Understanding User Navigation in Immersive Experience: an Information-Theoretic analysis

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ABSTRACT

To cope with the large bandwidth and low-latency requirements, Virtual Reality (VR) systems are steering toward user-centric systems in which coding, streaming, and possibly rendering are personalized to the final user. The success of these user-centric VR systems mainly relies on the ability to anticipate viewers navigation. This has motivated a large attention in studying the prediction of user's movements in a VR experience. However, most of these work lack of a proper and exhaustive behavioural analysis in a VR scenario, leaving many key-behavioural questions unsolved and unexplored: Can some users be more predictable than others? Do users have their own way of navigating and how much is this affected by the video content features? Can we quantify the similarity of users navigation? Answering these questions is a crucial step toward the understanding of user's behaviour in VR; and it is the overall goal of this paper. By studying VR trajectories across different contents and through information-theoretic tools, we aim at characterizing navigation patterns both for each single viewer (profiling individually viewers - *intra-user analysis*) and for a multitude of viewers (identifying common patterns among viewers - *inter-user analysis*). For each of these proposed behavioural analyses, we describe the applied metrics and key observations that can be extrapolated.

CCS CONCEPTS

• **Human-centered computing → User studies**; *Virtual reality*.

KEYWORDS

Virtual Reality, 360° video, user behaviour, information theory

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1 INTRODUCTION

One of the major challenge for the next decade is to design virtual and augmented reality systems (virtual reality systems at large) for real-world use cases such as healthcare, entertainment and, e-education. In these novel applications, the user becomes an active consumer that interacts with the content in a fully immersive environment. This interactivity however can push the limits of both connectivity and computation. To avoid this, Virtual Reality (VR) interactive systems will need to operate at scale in a personalized manner, remaining bandwidth-tolerant whilst meeting quality and latency criteria. This can be accomplished only by a fundamental revolution of the coding/streaming/rendering chain that has to put the interactive user at the heart rather than at the end of the chain - as is the case of classical non-interactive streaming systems. This highlights the need for VR systems to adapt to user's interactions and to develop user-centric VR systems, such as VR streaming platform, VR content design, and user-based Quality of Experience (QoE) assessment [4]. However how to model and predict user's interactions it is still an open challenge under investigation.

Despite a growing attention on anticipating viewer's movements during an immersive experience [8], an efficient prediction tool is still an open research. One major limitation is the lack of understanding of user's behaviour in a VR experience, which could be crucial for an efficient prediction. For example, it is not clear if the content has a dominant impact on user's navigation patterns; or if some users are more predictable than others. So far, the way in which users explore the VR content has been characterised in terms of angular velocity, frequency of fixation, and mean exploration angles [1, 13]. A more recent visual (and qualitative) tool used to study user's behaviour in VR is the heatmap, which identifies areas of the content mostly attended by viewers within a time interval [10, 13]. While these metrics and tool provide a general understanding of user's behaviour, they all fail in identifying similarity among viewers over time. For example, given a scene characterised by two focus of attentions (FoAs), we can identify two types of behaviour: users that move continuously back and forward from the two FoAs; others that display for a consistent interval the first FoA and afterwards move on the second one. On average, both types would spend the same amount of time displaying the two FoAs, leading to the same heatmap, despite their different navigation paths. Another possible metric to consider is the angular velocity, that could quantify the head motion speed, neglecting however the qualitative movements of the users. To further characterise users based on their VR interactions, a clustering algorithm for VR trajectories has been proposed in [11]. This provides a general idea of users similarity without offering however a quantitative metric. In summary, a proper quantitative metric for user's behaviour study in VR is still missing.

The analysis of trajectories in a 3D space is a common problem widely investigated across many disciplines. For example, human

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mobility is a multidisciplinary field of social science, neuroscience and transportation, that refers to movements of people in a spatio-temporal dimension, such as the daily life on earth's surface [3]. A common trend has been to adopt information-theoretic (IT) metrics to statistically characterise the uncertainty of human mobility patterns [14]. *Information theory* is indeed an important tool born for communication systems, which has been used in different domains to detect hidden interactions in complex systems [2].

