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Battle of minds: a new interaction approach in BCI games through competitive reinforcement

Yoones A. Sekhavat[1]

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Abstract
Brainwaves can be used as auxiliary inputs in the design of game mechanics for attention training games. Although attention training games are generally developed in the single-player mode, multi-player games can be more engaging and fun to play. This paper proposes a new interaction technique between players in multi-player car racing games, in which a novel competitive reinforcement approach is used to regulate difficulty parameters using brainwaves of players. The results of our experiments suggest that the competitive reinforcement is more effective to increase attention level as compared to positive and negative reinforcement conditions.

Keywords BCI games · Multiplayer video games · Competitive reinforcement

1 Introduction

Serious games are becoming an alternative educational method in various learning and rehabilitation fields [3, 24]. In attention training through neurofeedback, a user's concentration level is gathered by sensing Brain-Computer Interfaces (BCIs) and presented back to the user so that the user can try to adapt her state [4]. The use of neurofeedback has shown it to be effective in helping people treating attention deficits [11, 31]. Neurofeedback training is a long term process with an involvement of users in several training sessions [6, 23]. Such training activities are generally designed as repetitive tasks that can make users frustrated and tired. Incorporating games into an attention training system, in which a training task is designed as a therapeutic game, can result in a motivating and engaging environment [22]. Such serious games make training tasks fun to play and effective over a long-term engagement [15].

Generally, attention training games are developed as a single-player game. However, as argued in [21], the competitive multi-player gaming is more enjoyable than solo play. It is also shown that arousal ratings are higher when playing against a real person than playing against a computer. This paper shows the experience in design and development of a

✉ Yoones A. Sekhavat
sekhavat@tabriziau.ac.ir

[1] Faculty of Multimedia, Tabriz Islamic Art University, Azadi Blvd, Tabriz, Iran

multi-player attention training game, where electroencephalogram brainwaves (EEG signals) are used as auxiliary inputs for difficulty adjustment. We use NeuroSky MindWave [12] as a portable, noise-resistant, easy to set up and affordable EEG for gaming.

In cognitive games, rules and procedures of the games can be adjusted with the goal of encouraging players to maintain a particular cognitive state [5, 27]. While playing an attention training game, users are required to maintain their mental state as concentrated as possible to progress in the game. To achieve this goal, game mechanics can be adjusted using negative reinforcement [2] or positive reinforcement [20]. In the negative reinforcement, the reduction in attention results in creating barriers for the player, while achieving the right cognitive state (e.g., concentration) removes the barriers to progress in the game. For example, in [10], when the brainwaves of a player show reduction in attention, the game screen becomes foggy, making it difficult to detect and move the objects in the game. In this condition, a user needs to concentrate on the game to clear the gaming environment. On the other hand, in the positive reinforcement approach, an increase in the attention level results in providing facilities to progress in the game.

Although research has shown that positive feedback can enhance perceived competence and enjoyment more than negative reinforcement [20], to our knowledge, this problem is not studied for multi-player games. In the technique we propose, which is called *competitive reinforcement*, a change in the attention level of a player (calculated based on EEG signals) affects the gaming conditions of the opponents. In particular, an increase in the attention level of a player results in making difficult conditions for the opponents to compete in the game. On the other hand, reduction in the attention level affects the difficulty parameters of the opponents' game properties, such that facilitates the progress of opponents in the game. The technique we propose also adjust the difficulty parameters when the skills of players are not at the same level. This adjustment is performed with the goal of balancing the game to avoid big progress or regress in the game. A set of experiments have been proposed to evaluate the efficacy of competitive reinforcement in comparison to negative and positive reinforcement approaches. The attention training game we propose is a multi-player car racing game which employs brainwaves of players for difficulty adjustment. In summary, the contributions of this paper are:

– Proposing an engaging multi-player attention training game that encourages players to increase and maintain their attention level.
– Proposing the *competitive reinforcement* technique as a novel difficulty adjustment technique in multi-player games.
– Conducting a user experiment to study the effect of proposed technique on motivating players to increase attention level.

