Elicitation of Interaction Techniques with 3D Data Visualizations in Immersive Environment using HMDs

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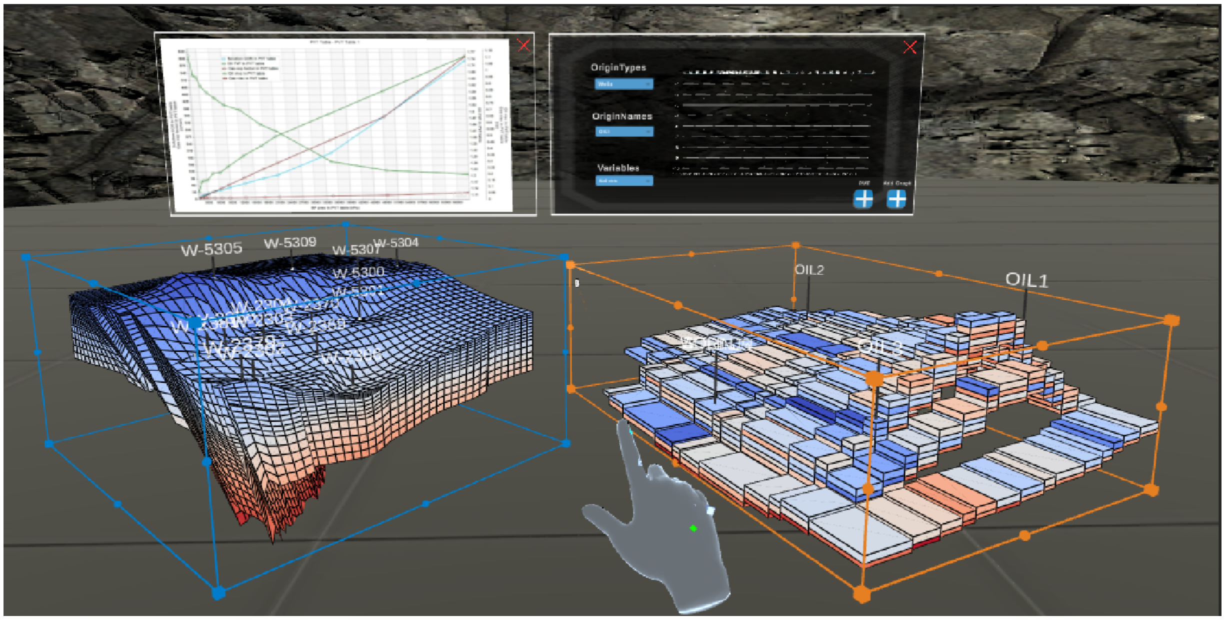

Figure 1: Analysis of reservoir engineering data through interaction with 3D data visualization of reservoir models [25].

Abstract

The design practices of current techniques for interacting with 3D data visualizations offered by state-of-the-art immersive head-mounted displays (HMD) are constrained by technological limitations and designer bias. We argue that understanding user-preferred interaction techniques with 3D data visualizations can lead to improved usability by helping system designers or architects formulate a set of interactions that are most intuitive and natural to the users.

Index Terms: User-centered design—Data Visualization—Interaction Techniques; Immersive analytics—Interaction; Visualization—3D—Interaction; Extended reality; Virtual reality; Augmented reality; Mixed reality; Head-mounted Display;

1 Introduction

With the advancement of extended reality (XR) technology such as virtual, augmented, and mixed reality, immersive tools are becoming more technologically powerful and fit for being widely used. Through innovations over time, the reach of XR platforms has gone way beyond just being an entertainment tool. XR applications are being used in sectors such as immersive analytics [25,42], training simulation for surgeons [2,7], pilots [9] or nuclear power plant operators [6], consumer product design [5], product marketing through virtual showrooms and exhibitions [10], behavioral research by replicating real-world conditions [11], data visualization [1,22] and remote collaboration [8].

3D data visualizations are one of the popular and useful paradigms offered by immersive technology as it provides a more realistic overview and detailed experience of data through a comprehensive spectrum of input and output modalities. It is becoming common practice to view, navigate, manipulate and analyze the visualized data in an immersive 3D real or virtual spatial context using XR HMDs like Hololens 2, and Varjo XR 3. Consequently, a growing number of applications are inspiring more focus on research of the interaction space concerning 3D data visualizations in immersive environments. The current state-of-the-art interaction devices mainly include controllers, controller gestures, haptic devices, wearable haptics, tangible interfaces, and human body gestures.