In this paper, we attempt to use tools from information theory to identify key behavioural aspects of users during an immersive experience. We are interested in *quantifying* similarities not only among different users but also for the same viewer across contents, leading to a two-fold investigation: an *intra-user behaviour analysis*, and an *inter-user behaviour analysis*. To the best of our knowledge this is the first work using IT metrics for analysing trajectories in VR context.[1] The intra-user behaviour analysis is aimed at understanding the level of interactivity of each single user across different contents. On the other hand, the inter-user analysis considers navigation across an entire group of viewers to asses if user's behaviour can help in the prediction of other viewer's behaviour. The main contributions of this work are the following:

- to adopt trajectory-based metrics from information theory to VR domain;
- to highlight the importance of looking at user's trajectories instead of more qualitative measures of user's interactions;
- to propose a behavioural study of users in a VR system looking for both an *intra-* and and *inter-user variability.*

We strongly believe these investigations can bring key-information in the understanding of any hidden patterns of immersive user's navigation. Our outcomes can be eventually exploited in algorithms to accurately predict where users most likely look at in the near future during an immersive experience. The remaining part of this paper is organised as follows: an overview of the proposed VR analysis framework is provided in Section 2. Section 3 describes IT metrics considered in this work. A deep user's analysis is presented in Section 4, highlighting both similarities in the history path of a single user and across an entire set of viewers; the main outcomes of this behavioural study are finally summarised in Section 5.

2 USER BEHAVIOUR ANALYSIS IN VR

Fig. 1 shows the framework used in this work to analyse VR users. The first step of any experimental study is the data collection (Fig. 1 A). In a VR scenario, the data is the set of *navigation trajectories* that identifies movements of users while experiencing an immersive content. In details, the VR content is typically an omnidirectional or spherical video, which represents an entire 360° environment on a virtual sphere. The viewer is virtually positioned at the centre of this sphere. To mimic a real-life scenario, the user cannot display the entire environment around him/herself, but only a restricted portion, named *viewport*. The user is provided by a VR device – typically an head-mounted display (HMD), that allows to change viewport according to user's viewing direction. Therefore, the sequence of spatio-temporal points representing over time the user's viewing direction on the sphere identifies user's navigation within an immersive experience. Formally, the VR user trajectory is denoted by $\{(x_1, t_1), (x_2, t_2), .., (x_n, t_n)\}$ where t_i is the data acquisition time (*i.e.*, video timestamp) with $t_i < t_{i+1}$, $\forall_{1\leq i<n}$, while x_i represents the spatial coordinates of the viewing direction (corresponding to viewport's centre). Based on the selected convention, x_i can be recorded in different formats: quaternion, spherical coordinates and Euler angles are the most common representations in VR. Some datasets containing these VR trajectories are already publicly available (Fig. 1 B). In particular, they provide a collection of head and/or eye-gaze positions as proxy of the viewing direction for a set of users which explored different VR images/videos [8]. In this work we use the 360° video dataset provided in [1]; further details on the database will be given in Section 4.1.

From the collected raw data, some pre-processing is usually needed (Fig. 1 C). In our case, user's trajectories are stored as quaternion, and not at a constant sampling rate. Thus, we firstly re-sampled all the collected data based on the frame rate of the corresponding video. For the sake of notation, in the following we denote the VR trajectory by $\{x_1, x_2, x_n\}$ omitting the timestamp t_i. Then, we converted the original format data (*i.e.*, quaternion) in two different formats more suitable for a user's analysis, neglecting in this way the viewport's rotation which is already well-known to not be so relevant. As depicted at the top of Fig. 1 C, the spatial position x_i is represented in spherical coordinates by latitude-longitude pair, i.e., $x_t = (\theta_t, \phi_t)$ with $0 \leq \theta_t < 2\pi$ and $0 \leq \phi_t \leq \pi$. To be compliant with most of the behavioural analysis tools, we also quantized the spherical content into regular block, each one with an assigned ID value (*i.e.*, $B_1, B_2, .., B_T$ in Fig. 1 C, lower part).

The data is then ready to be processed, Figure 1 D. This step is the core of our proposed VR analysis framework, and it is aimed at better understanding user's navigation within omnidirectional contents. The analysis highlights a two-line investigations:

a) **intra-user behaviour analysis** aims at characterizing the interaction of each user over time against different video contents. Studying single user's trajectory over time allows us to profile user or to identify recurrent navigation patterns.
b) **inter-user behaviour analysis** aims at studying a user behavior in correlation with others. The target here is to understand how much user's trajectories are informative in understanding/predicting other user's behaviors.

