2024 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW) | 979-8-3503-7449-0/24/$31.00 ©2024 IEEE | DOI: 10.1109/VRW62533.2024.00073

Exposing Movement Correlates of Presence Experience in Virtual Reality using Parametric Maps

Lukas Gehrke*
TU Berlin

Klaus Gramann
TU Berlin

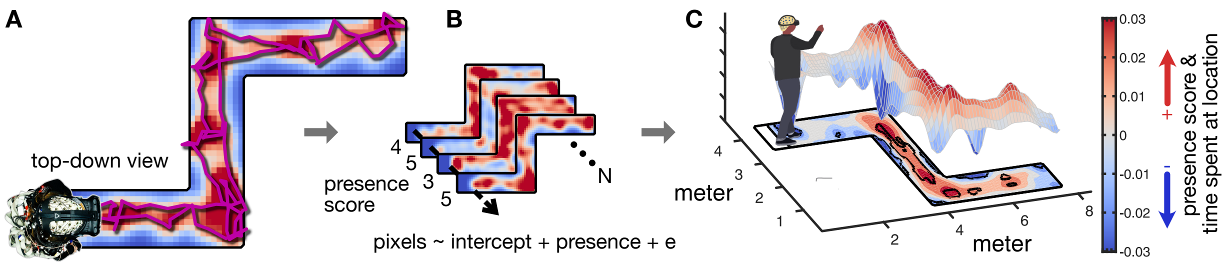

Figure 1: We propose parametric maps to study user behavior and experience and guide future design of room-scale VR applications. **A,** Top-down view on the participant equipped with a wireless VR headset and backpack PC at the start of a 'Z' maze. Motion capture of exploration paths (solid pink line) was spatially blurred using a Gaussian filter to obtain images/maps in B suited for across participants analyses of moderating variables. **B,** We constructed parametric maps of where participants spent time exploring the mazes as a function of their experienced presence. **C,** We found that with increasing presence, participants were more likely to stay in the center of the paths as well as in segments *presumably* critical for navigational success. Significant pixels at $p < 0.05$ are masked with a dotted line

Abstract

Genuine experiences where users feel a deep level of connection are the key quality of room-scale virtual reality (VR). The freedom to move promises natural sensory experiences stimulating a feeling of presence. However, users differ in their eagerness to move, some prefer movement by teleportation while others would keep walking forever. Such individual differences challenge the inclusive design necessary for bestseller applications. In this methodological research contribution, we propose to study user behavior and experience using parametric maps based on general linear models (GLM) to overcome limitations of traditional data aggregation techniques. In the investigated study, participants explored invisible mazes touching hidden walls for brief moments of visual guidance. We demonstrate that experienced presence correlated with where participants spent time exploring the VR. We found an increase in presence coinciding with participants being less likely to collide with invisible walls and spending more time in segments critical for navigational success.

Index Terms: Human-centered computing—Visualization—Visualization techniques—Treemaps; Human-centered computing—Visualization—Visualization design and evaluation methods

1 Introduction

Effective remote collaboration is facilitated by increasing the (psychological) depth of people's remote connections. One requirement for truly connected experiences is the strength of immersion into virtual environments. Room-scale VR significantly increases the users immersion by, first and foremost, allowing free movements, simulating *natural* real world sensory experiences due to locomotion. Further, synchronized motion capture allows avatar movements to be rendered to represent ones own body movements. In VR, several illusions, such as the place– and plausibility illusions, occur at the same time and are prerequisites for the user to feel present. Depending on the effectiveness of the employed illusions and whether multiple illusions work congruently, participants experience a feeling of presence in VR [21, 28]. Such illusions enrich and/or modify participants subjective experience in VR. Together, free movement, *realistic* avatar rendering, and contextual components of the VR experience coincide at the same time for the user to feel present. Therefore, designing immersive experiences for room-scale VR aims at facilitating the emergence of presence experience, ultimately providing the foundation for genuinely connected remote social experiences.

2 Parametric Maps to Investigate User Behavior and Experience

In order to scale immersive VR technology to a broader public with use cases ranging from remote office work to entertainment, inclusive design principles are of key importance to successfully design presence experience across a wide user base. Individual differences, for example the eagerness to physically move through virtual worlds, significantly challenge designing for presence experience, thereby challenging acceptance of VR technology in general [42]. Here, designers and developers would benefit from a better understanding of user behavior, being able to directly query the impact of certain characteristics of the user base. Specifically in room-scale VR applications, leveraging inherent motion capture provides the opportunity for a data-driven understanding of user behavior with a high spatial resolution. Spatial resolution here pertains to using motion capture data from room-scale VR to specify, for example, how much time the user spends at any given location in virtual space and how much of this behavior can, for example, be explained by the users' previous video game experience. However, many studies commonly consider aggregated data missing the opportunity to spatially resolve effects of interest.

In this methodological research contribution, we propose parametric maps as a way to study user behavior, and ultimately user experience, utilizing the inherent motion capture of current VR hardware that provides high resolution regarding the users' movement in virtual space. Specifically, we demonstrate using general linear model, *GLM*, in a mass-univariate application that allows linear decomposition of user behavior across all pixels of a given room-scale VR space. GLM encompasses familiar statistical models, like

*e-mail: lukas.gehrke@tu-berlin.de

979-8-3503-7449-0/24/$31.00 ©2024 IEEE
DOI 10.1109/VRW62533.2024.00073

linear regression and ANOVA as well as ANCOVA. It allows for t-tests and variance ratio tests, i.e. F-tests. Further, the approach is scalable to additional models in the broad *GLM family* therefore providing a framework with significant flexibility. The proposed analyses scheme is easily extendable to 3D space, i.e. voxels, for example to investigate individual differences in manual interaction scenarios.