The more immersive the environment is, the more the users, instinctively, will seek natural ways to interact with that environment. The necessity of being able to interact naturally in a human-computer setup gave birth to the paradigm of natural interactions such as gestures, gaze, expressions, movements, and speech, which assert that people should be able to interact with technology similar to how they would interact with the real world in everyday life [61]. The broad range of input modalities available in the immersive domain gives rise to a myriad of possible interactions for different use cases. In a sense, immersive technology offers more in the interaction domain than does our real world because virtual objects don't have to follow the laws of our physical reality. Due to their profound scope in immersive reality, interaction techniques that are natural to the users and conducive to the best user experience are determinants of the usefulness and success of XR platforms. That is why we should focus on analyzing user preferences first before implementing system interactions. Usually, designers or

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architects of the system define interaction vocabulary based on the interactions supported by the system's technology. This is where lies the design deficit [67] because of not including the user in the design process and restraining the design of interaction techniques within the boundaries of technological affordances [35]. Eliciting user preferences in the design phase is found to be necessary to develop more intuitive, easily learnable, and memorable system interaction methods [26, 30, 56]. Despite its necessity, there are very few papers published in the last decade that involves elicitation of interaction techniques in XR environments [58].

2 Related Work

In 2005, Wobbrock et al. [66] introduced the concept of maximum guessability when they ran an elicitation study on maximizing and evaluating the guessability of symbolic input. Then in 2009, Wobbrock et al. [67] ran a comparative study between the user-defined and author-defined gesture sets and demonstrated the limitations of the latter gesture set through elicitation of surface gestures. Their study reported that around 40% of designer-defined gestures could not make it to the gesture set defined by users.

Researchers have widely adopted the elicitation study approach for designing interaction techniques, especially gestures. They have gained promising gesture-design outcome from elicitation study done for systems including tabletops [56, 67], mobile platforms [32, 51, 53, 69], keyboards [18], tangible interfaces [23, 60], smartwatches [14], virtual reality [15, 38, 47, 68], and augmented reality [16, 50, 65].

The authors [44] found the benefit of generating multi-modal synonyms using a multi-modal elicitation study, which supports accessing the same functionality with different interaction modalities under different circumstances. They adopted a multi-user study design which surfaced relevant concerns such as accidentally striking a companion seated nearby while performing gestures or conversation getting combined with commands. Eventually, they proposed future work on comparison between single and multi-user elicitation methodologies to understand the trade-offs between the two. In addition to combining different modalities, using whole body gestures extends interaction possibilities [27, 28, 34, 36]. Foot gestures are reported as particularly beneficial in busy-hand or arm-fatigue situations [12, 16, 31]. Authors in [16] elicited hand and foot gestures for augmented reality maps. In this study, the participants could replace their suggested gestures at any point during the process of elicitation which meets one of the limitations of not letting users redesign their gestures in Wobbrock's work on surface gestures [67]. The study participants suggested numerous other inspirational hand and foot gestures, which could not be implemented due to the performance concern of the system.

Tang et al. [59], performed an elicitation study of game input in a public space to help inform better design decisions beyond the capability of today's sensors. The results show that users preferred in-air gestures instead of any touch and handheld interaction. The authors also found that users preferred less noticeable gestures out of concern for social acceptance. Considering the social awkwardness of large gestures [52], Chan et al. [26] introduced single-hand micro gestures (SHMG) to perform gestures naturally in public contexts.

T Pham et al. in [49], explored how the scale of 3D holograms impacts user preference for gestures used in AR environments. The authors concluded that designers should consider the scale of 3D objects in AR space while defining gesture sets instead of using generalized forms irrespective of their scales. Bhowmick et al. [20, 21] elicited gestures for small object selection in dense or occluded virtual environments in HMD. A work published by Moran-Ledesma et al. [43] explored user-defined gestures using physical props in virtual reality. Ganapathi et al. [34] studied the elicitation of body gestures for virtual locomotion in HMD interfaces in a sitting position. Investigating user-preferred interactivity in different body positions is important because not only does it benefit people in general but also findings of this research can be extended to the interaction space of different elderly or physically disabled user groups exploring the virtual environments.