For both directions, we propose to use information-theoretic (IT) metrics due to their powerful ability in quantifying interactions within the same or between different sources of information. In the following section, we present the metrics that we used for the proposed user's behaviour analysis in a VR scenario.

3 INFORMATION-THEORETIC METRICS

Information theory has been introduced by Shannon in [12] to answer fundamental questions on communication theory. Since then information-theoretic metrics have been applied to a much wider range of disciplines beyond communications, becoming a de-facto statistical tool for data analysis in fields such as physics, computer science, and neuroscience [15]. A key quantity in information theory is *entropy*, which relates to the *uncertainty* or *randomness* associated with an event. The less an event is certain, the more informative the event is, resulting in higher entropy. In

[1] Until now, entropy has been applied only to heatmap and not to user's trajectory as presented in this work.

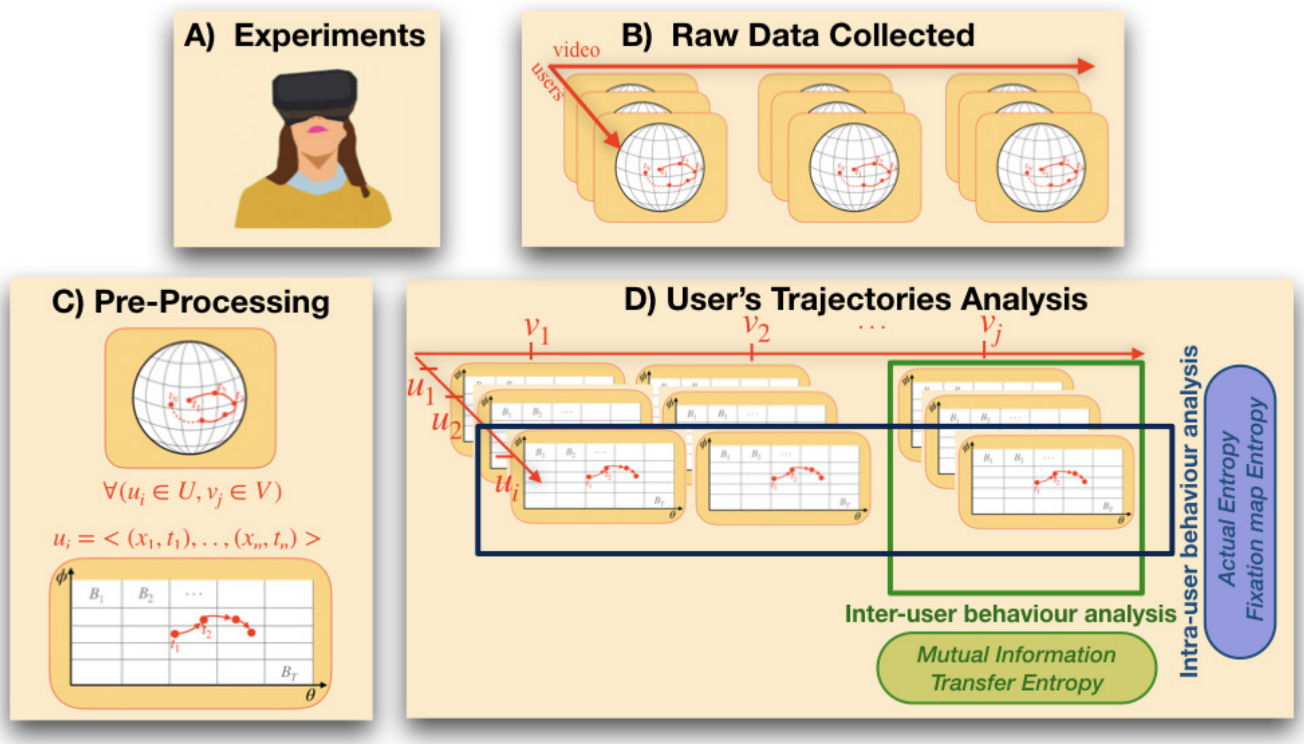


Figure 1: Overview of user behaviour analysis in a VR system: A) Collection of user's trajectories during immersive experiments. B) The raw data collected from different users and content are stored in a database. C) After a general pre-processing (i.e., re-sampling), the VR trajectories are transformed in the most suitable format for the final analysis. D) Information-theory metrics are applied to the VR trajectories looking for the desired characteristics: *intra-* and *inter-user behaviour analysis.*

