# Behavioural Analysis in a 6-DoF VR System: Influence of Content, Quality and User Disposition

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## ABSTRACT

This work presents an explorative behavioural analysis of users navigating in an immersive space aimed at enabling the next-generation multimedia systems. Our main goal is to understand how the user experience of immersive content with 6-Degrees-of-Freedom (DoF) is affected not only by the visual content and its quality but also by the disposition of the user. We based our investigations on traditional statistical metrics, on techniques that have been already used for 6-DoF, as well as adapted 3-DoF tools to be used in this new context. We show the limitation of each metric in giving a complete interpretation of user behaviour, and we draw insights on important factors to be considered when analysing and predicting navigation trajectories. Specifically, we have noticed in our behavioural investigations that the user disposition plays an important role in the way of interacting with the immersive content. This opens the gate to user profiles (i.e., a collection of key information that describes the behavioural features of a single or group of users) that would be beneficial for different purposes in future immersive applications such as enabling new modalities for live streaming services optimised per user profiles but also for user-based quality assessment methods.

## CCS CONCEPTS

• **Human-centered computing** → **User studies**; **Mixed / augmented reality**; **Virtual reality**; • **Information systems** → *Multimedia streaming*.

## KEYWORDS

Volumetric content, Point Cloud, User Behavioural Analysis, 6-DOF, Virtual Reality

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## 1 INTRODUCTION

Immersive Virtual Reality (VR), which allows people to be connected and feel present despite them being remote, has been recognised as one of the digital technologies that will rocket fuel our economy [16]. This has been even more amplified by the recent COVID-19 outbreak, during which immersive reality has been identified among the key technologies helping people overcome social boundaries [3], as well as providing new opportunities for businesses such as entertainment and live events [4, 10]. VR allows users to experience multimedia content in an immersive way, interacting with objects and the surrounding environment, as well as communicating and experiencing content with other users, which has been shown to increase the sense of presence and connectedness [12]. This level of immersiveness and realism offered in virtual realities, however, comes with many new open challenges: virtual interactions and photorealistic representations require both computational and bandwidth overhead for transmission and rendering [14, 23, 29]. In particular, due to their interactivity, each user will have a unique experience. The next-generation immersive multimedia systems need to understand, support, and harness such heterogeneity. Consequently, fundamentally new solutions are required to tailor the whole immersive experience to the final interactive users.

To enable such envisioned direction of future multimedia applications, it is fundamental to understand how users interact in immersive systems (*i.e.*, 3- and 6-Degrees-of-Freedom (DoF)) and thus, to be able to anticipate their behaviour [8, 18, 27]. In this regard, progress has been made in analysing and predicting navigation in 3-DoF , where the interaction is limited to changes in viewing angles. In particular, the way in which users interact in this type of system has been analysed in terms of general metrics such as angular velocity, frequency of fixation, heatmaps, and mean exploration angles [5, 6, 11, 13, 32]. While these traditional tools provide a general understanding of user behaviour, they neglect to offer deep insights into navigation dynamics, such as how much viewers interact in harmony among themselves. Furthermore, specific tools have been proposed, aimed at identifying behaviour similarities among users and across immersive content [17, 19]. On the other hand, understanding user behaviour in more challenging systems, such as 6-DoF spaces, where interactions are extended to spatial movements within the virtual space, has not been extensively considered in the literature yet. User behaviour in 6-DoF has been analysed in terms of completion time [15, 26], visual attention [1], total angular distance [25], average floor position [2], viewing angle and distance from the displayed content [31], the ratio of frames viewed while moving [20], as well as pairwise distance [30]. However, all these measures only consider one particular aspect of user behaviour, and therefore, do not offer a holistic way of representing and characterising user behaviour. Even more sophisticated measures, which aim at grouping users together based on common behaviour, only consider one object of attention, and still present limitations in how such behaviour is modelled [21].

In this paper, we conduct an exploratory behavioural analysis in 6-DoF immersive spaces aimed at detecting key aspects that influence the interaction in immersive environments with 6-DoF. In particular, our goal is to better understand how the way of navigating is affected by the content, its visual quality and the disposition of each user. To this aim, we consider not only more traditional behavioural metrics but also tools that have been specifically used for 6-DoF , as well as adapting 3-DoF metrics to be used in this new context. Our proposed analysis is based on a publicly available dataset of navigation trajectories collected in a 6-DoF VR scenario during a visual quality assessment study [25]. It presents a collection of navigation trajectories collected from the same user across different volumetric content and visual quality, allowing us insightful analysis. Specifically, a first investigation is carried out across all volumetric content, based on metrics such a distribution of viewing position and direction. We then narrow our focus to understand whether the perceived quality of the content under exam has any impact on the viewing behaviour, using metrics such as exploratory velocity, and total viewing time. Subsequently, we aim to characterise the behaviour of each user, considering their consistency in terms of entropy, distance, and change in viewing direction. Finally, we perform a clustering analysis to see whether the behaviour of each user would fall into similar patterns across content and qualities.

