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Game Player Modeling

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Synonyms

Player modeling; Preference modeling

Definition

Game player modeling is the study of computational models to gain an abstracted description of players in games. This description helps to detect, predict, and express the behavior and feelings of players and personalizes games to their preferences.

Introduction

Game player modeling is the study of computational models to gain an abstracted description of players in games. This description helps to detect, predict, and express the behavior and feelings of players and personalizes games to their preferences. These models can be automatically created using computational and artificial intelligence techniques which are often enhanced based on the theories derived from human interaction with the games (Yannakakis et al. 2013). It offers two major benefits. First, it helps in content customization to cover broader range of players with different skill levels and adapt challenges on the fly in response to the player's actions (Bakkes et al. 2012). Second, it works as a form of feedback for the game developers and designers so that they may add new innovative features to the games as well as develop new games that advance knowledge, synthesize experience, and escalate the interest of the player (Yannakakis et al. 2013).

The very first instance of research on player modeling was reported in the 1970s where Slagle and Dixon attempted to model the behavior of opponent players in the domain of classical games by assuming the elementary fallibility of the opponent (Slagle and Dixon 1970). Later on, a search method based on knowledge about opponent players (i.e., strengths/weaknesses) was invented in 1993 (Carmel et al. 1993). In 2000, Donkers improved opponent modeling by taking into account the computer player's uncertainty (Donkers 2003). Afterward, an increasing interest developed in the player modeling of modern video games to raise the entertainment factor (Charles and Black 2004). Recently, player modeling has extrapolated its perspective from opponent modeling to a number of other research topics including player satisfaction (Yannakakis 2008), modeling player's preferences (Spronck and Teuling 2010), runtime challenge adaptation

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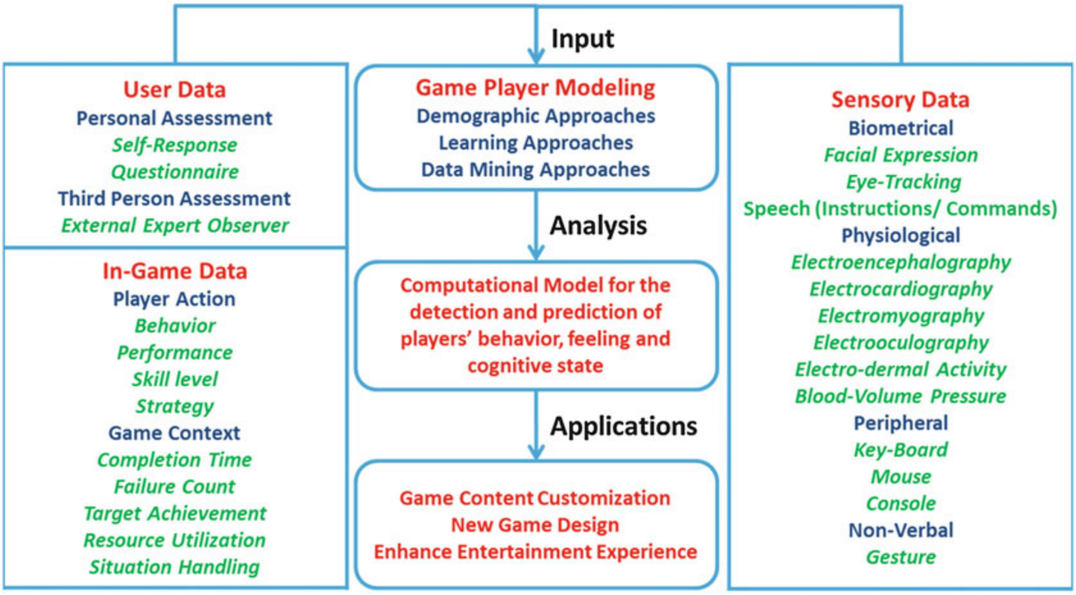
Game Player Modeling, Table 1 Techniques used for game player modeling based on the input data types

