilizing eyeblink occurrences, while the user is walking, to imperceptibly reposition the user in an IVE has been investigated. In addition, the study aims to understand the impact of walking speed on a user's perception thresholds for forward/backward repositioning during eyeblinks by comparing the estimated perception thresholds for repositioning during different walking speeds. It should be noted that, in psychophysics, the term "*perception threshold*" represents a stimulus intensity value at which the observer can only just identify the presence of that stimulus or recognize the difference between two stimuli [9]. The term "*perception threshold for repositioning*" here refers to the value of the translation gain applied to the participant's virtual perspective in the VE that just being detected by the participant.

II. RELATED STUDIES AND THEORETICAL BACKGROUND

A significant number of research studies have been conducted to address the issue of performing virtual locomotion within a VE. Several approaches to facilitating virtual locomotion in IVEs have been developed, with one such avenue being *Gait Negation Techniques* [10]. These techniques attempt to address the virtual locomotion problem in IVEs by introducing a mechanical apparatus that cancels the participant's movement by keeping the participant at the center of a physical space, e.g., *Omni-Directional Treadmills* (ODT) [11], *Virtuspheres* [12], *Circula Floor* [13], or *Cybercarpet* [14].

Other techniques for performing locomotion in IVEs include *Gesture-based approaches*, such as *Walking in Place* (WIP) [15] and *ArmSwinger* [16]. The idea behind these techniques is that movement is applied to the participant's virtual viewpoint during each frame, while performing walking-like gestures (for instance, walking in place or arm-swinging). Another approach to travel in VR is *Teleportation* [17], which works by teleporting the participant to a target location in a VE after they use a handheld controller to point towards the intended location. These approaches enable participants to explore a large area in a virtual environment while standing in a confined physical space in the real world. These innovations (that have been mentioned above) are considered to have made substantial contributions to solving the issue of performing virtual locomotion in VR. However, previous studies have also shown that using semi-natural and non-natural locomotion interfaces has negative impacts on the participant's VR experience, which are related to task performance, comfort and presence (i.e., the feeling of being "in" the VE) [18], [19]. A research study conducted by Marsh *et al.* [2] evaluated several types of locomotion interfaces, finding that these approaches could increase demands on spatial working memory. Such increased demands require participants to draw upon more cognitive resources than a locomotion interface that utilizes natural walking. Moreover, the kinematic parameters of the gait cycle using the discussed approaches differ from the locomotion interfaces utilized when deploying natural walking [20].

Various sensory stimuli act on one's senses simultaneously: examples include the vision system, which provides valuable information about our surroundings, as well as the vestibular system, which gives us information about balance and spatial orientation that enables us to coordinate movement with balance and stabilize our vision. Kinesthetic proprioceptive stimuli from the muscles, tendons, joints and ligaments inform the brain about the position, orientation, and movement of the musculature. All these various types of sensory information are fused by the brain to build a mental image of our body and the surrounding environment [21], [22]. Inconsistent information can induce simulator sickness [7]. Furthermore, using gait negation techniques is not feasible due to the limited scalability and the maintenance that these devices require after several working hours, in addition to the fact that these devices are bulky and occupy space when not in use.

Alternatively, real natural walking can be considered the most direct and obvious technique for travelling in a virtual environment [10]. Several perceptual and cognitive studies have demonstrated how virtual locomotion interfaces that utilize real walking have substantial benefits over other kinds of locomotion techniques in terms of sense of presence, the buildup of the cognitive map [1], the imposed cognitive load [2] and navigational search tasks [23]. Due to the physical movement, vestibular self-motion and kinesthetic proprioceptive information will be produced, leading to a more realistic and natural navigation experience. This sensory information in turn contributes to a higher level of spatial knowledge, particularly in a complex virtual environment. Accordingly, the participant's understanding of the virtual environment can be improved [10]. From a biomechanics perspective, moreover, the natural walking metaphor covers all events and phases in the gait cycle: these include initial contact, loading response mid-stance, terminal stance, the pre-swing events during the stance phases of the gait, and the initial swing, mid-swing and terminal swing events during the swing phase of the cycle [24]. However, in most cases, the area of the VE is larger than the physical area available in the real world. Consequently, mapping a participant's movement according to a 1:1 ratio in the VE could be problematic, as this would limit the navigational space in the IVE to the available physical area.

RDWT [3] is another approach to performing virtual locomotion in an IVE. It utilizes real walking, and works by imperceptibly manipulating the participant's virtual perspective during each frame in the VE. These manipulations map the participant's physical movement in the VE with a ratio that differs from 1:1. For instance, these manipulations may slightly rotate and/or shift the virtual world around the observer's virtual perspective in the VE, which causes the user to unconsciously compensate for these rotations and repositions. As a result, the participant could walk in circles in the physical world while perceiving a straight path in the VE. In cases where the participant reaches the boundary of the tracked physical space, a safety algorithm will intervene. This algorithm introduces explicit manipulation to the participant's virtual perspective in the VE in order to redirect him or her away from the boundaries and back to the tracked space, and is referred to as the *Reset Algorithm*. Utilizing physical walking provides consistent multi-sensory information, which is crucial for reducing simulation sickness and enhancing the presence (i.e., the feel of being inside the virtual space). One psychophysical study [4] has shown that RDWT is more or less similar to real walking in terms of producing the sensorimotor contingencies experienced by the user. As a result, the participant can walk anywhere in the IVE without noticing the introduced manipulations. Hence, RDWT is a promising approach for addressing natural virtual locomotion in VR, as it engages the user in a more natural manner. Nevertheless, there are negative side effects associated with RDWT use. For instance, calling on the reset algorithm is inherently disruptive due to the introduction of explicit manipulation of the participant's virtual perspective. This might induce simulator sickness and/or otherwise affect the participant's experience in the VE by causing a break in the presence.

Supporting free exploration in a VE utilizing RDWT requires a physical tracked space with an area of 40×40 meters [4]. However, these large spatial requirements of RDWT, which must be met to provide a walking experience similar to real walking, are considered a limiting factor that precludes its use in practical applications. Recent studies have suggested the possibility of reducing the RDWT's spatial requirements. More specifically, in one study conducted by Grechkin *et al.* [25], two types of manipulation (translation and curvature gains) were utilized simultaneously. The findings showed that combining both gains is highly efficient in a small real space. Moreover, in the research of Langbehn *et al.* [5], the curvature of curved virtual paths was altered by means of bend gain during a psychophysical experiment. However, these approaches do not support free exploration in the VE; in other words, the participant must follow a specific path (waypoints) while walking within the environment.

Reducing the spatial requirements of RDWT to facilitate their deployment in current consumer VR systems (such as HTC-Vive) remains challenging. This is especially true given that the current VR hardware industry is following a *Room-Scale-VR* design model, which assumes that all VR experiences will be possible within an area the size of a living room. Another challenge is that utilizing RDWT in room-scale VR experiences may impose unwanted side-effects, such as increased cognitive load. Humans' spatial working memory is derived from limited cognitive resources. One study conducted by Marsh et. al. [2] evaluated several types of semi-natural virtual locomotion interfaces in VR. Their findings showed that the less natural the locomotion interface, the greater the demand for spatial working memory. Hence, to address these issues, researchers have begun to seek out other approaches that may be integrated and utilized simultaneously with traditional RDWT, but that do not employ the same perceptual processes used by the classical RDWT. The reader is referred to Appendix A for brief information about the structure of RDWT and the utilized position/orientation manipulation methods.

A. VISUAL SUPPRESSION DURING EYEBLINKS AND MOTION PERCEPTION

As mentioned above, the use of eyeblinks has recently attracted research interest, as it enables imperceptible redirection of the participant in the VE. A healthy adult blinks roughly 10 to 20 times every minute [26], [27], with each blink lasting between 75 and 400 milliseconds [26], [28], [29]. A functional MRI study conducted by

Bristow *et al.* [22] investigated the effect of eyeblinks on vision cognition in the visual cortex. The findings showed that eyeblinks suppress activity in the visual cortex, as well as parts of another area in the brain—namely the parietal and prefrontal cortex—even when there is unchanging retinal stimulation. These areas are associated with integrating. information from several senses to build a coherent picture of the surrounding environment. Another study [30] determined that when our brains are not focusing on a task, the region known as the *default mode network* will be activated, allowing our mind to switch into ''idle mode''. In a later study, which investigated eyeblinks and their relation to brain activity [31], the researchers monitored 20 healthy participants using a brain PET scan as they watched video clips of a comedy show. The scientists found that at points where natural pauses occurred in the video clips, two things occurred: the breaks provoked a spontaneous blink in the participants, and the scan revealed a dip in the area of the brain that controls focus. During this short instant, the default mode network intervened, taking over for an inactive brain. The activation of this default mode network serves as a form of momentary rest for the mind that gives the brain a chance to go ''offline''. Hence, eyeblinks provide an opportunity to imperceptibly introduce discrete manipulation to the participant's virtual perspective in a VE.

On a related note, in a study by Langbehn *et al.* [32], the possibility of utilizing eyeblinks to reposition and reorient the participant was investigated. The findings showed the possibility of redirecting the participant using eyeblinks, thereby extending the RDWT detection threshold. Moreover, a later study conducted by Langbehn *et al.* [8] investigated a different approach, namely that of imperceptibly reorienting and repositioning a participant in an IVE utilizing visual suppression during eye blinking. One of the experiments conducted during this study involved estimating the repositioning detection thresholds for translation along three different axes based on the anatomical planes of the human body: the up axis, which indicates the opposite direction of the gravity vector; the right axis, which pertains to the direction from the user's left to right side; and finally, the forward axis, which indicates the direction of looking. For estimating the detection thresholds, a psychophysics method called two-alternative forced-choice (2AFC) for constant stimuli has been used. The findings of this experiment revealed that the translation along the up and right axes was easy to observe. Moreover, translation along the forward axis was tolerated better compared to the other axes. The range of the estimated detection threshold was around 0.04 to 0.09 meters. Table 1 shows how these values are distributed, with negative values representing translation in the opposite direction. Furthermore, in the study presented in [8], the perception threshold values were estimated for the participant when standing in place.

