

Walk The Line: Leveraging Lateral Shifts of the Walking Path as an Input Modality for Head-Mounted Displays

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Figure 1. Walk the Line leverages lateral shifts of the walking path as an input modality for HMDs. Options are visualized as *lanes* on the floor. Users select options by shifting the walking path sideways. Following a selection, sub-options of a cascading menu appear as new *lanes*.

ABSTRACT

Recent technological advances have made head-mounted displays (HMDs) smaller and untethered, fostering the vision of ubiquitous interaction in a digitally augmented physical world. Consequently, a major part of the interaction with such devices will happen on the go, calling for interaction techniques that allow users to interact while walking.

In this paper, we explore lateral shifts of the walking path as a hands-free input modality. The available input options are visualized as lanes on the ground parallel to the user's walking path. Users can select options by shifting the walking path sideways to the respective lane. We contribute the results of a controlled experiment with 18 participants, confirming the viability of our approach for fast, accurate, and joyful interactions. Further, based on the findings of the controlled experiment, we present three example applications.

Author Keywords

Augmented Reality; Head-Mounted Display; Input; Walking;

CCS Concepts

•Human-centered computing → Human computer interaction (HCI); User studies;

INTRODUCTION

While walking, we routinely respond to changes in the environment by adapting the trajectory of our walking path to avoid obstacles, such as oncoming pedestrians or pavement damages. These trajectory changes occur quickly and accurately and without changing the original direction of travel, but by laterally shifting the walking path. In this paper, we argue that such lateral shifts of the user can be leveraged as a novel input modality for interaction *on the go*.

Today, a large number of pedestrians use their smartphones as they walk, losing touch with the world around them [39]. Like distracted driving, distracted walking leads to potentially dangerous situations: The lack of (visual) attention causes pedestrians to walk into obstacles, or otherwise endanger themselves [61, 73]. As a possible solution, voice-based interfaces free the visual channel of users. However, such systems are prone to noisy environments, have social implications [34, 69] and interfere with the communication between people,

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whether it is a local conversation or a phone call. To overcome the limitations of interaction while walking, research proposed ways to mitigate for the situational hindrances [65] through increased button sizes [32] or content stabilization [56].

In this work, we go beyond the state-of-the-art by not only compensating for such situational hindrances but by actively exploiting the process of locomotion as an input modality: Recent advances in tracking and display technology enable realistic and robust Augmented Reality (AR) experiences with wireless and mobile head-mounted displays (HMDs). This potentially enables more comfortable and safer interaction while walking as the visual attention is no longer captured purely on a display [42]. In this paper, we propose to use HMDs to visualize different input options as augmented lanes on the ground parallel to the walking path of the user. By laterally shifting the path onto a lane and, subsequently, walking on the lane, users can select an option (see Figure 1).

The contribution of this paper is two-fold: First, we contribute the results of a controlled experiment assessing the efficiency and accuracy of such a walking-based interface. Second, based on the results of the controlled experiment, we present design guidelines together with three example applications.

RELATED WORK

There exists a large body of related work that inspired and shaped this work. The following section presents these related works in the areas of 1) interaction with HMDs, 2) interfaces for use while walking, and 3) locomotion as an input modality.

Interaction with HMDs

Since Sutherland's *Sword of Damocles* [70] in 1968, HMDs have become smaller [7] and wireless [20], increasing their mobility. This resulted in a constant stream of work on interaction techniques for such devices.

Previous work explored gestural interfaces for interacting with HMDs. As a prominent example, Mistry et al. [45] presented a sensor supporting natural gesture interaction and Colaco et al. [13] showed how to capture more fine-grained single-handed gestures. Other examples include finger-gestures [9], the use of a glove [31] or proximity-based interfaces [48]. Further, research proposed a combination with other modalities such as gaze [26, 68] or head-movements [37]. Despite the benefits (e.g., direct and fine-grained manipulation), hand gestures require the user's hands to be free. Moreover, gestures are prone to fatigue, also known as the *gorilla arm syndrome* [27].

As another approach, research showed how accessories could be used to interact. As prominent examples, Ashbrook et al. [3] presented a ring and Dobbelsstein et al. [15] proposed a belt for unobtrusive touch input. Further examples include augmentations to the user's pocket [16] or sleeves [63]. Despite their usefulness, accessory interfaces can be misplaced or lost and are missing means for direct manipulation of content.

Research further presented on-body [23] interfaces to interact by touching various body parts. Examples range from the arm [24, 81] and hand [71, 14, 47] to the face [66], cheek [84] or ear [40]. Wagner et al. [79] classified such on-body interactions into a body-centric design space. However, despite

the advantages of such techniques (e.g., body parts cannot be misplaced or lost), they require the user's hands to be free.

Foot-based interfaces have a long history in operating heavy machinery [4, 5] and have been explored in various areas of HCI [76]. In recent years, foot-based interfaces also received considerable attention for HMDs: Matthies et al. [44] presented a foot-based interface for Virtual Reality (VR) applications, and Fukahori et al. [22] leveraged the shifting of the user's weight for subtle gestures. Other examples include game controls [43] or data exploration [19]. However, the *Midas Tap Problem* [49] hampers the usage of foot-based interfaces while walking, as the system would have to distinguish intentional input from natural motion.

Interfaces for Use While Walking

The proliferation of smartphones and the increasing usage during walking [85] led to a stream of research to mitigate the situationally-induced impairments [65] and reduced safety [62] that are introduced through walking [59, 60] and additional encumbrances such as carrying objects [51, 52] or ambient noises [58]. Kane et al. [32] introduced the term Walking User Interfaces (WUIs) for interfaces that are explicitly designed "to compensate for the effects of walking on mobile device usability." The authors proposed increased button and text sizes to compensate for the reduced input performance. Further, Rahmati et al. [56] used content stabilization to compensate for the shaking introduced from walking. Further examples to help users to overcome the situational impairments include the usage of other keyboard layouts [11] or text input modalities beyond touch-typing [21].

Focusing on safety aspects, Beuck et al. [6] found that applications actively interrupting smartphone usage can help to prevent potentially dangerous situations. Shikishima et al. [67] showed how texting while walking can be detected. Further, Hincapie-Ramos et al. [28] presented an integrated alarm system that warns users of dangerous situations while being engaged with their smartphone. Further examples include other warning systems [82, 72, 77], obstacle detection [80], or specialized support for texting [35] or video watching [1].

While most research focused on smartphones, this paper argues that HMDs are a better fit for the requirements of a truly mobile user interface to be operated while walking: Such devices do not require the user to look down to operate. Further, the user's visual attention is not captured on an opaque screen, keeping the connection to the real world [42].

Highly related, Lages et al. [38] explored how different adaptation strategies of user interfaces can support the user in interacting with HMDs during walking. However, this very inspirational work focused on adapting the *output* to accommodate for the effects of walking. The authors did not address the changing requirements for *input* while walking.