2 Related work

Recently, some papers have studied using brain computer interface (BCI) technology to translate the user's attention state into game control [8, 13, 17]. In [28], a game protocol is proposed in which a player uses her attention to control the game by remembering numbers. Shenjie et al. proposed a game scenario that requires players to direct a ball on path using attention level [25]. Some others have used game scenarios based on EEG feedback to treat Attention Deficit Hyperactivity Disorder [1, 9, 14]

Although the main purpose of attention training games is helping players to self-regulate brain activity, such games should also motivate players in terms of enjoyment and engagement [5]. Generally, attention training games are developed as a single-player game. However, as discussed in [21], competitive multi-player gaming is more enjoyable than solo play and offers a social context for competition. According to [29], competition is the most important determinant of the enjoyment arising from playing games. A player's feeling to play against an opponent evokes a social-competitive situation that results in the engagement of the player in the game [19]. In addition, the nature of an opponent (i.e., computer, friend, or stranger) affects spatial presence and emotional responses. Research has shown that arousal ratings are higher when playing against a real person than playing against a computer [19]. As discussed in [30], playing against a real human being results in higher spatial presence and engagement compared to playing against a computer. According to Weibel's findings, playing against a human-controlled opponent can result in strong experience of presence, flow, and enjoyment than computer-controlled opponent [30].

To increase desired behavior in single-player attention training games, generally game mechanics are adjusted using negative reinforcement [5] (removal of a negative stimulus or barrier to progressing in the game) and positive reinforcement [20] (addition of a positive stimulus). Games for neurofeedback training tend to use negative reinforcement rather than positive reinforcement. The efficacy of negative or positive reinforcement approaches depends on the personality, where extroverts learn better under positive reinforcement, while introverts learn better under negative reinforcement [5]. As discussed in [26], although both negative and positive reinforcement approaches are effective for neurofeedback training, rewarding is more effective especially when working with children [26]. Reinschluessel et al. showed that positive reinforcement is more effective in encouraging players to keep their brain activity regulated [20]. They also argued that positive reinforcement is more successful at motivating players to be active in the game.

3 Attention training game

As a multi-player neurofeedback game, a car racing game is developed in this paper. Although the car racing game is selected to develop the competitive reinforcement approach, other multiplayer games can also be extended based on this concept. This concept can also be applied on the serious game/therapeutic scenarios that have already been developed. However, this can be performed on the games that their game mechanics allow multiplayer setting. In this mobile game, a player's car is accelerated by touching the gas pedal on the screen. A player can also reduce the speed of car by touching the brake pedal (near the gas pedal) on the screen. Turning to right and left are controlled by moving the mobile device, where the accelerometer is used to indicate the turning amount. This game provides a competitive and exciting atmosphere, in which two or more players compete against each other to gain the first place by driving their cars in a racing route. This game simulates physical driving in a virtual environment by providing actions such as accelerating, braking, and changing directions. In this game, human players compete against each other in a race track.

The car racing game developed in this paper gathers data from input devices (touch screen data to control the speed of the car, accelerometer data from the device's movements, and EEG coming from the BCI device), applies game rules, and finally, provides feedback to the player. This game is a multi-thread game, where a separate thread is dedicated to deal with EEG brainwaves. After the initialization phase, the main loop of the game is started, where user inputs are gathered from the input devices. The input manager is in charge of handling all inputs and preparing them for the processing phase. In the processing phase, game rules and mechanics are processed according to input values. Finally, in the

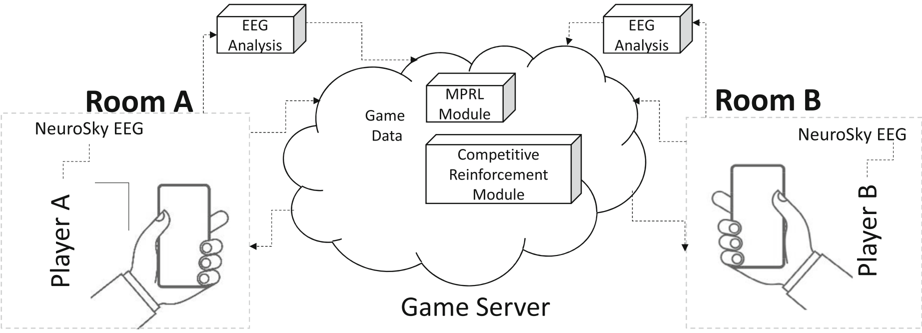

Fig. 1 The setting of using competitive reinforcement approach in the attention training game based on car racing

render module, the feedback is presented to the user through images and sounds. In this architecture, the BCI module is in charge of gathering and processing EEG brainwaves. After pairing the EEG device, brain signals are gathered continuously. This setting is shown in Fig. 1. Every second, the headset computes and delivers the attention measure. Although the details of computing attention measure is not revealed by the Neurosky manufacture, the unit of measuring attention is number between 0 and 100.