Self-motion perception integrates a large amount of sensory information from several systems, including vestibular, visual, and somatosensory. Visual information contributes substantially to self-motion perception during movement at

TABLE 1. Distribution of the detected thresholds for translation with respect to each axis [8].

Translation axis	Lower detection limit (m)	Upper detection limit (m)
Up	-0.04007	0.03988
Right	-0.03919	0.05162
Forward	-0.09754	0.07708

constant velocity [33], [34]. In many important activities, we count mainly on our visual system to perceive motion; for instance, identifying a moving object from a static background. Our visual system contains a neural configuration called the *Reichardt detector* [35], devoted to recognizing the motion of the visual features in the field of view, which pertains to the images of these features moving across the retina. The pattern of the movement occurs due to the motion of the visual features on our retina called *optic flow* [36]. Fig. 1 presents the optic flow field for forward and backward movement observed by a participant during forward and backward translation. The optic flow field depends on the direction and the speed of the observer's movement, as well as the depth structure of the observed perspective.

(a) (b)

FIGURE 1. Optical flow vector field patterns generated during observer movement in the environment; (a) during forward translation and (b) during backward translation.

Self-motion perception in the virtual world differs from that in the real physical environment. Specifically, previous studies have shown that discrepancies exist between virtual and real environmental perception; for instance, underestimation of distance occurs in the virtual environment compared to the real one [37], [37] and virtual speed during walking in a VE is also underestimated [38]. Moreover, the participants may have other difficulties in orienting themselves in a VE [39], [40]. However, this is beneficial in the RDWT context, because the participant can tolerate a specific amount of discrepancy between the visual perceived VE and the proprioceptive sensation in that VE [3], [39], [41]–[43]. Nevertheless, the participants in the IVE should have a consistent and instinctive VR experience. Moreover, a previous study has shown that walking speed in a VE tends to be misperceived [44]. The findings revealed that this misperception is related to the observed optic flow and the gaze direction during the translation. During forward translation, the participant experiences a radial flow in the central vision and lamellar optic flow in the periphery vision. Due to the

VR headset's limited field of view, the lamellar optic flow in the periphery vision will be obscured, which leads to speed misperception. Accordingly, it was hypothesized that the perceived self-motion due to the optic flow pattern experienced by the observer during walking (forward/backward translation) in an IVE can affect the perception threshold for repositioning during eyeblinks. As a result, the participant translates without being aware of introducing the translation gain into his/her virtual perspective during the occurrence of walking and blinking.

B. ESTIMATING STIMULUS INTENSITY IN PSYCHOPHYSICS

In psychophysics, there are several approaches to quantifying the value of stimulus intensity (psychometric threshold θ) that affects an observer's behaviour ψ. These approaches are divided into two categories: *Classical psychophysics methods* and *Adaptive methods.* One example of Classical psychophysical methods is that of constant stimuli [9]. In this technique, a set X of predetermined stimulus intensities $\{x_0, \ldots, x_n\}$ is examined. These predetermined samples are randomly introduced to the observer, and every value is evaluated several times. The outcome of the evaluation represents the psychometric function, which illustrates the accumulative responses of the observer to the stimulus level, as plotted in Fig. 2.

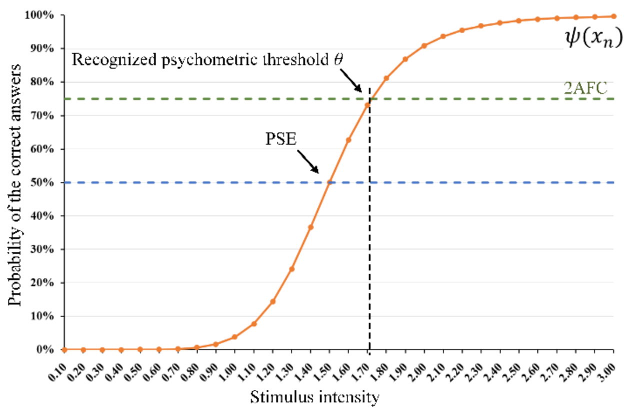


FIGURE 2. The psychometric function based on the distribution of the observed responses.

As a result, the psychophysical parameters can be estimated; these include the psychometric threshold value θ, the slope of the psychometric function $\psi(x_n)$ and the point of subjective equality (PSE), which represents the value of the stimulus intensity not recognized by the observer and located at the 50% probability point. As Fig. 2 shows, the threshold values above 75% of the probability of the correct answer are considered perceived values [9]. These evaluations are based on predetermined assumptions regarding the selection of the template psychometric function relating to the observed measurement (e.g., normal distribution, logistic distribution, step function, etc.) that determine the possible range of the stimulus intensity, where it is perceived that the psychometric threshold is located.

Approaches in the second category are referred to as adaptive methods. During these procedures, there is no predetermined stimulus intensity range for use in evaluating the possible psychometric threshold value in advance. The evaluation process begins with the introduction of a stimulus intensity (X_n) that is easily recognized by the observer. This value is used to produce an optimal stimulus intensity based on the participants' responses. That is, there are two possible observer responses: $r_i = 0$ for an incorrect (or miss) answer, and $r_i = 1$ for a correct (or hit) one.

$$\textit{for a correct answer } [R_n = 1|X_n] = \psi\,(X_n) \tag{1}$$

$$\textit{for an incorrect answer } [R_n = 0|X_n] = 1 - \psi\,(X_n) \tag{2}$$

The function y, which represents the adaptive procedure, aggregates the current stimulus intensity X_n with the previous one X_{n-1} and the related responses R_n at the current trial n and the target probability Φ in order to calculate the optimal stimulus intensity X_{n+1} for the next trial.

$$X_{n+1} = y(X_n, X_{n-1}, R_n, R_{n-1,}n, \Phi) \tag{3}$$

Classical psychophysics methods of experimentation are generally argued to be ineffective [9]. This is because the approach assumes that the psychometric threshold is obscure, and that the vast majority of the information is clustered at points on the psychometric function that provide little data about the estimated stimulus value. By contrast, the adaptive approach requires fewer trials to converge and estimate the threshold value θ, as it is more straightforward than the constant stimuli method [9]. Next, the theoretical aspects of the adaptive method utilized in our study will be explained.

1) UP/DOWN STAIRCASE PROCEDURE

Generally speaking, a simple staircase procedure begins the evaluation by introducing a high-intensity stimulus value that is easy to identify. During the experimental run, the intensity is reduced during each trial until a negative answer (miss) is given by the participant, at which point the direction of the staircase will be reversed. Next, the value of the stimulus is increased until the participant replies positively (hit), which will trigger another reversal. Once the termination criterion has been met, the values for the last of these reversal points are then averaged, as shown in Fig. 3. There are several types of staircase methods, including instance, transformed, weighted, and up/down design [45]. Each approach also uses different rules, such as up/down, step size and termination criteria. Fig. 3 illustrates the up/down staircase procedure.

2) TRANSFORMED UP/DOWN STAIRCASE PROCEDURE

In this method, the decision to decrease the stimulus intensity is based on several previous trials instead of only the most recent one. For instance, the rule that increases stimulus intensity after every negative reply could be modified, as in the simple staircase procedure. However, stimulus intensity decreases only after several consecutive positive replies, since the last adjustment is in stimulus intensity. For example,

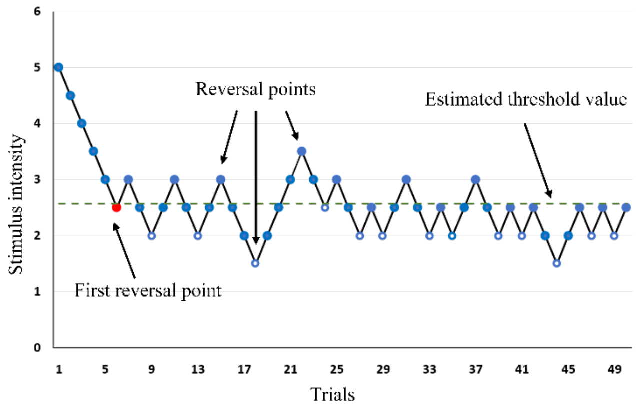


FIGURE 3. **The track of a simple staircase procedure using a 1 up/1 down rule. The empty circles represent incorrect responses, while the filled ones represent correct responses.**

the stimulus intensity can be decreased after two consecutive positive responses, a method called the 1 up / 2 down-rule, as shown in Fig. 4. Alternatively, a 1 up / 3 down rule could be deployed, in which the stimulus intensity is decreased after three consecutive positive responses [45], [46].

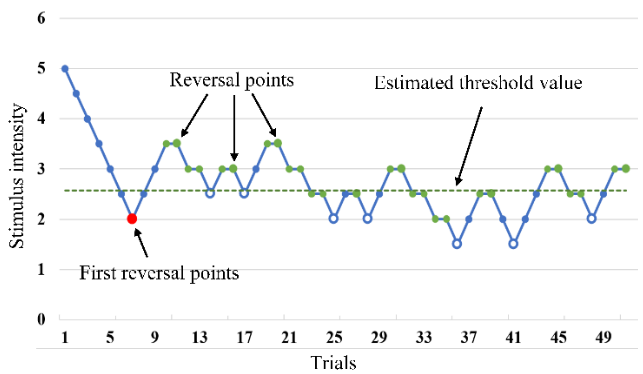


FIGURE 4. **A track of a transformed-up/down staircase procedure using the 1 up / 2 down rule. The red point represents the first reversal point; the dotted line represents the estimated threshold value.**

3) WEIGHTED UP/DOWN STAIRCASE METHOD

In this approach, the size of the step-down and the size of the step-up are unequal [46], with the step size being evaluated by the rule targeting a specified probability value:

$$\frac{S_{dw}}{S_{up}} = \frac{1-\Phi}{\Phi} \tag{4}$$

where S_{dw} represents the size of the step-down, S_{up} is the size of the step-up, and the target's correct probability is denoted by Φ. Fig. 5 illustrates the weighted-up/down staircase approach.