other words, the entropy is a measure of information required on average to describe a random variable [2]. More formally, given a random variable X, with x being one possible realisation of X, the entropy is measured by:

$$H(X) = -\sum_{x \in X} p(x) \log\left(p(x)\right) \tag{1}$$

where $p(x)$ is the probability of experiencing the event x. An event occurring with high-probability $p(x)$ is poorly informative (low entropy). Conversely, the occurrence of a very unlikely event carries a large information. The concept of information reflected by the entropy is highly related with the degree of *predictability* of a variable, with low values of entropy for highly predictable events. Authors in [14] exploited this correlation by using the entropy as a proxy of predictability of human mobility patterns. Specifically, they introduced the *actual entropy* to measure the information (and predictability) carried within a given trajectory, considering both the visiting rate but also the temporal order of visited areas. The actual entropy can be estimated from the past history of user's trajectory by Lempel-Ziv compression algorithm [16]. Let $X = \{x_1, x_2, \dots, x_n\}$ be a trajectory of n points sampled at periodic time with x_t being the position at the t-th time-slot, and let $\{x_t, x_{t+1}, \dots x_{(t-1)+\lambda}\}$ be a subsequence of X starting at time t and spanning λ time-slots, the actual entropy assumes the following form:

$$H^{act}(X) \approx \left(\frac{1}{n}\sum_{t=1}^{n} \lambda_t\right)^{-1} \log_2(n) \tag{2}$$

where λ_t is the length of the shortest subsequence in X starting at timeslot t and not appearing between time 1 and $t-1$.

An other fundamental metric of information theory is the Mutual Information (MI). This metric measures the reduction of uncertainty of a random variable X provided by the knowledge of a second variable Y [2]. A large MI indicates that most of the information about X can be inferred from Y reducing therefore the uncertainty on X. Recalling the conditional entropy $H(X|Y)$ as the uncertainty of X given Y, the MI is defined for two variables X and Y as:

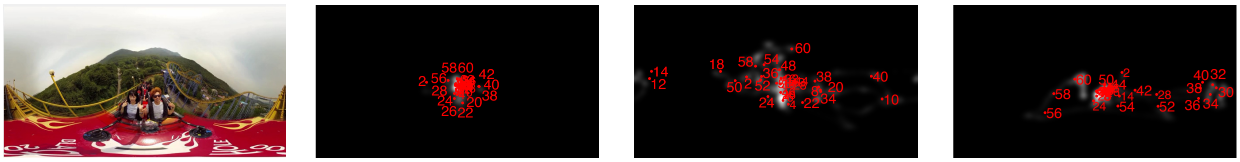
$$\begin{aligned} I(X,Y) &= H(X) - H(X|Y) = \\ &= \sum_{x \in X, y \in Y} P(x,y) \log\left(\frac{P(x,y)}{P(x)P(y)}\right) \end{aligned} \tag{3}$$

where $p(x,y)$ is the joint probability of experiencing both events x and y, and $P(x)$, $P(y)$ their marginal distributions. To note that MI is zero if the two variables are uncorrelated, *i.e.*, $p(x,y) = p(x)p(y)$.

Finally, Transfer Entropy (TE) is a conditional entropy that considers not only the occurrence of events but also their temporal ordering. This metric measures the reduction of uncertainty about the future value of a variable (Y_{future}) by knowing the whole past history of itself (Y_{past}) and of a second variable (X_{past}). Therefore, TE is defined as follow:

$$\begin{aligned} &TE(X \to Y) = \\ &= H(Y_{future}|Y_{past}) - H(Y_{future}|X_{past}, Y_{past}). \end{aligned} \tag{4}$$

In contrast with MI, TE measures better the influence from X to Y.



