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Visualizing navigation difficulties in video game experiences

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Abstract—When developing video games, gameplay metrics allow to track and analyze the behaviors of users interacting with the game. Here, we propose to harness player’s spatial trajectories to objectively quantify their gaming experience. Spatial trajectories are complex signals that are determined both by the players and by the topology of the virtual spaces they evolve in. In this paper, we propose a new methodology to measure and visualize how the entropy of trajectories is distributed in virtual spaces, and explain how it can inform game developers on the design of the game levels. We apply our method on the Sea Hero Quest dataset, consisting of the trajectories of over 4 millions players finding their way in water mazes.

Index Terms—video-game, trajectory, environment, entropy, game design, player experience

I. INTRODUCTION

User-oriented testing is central in game production, since the quality of the game is directly related the user experience. Traditionally, the game industry used to implement informal testing methods based on the subjective reports of testers. These methods became outdated as game designs became more complex and lead to a wider variety of player behavior. To overcome these limitations, several objective metrics have been proposed to quantify the game design [1] [2].

Most metrics have been developed in the context of highly interactive games (Adventure Role Playing Games, Action Shooters, etc.), and rely on the quantity and quality of events linked to the player activity, such as deaths, kills, and their circumstances. However, these approaches do not generalize to other types of games, in particular to spatial navigation games where the players need to find their way in an open environment.

In such case, player’s trajectories are an interesting signal to analyse, as a trajectory can be understood as the product of a player, with its determinants (biological and sociological alike) influencing its behaviour, and a level, with its map and topological features. Therefore, the trajectory can give insights both on the difficulty of the task, and assess the usability of the game for different demographic groups of players.

In this paper, we propose a method to analyse gamers’ behavior from this perspective. We apply our method to the data collected in Sea Hero Quest (SHQ), a spatial navigation video game where players need to find their way in various water mazes (see Fig 1). As the players evolve in the levels of the game, their spatial trajectories are recorded and they can fill in some demographic information such as their age and gender. SHQ has been developed in the context of Alzheimer’s

disease research, and has collected data from over 4 millions players worldwide [3].

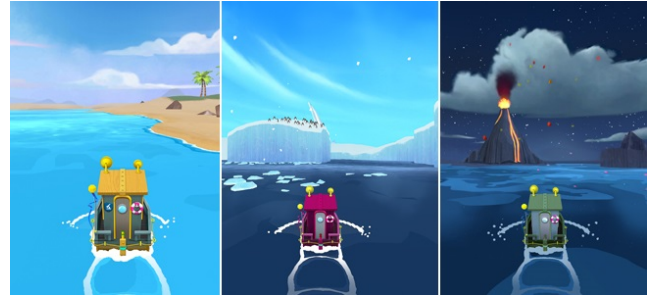


Fig. 1. Screenshots from Sea Hero Quest

Because it was developed in cooperation with a behavioural neuroscience research team with the purpose of challenging the navigation abilities of players, it offers an appropriate playground to test and propose a trajectory-based dedicated analysis tool for virtual spaces in video games.

In the following we will first define the entropy of a trajectory, and explain how it can be used to understand how the layout of a given game level elicit different spatial behaviors among players. We will describe two methods to compute and visualize this information, and apply it on three different levels from the SHQ dataset.

II. TRAJECTORIES AS INFORMATION

Entropy, as defined from an information theory standpoint, is a measure of information, or uncertainty. Despite its formal simplicity, it has been successfully applied to many research problems, including space analysis [4], signal processing [5], or trajectory analysis [6].

A. Measuring the entropy of a trajectory

We define a trajectory’s entropy with respect to all the other trajectories. A trajectory with a high entropy means it differs comparatively to the other trajectories.

We compared two entropy definition, Shannon Entropy and Collision Entropy, and decided to use the latter here because it provided the best visualization. Collision Entropy is defined as:

$$H_2(X) = -\log \sum_i^N P(X_i)^2 \quad (1)$$

We need to define P and X in this context. Because trajectories are temporal signals, X is the time-series T of

$x - y$ coordinates sampled from a trajectory. To compare the trajectories to each other, we normalize their length by resampling trajectories using bicubic interpolation. Therefore, we have

$$T = \{(x, y)\}_{i=0}^N, T \in \mathbb{T} \quad (2)$$

Where T is a trajectory and (T) is the set of all trajectories.