4) TRANSFORMED–WEIGHTED UP/DOWN STAIRCASE METHOD

In this procedure, the sizes of the steps up and down are unequal (as in the weighted up/down method). Additionally,

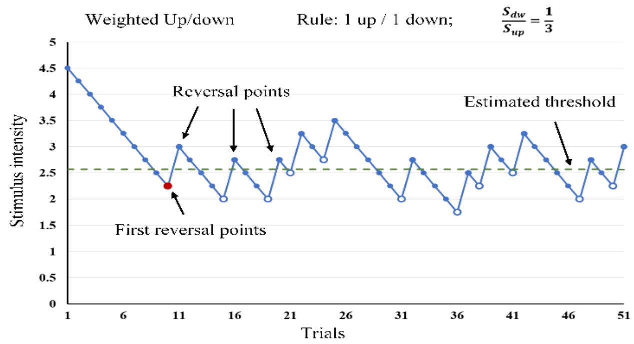


FIGURE 5. **A track of the weighted up/down staircase procedure using the 1 up / 1 down rule. The empty circles represent incorrect responses, while the filled ones represent correct responses.**

the stimulus intensity is decreased after a specified number of consecutive missed (incorrect) replays, as with the transformed up/down method [46]. The following equation describes the correct proportion targeted with this approach:

$$\Phi = \left(\frac{s_{up}}{s_{up} + s_{dw}}\right)^{\frac{1}{c}} \tag{5}$$

where S_{dw}, S_{up} and Φ are denoted as above, while c represents the number of consecutive replays. Fig. 6 illustrates the track of the staircase procedure utilizing the transformed–weighted up/down procedure.

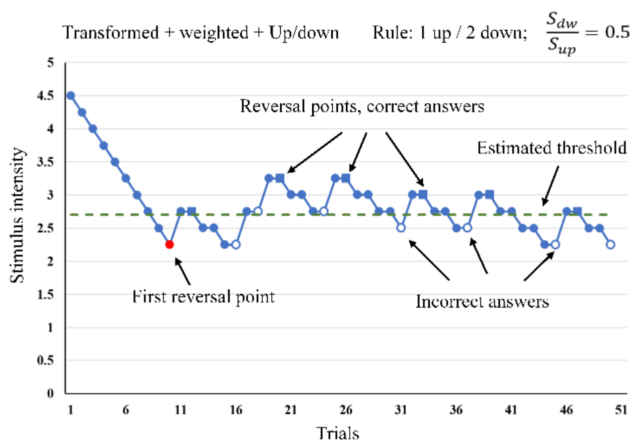


FIGURE 6. **A track of transformed–weighted up/down staircase procedure using the 1 up / 2 down rule with a 0.5 S_{dw}/S_{up} ratio. Empty circles represent incorrect answers (miss), while filled in ones represent the correct answer (hit).**

C. AIM AND SCOPE

The main objectives of this study can be summarized as follows:

- To examine the ability to utilize eyeblinks to reposition (forward/backwards) the participant when these occur during the participant's forward translation in the IVE.
- To estimate the perception thresholds for forwards/back wards discrete repositioning when eyeblink occurs during the participant's forward translation in the IVE.

- To investigate the impact of walking speed on the perception threshold for forward/backward discrete repositioning when eyeblink occurs during the participant's forward translation in the IVE.

Based on the literature discussed above, it was hypothesized that a proportional relationship between the perception threshold for imperceptible repositioning and the participant's walking speed. It was concluded that it is possible to imperceptibly reposition a participant during eyeblink at a greater distance while walking fast, compared to the same situation when walking slower. Most of the time, we are more accustomed to walking in the forward direction (the viewing direction) than in other directions. Hence, an initial objective of the project was estimating the perception thresholds for forward/backward repositioning during forward walking and eyeblink occurrences along the forward "z" axis (based on the left-handed coordinate system). The findings extend the position manipulation methods of current RDWT. This research is part of an ongoing study aimed at implementing a sophisticated redirected walking controller, which utilizes two different manipulation approaches simultaneously: continuous (classic) and discrete (during eyeblink occurrence). Each approach taps into a different perceptual process to minimize the cognitive load and reduce the spatial requirements for RDWT while also supporting free exploration in the IVE.

III. RESEARCH METHODOLOGY

In this section, a study has been conducted earlier will be discussed. The study was aimed to prove the concept of utilizing eyeblink to implicitly reposition a participant, along with the utilized perception threshold estimator and its design aspects. Additionally, the procedure followed when conducting the experiment will be discussed. Finally, the apparatus used for this purpose will be described.

A. PROOF OF CONCEPT

Before conducting this research study, a preliminary investigation has been carried out on the feasibility of utilizing the eyeblink to imperceptibly reposition a participant during forward translation. Additionally, the utilized approach to estimate the perception thresholds for discrete repositioning during eyeblinks has been evaluated. During the preliminary study, a group of 12 students participated in the experiment. The average participant age was 27 years, with a standard deviation of SD = 4.63 years. During this experiment, the single reposition value (0.5 meters) was tested; here, the walking speed of the participant was around 3km/h or around 0.86 m/s.

During the experiment, the participant walked along a straight path in the IVE exploring his or her surroundings, whereas in the real environment, he/she was walking on a treadmill in the laboratory with a constant walking speed (0.86 m/s). To evaluate the repositioning, the method of two-alternative forced-choice tasks were used. The repositioning perception threshold test value was evaluated several (30) times by each participant under two different conditions: first, during eyeblinks; second, when repositioning was occurring in random periods without eyeblinks. Fig. 7 presents the mean values for the percentage of correct answers (hit) with respect to the total number of tests for the two conditions discussed above. The findings of the preliminary study show that the percentage of correctly recognized repositioning during eyeblink occurrences was (30.75%) lower than that for the other case (78.25%), in which the repositioning took place during periods where no eyeblinks occurred.

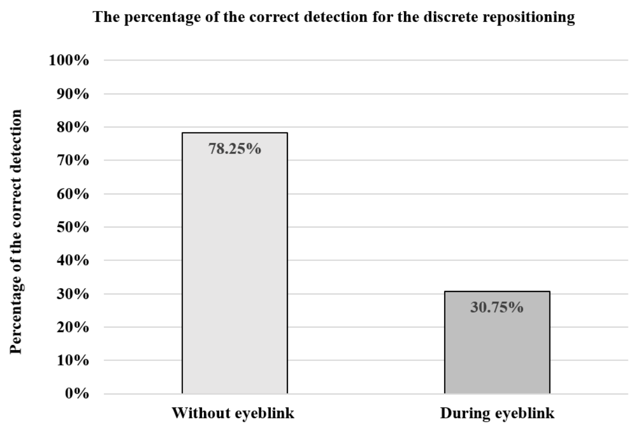


FIGURE 7. The mean of the percentage of the correct detection of repositioning for two different cases: when eyeblink occurred and when no eyeblink took place.

Although it seems evident that, during eyeblinks, the participant will not easily detect the repositioning introduced to his or her virtual viewpoint in VE, it was important to conduct the preliminary study to verify the proof of concept and accordingly to develop a convenient procedure for estimating the perception thresholds for repositioning during eyeblink occurrence.

B. EXPERIMENTAL DESIGN

Previous studies of the redirected walking technique [4], [8] have utilized a classical psychophysical procedure, called the two-alternative forced-choice task (2AFC) for constant stimuli, in order to estimate the perception thresholds for continuous orientation and position manipulations. To utilize this approach, it is necessary to make an assumption about the range of the tested threshold values in advance before the experiment begins, even though no knowledge about the psychometric threshold value is available. Moreover, all thresholds in the assumed range need to be evaluated several times. If only the threshold is needed, a large number of trials and a lot of time is required for convergence [9]. Estimating the perception threshold for repositioning during eyeblinks requires a different approach because the stimulus is applied only during a limited duration (i.e., during the eyeblinks); this is in contrast to a previous study of RDWT [4], where the translation gain was applied constantly to the participant's virtual perspective. Consequently, the participant needs to spend more time (due to the nature of the eyeblink rate) in the experimental VE to evaluate all the tested threshold values. As mentioned earlier, it has been proven that prolonged VR exposure causes simulator sickness [47]–[49]; therefore, it was important for us to minimize VR exposure time during the experiment to reduce the risk that the participants would suffer from cybersickness and ruin the estimated thresholds.

For this study, an adaptive procedure has been adopted, called the *Staircase Transformed and weighted-up/down method*, to estimate the perception threshold for forward and backward translation during eyeblinks, as it requires fewer trials to converge compared to 2AFC for constant stimuli. As a result, the adaptive procedure reduces the experiment time, and hence the VR exposure. For our experimental setup, the 1 up / 2 down rule was selected, with a ratio equal to 0.5488 for down step-size to up step-size. For the termination conditions, the number of reversal points required was set to 25 (after dropping the first reversal point), without limiting the maximum number of trials. After solving equation (5), the proposed setup reliably targeted the correct probability of $\Phi = 80.35\%$ [45]. The 1 up / 2 down rule was chosen over the 1 up / 3 down one because the former required fewer trials to converge. Despite the difference between the target probability Φ of both rules (the 1 up / 3 down rule can converge reliably to 83.15% [45] compared to the 1 up / 2 down rule, which has a correctness probability equal to 80.35%), we had to find a compromise between the convergence duration and targeting the correct probability, as there is no significant difference between the targeted probability Φ of both rules.

