Questset: A VR Dataset for Network and Quality of Experience Studies

Sara Baldoni, Federica Battisti, Federico Chiariotti, Fabio Mistrorigo, Alfi Baqiatus Shofi, Paolo Testolina, Alessandro Traspadini, Andrea Zanella, and Michele Zorzi*
Department of Information Engineering, University of Padova
Padua, Italy

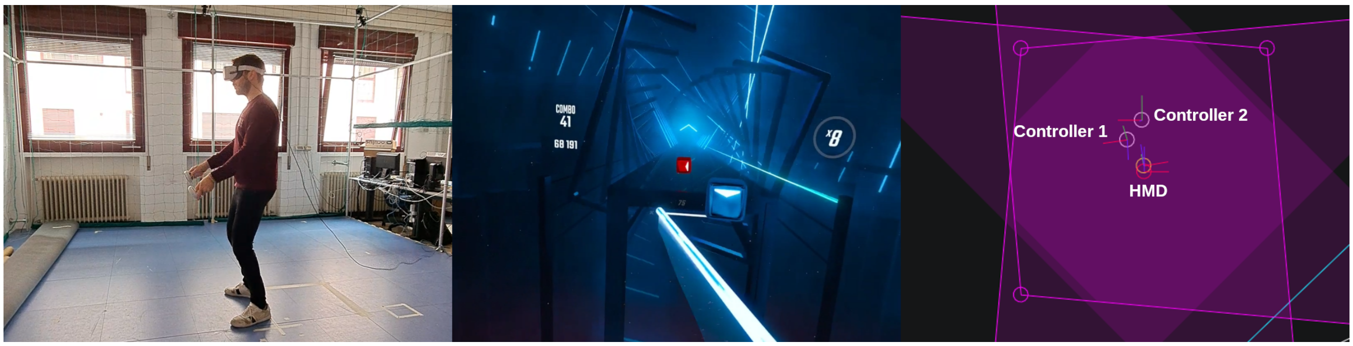


Figure 1: The experimental environment, in the real and virtual worlds, and the movement capture software interface.

ABSTRACT

The rapid development of Virtual Reality (VR) technology has led the industry and research community to look at its major challenges with increased interest. The main challenge in ensuring a high Quality of Experience (QoE) for users is represented by cybersickness, a phenomenon similar to motion sickness experienced by many VR users, while at the same time, the high data rates needed by VR require the definition of traffic models for network optimization. These two problems are intertwined, but have never been studied jointly before due to the lack of suitable datasets. In this paper, we present Questset, the first dataset designed for this purpose. Questset contains over 40 hours of VR traces from 70 users playing commercially available video games, and includes both traffic data for network optimization, and movement and user experience data for cybersickness analysis. Therefore, Questset represents an enabler to jointly address the main VR challenges in the near future.

CCS CONCEPTS

• **Human-centered computing** → **Virtual reality**; **User studies**; • **Information systems** → **Multimedia streaming**; • **Networks** → *Network measurement*.

KEYWORDS

Virtual Reality, User Dataset, Cybersickness, Traffic Modeling

ACM Reference Format:
Sara Baldoni, Federica Battisti, Federico Chiariotti, Fabio Mistrorigo, Alfi Baqiatus Shofi, Paolo Testolina, Alessandro Traspadini, Andrea Zanella, and Michele Zorzi. 2024. Questset: A VR Dataset for Network and Quality of Experience Studies. In *ACM Multimedia Systems Conference 2024 (MMSys '24), April 15–18, 2024, Bari, Italy*. ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3625468.3652187

1 INTRODUCTION

The fast-paced development of Head-Mounted Display (HMD) technology over the past decade has turned VR from an experimental concept to a commercial reality: the relatively low price of high-end devices and the better quality of VR content have led to an explosive market growth. Recent market surveys estimate that the number of VR users will reach over a billion [23], and the development of virtual technologies and applications has been accelerated by the effects of the COVID-19 lockdowns and travel restrictions.

However, VR faces two major challenges to achieve widespread adoption: the cybersickness [2] phenomenon and mobile network support and Quality of Service (QoS) provisioning. Cybersickness is similar to motion sickness, with symptoms including nausea, discomfort, headaches, and disorientation, and is partly caused by a sensory input mismatch [26], as movements in the virtual world are inconsistent with proprioceptive stimuli. Network issues such as latency [20] and jitter [27] can exacerbate the issue, introducing additional delays and making compensation more difficult. This

*The email addresses for S. Baldoni, F. Battisti, F. Chiariotti, P. Testolina, A. Traspadini, A. Zanella, and M. Zorzi are {name.surname}@unipd.it. The email addresses for F. Mistrorigo and A. B. Shofi are {name.surname}@studenti.unipd.it. The author list was ordered alphabetically. S. Baldoni, F. Battisti, F. Chiariotti, P. Testolina, and A. Traspadini were equal contributors, working on the experimental protocol definition, data acquisition and clean-up, and paper writing. F. Mistrorigo and A. B. Shofi contributed in the experiments and data acquisition. A. Zanella and M. Zorzi contributed to the paper writing, project management, and supervision.