In conclusion, the main research questions we aim at answering in this study are the following:

- How does the user behaviour change based on the dynamism of volumetric content?
- Does the volumetric content quality have an impact on the user navigation?
- Are users consistent in their navigation across different content (and quality)?
- Which behavioural metric provides a more complete interpretation of the user behaviour in 6-DoF?

By answering these questions, our exploratory analysis provides key insights into the open problem of behavioural analysis in a 6-DoF system. As main outcomes, we indeed show a relevant influence on the way of navigating within a 6-DoF system given by the disposition of each user rather than the characteristics of the observed volumetric content (*i.e.*, its dynamics and visual quality); we also underline the importance of having extensive collections of 6-DoF navigation trajectories and holistic metrics capable of characterising the behaviour of users in its entirety, such as in terms of spatial and viewing movements but also personal thinking disposition.

## 2 PROPOSED DATA ANALYSIS SETTINGS

In this section, we define our proposed behavioural analysis in a 6-DoF VR system. Specifically, we describe the analysed navigation dataset and then, the proposed approach of behavioural analysis.

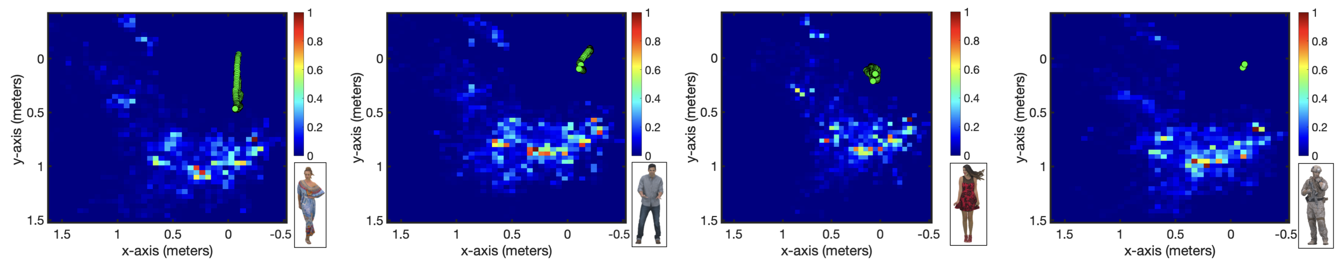
### 2.1 User Navigation Dataset

Datasets with navigation trajectories collected in a 6-DoF VR environment are still very limited. Thus, we based our investigations on one of the few publicly available datasets presented in [25]. The dataset presents navigation trajectories of 27 users participating in a visual quality assessment study in VR: the interaction data are collected not only across a group of viewers but also from the same user and across different content qualities. For the study, four dynamic point cloud sequences were employed [7], namely *Long dress* (PC 1), *Loot* (PC 2), *Red and black* (PC 3) and *Soldier* (PC 4). Each sequence was distorted at four different bit rate levels with two compression algorithms: the MPEG anchor codec proposed in [9], and the upcoming MPEG standard V-PCC [23]. In the following, we name the two compression codecs as $C1$ and $C2$, respectively, while the bit rate levels, from low to high quality, as $R1$ to $R4$. Hidden references ($R0$) were additionally employed in the test, for a total of 36 stimuli. A single volumetric content was rendered in the VR scene, and users were asked to focus on the volumetric content for the entire session and to rate its visual quality before moving to the next content. Specifically, each participant was free to decide how long to display the same visual content.

### 2.2 Methodology

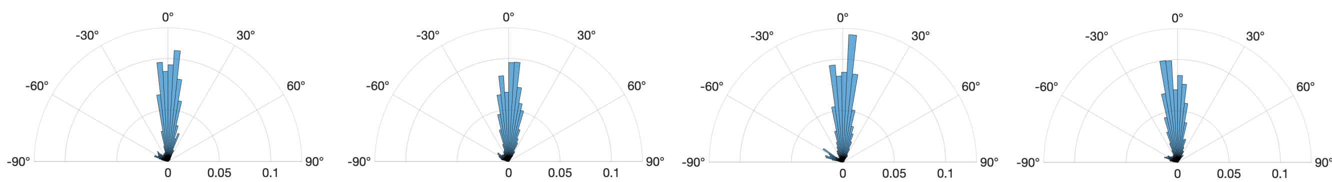
In our behavioural analysis, we follow two main lines of investigation: one general aimed at detecting how the volumetric content, in terms of its dynamic and quality, influences the way in which users navigate in the VR environment; the second is instead focused on detecting consistency in the behaviour of a single user.