Bahnmüller et al. [17] explained how the participants completed a training phase to familiarize themselves with the interaction techniques they were going to use to execute continuous manipulations of virtual objects. User-defined interaction methods include high guessability [66], which consequently improves learnability [17] that can potentially reduce training time and subsequent user discomfort.

Despite having many contributions to the design process of different interactive systems, it is reported that the number of elicitation studies is significantly lower compared to assessment and comparison studies [58]. Elicitation studies have shown potential in the interaction space of different devices and there is a multitude of factors that impact the interaction patterns. Hence, it is high time we put our research focus on interaction techniques in the XR environment to navigate through or manipulate 3D visualizations under different circumstances.

3 Eliciting Natural Interaction Techniques

In an elicitation study, researchers acquire data by incorporating users in the design process, which is inspired by the concept of participatory design [55]. A Study of elicitation is defined as the study or experiment (see Fig. 2) where users are asked to define their techniques to interact with the system instead of the system defining those techniques for them.

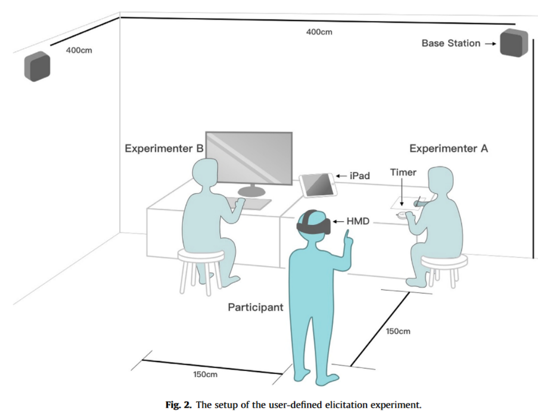

Figure 2: An example setup of the user-defined elicitation experiment [37]

3.1 Factors Impacting Elicitation

Actions or tasks such as selection, translation, and scaling are called referents. During the study of elicitation, users are asked to propose their preferred interaction techniques corresponding to each referent. Usually, an experimenter, acting as the wizard of oz [29], responds to the user-defined interaction on behalf of the system showing the post-interaction state to the user. User-generated interaction techniques can be impacted by legacy bias [66], which is defined as users being biased by prior experience with conventional interfaces such as WIMP (windows, icons, menus, and pointers). Although many claim these biases to be preventing users from being open and creative in the process of elicitation and limiting them within the implicit technological barrier of previous systems [45], there are also positive implications to these biases as their knowledge of past systems can be transferred to new ones reducing the effort in learning new techniques [39]. To reduce these biases from the elicited data, different measures have been proposed in [45] such as *production* that involves multiple interaction proposals for each referent, *priming* that concerns informing about technology before the study, and *partners* where users participate in groups during the process of elicitation. Along with user-defined symbols, researchers collect think-aloud data and prepare a post-questionnaire phase where users are asked about the motivation behind their suggestions per referent, conceptual complexity, satisfaction with their generated symbols, comfort with the elicited techniques, and many other aspects that would help the researchers get important insights into users' mental models.

3.2 Evaluating Elicited Data

Wobbrock et al. [66] introduced agreement score, a formula for finding the most popular gesture for a given referent. Quantitative evaluation of elicited data is usually done by comparing the agreement scores. Suppose, for any referent, a total of 10 gestures are elicited. Then researchers manually sort these gestures into different classes following their similarity criteria. The class with the highest agreement score is included in the final user-defined set. The process of manual categorization by the researchers brings subjectivity into the magnitude of the consensus as the similarity criteria chosen by the researchers are subjective and vary from one study to another [28, 44, 53, 57]. To resolve this, an objective approach called dissimilarity measure is introduced [63] where this subjective phase of elicitation is replaced by the calculation of dissimilarity values.

The use of agreement score is limited to studies where each participant suggests exactly one interaction per referent. Since the adoption of *production* feature to reduce legacy bias lets users propose multiple interaction synonyms for each referent, the use of agreement scores is no longer applicable here since different proposed techniques can have the same agreement score [44]. Morris et al. [44] introduced metrics like *max-consensus* and *consensus-distinct ratio* to evaluate *production-based* elicitation studies. The max-consensus metric represents the percentage of participants proposing the most popular combination of modalities and referents. In consensus-distinct ratios, participants report how many distinct interactions they suggest for a given referent or referent/modality combination that met a given consensus threshold. These two metrics are supposed to provide both the peak and spread of the agreement.