A Sample thumbnail frame of video ID 03

B **User 30**: $H^{act}(X) = 0.12$ $H(M) = 0.21{\cdot}10^{-2}$

C **User 48**: $H^{act}(X) = 0.65$ $H(M) = 0.43{\cdot}10^{-2}$

D **User 49**: $H^{act}(X) = 0.28$ $H(M) = 0.32{\cdot}10^{-2}$

Figure 2: Examples for ID 03 (A) of fixation maps of 3 users (B, C, D). In red, fixation positions and the corresponding timestamp.

ID	Name Video	Selected Segment	Description
01	Diving	00:40 - 01:40	No main FoA
02	Paris	00:00 - 01:00	Scene cuts with always one or more FoAs
03	Rollercoaster	01:05 - 02:05	One main FoA
04	Timelapse	00:00 - 01:00	moving FoAs distributed on the horizon line
05	Venice	00:00 - 01:00	No main FoA

Table 1: Key features of the sequences from [1].

4 RESULTS

In the following, we first describe the dataset used in our VR behavioural analysis. We then provide and comment experimental results for both *intra-* and *inter-user behaviour analysis* (Fig 1 D). In more details, we adopt the metrics described in the previous sections, in the case of X and Y being user's trajectories.

4.1 VR Trajectory Dataset

To apply our proposed framework of user behaviour analysis, we chose the dataset published by Corbillon *et al.* [1]. This dataset collects navigation trajectories of 57 users who navigated within 5 omnidirectional sequences. Table 1 shows a wide selection of content features of this dataset in terms of FoAs, scene cuts, etc..

4.2 Intra-User behaviour analysis

Our first direction of VR user analysis aims at characterising each user individually looking for patterns over time and across different contents. For example, some viewers could be generally interested in exploring the immersive video, independently from the content, and others be always static.

To study independently the behaviour of each user while navigating, we adopt the actual entropy ($H^{act}(X)$) which quantifies the similarities over time within the same variable. We compare the actual entropy with the entropy of fixation map, $H(M)$, evaluated as the entropy of all fixation points[2] per user for each video recorded during experiment per user for each video. This metric is typically used to evaluate model of visual attention, and gives a qualitative idea about the dispersion of movements over time. In both metrics, a low value of entropy means that the user is focused on a restricted area; while high value stands for more exploratory movements. The main difference between the two metrics is that the actual entropy considers temporal order of navigation points which is neglected by the fixation map entropy. Fig 2 shows one frame selected from video ID 03 (Fig. 2A) and fixation maps evaluated by three different users (users 30, 48 and, 49). Corresponding values of the entropy metrics are also provided in each subfigure caption (Fig. 2B–2D). For user 30 both metrics are in agreement as they are both low. This is explained by the very focused fixation map shown in Fig. 2B. Conversely, fixation maps of users 48 and 49 are more spread along the equatorial area (Fig. 2C and Fig. 2D, respectively). This leads to higher values of entropy, as already anticipated. Interestingly, there is a significant difference in terms of actual entropy for these last two viewers (0.65 for user 48 and 0.28 for user 49), difference that is not fully captured by the entropy of fixation map. Looking at the distribution of timestamps (*i.e.*, red numbers appearing in the fixation maps), we can notice that user 48 is navigating more randomly inside the content. User 49 is also moving within the content, but his/her fixation points are more contiguous over time. For instance, from time 30 to 40 the user remains in the right side of the panorama. Therefore, actual entropy seems to detect discontinuity and randomness in the trajectories better than $H(M)$.

Beyond the above visual results, Fig. 3 provides a more exhaustive analysis of the actual entropy for the entire dataset. In particular, Fig. 3A depicts the actual entropy (bar plot), and the entropy of fixation map (red diamond) per user and per video. It is worth noting that most of the users preserve consistent behaviour across videos. Users with high value of actual entropy in a single video tend to experience high actual entropy also for other videos (see user 6); the same for small values of actual entropy (see user 50). This is a remarkable observation as it shows that users can be profiled across different videos. This is confirmed by the statistical analysis for all users across videos showed in Fig. 3B, which provides box plot of the actual entropy. The variance of the actual entropy is indeed kept small for the majority of the viewers. Finally, even if the content might not play the dominant role in defining user's behaviour, it is still worth mentioning that it plays an important influence. Fig. 3C depicts the probability distribution of the actual entropy per video. This plot shows that video ID 02 (one main FoA) has the lowest mean value and small variance of actual entropy; conversely video with more FoAs, such as video ID 01 and 04, are characterised by higher mean value and variance of the metric. This means that the way in which users navigate within the omnidirectional content is more diversified when there are more FoAs.