MMSys '24, April 15–18, 2024, Bari, Italy

ACM ISBN 979-8-4007-0412-3/24/04.
https://doi.org/10.1145/3625468.3652187

Dataset	Year	Headset	Users	Content			Interactive	Traffic	Movements		SSQ
				Total	User	Length			Head	Controllers	
[22]	2017	Oculus Rift	30	60	60	10 sec.	✗	✓	✗	✗	✗
[16]	2017	Oculus Rift DK2	50	10	10	60 sec.	✗	✓	✓	✗	✗
[4]	2017	Razer OSVR HDK2	59	3	3	70 sec.	✗	✓	✓	✗	✗
[16]	2017	Oculus Rift DK2	50	10	10	60 sec.	✗	✓	✓	✗	✗
[29]	2017	HTC Vive	40	48	48	20-60 sec.	✗	✓	✓	✗	✗
[28]	2017	HTC Vive	48	18	18	2-10 min.	✗	✓	✓	✗	✗
[31]	2018	HTC Vive	30	48	48	10-30 sec.	✗	✓	✗	✗	✗
AVTrack360 [7]	2018	HTC Vive	48	20	20	1-2 min.	✗	✗	✓	✗	✓
VQA-ODV [14]	2018	HTC Vive	221	60	60	10-30 sec.	✗	✓	✓	✗	✗
PVS-HM [30]	2018	HTC Vive	58	76	76	10-80 sec.	✗	✓	✓	✗	✗
[11]	2018	Oculus Rift CV1	20	8	8	1-6 min.	✗	✗	✓	✗	✓
[18]	2019	Oculus Go	60	28	14	60 sec.	✗	✓	✓	✗	✓
[12]	2021	Cardboard	2	4	4	20-30 min.	✓	✓	✗	✗	✗
[32]	2021	Meta Quest 2	1	2	2	30 sec.	✓	✓	✗	✗	✗
OpenNEEDS [6]	2021	Oculus Rift	44	2	2	2-5 min.	✓	✗	✓	✓	✗
[25]	2022	HTC Vive Pro Eye	20	3	3	30 sec.	✓	✗	✓	✗	✓
[21]	2022	Oculus Quest 1	153	3	1	14 min.	✓	✗	✓	✗	✓
[5]	2022	Meta Quest 2	30	5	5	3-5 min.	✓	✗	✓	✗	✓
[19]	2023	Meta Quest 2	1	5	5	4-17 min.	✓	✓	✗	✗	✗
Questset	**2024**	**Meta Quest 2**	**70**	**4**	**2**	**10-20 min.**	✓	✓	✓	✓	✓

Table 1: Existing datasets on VR content.

relates to the second challenge: as the expected bitrate of high-quality VR applications is extremely high, providing latency and jitter guarantees is a difficult problem. The 6th Generation (6G) of cellular networks is expected to address these problems, leveraging eXtended Reality (XR) to enable immersive communications and a number of applications, ranging from education and gaming to industrial Internet of Things (IoT) [1, 9].

Several recent studies have modeled the effect of network QoS parameters on user QoE, measured through either objective metrics or experiments in controlled testbeds [13, 15]. However, the traffic models for VR applications are still lacking in the literature: aside from our own previous work, which analyzed traffic traces over a Cardboard-like application [3], relatively few source models of VR applications exist [19]. On the other hand, the QoE community has an extensive experience with cybersickness studies, often conducted through the use of the Simulator Sickness Questionnaire (SSQ) [10], but the correlation between the user's movements [21] and cybersickness is still relatively poorly understood.

In this context, large-scale datasets combining traffic and user data are crucial both to construct traffic models and to predict the QoS, as well as the risk of cybersickness. However, most large datasets in the literature are rather limited: older datasets in the literature have a large number of users and content types [14, 30], but are limited to static content, i.e., non-interactive video in which the user only has 3 degrees of freedom. Furthermore, relatively few of these datasets include cybersickness-related data such as user questionnaires [7, 11, 18]. Some more recent studies involve a large number of users exploring interactive content, and measure cybersickness through an SSQ [21, 25], but do not include traffic traces and use *ad hoc* applications. Recent traffic datasets include relatively few traces from a handful of users, but use commercially available games [12, 19, 32]. The existing datasets and their main features are summarized in Table 1, which lists the selected HMD, the number of participants, the total number of games or videos used in the experiments, the number of conditions (i.e., game/video) experienced by each participant, and the duration of each condition. The nature of the collected data is also listed: most datasets do not include some types of data, e.g., the non-interactive datasets do not have controllers, and as such do not include controller movements. To the best of our knowledge, no datasets with traffic, motion, and cybersickness data existed in the literature prior to this work.

