# Player Experience Information Evaluation in 3D Virtual Environments

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## ABSTRACT

A method to evaluate the amount of information a player can get during the process of exploring in a virtual scene is proposed. A novel perception probability estimation method is used to decide the probability distribution among task-related objects in the scene. The perception probability is then used into Shannon entropy equation to calculate the experience information amount. A user study is conducted to verify the effectiveness of the method proposed. The potential use of the method in the application of player type classification is presented in a game scene along with a questionnaire system.

## CCS CONCEPTS

**• Human-centered computing → User models**; **• Computing methodologies → Perception**; **• Applied computing → Computer games**;

## KEYWORDS

Shannon entropy, player modeling, experience evaluation, game analytics

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## 1 INTRODUCTION

To evaluate how much information the players can get from the 3D virtual scene is vital in helping the designers know better about the experience and response of their users. It can also be used as a metric to do player data analytics. The rendered images of virtual scenes in screens, through virtual camera controlled by the player, is an important way to let the player get information from the 3D virtual environments. Many design ideas have to be expressed based on the perception of elements in the screen.

An experience information evaluation method is proposed in this paper. After the player finishes playing a game scene, the perception probability of each object is estimated. Based on the object perception probability, the total amount of useful information he or she can get from the game scene is calculated using Shannon entropy.

A preliminary user study experiment has been conducted to verify the efficiency of the method proposed. The results show that experience information calculated by our method has a very strong relationship with the performance of participants. Finally, we show how to apply it into the application of player type classification in a real game demo.

## 2 RELATED WORK

Research on user experience (UX) evaluation in interactive virtual environment has received much attention in recent years. Readers are referred to a HCI series book [3] for research trend in this field.

User experience evaluation methods can be applied at any stage in the design and development life cycle [3]. This term was rarely used in the games industry [10], but became extremely prominent in the field of HCI. Today the communities of human-computer interaction and game research are starting to learn from each other [4].

User-oriented game testing [9] during production and post launch has been performed for decades and formed a key aspect of game production. However, user-oriented game testing has traditionally been performed using informal methods such as surveys and interviews [17] which are time-consuming and not straightforward.

Paper [16] explored an intuitive way to make full use of player data to help designers deal with key events and game parameters in the game. The authors followed a user-centered design process developing a novel visualization system with game analysts and testing with real data of a popular MOBA game. The evolution of players' positions, status and the occurrences of events can be presented to the data analytics team efficiently.

Knowing how much information can be perceived by the user is vital for user experience evaluation. Recently, information theory has been successfully introduced into several computer graphics related fields, such as the analysis of scene complexity [11], shape similarity [13], 3D mesh simplification [6], viewpoint selection [12], 3D mesh distortion metric [23] and terrain navigation [21]. This is an area of key interest to all games because the experience of the user (player) is directly related to the experience of navigating through, and interacting with the game world [25][8]. However, evaluating user behavior driven information in interactive 3D virtual environments still remains largely unexplored.

Summarized in paper [3], UX evaluation methods can be classified into methods that involve the user, methods that are based on user data, but enable automated testing or analysis [5], and methods


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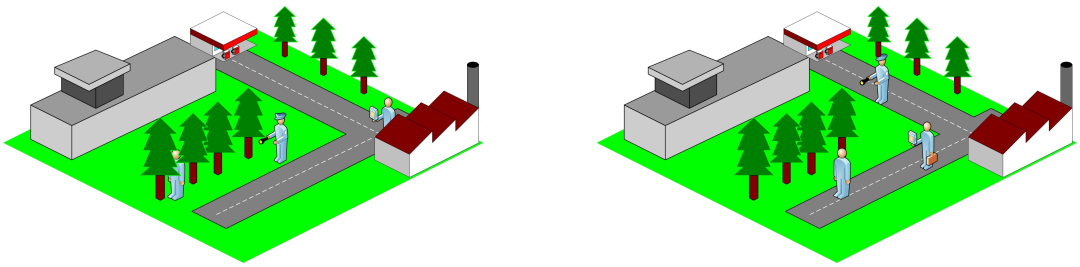


(a) With lower entropy (b) With higher entropy

**Figure 1: Two illustrated screen shots for a game scene, the Shannon entropy is lower in (a), while it is higher in (b).**

that are applied or conducted by experts. The method to evaluate user experience information in this paper can be classified into the type that based on user data, but enable automated testing or analysis. We use player perception data, based on the interaction between the player and the game scene through controlling the virtual camera, to estimate the perception degree of task-related objects. It then is used to calculate the information the player can get through Shannon entropy equation.