Locomotion as Input

Research showed how the movement of the user's body during locomotion, as well as the changing spatial relationships between users and objects, could be used as an input dimension for both, implicit and explicit interactions.

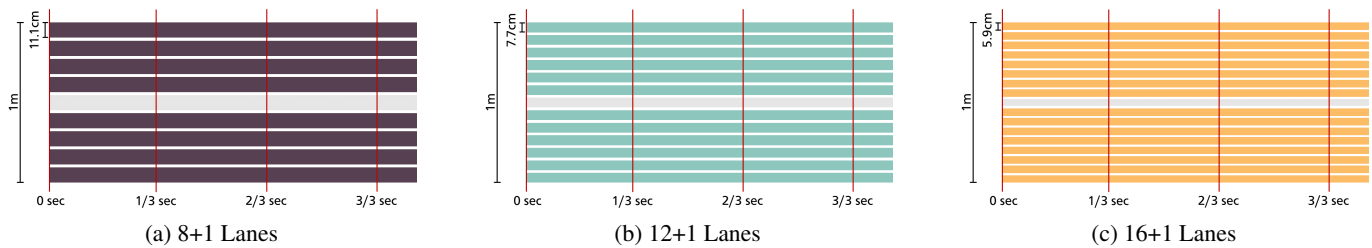


Figure 2. The levels of the two independent variables, number of lanes and selection time, as tested in the experiment.

Popular examples of implicit interaction can be found in context-aware computing systems [10], e.g., for mobile navigation. Such systems use the (global) spatial position as input and present navigation instructions through a variety of output modalities such as screen-based [36], augmented [50], vibrotactile [75, 74] or audio [29], or a combination of these. Further, Dow et al. [17] showed how the spatial location of a user could be used to start the playback of location-specific content. Further, Vogel et al. [78] showed how to use the spatial position of users relative to a public display to switch between different modes of interaction implicitly.

In recent years, research proposed more explicit methods for interacting with HMDs through walking. As the most prominent example, it is a widespread interaction paradigm in VR and (mobile) AR to approach virtual objects in order to interact with them in place [2, 30, 57]. In such systems, the user's spatial movement acts as a mean for *selection* or *browsing* of virtual objects. Further, Piekarski et al. [54] proposed walking as an input modality for AR scene modeling. However, to the best of our knowledge, prior work did not explore how the locomotion of users during walking itself can be leveraged as a generic *input* dimension for interaction with HMDs yet.

CONCEPT

In this paper, we investigate interaction while walking, leveraging lateral shifts of the walking path as an input modality. For this, we consider a system that displays multiple lanes parallel to the walking path of the user. Each lane represents an option the user can select. The lanes can be arranged on both sides of the user's walking path (see Figure 1). The specific visualization of the lanes can be tailored to the application and adapted to the current situation of the user. For example, it can contain icons or text or can be connected to bubbles floating in the air which describe the information to be selected.

To interact with the system, users shift their path sideways until they walk on the desired option lane. The system highlights the lane the user is currently walking on by changing the color of the respective lane. This color change affects the entire lane, which is also visible in front of the user. Therefore, users do not have to look to the ground to interact with the system, but can keep their head up even with the limited FoV of today's devices. By walking along one of the lanes for a certain period of time, the respective option can be selected, analogously to the concept of selection by dwell time in eye-gaze interaction [55]. This *selection time* is visualized to the user by changing the opacity of the lanes: While walking on a lane, all other lanes are gradually faded out.

In addition to the option lanes, our concept proposes a non-active *null lane* that covers the path directly in front of the user, which remains free. Therefore, if users continue walking straight ahead without adjusting their path, we do not interpret this as an interaction and do not trigger any actions.

METHODOLOGY

The design of a system based on the presented concepts concerning the width of lanes, as well as the necessary selection time, is strongly dependent on environmental influences (e.g., available space, obstacles, or oncoming pedestrians). Therefore, we focused on thin lanes and short selection times to establish a lower bound and baseline for accurate and efficient interactions with such a system. To investigate the influence of these two factors, we conducted a controlled experiment focusing on the following research questions:

RQ1 How does the width of the *lanes* affect the accuracy, efficiency, and user experience of the system?

RQ2 How does the *selection time* affect the accuracy, efficiency, and user experience of the system?

RQ3 Are there interaction effects between the width of the lanes and the selection time on the accuracy, efficiency, and user experience?

Design and Task

We designed a controlled experiment in which users interacted with a system as described in section 3. The participants' task was to laterally shift their walking path to the highlighted target lane and stay within its bounds for a certain period of time while keeping average walking speed.

As the first independent variable, we varied the *number of lanes* on a fixed-width interaction area. We varied the equal-sized width of the lanes to fill the available interaction space, thus also varying the width of the individual lanes.

As the second independent variable, we varied the *selection time* as the time participants had to walk on a lane to select it. Shorter dwell times on a lane did not select the respective lane and could be used to cross lanes to reach targets on the side.

We varied both independent variables in a repeated measures design with three levels each (*number of lanes*: 8-lane, 12-lane, and 16-lane, *selection time*: $\frac{1}{3}$ s, $\frac{2}{3}$ s, and $\frac{3}{3}$ s), resulting in a 2-factorial study design with a total of $3 \times 3 = 9$ conditions (see Figure 2). We chose the levels based on the goal of establishing a lower limit for accurate and efficient interactions. Further,

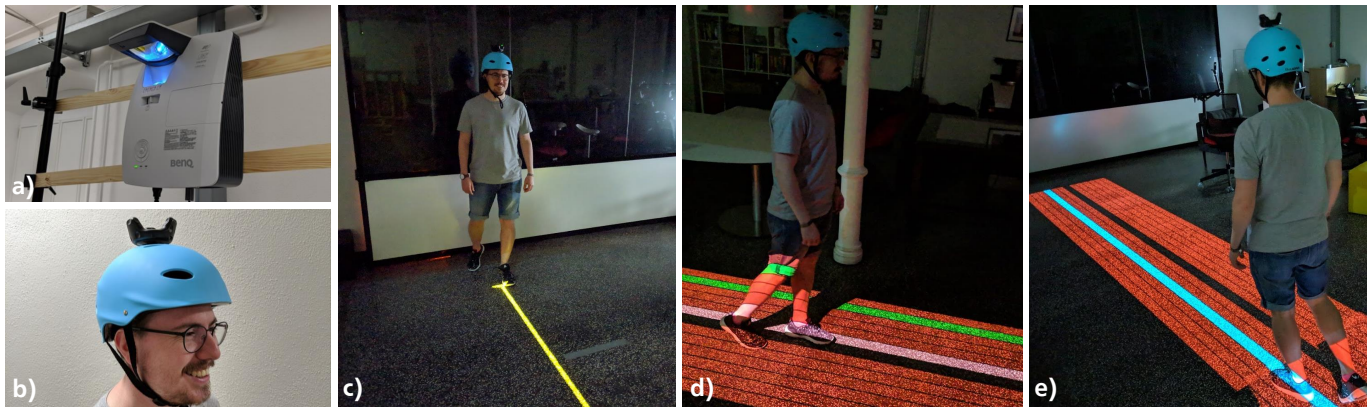


Figure 3. Setup and procedure of the experiment: We used two projectors (a) for visual output and tracked the participants using an HTC VIVE Tracker (b). Participants initiated each trial by starting to walk (c). In the following, the system projected the lanes with a highlighted target lane (d). The participants’ task was to shift their path to the target lane (e) and stay within the bounds for the respective *selection time* of the condition.

