Journal of Zhejiang University SCIENCE A
ISSN 1673-565X (Print); ISSN 1862-1775 (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

Science Letters:

Human-centered modeling for style-based adaptive games*

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Received Aug. 11, 2008; Revision accepted Feb. 13, 2009; Crosschecked Feb. 16, 2009

Abstract: This letter proposes a categorization matrix to analyze the playing style of a computer game player for a shooting game genre. Our aim is to use human-centered modeling as a strategy for adaptive games based on entertainment measure to evaluate the playing experience. We utilized a self-organizing map (SOM) to cluster the player's style with the data obtained while playing the game. We further argued that style-based adaptation contributes to higher enjoyment, and this is reflected in our experiment using a supervised multilayered perceptron (MLP) network.

Key words: Player modeling, Categorization matrix, Adaptive games, Human-centered modeling, Data clustering

doi:10.1631/jzus.A0820593 **Document code:** A **CLC number:** G89

INTRODUCTION

Most researches into games concentrate on improving the game character and this is not sufficient. A game needs to behave interestingly enough for the player. Thus, an innovative approach looking into what is fun and the overall environment that contributes to fun is a more reasonable strategy. Much research work on behavioral, cultural and new media studies argues that the concept of pleasurable play derives from elements beyond the game design (Clarke and Duimering, 2006; Kerr *et al*., 2006).

Human-centered modeling approach involves investigating the human interactivity, which includes understanding or emulating human behaviors. In this letter, we apply this approach to computer game player modeling and derive the playing style from players' implicit behaviors. This approach adopts the human computing concept proposed by Pantic *et al*.(2006), into digital games, acting as a forefront of interactive and adaptive games design. Opposed to other adaptive digital games method focusing on creating a more intelligent game platform (Thurau *et al*., 2004; Spronck *et al*., 2006), our approach is to measure the player behavior, to adapt the game from the playing style and to address the issue of creating pleasurable games.

The key idea of player modeling is to capture the gaming style and to adapt a fun game to the player. In order to achieve this goal, we have developed a player categorization matrix as a guideline to determine the player's playing style. This letter uses FM1, a simple 2D shooting game for the experiment. Here, we propose to use a self-organizing map (SOM) to categorize similar behavioral data collected from players during the game. This unsupervised clustering will organize the players' data into groups, which we term as 'style-based player model'. Therefore, the aim of this letter is to adopt this idea to test how a personalized-style-based game adaptation can be more relevant and interesting.

Several researches focusing on changing gaming environment according to fun factor in a specific game as done by (Togelius *et al*., 2007; Yannakakis and Hallam, 2007) claimed to have a better entertainment for player. Our goal is to take a different approach in the similar domain, using behavioral experience of the active player within the game domain for sustaining pleasurable gaming

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* Project supported by the Soongsil University Research Fund and the Information Technology Research Center (ITRC) Support Program of the Ministry of Knowledge Economy (MKE), Korea

experience (Kerr *et al*., 2006). In order to verify this, a separate multilayered perceptron (MLP) was used to train and obtain the entertainment level after a game has been played to verify that style-based adaptation from player modeling can measure a better gaming experience. The results show a positive relationship between personalized-style-based modeling and entertainment measure.

PLAYER MODELING

Player model and behavior analysis

Understanding of players' traits and behaviors plays an essential role in creating a better gaming experience for players. Similar work on player modeling and adaptive games based on player-centered design has been done by Houlette (2003) and Charles *et al*.(2005). We propose player modeling with selected gaming features to identify the player's personal playing style. The reason is to track the player's personal preference or behaviors in the game. This preference is used for style-based adaptation and to increase fun for players.

Player modeling is described in Fig.1. It consists of capturing behavioral data during the game and clustering with dimension reduction through SOM to group them according to the characteristics of the behavioral data.

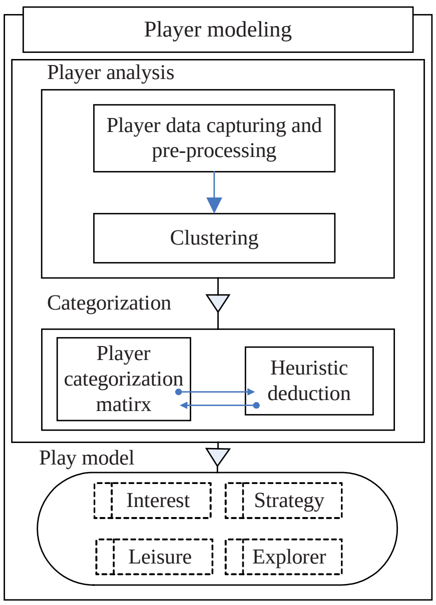

Fig.1 Player modeling

Player categorization matrix and heuristic deduction are used to deduce the groupings according to the characteristics of the behavioral data. The behavioral data obtained from players in the game include a player's activeness, sub and main weapon types, sub and main weapon power levels, score, bomb usage, a player's character life count, and a player's character life continuation count.