This paper presents Questset, a large dataset that will allow researchers to study both traffic statistics and models and the potential precursors of cybersickness over commercial games. We recorded traffic and movement data from gameplay experiences using a Meta Quest 2 headset, considering 4 commercially available games and instructing each participant to play two of them. The experimental protocol was approved by the ethical committee of the Human-Inspired Technology center (HIT) of the University of Padova, Italy, with protocol number 2023_204R1, and the experimental environment is shown in Fig. 1. The dataset includes traces and questionnaire responses from 70 participants, 60 of which experienced at least 10 minutes in VR for each game. To the best of our knowledge, this is the first large dataset to include both traffic and movement data, as well as cybersickness information, bridging the gap between the two types of studies and allowing the QoE and network engineering communities to work on data from a state of the art device and widely used games. To the best of our knowledge, this is the largest existing VR dataset, with a total duration of over 40 hours.

The rest of the paper is organized as follows: first, Sec. 2 describes the experimental protocol. Sec. 3 then describes the dataset content and organization, while a preliminary analysis of the data is presented in Sec. 4. Finally, Sec. 5 concludes the paper and presents possible extensions and uses of the dataset.

2 EXPERIMENTAL PROTOCOL

In the following, we describe the experimental protocol, which was approved by the ethical committee and followed with all participants. The experiments took place in a laboratory with an open area measuring 3.6 m by 4 m. The boundaries of the play area were defined to leave at least 0.5 m on each side and the headset was connected using a 5 m USB 3.2 Gen 1 Type-C cable to a PC. The cable was suspended above the participant's head to avoid any risk of injury, and the PC rendered the game content. The PC had an Intel Core i7-9700K processor with a 3.6 GHz clock frequency, 64 GB of RAM, and an nVidia RTX 2080TI GPU, and the games were launched through the Steam VR platform on Windows 11. The HMD was a Meta Quest 2.

Acquisition setup and games. We collected traffic and movement data for each participant while using four VR commercial games selected based on the type of required movement (i.e., fast and slow) and the type of content. The games included in the dataset are Forklift Simulator 2019[1] (a driving simulation game), Cooking Simulator VR[2] (a cooking game), Medal of Honor: Above and Beyond[3] (a first-person shooter game, in the following Medal of Honor), and Beat Saber[4] (a rhythm game). The participants were split in two groups, and each group played one fast and one slow game. More in detail, group 1 played Beat Saber (fast) and Cooking Simulator VR (slow), while group 2 experienced Medal of Honor (fast) and Forklift Simulator 2019 (slow). Half of the participants played the fast game first, while the other half played the slow game first.

We report in Table 2 the description of the selected levels, since each game has a different structure. More specifically, we considered three Beat Saber play options, i.e., mono-directional (0°), bi-directional (90°), and omni-directional (360°), at three different levels (easy, medium, and hard). For Forklift Simulator we selected a set of levels with increasing difficulty, all of which were on the four-wheel sit down counterbalanced forklift. If the participant failed a level in either of these two games, they had to repeat it until they passed it or the experiment was over. On the other hand, we did not use a similar level progression for Cooking Simulator and Medal of Honor. For Cooking Simulator, we only considered two recipes with increasing complexity due to their duration. For Medal of Honor, we opted for a survival task whose goal was to live as long as possible, which was repeated for at least 10 minutes.

Participant selection. Participants were between 18 and 35 years old, with no history of balance issues, brain injuries, inner ear problems, or vertigo. As the games involved flashing lights and rapid movements, potential participants with a history of epileptic attacks or seizures were discarded. As part of the experimental protocol, participants were informed of the potential risks and nature of the experiment, and were told to take off the headset and withdraw from the experiment if they had any serious symptoms of cybersickness (e.g., loss of balance or nausea). Participants also took a visual acuity test and the Ishihara color blindness test [8, 17]. Colorblind participants were excluded from group 1, as Beat Saber includes color-based choices as part of the gameplay. Participants requiring corrective glasses or contact lenses were allowed to use them during the experiment. Participants with strong moral objections to simulated violence were allowed to opt out from participating in group 2, as Medal of Honor is a first-person shooter game in a war setting.

[1]https://store.steampowered.com/app/939450/Forklift_Simulator_2019/
[2]https://store.steampowered.com/app/1358140/Cooking_Simulator_VR/
[3]https://store.steampowered.com/app/1402320/Medal_of_Honor_Above_and_Beyond/
[4]https://store.steampowered.com/app/620980/Beat_Saber/

Game	Task	Levels
Beat Saber	Training	Tutorial
	Session	Beat Saber song - Easy (0°, 90°, 360°)
		$100 Bills song - Normal (0°, 90°, 360°)
		$100 Bills song - Hard (0°)
Cooking Simulator VR	Training	Cooking School
	Session	Fried Shrimp
		Baked Cod
Medal of Honor	Training	Firing Range
	Session	Survive - Bullets and Bulkheads
Forklift Simulator 2019	Training	Controls (1A)
	Session	Starting and driving (2A, 2B)
		Driving forward (3A, 3B, 3C, 3D)
		Driving backward (4A, 4B, 4C, 4D)

Table 2: Selected game levels.