the design included two repetitions per target lane in each condition, resulting in a total of $3 \cdot (8 + 12 + 16) \cdot 2 = 216$ trials per participant. We counterbalanced the order of the conditions using a Balanced Latin Square design. For each condition, the system randomized the series of targets while assuring that each target was repeated two times.

To specify the dimensions of the longitudinal area used in the study, we started from the typical width of a sidewalk of 2.5 m [33]. We halved the available width to take into account oncoming traffic from other pedestrians and decreased a safety distance of 0.25 m, resulting in 1 m of interaction width. Since the experiment varied the *number of lanes* on a fixed-width area, we also varied the *width* of the individual lanes. Therefore, the width of the individual lanes in each condition was $1 \text{ m} / (\text{number of lanes} + 1)$, resulting in an absolute lane width of $\sim 11 \text{ cm}$ (for the 8-lane conditions) to $\sim 6 \text{ cm}$ (for the 16-lane conditions). For the length of the area, we opted for 20 m as informal pre-tests showed that this distance allowed the participants to perform the interaction in all conditions without reaching the end of the area.

Study Setup and Apparatus

We opted against using AR glasses as today’s devices still suffer from technical limitations (e.g., weight, limited field of view, unreliable tracking) that could influence the measurements, rendering the results unusable for future developments.

Therefore, we build a setup consisting of two short-throw 1080p projectors (BenQ MH856UST) to simulate the visual output. For this, we mounted the two projectors at a distance of 7 m to wooden slats, which we, in turn, attached to two tripods at the height of 3.5 m (see Figure 3, a). This setup allowed to cover a range of 20 m with visual output. We combined this visual output with the robust and accurate tracking of participants using an HTC VIVE Tracker (position tracking error $< 0.02 \text{ cm}$ [53]). For this, we mounted two VIVE Lighthouses at the far edges of the area covered by visual output to allow the same physical space to be tracked by the system. The implementation used OpenCV to calibrate¹ the

¹https://docs.opencv.org/2.4/doc/tutorials/calib3d/camera_calibration/camera_calibration.html

projected image with the tracking of the VIVE system by displaying calibration points and positioning a VIVE Tracker on the displayed positions, achieving a $3 \text{ m} \times 20 \text{ m}$ interaction space with combined input and output.

We modified a bicycle helmet and equipped it with a VIVE Tracker to capture the position of the participants’ heads in space (see Figure 3, b). We opted to use the head position of the participants as input for the system (in contrast to, for example, the position of the two feet) to simulate the type of tracking available in today’s HMDs. A desktop PC located next to the study area orchestrated the VIVE tracking as well as the two projectors. The PC was further used to render the visual output as well as for data logging. Figure 3 depicts the complete setup and apparatus of the study.

Further, the desktop PC hosted a study operator application that allowed the investigator to set the task. For each trial, we logged the following dependent variables:

Trajectory as the trace of the participants’ *walking path* (i.e., the path of the participants’ head movements),

Task Completion Time (TCT) as the time between displaying the task and entering the lane which was subsequently selected (i.e., the time until the activation of the lane minus the *selection time*),

Accuracy Rate as the rate of successfully selecting the target lane of the trial,

Stabilizing Error Rate as the rate of participants walking past the boundaries of the target lane after initially reaching it. This includes overshooting errors (i.e., leaving the target lane while maintaining the initial direction of the lateral shift) as well as swing-back errors (i.e., leaving the target lane in the opposite direction to the initial shifting direction).

We conducted the experiment in a room of our institute’s building, where there was a sufficiently large area available. For the duration of the study, we closed the area to regular public access in order to exclude external influences.

Procedure

After welcoming the participants, we introduced them to the concept and measured their body height as we expected it to influence the performance. In the following, we asked the participants to fill a consent form and an introductory questionnaire asking for demographic data. After calibrating the system, we asked the participant to put on the modified bicycle helmet. To avoid learning effects, the participants began the study by freely testing the system.

To start the first condition, we asked the participants to go to the starting position. Participants were free to start each trial whenever they wanted by starting to walk (see Figure 3, c). After a few steps (i.e., after reaching an average walking speed of around 1-1.5 m/s [8]), the system showed the task to the participants (see Figure 3, d). The system randomly selected the exact starting point (2 +/- .5m) of each trial in order to avoid influencing the participants by learned positions. The interface consisted of red lines, indicating the *number of lanes* of the condition. The system highlighted the target with green and the currently active lane with a lighter gradation of red (for the regular lanes, see Figure 3, d) or blue (for the target, see Figure 3, e). After leaving the *null lane*, the system showed the *selection time* by fading out the other lanes. The selection timer was reset once the participant left a lane and restarted for the newly active lane. When the participant walked on a lane for the *selection time* of the condition, the system logged the result and signaled the end of the trial with a sound. If the participant had not made a selection by the end of the interaction space or selected a wrong lane, the system logged this as a failed attempt. Finally, the participant walked back to the starting position and proceeded to the next trial.

We instructed the participants to maintain their average walking speed over the entire course. After each condition, we asked the participants to fill a questionnaire regarding their experiences on a 5-point Likert-scale (1: strongly disagree, 5: strongly agree). Additionally, the participants filled a NASA TLX [25] questionnaire. We enforced a 5-minute break between the conditions. During this break, the participants gave qualitative feedback in a semi-structured interview. Each experiment took about 80 minutes per participant.

Participants

We recruited 18 participants (8 male, 8 female, 2 identified as gender variant/non-conforming), aged between 16 and 55 ($\mu = 30.83$, $\sigma = 9.6$). All participants voluntarily took part in the study and we paid no compensation.