**Behavioural analysis across content and quality.**
Inspired by similar behavioural analysis frameworks presented in [18, 31] but related to different conditions, such as 3-DoF VR and 6-DoF Augmented Reality (AR) systems, we start our study by adopting well-known and general metrics. In detail, we analyse the user behaviour via visual and quantitative tools, namely the heatmap of user position on the floor (plane $XY$) and the distribution of viewing direction per user across the different volumetric content. We also show the relative distance that each user took on average with the displayed sequence. Then, we move a step forward considering how the user behaviour changes based on the perceived quality of the content. We do this by displaying the distribution of spatial velocity on the floor and the total time spent in each quality session per content. While these aforementioned behavioural investigations based on statistical tools or heatmaps provide a general understanding of the users' behaviour, they fail in detecting deep insights into the dynamics of the navigation. Specifically, these metrics are highly informative about the spatial behaviour (from which position on the floor and viewing direction do users tend to look at the content) but only partially informative about the temporal behaviour (we can deduce how much change the user behaviour, but not really if viewers are interacting similarly over




(a) Floor Heatmap *Long dress* (PC 1) (b) Floor Heatmap *Loot* (PC 2) (c) Floor Heatmap *Red and Black* (PC 3) (d) Floor Heatmap *Soldier* (PC 4)

**Figure 1: Spatial distribution of user while navigating Human Body Point Clouds [7] content used in the collection of a public available dataset presented in [25]. The centroid position of the volumetric content is represented by a sequence of green points on the floor.**



(a) Viewing direction distribution in PC 1 (b) Viewing direction distribution in PC 2 (c) Viewing direction distribution in PC 3 (d) Viewing direction distribution in PC 4

**Figure 2: Distribution of user's viewing direction in the horizontal plane. The volumetric sequence was placed at the center of the system (*i.e.*, viewing direction equal to 0°).**

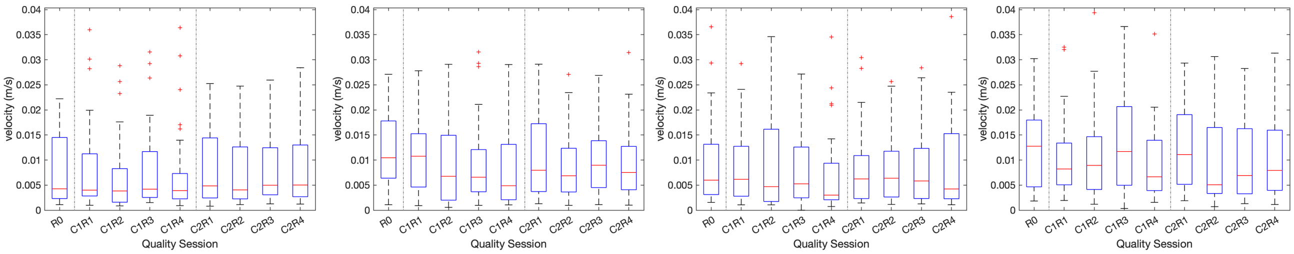
time). For instance, the heatmap allows us to identify areas of the virtual floor (plane $XY$) mostly attended by viewers within a time interval but neglects the temporal information by aggregating data over time into a single picture. This might lead to loss of useful information, especially in scenarios with dynamic content such as in our case.

**Behavioural analysis across users.**
In order to understand if users are consistent in their navigation over time or to detect viewers who are navigating in a similar way, without neglecting the temporal information, we continue our investigations adopting trajectory-based tools. Similarly to the work proposed in [19], we carry out our second line of behavioural analysis exploiting tools from information theory such as actual entropy, which quantify randomness and uncertainty in mobility trajectories [24]. In particular, the actual entropy is low for users that experience "repetitive" behaviour (trajectories) over time, leading to promising highly predictable users. Specifically, we applied this tool to the navigation movements of users on the virtual floor. Given a generic 6-DoF user $i$ displaying a volumetric content of duration $T$, we formally define the navigation trajectory on the floor as $[(x,y)^i_1, (x,y)^i_2, \dots, (x,y)^i_T]$ where $(x,y)^i_t$ is the position on the floor (plane $XY$) of the user $i$ at a given timestamp $t$. We then compare the actual entropy with the speed in exploring the virtual environment, and viewing direction changes. Finally, we perform a clustering analysis to discover general trends of users navigation and, consistency in terms of displayed content across perceived visual qualities. We applied the state-of-the-art clustering developed for 3-DoF user [17] following the approach proposed in [22] to adapt it to our scenario. Differently from the previous works which use this tool to compare the navigation of different viewers [18, 22], we detect clusters among the navigation trajectories experienced from a single user for the same volumetric content but across the different quality stimuli. We adopt as pairwise similarity metric the viewport overlap ratio among the elements to be analysed. More formally, given two navigation trajectories experienced by a generic user $i$ while displaying the same volumetric content at quality $r$ and $q$ respectively, we denote their displayed viewport as $\mathcal{S}^{(i,r)}_t$ and $\mathcal{S}^{(i,q)}_t$. Thus, their overlap ratio is defined as the cardinality of the set of points of the volumetric content falling within the intersection of the two viewport, $\mathcal{S}^{(i,r)}_t \cap \mathcal{S}^{(i,q)}_t$. Two users are then considered similar if their pairwise overlap ratio is above a given threshold (in our case equal to 0.75). This approach allows us to assess in an objective way users similarities across the different quality sessions experienced by the same viewers. In fact, we aim at detecting the consistency in the user behaviour, and understanding how the user disposition influences the way of navigating within an immersive environment.