After the termination criteria were met, the perception threshold for each individual in the population was estimated by finding the median of the reversal points. The median was opted to be used rather than the mean because it is more robust against outliers. The final perception threshold value for the population was calculated by using regression analysis to analyze the collected observations. During the experimental design, the practical recommendation proposed in a study by García-Pérez [45] has been followed, which was based on simulating a large number of up/down staircase procedures to obtain the most optimal result. Selecting the initial value for the stimulus intensity to start the experiment plays a significant role in how much time the session can take: that is, if the stimulus intensity evaluation process begins from a point near the expected value, it will take less time to converge compared to the case in which the initial stimulus intensity is far away from the actual psychometric threshold value. As there was no idea where the actual psychometric threshold was located, we decided to start from undetected stimulus intensity (in our case, 0.1 meters) and increased it during each trial until the participant successfully recognized this intensity, which triggered the first reversal point. Next, the value of the stimulus intensity was reduced by an amount equal to the down-step size with each trial until the observer made a mistake; this would trigger the second reversal point, and so on until the termination criterion was met. Several other points needed to be considered during the experiment, as follows:

- *Adaptation:* Owing to the long period of VR exposure, the participant will learn how to distinguish and recognize the injected translations by developing a strategy of comparing other cues in the VE (this observation has been noticed during the preliminary investigation that has been carried out before). Hence, the experiment was divided into several sessions to reduce VR exposure time in the experiment.
- *User Attention:* If the participant is distracted by another activity—for example, solving a simple math problem (e.g., adding two numbers) or searching for a specific object in the VE—it is more likely that the repositioning will not be noticed, sometimes even when the repositioning gain is above the threshold value.
- *Bias Due to Prior Knowledge:* As the participants knows in advance that they will be repositioned after an eyeblink occurrence, they are more likely to select an answer indicating that repositioning has occurred, even when they are unsure. During the experiment, all participants were made aware that we were going to reposition them after an eyeblink had occurred; however, they were also told that the repositioning would not occur during every eyeblink (to reduce the prior knowledge bias).

TABLE 2. Distribution of participants' count regarding VR experience based on the Likert scale.

Likert scale	Participant count
Absolute Beginner	9
Beginner	3
Moderate	6
Skilled	5
Expert	2
Total count	25

C. POPULATION

During this study, 25 participants completed the experiment, including 21 males. The average age was 26.7 years, with a standard deviation of $SD = 7.71$ years. Most participants were students obtaining class credits in our department, with many of them being familiar with VR and 3D gaming. The other participants were external volunteers with little prior experience in VR. The participants' experience in 3D gaming was rated using a Likert scale, ranging from 1 for an inexperienced participant (never used a VR headset before) to 5 for an expert participant. The average experience level of the population was 2.68; $SD = 1.287$. Table 2 presents the distribution of participants' count with respect to their experience based on the Likert scale. The total time spent by all participants collecting data in the scene was approximately 86 hours. Two datasets were eliminated from the study because the participants scored highly on simulator sickness questionnaires.

D. PROCEDURE

One experiment has been conducted with two different setups. The first involved estimating the perception threshold for forward repositioning, while the second was for backward repositioning during forward translation when an eyeblink occurred. The difference between both setups was the sign of the discrete translation gain: for backward repositioning, the tested thresholds had a negative value, while for forward repositioning, this value was positive. Moreover, A minimum threshold value for walking speed at 0.3 m/s was set; below this speed, repositioning during eyeblinks was deactivated, as the participants could easily detect the discrete repositioning under these circumstances. The perception threshold for repositioning was evaluated at three different walking speeds: slow, or 0.58 m/s (≈2 km/h), medium, or 0.86 m/s (≈3 km/h) and fast, or 1.1 m/s (≈4 km/h). Unfortunately, little is known about the implications of eyeblinks on the perception thresholds of repositioning in IVE. No specific guidelines or recommendations about walking speed selection has been found in the context of this research area. However, selecting the test walking speeds during this study should fulfil the following points to obtain perception threshold values that are generalized to the greatest extent possible:

- The range of the tested walking speeds should be within the range at which the participant is used to walking most of the time in real environments.
- The participant should be able to distinguish the difference between the selected test walking speeds.
- The participant should be comfortable and safe while walking on the treadmill and wearing the VR headset for a long period of time, to avoid negative effects on participant performance due to potential exhaustion and the loss of motivation to finish the experiment.

The procedure utilized during the experiment began when the participant arrived. He or she was given a brief description of the experiment and asked to read the consent form, which he/she then signed if willing to participate. Next, the instructor explained the experimental tasks. The first was to fill out a questionnaire requesting demographic information and 3D gaming experience. Next, the participant filled out a simulation sickness questionnaire (SSQ) before he/she started the experiment. After explaining the task, a five-minute trial session was executed; this allowed the participants to adapt to walking on the treadmill and to ensure that they had understood the task to be performed. After finishing the training session, the first trial was started, as explained above. Once an eyeblink occurred while walking in the IVE, an initial threshold value was introduced to the participant's virtual perspective in VE to be evaluated. Three seconds after introducing the threshold value, a user interface prompted the participant to submit his or her reply. This cycle was repeated until the termination conditions were met. Fig. 8 presents the algorithm flowchart used for estimating the perception threshold for repositioning using the proposed estimator.

To give some perspective regarding the experimental duration, let us consider some numbers. A healthy adult blinks roughly between 10 to 20 times per minute [26], [27]. After introducing the stimulus (translation threshold that needs to be tested) there was a waiting period of three seconds to give the observer time to evaluate the surrounding environment. Next, the user interface would pop up to ask the participant whether any translation had been recognized. During threshold evaluation, blink detection was suspended until the participant submitted his or her response; this step prevented the observer from performing too many simultaneous eyeblinks, which could have corrupted the collected data. The task of submitting the participant's reply took approximately 10 seconds. After adding up these durations, it was found that it took 13 seconds to collect one reply from an observer. Given the time required for the next eyeblink to occur, we ended up getting three to four responses per minute. During the study, it has been determined that each session required approximately 70 to 80 trials to converge; thus, a single session took roughly 20 to 25 minutes. Three different walking speeds has been tested to estimate the perception thresholds for backwards and forwards translation, thereby yielding a total of six sessions for each participant. During the day, each participant

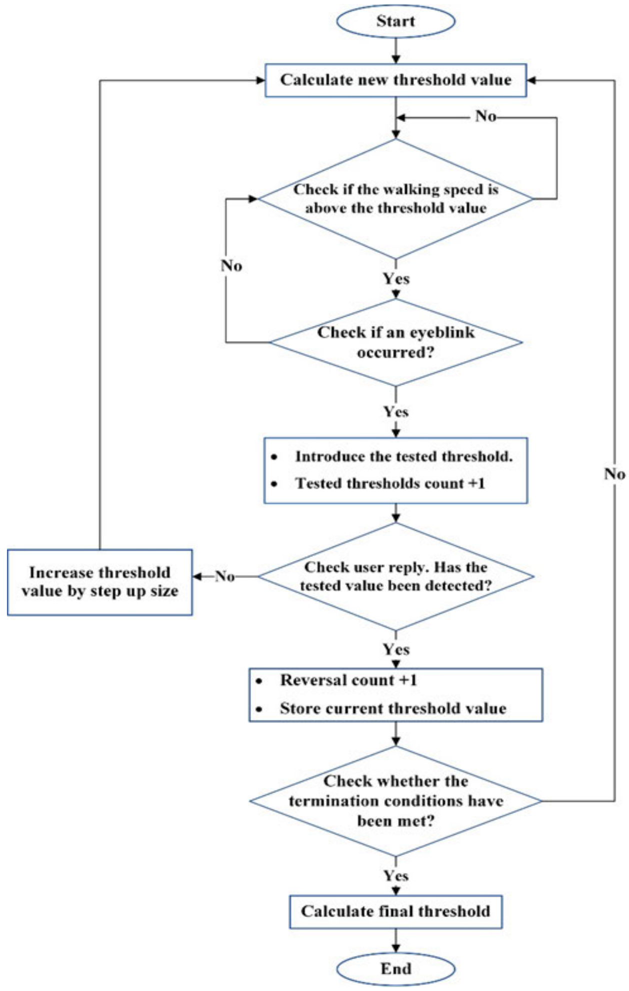


FIGURE 8. The proposed algorithm to estimate the perception threshold for discrete repositioning utilized by the estimator during eye blinking.

performed only two sessions (one for estimating the forwards translation threshold and the other for estimating the backwards one), with a mandatory adequate break between each to give the participant enough time to recover. After finishing each trial, they filled in the SSQ questionnaire to assess their simulator sickness exposure score; the participant was to be excluded from the experiment if they had been severely affected. For more information about the SS and how the SSQ score was calculated, please refer to Appendix B. Finally, a debriefing session has been conducted for each participant after the experiment was complete, during which we asked about their VR experience during the experiment and whether they had had any difficulty or experienced any other issues during the session. We further asked about the strategy they had followed to recognize the introduced translations. Fig. 9 shows two participants undergoing the experiment in our laboratory.

FIGURE 9. Two participants performing the walk on the treadmill during the experiment.

E. HARDWARE AND SOFTWARE EQUIPMENT

During the experiment, an HTC Vive Pro Eye VR-headset was utilized to test the translation offset threshold values. The game engine used to implement the VE (experimental scenario) was Unity 3D 2019. The PC used had 16 GB of RAM, an Intel Core i7 6th generation processor, and two NVIDIA GeForce GTX 980Ti graphic cards. Additionally, an HTC-Vive tracker was used to track the position of the treadmill in the physical space and to get input from the participants using custom push-buttons. Furthermore, a commercial treadmill to control the walking speed has been used. For eyeblink detection, the HTC Vive Pro eye VR-headset was employed, which has a built-in eye tracker.