Following below, we demonstrate the proposed analyses scheme showing how differences in subjectively reported experienced presence impacts participants movement profiles in a *beyond* room-scale VR spatial exploration task. However, we situate our approach specifically as a tool for statistical assessment of spatially resolved multimodal data streams in the related works section as we believe it best highlights the usefulness of the method. Then, we guide the reader in a step-by-step fashion through the pre-processing, model fitting, and inference steps in order to construct *parametric maps*. To highlight potential benefits when considering individual characteristics, we close with a linear regression scheme predicting presence via individual characteristics.

3 RELATED WORK

Recently, several visualization approaches have been developed to facilitate understanding of user behavior and experience through the use of multimodal data. To visualize user states as a function of spatial location, these approaches use different forms of motion capture like eye-tracking and rigid body capture. In a recent work, Kepplinger et al. demonstrated a joint visualization of gaze and affective state sampled during exploration of a VR game scenario [27]. Here, several professional game developers argued in favor of the utility expressing gaze and affective state as a function of space. In a similar approach, albeit on a different spatial scale, arousal was reported during exploration of an amusement park to localize areas of high arousal states [20]. Here, the authors present a device to simultaneously record physiological measures like electrodermal response (EDA) and electrocardiography (ECG) alongside GPS to express arousal as a function of space, see [8] for an extended description of their approach. These and similar visualizations are overcoming traditional approaches making use of aggregate data only. In order to address a given VR research challenge, specific aspects of the users behavior are discretized from the continuous motion capture stream. Aggregate data, such as averaged time spent in a specific area of interest (AOI) or average and maximum speed while moving along a specific trajectory are the simplest way to meet the researchers data processing requirements. Such a straight forward feature extraction scheme is widely established throughout diverse research communities as a top-down approach, driven by personal experience, expertise and interest. For example, average time spent in a specific location as well as velocity aggregates have proven to be informative about crowd interaction [34] and collaboration [41]. Increasing the level of abstraction, feature extraction and classification guided by expert knowledge is useful in several research domains, including rehabilitation sciences with a motivation to derive informative features about rehabilitation progress, for example in reaching [9] and gait applications [50]. Extracting features of interest can be guided by expert knowledge, implemented as a tedious manual process, or in an automated fashion using machine-learning [5].

We argue that a data-driven, continuous, assessment of movement behavior may provide both researchers and developers with a better understanding of *contextual* influences of interest. The current work significantly extends previous visualization approaches by adding a layer for statistical analyses. As referenced above, we chose to demonstrate our approach using presence experience as a psychological phenomenon of interest.

3.1 Natural behavior as a precursor of presence experience

To this day, human development can be explained by the need to interact with a physical reality. Growing up, the human brain *presumably* develops as a model of the latent hidden variables, for example gravity, governing the observable behavior of cause and effect in the environment, like an apple falling from a tree [13]. Understanding cognition as a predictive process holds that brains constantly compare what is effectively happening in the world with what was predicted to happen [6], for example inferring the trajectory of a thrown ball and successfully catching it.

Successful immersion into virtual worlds relies on matching expectations that were substantiated in the non-virtual physical reality. Assuming that to experience presence in virtual environments equals treating what you perceive as a part of the reality you are currently in, many researchers have argued for an increase in ecological validity through VR experimentation. The assumption is that participants under the influence of successful VR illusions experience presence and therefore behave *realistically* or with higher ecological validity [3, 36, 37, 52]. This work exhibits an approach to quantify such claims using spatial behavior of users sampled with high precision in order to guide future design decisions in research and application. We point out, that this approach is scalable to investigations of spatially resolved behavioral, psychometric and bio-physiological parameters such as controller jerk, hit accuracy in video games or electroencephalographic (EEG) parameters.

3.2 Presence experience impacts behavior

Many studies have investigated participants under VR illusions employing (A) emotionally charged stimulus material or (B) embodiment illusions. Considering (A), Diemer et al. provide a thorough overview of the intricate interplay between presence and reactions to emotionally charged stimulation in VR [11]. The authors observed a consistent link between presence and the emotional experience in VR. They argue, that by varying degrees of arousal, presence impacts psychological as well as physiological responses. Considering (B), Maister et al. highlight one relevant aspect from the rich literature on the effects of full-body embodiment into avatars [30]. The proteus effect characterizes behavioral perturbations depending on avatar body attributes. Yee et al. showed that participants being immersed into an 'attractive' avatar moved closer into the interpersonal space of another person [55]. Further, Banakou et al. demonstrated that for participants that were embodied into an avatar with a children's body, the size of objects was overestimated as compared to a non-embodied baseline [2].

One of the key VR illusions contributing to the subjective construct of presence is the place illusion which can be defined as the perception of oneself being present in a virtual place where one can act, react, and impact the surroundings [47]. Therefore, self-location, sense of agency, and spatial awareness of the surroundings are strongly impacted by the place illusion and modify behavior [28]. When one perceives oneself in control of ones own actions and observed action consequences in the virtual surroundings, spatial exploration behavior becomes a part of a learning process to adapt motor behavior to the surroundings as opposed to a random chain of actions executed by the user to explore, for instance, only the VR technology itself [51]. Together, these examples illustrate that presence experience directly impacts cognition, the predictive action-perception cycle.