3.1 Integrating EEG

Research has shown that a game just based on EEG signals provides a limited interaction and does not result in enough engagement of players [10]. On the other hand, combining EEG signals with traditional interaction mechanics can result in better and engaging scenarios. We used NeuroSky's MindWave Mobile headset to measure the brain activity of players. This EEG device measures brainwaves on the forehead with dry electrodes as shown in Fig. 2. This EEG kit processes the raw EEG output to produce attention and meditation values. This product has potential of becoming a mass usage device because of the low price, availability of SDKs, resistance to noise, and ease of usage [5]. Although most of

Fig. 2 Playing Battle of Minds using NeuroSky MindWave as an input device to regulate game properties (right) and a scene of car racing game developed based on competitive reinforcement (right)

the signals collected by this device correspond to the frontal lobe that limits the capturing of mental activity, research has proved the potential of this device in measuring attention level. NeuroSky's ThinkGear PlugIn was used in Unity game engine to develop the prototypes. The output frequency of the headset's data was smoothed by using a simple moving average window over three seconds.

To integrate the concentration level into the mechanics of the car racing game, a sigmoid function was used to map concentration level with difficulty parameters. This function makes it possible to create a high response when the concentration is increased from low to medium-high. On the other hand, when a player is already concentrated, small changes in the concentration are also visible. Similar to [20], game properties were mapped to discrete categories to provide a better game experience. When a player's concentration level is changed and set into a different category, difficulty parameters are smoothly accelerated or decelerated until reaching the next threshold.

3.2 Incorporating difficulty adjustment

Based on the theory of fun, balanced challenge is a major factor to create an enjoyable gaming experience [18, 32]. Multi-player games such as racing games are played by diverse players. To avoid situations where players become frustrated because the game is too difficult, or bored because the game is too easy, it is important to adjust the challenges of a game according to the skills of the players. A successful handling of challenges leads to positive affect, which is connected to high arousal. Therefore, playing a video game is expected to be enjoyable only if sufficient number of competitive challenges are handled by the user. This results in a need to regulate the probability of success and failure in competitive situations according to the players' skills using difficulty adjustment techniques.

Unlike single player games, difficulty adjustment in multi-player games is not straightforward. In multi-player games, players with different skill levels operate in the same area, where the adjusting the difficulty parameters of one player may affect other players in an undesirable way. In particular, in our multi-player driving game, players drive in the same virtual space, where their decisions and actions affect other drivers. Generally, difficulty adjustment techniques are episodic, where the adjustment of difficulty parameters occurs in predefined episodes. In the case of long periods, players have to wait for a long time to see the effect of changes on difficulty parameters, while different things may happen during this time. On the other hand, players do not have enough time to adapt themselves with the new conditions in the short periods.

Difficulty parameters in the game Three parameters affecting the performance of the players during the game are *maximum speed*, *number of gears*, and *torque*. Maximum speed is a limiting factor, where a player's car cannot go beyond the maximum speed. The number of gears has an inverse relation with acceleration, where increasing the number of gears results in reducing acceleration. Torque is a rotational force coming from the engine to drive the wheels, where more torque means more force you have to accelerate the car. The game we develop uses a physics module in which all of these parameters are implemented. This physics module is an adapted version of an open source physics machine available in www.bonecrackergames.com. Some changes have been made on this version to apply competitive reinforcement.

4 Competitive reinforcement

In this paper, we propose the concept of competitive reinforcement in multi-player games and apply it an attention training game. According to this concept, a player is rewarded for achieving and maintaining a good concentration level by making difficult competition conditions for the opponents of this player. In our car racing game, this is realized by reducing the maximum speed, increasing the number of gears and reducing the torque of opponents' cars. On the other hand, the opponents are rewarded if the player does not maintain a good concentration level. This is performed by increasing the maximum speed, reducing the number of gears and increasing the torque of opponents' cars. In particular, the lower the focus, the better driving conditions for the opponents.

To ensure establishing *flow* state in the players, wins/losses margin in a game must be small [22]. In the context of the car racing game we propose, the distance between a player's car and other cars can indicate the progress of this player in the game. Therefore, given $d_{i,j}$ as the distance between car i and car j, cumulative distance D for n cars must be minimized. A small cumulative distance implies that players are engaged in the game and try to get a better score by becoming better in the game.

$$D = \sum_{i=1}^{n} \sum_{j=1}^{n} d_{i,j}/2 \tag{1}$$

The technique we propose performs difficulty adjustment in three different phases including *boredom*, *frustration* and *competition* phases (Fig. 3). In the boredom phase, the player's car is considerably ahead of other cars, where this player is most likely to win the game. On the other hand, in the frustration phase, the player's car is far behind other cars, where the player is unlikely to win the game. The battle of minds occurs in the competition phase, where the output of the BCI devices are used for competitive reinforcement. The purpose of difficulty adjustment in boredom and frustration phases is directing players to the