# 3 EXPERIMENTAL RESULTS

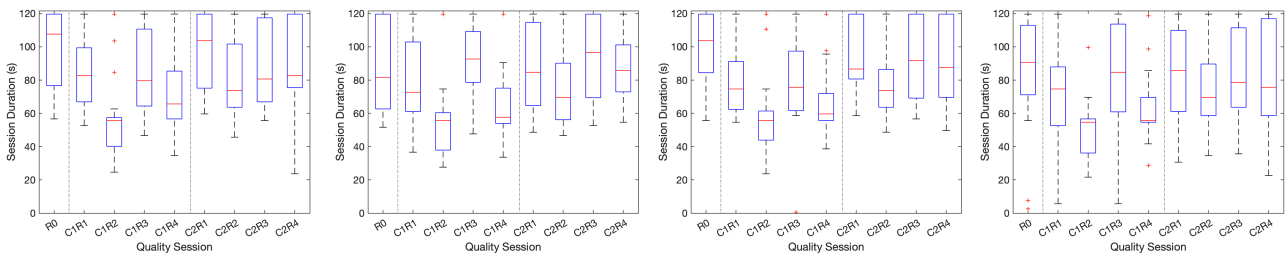
## 3.1 Behavioural Analysis Across Content and Quality

We now present our results of a more general analysis of users movements within the virtual environment. Here, the key novelty is to investigate at first the user behaviour with respect to the volumetric sequence and its dynamics only, then also to its visual quality. This analysis leads to the following observations (supported in the remaining of the section): dynamic sequences bring greater




(a) PC1 (b) PC2 (c) PC3 (d) PC4

**Figure 3: Distribution per volumetric content of the exploratory velocity on the floor (plane $XY$) across quality stimuli.**




(a) PC1 (b) PC2 (c) PC3 (d) PC4

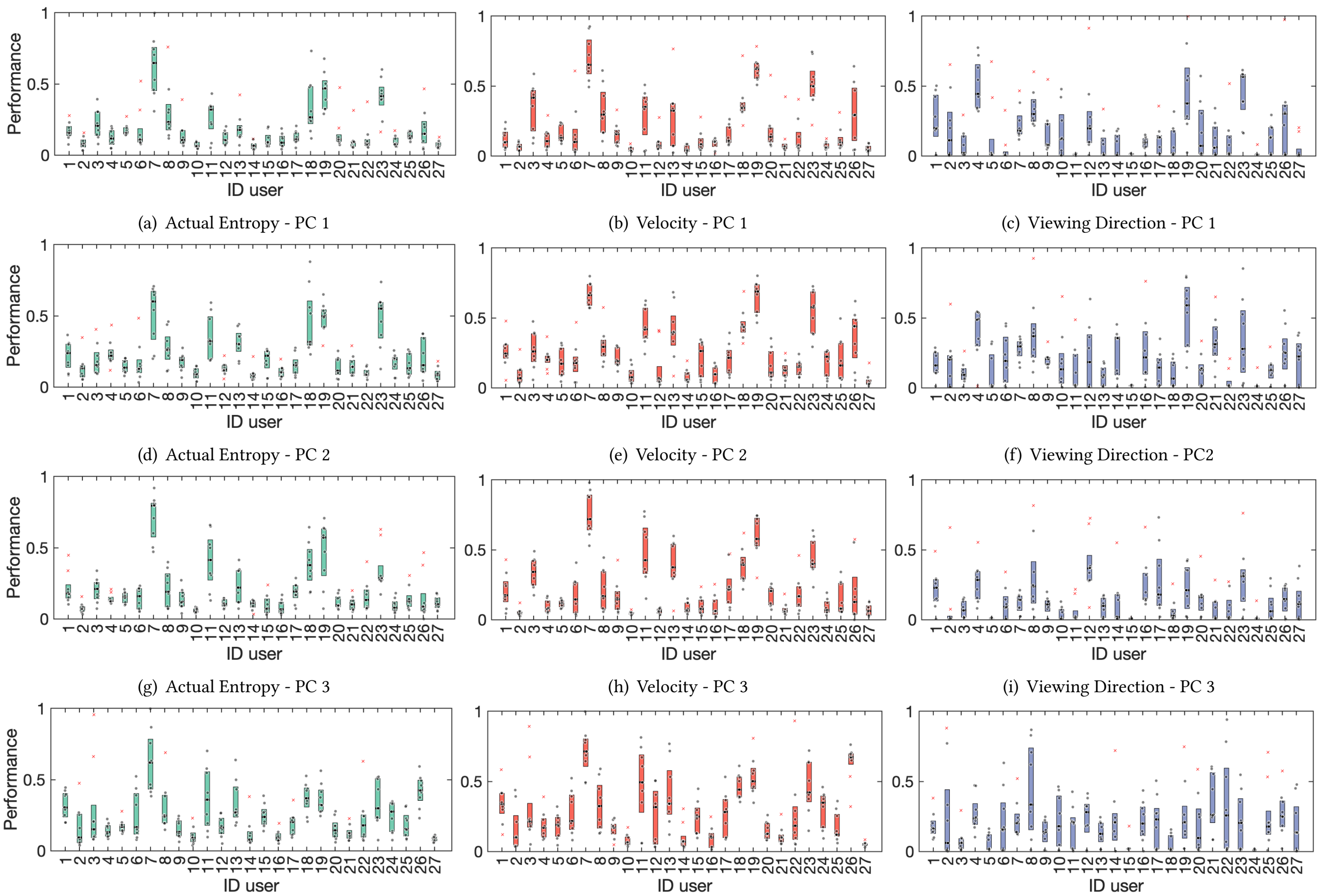
**Figure 4: Distribution per volumetric content of the interactive time spent in each quality session across user.**