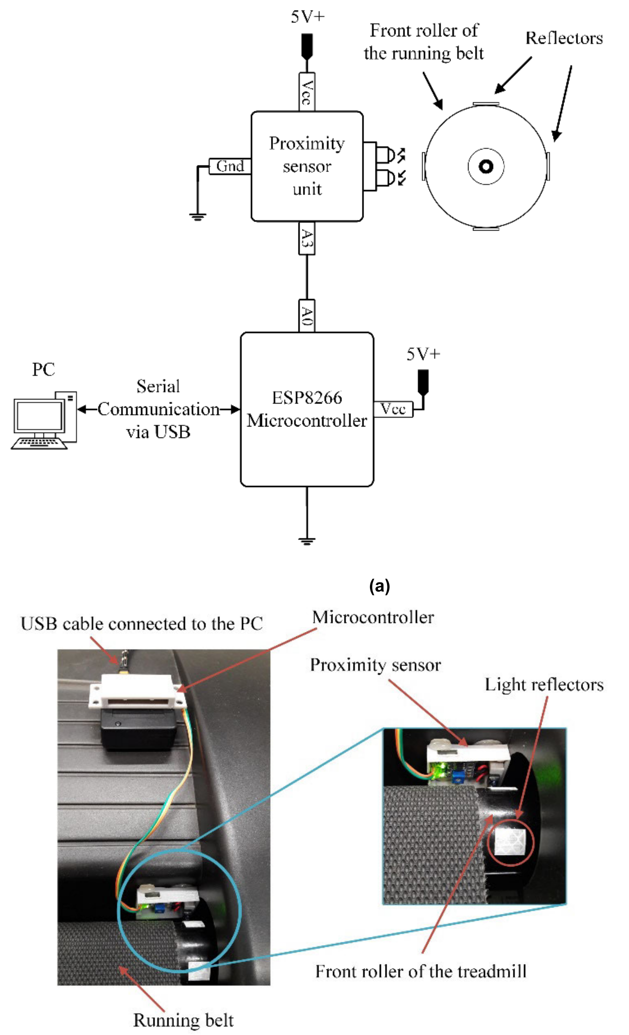
1) CONTROLLING PARTICIPANT WALKING SPEED

For our proposed study, a way to control the participant's walking speed in the real world during the test sessions was required. In our first attempt to solve this issue, a software speed indicator has been implemented, which estimated walking speed by utilizing the VR-headset position information. The speed indicator was rendered on the top side of the participant's field of view in the VE; if their walking speed was within the intended range, the indicator would turn from red to green. However, after testing this approach to controlling the participant's walking speed, we found it was very difficult for them to maintain a steady walking pace. To do so, they would have to consciously try to keep their walking speed constant by simultaneously observing the speed indicator in the scene. These two tasks induced a high cognitive load and obstructed the participant from performing any additional tasks (such as submitting their replies). Moreover, the participants could not precisely estimate their walking speed. Thus, we opted to use a traditional linear treadmill, equipped with an on-board computer, which precisely controlled the walking speed. Additionally, a speed estimator using an ESP8266 microcontroller was implemented to detect the running belt speed on the treadmill. This was connected to the computer via USB and sent the estimated walking speed at a reading rate of 5 Hz/s, with an accuracy of ± 13.3 cm/s. Fig. 10 presents a schematic diagram of the walking speed estimator and its prototyping. The estimated walking speed was used as feedback to generate virtual optic flow in the VR headset, which mimicked the real optic flow perceived by the participant during real walking. Generating the virtual optic flow was achieved by moving the participants' virtual perspective in the VE, with speed equal to the walking speed estimated from the treadmill.

2) EYEBLINK DETECTION

Unfortunately, when this research was started, eye-tracking was not standard in consumer VR headsets. Nevertheless, there were some third-party eye-tracking solutions available as add-ons to the VR-headset, such as *Tobii* and *Pupil Labs*. However, these solutions do not detect eyeblinks nor classify the eye state (i.e., whether the eye is closed or open). Moreover, detecting eyeblinks for a VR headset can be a tricky task due to the narrow timeframe of the eyeblink event duration. In a previous study [50], this issue has been addressed by developing an algorithm and implementing the required hardware to detect eyeblinks in VR headsets. The proposed approach was able to detect eyeblinks within 11 milliseconds of their occurrence, which provided enough time to reposition the participant during an eyeblink. Fig. 11 presents a prototype of the eyeblink detection sensor and how it was mounted inside the VR-headset.

Our prototype has been used during the pilot study and the early stage of this research to test our hypothesis. Fortunately, during the recruiting phase, the HTC-Vive Pro Eye was introduced to the market, which incorporates an integrated eye-tracker with higher accuracy than our prototype. Although this sensor can estimate eye gaze direction and eye openness, however, eyeblink detection functionality is not available. We were further aware that the algorithm developed for our previous study cannot be used, as the video stream from the sensor is not exposed by the eye-tracking SDK (SRanipal SDK) of the HTC-Vive Pro Eye VR-headset. Therefore, the eye openness parameters were used from the



(b)

FIGURE 10. Prototyping of the running speed estimator circuit and how the proximity sensor was used to estimate the walking speed: (a) electronic schematic; (b) practical implementation on the treadmill.

FIGURE 11. The eye utilized tracker during the early phase of the study, including a close-up of the prototyped image sensor and how it is mounted inside the HTC-Vive VR-headset [50].

SRanipal SDK to implement eyeblink detection and eye state classification. Fig. 12 presents a flowchart of the finite state machine (FSM) for eyeblink detection.

There are two parameters used to describe eye openness in the SDK, one being for the left eye and the other for the right. The values of these parameters range from 1 for full eye-opening to 0 for full eye closure. Both parameters has

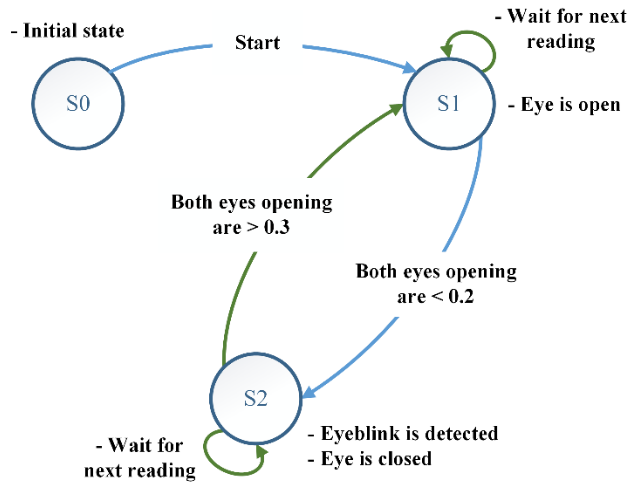


FIGURE 12. The finite state machine for identifying eyeblinks, utilizing the eye-opening parameter in the SRanipal SDK.

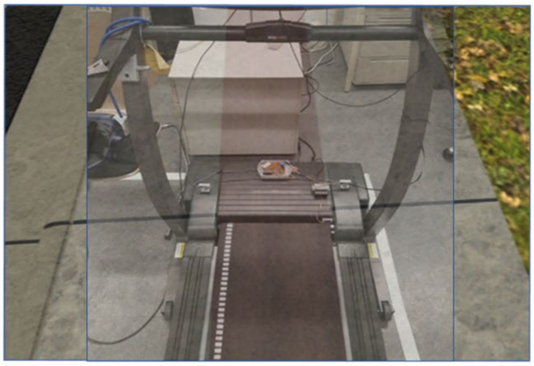
been used to ensure that both eyes were fully closed simultaneously (indicating eyeblink occurrence). Fig. 12 shows the FSM used during the implementation of eyeblink detection. It consists of three states: "S0" represents the initial state, while "S1" indicates that both eyes are in the open state and waiting for the next reading. If both parameters (left and right eye openness) are below 0.2, "S1" will translate to "S2", which indicates an eyeblink, and the eye state will be classified as closed. The current state will wait for a new reading for both eye parameters; if both values exceed 0.3, "S2" will translate back to the "S1" state (i.e., the eyes have been reopened) and a new detection cycle will begin. During the implementation of the eyeblink detection algorithm, the values 0.05 and 0.1 were used as thresholds for detecting eye-closure and eye-opening, respectively. However, a delay during eyeblink detection was noticed due to latency in the eye-tracking sensor of the VR-headset, such that the participant was sometimes able to notice the implicit translations in the scene, which could not be tolerated in the experiment. To overcome this issue, the threshold values were increased to 0.2 and 0.3 for eye closure and eye-opening, respectively; this enabled us to achieve early detection for eye closure and openness, and accordingly to detect the eyeblink.

3) SAFETY PRECAUTIONS DURING THE USE OF THE TREADMILL IN VR

Using a treadmill in VR can be dangerous, resulting in potential injury to the participants if safety measures are ignored. Hence, safety precautions were developed and implemented to address all possible threats that could compromise the participants' safety during the experiment, which are discussed in detail below.

a: IMPLEMENTING VISUAL REPRESENTATION FOR THE TREADMILL BELT IN THE VE

During the study, we found using the treadmill in VR to be quite a challenging task if there was no visual feedback provided to help the participants orient themselves while walking



(a)

(b)

FIGURE 13. Implemented visual representation for the treadmill belt in VE: (a) the highlighted walkable area of the pathway in the scene; (b) overlapping images of the physical and virtual world, showing the alignment between the treadmill belt and the highlighted walkable area in the VE.