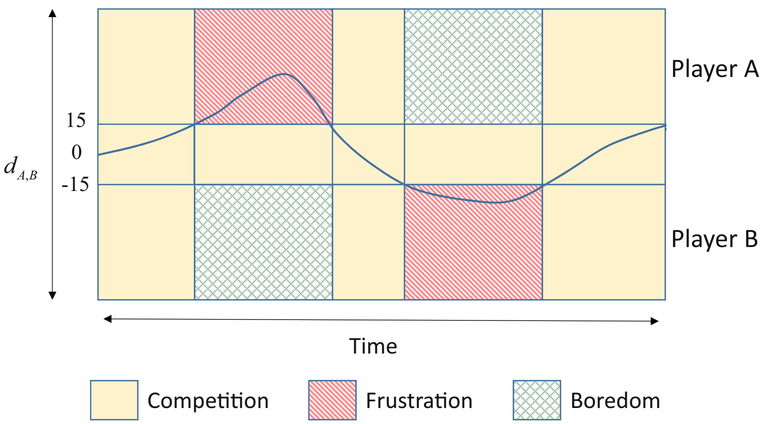

Fig. 3 A diagram showing how two opponents' phases are changed based on the distance between the players' cars in the car racing game

competition zone. The border between different zones are determined based on cumulative distance of a player from other players.

4.1 MPRL in boredom and frustration zones

To modify difficulty parameters in boredom and frustration zones, we employ our Multiple Periodic Reinforcement Learning (MPRL) technique, which is a probabilistic two-level technique for difficulty adjustment. This probabilistic technique includes direct and indirect actions, where indirect actions are in charge of increase/decrease in the probability of running direct actions. On the other hand, direct actions are in charge of increase/decrease in difficulty parameters.

An adaptive uni-chromosome controller is used to indicate how difficulty parameters (including max-speed, num-gears and torque) can be modified based on positive and negative reinforcement (Fig. 4). This chromosome stores three real numbers corresponding to three game properties. This is an array of three real numbers, where each position in the chromosome corresponds to the probability of a decrease or an increase in the parameters. In each period, any of decrease or increase controllers can be activated based on the activation probabilities in the chromosome. In this chromosome, C_i is the i^{th} place in the chromosome, where $i = 0$, $i = 2$ and $i = 4$ corresponds to increasing max-speed, num-gears and torque, respectively, and $i = 1$, $i = 3$ and $i = 5$ corresponds to decreasing max-speed, num-gears and torque. $|C_i|$ represents the probability of this action. The activation of an increase/decrease in a parameter leads to 10% increase/decrease in that parameter. In the technique we propose, all actions have a chance to be performed at different periods. The details of adjustment algorithm used in boredom and frustration zones are provided in our previous work [22].

4.2 Battle of minds through competitive reinforcement

The competitive reinforcement technique proposed in this paper is applied in the competition zone. The BCI device through neurofeedback is incorporated in this technique, where the attention level of a player affects the difficulty parameters of the opponents. In particular, increasing the attention level of a player negatively affects the difficulty parameters of other players, where it makes difficult for them to compete with this player. On the other hand, reduction in the attention level modifies the difficulty parameters of other opponents,

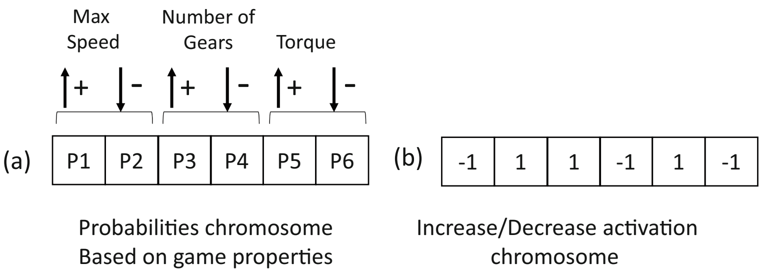

Fig. 4 Uni-Chromosome Controller used to indicate the probabilities of activating/deactivating game properties (**a**), an example of activation/deactivation chromosome based on the probabilities (**b**)

such that facilitates the progress of them in the game. We argue this type of reinforcement is more compatible with competition theories in terms of encouraging players to compete in engaging scenarios. Unlike boredom and frustration zones, in which the performance of players in terms of progress in the game are used for difficulty adjustment, the input values in the competition zone are the attention levels of players.

The details of adjustment based on attention level is shown in Fig. 5. When two players are in the competition zone, the attention level of the opponent affects the chromosome controller. On the other hand, when a player is in the frustration or boredom zones, the scores of the player (the distance from other cars) affects the chromosome controller to adjust the game properties.