Analysis

We analyzed the recorded data using two-way repeated-measures (RM) ANOVAs with the *number of lanes* and the *selection time* as two factors to uncover significant effects. We tested the data for normality using Shapiro-Wilk's test without any significant deviations. In cases where Mauchly's test indicated a violation of the assumption of sphericity, we corrected the tests using the Greenhouse-Geisser method and report the ϵ . When the RM ANOVA indicated significant results, we used Bonferroni corrected pairwise t-tests for post-hoc analysis. We further report the eta-squared η^2 as an estimate of the

effect size and use Cohen's suggestions to classify the effect size as small, medium, or large [12]. Further, as an estimate of the mean response of the individual factors, we report the estimated marginal mean (EMM) as proposed by Searle et al. [64]. For the analysis of the NASA TLX questionnaires, we applied the raw method, indicating an overall workload as described by Hart et al. [25]. For the analysis of the non-continuous data of the Likert questionnaires, we performed an Aligned Rank Transformation as proposed by Wobbrock et al. [83].

RESULTS

In the following section, we report the results of the controlled experiment investigating the research questions RQ1 - RQ3.

Accuracy

We analyzed the accuracy of participants as the rate of successful trials. The analysis revealed that the *number of lanes* had a significant ($F_{2,34} = 27.05$, $p < .001$, $\eta^2 = .134$) influence on the participants' accuracy with a medium effect size. Post-hoc tests confirmed significant differences between the 8-lane (EMM $\mu = 85.8\%$, $\sigma_{\bar{x}} = 2.2\%$) and 16-lane (EMM $\mu = 70.1\%$, $\sigma_{\bar{x}} = 2.2\%$) conditions as well as between the 12-lane (EMM $\mu = 80.4\%$, $\sigma_{\bar{x}} = 2.2\%$) and 16-lane conditions (both $p < .001$).

Further, the analysis showed a significant ($F_{1.44,24.45} = 37.57$, $p < .001$, $\epsilon = .719$, $\eta^2 = .307$) effect for the *selection time* on the participants' accuracy with a large effect size. Post-hoc tests confirmed significant differences between the $\frac{1}{3}$ s (EMM $\mu = 65.2\%$, $\sigma_{\bar{x}} = 2.4\%$) and both, the $\frac{2}{3}$ s (EMM $\mu = 88.5\%$, $\sigma_{\bar{x}} = 2.4\%$) and the $\frac{3}{3}$ s (EMM $\mu = 82.6\%$, $\sigma_{\bar{x}} = 2.4\%$) conditions (both $p < .001$).

Additionally, the analysis showed significant ($F_{2.57,43.74} = 4.28$, $p < .05$, $\epsilon = .643$, $\eta^2 = .033$) interaction effects between both factors with a small effect size.

In our experiment, we found accuracy rates ranging from EMM $\mu = 93.6\%$, $\sigma_{\bar{x}} = 3.1\%$ (8-lane, $\frac{3}{3}$ s) to EMM $\mu = 58.9\%$, $\sigma_{\bar{x}} = 3.1\%$ (16-lane, $\frac{1}{3}$ s). Figure 4a depicts the measured accuracy rates for all conditions in the experiment.

Stabilizing Error

We calculated the stabilizing error rate by counting the number of trials when participants left the target lane after initially reaching it. The analysis showed a significant ($F_{2,34} = 127.3$, $p < .001$, $\eta^2 = .45$) influence of the *number of lanes* on the stabilizing error rate with a large effect size. Post-hoc tests confirmed significantly higher stabilizing error rates for higher *numbers of lanes* (and thus smaller lanes) between all levels (8-lane: EMM $\mu = 16.2\%$, $\sigma_{\bar{x}} = 3.5\%$, 12-lane: EMM $\mu = 36.8\%$, $\sigma_{\bar{x}} = 3.5\%$, 16-lane: EMM $\mu = 61.7\%$, $\sigma_{\bar{x}} = 3.5\%$, all $p < .001$).

Further, the *selection time* also proved to have a significant ($F_{2,34} = 67.07$, $p < .001$, $\eta^2 = .164$) influence on the stabilizing error rate in the experiment with a large effect size. Post-hoc tests confirmed significantly higher stabilizing error rates for longer selection times between all levels ($\frac{1}{3}$ s: EMM $\mu = 24.3\%$, $\sigma_{\bar{x}} = 3.3\%$, $\frac{2}{3}$ s: EMM $\mu = 38.7\%$, $\sigma_{\bar{x}} = 3.3\%$, $\frac{3}{3}$ s: EMM $\mu = 51.8\%$, $\sigma_{\bar{x}} = 3.3\%$, all $p < .001$).

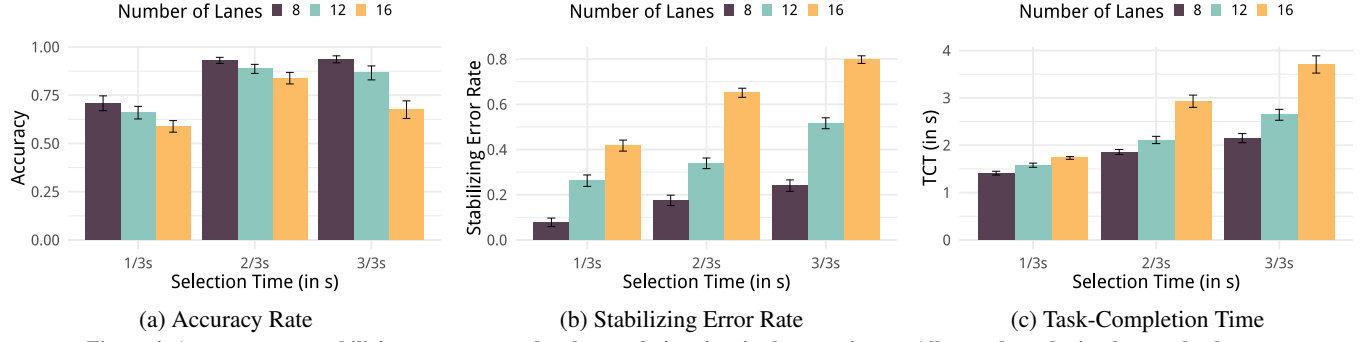


Figure 4. Accuracy rate, stabilizing error rate and task-completion time in the experiment. All error bars depict the standard error.

Lastly, the analysis also showed significant ($F_{4,68} = 6.73$, $p < .001$, $\eta^2 = .023$) interaction effects between both factors with a small effect size.

We found stabilizing error rates ranging from EMM $\mu = 7.8\%$, $\sigma_{\bar{x}} = 4.1\%$ (8-lane, $1/3$ s) to EMM $\mu = 79.8\%$, $\sigma_{\bar{x}} = 4.1\%$ (16-lane, $3/3$ s). Figure 4b depicts the measured stabilizing error rates for all conditions in the experiment.

Task Completion Time

We measured the task-completion time (TCT) as the time to successful activation of a lane and subtracted the respective selection time of the condition to make the TCTs comparable. The time was measured from the moment the target was displayed to the participant. The analysis only considered the TCTs of the successful trails, as the different accuracy rates would otherwise influence the results.