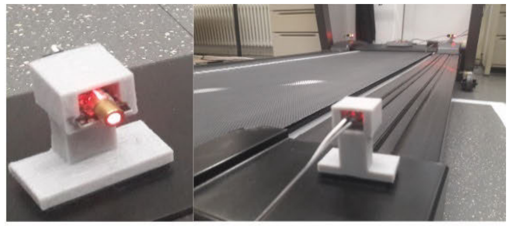
on the running belt of the treadmill. In the experimental scenario, the running belt of the treadmill was introduced as a pathway in the VE, a partial area of which was designated the walkable area, such that the width of the shaded area of the pathway in the VE matched that of the running belt in the physical space. The participant had to walk on the pathway within the marked area (as illustrated in Fig. 13) to avoid possible injury.

b: LASER BEAM TO PREVENT THE PARTICIPANT FROM STEPPING OFF THE TREADMILL BELT

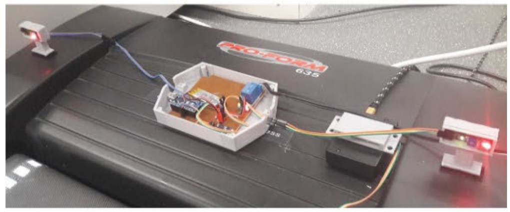
Another safety feature was implemented on the treadmill, whereby it would stop immediately if the participant was about to step off it. This involved utilizing a custom laser beam source and proximity sensor, such that the participant's foot would cut out the laser beam's path. A custom-built circuit was used to detect this event and electrically disengage the treadmill motor to stop the belt from running. Fig. 14 illustrates how the custom proximity sensor was mounted on the treadmill.

c: UTILIZING THE TREADMILL's SAFETY KEY TO INTERRUPT ITS OPERATION

The built-in safety key on the treadmill console was used to interrupt its operation immediately in the case that something



(a)



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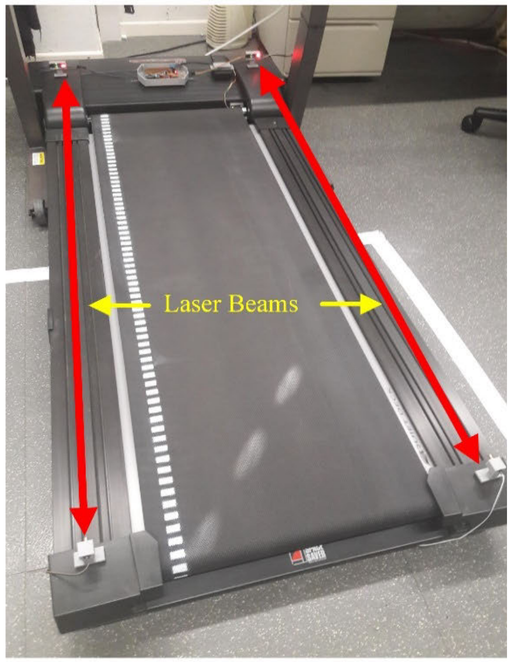

(c)

FIGURE 14. Implementing a custom laser beam proximity sensor for the treadmill: (a) laser LED; (b) controller circuit board; (c) mounting the proximity sensor.

went wrong. The participant had to attach the safety key to their clothes and insert it in its designated place on the console to activate the treadmill. Fig. 15 illustrates how the safety key was used in our proposed setup.

d: ABILITY TO SUBMIT A RESPONSE WITHOUT USING THE HTC VIVE HANDHELD CONTROLLERS

Another issue was tackled during the experiment by allowing participants to submit their reply without using the HTC Vive Controllers. This issue was addressed by utilizing the HTC Vive tracker to implement customized equipment to receive input from the participant. The tracker was equipped with

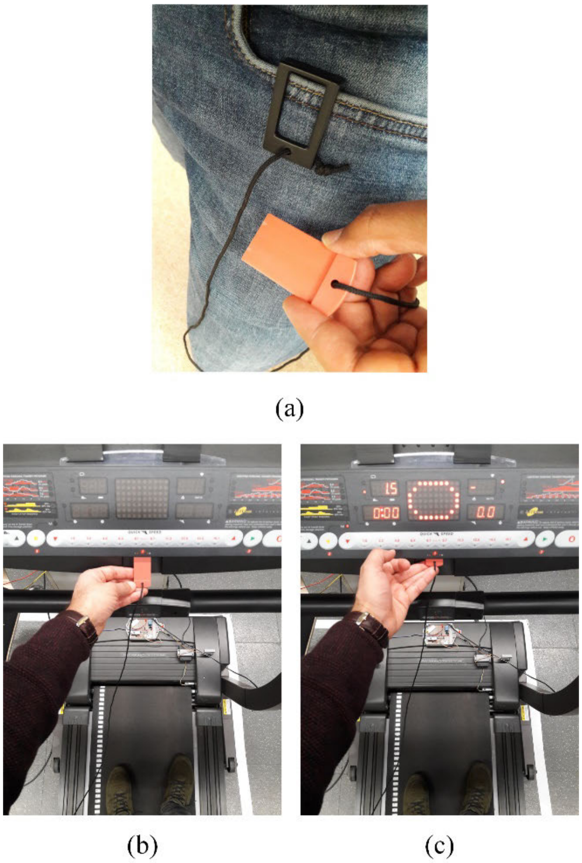

FIGURE 15. **Utilizing the safety key of the treadmill in our experiment: (a) attaching the clip of the safety key to the participant's clothing; (b) inserting the safety key into the treadmill console to activate it; (c) the treadmill is active after inserting the safety key.**

a pogo pin pad with six pins for implementing customized buttons [51]. Fig. 16 presents the HTC Vive tracker and the electrical reference design of the pogo pins.

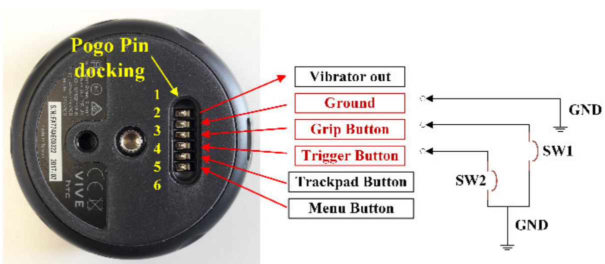

FIGURE 16. **HTC Vive tracker and pogo pins configuration.**

Two customized push-buttons (SW1 and SW2, as shown in Fig. 16) was installed to allow the participant to submit two different choices relating to the 2AFC tasks. The two push-buttons were mounted on the treadmill handles, enabling the participants to easily submit their responses. Fig. 17 illustrates how the customized push buttons were arranged. Additionally, the HTC Vive tracker was used to determine the location of the treadmill in physical space in order to align it with the virtual pathway in the VE.

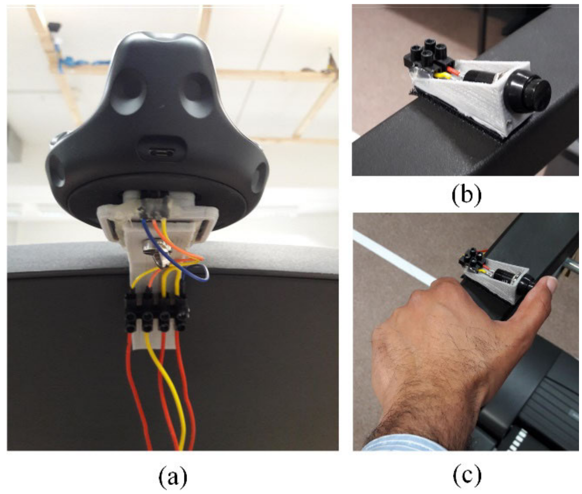

FIGURE 17. **Attaching the HTC Vive tracker and push-button to the treadmill: (a) the tracker is mounted on the customized 3D printed holder and attached to the treadmill display panel; (b) mounting the push-button on the treadmill; (c) the push-button in use.**

IV. DATA ANALYSIS AND EXPERIMENTAL RESULTS

During the study, regression analysis was utilized to evaluate the collected data in order to develop an understanding of the relationship between the walking speed and the perception threshold for participant repositioning during forward translation and eyeblink occurrence. The dataset collected from the experiment was presented as bivariate data (x,y), where x is the independent variable representing the walking speeds, while y is the dependent variable pertaining to the observations collected during the experiment. Equation (6) represents the *least-squares regression line* (*LSRL*):

$$Y = C_0 + C_1 X \tag{6}$$

where C_0 is a constant (representing the y-intercept of the regression line), C_1 is the regression coefficient, X is the walking speed, and Y is the value of the predicted threshold for the population.

For a random sample of observations, the regression line for the population was estimated by the following equation:

$$\hat{y} = c_0 + c_1 x \tag{7}$$

where c_0 is a constant, c_1 is the regression coefficient, $\hat{y}$ represents the estimated threshold value, and x is the walking speed. The constant c_0 and the regression coefficient c_1 were solved by the following equations:

$$c_1 = \frac{\sum\left[(x_i - \bar{x}) \times (y_i - \bar{y})\right]}{\sum\left[(x_i - \bar{x})^2\right]} \tag{8}$$

$$c_0 = \bar{y} - c_1 \times \bar{x} \tag{9}$$

where x_i represents the x value of observation i (which is the tested walking speed), y_i is the y value of the observation i (which represents the estimated perception threshold for the ith participant), $\bar{x}$ is the mean of x, and $\bar{y}$ is the mean of y. Additionally, the coefficient of determination R^2

was calculated to assess how well the regression predictions approximate the observed data points. The R^2 was calculated according to equation (10) below:

$$R^2 = \left\{ \frac{\left(\frac{1}{N}\right) \times \sum [(x_i - \bar{x}) \times (y_i - \bar{y})]}{(\sigma_x \times \sigma_y)} \right\}^2 \tag{10}$$

where N represents the number of observations in the population, x_i and y_i are as described above, σ_x is the standard deviation of the tested walking speeds, and σ_y is the standard deviation of the observed threshold value.

Furthermore, the correlation coefficient ρ was calculated to measure the strength of association between the walking speed and the perception threshold. The absolute value of ρ indicates how strongly both variables are associated, while the sign indicates the direction of the relationship: if ρ is positive, this means there is a proportional relationship between both variables, while a negative ρ value indicates inverse proportionality between both variables. The correlation coefficient was calculated by means of the following equation.

$$\rho = \left[\frac{1}{N}\right] \times \sum \left\{ \left[\frac{(x_i - \mu_x)}{\sigma_x}\right] \times \left[\frac{y_i - \mu_y}{\sigma_y}\right] \right\} \tag{11}$$

where ρ is the correlation coefficient, N is the number of observations in the population, μ_x is the population mean for the independent variable (walking speeds) and μ_y is the population mean of the dependent variable, that is, the collected observations (the estimated perception thresholds for the participants).