Procedure. After each participant had taken the required vision tests and signed the consent form, the procedure followed these steps:

(1) *Survey* about the user's personal information (i.e., gender and age), and prior VR and gaming experience.
(2) *Initial SSQ* to assess the presence of existing symptoms prior to the start of the experiment.
(3) *Game* 1 *training*: to help participants get familiar with the environment and application, the experiment began with a training phase. The duration of the training phase depended on the game's complexity and on the participant's prior expertise, and ranged from 1-2 minutes in Beat Saber to up to 10 in Medal of Honor and Cooking Simulator.
(4) *Game* 1 *session*: after the training, the recorded gaming session started. The target duration was set to 10 minutes. In case of sickness, the session was interrupted. After 10 minutes, the participants could stop whenever they wanted, but in any case before 20 minutes.
(5) *Post-game SSQ* to assess the onset of cybersickness symptoms after Game 1.
(6) 15 minute *break*.
(7) *Post-break SSQ* to assess the status of the participant after the break.
(8) *Game* 2 *training*, following the same procedure.
(9) *Game* 2 *session*, with the same rules as step 4.
(10) *Final SSQ* to assess the presence of cybersickness symptoms.

Each game was considered as complete if the participant played for at least 10 minutes, excluding the training session. Only 10 users did not complete the two games due to cybersickness, and are clearly marked in the dataset.

3 DATASET DESCRIPTION

Traffic Data. The traffic data was collected using Wireshark, which stores the packets exchanged between the server and the HMD through the Universal Serial Bus (USB) protocol in Packet CAPture (PCAP) files. Given the large size of the PCAP files, between 0.6 and 1 GB/min, and the fact that the packets are encoded through a proprietary protocol [24] we extracted only the relevant information to study the network traffic, i.e., the packet time stamp, the direction of the communication (Uplink (UL)/Downlink (DL)), and the packet size.

Movement Data. The movement data was recorded using OculusMonitor[5], which was modified to use absolute timestamps from the system clock instead of relative ones. This was required to synchronize the movement and packet traffic data. After synchronizing the data with the corresponding traffic trace, we subtracted the experiment start time from both to ensure the anonymity of the participants. OculusMonitor captures the movement data as measured by the HMD and the two controllers. The movement files contain the position and orientation of the headset and controllers, expressed using quaternions relative to the initial pose, as well as continuous pressure information over a 0 to 1 scale for both trigger and grip buttons. Other data in the output file include the combination of other buttons that was pressed at any time. Each sensor recording is timestamped, and the sampling frequency is approximately 60 Hz (that is different from the frame rate, which is $\sim$ 72 Hz). The traffic and movement traces have been aligned, so that the sampling time for both is relative to the start of the acquisition.

Questionnaires. The dataset additionally includes a file for the initial survey and a file for the SSQs. The initial survey file contains a row for each participant and stores participant's ID, age, gender, previous experience in VR and in gaming in a 1 to 5 scale. The SSQ file stores four rows for each participant, corresponding to the four SSQs filled as detailed in Sec. 2. Each row contains the participant ID, the questionnaire number (from 1 to 4), the ratings for the SSQ symptoms (None, Slight, Moderate, and Severe), and optional notes.

3.1 Dataset Organization

The dataset is organized as represented in Fig. 2. It consists of two main parts: complete and incomplete experiments. The former corresponds to the data collected from 60 participants who experienced at least 10 minutes for each of the two VR games and could complete the entire experiment, according to the protocol reported in Sec. 2. The latter stores the data of 10 additional participants who felt sick during the experiment and could not complete it. The corresponding traces are thus either shorter than 10 minutes or partial, and some participants only played the first game before they withdrew. The data for each user is saved in a directory named group<G>_order<O>_user<u> according to the group<G>_order<O>_user<u>_<g>_<t> format:

- $G \in \{1, 2\}$ is the group ID, with 1 and 2 representing the two groups;
- $O \in \{1, 2\}$ indicates whether the slow game was played first (1) or second (2);
- $u \in \{0, 1, \ldots, N_{usr} - 1\}$ is the user ID, with N_{usr} corresponding to the number of users per group-order combination. $N_{usr} = 15$ for all the groups in the Complete dataset, whereas the number of users in the Incomplete part varies;
- $g \in \{\text{slow}, \text{fast}\}$ indicates whether the game is fast or slow;
- $t \in \{\text{movement}, \text{traffic}\}$ is the type of data.

[5]Available at https://communityforums.atmeta.com/t5/VR-Experiences/Oculus-Monitor-v0-2-2-27-Mar-20/td-p/708659

```
Dataset
├── Complete
│   ├── group<G>_order<O>_user<u>
│   │   └── group<G>_order<O>_user<u>_<g>_<t>.csv
│   ├── SSQ.csv
│   ├── Initial survey.csv
│   └── dataset_info.csv
└── Incomplete
    ├── group<G>_order<O>_user<u>
    │   └── group<G>_order<O>_user<u>_<g>_<t>.csv
    ├── SSQ.csv
    ├── Initial survey.csv
    └── dataset_info.csv
```

Figure 2: Dataset organization.

		Group ID	
		1	2
Game speed	Fast	Beat Saber	Medal of Honor
	Slow	Cooking Sim.	Forklift Sim.

Table 3: Mapping among Group ID, Game speed and VR application.

Both the complete and incomplete data folders additionally include a dataset information file that summarizes the content of each folder (i.e., file paths, group, order, game speed, game name, participant ID, and duration of the traffic and movement files). Table 3 reports the mapping between the IDs and the VR application names. The IDs are completely anonymized, according to the GDPR regulation for privacy protection[6].