4 USER STUDY

To demonstrate our proposed method, we investigated whether the level of experienced presence impacts the spatial exploration behavior of participants in a beyond room-scale VR. Here, we used data from a study by Gehrke et al. that uses the *invisible maze task* mimicking a real-world exploration situation such as finding your

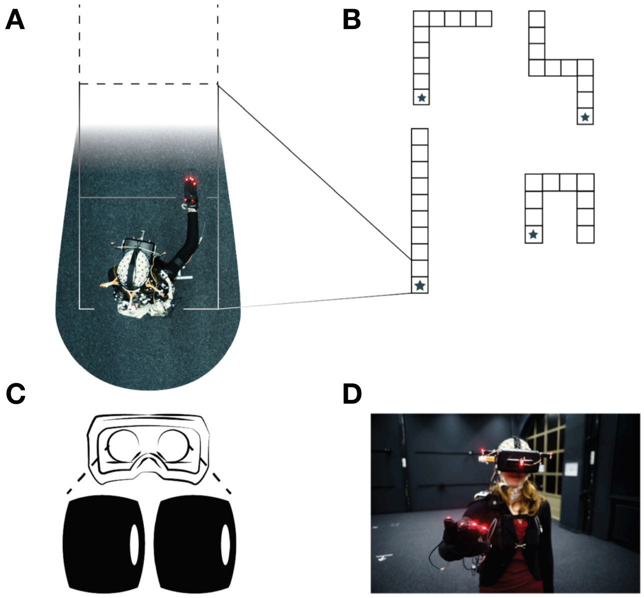

Figure 2: Invisible Maze Task, **A,** Participant from a bird's eye view. **B,** Participants were instructed to explore four different mazes and return to the start. [18]**C,** First-person view in binocular 'VR optics' of a wall touch. **D,** Participants were equipped with 160 channels wireless EEG, head-mounted virtual reality goggles and LEDs for motion capture.

way in complete darkness [17, 18, 32]. We conducted the following two-step analysis. First, we constructed parametric maps to assess where participants exploration behavior was impacted as a function of experienced presence. To this end, we investigated fine-grained behavior at each single point in space by conducting mass-univariate pixel-by-pixel modeling of experienced presence on time spent at each location, i.e. pixel. To situate our findings on an individual differences level we followed up with a linear regression scheme, now using aggregated data. We predicted experienced presence using participants characteristics such as video game experience and perspective taking ability (see further details below).

4.1 Participants, Procedure, Task and Setup

Thirty-two healthy participants (aged 21–45 years, 14 men) participated in the experiment [17, 18]. All participants gave written informed consent to participation and their experimental protocol was approved by the local ethics committee (protocol: GR_08_20170428). Three participants were excluded from data analysis due to incomplete data or difficulties in complying with task requirements.

4.1.1 The Invisible Maze Task

In the experiment participants freely explore a sparse invisible maze environment by walking through virtual mazes and probing for visual feedback when touching the virtual wall of a 1m wide path with their *right* hand. The stimuli were presented using an Oculus Rift DK2 VR headset in combination with a dedicated optical tracking system. Upon collision of the *right* hand with an invisible wall, a white disc appears 30 cm behind the collision point parallel to the invisible wall much like the beam from a torch in a cave, see figure 2 C (consult [18] for extensive details on the task, instrumentation, and data collection). The left hand was not tracked and participants were instructed to keep the left arm close to their body. Performing the task, participants explored four different mazes in the order, 'I', 'L', 'Z' and 'U', see figure 2 B. The task was designed to emphasize participants internal build-up of a spatial representation of the maze layout. Doing the task, participants displayed a behavior that is reported to be comparable to explorative wall touches in the dark to find the way.

For each maze the procedure was as follows: participants were briefly disoriented and then positioned facing the open side of the path. Then, participants were directed to explore the invisible path until they reached a dead end, and subsequently to find their way back to the starting position. At the end of each maze trial, participants received a gamified feedback and were then asked to draw a sketch map of the maze from a bird's eye view as an index of spatial learning. The procedure was repeated three times in a row for each maze to foster spatial learning.

The complete experiment, including preparation of physiological measures (Electroencephalogram, EEG) took approximately 4 hours. Preceding and following the task, participants completed a set of questionnaires to assess demographics, spatial abilities, and presence. Synchronized motion capture was collected with behavioral events alongside high-density EEG. For the inquiry in this paper, data of the three exploration phases were aggregated.

4.1.2 Assessing presence

To assess experienced presence, the igroup presence questionnaire [43] was administered following each individual maze exploration. For our analyses only the first item of the questionnaire was considered, the general subjective presence measure (G1), which represents the sense of being in a place, i.e. 'In the computer generated world I had a sense of "being there"' rated from 'not at all' to 'very much' on a 7-point Likert scale [43, 49].

4.2 Statistical Analyses

Enabling our proposed analyses framework, two key challenges must be addressed. First, capturing (rigid body) motion in 3D. With state-of-the art VR hardware sampling motion data at around 90Hz accessing and recording pose data, position and orientation, is possible[1]. Further libraries to synchronize data streams across the network exist[2] providing affordable alternatives to dedicated systems. Second, in order to compare pixel-wise motion data across participants, each participant should exhibit data points at each pixel. Therefore, decreasing spatial resolution by sub-sampling and/or smoothing can be employed to address the second challenge.

The proposed analyses approach can be summarized into three separate steps:

- **Single-subject summary (or first-level).** With this analyses, we were interested in expressing where participants spent most of the time exploring the mazes as a function of experienced presence. Hence, we investigated the location in 2D (X,Y) of the VR headset rigid body, see 2. To speed up subsequent analyses, we first sub-sampled the motion capture to 1Hz. Then we computed individual averages of these motion capture data (position over time) for each maze. We averaged across the three repeated explorations per maze, as we were not interested in changes over repeated trials but in expressing exploration behavior as a function of experienced presence more generally. With an average exploration duration of 3 minutes, for each maze and participant 180 samples were kept in x and y, discarding the third dimension (up-down) in this analyses, 1 (left) shows one exploration phase of one subject with lines plotted to connect each sample.