A. PERCEPTION THRESHOLD FOR IMPERCEPTIBLE FORWARD REPOSITIONING

During this experiment, the Staircase Transformed and weighted up/down method (discussed in section III) was has been used to ascertain how far we could imperceptibly reposition a participant in the forward direction during forward walking and eyeblink occurrence. Three different walking speeds were tested, namely 0.56, 0.83, and 1.1 m/s. Fig. 18 plots the distribution of the collected observations (the estimated perception threshold value for each participant) with respect to the walking speed, along with the predicted perception thresholds for forward repositioning for the entire population with respect to the tested walk speeds.

Table 3 presents the estimated perception threshold values for forward repositioning based on the walking speeds. The coefficient of determination R^2, correlation coefficient ρ, p-value, and standard error are also displayed.

B. PERCEPTION THRESHOLD FOR IMPERCEPTIBLE BACKWARD REPOSITIONING

During the experiment, the perception threshold for backward repositioning was estimated using the Staircase Transformed and weighted up/down method to ascertain how far the participant could be repositioned in the backward direction during their forward walking when an eyeblink occurred. Three different walking speeds were tested: 0.56, 0.83, and 1.1 m/s.

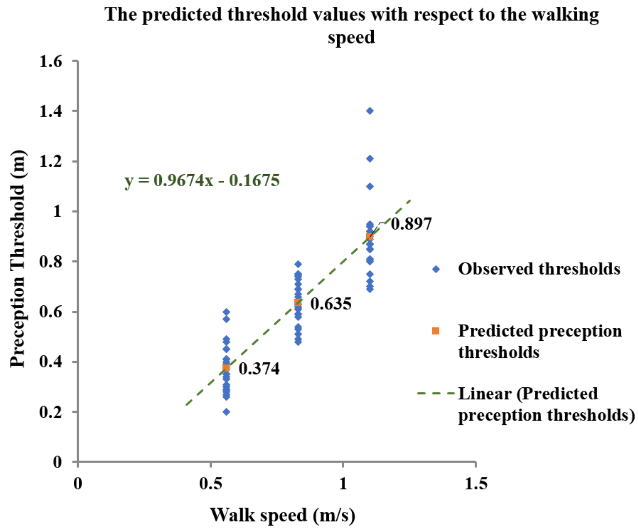

FIGURE 18. The distribution of the observed perception threshold values for forward discrete imperceptible repositioning for the population concerning the walking speed. The blue points represent the collected perception threshold values for each participant in the population, while the orange points represent the estimated perception threshold values for the population with respect to the walking speed.

TABLE 3. Estimated perception thresholds for forward repositioning based on the participants' walking speeds (all threshold values in the table are in meters).

Walking speeds:	0.56 m/s	0.83 m/s	1.1 m/s
Predicted threshold values	0.374	0.635	0.897
Mean	0.370	0.643	0.893
Median	0.350	0.630	0.870
Standard deviation	0.097	0.018	0.155
Minimum value	0.2	0.48	0.69
Maximum value	0.6	0.79	1.4
P-value		< 0.001	
R^2		0.773	
ρ		0.879	
Standard Error		0.117	

Fig. 19 shows the distribution of the collected observations (the estimated perception threshold value for each participant), with respect to the walking speed. It further shows the predicted perception thresholds for backward repositioning for the entire population.

Table 4 presents the estimated perception threshold values for backward repositioning based on the walking speeds. The coefficient of determination R^2, correlation coefficient ρ, p-value and standard error are also listed.

V. DISCUSSION AND LIMITATIONS

Figures 17 and 18 show the output of the regression analysis for the collected observations for forward and backward imperceptible repositioning during the experiment. As discussed above, the independent variable (x) represents the walking speed, while the (y) variable pertains to the observed

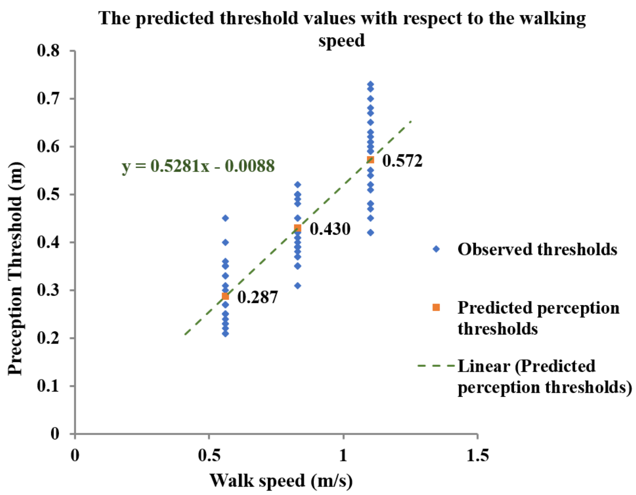

FIGURE 19. The distribution of the observed perception threshold values for backward discrete imperceptible repositioning of the population with respect to the walking speed. The blue points represent the collected perception threshold values for each participant in the population, while the orange points refer to the estimated perception threshold values for the population with respect to the walking speed.

TABLE 4. The estimated perception thresholds for backward repositioning based on the participants' walking speeds (all the threshold values are in meters).

Walking speeds:	0.56 m/s	0.83 m/s	1.1 m/s
Predicted threshold values	0.287	0.430	0.572
Mean	0.292	0.420	0.578
Median	0.290	0.410	0.595
Standard deviation	0.013	0.012	0.019
Minimum value	0.21	0.31	0.42
Maximum value	0.45	0.52	0.73
P-value		< 0.001	
R^2		0.730	
ρ		0.855	
Standard Error		0.071	

perception threshold estimated using the Staircase Transformed and weighted up/down method. During the experiment, three different walking speeds were tested; hence, the independent variable had discrete values. Figure 18 shows the predicted perception threshold values for forward discreet repositioning for the entire population (the orange data points in the graph.) These values are 0.374, 0.635 and 0.897 meters for walking speeds of 0.56, 0.83 and 1.1 m/s, respectively. The correlation coefficient $\boldsymbol{\rho}$ was calculated, and $\boldsymbol{\rho} = \mathbf{0.879}$, as shown in Table 3. The value of the correlation coefficient indicates a strong relationship between the walking speed and the observed perception threshold value. Moreover, the sign of the correlation value indicates a proportional relationship between the walking speed and the perception threshold value. Additionally, Fig. 18 plots the trend line of the regression analysis and the equation that predicts the perception threshold for forward repositioning with respect to walking speed. The coefficient of determination ($\boldsymbol{R^2} = \mathbf{0.773}$) shows that the proposed model fits the perception threshold values for forward repositioning of the population by about 77.3%.

Similarly, Fig. 19 shows the results of the regression analysis for the perception threshold values for backward repositioning. The predicted threshold values for the population are 0.287, 0.430 and 0.572 meters for walking speeds of 0.56, 0.83 and 1.1 m/s, respectively. In general, the values of the predicted perception threshold for backward imperceptible repositioning are smaller than those for forward imperceptible repositioning, indicating that the participants were more sensitive to the former than the latter. Furthermore, Fig. 19 shows that the regression line exhibits a positive slope value, indicating a proportional relationship between walking speed and the perception threshold value. This relationship is also confirmed by the sign and value of the correlation coefficient $\boldsymbol{\rho} = \mathbf{0.854}$, which indicates a strong relationship between walking speed and the observed perception threshold values.

As discussed above, several variables can affect the perception threshold for discrete repositioning during eyeblinks when the participant is walking. The nature of the VE plays a significant role. For instance, in a seamless VE, it is more difficult for the participant to notice the injected translation. Consequently, it is possible to reposition the participant using a translation value above the estimated threshold value; this is due to the lack of unique nearby features (cues) that help them to evaluate the egocentric walking speed and the perceived distance walked in the VE. Hence, during the design phase, close attention was paid to the details along the walking path in the VE, purposely introducing features such as banks, hydrants, street signs, parked cars etc. This was to ensure that there were always enough features around to assist the participants in orienting themselves, thereby preventing the experimental scene from becoming a seamless VE. Additionally, the accuracy of the eyeblink detection plays a significant role in the success of estimating the psychometric threshold. This detection process should not make any positive false detections, as these will cause the participant to notice the translation injected into his or her perception in the VE. Hence, the timing of introducing the tested threshold value to the participant's virtual perspective is critical. Furthermore, false-negative errors (lapses) caused by the participants when they accidentally respond with a wrong answer could cause misleading factors in the estimation of the perception threshold.

During the debriefing sessions, the participants were asked about what strategy they had used to check whether they had been repositioned after an eyeblink occurrence. Eighty-four percent stated that they were using the nearby objects, such as a parked car, streetlamp, or a tree (a unique near object) to verify whether they had been repositioned following eyeblink occurrences. This use of nearby objects indicates that the participants were using a monocular cue called Motion Parallax to evaluate the surrounding environment in order to verify repositioning during eye blinking. Previous studies [37], [38], [44] have shown that the experienced optic flow pattern plays a significant role in self-motion perception in VE (for instance, the walked distance and speed). Therefore, the possibility of detecting an injected translation is high when the value of the horizontal angle between the gaze direction and the direction of walking is also high.

In real life, the task of travelling is a secondary goal; we travel from one point to another to perform a specific task. During the experiment, the participants were aware that they were being repositioned during their walking, and they were actively comparing and looking around to detect the repositioning events. However, we found that if the participants were busy with another task at the time, it was possible to reposition them using translation values much larger than the estimated perception threshold. Hence, during the study, the worst-case scenario was considered by assuming the travel task was the primary task for the participants when walking in the VE.

Regarding the usability of the proposed repositioning approach, two points need to be considered before repositioning participants during their walk after an eyeblink has occurred. First, the method of repositioning is intended to be used in an outdoor IVE, such as walking down a street or in a park (any wide-open space). However, this approach is not feasible for indoor environments, as the participant's walking speed barely exceeds the minimum walking speed threshold (0.3 m/s). Second, in general, there are three goals when travelling in an IVE: exploring, searching and maneuvering [10]. The lattermost pertains to fine-tuning the participant's position, such as by adjusting it in front of a bulletin board at a bus station to improve the readability so that the participant can see when the next bus is coming. This maneuvering can occur in either an outdoor or indoor environment. During maneuvering, it is not possible to apply discrete translation to the participant's perspective in the VE without this being noticed by them; as a result, they might drift away from the intended position.