**Table 1: Mean relative distance per user (ID) on the floor with each volumetric content (PC1-4). The values are in meters.**

| ID | PC1 | PC2 | PC3 | PC4 | ID | PC1 | PC2 | PC3 | PC4 |
|---|---|---|---|---|---|---|---|---|---|
| 01 | 1.56 | 1.23 | 1.28 | 1.23 | 15 | 1.19 | 1.14 | 0.99 | 1.10 |
| 02 | 1.69 | 1.49 | 1.45 | 1.43 | 16 | 1.55 | 1.32 | 1.36 | 1.33 |
| 03 | 1.34 | 1.20 | 1.19 | 1.20 | 17 | 1.15 | 1.00 | 0.98 | 0.99 |
| 04 | 1.14 | 1.00 | 0.93 | 0.97 | 18 | 1.28 | 1.20 | 1.15 | 1.15 |
| 05 | 1.13 | 0.92 | 0.98 | 0.93 | 19 | 1.40 | 1.26 | 1.17 | 1.18 |
| 06 | 1.70 | 1.46 | 1.48 | 1.51 | 20 | 1.20 | 1.08 | 1.05 | 1.08 |
| 07 | 1.27 | 1.11 | 1.08 | 1.10 | 21 | 1.08 | 0.94 | 0.92 | 0.92 |
| 08 | 1.42 | 1.24 | 1.36 | 1.32 | 22 | 1.45 | 1.19 | 1.28 | 1.20 |
| 09 | 1.40 | 1.13 | 1.17 | 1.14 | 23 | 1.21 | 1.03 | 1.00 | 1.04 |
| 10 | 1.29 | 1.12 | 1.14 | 1.11 | 24 | 1.73 | 1.68 | 1.47 | 1.54 |
| 11 | 1.25 | 1.06 | 1.16 | 1.10 | 25 | 1.58 | 1.30 | 1.33 | 1.32 |
| 12 | 1.61 | 1.31 | 1.42 | 1.27 | 26 | 1.41 | 1.15 | 1.26 | 1.07 |
| 13 | 1.23 | 1.02 | 1.02 | 1.00 | 27 | 1.59 | 1.37 | 1.39 | 1.36 |
| 14 | 1.51 | 1.33 | 1.34 | 1.30 | All | **1.38** | 1.20 | 1.20 | *1.18* |

dispersion in exploratory movements; the visual quality of the content barely affects the way of navigating while compromises the interaction time which increases with the quality.

Figure 1 shows per each content the heatmap of the most visited location over time computed by aggregating all the position data on the floor collected in the analysed dataset. The volumetric content is initially placed approximately at the center of the floor plane, *i.e.*, (0.01,-0.04) on the $XY$ plane. Since the sequences used in the analysed navigation collection are dynamic, we also represent in the figure their position over time with a trajectory of green dots. It can be noticed that the first two sequences, PC 1 and 2, are the more dynamic in contrast with the latest two which mainly stay in the proximity of their initial position. Moreover, PC 3 is moving around itself while PC 4 stays in the same position. Complementary results are given in Figure 2 by the distribution of the user viewing direction in the horizontal plane $XY$ per each volumetric content. The origin of the system, where the volumetric content is initially positioned, correspond to viewing direction 0. Figure 1 shows that in general users prefer visualising all the sequences from a frontal position. This insight is also reinforced by Figure 2 which proves that the most attended viewing direction across content is towards the point cloud (*i.e.*, viewing direction equal to 0). We can also notice that PC 3 is the least explored content, probably due to the fact that the sequence is already moving around itself, giving the possibility to the users to see all its details from a static position. The shadow of the user positions across time in Figure 1 (c) is indeed quite compact in contrast with the other three content represented in Figure 1 (a, b, d). In addiction, Figure 2 (c) shows a more consistent attended viewing direction by participants in comparison with the others. On the contrary, the more dynamic sequences PC 1 and 2 led the participants to move more around them and thus, to display the content from different perspective. To be noted, even if less dynamic, PC 4 was the most favourite sequence by participants for the clear facial expressions and slower movements, as reported in [25]. In this case, users tend to display the volumetric point cloud from a very close position. In fact, Table 1 reports the mean values of relative distance that each user took over time with the displayed content. We can notice that on average participants were more distant from PC 1 (*i.e.*, the most dynamic sequence) with respect to the less dynamic PC 4. The two remaining content, PC 2 and 3,