[1]https://brekel.com/openvr-recorder/

[2]See for example https://github.com/sccn/labstreaminglayer and http://openvibe.inria.fr/, with predominant application across the neurosciences.

- **Enabling group-level inference.** Next, a 2D histogram with fixed edges to maintain equal resolution across participants was computed. In order to increase overlap across participants (second challenge, see above) a 2D (square sized) Gaussian blur was applied to the histogram image. A sigma of 1.5 was chosen for the 2D filter kernel as it resulted in a good overlap across participants while maintaining spatial specificity.

- **Group-level inference (or second-level).** To investigate the impact of experienced presence on each parameter, we calculated a linear regression at each pixel of the map. We specified the model as $pixels \sim intercept + presence + error$, hence at each pixel we fit a linear regression across participants with presence scores as the predictor variable. Pixels with data of fewer than 12 participants (critically low N) were kept as 'NaN' and not subjected to linear regression analyses. Plotting resulting regression estimates yields a 2D parametric map. Uncorrected p-values were used to plot a contour at significant effects with $p < .05$. The Matlab code used to construct the parametric maps is available online[3]. In order to keep the focus of this report on the potential opportunities and due to the exploratory nature of our investigation, we chose not to implement robust statistics and correction for multiple comparisons and direct interested readers elsewhere [38, 54]. Furthermore, accurate correction for multiple comparison correction must consider the shape of the p-values map. In other words, some form of cluster-based statistic taking into account values of neighboring pixels is preferable. Such cluster-based statistics exist, for example cluster-mass and threshold-free cluster enhancement, but are not trivial to report [39].

4.2.1 Predicting Presence using Participant Descriptives

To follow up our spatially-resolved analyses and situate our findings more generally, we zoomed out and set out to predict presence scores using aggregate data and participant descriptors. We computed a least squares regression entering the IPQ presence (G1) scores as the dependent variable using R [40]. To accentuate the effect of aggregating motion capture data, we included aggregates of the exploration duration in the model. We aggregated over mazes and runs. Further we added participants video game experience, biological sex and perspective taking and orientation ability into the regression model. For a detailed explanation of each predictor consult the data source [18].

Predictors that did not significantly add to the explanatory power of the regression model were localized using a step-wise model selection procedure based on Akaike's information criterion (AIC). The procedure was computed using 'stepAIC' of package 'MASS' [1,53]. This data-driven procedure was selected to exclude the likely problem of over-fitting for the final reported model and to increase the usability of the approach by minimizing the number of included predictors. To assess the predictive accuracy of the reduced model, a 5 fold cross-validation was computed to obtain a robust mean absolute error [15, 33]. With 29 participants, each training fold consisted of either 23 or 24 participants with either 5 or 6 participants in the evaluated test fold. The R code is available online online[4] and the data can be made available upon request.

5 Results

We confirmed that the level of experienced presence impacted spatial exploration behavior in VR. Interestingly the effect was similar across different mazes with a pattern of increasing presence associated with staying longer in the center of the maze and spending more time in segments *presumably* critical for navigational success, i.e. corners. To emphasize the importance of considering individual differences when designing room-scale VR for a broad public, we carved out significant individual characteristics predicting the level of experienced presence, potentially of use for directing future design decisions.

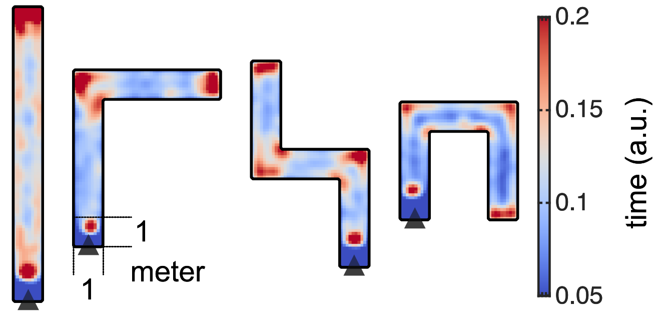

Figure 3: Time spent at each location (grand-average) in each of the four mazes: 'I', 'L', 'Z' and 'U'. The whole lab space covered roughly 12 by 8 meters in size. Mazes are constructed of ten 1x1 meter squares. Warmer colors, i.e. red, indicate a longer time spent at that location. Green triangles indicate participants starting position.

5.1 Exploration behavior expressed as a function of presence

First, averaging spatially-resolved exploration time across participants revealed that participants spent more time in dead-ends as well as in areas including corners. The effect was observed across all mazes (see red colors in figure 3). Conversely, less time spent and faster movement was observed for pixels of straight segments of the mazes. As expected, participants also spent more time at the beginning of the trial, taking a moment before starting to move. Together, these findings confirmed our intuitive expectations of spatial exploration behavior.