As shown in the Battle of Minds algorithm (Algorithm 1), the distance between two players determines the phase of each player in the game. Once a player is in the frustration zone, the opponent is in the boredom zone. On the other hand, once a player is in the boredom zone, the opponent moves to the frustration zone. Accordingly, when the distance between two players are less the specified threshold, both of the players are moved to the

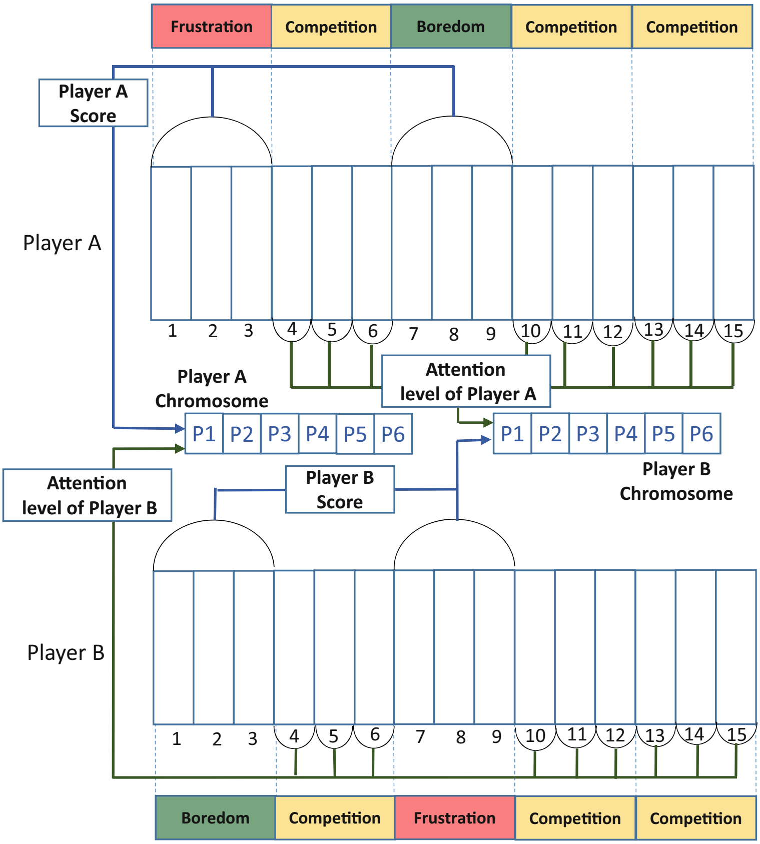

Fig. 5 The architecture of proposed difficulty adjustment technique, that uses players' scores in Boredom and Frustration phases, and attentional level of opponent in the competition phase

competition zone. Since the basic level of attention in players can be different, we measured the attention ratio for each player and took the maximum as a reference point throughout the game. Then, we mapped this attention ratio to a 100% scale. This normalized attention value makes it possible to find the difference between the attention level of participants, and consequently, rewarding or punishment values for the participants (rw_A and rw_B).

Change to chromosome values are calculated based on reinforcement learning technique. As shown in the Algorithm 1, the learning rate (α) indicates to what extent the algorithm must explore new conditions or exploit the previous learnings. In this algorithm, $state(p)$ denotes the state of the chromosome before an update. ($state(p) = 1$ if the chromosome was active in the previous round, and $state(p) = -1$ if the chromosome was not active). After evaluating the attention values, the controller chromosome C is updated. C_i is the i^{th} place in the chromosome representing the probability of activating/deactivating of decrease/increase of a game property (maximum-speed, num-gears, torque).

One problem with the competitive reinforcement is that a change in the attention level does not have an instantaneous feedback and affects opponent's car after a certain amount of time. As shown in Fig. 5, to provide instantaneous feedback of attention level, the frequency of updating chromosome controllers in the competition zones are more than this frequency for boredom and frustration zones (three times). In addition, a concentration meter shown on the top left corner of the screen informs to what extent this user is concentrated on the game.

5 Evaluation

A set of experiments were conducted to evaluate the competitive reinforcement technique using the multi-player car racing game. In particular, we studied if competitive reinforcement works better than positive and negative reinforcement at motivating players to increase their attention and yielding positive effects. To this end, feedback from the users in terms of BCI signals as well as data from self-reported questions were gathered.

5.1 Participants

For this study, 24 subjects were recruited from a local university including 6 females and 18 males aged 20 to 26 (mean of 22). We arranged one-on-one game sessions, where two players were asked to compete against each other to win the car racing game. Consequently, given 24 participants, 12 sessions were held to perform the experiments (four sessions under each reinforcement condition).