Data type	Techniques		
	Supervised learning	Unsupervised learning	Other
User data	Supervised learning (shaker et al. 2010)	Probabilistic learning (Togelius et al. 2014)	Rating-based approach (Mandryk et al. 2006)
	Neural network (Schmidhuber 2006)		
	Committee selection strategy (Togelius et al. 2014)	Clustering (Yannakakis et al. 2013)	Active learning (Togelius et al. 2014)
	Classification and regression (Yannakakis et al. 2013)		
Sensory data	Neuroevolution (Pedersen et al. 2009)		Cognitive appraisal theory (Frome 2007)
			Usability theory (Isbister and Schaffer 2008)
	Neural network and clustering (Charles and Black 2004)		Belief-desire intention (Ortega et al. 2013)
			Facial action coding system (Ekman and Friesen 1978)
In-game data	Neural network (Charles and Black 2004; Pedersen et al. 2009)	Clustering (Drachen et al. 2009)	
	Supervised learning with labels (Togelius et al. 2014)		
	Multilayer perceptron (Togelius et al. 2006)		
	Sequential minimal optimization (Spronck and Teuling 2010)		

(Yannakakis et al. 2013), playing style, and learning effective game strategies (Lockett et al. 2007). A comprehensive history of player modeling is given in (Bakkes et al. 2012).

A player model can have three types of inputs: user data, sensory data, and in-game data (Yannakakis et al. 2013; Martinez and Shichuan 2012). User data includes personal assessment and third-person observation. The negligible limitations of user data are non-relevant data assessments, short-time memory, and player's self-deception (Yannakakis 2012). Sensory data includes data collected from the sensors mounted on the player's body or in the player's surroundings. The most common sensor data includes biometrical (Gunes and Piccardi 2006), physiological (Drachen et al. 2010; Martinez et al. 2013), peripheral (Omar and Ali 2011), and nonverbal natural user interface with the games (Amelynck et al. 2012). However, the sensor's interface with the player faces challenges when it comes to accuracy and performance. In-game data is based on the player's actions taken within the game to infer performance, skills, strategies, behavior, and game contexts including level completion time, mission failure counts, resource utilization, situation handling, and target achievements (Nachbar 2013; Kim et al. 2012; Weber et al. 2011). The big challenge is to interpret the raw data correctly for high-level player modeling using limited amount of data.

Based on the type of the input data, several learning and data mining approaches are used for player modeling as can be seen in Table 1. The effectiveness of the modeling technique based on user data is calculated using demographic/stereotype approaches (Butler et al. 2010). The major challenge in such models is that they are limited to deal with situations where individuals greatly deviate from the average. The sensory data is correlated to the player's behavior, emotions,



Game Player Modeling, Fig. 1 Inputtypes, modeling approaches, analysis, and applications of game player modeling

preferences, cognitive, and affective states (Drachen et al. 2009). Physiological signals are correlated to arousal and valance using Plutchik's emotion wheel and the valence-arousal scale by Russell (1980), facial expressions using continuous, categorical, and active appearance models, speech or psycholinguistic narrations using PERSONAGE, and psychological factors using Big Five model (Lankveld 2013). In-game data features collected during the game play are used to identify or predict the type of the players which can then be further used for personalized component generation or level modifications (Drachen et al. 2009). An overview of input data gathering, modeling approaches, computational analysis, and applications of game player modeling is shown in Fig. 1.

Although a lot of work has been done on the player modeling, several remaining issues need to be addressed. For instance, sensory data-based models lack non-obtrusive data assessment, data reliability, data validity, vigilance recognition, and quick reactivity. User data-based models exhibit low correlation with the data collection time and the particular situation. In-game data-based models are restricted to particular players' personal interests in game, expert level, mood, enthusiasm, and surrounding environment, making it difficult to generalize for all players. However the generalization problem is resolved by continuously comparing and adjusting procedural personal behavior with human behavior and active player modeling (Holmgard et al. 2014; Togelius et al. 2014). Furthermore, hybrid approaches are used to overcome the issues of individual data-based player models (Arapakis et al. 2009; Kivikangas et al. 2011; Nogueira et al. 2013a, b). Game player modeling is also experimented in some commercial games (e.g., Tomb Raider, Civilization IV, and Left 4 Dead), but there are still some problems of generalization (Drachen et al. 2009; Spronck and Teuling 2010; Ambinder 2011). Even though player modeling can be generalized, there is still a gap between the player's characteristics within a game and the real world which needs to be bridged in the future research (Holmgard et al. 2014).

Cross-References

▶ Constructing Game Agents Through Simulated Evolution

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