(a) Actual Entropy - PC 1
(b) Velocity - PC 1
(c) Viewing Direction - PC 1
(d) Actual Entropy - PC 2
(e) Velocity - PC 2
(f) Viewing Direction - PC2
(g) Actual Entropy - PC 3
(h) Velocity - PC 3
(i) Viewing Direction - PC 3
(j) Actual Entropy - PC 4
(k) Velocity - PC 4
(l) Viewing Direction - PC 4

**Figure 5: Behavioural analysis across users per each volumetric content in terms of actual entropy of the navigation trajectory on the floor (plane $XY$), exploratory velocity and changes of the viewing direction. All the results are normalised to be easily compared.**

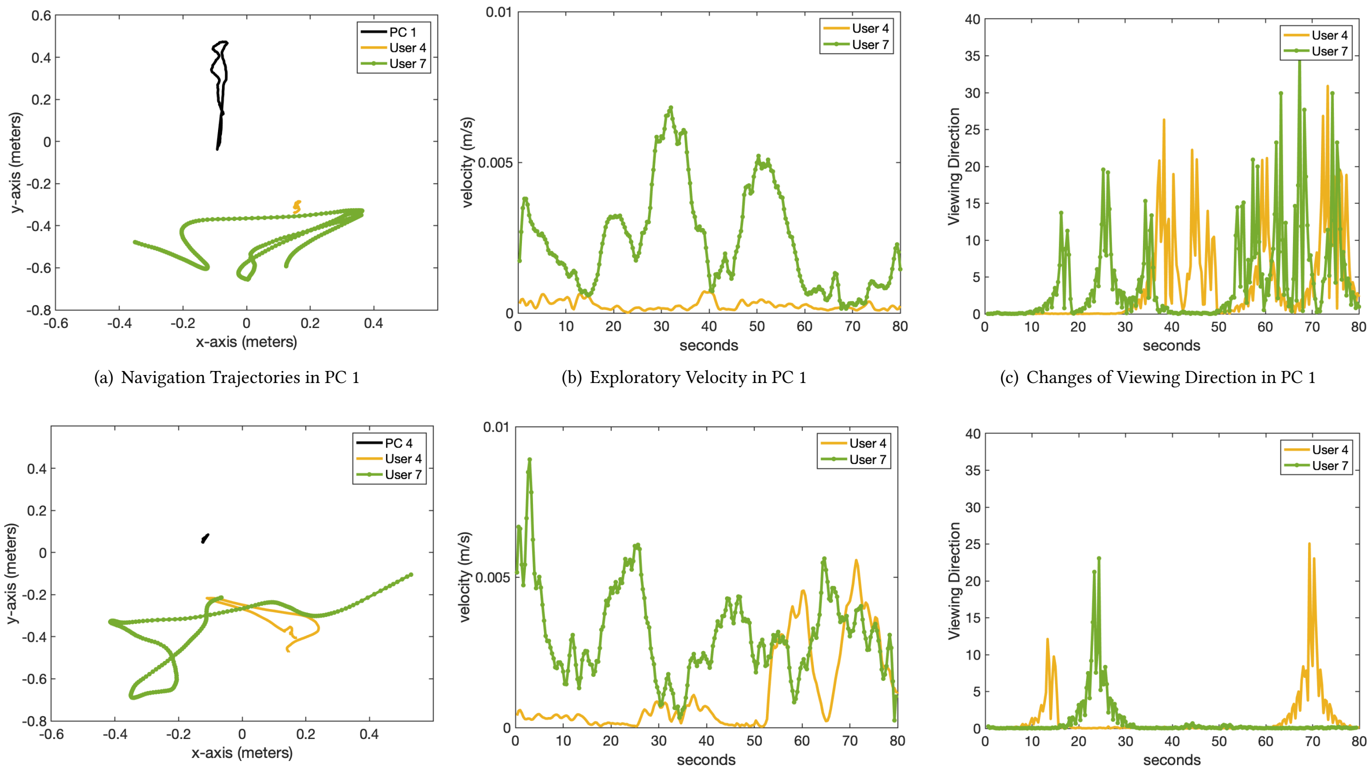
were instead experienced on average by a similar relative distance.

We now move a step forward in the analysis and check how the user behaviour changes based on the perceived quality of the content. To this aim, we investigate in Figure 3 how the content quality affects the immersive experience in terms of exploratory velocity on the floor. As a result, the total averaged velocity shows that no visible trend is present for different content stimuli. To further validate this observation, we also compute the Pearson Correlation Coefficient (PCC), a linearity correlation coefficient. In this case, the PCC is always below 0.6 in all the couples of stimuli and on average equal to 0.5772±0.0057, showing a roughly linear correlation among the different quality levels. As described in Section 2.1, since the navigation trajectories have been collected during a quality assessment study, each participant was free to decide how long to display a given representation before scoring the perceived quality and move to the next stimulus. Figure 4 depicts the distribution of the time spent by users per each stimulus across volumetric content. A clear trend can be observed: the time that users spend in displaying the different versions of the same content increases with the quality. This is particular evident for versions encoded with *C2* (*i.e.*, the upcoming MPEG standard V-PCC). Except for PC 2 in Figure 4 (b), the stimulus experienced for the longest time is indeed the reference. A similar correlation between the interaction time and the quality of the displayed representation was also detected in user while performing subjective quality assessment of light field content [28].