5.2 Procedure

We manipulated the type of reinforcement as an independent variable to determine whether this parameter has an effect on the performance of participants. Based on this variable, participants were assigned to one of positive, negative and competitive reinforcement conditions. Since the environment and the gaming scenarios were the same, in order to prevent the learning effect, we designed a between-subjects study, where each participant was exposed only to one of the reinforcement techniques. Four dependent variables were measured in the study were the efficiency of motivating players to increase attention, core gaming experience, social presence and intrinsic motivation.

Algorithm 1 Battle of minds algorithm.

Data: Difficulty parameters of players, attention level of players, position of the players on the road.
Result: controller chromosome is updated C.
Let C_A and C_B the controller chromosome of player A and player B, respectively.
Let T_A and T_B the attention level of player A and player B, respectively.
Let P_A and P_B the attention level of player A and player B, respectively.
Let t the evaluation counter.
Let $distance$ the distance threshold (determined by a therapist).
Initialize chromosome C_A and C_B with zero numbers.
repeat
    if $P_A - P_B > distance$ **then**
        $pahse_A = Frustration, pahse_B = Boredom$
    else if $P_B - P_A > distance$ **then**
        $pahse_A = Boredom, pahse_B = Frustration$
    else
        $pahse_A = competition, pahse_B = competition$
    end
    if $pahse_A$ *and* $phase_B \neq competition$ **then**
        Run MPRL algorithm for difficulty adjustment to push player to the competition zone
    else
        $T_A =$ (avg of player A's attention over 3 seconds)
        $T_B =$ (avg of player B's attention over 3 seconds)
        Normalize T_A and T_B (according to their base values)
        $rw_A = (T_A - T_B) * \beta * (P_A - P_B)$
        $rw_B = (T_B - T_A) * \beta * (P_B - P_A)$
        rnd = Random(0,1);
        if $(rnd \leq 0.3\,)$ **then**
            for *p = 1 to 6* **do**
                if *p is even)* **then**
                    $C_p = (1-\alpha) * C_p + \alpha * (state(p) + rw)$
                if *p is odd)* **then**
                    $C_p = (1-\alpha) * C_p - \alpha * (state(p) + rw)$
            end
        for *p = 1 to 6* **do**
            with the probability of C_i in C, run the corresponding direct action
        end
    end
until *the game is in progress*;

Given 24 participants in the between subjects design, 12 sessions were held to perform the experiments in one-on-one games. Consequently, four sessions were held in each CR, NR and PR conditions. Although all scenarios were player vs. player situations, only in the CR scenarios one player could influence the other's game states. In the announcement to recruit players, we asked players to bring their friend to participate in the experiments. Participants were placed in different rooms where they could not see/hear each other. We obtained ethical approval from the local university to perform the experiments. Since wearing EEG device for the first time could be stressful, we explained to the participants that this device is not affecting their minds and we are just reading their attention activities. Participants were free to leave the experiments if they were not comfortable with the experiments. However, all participants completed the tasks.

The baseline concentration level was used during the game as a reference point to determine how well the player is focusing on the game. To this end, we asked participants to look a screenshot of the game for two minutes while their eyes were open. The average of attention in this two minutes period was considered as baseline value of attention for that participant.

The study was performed by making each subject to play mobile car racing game, while wearing the BCI device. After completing an informed consent, participants were trained for five minutes to become familiar with the controls of the game. Participants were asked to fill a questionnaire including demographic information as well as their game expertise. We used GEQ (Game Experience Questionnaire) [7], which is widely used to evaluate the quality of experience (using the core module of GEQ including 33 questions) and social presence (using the social presence module of GEQ including 17 questions). Participants were also asked to answer Intrinsic Motivation Inventory questions [16] to measure intrinsic motivation corresponding to dimensions of interest and enjoyment within a game-play (18 questions with using a 5-point Likert scale).

After explaining test conditions, a NeuroSky MindWave device was fitted to the participant's head. Participants played the game for 15 minutes, where they were asked to keep their concentration level as high as possible while playing. We asked participants to play the game in a private room in the Cognitive Augmented Reality lab at Tabriz Art University.

MindWave headset has noise filters in place in order to ensure any head movements, muscle artifacts noises are filtered out of the raw EEG before the calculation of the attention. However, we tried to control experiments as much as possible to avoid the noises and artifacts. In particular, we asked participants to avoid eye blinks, body movements, head movement, coughing and any other movements that may create an artifact during the experiments. The experiments were performed between 9:00 AM and 11:00 AM for all participants.

6 Results

In the following, the results of various experiments in terms of the efficacy of attention training, intrinsic motivation, and combination of these variables are provided.