The analysis showed a significant ($F_{2,34} = 117.8$, $p < .001$, $\eta^2 = .262$) influence of the *number of lanes* on the TCT with a large effect size. Post-hoc tests confirmed rising TCTs for higher numbers of lanes between all levels (8-lane: EMM $\mu = 1.81$ s, $\sigma_{\bar{x}} = 0.07$ s, 12-lane: EMM $\mu = 2.11$ s, $\sigma_{\bar{x}} = 0.07$ s, 16-lane: EMM $\mu = 2.79$ s, $\sigma_{\bar{x}} = 0.07$ s all $p < .001$).

Interestingly, despite subtracting of the selection time from the TCT, the analysis also showed a significant ($F_{2,34} = 123.3$, $p < .001$, $\eta^2 = .413$) effect of the *selection time* on the TCT with a large effect size. Post-hoc tests confirmed significantly higher TCTs for higher selection times between all levels ($1/3$ s: EMM $\mu = 1.57$ s, $\sigma_{\bar{x}} = 0.08$ s, $2/3$ s: EMM $\mu = 2.30$ s, $\sigma_{\bar{x}} = 0.08$ s, $3/3$ s: EMM $\mu = 2.83$ s, $\sigma_{\bar{x}} = 0.08$ s, all $p < .001$). As depicted in figure 4c, the TCTs for the different selection times are close together for the 8-lane conditions. For higher numbers of lanes, the TCTs grow faster for longer selection times.

Further, the analysis again showed significant ($F_{2,71,46.06} = 25.3$, $p < .001$, $\epsilon = .677$, $\eta^2 = .073$) interaction effects between the factors with a medium effect size.

The graphical analysis of the TCTs showed strong visual correlations with the stabilizing error rates as presented above (see Figure 4b and 4c). Calculating Pearson's r supported the visual impression by confirming a very strong [18] correlation between *stabilizing error rate* and *TCT* ($r = .925$, $p < .001$).

We found TCTs ranging from EMM $\mu = 1.41$ s, $\sigma_{\bar{x}} = 0.10$ s (8-lane, $1/3$ s) to EMM $\mu = 3.71$ s, $\sigma_{\bar{x}} = 0.08$ s (16-lane, $3/3$ s). Figure 4c depicts the measured TCTs for all conditions.

Walked Distance

To take into account different walking speeds of the participants, we analyzed the walking distance necessary to activate a target. Similar to the TCT, we only considered the distance that was necessary to select a lane without the distance walked during the *selection time* of the respective condition. Therefore, the system measured the distance the participants walked from the beginning of the task within the TCT as defined above.

The analysis showed a significant ($F_{1,45,24.65} = 84.0$, $p < .001$, $\epsilon = .725$, $\eta^2 = .159$) influence of the *number of lanes* on the distance with a large effect size. Post-hoc tests confirmed significantly higher distances for higher *numbers of layers* between all levels (8-lane: EMM $\mu = 2.06$ m, $\sigma_{\bar{x}} = 0.18$ m, 12-lane: EMM $\mu = 2.43$ m, $\sigma_{\bar{x}} = 0.18$ m, 16-lane: EMM $\mu = 3.11$ m, $\sigma_{\bar{x}} = 0.18$ m, all $p < .001$).

As for the TCT, the analysis also showed a significant ($F_{1,41,23.89} = 102.5$, $p < .001$, $\epsilon = .703$, $\eta^2 = .263$) effect for the *selection time* on the distance with a large effect size. Again, post-hoc tests confirmed significantly higher distances for higher selection times between all levels ($1/3$ s: EMM $\mu = 1.80$ m, $\sigma_{\bar{x}} = 0.18$ m, $2/3$ s: EMM $\mu = 2.63$ m, $\sigma_{\bar{x}} = 0.18$ m, $3/3$ s: EMM $\mu = 3.17$ m, $\sigma_{\bar{x}} = 0.18$ m, all $p < .001$).

Further, the analysis showed significant ($F_{2,96,50.32} = 21.9$, $p < .001$, $\epsilon = .74$, $\eta^2 = .042$) interaction effects between both factors with a small effect size.

As for the TCT, the visual analysis of the measured distances again showed correlations with the stabilizing error rates (see Figure 4b and 5). Again, calculating Pearson's r supported the visual impression, confirming a strong correlation between the *stabilizing error rate* and the needed *distance* to walk ($r = .924$, $p < .001$).

We found distances ranging from EMM $\mu = 1.62$ m, $\sigma_{\bar{x}} = 0.19$ m (8-lane, $1/3$ s) to EMM $\mu = 4.07$ m, $\sigma_{\bar{x}} = 0.19$ m (16-lane, $3/3$ s). Figure 5 depicts the measured walking distances for all conditions in the experiment.

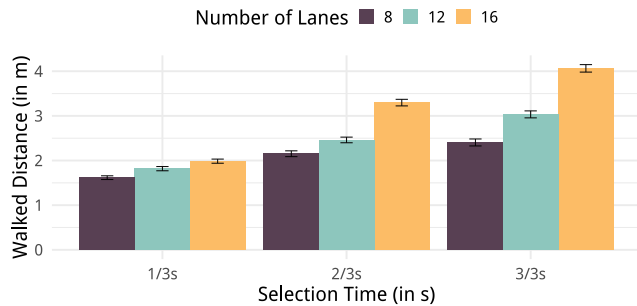


Figure 5. The measured distances to selection in the controlled experiment. All error bars depict the standard error.

TLX

To assess the differences in the mental load induced by the two factors, we analyzed the influence of the factors on the Raw Nasa-TLX (RTLX). The analysis showed a significant ($F_{1,43,24.36} = 18.96, p < .001, \epsilon = .716, \eta^2 = .104$) influence of the *number of lanes* with a medium effect size. Post-hoc tests confirmed significantly higher values for the 16-lane (EMM $\mu = 43.9, \sigma_{\bar{x}} = 2.99$) conditions compared to both, the 8-lane (EMM $\mu = 29.4, \sigma_{\bar{x}} = 2.99$) and 12-lane (EMM $\mu = 33.7, \sigma_{\bar{x}} = 2.99$) conditions (both $p < .001$).

Further, the analysis showed a significant ($F_{1,18,20.01} = 21.7, p < .001, \epsilon = .588, \eta^2 = .182$) effect for the *selection time* on the RTLX with a large effect size. Post-hoc tests confirmed significantly higher values for the $\frac{1}{3}$ s (EMM $\mu = 47.0, \sigma_{\bar{x}} = 3.16$) conditions compared to the $\frac{2}{3}$ s (EMM $\mu = 29.1, \sigma_{\bar{x}} = 3.16$) and $\frac{3}{3}$ s (EMM $\mu = 30.9, \sigma_{\bar{x}} = 3.16$) conditions (both $p < .001$).