## 3.2 Behavioural Analysis Across Users

While the previous analysis allowed us to characterise the user behaviour in terms of spatial displacement and generalise their exploratory movements across content and visual quality, we are now interested in extending this analysis towards a deeper comparison for the same viewer across different content.

Figure 5 in the first column shows the distribution of the actual entropy evaluated as described in Section 2.2 per each user across the volumetric content. We also take into consideration the velocity of exploratory movements on the floor (Figure 5 second column)

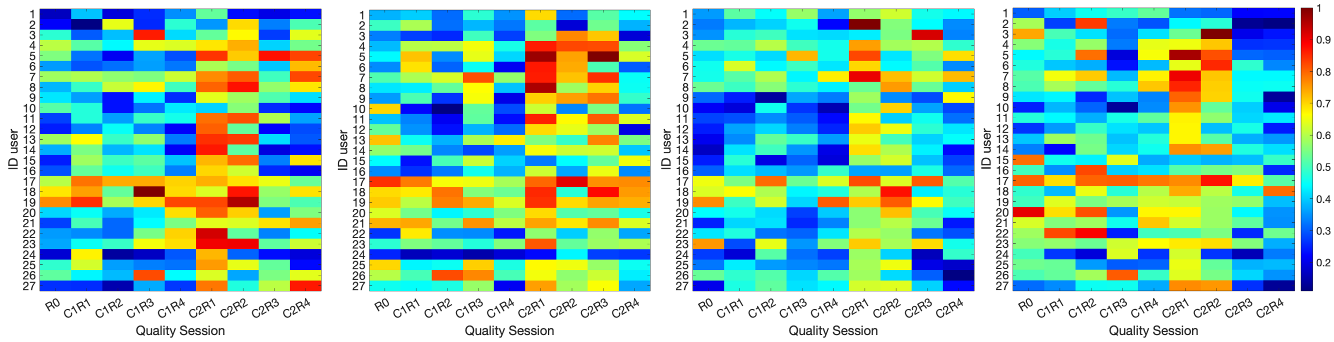



(a) Navigation Trajectories in PC 1
(b) Exploratory Velocity in PC 1
(c) Changes of Viewing Direction in PC 1
(d) Navigation Trajectories in PC 4
(e) Exploratory Velocity in PC 4
(f) Changes of Viewing Direction in PC 4

**Figure 6: Comparisons of experienced navigation in two volumetric content (PC 1 in the first row and PC 4 in the second one) by two users with high and low values actual entropy (User 7 and 4, respectively). From left to right: user and volumetric content navigation trajectories on the floor; exploratory velocity over time; change of viewing direction over time.**

and changes in the viewing direction (Figure 5 third column). All these values are normalised for their maximum value in order to be easily comparable in the same figure. As already shown for 3-DoF users while experiencing omnidirectional content in [19], it is interesting to notice that 6-DoF users preserve a consistent behaviour across sequences. Participants with high value of actual entropy for a single point cloud tend to experience high actual entropy also for others (see User 7 or 19 in the first column of Figure 5); the same for small values of actual entropy (see User 4 or 16 in the first column of Figure 5). This is a remarkable observations showing that 6-DoF users can be profiled across different content in terms of actual entropy. Moreover, we can notice comparing the first and second column of Figure 5 that high values of actual entropy correspond to high exploratory velocity, as expected, since the actual entropy is performed based on the navigation trajectory on the floor. More interestingly, participants with these high values of actual entropy are in general characterised by a low quantity of changes in the viewing direction (Figure 5 third column). To better understand this observation, we show as example in Figure 6 how two different users explore PC 1 and 4. Here, we consider navigation while displaying the sequence in the reference format (*R*0). We select User 4, which is characterised by low actual entropy across the entire dataset, and User 7, which instead has high values of actual entropy. Despite the different dynamics of the volumetric content (*i.e.*, PC 1 is moving over time while PC 4 is more stationary), User 7 is more inclined to move inside the virtual space for both the sequence as shown in Figure 6 (b) and (d). On the contrary, the spatial movements and thus, the exploratory velocity of User 4 are quite limited. However, this participant shows a preference in exploring the immersive sequences by changing the only viewing direction as shown in Figure 6 (c). Intuitively, we can notice that there are viewers who prefer experience immersive content changing their physical position while being always focused on their center of attention; others instead, have the tendency to only change their viewing direction from a fixed location.