4.3 Inter-User behaviour analysis

While the intra-user analysis provides a way to profile each user based on his/her way of navigating within VR contents, we are now interested in extending the behavioural analysis with a comparison among users. In particular, we aim at measuring key differences among navigation patterns of different viewers over time within the same content. To carry out this inter-user behaviour analysis, we use Mutual Information (MI) and Transfer Entropy (TE). As defined in Section 3, these two entropy-based metrics allow us a pairwise similarity analysis among users considering their positions over time (*i.e.*, their trajectories).

[2] In this work, we consider user's head positions as proxy of their fixation points.

Figure 3: Intra-user behaviour analysis: A entropy of each user per video; B statistical analysis of the entropy for all users across the dataset; C probability distribution of actual entropy for each video across users.

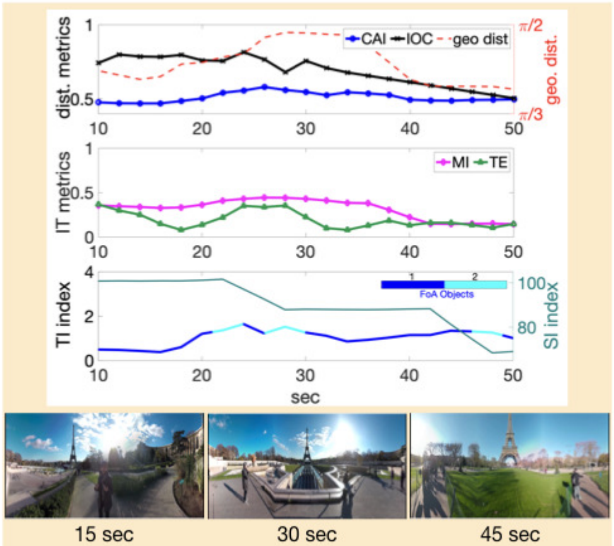
As benchmarking, we also analyse user's behaviour with two tools existing in the literature and based on the distance among users: Inter-Observer Coungrency (IOC), and clique-based clustering algorithm for VR trajectories. The first metric has been proposed in [7] as a measure of similarity for users viewing traditional images, and it is based on a one-to-all comparison (*i.e.*, the heatmap of a single user is compared against the one computed based on all other users). Instead, the clique-based clustering detects viewers that display similar viewports while consuming an immersive content [11]. In other words, this algorithm identifies group of users based on their consistency in the navigation. Thus, we define a Clique-Index (CI) to quantify the consistency among users detected by the clique-based clustering. Given the set of clusters at instant t, the CI for a user u is the number of users in the same cluster of u at time t (*i.e.*, $w_t(u)$) normalised per the size of the maximal cluster (*i.e.*, in terms of number of elements) at time t (*i.e.*, $w_t^{max} = \max_u w_t(u), \forall u$). More formally:

$$CI(u) = \frac{w_t(u)}{w_t^{max}}, \quad \forall t = 1, ..., T \tag{5}$$

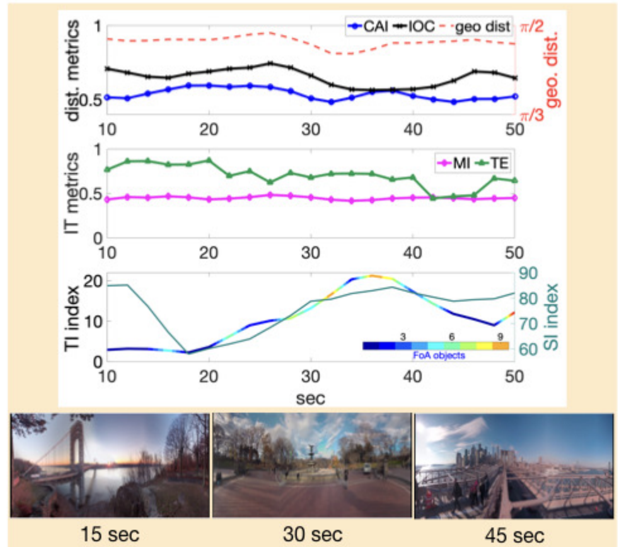
where T is the total length of the analysed video.