Player categorization matrix

Player categorization matrix in this letter is derived from motivation in (Bartle, 1996) for multi-user dungeon (MUD) games. We develop a new categorization matrix for the shooting game genre, as shown in Fig.2. The *x*-axis represents weapon usage and the *y*-axis represents the movement of the player character in the game. The derivative of four general styles is mainly influenced by the movement and the weapon selection in the game. However, other behavioral traits such as score also contribute to the final classification of the style. This typing strategy is being localized for the shooting game genre based on the behavioral data that reflect the player's style. Therefore, the player categorization matrix is proposed.

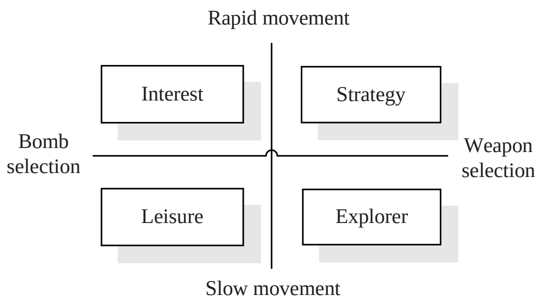

Fig.2 Player categorization matrix

The player categorization matrix makes it possible to generally classify the four styles as strategy, interest, leisure and explorer. A strategic player has rapid movement with a vast selection of weapons. A player who presents relatively fast movement but limits his/her usage of weapon to direct bombing shows an interest style. On the contrary, a player who presents slow movement but limits his/her selection of attack tools to direct bombing is a leisure player. The last category is an explorer whereby the player shows slower movement with an attempt to select vast weapon types to explore and test. We map players' styles with this matrix.

Self-organizing map and clustering

Players' data were captured in a timely sequence during the gaming session. In a preliminary experiment conducted on potential players, we obtained the data in nine dimensions (nine parameters captured in a game play) and used SOM for dimension reduction into 2D data, whose Euclidean distance to all weight vectors was computed whereby the winner neurons determined the cluster that each datum belongs to. Each player's datum was self-organized with SOM to categorize his/her playing style.

SOM grouped the data into four distinctive clusters. Based on the characteristics of the four clusters, the normalized mean of each cluster is shown in Fig.3. We have represented qualitative parameters with a numbering system coding the types of weapons and power. Two types of main weapons were coded as 0 for wide and 1 for concentrated. Sub-weapons will have 0 for straight, 1 for semi-auto and 2 for fully-auto. Meanwhile, power level was in an ascending format. The *y*-axis is a normalized mean for each parameter; the *x*-axis shows each parameter (behavioral data). As an example, cluster 1 has the characteristics of a strategic player whereby it shows a high activeness with usage of weapons (mostly wide and straight control without auto monitor) instead of more bombs. Clusters 2, 3 and 4 are labeled as Leisure, Interest and Explorer, respectively.

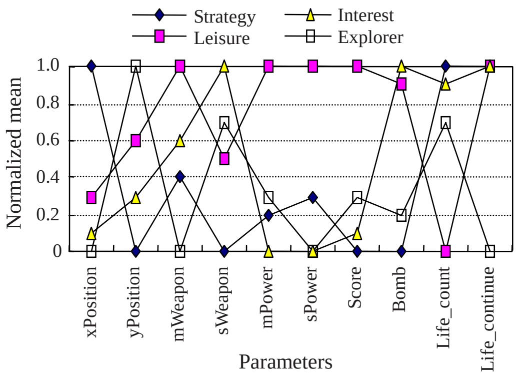

Fig.3 Summary of normalized mean for each cluster and parameter

Sample players were selected to play the game, and the data were obtained in a fixed interval. Fig.4 shows a player's model while playing the game. In this model, the game playing shows a trend of trying to find a footing in the gaming session. This graph shows that the player changed from one category to another in the first quarter of the gaming session. It starts with an emphasis on the explorer type as well as a mixture of leisure and strategy styles. From the second quarter onwards, the player shows a consistent style of leisure with occasional hits in the strategy style in quarters three and four. Here, the categories were mapped and derived from the behavioral data in each group (self-organized by SOM) referring to the player categorization matrix. We describe the style for this player as leisure, as it dominates the playing pattern throughout the game.