Second, we investigated the effect of presence on time spent exploring mass-univariately for all locations in all mazes. With increasing presence scores, time spent at the center of the straight paths increased, for example in maze 'I' at [3.5, 1.5] $beta = .027, t_{(28)} = 2.76, p = .01, R^2 = .23$ and 'Z' at [1.8, 10] $beta = .039, t_{(28)} = 3.34, p < .01, R^2 = .34$, see figure 4 A. Further, increasing presence scores correlated with more time spent at the center of the paths in corners, for example in maze 'L' at [-1, 3.5] $beta = .037, t_{(28)} = 2.33, p = .03, R^2 = .19$ and 'U' at [0.5, 17.5] $beta = .034, t_{(28)} = 2.44, p = .02, R^2 = .19$. Conversely, closer to the maze boundaries, we observed a negative effect with increasing presence scores correlating with less time spent in these areas, specifically in the most challenging mazes 'Z' at [2, 11.5] $beta = -.073, t_{(28)} = -4.16, p < .01, R^2 = .40$ and 'U' at [0.5, 17] $beta = -.143, t_{(28)} = -4.05 p < .01, R^2 = .40$. Taken together, with an increase in experienced presence, participants spent more time firmly located at the center of the path, specifically along the straight segments in the 'I' and 'Z' maze as well in navigationally relevant corners of mazes 'L', 'Z' and 'U'. Further underlining this observation, higher reported presence scores negatively correlated with the time spent close or even colliding with the maze walls.

5.2 Video game experience, biological sex and perspective taking predict presence experience

After a step-wise model selection, three predictors remained in the model predicting presence. Including exploration duration (aggregate) did improve the models explanatory power and was excluded. Hence, three predictors remained after a step-wise model selection, explaining 53,4% of the variation in experienced presence ($F_{(3,25)} =$

[3]https://github.com/lukasgehrke/mobi-3D-tools
[4]https://github.com/lukasgehrke/IEEE-VR-Spatial-exploration

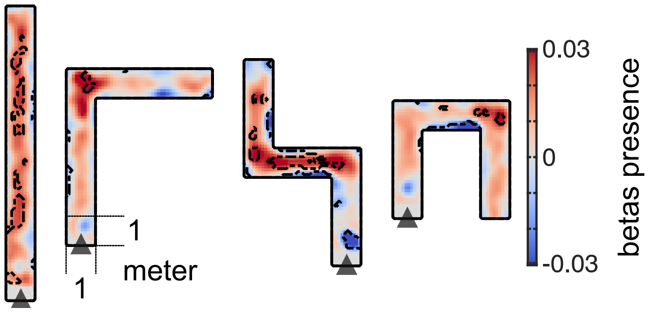

Figure 4: Map of the impact of presence on the time spent at every location (betas) in each of the four mazes: 'I', 'L', 'Z', 'U'. Green triangles indicate participants starting position. Warmer colors refer to a positive regression estimate. The values can be understood in the sense that for each 1 point increase in reported presence, participants stayed 'z' seconds longer at location 'xy'. Significant pixels at $p < 0.05$ are masked with a dotted line

$11.69, p < .001$, adjusted $R^2 = .534$). Participants' predicted presence score was equal to $8.15 - 1.2(VideoGameExperience) + 2.61(BiologicalSex) - 0.02(PTSOT)$ where biological sex was dummy-coded as 0 = Male, 1 = Female, increasing video game experience was coded with higher scores and decreasing perspective taking ability with higher scores. Video game experience ($t_{(25)} = -4.7, p < .001$), biological sex ($t_{(25)} = 5.6, p < .001$) as well as perspective taking ability ($t_{(25)} = -2.52, p = .02$) were significant predictors of presence. Cross-validation of the three predictor model above yielded a combined average 0.76 mean absolute error. Hence, using video game experience, biological sex as well as perspective taking ability we were able to predict experienced presence with a deviation of ± 0.75 points from the true value on the 'IPQ Likert scale'.

6 Contribution, Benefits & Limitations

With the presented approach we aim to promote benefits of greater spatial resolution of movement behavior to assess a variety of phenomena moderating, for example, the presence experience in VR. Here, a grand average of, e.g. time spent exploring mazes, provides only limited insights due to its spatial dependence. Some participants may spent more time in the corners but walk faster along straights segments while other participants might wander through the mazes with a constant walking speed, not adapting to the features of the environment. Without a two-dimensional resolution, the two different behaviors would average out to the same amount of time spent in a maze. Therefore, we constructed spatial parametric maps mimicking established data analyses procedures in cognitive neuroscience. For the ground work motivating our proposal, as well as a discussion of the state-of-the-art methods linking behavior to brain activity across the cognitive neurosciences consult [4, 14]. With this paper, we hope to motivate developers and researchers to use parametric mapping using the inherent motion capture capabilities of VR technology for a data-driven understanding of user behavior and, ultimately, user experience. We introduced parametric maps, expressing VR exploration behavior as a function of experienced presence as an exemplary predictor variable related to the subjective user experience.

In the user study we showed that increasing subjective presence scores coincided with an increased time spent at the center of the paths' through our simple *invisible* mazes. In turn, this effect translated to participants with high presence scores spending less time closer to the walls, or crashing into them, presumably relating to high spatial awareness. The spatial specificity of our reported effect accentuates that aggregate behavioral metrics, such as average speed or time spent across one maze exploration, may miss critical information. Here a finer resolution has proven to be beneficial.

Regardless, our analyses exposed that high presence scores coincided with more time spent in the corners, further underlining the hypotheses of increasing spatial awareness with increasing presence. Sense of embodiment has frequently been included as a key component in psychological models of presence experience with a sense of self-location as one emergence of embodiment [28]. This sense of a virtual self is a logical prerequisite for spatial anchoring and reduced cognitive effort when imagining a third-person allocentric perspective of space. Here additional mental transformations potentially disrupt the presence experience by violating the *natural* experience of the predictive brain [21]. In consequence, solving spatial task, for example requiring perspective taking, depend on individual abilities and preferences for specific spatial strategies but appear to be 'easier' with a congruent sense of embodiment [10, 22–26, 35].