In the final investigation, we check how the behaviour of a single user changes across the different quality stimuli through a state-of-the-art clustering algorithm as described in Section 2.2. We show these results in Figure 7 in terms of the probability per user to have the navigation trajectory of each quality session as a single cluster. Specifically, a probability equal to 1 means that a user experiences a particular quality stimulus of the volumetric content in a completely different way with respect to the other sessions, such that is detected as a single cluster (*i.e.*, outlier). Conversely, the lower this probability, the more similar the user behaviour is among the different quality sessions per the same volumetric content. In




(a) PC1 (b) PC2 (c) PC3 (d) PC4

**Figure 7: Probability per user to have each quality session as a single cluster.**

Figure 7, we can notice consistent behaviour per user across the different quality sessions. For instance, User 1 has a low probability of forming a single cluster across all the quality stimuli in all the displayed content. Conversely, User 17 has a quite high probability to have all the quality representations as a single cluster. Therefore, while User 1 appears to navigate in a similar way across the quality sessions (*i.e.*, low probability to have single clusters), User 17 is more eclectic in its way of navigating such that its navigation trajectories result in single clusters. It can also be noted that, similarly to the interactive time in Figure 4, the versions encoded with $C2$ at low quality $R1$ and $R2$ are atypical: the probability per user across all the volumetric content to have their navigation trajectory as a single cluster is quite high, thus indicating an outlier behaviour in these specific stimuli due to the low quality of the content.

## 4 DISCUSSION

We have presented an exploratory behavioural analysis in 6-DoF VR spaces for the first time, aimed at understanding how the way of navigating is affected by the content, its visual quality and the disposition of each user. Behavioural analysis of 6-DoF users is still quite limited in the literature; as such, there are no reference behavioural protocols available to detect viewers who are displaying the immersive content in a similar way over time. Thus, to be as general as possible, we considered a wide range of metrics looking for a complete interpretation of user behaviour. Other than traditional visual and quantitative metrics (*e.g.*, heatmap and exploratory velocity), we have also taken into account behavioural tools that have been specifically used for 6-DoF [22], as well as adapting 3-DoF metrics to be used in this new context [19]. With this variety of metrics to assess user similarity in a simple and objective way, we have carried out a first generic investigation aimed at detecting how user behaviour changes based on the displayed volumetric content. We have noticed that the more dynamic are the displayed sequences, the more dispersive is the way users move around the immersive content. On the other hand, the presence or not of visual impairment in the displayed sequence does not affect the user movements during the immersive experience. However, the visual quality of the content compromises its attractiveness to users who decide to spend less time displaying sequences of poor quality. Given these overall observations that characterise the entire group of studied users, we have then narrowed our investigations to detect any consistency in the behaviour of each individual viewer across the different content (and quality). By measuring the actual entropy of navigation trajectory on the floor, we have identified for some users consistent patterns across different content, similarly to 3-DoF users as shown in [19]. Some users experience a more static and thus, predictable trajectory regardless of the content characteristics, in terms of both dynamics and quality. Specifically to our scenario, we have noticed that these viewers, who are less inclined in spatial movements, are more in favour to exploring the immersive content with only the movements of their head and, therefore, change the direction of observation. Finally, we have also observed that these behavioural consistencies are intrinsic to the single user and do not depend on the visual quality. Thus, the influence of the user disposition seems more assertive in the way of exploring the immersive content despite its features (*i.e.*, dynamism and visual quality). This is a remarkable observation as it shows that users can be profiled across different volumetric content.

Our extensive investigations have thus brought key information in the understanding of any hidden patterns of immersive users' navigation that can be eventually exploited in algorithms to accurately predict where users most likely look in the near future during an immersive experience. However, they have also risen some critical issues to be considered to enable the next-generation immersive applications. As already mentioned, the lack of a robust and holistic metric capable to capture user behaviour in its globally makes behavioural analysis not straightforward. From here, the need of developing new metrics and methodologies to be able to properly analyse user behaviour in 6-DoF. Finally, it is worth mentioning that further behavioural investigations in 6-DoF systems are currently hindered by the lack of publicly available datasets that both represent realistic and heterogeneous immersive objects and collect users' navigation trajectories while experiencing them. We have considered in our study only a single publicly available dataset of navigation trajectories collected in a 6-DoF VR scenario, limiting our behavioural insights to the feature of this database. For example, the volumetric sequences taken under exam are only human representations and neglect audio information. Extending such immersive databases to different objects and multi-modal sequences would be of broad interest to further explore, for instance, the effect of the visualised content and audio on user interaction.

## 5 CONCLUSION

In this paper, we have presented an exploratory analysis of users while displaying volumetric content within a 6-DoF environment. We were interested in understanding how the way of navigating is affected by the content and its features, such as dynamics and quality, but also by the intrinsic disposition of the single user. Our results have shown that users can be profiled based on their interactivity: viewers tend to preserve similar navigation types (highly erratic or quite static) independently by the volumetric content. Moreover, in order to be as general as possible, we have applied many different behavioural tools, from more traditional statistical metrics to trajectory-based techniques. As consequence, we have highlighted the need to develop new metrics and methodologies to be able to properly analyse the user behaviour in 6-DoF. In future work, we will indeed investigate new metrics that better describe user similarity. We will also extend our analysis to multi-modal datasets to have a more complete overview of user behaviour in a 6-DoF environment.

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