3.2 Application Programming Interface

In the Application Programming Interface (API)[7] we provide some tutorials and examples, and a set of utility functions to read, analyze, and manipulate the data.

Specifically, for the traffic traces we implemented a script to perform the clustering of the packets containing data of the same frame. In order to do this, we considered two factors: firstly, the capacity of the USB-C link is extremely high, and secondly, the frame rate was set to 72 Hz (corresponding to an inter-frame period of about 14 ms). We then considered only downlink (i.e., from the PC to the headset) packets larger than 5 kB, as smaller packets are usually meant for audio and control purposes. Packets were grouped together if the inter-packet time in the trace was lower than a threshold value

[6]Questset is available at https://researchdata.cab.unipd.it/1179/
[7]Available at https://github.com/signetlabdei/questset

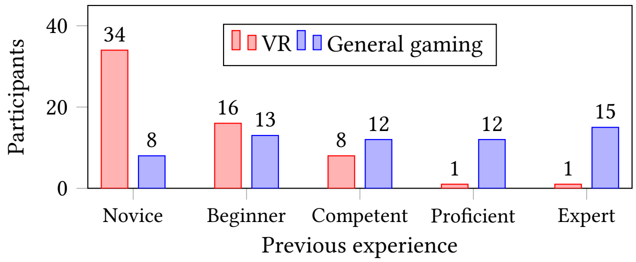


Figure 3: Participants' previous experience (considering the 60 complete traces).

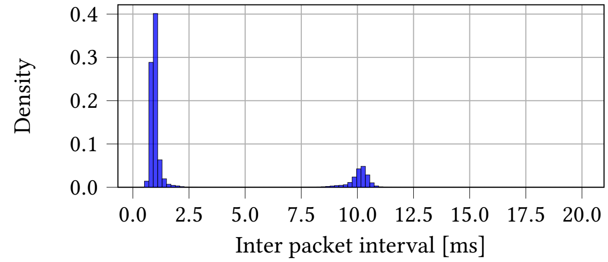
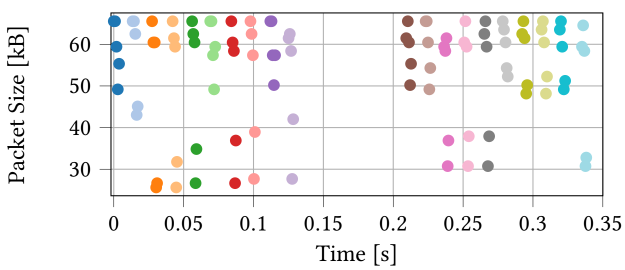
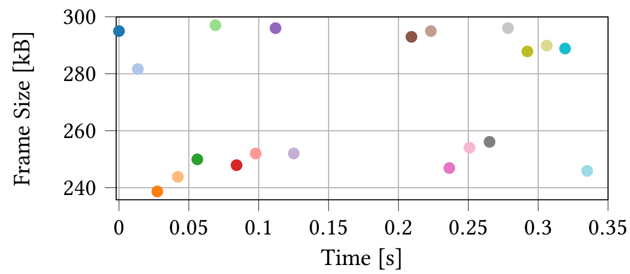


Figure 4: Bimodal distribution of the DL inter packet interval from all the traffic traces.



(a) Packet size. The marker color represents the frame that the packets are associated with. The packets are clustered based on their time proximity.



(b) Frame size. Note that the frames are spaced evenly, corresponding to the 72 frames per second (FPS), but for a wide gap between 0.13 and 0.2 seconds.

Figure 5: Downlink traffic over time in a 350 ms window for a sample Medal of Honor trace (User 0 Order 1).

of 5 ms. We also considered so-called "skipped" frames: in some cases, no packet larger than 5 kB was transmitted over multiple frame times. This phenomenon is due to the predictable nature of some frames, which do not need to be re-rendered. The script adds a frame with size 0 for every frame period without any packets.

To facilitate the analysis of the movement traces, we released the functions to convert the angular movement representation from quaternions to Euler angles, i.e., yaw, pitch, and roll, as well as the key used to read the coordinates and a test trace with a pre-defined movement sequence, which can be used to verify the correctness of movement interpretation code.

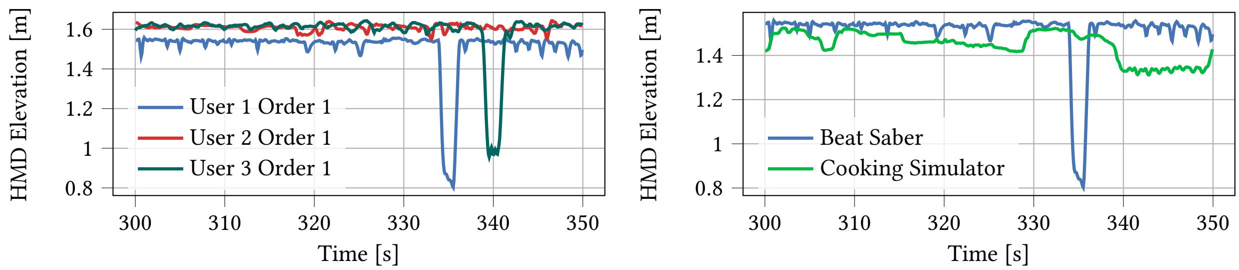
4 PRELIMINARY ANALYSIS

Initial survey. The participants who completed the test were aged between 18 and 35 years, with an average of 26.38 (±3.47) years. They had various levels of previous experience both in terms of general gaming and VR, but the majority of the participants were novice VR users, as reported in Section 3.2.