VI. CONCLUSION AND PROPOSALS FOR FUTURE WORK

The results of the present study have shown that the perception threshold for forward/backwards discrete implicit repositioning during forward walking and eyeblink occurrences increases proportionally to the walking speed. An experiment was performed with two different setups to estimate the perception threshold values. In the first experimental setup, the perception threshold for forward repositioning in a VE during forward walking and eyeblink occurrences was investigated. In the second experimental setup, the perception threshold for backward repositioning in a VE during forward walking and eyeblink occurrences was examined. Regression analysis was used to evaluate the collected observations. The perception threshold values were evaluated for three walking speeds (slow (0.58 m/s), moderate (0.86 m/s) and fast (1.11 m/s)) during both experimental procedures. The estimated threshold values for forward repositioning were 0.374, 0.635 and 0.897 meters for these speeds, respectively, while those for backwards repositioning were 0.287, 0.430 and 0.572 meters for the mentioned speeds, respectively.

These findings extend the repositioning methods of the current RDWT. They will aid in the development of a composite RDW controller that utilizes continuous and discrete implicit repositioning and reorientation methods simultaneously. Furthermore, these outcomes allow for the discrete repositioning method to use dynamic repositioning gain calculated based on the participant's walking speed. This will in turn facilitate a reduction in the spatial requirement of RDWT and support the infinite free exploration of IVEs, while keeping the side effects of RDWT (such as simulator sickness and cognitive load) at minimal levels.

Regarding future research, the possibility of extending the usage of curvature and bend gains a discrete manipolation form during eye blinks need to be investigated. Additionally, we plan to conduct an exploratory case study regarding the use of a composite RDW controller that utilizes imperceptible continuous repositioning and reorientation methods in addition to imperceptible discrete repositioning during eyeblinks, with dynamic repositioning gain based on the walking speed, with the goal of reducing the RDWT spatial requirements while simultaneously supporting infinite free exploration in an IVE.

APPENDIX A
BRIEF DESCRIPTION OF THE REDIRECTED WALKING TECHNIQUE AND ITS OPERATION

The redirected walking technique has evolved considerably over the past decade since it was first proposed by Razzaque [3]. A redirected walking controller consists of several algorithms that work together to guide the participant through the VE by imperceptibly, or in some cases explicitly, manipulating his or her position and/or orientation in the real space.

1) STEERING ALGORITHMS

These are responsible for applying the steering parameters (rotation, translation, curvature, and bending gains) to the participant's viewpoint while they walk through an IVE. The participant's movement can be scaled down by a negative gain or scaled up by a positive one based on the user's location and planned trajectory in the real world, in addition to the pre-planned trajectory in the virtual world [4]. Examples of such steering algorithms have been proposed in generalized redirected walking techniques in [52], [53], and include Steer-to-Centre, Steer-to-Orbit, Steer-to-Multiple-Target and Steer-to-Multiple-plus-Centre. These algorithms use the same redirecting parameters mentioned above [4], [5]; however, they differ in terms of where the participant is being redirected.

2) PARTICIPANT PATH PREDICTION ALGORITHM

To redirect the participant efficiently in the real world, the walking trajectory in an IVE should be known. The participant virtual path prediction algorithm provides the ability to determine his or her future virtual path in the IVE. In prior research, the participant's virtual path was planned using fixed waypoints [3], [54], such that their walking plan was already predetermined. However, unrestricted exploration of the IVE is not possible when predetermined waypoints are used to navigate the environment. By contrast, generalized redirected walking techniques aim to provide the ability to explore the IVE freely to some extent. Hence, the participant's virtual path should be previously known in order to plan the physical path for the participant during runtime. Several methods have been proposed to predict a participant's virtual path in a VE, which can be classified into two categories, namely short-term and long-term path prediction approaches. The user's short-term virtual path can be predicted based on his or her walking behaviour, such as current position, velocity, torso and gaze direction, and the structure of the VE; for instance, using a prediction control model to predict the participant's trajectory for a short period of time [53], [55]. On the other hand, long-term virtual path prediction is based on advanced planners [56], which analyze the navigation mesh (the walkable area in the VE) to calculate the skeleton graph (a simplified representation of the walkable areas in the VE). Based on the participants' current position and the skeleton graph, their possible paths are estimated.

3) RESET ALGORITHM

This algorithm is responsible for preventing the participant from colliding with the boundaries of the tracked space by instructing him or her to perform some mandatory actions to bring him or her onto the right course again. The reset algorithm intervenes if the steering algorithm fails to redirect the participant away from physical obstacles, such as the boundaries of the tracked area. The reset algorithm interrupts the participant's VR session by using audio distractors, such as verbal commands instructing them to turn in a specific direction or to step back [3], [57]. Another method involves the use of visual distracters, which instruct the participant by using graphical signs to stop and reorient him/herself by rotating their head back and forth [54]. Meanwhile, the whole scene is rotated around the participant's virtual viewpoint to bring them back onto the right trajectory. Calling up the reset algorithm could disorient the participant (sometimes inducing simulator sickness) and affect the VR experience by causing a break in the presence; hence, it is not desirable to frequently call this algorithm.

4) MANIPULATIONS UTILIZED BY RDWT

The manipulations applied by RDWT can be divided into two categories: environmental and perspective. This classification is based on the way in which the manipulation parameters (translation/rotation) are introduced into the participant's virtual perspective in the VE. Environmental manipulation involves modifying the architecture of the IVE to affect participants' walking path. One example of this is an approach proposed by Suma *et al.* [58] based on a phenomenon called change blindness, which can be defined as an individual's inability to identify changes in the surrounding environment [59]. During the study, the door orientation was modified without the participants' knowledge; consequently, their walking path would be affected. Another approach within the same category proposed by Suma *et al.* is called Impossible Spaces [60]. During the study, a virtual indoor environment was compressed inside the available physical space by overlapping the room architecture in the VE. By contrast, perspective manipulation methods involve applying manipulation parameters directly onto the virtual perspective of the participant in the IVE. The perspective parameters are divided into two subcategories: continuous and discrete manipulations. An example of continuous manipulation gains involves deploying conventional steering algorithms, which continuously apply manipulation parameters, such as translation gain ($T_g = \frac{Translation_{virtual}}{Translation_{real}}$), rotation gain ($R_g = \frac{Rotation_{virtual}}{Roration_{real}}$), curvature gain ($C_g = \frac{1}{r}$) where r is that the radius of a circular path within the physical world onto which the participants are redirected while perceiving a straight path in the VE, and bending gain ($B_g = \frac{Radius_{virtual}}{Radius_{real}}$). These gain values should not exceed the perception thresholds for this manipulation [4]. Applying these gains to a participant's virtual viewpoint will scale and/or bend his or her walking trajectory in the VE [5], [61] as well as increase/decrease the rotations of his or her virtual perspective caused by physical rotations [3]. In other words, the participant could perceive him/herself as walking in a straight path in the VE, while he or she is actually walking in a circular path in the real world. In contrast, the discrete manipulation is applied for short intervals during specific events, such as during a saccade (the rapid concurrent movement of both eyes between two or more fixation points [62]) or eyeblinks. Fig. 20 presents an overview of the categories of utilized manipulation methods.

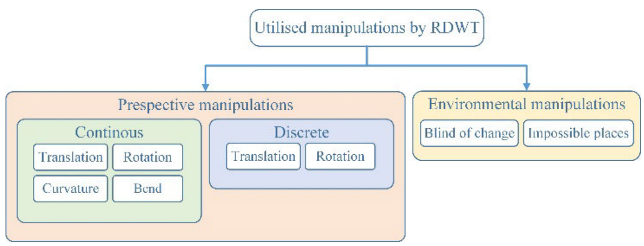

FIGURE 20. Utilized manipulation parameters by RDWT and its categories.

APPENDIX B
SIMULATOR SICKNESS AND THE SSQ QUESTIONNAIRE

Simulator sickness is defined as "a syndrome similar to motion sickness, often experienced during simulator or another virtual reality (VR) exposure" (Dużmańska *et al.*, 2018 [49], p1). The exact reason why simulator sickness (or cybersickness) occurs remains unclear. However, the latest theory points to the sensory conflict between the visual perception and other senses, such as between proprioception and the vestibular system (the inner ear). Simulator sickness is a major concern that could have compromised the experimental results. Thus, we took several precautions to reduce its effect on the participant and to keep the SSQ score as low as possible, thereby ensuring the accuracy of the participants' responses during the experiment.

The first precaution was providing the participant with a pre-training session, enabling him or her to adapt. One previous research study has indicated that such adaptation reduces simulator sickness because the reactions in the virtual environment due to the participants' actions begin to match their expectations [49]. Hence, pretraining sessions are essential for the participants before starting the actual experiment. Additionally, some recommendations outlined in a previous study [63] was followed which help to reduce the side effects of simulator sickness, such as keeping the laboratory atmosphere fresh and well-ventilated; it is also recommended to ensure that the participants are hydrated before starting the experiment. As another precaution, we used Kennedy's simulator sickness questionnaire (SSQ) [64] to quantify the severity of the sickness experienced by participants. If the participant's total score was high (severely affected), his or her responses were discarded from the population.

LIST OF ABBREVIATIONS

IVE	Immersive virtual environment
RDWT	Redirected walking technique
RDW	Redirected walking
SD	Standard deviation
SS	Simulator sickness
SSQ	Simulator sickness questionnaire
VE	Virtual environment
VR	Virtual reality
2AFC	Two-alternative forced choice

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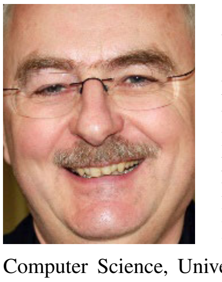

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