Using participants individual characteristics, we were able to predict presence scores with an average deviation of ± 0.75 from the true reported score. Employing a data-driven model selection procedure determined that apart from video game experience, biological sex as well as perspective taking ability, no other predictor significantly contributed to the linear regression scheme. Interestingly, increasing video game experience negatively impacted presence scores, conflicting with previous findings [29]. We hypothesize that this could be explained by the overly sparse visuals of the virtual environment in the *invisible maze task*. Participants with significant video gaming experience might perceive the world as too reduced and artificial compared to usually rich rendering of video games. With regards to the impact of biological sex, we contribute one more example of contradictory results in the literature [7]. Based on our outcome, however, we cannot argue that the underlying differences in the task were due to a spatial component or rather the interaction with an unknown sparse virtual environment and refer to a detailed discussion on the topic [12]. Ultimately, perspective taking ability had a limited influence on predicting subjective presence. Increasing perspective taking scores, referring to an angular error in a mental triangulation task, negatively impacted the subjective feeling of presence. We hypothesize that the experience of presence may arise earlier in individuals that feel oriented and that are aware of their spatial surroundings. As such, spatial awareness is useful when solving tasks in unfamiliar environments [48].

7 Conclusion

With this work we motivate continuous, spatially resolved, analyses to understand individual characteristics explaining exploration behavior in VR, ultimately explaining user experience. However, user experience is subjective and traditionally assessed via questionnaires following the experience to be evaluated. The here presented approach exhibits several advantages. First, a continuous assessment is desirable over a discrete sampling after the VR experience and second, using active and continuous behavioral parameters without interrupting the ongoing experience to administer the questionnaire allows for a non-distorted assessment of presence.

7.1 Towards an unobtrusive, spatially resolved understanding of user experience

With this work we showed that observing finely resolved overt behavior may provide insights into the subjective user experience, such as presence experience. However, using post-experience questionnaires to 'measure' presence experience is problematic [46]. Recently, increasing efforts have been made to investigate the physiological basis of presence experience in real-time. Using physiological methods holds the potential to overcome indirect, post-experience, measurements, allowing to directly assess the physiological source that realizes the subjective experience, i.e. the brain [16,19,44,45]. Gehrke et al. (2019, 2022) demonstrated that neural responses associated with mental error-processing following visuo-haptic mismatches in VR can be detected using EEG [16, 19]. Si-Mohammed and colleagues (2020) were able to use this EEG signature in a brain-computer interface classification scheme exhibiting high classification accuracy in a similar paradigm exhibiting graphical glitches in VR. These promising findings, hint at future applications in room-scale scenarios, picking up scenarios where a loss of immersion occurs in near real-time. Here, additional wearable sensors can supplement brain recordings to, for example, measure affective responses [31].

To sum up, we propose a method to investigate user experience in VR by using a spatially resolved analyses approach of ongoing behavior, providing designers and researchers a tool to guide future design decisions. Investigating how individual characteristics and the current spatial context influences user experience provides the opportunity for inclusive design decisions driving VR technology acceptance across the broad public. Ultimately, we believe our approach can further be nurtured by unobtrusive, continuous (neuro-)physiological measurements for a multi-dimensional assessment of user experience.

References

[1] H. Akaike. Information Theory and an Extension of the Maximum Likelihood Principle. 1998. doi: 10.1007/978-1-4612-1694-0_15

[2] D. Banakou, R. Groten, and M. Slater. Illusory ownership of a virtual child body causes overestimation of object sizes and implicit attitude changes. *Proceedings of the National Academy of Sciences of the United States of America*, 2013. doi: 10.1073/pnas.1306779110

[3] C. J. Bohil, B. Alicea, and F. A. Biocca. Virtual reality in neuroscience research and therapy, 2011. doi: 10.1038/nrn3122

[4] D. A. Bridwell, J. F. Cavanagh, A. G. Collins, M. D. Nunez, R. Srinivasan, S. Stober, and V. D. Calhoun. Moving beyond ERP components: A selective review of approaches to integrate EEG and behavior, 2018. doi: 10.3389/fnhum.2018.00106

[5] J. Bütepage, M. J. Black, D. Kragic, and H. Kjellström. Deep representation learning for human motion prediction and classification. In *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*, vol. 2017-Janua, pp. 1591–1599, 2017. doi: 10.1109/CVPR.2017.173

[6] A. Clark. Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, 36(3):181–204, 2013. doi: 10.1017/S0140525X12000477

[7] E. Coluccia and G. Louse. Gender differences in spatial orientation: A review. *Journal of Environmental Psychology*, 2004. doi: 10.1016/j.jenvp.2004.08.006

[8] F. Courtemanche, P. M. Léger, A. Dufresne, M. Fredette, É. Labonté-Lemoyne, and S. Sénécal. Physiological heatmaps: A tool for visualizing users' emotional reactions. *Multimedia Tools and Applications*, 77(9):11547–11574, 2018. doi: 10.1007/s11042-017-5091-1

[9] A. De Los Reyes-Guzmán, I. Dimbwadyo-Terrer, F. Trincado-Alonso, F. Monasterio-Huelin, D. Torricelli, and A. Gil-Agudo. Quantitative assessment based on kinematic measures of functional impairments during upper extremity movements: A review. *Clinical Biomechanics*, 29(7):719–727, 2014. doi: 10.1016/j.clinbiomech.2014.06.013

[10] A. Delaux, J.-B. de Saint Aubert, S. Ramanoël, M. Bécu, L. Gehrke, M. Klug, R. Chavarriaga, J.-A. Sahel, K. Gramann, and A. Arleo. Mobile brain/body imaging of landmark-based navigation with high-density EEG. *Eur. J. Neurosci.*, (May 2020):1–27, Mar. 2021.