Traffic Data. As anticipated, to analyze the video stream traffic we filtered the data by only keeping the DL packets with a minimum packet size of 5 kB. We removed the size of the USBPcap pseudoheader (27 B) from each packet to consider only the payload data. Each frame is divided into multiple packets, and, as shown in Section 3.2, the distribution is bimodal, with a higher density of samples around 1 ms and 10 ms. This is due to the fact that each frame transmitted from the server to the HMD is fragmented into multiple packets, that are transmitted within a short time window (1 ms). The distribution component around 10 ms corresponds to the time duration between the last packet of a frame and the first packet of the subsequent frame.

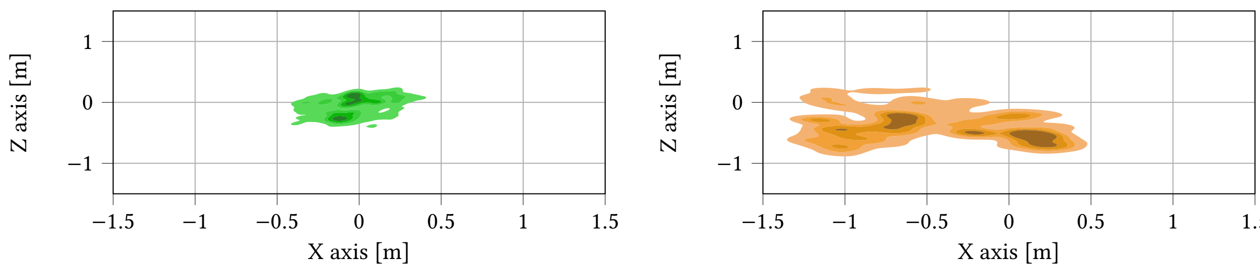
To clarify this phenomenon, Fig. 5 depicts a 350 ms window of a traffic trace from Medal of Honor. Specifically, Fig. 5a shows the size of individual packets. We can observe that the packets are clustered in short bursts, which correspond to frames being fragmented into multiple packets. This is due to the maximum packet size of 65508 B defined by the USB-C standard. To illustrate this, we represent the different clusters with different color, and report the frames with the corresponding color in Fig. 5b, obtained by aggregating the clustered packets. Additionally, we can observe that the inter-frame interval is aligned with the frame rate of the video rendering (which is $\sim$ 72 Hz). However, there is a wider gap between 0.13 and 0.2 s. Indeed, we observed frequent gaps of about 70 ms during which no significant frame data is transmitted. This corresponds to the "skipped" frames we discussed above.

Movement Data. From the movement traces, we extracted the position of the HMD over time. Fig. 6a shows the elevation of the HMD over a 50-second window for 3 users playing Beat Saber. As expected, the HMD elevation exhibits small variations, since the users are mostly standing in a stationary position during gameplay. However, at 335s, user 1 crouched down to avoid an in-game obstacle, and the same occurred for user 3 at 340s. Fig. 6b shows the elevation of the HMD over time for user 1 while playing Beat Saber and Cooking Simulator VR. In Cooking Simulator VR, the movement of the HMD is less repetitive because users are required to perform a variety of tasks, such as moving around the kitchen, gathering ingredients, and leaning in to reach objects on tables and shelves.

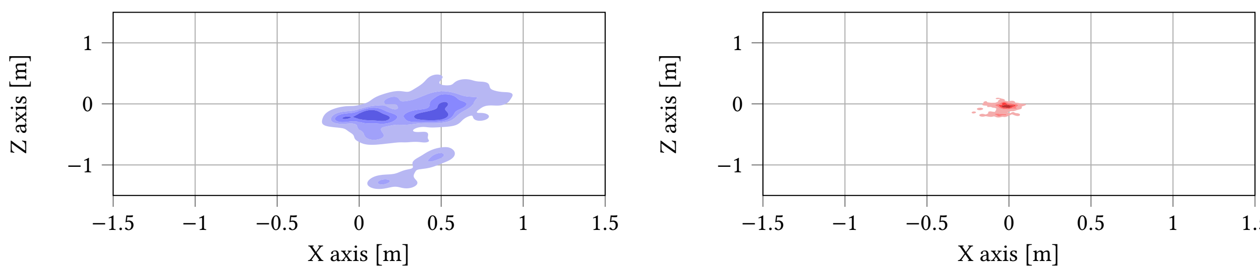


(a) 3 users playing Beat Saber. **(b) User 1 Order 1 playing Beat Saber and Cooking Simulator.**

Figure 6: Elevation of the HMD over time in a 50 s window, for 3 different users playing Beat Saber (Fig. 6a) and for the same user playing Beat Saber and Cooking Simulator (Fig. 6b).