The perception probability used in Shannon entropy equation is estimated by recorded participants' real-time potential interests on particular objects. It meets the current ISO definition on user experience, focuses on a person's perception and the responses resulting from the use or anticipated use of a product, system, or service [18]. That better reflects the real-time exploration interests than questionnaires used in many other user interaction evaluation researches, such as the recently published paper [24].

# 3 METHODOLOGY

## 3.1 Information calculation

Shannon entropy [22] is an efficient and quantitative way to calculate the information in the contents. Shannon entropy of a discrete random variable $X$ with values in the set $\{x_1, x_2, ..., x_n\}$ is defined by

$$H(x) = -\sum_{i=1}^{n} p(x_i) \log_b p(x_i) \tag{1}$$

where $p$ is the probability distribution of $X$. A source set with non-uniform distribution will have less entropy than those with uniform distribution. Intuitively, the more equal the distribution of $X$ is, the higher the Shannon entropy of this set will be. It is reasonable that the player who pays equal attention to the objects he or she finds in the virtual scene gets more information from the scene than those who just pay attention on some of the objects and disregard others.

In order to estimate how much information can be obtained from a viewpoint when observe a 3D model, Vázquez et al. proposed a measure called viewpoint entropy [26]. They calculate probability distribution in the relative area of the projected faces over the sphere of directions centered in the viewpoint. Based on Equation 1, they define viewpoint entropy as

$$I(S, p) = -\sum_{i=0}^{N_f} \frac{A_i}{A_t} log_b \frac{A_i}{A_t} \tag{2}$$

where $N_f$ is the number of faces in the scene, $A_i$ is the projected area of face $i$ over the sphere, $A_0$ represents the projected area of background in open scenes, $A_t$ is the total area of the sphere. $b$ is the base of logarithm which is 2 in this case, so the result is in bits.

We argue that the probability distribution of each face in a 3D mesh lacks theoretical basis, as a single face has no semantic meaning for a 3D mesh. Furthermore, 3D meshes can be simplified or refined that changes the tessellation, and results in different faces for the same 3D mesh.

The information a player gets in a virtual scene is mainly from the vision. So we use the perception as the distribution factor of objects in the scene. The objects in the scene can be divided into background and task-related. The former type is used for decoration, which has less influence on the information acquiring of the player. The information is mainly from the latter ones such as NPC, pickup items, other players, interactive items, etc. In most cases only task-related objects are counted as contributing to the information result.

The main challenge of the calculation is how to decide each object's probability of perception.

## 3.2 Perception probability

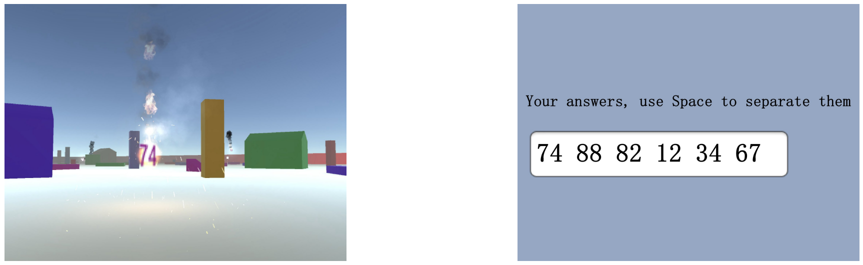
We use a method called implicit measures of user attention proposed in our previous paper [14] to evaluate the distribution of the player's attention on each object in the 3D environment. It can estimate the perception degree of each object during the exploring process of the player. The equation of implicit measures of user attention is

$$G = \int (\lambda_C C(t) + \lambda_O O(t) + \lambda_R R(t)) \mathrm{d}x \tag{3}$$

where $C(t)$, $O(t)$, and $R(t)$ represent three factors of the object perceived by the player in time $t$ respectively. They are centrality [20], occlusion [19], and projected area [15]. They can be easily recorded using object's transform information in virtual camera coordinate system. For more details about the equation, readers are referred to the paper [14].

In order to estimate the probability of the object' perception during the player's exploration in the scene, we divide the perception calculated by Equation 3 by the exploring time

$$P_{obj} = \frac{G_{obj}}{T} \tag{4}$$




(a) The verification user study scene

(b) The user answering stage

**Figure 2: Two screen shots of the user study scene to verify the effectiveness of our method. (a) is the screen shot of the participant exploring the scene, while (b) is the screen shot of the participant inputing the answers.**

where $G_{obj}$ is the perception calculated by Equation 3, and $T$ is the explore time of the player. The equation indicates the perception probability of the object through the exploring process of the player.

