Chapter 97
Dynamic Difficulty Adjustment by Facial Expression

Nan Xiang, Lili Yang and Mingmin Zhang

Abstract To enhance players' game experience is one of the most important targets in game exploring. In this paper we integrated a dynamic game difficulty adjustment (DDA) method into Tetris that using Active Shape Model (ASM) and HMM to recognize emotion states of players' from camera and utilizing Kalman filter to dynamically detect the experience of players. According to the users' experience then adjusted the speed of game. Experiments shown that our DDA method could give player better game experience.

Keywords Affective computing · Dynamic difficulty adjustment · Facial expression · Game intelligence · Kalman filter

97.1 Introduction

In the past decade, researchers and game explorers lay their efforts mainly on the visual realism of game performance to enhance the players' game experience. As a result, game performance on 3D model rendering, character's animation, NPC's intelligence, fluid simulation, social interaction environments etc. have made remarkable achievements. To increase players' experience, a computer game must be balanced well. For instance, a game must provide meaningful choices, the role of chance should not be so great that player skills become irrelevant, and players must perceive the game to be fair [1], otherwise the player should lose their interesting. This is so called Dynamic Difficulty Adjustment (DDA) and Dynamic

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Game Balancing (DGB). In addition, players' emotion plays an important role in game experience. The gaming community has recently recognized the importance of emotion in the development of more engaging games, and the area of affective gaming is receiving increasing attention [2]. Many psychophysiological studies have been made to investigate different traits of game-play experience and several games have been developed in laboratories exploring the possibility of adapting the game-play to the player's state [3]. This provides us a practicable method to avoid undesired player emotions such as frustration by dynamically adjusting game parameters especially game difficulty level.

In common video games, the level of game difficulty cannot be changed within each stage of game. Although there is a training model for player to learn the game mechanics, however once the player set the game difficulty, it is easy for him to feel frustrated as the mission is too difficult to accomplished or too tedious without any challenges. Most large games adjust the game parameters in their new versions which often take a long time to be released. Currently, players' in-game performances such as the rate of successful shots or hits, number of life points, time left to complete a task are used for dynamic game balancing [3–8]. However, as players' hobbies, performance and responses are various with their emotional states which also dynamically changes with the game progress, game adaptation should take the emotional response of the player into account more than in-game performance. Physiological signals such as Blood Volume Pulse (BVP), Heart Rate (HR) and Electrodermal Activity (EDA) are used to detect the arousal of emotion. Unfortunately, all these method need to contact the equipment to players, as a result, players will probably not accept this kind of detection in game.

Take these into account, we provide an emotion based dynamic game adjusting prototype Emotetris which utilizes face expression captured from camera to detect the players' emotional states and then adjust game difficulty level dynamically according to these emotional states. Our method is grounded on the user-centric design by adjusting the difficulty level of the game to maximize the user's experience which is deviated from the traditional game-centered system. Traditional systems based on the gradual and consistent augmentation of the difficulty level treat all users equally and ignore the broad diversity of their gaming skills, and preferences [9].

97.2 Background

To enhance players' game experience is one of the most important targets in game exploring. In Ermi's study, immersion is composed by sensory immersion, challenge-based immersion and imaginative immersion [10]. Wijnand considered flow, an optimal state of enjoyment where people are completely absorbed in the activity. In the gaming domain, immersion is mostly used to refer to the degree of involvement or engagement one experiences with a game [11]. Lennart explored well-accepted common meanings of certain user experiences such as flow and immersion instead of a more through understanding of loosely defined subjective experiences [12]. Kiel pointed two kinds of frustration during games, the at-game-frustration and in-game-frustration. The first is due to lack of skill during game playing and the second in caused by difficult game levels [13]. The players' experiences study is not limited in traditional PC games but also extend to other platforms such as mobile games [14, 15].