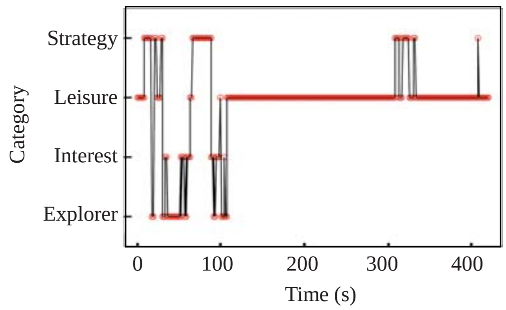

Fig.4 Sample player model

ENTERTAINMENT MEASURE

Pleasurable games

Modeling players to obtain their behaviors and styles serves as an initial work towards the goal of creating pleasurable games. Arguments on what is fun in a game and how to model fun have been described by Yannakakis and Hallam (2007) in terms of entertainment modeling, based on quantifying Malone (1981)'s theory of fun. Our experiment in the following subsection to aggregate the behavioral data into five different sets for training is influenced by this work.

Other notable works on pleasurable games for new media and cultural studies contribute to our understanding of creating fun by adapting the game accordingly. Salen and Zimmerman (2003) theorized pleasure based on a dichotomy between game and play, whereby the player's effort in interacting with the rules in the game contributes to the sensation. Our approach suggests that the game is fun when the player feels that it is suited to his/her playing style.

Experiment on adaptation and entertainment measure

In a different experiment for better entertainment measure based on the gaming style, we aggregated the same set of data into five main parameters in an offline pre-processed mode. In this letter, we propose to use an MLP for entertainment capture, similar to (Yannakakis and Hallam, 2007), for entertainment modeling.

We used five aggregated data as new parameters to measure entertainment. They were aggregated from the existing data, namely average activeness (player movement), average standard deviation of player movement, total score, total bombs used, and total time completing the game. These five aggregated data were pre-processed from the nine parametric data obtained in the earlier experiment.

This experiment used two pre-altered well-behaved games, namely strategy and leisure games. The altered games are based on their characteristics described earlier in this letter. Five players took part in an unbiased procedure. They were given five sets of both games in random fashion and were asked to rank which game was more enjoyable after each set. No information about the game style was given to players to avoid bias. Players chose to play as many rounds as they preferred and we obtained 150 sets of data labeled ‘enjoy’ or ‘not enjoy’. These data were to be used as supervised learning data in the MLP.

The MLP architecture consists of five input features, one hidden layer and the output of ‘enjoy’ or ‘not enjoy’. Based on our training data, this model can generate an accuracy of 76.3% for the prediction of the enjoyment level. We used this model to test a player’s enjoyment before and after adaptation in offline mode. A cross-check on the survey results shows that 84% of all sets of games are rated as better enjoyment when the preferred game style is given to the player.

ADAPTIVE GAMES

In this letter, we argue that the key factor for improving the entertainment level in a shooting game lies in creating a level of personalization based on a player’s behavioral traits. This remains our adaptation strategy based on human-centered modeling.

Our proposal that the adaptation based on a player’s playing style will increase the entertainment level was verified through the player modeling methodology and experiments on entertainment measure. We do not rule out the possibility of a player being categorized into multiple types, but our modeling results show notable dominance on a single style.

This research adopts a strategy of maintaining the player’s level of interest and achieves a good playability in the game through custom adaptation to the particular player (Charles and Black, 2004; Charles *et al*., 2005). The adaptation is based on player style matched with a pre-defined game. Here, we have tested using offline changes to measure the entertainment.

CONCLUSION

In this letter, we propose to use a human-centered approach as a modeling strategy to discover the playing style in a shooting game. We argue that style-based adaptation can increase the entertainment value of the game.

Our experiment uses a dimension reduction technique with the player categorization matrix to classify the playing style. A player model was generated and the entertainment level was measured with a trained MLP. The initial performance testing shows a promising result. In this way, we have demonstrated that style-based adaptation is a way to adapt the game to increase the entertainment level in a shooting game.

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