Set $P_{obj}$ as the probability parameter of Equation 1, the information a player gets after exploring a virtual scene can be estimated use the equation below

$$E = -\sum_{i=1}^{n} P_i \log_2 P_i \tag{5}$$

where $P_i$ is the perception probability of object $i$ calculated by Equation 4. We call it player experience information equation, as it can be used as a indicator to tell the information amount that the player experience from the game scene.

It can be seen from Figure 1. The three characters in the first screen shot showed in Figure 1(a) have different probability to be perceived by the player based on Equation 4. The character with a hat stays in the middle of the screen and without any occlusions, so he has much higher perception probability than the other two characters that are partially blocked and stay away from the screen center. While in the second screen shot showed in Figure 1(b), the three characters have similar probability to be perceived by the player, as they all stay near the screen center without any occlusions. So the Shannon entropy of the first screen shot in Figure 1(a) is lower than the second one in Figure 1(b) according to the result calculated by Equation 5.

# 4 USER STUDY EXPERIMENTS

## 4.1 Method verification

In order to verify the effectiveness of our method, we conducted a preliminary user study experiment. We believe that the more information a player can get from the scene, the better understanding about the scene he or she can achieve. There are 6 game objects distributed randomly in the user study scene. Each object shows a random double-digit. The participants are required to try their best to find out and remember these digits, and repeat them after the level is finished. The screen shots of the user study application can be seen in Figure 2.

There are 45 valid user study results. We divide them into 3 groups based on their performances of remembering the digits in the user study scene. They are perfect group, fair group, and poor group. Participants in perfect group can find out and remember

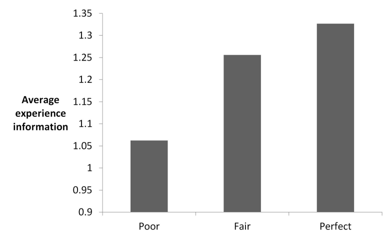



**Figure 3: Average player experience information calculated by our method for different performance levels of participants.**

all 6 digits, 4 or 5 digits are remembered by participants in fair group, while only 3 or below number of digits are remembered in poor group. We calculate the average experience information of participants in each group as showed in Figure 3. Participants with lower scores have obvious smaller average experience information than those with higher scores. Thus, Our method can successfully estimate the information amount that the player gets in the playing process.

## 4.2 Player classification

There are many articles that focus on the research of player classification [7]. The concept of player types starts with Bartles's work on MUDs [2] and continues to more recent, empirical research [7]. The players are divided into four types according to paper [2], achievers, killers, socialisers, and explorers. According to how much the player putting the emphasis on interaction rather than action, players can be divided into leisure (socialisers and explorers) and hardcore (achievers and killers) types.

The second user study scene, which aims at exploring the potential use of the method proposed in this paper into player classification. A mini 3rd person RPG game is developed. In the game, players can explore, pick up items, attack monsters and interact with NPCs just like they do in other regular RPG games. The player experience information is calculated using Equation 5.

The participants are required to do a questionnaire of player classification based on Bartle's taxonomy[2], the data set is available on-line [1]. The result of the questionnaire is used as a benchmark

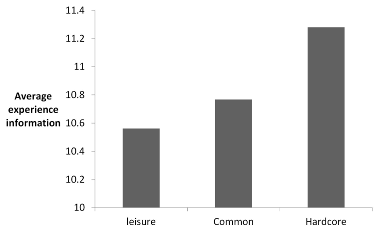



**Figure 4: Hardcore players have higher experience information estimated by our method than leisure players.**

to check the variation of experience information on the types of participants.

There are 39 valid results. The participants are divided into 3 groups according to their Bartle's questionnaire results. They are hardcore, common, and leisure. The average experience information of each group can be seen in Figure 4. The hardcore players tend to interact with objects to achieve particular game goals in the game world that makes their experience information high. The leisure players, however, don't always treat the game seriously. They don't care whether or not most task-related objects are explored. So their experience information values are normally low. Therefore, we can use the experience information as a indicator to separate the immersion of players.

## 5 CONCLUSION

A perception method is proposed to estimate the probability of objects to be perceived in the scene. We use it into Shannon entropy equation to calculate the experience information amount of players during exploring the virtual environments. A user study scene is conducted to verify the efficiency of the method. A game demo and a questionnaire application are used to show its application in player classification.

This method is easy to be embedded into current games and other applications, since only in-game data is required. Reliable results can be achieved according to the experiment results.

The user study applications, more user study results, and the questionnaire application developed based on Bartle's taxonomy [1] can be found in the author's website (https://hanhonglei.github.io/).

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