The relations between physiological signals and players' emotional activities have been studied in many works [9, 16–20]. These researches showed that high EDA values correlate with high arousal and that a high level of arousal can be indicative of a high level of challenge, frustration, and/or excitement. Players are engaged in low speed of heart rate and frustrated in high speed of heart rate. Although these signals could be used to detect the arousal of emotional activates, yet it is hard to distinguish some distinct experiences which have the same physiological reactions, for example, being frustrated and being immersed.

The other methods are to utilize game AI to dynamically adjust the difficulty level. Gaussian Mixture Module and multivariate pattern mining were used to model the player's reaction pattern [21, 22]. NPCs behaviors are controlled by reinforce learning algorithm [6, 7]. They did not, however, change the game environment or adjust the difficulty of the game level during play. By conducting a cheap, abstract simulation of the player's progression through state space, Hunicke [4] used Hamlet system to predict when the player is repeatedly entering an undesirable loop, and help them get out of it. Joost [23] proposed an adaptation approach that uses expert knowledge for the adaptation. They used a game adaption model and organized agents to choose the most optimal task for the trainee, given the user model, the game flow and the capabilities of the agents. Hom [24] used AI techniques to design balanced board games like checkers and Go by modifying the rules of the game, not just the rule parameters.

97.3 Program

In this section we first introduce how to generate the facial feature points and then construct HMMs to distinguish emotions.

97.3.1 Facial Feature Detection and Emotion Recognition

System adopts the Active Shape Model (ASM) animation algorithm to facial feature point detection. Model total includes 77 feature points as shown in Fig. 97.1. In order to establish facial feature point, the system divides face into upper, middle and lower areas, thus other points of face can be determined through relevant constraints on linear interpolation. To estimate the emotional states of players' captured from camera we adopted HMM. We exploited the facial feature

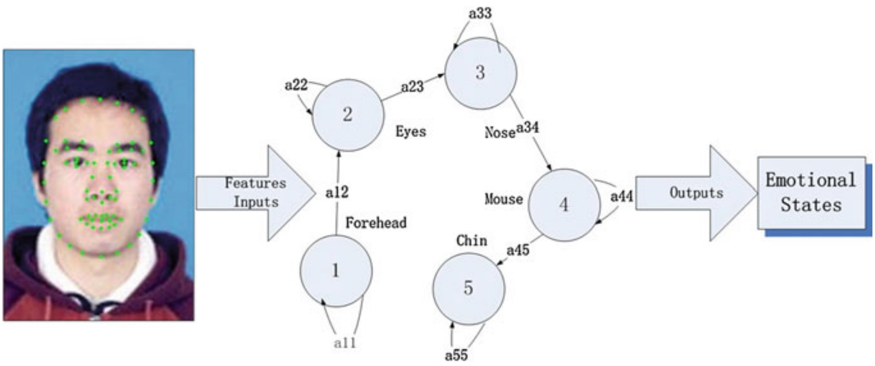

Fig. 97.1 Facial feature detection and emotion recognition

points as the observations of HMMs and then the players' emotions could be generated from facial images using HMMs by assigning each of these regions to a HMM. For more details about the emotion recognition process please find our previous research [25].

97.3.2 Facial Feature Detection and Emotion Recognition

After generating the facial expressions of players', we would calculate his or her game experience with their game performances. The numbers of lines that had been eliminated and had not been eliminated represented as le_n and lr_n, by player over time, were utilized to represent their in-game performance. Ground on the theory of Kalman filter, the expressions of player were treated as an observational variable to adapt the prediction of experience.