Equipped with the above notation, we can now provide the inter-user behaviour analysis. First, we split each content in temporal segments of duration 2 sec., *i.e.*, typical chunk length in video streaming systems. Then, we compute per each segment MI and TE between users adopting the software provided by [15], and heatmaps by the tool presented in [6]. To preserve consistency, we compute clique-based clusters (*i.e.*, trajectory-based format) over a time-window of 2 sec.. Finally, to verify a correlation between user's movements and video content, we also evaluate content characteristics in terms of temporal and spatial information indexes (TI and SI, respectively) [5] and, number of main FoA objects detected in the scene by a Multiple Object Tracking tool [9].

For the sake of brevity, we focus on results carried out by only two videos, namely ID 02 and ID 04. In particular, these videos cover different content characteristics as shown in the selected frames provided on the bottom Fig. 4A and Fig. 4B. Specifically, video ID 02 has always one or two static main objects in the scene: a tourguide and the Eiffel Tower in the first two frames; only the tower toward the end of the video. On the contrary, video ID 04 is rather characterised by many fast-moving objects. These intuitions are confirmed by content information metrics (*i.e.*, TI, SI indexes and number of FoA detected objects) provided in the bottom subplot of Fig. 4A and 4B. The number of detected FoAs is identified by the colour code of the TI curve. Video ID 02 has only one or two FoA objects, and a TI index much lower than the one for video ID 04. Conversely, video ID 04 has more FoA objects with a peak of 9 around the middle of the sequence. The remaining subplots of Fig. 4 show the inter-user metrics introduced in Sec.3 as a function of time, and averaged across users. In the top subplot there are metrics based on spatial distance such as CI and IOC compared with the averaged pairwise geodesic distance between users over time (red dashed line). The middle subplot depicts instead the IT metrics MI and TE. The entropy-based metric TE seems to reflect quite well the content information, especially the TI index and the number of FoA objects. In video ID 02 (Fig. 4A), TI increases around 20-30s and FoA objects are two instead of one. Users react by having a more exploratory trajectories – reflected by higher geodesic distance.



A Video ID 02



B Video ID 04

Figure 4: Inter-user behaviour analysis in two videos: top subplot shows distance metrics (*i.e.*, CAI and IOC), middle one IT metrics (*i.e.*, MI and TE), bottom one content information (*i.e.*, TI, SI indexes and number of FoAs. The latter is reflected by the colour of the curve.) In the bottom, there are 3 thumbnail frames corresponding to 3 different temporal instant of the video.

This increase of randomness in the trajectories is measured well by the TE that peaks in this temporal range. Finally, video ID 04 has many more FoA detected objects than ID 02. This leads to a more random navigation of viewers, proved by higher TE values. This difference is captured by TE but not by the spatial metrics, top subplot in both figure. This preliminary study has then shown a tight correlation between content information and TE.

5 CONCLUSION

In this paper, we proposed a novel behaviour analysis in a VR scenario aimed at characterising navigation patterns across content or across users. This is carried out by considering a space-time trajectory domain rather than only a spatial domain. By leveraging on the knowledge from different disciplines, we based our behavioural investigation of VR viewers on *information-theoretic metrics*. The key intuition is to show that these IT metrics allow us to *quantify* the actual behaviour of user's navigation. We conduced an *intra-user behavioural analysis* focused on understanding the behaviour of each individual when navigating in VR. By measuring the actual entropy of navigation trajectory, we identified for some users consistent patterns across different contents. For example, some users experience a more predictable trajectory for all videos. We also observed a correlation between content and actual entropy: the lack of a dominant FoA leads to more discontinuity and randomness in navigation trajectories. As second step, an *inter-user behavioural analysis* was carried out, aimed at understanding how much information about a single content can be extracted when observing an entire population of viewers. The transfer entropy showed to better quantify behavioural similarity among users rather than the metrics based on spatial distribution. Future work will focus on a better understanding of how viewer's profiling and common behavioural information among users could be eventually exploited in a predictive algorithm for VR trajectory.

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