Evaluation techniques like closed elicitation and reverse elicitation extend and strengthen the evaluation process of elicitation studies. The concept of framed guessability [24] by Cafaro et al. introduced us to methods like open and closed elicitation. Open elicitation is the regular elicitation process where users come up with interactions for different referents. Closed elicitation is a process where users choose symbols from the pre-defined set instead of creatively formulating their own. Closed elicitation is found to help converge to a better agreement among participants due to their limited options to choose from [64]. That is why it is suggested that a closed elicitation study should follow an open one to help limit the size of consensus set [64]. On the other hand, *reverse elicitation* is an end-user identification study that helps evaluate the guessability of elicited data by reversing the process of elicitation [13]. In this reverse elicitation process, participants are shown an interaction symbol and asked to suggest a referent invoked by it. Besides, some qualitative evaluation metrics help us understand different aspects of user experience with a user-defined set such as goodness of fit [67], memorability [46], ease of execution [67], and ease of conception [41].

4 Interaction With Immersive 3D Data Visualization

Popular 3D visualizations used in immersive environments are volumetric (see Fig. 3(d)), charts, graphs, plots, 3D field visualizations, geographic, Kohonen, flow (see Fig. 3(a)) and network maps (see Fig. 3(b)). Immersive technology offers added perspective to view and manipulate data with higher dimensions in a 3D environment by enabling six degrees of freedom for users [62]. Smartphones and tablets can be used for XR experience, however, the spatial feature of

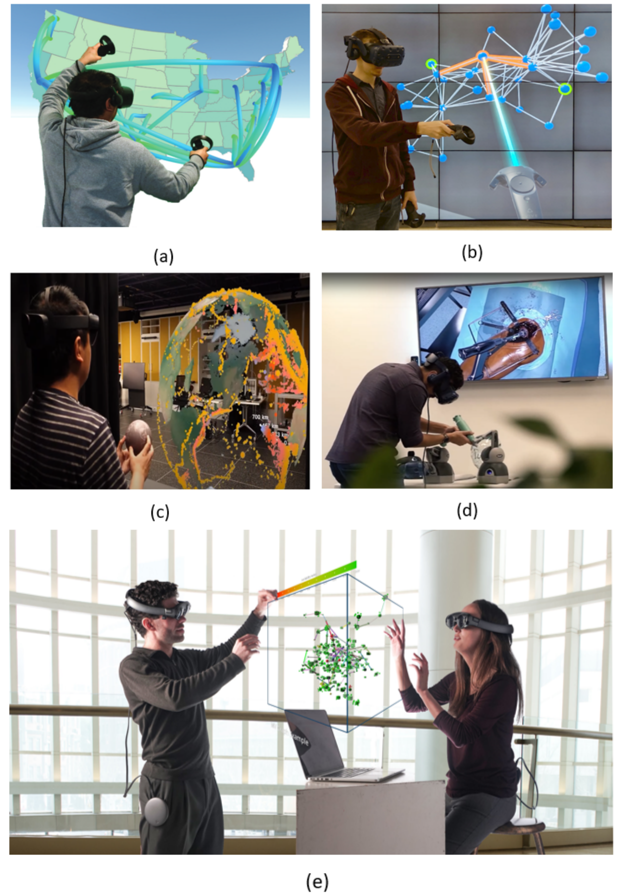

Figure 3: a)An example of scaling a map with bi-manual controller gestures [48]. b) A user interacts with an immersive 3D network visualization using a head-mounted display and controllers [40]. c) A tangible globe for manipulating virtual globe visualization [54]. d) Surgeons practice via simulation in HapticVR developed by FundamentalVR [33]. e) Immersive collaboration with Tableau data visualization [4].

3D data visualizations through HMDs provides users with the ability to overcome boundaries of the physical world around them and be in environments of any scale or context. Users can also place themselves inside visualizations if needed to get a more detailed view of the data units. The purpose of 3D visualizations of both spatial and abstract data is to make the process of analysis more effective for the analysts and help them make reliable decisions faster. A big part of this process includes interacting with data. Each 3D data visualization involves a set of tasks that are specific to that visualization and some tasks that are common across different visualizations. Taking earlier classification systems under consideration, authors in [19] organized the axis of the 3D visualization task taxonomy into three high-level task groups, first: volumetric view and object manipulation, second: define, place and manipulate visualization widgets, and third: select and annotate 3D data. Each system of visualization is unique in terms of its scheme of task interactions. This inspires more research in visualization-specific interaction spaces.