Assuming $S_n = \{bore, relas, engaged, frustrated\}$ represents the player's state when the nth diamond was dropping, $P_n = (le_n, lr_n)$ is a vector denoted the in-game performance state, then

$$S'_n = AP_{n-1} + U \tag{97.1}$$

where S'_n is the predicted player's experience state, and A is translation matrix, U is covariance.

$$S_n = S'_n + (BE_n - AP_{n-1})kg \tag{97.2}$$

B is control matrix, E_n represents the expression of player's face, kg denotes the Kalman gain.

$$kg = BQ'_nB'/(BQ'_nB' + V) \tag{97.3}$$

$$Q'_n = AQ_{n-1}A' + U \tag{97.4}$$

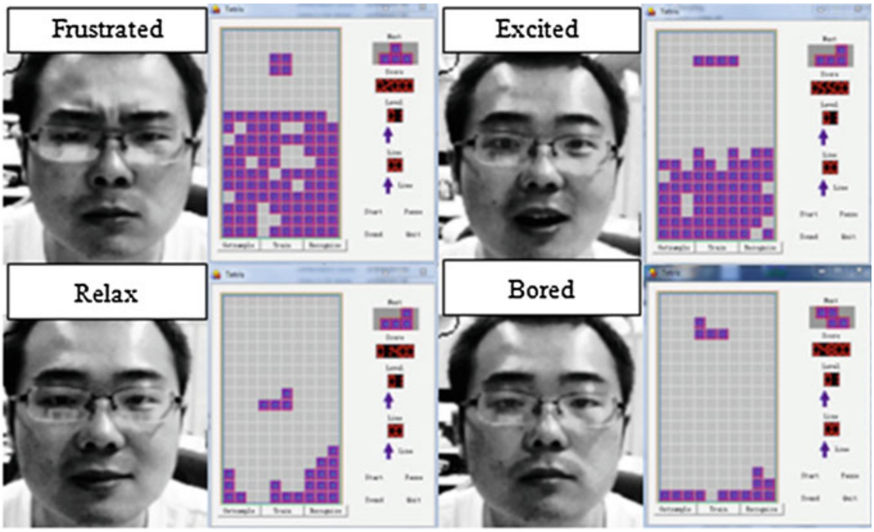

Fig. 97.2 The sample facial expressions and game results in four kinds of game mood

Q_n represents the optimal covariance. All these parameters are set according to experiments.

97.4 Experimental Results

In this section we would show the adjustment strategy in our DDA system and give the user study result.

97.4.1 Recognition and Adjustment

The computer that we run this system has Dual-Core E5300 CPU and 4G memory. Every new player's expression would be sampled and trained before starting game.

We integrated difficulty adjustment into Tetris to evaluate the performance of algorithm. The speed of dropping diamond is the parameters to be adjusted for it can affect players directly. Figure 97.2 showed the player's standard facial expression when he was frustrated, flow and excited, flow and relax and bored according to the game results. The adjustment strategy can be found in Table 97.1, when player is frustrated, the game should slow down. Flow means a good game experiences and the speed should be kept on. When players are bored they may need change the speed or a rest. Good in-game performances do not means speed up and bad in-game performances do not mean slow down, they are related to the player's game mood. For example, players may consider eliminating many lines in one time.

Table 97.1 Adjustment strategy

	Frustrated	Flow and excited	Flow and relax	Bored
Good performances	Slow down	Keep on	Speed up/keep on	Speed up
Bad performances	Slow down	Keep on	Keep on	Need a rest

97.4.2 User Study

To estimate the players' experience, 20 volunteers who had no research background on dynamic difficulty adjustment were participated in our experiment. They first played the game with difficulty adjustment only according to their in-game performances and then play in the expression based adjustment mode. After trying two kinds of game mode, they were asked two questions: does the game make adjustment in time and which mode is better? For the first question, 16 players thought the game could make in time adjustment when they was frustrated or bored. For the second question, 14 players considered the expression based game adjustment is better than in-game performances based adjustment in bringing them better game experiences.

97.5 Conclusion

In this paper, we provided an effective method in improving players' game experiences. Our method combined the in-game performances and facial expressions of players to dynamically adjust the game difficulty. Experiments shown that, only employing in-game performances cannot make a just decision in changing game parameters. Dynamic difficulty adjustment can attract players' attention when they were bored and release the pressure when they were frustrated. However, how to change the game parameters in a certain situation is due to the custom of different players. Our next work was to propose special solution for different players in different game styles.

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