[11] J. Diemer, G. W. Alpers, H. M. Peperkorn, Y. Shiban, A. Mühlberger, and D. J. Oathes. The impact of perception and presence on emotional reactions : a review of research in virtual reality. 6(January):1–9, 2015. doi: 10.3389/fpsyg.2015.00026

[12] A. Felnhofer, O. D. Kothgassner, L. Beutl, H. Hlavacs, and I. Kryspin-Exner. Is Virtual Reality made for men only? Exploring gender differences in the sense of presence. *Annual Conference of the International Society on Presence Research*, 2012.

[13] K. Friston. The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, 11(2):127–138, 2010. doi: 10.1038/nrn2787

[14] K. J. Friston, A. P. Holmes, K. J. Worsley, J. oline, C. D. Frith, and R. S. Frackowiak. Statistical parametric maps in functional imaging: A general linear approach. *Human Brain Mapping*, 1994. doi: 10.1002/hbm.460020402

[15] J. Fürnkranz, P. K. Chan, S. Craw, C. Sammut, W. Uther, A. Ratnaparkhi, X. Jin, J. Han, Y. Yang, K. Morik, M. Dorigo, M. Birattari, T. Stützle, P. Brazdil, R. Vilalta, C. Giraud-Carrier, C. Soares, J. Rissanen, R. A. Baxter, I. Bruha, R. A. Baxter, G. I. Webb, L. Torgo, A. Banerjee, H. Shan, S. Ray, P. Tadepalli, Y. Shoham, R. Powers, Y. Shoham, R. Powers, G. I. Webb, S. Ray, S. Scott, H. Blockeel, and L. De Raedt. Mean Absolute Error. In *Encyclopedia of Machine Learning*. 2011. doi: 10.1007/978-0-387-30164-8_525

[16] L. Gehrke, S. Akman, P. Lopes, A. Chen, A. K. Singh, H.-T. Chen, C.-T. Lin, and K. Gramann. Detecting Visuo-Haptic Mismatches in Virtual Reality Using the Prediction Error Negativity of Event-Related Brain Potentials. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI '19, pp. 427:1—-427:11. ACM, New York, NY, USA, 2019. doi: 10.1145/3290605.3300657

[17] L. Gehrke and K. Gramann. Single-trial regression of spatial exploration behavior indicates posterior EEG alpha modulation to reflect egocentric coding. *Eur. J. Neurosci.*, (December 2020):1–18, Feb. 2021.

[18] L. Gehrke, J. R. Iversen, S. Makeig, and K. Gramann. The invisible maze task (IMT): Interactive exploration of sparse virtual environments to investigate action-driven formation of spatial representations. In S. Creem-Regehr, J. Schöning, and A. Klippel, eds., *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11034 LNAI, pp. 293–310. Springer International Publishing, Cham, 2018. doi: 10.1007/978-3-319-96385-3_20

[19] L. Gehrke, P. Lopes, M. Klug, S. Akman, and K. Gramann. Neural sources of prediction errors detect unrealistic VR interactions. *J. Neural Eng.*, 19(3), May 2022.

[20] V. Georges, F. Courtemanche, M. Fredette, and P. Doyon-Poulin. Emotional Maps for User Experience Research in the Wild. pp. 1–8, 2020. doi: 10.1145/3334480.3383042

[21] M. Gonzalez-Franco and J. Lanier. Model of illusions and virtual reality. *Frontiers in Psychology*, 2017. doi: 10.3389/fpsyg.2017.01125

[22] K. Gramann. Embodiment of Spatial Reference Frames and Individual Differences in Reference Frame Proclivity. *Spatial Cognition and Computation*, 13(1):1–25, 2013. doi: 10.1080/13875868.2011.589038

[23] K. Gramann. Embodiment of Spatial Reference Frames and Individual Differences in Reference Frame Proclivity Spatial Cognition & Computation : An. (August):37–41, 2013. doi: 10.1080/13875868.2011.589038

[24] K. Gramann, F. U. Hohlefeld, L. Gehrke, and M. Klug. Human cortical dynamics during full-body heading changes. *Sci. Rep.*, 11(1):18186, Sept. 2021.

[25] K. Gramann, H. J. Müller, E.-M. Eick, and B. Schönebeck. Evidence of separable spatial representations in a virtual navigation task. *Journal of experimental psychology. Human perception and performance*, 31(6):1199–1223, 2005. doi: 10.1037/0096-1523.31.6.1199

[26] S. Jeung, C. Hilton, T. Berg, L. Gehrke, and K. Gramann. Virtual reality for spatial navigation. *Curr. Top. Behav. Neurosci.*, Dec. 2022.

[27] D. Kepplinger, S. Kriglstein, and M. Lankes. See , Feel , Move – Player Behaviour Analysis through Combined Visualization of Gaze , Emotions , and Movement. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 1–14, 2020.

[28] K. Kilteni, R. Groten, and M. Slater. The Sense of Embodiment in virtual reality, 2012. doi: 10.1162/PRES_a_00124

[29] K. Lachlan and M. Krcmar. Experiencing presence in video games: The role of presence tendencies, game experience, gender, and time spent in play. *Communication Research Reports*, 28(1):27–31, 2011. doi: 10.1080/08824096.2010.518924

[30] L. Maister, M. Slater, M. V. Sanchez-Vives, and M. Tsakiris. Changing bodies changes minds: Owning another body affects social cognition, 2015. doi: 10.1016/j.tics.2014.11.001

[31] J. Marín-Morales, J. L. Higuera-Trujillo, A. Greco, J. Guixeres, C. Llinares, E. P. Scilingo, M. Alcañiz, and G. Valenza. Affective computing in virtual reality: emotion recognition from brain and heartbeat dynamics using wearable sensors. *Scientific Reports*, 8(1):1–15, 2018. doi: 10.1038/s41598-018-32063-4

[32] M. Miyakoshi, L. Gehrke, K. Gramann, S. Makeig, and J. Iversen. The AudioMaze: An EEG and motion capture study of human spatial navigation in sparse augmented reality. *Eur. J. Neurosci.*, 54(12):8283–8307, Dec. 2021.