6.1 Efficacy of attention training

The purpose of the study was to investigate if competitive reinforcement (CR) works better than positive reinforcement (PR) and negative reinforcement (NR) at motivating players to increase and maintain their attention level as high as possible.

Every second, the headset computes and delivers the attention measure. This measure is trade secret and the function of computing attention based on mind waves are not revealed by the manufacture of this device. However, the unit of measuring attention is number between 0 and 100 indicating the attention level of a participant. While the metric is a value between 0 and 100, this is not an absolute value. More specifically, this range is split into

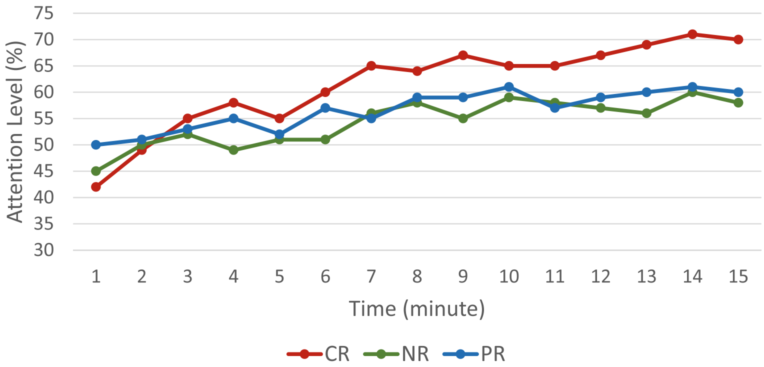

Fig. 6 The average attention level of participants in PR (positive reinforcement), NR (negative reinforcement) and CR (competitive reinforcement) conditions for each minute of play

different zones representing various attention states. The headset has noise filters in place in order to ensure any head movements, muscle artifacts noises are filtered out of the raw EEG before the calculation of the attention.

The average attention level of participants in PR, NR and CR conditions for each minute of play are shown in Fig. 6. According to this figure, participants in the CR condition were more successful at increasing their attention level. A pair-wise analysis of data using ANOVA (see Table 1) found statistical significance in the differences between CR and PR, and between CR and NR. We conclude that CR works better than PR and NR conditions to increase and maintain attention level. Although the average of attention level for PR condition is more than this value for NR condition, the average of attention level while playing the game did not change sufficiently to satisfy statistical significance.

6.2 Intrinsic motivation

We were also interested to study if players enjoy the competitive reinforcement condition more than other conditions. The results of ANOVA with CR, PR and NR conditions showed that although intrinsic motivation factor for CR condition was more than this value for PR and NR, there was no significant effect of game condition on intrinsic motivation (see Table 2). Comparison of Intrinsic Motivation values showed that the players perceived that they invested more effort in the CR condition than PR condition and NR conditions. The results showed that using CR yielded more effort for players than PR and NR conditions, that can lead to greater increases in the attention level. However, no pairwise comparisons were significant.

Table 1 Pair-wise comparison of attention for positive (PR), negative (NR) and competitive reinforcement (CR) using ANOVA (significance level= 1%)

Comparison of prototypes	ANOVA results
CR(M=61.466) vs. PR(M=56.600)	$F(2, 21) = 4.319,\ p = 0.0469$ *
CR(M=61.466) vs. NR(M=54.333)	$F(2, 21) = 8.708,\ p = 0.0063$ *
NR(M=54.333) vs. PR(M=56.600)	$F(2, 21) = 2.330,\ p = 0.1380$

Table 2 Pair-wise comparison of Intrinsic Motivation for positive (PR), negative (NR) and competitive (CR) conditions using ANOVA (significance level= 1%)

Comparison of prototypes	ANOVA results
CR(M=2.236) vs. PR(M=2.028)	$F(2, 21) = 2.333,\ p = 0.100$
CR(M=2.236) vs. NR(M=1.840)	$F(2, 21) = 2.144,\ p = 0.121$
NR(M=1.840) vs. PR(M=2.028)	$F(2, 21) = 2.385,\ p = 0.136$

6.3 Game experience

In terms of core gaming experience, a pair-wise analysis of data using ANOVA (see Table 3) found statistically significant differences between CR and PR conditions, and between the CR and NR conditions. However, the difference between PR and NR conditions was not statistically significant. As a result, we conclude that using competitive reinforcement yielded better quality of experience than positive and negative reinforcement conditions. However, in terms of social presence, a pair-wise analysis of data using ANOVA (see Table 4) found no statistical significance in the differences.