We define $P_i(T_i)$, the probability of the i -th sample of a trajectory T , as the probability density function of its emission by the gaussian-mixture distribution \mathcal{D}_i (with k components parametrized by their mean μ , their deviation σ , and their weight in the mixture α) estimated from every i -th samples from every trajectory in \mathbb{T} using Kernel Density Estimation algorithm.

$$\mathcal{D} = \{(\mu_0, \dots, \mu_k), (\sigma_0, \dots, \sigma_k), (\alpha_0, \dots, \alpha_k)\}_{i=0}^N, \quad (3)$$

$$\mathbb{P}(s|d) = \sum_{j=0}^k \mathcal{N}(d, \mu_j, d, \sigma_j) \cdot \text{pdf}(s) \times d, \alpha_j \quad (4)$$

$$P_i(T_i) = \mathbb{P}(T_i | \mathcal{D}_i) \quad (5)$$

Therefore we have

$$H_2(T) = -\log \sum_i P_i(T_i)^2 \quad (6)$$

B. Sliding window entropy

Previously defined metric flattens the trajectory along the temporal and spatial dimensions, producing a single value. This gives insights about which trajectories might be outliers, but doesn't allow for visualisation and analysis of the trajectory in itself.

To do so, we define a sliding window version of the function, which computes the entropy of every k -long subsequence of the trajectory (we use shorter subsequences at the start and end of the trajectory to keep its length). We have

$$\begin{aligned} sw_H_2(T) = \{ & H_2(T_{0:k/2}), \\ & \dots, \\ & H_2(T_{i-k/2:i+k/2}), \\ & \dots, \\ & H_2(T_{N-k/2:N}) \} \end{aligned} \quad (7)$$

III. FROM TEMPORAL TO SPATIAL ANALYSIS

While entropy time-series can be used to analyse trajectories with regard to each other, as time-series, they cannot inform about the virtual space they were defined in. In order to visualize the influence of the level's topology on trajectories entropy, we need to move from the temporal domain to the spatial domain.

A. Visualizing entropy

To do so, we propose to build a heatmap of the mean entropy at each coordinate of the map. This allows to identify points where players converges, and ones that are visited infrequently. This differs from the two-dimensional histogram heatmap, as the entropy heatmap doesn't have any knowledge of the the number of players that visited each coordinate.

To demonstrate the proposed technique, we use 5000 trajectories from levels 7, 21 and 57 from the Sea Hero Quest dataset. We use those levels as they offer three different kind of topologies while still being complex enough so that different strategies can appear. Figure 2 shows those heatmaps. We can see secondary strategies appear as high-entropy areas, comparatively to main strategies which are low-entropy areas. Level 21's heatmap also shows areas of low entropy near walls on the bottom-left part of the map, which suggests that players tend to stick to the wall in this area while turning. Checkpoints appear as low-entropy points.

As an example of what this tool can reveal, here it shows that players who don't follow the main strategy aren't necessary lost, as we can see clear straight lines of high-entropy in levels 7 and 57, but instead adopt different strategies. This doesn't tell if those strategies are optimal or not.

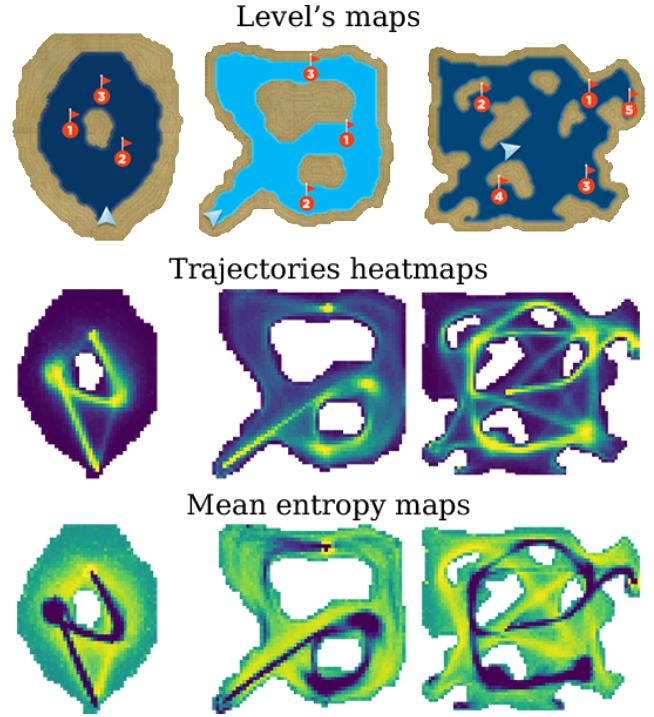


Fig. 2. Top: Maps of level 7, 21 and 57 (left to right). The grey arrow indicates the starting position, the circled numbers indicate the ordered checkpoints. Middle: Trajectories heatmaps. Brighter colours denotes frequent visitation. Bottom: Entropy heatmaps computed from 5000 trajectories in each level. Darker colors denotes lower entropy while brighter colors denotes higher entropy.