Authors in [19] also summarize both 3D manipulations and visualization-specific interaction techniques into four paradigms namely tactile, tangible, mid-air gestural, and hybrid interaction. Each of these paradigms has its pros and cons under different circumstances. Essentially, designers of immersive 3D data visualization applications need to understand the trade-offs between these paradigms and form an interaction space most suitable for the potential users of that system. Because of the sense of realism posed by XR environments, which matches the 3D perspective of the real world, designers are inclined to deliver natural interactions to the XR platform users. XR offers more opportunities for interactions as it opens up opportunities for various input modalities such as controllers/ tangible devices, body gestures, speech, and eye movement that are eligible to be used in combination with each other. Therefore, the designers need to consider what kind of interaction methods could minimize the potential fatigue brought upon the users due to possible increased exposure to interactivity [47]. The learnability of the interaction vocabulary impacts the training time required by the analysts to get familiarized with the system of interactions. The memorability and ease of execution of interaction techniques influence the efficiency of the analysis process.

HMD controllers are a widely used mode of interaction in an immersive environment. A controller can be used both as a pointing device for direct manipulation (see Fig. 3(b)) or as a sensor to capture the user's gestural input (see Fig. 3(a)). A tangible user interface (TUI) can share the shape of the data, acting not only as the physical representation of data but also as a device to interact with the data (see Fig. 3(c)). TUI can also have more of an abstract physical form providing passive haptic feedback instead of having a visual context similar to data (see Fig. 3(d)). Due to recent breakthroughs in hand and eye tracking functionality [3], gestures (see Fig. 3 (a),(e)) have become a prominent interaction modality. The use of mix-modal interactions e.g. gesture with speech has become a way of conveying more complex and abstract commands by overcoming the limitations of individual modality [44]. The preferred interaction techniques in XR platforms can vary in terms of the type of data to interact with, tasks associated with the visualized data, position of the data relative to the user, scale of the environment, single vs collaborative systems, dense vs sparse visualizations, body position of users, demography, culture and physical or mental ability of users, social acceptance of the physical world around the user. Keeping these factors in mind, designers of interaction techniques must focus on providing the best possible experience for their users through forming effective and natural sets of interaction methods. Elicitation studies can help them build such an interaction vocabulary by identifying what users consider natural.

5 Conclusion

In this study, we put forward our arguments on the importance of elicitation in the design phase of forming user interaction methods for 3D data visualization interaction space in an immersive environment using HMDs. Through interaction with 3D data visualizations using HMD, data experts can immerse themselves in an extended world of information. This provides the analysts more degrees of freedom in terms of interaction that enforces better analytic experience and formulation of results through more meaningful and engaging observation of data. Therefore, it is time we brought our focus to finding the most efficient way of designing interactions for data experts. Elicitation studies have been much promising in this regard as it aims to extract the naturalness from the user. There is significant research scope for elicitation studies of interaction with 3D data visualizations considering the multidimensional factors influencing interactions such as scale, position of 3D data visualizations, user groups, type of tasks, social awareness, and the demographic and cultural viewpoint of the users. Therefore, we should emphasize utilizing the potential of elicitation studies to reduce the uncertainty that the interaction methods posit by including users in the design process and thus acquiring useful insights and guidelines for developing the final set of interaction vocabulary for any system.

References

[1] CSynth – Bio-Visualisation made interactive.

[2] FUNDAMENTAL SURGERY - The Virtual Reality Surgical Simulator.

[3] HoloLens 2—Overview, Features, and Specs | Microsoft HoloLens.

[4] Tableau in HoloLens 2 & Oculus.

[5] Case Volvo & Varjo: World's First Mixed & Virtual Reality Test Drive, Nov. 2019.

[6] Virtual Reality VR in Nuclear Power Plant Operator Training - Case Fortum, Aug. 2019.

[7] VR in surgery: Varjo delivers the fidelity that surgeons demand., Feb. 2019.

[8] Virtual Collaboration with Varjo & MeetinVR Varjo.com, May 2020.