Lastly, the analysis showed significant ($F_{4,68} = 3.12, p < .05, \eta^2 = .022$) interaction effects between the factors with a small effect size.

We found RTLX values ranging from EMM $\mu = 20.7, \sigma_{\bar{x}} = 3.8$ (8-lane, $\frac{3}{3}$ s) to EMM $\mu = 51.9, \sigma_{\bar{x}} = 3.8$ (16-lane, $\frac{1}{3}$ s). Figure 6 depicts the measured walking distances for all conditions in the experiment.

Height

To assess the influence of the participants height and, thus, differences in step sizes, we calculated the between subject effects of the *height* on the independent variables. However, the analysis did not show any influence on the *accuracy* ($F_{1,16} = 1.78, p > .05$), the *stabilizing error* ($F_{1,16} = 1.31, p > .05$), the *TCT* ($F_{1,16} = .09, p > .05$) nor on the *distance* ($F_{1,16} = 1.15, p > .05$).

Location of the Target Lane

We analyzed the effect of the location of the target lane by comparing the measurements grouped by *outer* (i.e., lanes on the far left and right as well as the lanes next to the central *zero-lane*) and *inner* (i.e., all other lanes) target lanes.

The analysis showed a significant influence of the target location on the *accuracy* ($F_{1,17} = 35.95, p < .001, \eta^2 = .058$)

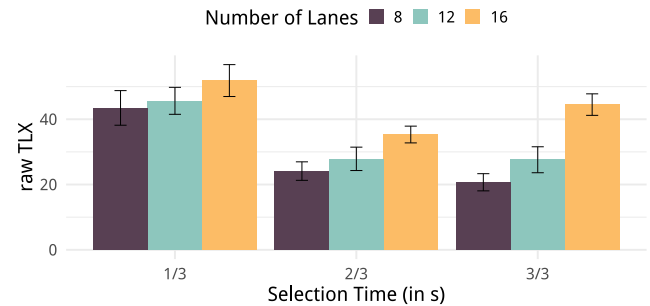


Figure 6. The Raw Nasa-TLX measured in the controlled experiment. All error bars depict the standard error.

with a small effect size. Post-hoc tests confirmed significantly higher accuracy rates for outer (EMM $\mu = 85.0\%, \sigma_{\bar{x}} = 2.01\%$) compared to inner (EMM $\mu = 75.4\%, \sigma_{\bar{x}} = 2.01\%$) target lanes ($p < .001$).

Besides the accuracy, the analysis did not show any significant effects for the *stabilizing error rate* ($F_{1,17} = 3.49, p > .05$), the *TCT* ($F_{1,17} = 2.43, p > .05$) nor the *walked distance* ($F_{1,17} = 1.92, p > .001, \eta^2 = .001$).

Questionnaire

After each condition, participants answered questions regarding their experiences on a 5-point Likert-scale (1: strongly disagree, 5: strongly agree). The following section analyses the participants' answers.

Confidence

We asked the participants about their *confidence* to have successfully hit the target lanes in the condition. We found a significant ($F_{2,34} = 61.92, p < .001$) effect of the *number of lanes* on the participants' confidence. Post-hoc tests confirmed significantly lower approval for the 16-lane conditions compared to the 8-lane and 12-lane conditions (both $p < .001$).

Additionally, the analysis showed a significant ($F_{2,34} = 16.67, p < .001$) effect for the *selection time* on the participants' confidence. Post-hoc tests revealed significantly lower approval rates for the $\frac{1}{3}$ s conditions compared to the $\frac{2}{3}$ s and $\frac{3}{3}$ s conditions (both $p < .001$).

We found significant ($F_{4,68} = 6.11, p < .01$) interaction effects. Figure 7 (left) depicts all the answers of the participants.

Convenience

Further, we asked the participants if the combination of *number of lanes* and *selection time* was convenient to use. The analysis showed a significant ($F_{2,34} = 48.53, p < .001$) effect for the *number of lanes* on the participants' ratings of the convenience. Post-hoc tests revealed significantly higher convenience ratings for 8-lane and 12-lane conditions compared to 16-lane conditions (both $p < .001$).

Further, we found a significant ($F_{2,34} = 11.47, p < .001$) influence of the *selection time* on the ratings. Post-hoc tests confirmed significantly higher approval ratings for $\frac{2}{3}$ s ($p < .001$) and $\frac{3}{3}$ s ($p < .01$) compared to $\frac{1}{3}$ s conditions.

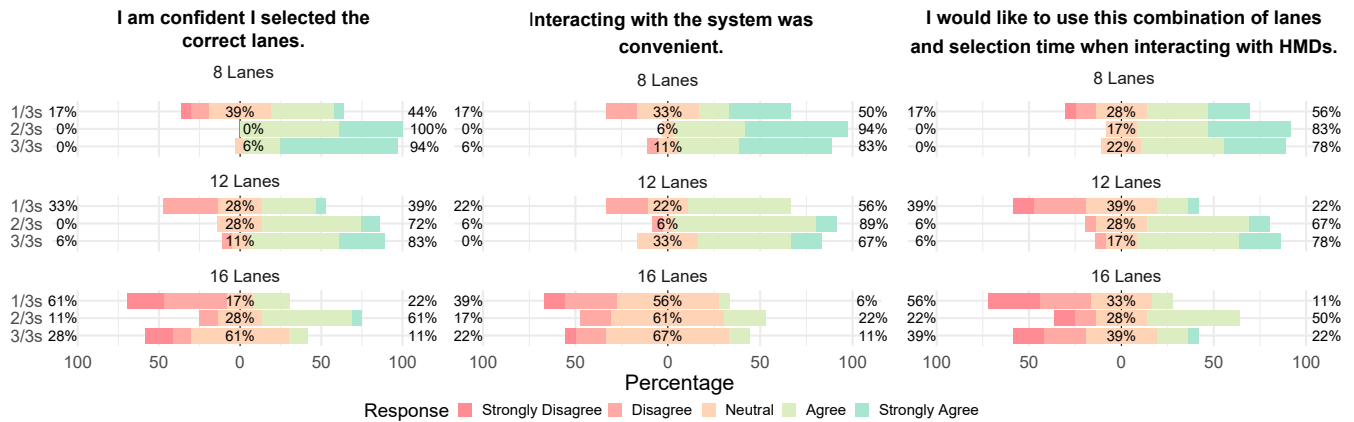


Figure 7. The participants' answers to our three questions in the Likert-questionnaires.

We found no interaction effects ($F_{4,68} = 0.16, p > .05$). Figure 7 (middle) depicts all the answers of the participants.