[33] F. Mosteller and J. W. Tukey. Data Analysis, Including Statistics. In *The handbook of social psychology: Vol. 2. Research methods*. 1968.

[34] M. G. Nelson, A. Koilias, S. Gubbi, and C. Mousas. Within a virtual crowd: Exploring human movement behavior during immersive virtual crowd interaction. In *Proceedings - VRCAI 2019: 17th ACM SIGGRAPH International Conference on Virtual-Reality Continuum and its Applications in Industry*, 2019. doi: 10.1145/3359997.3365709

[35] X. Pan and A. F. C. Hamilton. Why and how to use virtual reality to study human social interaction: The challenges of exploring a new research landscape. *British Journal of Psychology*, 109(3):395–417, 2018. doi: 10.1111/bjop.12290

[36] T. D. Parsons. Virtual reality for enhanced ecological validity and experimental control in the clinical, affective and social neurosciences. *Frontiers in Human Neuroscience*, 2015. doi: 10.3389/fnhum.2015.00660

[37] T. D. Parsons, A. Gaggioli, and G. Riva. Virtual reality for research in social neuroscience. *Brain Sciences*, 7(4):1–21, 2017. doi: 10.3390/brainsci7040042

[38] C. R. Pernet, N. Chauveau, C. Gaspar, and G. A. Rousselet. LIMO EEG: A toolbox for hierarchical linear modeling of electroencephalographic data. *Computational Intelligence and Neuroscience*, 2011(February), 2011. doi: 10.1155/2011/831409

[39] C. R. Pernet, M. Latinus, T. E. Nichols, and G. A. Rousselet. Cluster-based computational methods for mass univariate analyses of event-related brain potentials/fields: A simulation study. *Journal of Neuroscience Methods*, 250:85–93, 2015. doi: 10.1016/j.jneumeth.2014.08.003

[40] R Foundation for Statistical Computing. *R: a Language and Environment for Statistical Computing.* 2018.

[41] A. Ríos, M. Palomar, and N. Pelechano. Users' locomotor behavior in collaborative virtual reality. In *Proceedings - MIG 2018: ACM SIGGRAPH Conference on Motion, Interaction, and Games*, 2018. doi: 10.1145/3274247.3274513

[42] C. Sagnier, E. Loup-Escande, D. Lourdeaux, I. Thouvenin, and G. Valléry. User Acceptance of Virtual Reality: An Extended Technology Acceptance Model. *International Journal of Human-Computer Interaction*, 00(00):1–15, 2020. doi: 10.1080/10447318.2019.1708612

[43] T. W. Schubert. The sense of presence in virtual environments:. *Zeitschrift für Medienpsychologie*, 2003. doi: 10.1026//1617-6383.15.2.69

[44] H. Si-mohammed, C. Lopes-dias, M. Duarte, C. Jeunet, and R. Scherer. Detecting System Errors in Virtual Reality Using EEG Through Error-Related Potentials. (1):653–661, 2020. doi: 10.1109/VR46266.2020.00-16

[45] A. K. Singh, H. T. Chen, Y. F. Cheng, J. T. King, L. W. Ko, K. Gramann, and C. T. Lin. Visual Appearance Modulates Prediction Error in Virtual Reality. *IEEE Access*, 6:24617–24624, 2018. doi: 10.1109/ACCESS.2018.2832089

[46] M. Slater. How colorful was your day? why questionnaires cannot assess presence in virtual environments. *Presence*, 13(4):484–493, Aug. 2004.

[47] M. Slater. Place illusion and plausibility can lead to realistic behaviour in immersive virtual environments. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1535):3549–3557, 2009. doi: 10.1098/rstb.2009.0138

[48] M. Slater. Immersion and the illusion of presence in virtual reality. *British Journal of Psychology*, 109(3):431–433, 2018. doi: 10.1111/bjop.12305

[49] M. Slater and M. Usoh. Representations Systems, Perceptual Position, and Presence in Immersive Virtual Environments. *Presence: Teleoperators and Virtual Environments*, 1993. doi: 10.1162/pres.1993.2.3.221

[50] J. Taborri, E. Palermo, S. Rossi, and P. Cappa. Gait partitioning methods: A systematic review, 2016. doi: 10.3390/s16010066

[51] N. Tan, G. Pruvost, M. Courgeon, C. Clavel, Y. Bellik, and J. C. Martin. A location-aware virtual character in a smart room: Effects on performance, presence and adaptivity. In *International Conference on Intelligent User Interfaces, Proceedings IUI*, 2011. doi: 10.1145/1943403.1943475

[52] M. J. Tarr and W. H. Warren. Virtual reality in behavioral neuroscience and beyond. *Nat Neurosci*, 5 Suppl:1089–92., 2002. doi: 10.1038/nn948

[53] W. N. Venables and B. D. Ripley. *Modern Applied Statistics with S Fourth edition by*. 2002. doi: 10.2307/2685660

[54] R. R. Wilcox. *Introduction to Robust Estimation and Hypothesis Testing: 4th Edition*. 2016.

[55] N. Yee and J. Bailenson. The proteus effect: The effect of transformed self-representation on behavior. *Human Communication Research*, 2007. doi: 10.1111/j.1468-2958.2007.00299.x