[9] Case Finnish Air Force: Future of Pilot Training with LVC & Mixed Reality, Jan. 2021.

[10] Case MUJI: Using VR in retail to achieve a deeper customer connection, Jan. 2022.

[11] Transforming Anatomy Education with Virtual and Mixed Reality, Feb. 2022.

[12] J. Alexander, T. Han, W. Judd, P. Irani, and S. Subramanian. Putting your best foot forward: investigating real-world mappings for foot-based gestures. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 1229–1238, 2012.

[13] A. X. Ali, M. R. Morris, and J. O. Wobbrock. Crowdlicit: A system for conducting distributed end-user elicitation and identification studies. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1–12, 2019.

[14] S. S. Arefin Shimon, C. Lutton, Z. Xu, S. Morrison-Smith, C. Boucher, and J. Ruiz. Exploring non-touchscreen gestures for smartwatches. In *Proceedings of the 2016 chi conference on human factors in computing systems*, pp. 3822–3833, 2016.

[15] R. Arora, R. H. Kazi, D. M. Kaufman, W. Li, and K. Singh. Magicalhands: Mid-air hand gestures for animating in vr. In *Proceedings of the 32nd annual ACM symposium on user interface software and technology*, pp. 463–477, 2019.

[16] C. R. Austin, B. Ens, K. A. Satriadi, and B. Jenny. Elicitation study investigating hand and foot gesture interaction for immersive maps in augmented reality. *Cartography and Geographic Information Science*, 47(3):214–228, 2020.

[17] A. Bahnmüller, A. S. Muhammad, G. Albuquerque, and A. Gerndt. Evaluation of interaction techniques for early phase satellite design in immersive ar. In *2020 IEEE Aerospace Conference*, pp. 1–8. IEEE, 2020.

[18] G. Bailly, T. Pietrzak, J. Deber, and D. J. Wigdor. Métamorphe: augmenting hotkey usage with actuated keys. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 563–572, 2013.

[19] L. Besançon, A. Ynnerman, D. F. Keefe, L. Yu, and T. Isenberg. The state of the art of spatial interfaces for 3d visualization. In *Computer Graphics Forum*, vol. 40, pp. 293–326. Wiley Online Library, 2021.

[20] S. Bhowmick. Exploring body gestures for small object selection in dense environment in hmd vr for data visualization applications. In *2021 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, pp. 713–714. IEEE, 2021.

[21] S. Bhowmick, P. Kalita, and K. Sorathia. A gesture elicitation study for selection of nail size objects in a dense and occluded dense hmd-vr. In *IndiaHCI'20: Proceedings of the 11th Indian Conference on Human-Computer Interaction*, pp. 12–23, 2020.

[22] R. Brandom. Bloomberg shows off a virtual news terminal in Oculus Rift, June 2014.

[23] S. Buchanan, B. Floyd, W. Holderness, and J. J. LaViola. Towards user-defined multi-touch gestures for 3d objects. In *Proceedings of the 2013 ACM international conference on Interactive tabletops and surfaces*, pp. 231–240, 2013.

[24] F. Cafaro, L. Lyons, and A. N. Antle. Framed guessability: Improving the discoverability of gestures and body movements for full-body interaction. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pp. 1–12, 2018.