6.4 Combination of variables

To test the effect of independent variable (CR, NR and PR) on three dependent variables (attention, intrinsic motivation and game experience), we used repeated measure MANOVA to cater for and assess multiple response variables simultaneously. The results showed that there was a statistically significant difference in players' behavior F (3,23) = 5.1654, $p <$ .05; Wilk's lambda (Λ) is 0.612. Such a finding suggests that the behavior of a player appears to be a affected by the type of reinforcement in the car racing game.

6.5 Limitations

Due to the between subjects design, only four game sessions were held in each condition. Since we separately compute the results for each participant, we could obtain 2 results in each session (one for each player). One limitation of the experiments was in the matching of players. Since we asked participants to bring their friend to the experiment, we did not have a control on the skill of players. Consequently, it was possible to match a beginner with a professional player. Since each 'session' effectively constitutes a sample due to the pairing of participants, this could affect the results. Further research is required to study the effect of matching technique on the proposed scenarios. We also need to repeat the experiments with a professional EEG device with more channels to have better estimation of attention. Another limitation of this work that we aim to address in the future work is that neurofeedback training should occur over multiple sessions in a long period and participants may need more time to figure out how to self-regulate their attention. We also aim to test the concept of competitive reinforcement for more than two players.

Table 3 Pair-wise comparison of Core Gaming Experience for positive (PR), negative (NR) and competitive reinforcement (CR) using ANOVA (significance level= 1%)

Comparison of prototypes	ANOVA results
CR(M=2.916) vs. PR(M=2.343)	$F(2, 21) = 14.08,\ p = 0.0015$ *
CR(M=2.916) vs. NR(M=2.183)	$F(2, 21) = 16.06,\ p = 0.0008$ *
NR(M=2.183) vs. PR(M=2.343)	$F(2, 21) = 2.385,\ p = 0.1360$

Table 4 Pair-wise comparison of Social Presence for positive (PR), negative (NR) and competitive reinforcement (CR) using ANOVA (significance level = 1%)

Comparison of prototypes	ANOVA results
CR(M=2.521) vs. PR(M=2.435)	$F(2, 21) = 3.21,\ p = 0.185$
CR(M=2.521) vs. NR(M=2.296)	$F(2, 21) = 2.86,\ p = 0.221$
NR(M=2.296) vs. PR(M=2.435)	$F(2, 21) = 2.385,\ p = 0.205$

7 Conclusion and future work

Research has already shown the potential of using BCI tools to improve the attention level of persons with attention deficit. In neurofeedback training games, it is crucial to maximize both therapeutic efficacy and player engagement. Unlike existing attention training games using BCI tools that are generally developed as a single-player games, in this paper we developed a multi-player attention training games. In particular, we proposed the concept of *competitive reinforcement* in a multi-player car racing game.

We argue that the problem with the negative reinforcement is that a player does not know how to tackle the obstacles and progress in the game if this player has a considerable attention deficit. This can result in demotivation to continue trying, and consequently prevents participants to acquire the attention skill. Although research has shown the outperformance of positive reinforcement to tackle this problem, the competitive feature of multi-player games, where the player is encouraged to affect other players while playing is not considered in the positive reinforcement. To address this problem, we proposed a technique that uses negative and positive reinforcement techniques to bring all players in the competition zone regardless of their skill levels. Then, in the competition zone, the battle of minds occurs where competitive reinforcement technique is used to adjust the difficulty parameters.

The results of our experiments suggest that the competitive reinforcement is more effective at helping players to increase attention level as compared to positive and negative reinforcement conditions. We also found a significant difference in the gaming experience of competitive reinforcement in comparison to positive and negative reinforcement. We argue that the use of competitive stimulus generated more positive affect because of using encouraging game mechanic. However, we did not find any differences in the social presence, suggesting that all three conditions satisfy social presence similarly while playing.

This research opens up new possibilities for collective training in cognitive issues. Generally, cognitive training scenarios for attention, memory, time perception and other issues are designed as single player tasks. However, new research can be performed to study the effect of this multiplayer setting on the performance and the engagement of players.

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Yoones A. Sekhavat is an Assistant Professor in Faculty of Multimedia at Tabriz Islamic Art University. He holds a PhD in Computer Science from Memorial University of Newfoundland, Canada (2013). He also holds a post-doc from University of Alberta in Canada (2014). His research has been published in Multimedia Tools and Applications, IEEE Transactions on Multimedia, IEEE Transactions on Human- Machin Systems, IEEE Transactions on Knowledge and Data Engineering, International Journal of Artificial Intelligence tools, and International Journal of Computer Games Technology. He is the head of Cognitive Augmented Reality lab (www.carlab.ir) in Tabriz Islamic Art University. His main research area in this lab is serious games, and various aspects of multimedia contents.