(a) Beat Saber (User 1 Order 1). **(b) Cooking Simulator (User 1 Order 1).**



(c) Medal of Honor (User 5 Order 1). **(d) Forklift Simulator (User 5 Order 1).**

Figure 7: User movement heatmap on the horizontal plane (X and Z coordinates).

On the other hand, Fig. 7 depicts the position of the HMD in the horizontal plane and the user's movement during the first 600 s of a session of the 4 games. The heatmap shows that Cooking Simulator VR and Medal of Honor require more physical movement from the user compared to Beat Saber, where the user primarily stands in a stationary position and moves their arms to cut the cubes. Forklift Simulator is a seated game, which restricts the movement of the HMD to a few centimeters.

5 CONCLUSIONS

In this work, the Questset dataset has been presented. The dataset is composed of more than 40 hours of recording and includes VR traffic and movements traces as well as users' general information and cybersickness feedback. The data have been collected through the involvement of 70 participants who played commercial games using a Meta Quest 2 headset.

Due to the size of the dataset and the type of recorded information, Questset is a key enabler for the analysis of VR network traffic, user movements, and QoE. It can be employed for characterizing VR traffic for network optimization and for investigating users' behavior and cybersickness onset. Moreover, although these topics are usually studied separately, a joint analysis could allow the two communities to gain useful and novel insights into their relation. For this reason, the dataset contributes to addressing the challenges which hinder VR evolution and opens new research directions.

ACKNOWLEDGMENTS

This work was partially supported by the National Institute of Standards and Technology (NIST) under award no. 60NANB21D127 ("Modeling VR/AR traffic to create solutions for next-generation networks"), and by the European Union under the Italian National Recovery and Resilience Plan (NRRP), as part of the NextGenerationEU framework, partnership PE_0000001 "RESTART" on telecommunications of the future.

REFERENCES

[1] ATIS. 2023. 6G Roadmap for Vertical Industries. White paper.