Willingness to Use

As a last question, we asked the participants if they would like to use this combination of the *number of lanes* and the *selection time* for interacting with HMDs. The analysis showed a significant ($F_{2,34} = 28.13, p < .001$) influence of the *number of lanes* on the participants' ratings. Post-hoc tests revealed significantly rising approval ratings for lower numbers of lanes between all levels ($p < .01$ comparing 8-lane and 12-lane, otherwise $p < .001$).

Further, the analysis unveiled a significant ($F_{2,34} = 17.86, p < .001$) influence of the *selection time* on the ratings. Post-hoc tests showed significantly lower rates for $\frac{1}{3}$ s conditions compared to $\frac{2}{3}$ s and $\frac{3}{3}$ s conditions (both $p < .001$).

The analysis did not indicate any significant ($F_{4,68} = 1.59, p > .05$) interaction effects between the two factors. Figure 7 (right) depicts all the answers of the participants.

Qualitative Results

In general, all participants showed strong approval for the idea of hands-free interaction with HMDs through walking. Asked for the reasons, participants told that it felt “*fun*” (P8), “*novel*” (P15), “*fast*” (P12) and “*convenient*” (P1,8), and would be especially “*helpful [...] while doing other things*” (P8).

The participants noted that the *number of lanes* had a strong influence on their experience. P14 summarized: “With many lanes it is frustrating. I have to concentrate a lot to accomplish that.” P8 added: “With the small lanes, it almost feels like I have to walk on a balance beam.”

Concerning the *selection time*, the opinions of the participants diverged. While almost all participants agreed that $\frac{1}{3}$ s is “*too short*” (P1, P2, P8, P13, P17), both other selection times were equally popular. P7 explained the problem of identifying the “best” selection time: “It’s complicated. With the thin lanes, I’m annoyed [...] by too much [selection] time because balancing is difficult. With the wide lanes, on the other hand, I find longer [selection] times easier.”

DISCUSSION

The results of our controlled experiment suggest that the usage of lateral shifts of the walking path of users provides a viable interaction technique for HMDs. The analysis showed the highest accuracy rates ($\approx 94\%$) for 8 interaction lanes (with an additional inactive *zero lane* in the middle, resulting in a lane width of 11 cm) with a selection time of $\frac{2}{3}$ s. In the following section, we discuss the results of the experiment with respect to the research questions as presented above.

RQ1: Influence of the Number of Lanes

The analysis revealed a strong dependence of both, the accuracy and the efficiency, on the *number* and - since we varied the number of lanes on a fixed-width area - the *width* of lanes. Higher numbers of lanes reduced the accuracy across all conditions. Further, higher numbers of lanes also led to higher TCTs and increased the walking distance, decreasing efficiency.

We attribute the reduced accuracy and efficiency for higher numbers of lanes to the higher stabilizing error rates through overshooting and swing-back errors caused by thinner lanes. This effect was further amplified by the natural lateral oscillation of the head that occurs during walking: The steps cause the head to constantly move slightly to the left and right of the actual path while walking, causing participants to oscillate out of the target lane. At comfortable walking speeds of around 1-1.5 m/s [8], this effect occurs at the stride frequency of approximately 1 Hz, and is responsible for a lateral translation of 10 mm to 15 mm in each direction [46]. This equates to 9-14% (for the 8-lane conditions) and up to 17-25% (for the 16-lane conditions) of the lane widths tested in the experiment.

Further, the analysis showed significantly higher RTLX values indicating a higher mental load for higher numbers of lanes. The results of the Likert-questionnaires supported the general discomfort of the participants with higher numbers of lanes. The participants answered all three questions - regarding confidence, convenience, and willingness to use - with significantly lower scores for 16-lane compared to 12-lane and 8-lane conditions. The qualitative feedback of the participants further supported these findings, most of whom were in favor of lower lane numbers.

RQ2: Influence of the Selection Time

Concerning the *selection time*, we found a more complicated relationship to the accuracy than with the *number of lanes*. The analysis showed that different selection times had a strong influence on accuracy. Surprisingly, the middle selection time (2/3 s) was the one that achieved the highest accuracy rates.

On the one hand, too short selection times led to participants accidentally selecting wrong lanes, as they spent too much time over an intermediate lane when changing lanes, thus decreasing accuracy. On the other hand, too long selection times increased the chance of participants accidentally leaving the target lane before the selection, as indicated by increased stabilizing error rates for higher selection times measured in the experiment. We observed during the experiment that - after such an incident - participants very carefully re-approached the target lane in order not to overshoot again, spending long periods of time on the adjacent lane. This behavior increased the chance of accidentally selecting a wrong target lane and, thereby, again reduced the accuracy.

Interestingly, we also found an influence of the *selection time* on the efficiency of participants, even though we explicitly subtracted the respective *selection time* from the task-completion time. We attribute these effects to the extended periods of time participants had to stay on a lane, increasing the chance of accidentally oscillating out of the lane and, thus, restarting the *selection time*. The restarted timer increased the TCT and, thereby, the necessary distance. The analysis of the data provided further support for the assumption that the increased TCT for higher numbers of lanes and higher selection times are related to oscillating out of the target lane: We found a strong correlation between stabilizing error rates, measured as the rate of trials in which the target lane was left, and the TCT.

While the analysis of the RTLX and the Likert questionnaires showed no differences between 2/3 s and 3/3 s conditions, both were rated significantly better than the 1/3 s conditions. The qualitative feedback of participants supported this result: While participants' opinions were mixed for the "best" condition between 2/3 s and 3/3 s, there was a clear agreement that 1/3 s was too short.

RQ3: Interaction Effects between Number of Lanes and Selection Time

The analysis of the experiment showed interaction effects between the *number of lanes* and *selection time* for both, the accuracy and the efficiency measurements. We attribute this effects to a mutual reinforcement of the influences of the individual factors described above: Lower numbers and, thus, wider lanes led to an increased width of the intermediate lanes between the participant and the target lane. With shorter selection times, this resulted in lower accuracy rates, because a larger lateral distance had to be crossed, resulting in more false selections in between. The reverse effect applies for higher numbers of and, thus, thinner lanes: Due to the thinner lanes, it generally became more difficult for the participants to select a lane by walking on it, resulting in lower efficiency and accuracy rates. This effect is further intensified by forcing the

user to walk longer on the lane through higher selection times, increasing the chance of accidentally walking out of the lane.

Taken together, this explains the interaction effects found in the experiment on accuracy and efficiency: Wider lanes require longer selection times, thinner lanes require shorter selection times to attain high accuracy and effectiveness.

IMPLEMENTATION AND EXAMPLE APPLICATIONS

Based on the results of the study, we implemented a walking-based input modality for the Microsoft HoloLens. The results of the experiment proved the accuracy of the inside-out tracking of the Microsoft HoloLens (average deviation of 1.25 cm [41]) to be sufficient for a real-world implementation of our concepts.