[25] S. Cartwright, S. Samoil, B. Lawton, D. Hu, S. Xie, E. Wang, A. Amin-

beidokhti, S. Dawar, R. Dalton, P. Daeijavad, et al. Enhancing reservoir engineering workflows with augmented and virtual reality. In *SPE Canadian Energy Technology Conference*. OnePetro, 2022.
[26] E. Chan, T. Seyed, W. Stuerzlinger, X.-D. Yang, and F. Maurer. User elicitation on single-hand microgestures. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pp. 3403–3414, 2016.
[27] Z. Chen, X. Ma, Z. Peng, Y. Zhou, M. Yao, Z. Ma, C. Wang, Z. Gao, and M. Shen. User-defined gestures for gestural interaction: extending from hands to other body parts. *International Journal of Human–Computer Interaction*, 34(3):238–250, 2018.
[28] S. Connell, P.-Y. Kuo, L. Liu, and A. M. Piper. A wizard-of-oz elicitation study examining child-defined gestures with a whole-body interface. In *Proceedings of the 12th International Conference on Interaction Design and Children*, pp. 277–280, 2013.
[29] N. Dahlbäck, A. Jönsson, and L. Ahrenberg. Wizard of oz studies—why and how. *Knowledge-based systems*, 6(4):258–266, 1993.
[30] H. J. Fariman, H. J. Alyamani, M. Kavakli, and L. Hamey. Designing a user-defined gesture vocabulary for an in-vehicle climate control system. In *Proceedings of the 28th Australian Conference on Computer-Human Interaction*, pp. 391–395, 2016.
[31] Y. Felberbaum and J. Lanir. Better understanding of foot gestures: An elicitation study. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pp. 1–12, 2018.
[32] M. Ferron, N. Mana, and O. Mich. Designing mid-air gesture interaction with mobile devices for older adults. In *Perspectives on human-computer interaction research with older people*, pp. 81–100. Springer, 2019.
[33] FundamentalVR. HapticVR System, May 2020.
[34] P. Ganapathi and K. Sorathia. Elicitation study of body gestures for locomotion in hmd-vr interfaces in a sitting-position. In *Motion, interaction and games*, pp. 1–10. 2019.
[35] W. W. Gaver. Technology affordances. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pp. 79–84, 1991.
[36] J. Guerrero-García, C. González, and D. Pinto. Studying user-defined body gestures for navigating interactive maps. In *Proceedings of the XVIII International Conference on Human Computer Interaction*, pp. 1–4, 2017.
[37] W. Hou, G. Feng, and Y. Cheng. A fuzzy interaction scheme of mid-air gesture elicitation. *Journal of Visual Communication and Image Representation*, 64:102637, 2019.
[38] H. Jahani and M. Kavakli. Exploring a user-defined gesture vocabulary for descriptive mid-air interactions. *Cognition, Technology & Work*, 20(1):11–22, 2018.
[39] A. Köpsel and N. Bubalo. Benefiting from legacy bias. *interactions*, 22(5):44–47, 2015.
[40] J. Kotlarek, O.-H. Kwon, K.-L. Ma, P. Eades, A. Kerren, K. Klein, and F. Schreiber. A study of mental maps in immersive network visualization. In *2020 IEEE Pacific Visualization Symposium (PacificVis)*, pp. 1–10. IEEE, 2020.
[41] C. Kühnel, T. Westermann, F. Hemmert, S. Kratz, A. Müller, and S. Möller. I'm home: Defining and evaluating a gesture set for smart-home control. *International Journal of Human-Computer Studies*, 69(11):693–704, 2011.
[42] B. Lawton, H. Sloan, P. Abou Gharib, F. Maurer, M. Guarido de Andrade, A. Fathalian, and D. Trad. Siera: The seismic information extended reality analytics tool. In *Companion Proceedings of the 2020 Conference on Interactive Surfaces and Spaces*, pp. 73–77, 2020.
[43] M. Moran-Ledesma, O. Schneider, and M. Hancock. User-defined gestures with physical props in virtual reality. *Proceedings of the ACM on Human-Computer Interaction*, 5(ISS):1–23, 2021.
[44] M. R. Morris. Web on the wall: insights from a multimodal interaction elicitation study. In *Proceedings of the 2012 ACM international conference on Interactive tabletops and surfaces*, pp. 95–104, 2012.
[45] M. R. Morris, A. Danielescu, S. Drucker, D. Fisher, B. Lee, M. Schraefel, and J. O. Wobbrock. Reducing legacy bias in gesture elicitation studies. *interactions*, 21(3):40–45, 2014.
[46] M. A. Nacenta, Y. Kamber, Y. Qiang, and P. O. Kristensson. Memorability of pre-designed and user-defined gesture sets. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pp. 1099–1108, 2013.
[47] V. Nanjappan, H.-N. Liang, F. Lu, K. Papangelis, Y. Yue, and K. L. Man. User-elicited dual-hand interactions for manipulating 3d objects in virtual reality environments. *Human-centric Computing and Information Sciences*, 8(1):1–16, 2018.