In order to get visually readable heatmaps, because of the minuscule entropy that can be reached near checkpoints, we

transform the values using a sigmoid function after standard scaling the map values.

B. Explaining variance

Another way to move from the temporal to spatial domain is to visualize the variance of the temporal domain in the spatial domain.

To do so, we compute the first component of the Principal Component Analysis (PCA) of the trajectories' entropy time-series, which have been normalized so that at every time-index the entropy averages to 0 with a standard deviation of 1. We can then analyse the time-indices contribution to the component, and extract its peaks. The first and last 10 time indices are ignored as they present a really high fluctuation in contribution, while being of low interest, as all players are in the same small area at those times. Since we are interested in the magnitude of the contribution regardless of its sign, we square the contribution values before extracting its peaks. Figure 3 illustrates the peak extraction procedure for level 57.

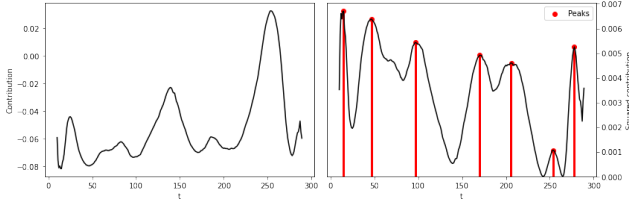


Fig. 3. Left: Time index contribution to the first component of a PCA of the trajectories' entropy for level 57. Right: The contribution is squared and its peaks are labelled (red vertical lines).

For each identified peak, we plot the position of the players at that time. Fig 4 shows those plots for the four biggest peaks for levels 7, 21, and 57. The distribution of players at those indices varies a lot between levels. Level 21 shows a lot more dispersion, which explains why there aren't any clear high-entropy secondary strategies appearing on its heatmap in figure 2. This may mean, that, despite the level's simplicity compared to level 57, some players have a harder time orienting themselves.

IV. CONCLUSION

To our knowledge, this study is the first where players' trajectories are used as a feature to analyse the virtual environment they were defined in, and try to visualize its challenges and influences on player's behaviour.

We believe that looking at trajectories through an information theory perspective can produce analysis tools that can help understanding the relationship between players and virtual spaces in video games. As digital platforms for video games have become the norm, we have seen an increase in video-games that go through a long period of open beta testing phase, a phenomenon which has enabled developers to get more feedback from players, more data to analyse, and improve their games. Being able to use this wealth of data, with dedicated tools designed for complex spaces, can

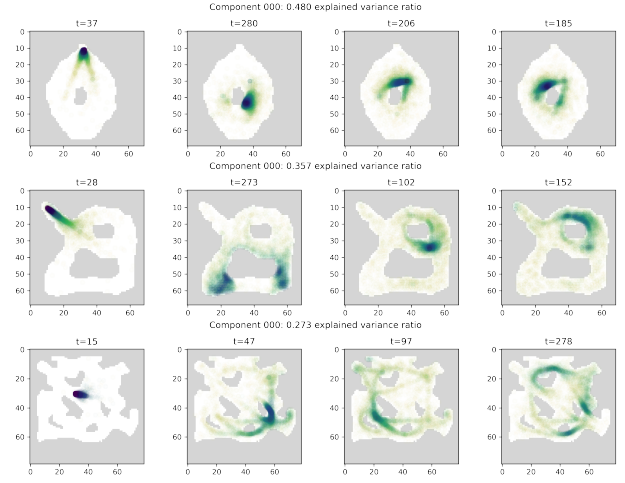


Fig. 4. Distribution of the positions of the players at the times corresponding to the 4 largest entropy peaks extracted through the procedure described in Fig 3. Top to bottom: Level 7, 21, and 57. Darker dots means lower entropy. The low entropy modes reveals the Kernel Density Estimation used to learn the probability density function.

only help them. And, as the Sea Hero Quest project has demonstrated, well thought virtual spaces can not only provide the player with a better experience, but also help researchers to understand the determinants of navigation ability.

There are a few ways we can further the development of this tool. Because we need to estimate distributions over time, we have had to normalize the length of trajectories through resampling, which means that information was lost in the process. We will have to research methods which don't rely on resampling to avoid this loss of information.

Another axis of research could be to use this tool to visualize if different group of people behave differently, why, and how.

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