The software augments lanes to the ground in front of the user, parallel to their walking path. Using the internal inside-out tracking of the HoloLens, the system calculates the intersection between the orthogonal projection of the user's head position and the augmented lanes to identify the currently selected lane. The implementation works as a standalone application without modifications to the HoloLens or additional external tracking.

Example Applications

To show the practical applicability of our concept, we implemented three example applications: Assistant, Camera and Music Walker.

Assistant

Assistant is a personal assistance service, which - similar to commercial assistance solutions like Google Assistant, Alexa, or Cortana - can offer personalized recommendations. For this, an unobtrusively visualized assistant lane is displayed at the right edge of the user's field of view. If users want to access the service, they shift their walking path to the lane. This movement opens various options that allow the user to access personalized local services such as recommended restaurants or shops (see Figure 8a). By selecting an element through walking on it, the user can walk further down the options tree of a cascading menu.

Camera

By entering the photo lane, the user can activate the camera. Exiting this lane to the "take a picture" side starts a countdown to take a picture of the current view of the participant without the augmented content. The user can then apply various filters to the image, which are displayed as new lanes. The effect of each filter is previewed as soon as the user enters the corresponding lane (see Figure 8b). By walking on a lane for a longer time, the user can select one of the filters and, in the next step, share the edited photo to different social media platforms, again visualized as newly appearing lanes.

Music Walker

Music Walker is a music player application. The user can continuously change the volume by walking on the *volume up* or *volume down* lane. The longer the user stays on a lane, the further the volume is increased or decreased, respectively. Further, the *playlist* lane allows the user to walk up a list of the upcoming tracks. Leaving the lane allows the user to select a new song. Figure 8c depicts the interaction.

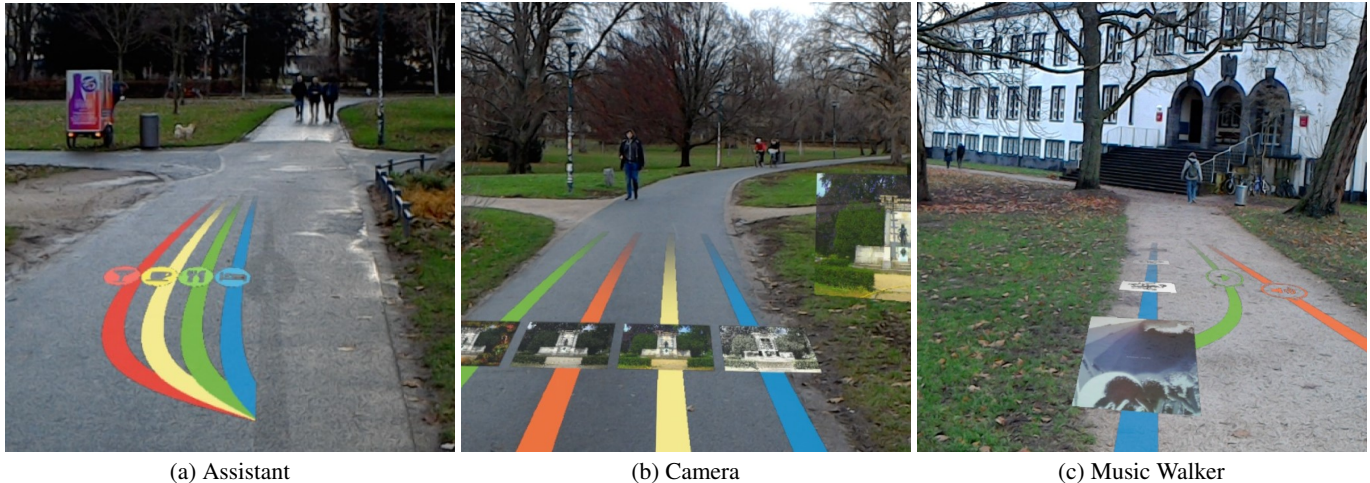


Figure 8. Screenshots of the example applications. *Assistant* (a) allows users to explore nearby services (e.g., coffee shops, hotels). *Camera* (b) allows users to take pictures, apply filters and share the results to social media platforms. *Music Walker* (c) allows users to walk through the playlist and select songs by leaving the lane. Further, users can continuously change the volume by walking on the respective lane.

LIMITATIONS AND FUTURE WORK

We are convinced that the presented results provide valuable insights to the applicability of our concept. However, the study design, as well as the results of the experiment, impose some limitations and directions for future work.

Real-World Applicability

In this paper, we presented an experiment that deliberately investigated thin lanes and short selection times to provide a baseline of the performance users can achieve for future developments. To be able to address the mere impact of these factors adequately, we excluded possible influencing factors such as technical limitations of current-generation HMDs (e.g., the small field of view) and external factors (e.g., oncoming pedestrians or blocking of the path) from the experiment.

While we are convinced that the technical limitations will be resolved in the coming years through further technical advances, questions remain on how to handle external factors. Such external factors could a) render intentional interactions with the system impossible, or could b) cause unintentional interactions with the system. As an exemplary solution, such obstacles could be detected by the cameras of the HMD or by sensors embedded in the smart city. This information could then be used for routing the lanes around obstacles or postpone any selection behind the obstacle. In addition, lane widths and selection times can be adapted to the current situation of the user to allow appropriate interaction at any time. Future work is necessary to conclude on these challenges.

Continuous Interaction

The experiment focused on discrete interaction steps, that is, the sequential calling of options. We chose this approach to define the basic requirements for the design of such interfaces in terms of minimum width and time needed to interact. However, we are confident that such walking-based interfaces can also be used for continuous interaction. For such interfaces, a) the deviation of the user from the direct path or b) the time

spent on a lane could be mapped directly to a cursor or other interface elements. Future work in this area is necessary to assess the accuracy and efficiency of such interfaces.

Shapes beyond Straight Lines

In this paper, we investigated the deviation from a straight line in front of the user as an input modality. In many real-world scenarios, however, a straight line may not be a suitable baseline for interaction (e.g., obstacles, directional changes of the user). Therefore, further work in this field is necessary to conclude on these challenges.

Other modes of Locomotion

In this work, we investigated how lateral shifts can be used as an input modality while walking. However, we are confident that this type of interaction can also be of great use for other modes of locomotion such as jogging, cycling, riding e-scooters, or when using wheelchairs. Future work is necessary to assess the influence of other modes of locomotion and, thus, also speeds on the feasibility, accuracy, efficiency, and safety of such interfaces.

CONCLUSION

In this paper, we explored how lateral shifts of the user's walking path can be leveraged as an input modality for HMDs. Therefore, our system augments lanes parallel to the user's walking path on the floor in front of the user, representing individual options. The user can select one of these options by shifting the walking route sideways. The results of the controlled experiment confirmed the viability of such interfaces for fast, accurate, and fun interactions. We are convinced that our concept represents a first step towards more comfortable and safe interaction with HMDs *on the go*.

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