[2] Polona Caserman, Augusto Garcia-Agundez, Alvar Gámez Zerban, and Stefan Göbel. 2021. Cybersickness in current-generation virtual reality head-mounted displays: systematic review and outlook. *Virtual Reality* 25, 4 (2021), 1153–1170.
[3] Federico Chiariotti, Matteo Drago, Paolo Testolina, Mattia Lecci, Andrea Zanella, and Michele Zorzi. 2023. Temporal Characterization and Prediction of VR Traffic: A Network Slicing Use Case. *IEEE Transactions on Mobile Computing* (2023).
[4] Xavier Corbillon, Francesca De Simone, and Gwendal Simon. 2017. 360-degree video head movement dataset. In *8th Multimedia Systems Conference (MMSys)*. ACM, 199–204.
[5] Jiong Dong, Kaoru Ota, and Mianxiong Dong. 2022. Why VR games sickness? an empirical study of capturing and analyzing VR games head movement dataset. *IEEE MultiMedia* 29, 2 (2022), 74–82.
[6] Kara J Emery, Marina Zannoli, James Warren, Lei Xiao, and Sachin S Talathi. 2021. OpenNEEDS: A dataset of gaze, head, hand, and scene signals during exploration in open-ended VR environments. In *Symposium on Eye Tracking Research and Applications (ETRA)*. ACM.
[7] Stephan Fremerey, Ashutosh Singla, Kay Meseberg, and Alexander Raake. 2018. AVtrack360: An open dataset and software recording people's head rotations watching 360° videos on an HMD. In *9th Multimedia Systems Conference (MMSys)*. ACM, 403–408.
[8] S Ishihara. 1917. *Tests for Colour-Blindness*. Handaya, Tokyo.
[9] ITU-R. 2023. Framework and overall objectives of the future development of IMT for 2030 and beyond. Rec. ITU-R M.2160.
[10] R. S. Kennedy, N. E. Lane, K. S. Berbaum, and M. G. Lilienthal. 1993. Simulator Sickness Questionnaire: An Enhanced Method for Quantifying Simulator Sickness. *The International Journal of Aviation Psychology* 3, 3 (1993), 203–220.
[11] Sebastian Knorr, Cagri Ozcinar, Colm O Fearghail, and Aljosa Smolic. 2018. Director's cut: a combined dataset for visual attention analysis in cinematic VR content. In *15th European Conference on Visual Media Production (CVMP)*. ACM.
[12] Mattia Lecci, Matteo Drago, Andrea Zanella, and Michele Zorzi. 2021. An open framework for analyzing and modeling XR network traffic. *IEEE Access* 9 (2021), 129782–129795.
[13] Kuan-Yu Lee, Jia-Wei Fang, Yuan-Chun Sun, and Cheng-Hsin Hsu. 2023. Modeling Gamer Quality-of-Experience Using a Real Cloud VR Gaming Testbed. In *5th International Workshop on Immersive Mixed and Virtual Environment Systems (MMVE)*. ACM, 12–17.
[14] Chen Li, Mai Xu, Xinzhe Du, and Zulin Wang. 2018. Bridge the gap between VQA and human behavior on omnidirectional video: A large-scale dataset and a deep learning model. In *26th International Conference on Multimedia (MM)*. ACM, 932–940.
[15] Yen-Chun Li, Chia-Hsin Hsu, Yu-Chun Lin, and Cheng-Hsin Hsu. 2020. Performance measurements on a Cloud VR gaming platform. In *1st Workshop on Quality of Experience in Visual Multimedia Applications (QoEVMA)*. ACM, 37–45.
[16] Wen-Chih Lo, Ching-Ling Fan, Jean Lee, Chun-Ying Huang, Kuan-Ta Chen, and Cheng-Hsin Hsu. 2017. 360° video viewing dataset in head-mounted virtual reality. In *8th Multimedia Systems Conference (MMSys)*. ACM, 211–216.
[17] Hatem M Marey, Noura A Semary, and Sameh S Mandour. 2015. Ishihara electronic color blindness test: An evaluation study. *Ophthalmology Research: An International Journal* 3, 3 (2015), 67–75.
[18] Afshin Taghavi Nasrabadi, Aliehsan Samiei, Anahita Mahzari, Ryan P McMahan, Ravi Prakash, Mylène CQ Farias, and Marcelo M Carvalho. 2019. A taxonomy and dataset for 360° videos. In *10th Multimedia Systems Conference (MMSys)*. ACM, 273–278.
[19] Marina Polupanova. 2023. VR Traffic Dataset on Broad Range of End-User Activities. *Data* 8, 8 (2023), 132.
[20] Yeongil Ryu and Eun-Seok Ryu. 2021. Overview of motion-to-photon latency reduction for mitigating VR sickness. *KSII Transactions on Internet and Information Systems (TIIS)* 15, 7 (2021), 2531–2546.
[21] Nathan C Sepich, Angelica Jasper, Stephen Fieffer, Stephen B Gilbert, Michael C Dorneich, and Jonathan W Kelly. 2022. The impact of task workload on cybersickness. *Frontiers in Virtual Reality* 3 (2022), 943409.
[22] Ashutosh Singla, Stephan Fremerey, Werner Robitza, Pierre Lebreton, and Alexander Raake. 2017. Comparison of subjective quality evaluation for HEVC encoded omnidirectional videos at different bit-rates for UHD and FHD resolution. In *25th International Conference on Multimedia (MM) Workshops*. ACM, 511–519.
[23] Huawei Technologies. 2020. *Intelligent world 2030: building a fully connected, intelligent world*. Technical Report.
[24] Rahmadi Trimananda, Hieu Le, Hao Cui, Janice Tran Ho, Anastasia Shuba, and Athina Markopoulou. 2022. OVRseen: Auditing Network Traffic and Privacy Policies in Oculus VR. In *Proceedings of the 31st USENIX Security Symposium (USENIX Security 22)*.
[25] Jialin Wang, Hai-Ning Liang, Diego Monteiro, Wenge Xu, and Jimin Xiao. 2022. Real-time prediction of simulator sickness in virtual reality games. *IEEE Transactions on Games* (2022).
[26] Séamas Weech, Jessy Parokaran Varghese, and Michael Barnett-Cowan. 2018. Estimating the sensorimotor components of cybersickness. *Journal of Neurophysiology* 120, 5 (2018), 2201–2217.
[27] James P Wilmott, Ian M Erkelens, T Scott Murdison, and Kevin W Rio. 2022. Perceptibility of Jitter in Augmented Reality Head-Mounted Displays. In *International Symposium on Mixed and Augmented Reality (ISMAR)*. IEEE, 470–478.
[28] Chenglei Wu, Zhihao Tan, Zhi Wang, and Shiqiang Yang. 2017. A Dataset for Exploring User Behaviors in VR Spherical Video Streaming. In *8th Multimedia Systems Conference (MMSys)*. ACM, 193–198.
[29] Mai Xu, Chen Li, Yufan Liu, Xin Deng, and Jiaxin Lu. 2017. A subjective visual quality assessment method of panoramic videos. In *International Conference on Multimedia and Expo (ICME)*. IEEE, 517–522.
[30] Mai Xu, Yuhang Song, Jianyi Wang, MingLang Qiao, Liangyu Huo, and Zulin Wang. 2018. Predicting head movement in panoramic video: A deep reinforcement learning approach. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 41, 11 (2018), 2693–2708.
[31] Yingxue Zhang, Yingbin Wang, Feiyang Liu, Zizheng Liu, Yiming Li, Daiqin Yang, and Zhenzhong Chen. 2018. Subjective panoramic video quality assessment database for coding applications. *IEEE Transactions on Broadcasting* 64, 2 (2018), 461–473.
[32] Sihao Zhao, Hatem Abou-zeid, Ramy Atawia, Yoga Suhas Kuruba Manjunath, Akram Bin Sediq, and Xiao-Ping Zhang. 2021. Virtual reality gaming on the cloud: A reality check. In *Global Communications Conference (GLOBECOM)*. IEEE.