[48] R. Newbury, K. A. Satriadi, J. Bolton, J. Liu, M. Cordeil, A. Prouzeau, and B. Jenny. Embodied gesture interaction for immersive maps. *Cartography and Geographic Information Science*, 48(5):417–431, 2021.
[49] T. Pham, J. Vermeulen, A. Tang, and L. MacDonald Vermeulen. Scale impacts elicited gestures for manipulating holograms: Implications for ar gesture design. In *Proceedings of the 2018 Designing Interactive Systems Conference*, pp. 227–240, 2018.
[50] T. Piumsomboon, A. Clark, M. Billinghurst, and A. Cockburn. User-defined gestures for augmented reality. In *IFIP Conference on Human-Computer Interaction*, pp. 282–299. Springer, 2013.
[51] B. Poppinga, A. Sahami Shirazi, N. Henze, W. Heuten, and S. Boll. Understanding shortcut gestures on mobile touch devices. In *Proceedings of the 16th international conference on Human-computer interaction with mobile devices & services*, pp. 173–182, 2014.
[52] J. Rico and S. Brewster. Usable gestures for mobile interfaces: evaluating social acceptability. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 887–896, 2010.
[53] J. Ruiz, Y. Li, and E. Lank. User-defined motion gestures for mobile interaction. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pp. 197–206, 2011.
[54] K. A. Satriadi, J. Smiley, B. Ens, M. Cordeil, T. Czauderna, B. Lee, Y. Yang, T. Dwyer, and B. Jenny. Tangible globes for data visualisation in augmented reality. In *CHI Conference on Human Factors in Computing Systems*, pp. 1–16, 2022.
[55] D. Schuler and A. Namioka. *Participatory design: Principles and practices*. CRC Press, 1993.
[56] T. Seyed, C. Burns, M. Costa Sousa, F. Maurer, and A. Tang. Eliciting usable gestures for multi-display environments. In *Proceedings of the 2012 ACM international conference on Interactive tabletops and surfaces*, pp. 41–50, 2012.
[57] C. Silpasuwanchai and X. Ren. Jump and shoot! prioritizing primary and alternative body gestures for intense gameplay. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 951–954, 2014.
[58] B. Spittle, M. Frutos-Pascual, C. Creed, and I. Williams. A review of interaction techniques for immersive environments. *IEEE Transactions on Visualization and Computer Graphics*, 2022.
[59] Y.-C. Tung, C.-Y. Hsu, H.-Y. Wang, S. Chyou, J.-W. Lin, P.-J. Wu, A. Valstar, and M. Y. Chen. User-defined game input for smart glasses in public space. In *Proceedings of the 33rd Annual ACM conference on human factors in computing systems*, pp. 3327–3336, 2015.
[60] C. Valdes, D. Eastman, C. Grote, S. Thatte, O. Shaer, A. Mazalek, B. Ullmer, and M. K. Konkel. Exploring the design space of gestural interaction with active tokens through user-defined gestures. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 4107–4116, 2014.
[61] A. Valli. The design of natural interaction. *Multimedia Tools and Applications*, 38(3):295–305, 2008.
[62] C. S. Vann. Six degree of freedom sensor. 3 1999.
[63] R.-D. Vatavu. The dissimilarity-consensus approach to agreement analysis in gesture elicitation studies. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1–13, 2019.
[64] S. Villarreal-Narvaez, J. Vanderdonckt, R.-D. Vatavu, and J. O. Wobbrock. A systematic review of gesture elicitation studies: What can we learn from 216 studies? In *Proceedings of the 2020 ACM Designing Interactive Systems Conference*, pp. 855–872, 2020.
[65] A. S. Williams, J. Garcia, and F. Ortega. Understanding multimodal user gesture and speech behavior for object manipulation in augmented reality using elicitation. *IEEE Transactions on Visualization and Computer Graphics*, 26(12):3479–3489, 2020.
[66] J. O. Wobbrock, H. H. Aung, B. Rothrock, and B. A. Myers. Maximizing the guessability of symbolic input. In *CHI'05 extended abstracts on Human Factors in Computing Systems*, pp. 1869–1872, 2005.
[67] J. O. Wobbrock, M. R. Morris, and A. D. Wilson. User-defined gestures for surface computing. In *Proceedings of the SIGCHI conference on*

human factors in computing systems, pp. 1083–1092, 2009.

[68] H. Wu, Y. Wang, J. Qiu, J. Liu, and X. Zhang. User-defined gesture interaction for immersive vr shopping applications. *Behaviour & Information Technology*, 38(7):726–741, 2019.

[69] H. Wu and L. Yang. User-defined gestures for dual-screen mobile interaction. *International Journal of Human–Computer Interaction*, 36(10):978–992, 2020.