

Assessing Engagement in an Emotionally-Adaptive Applied Game

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ABSTRACT

In recent years, the interest to the area of computer games for educational purposes increased due to their positive outcomes and effects in technology-enhanced learning. One of their chief merits is retaining the learning motivation and engagement of players during all time of the game. Therefore, it is necessary educational games to be able to adjust their features such as task difficulty, object speed, learning content, etc. according to the current emotional state of the player and, as well, to his/her playing style. In this paper, we present a dynamic mechanism for affective game adaptation based on both emotion and arousal estimation. The mechanism is implemented within an applied video game named “Rush for Gold” designed for implicit recognition of playing or learning styles. The paper outlines, analyzes and discusses results of an experimental study related to player’s engagement in affective applied adaptation.

CCS Concepts

• Applied computing~Computers in other domains • Applied computing~Personal computers and PC applications
• Applied computing~Computer games • Human-centered computing~Human computer interaction (HCI) • Human-centered computing~HCI design and evaluation methods
• Human-centered computing~Laboratory experiments.

Keywords

Applied game; adaptation; engagement; emotion; arousal; EDA; playing style.

1. INTRODUCTION

Emotions that player experiences during the game are crucial for keeping him/her in flow [1] and for provoking high immersion and engagement. If the player emotional state could be controlled by the game, this may lead to an increase in player’s attention, interest, and sense of satisfaction.

There are different techniques allowing games to recognize human emotions, such as analyzing player responses and reactions, self-reports, emotional recognition based on facial expressions and measuring of changes in psychophysiological

characteristics of the player [2].

Therefore, a game can be adapted to player’s emotional states by adjusting its mechanics, dynamics and aesthetics. This will result not only in an increase of player immersion but also in enhanced interactions between player and game. Hence, an affect-based adaptation implemented in an educational game can improve learning process, attention of students to didactic content and activities, and learning outcomes [3].

Human personality and player traits are important features of playing characters and offer, together with player’s performance and emotional state, a solid groundwork for player-centric game adaptation [4]. Player-centric models allow designers to tailor gameplay to an individual with specific playing style determining player’s needs, preferences and motivations [5]. Adjusting various features of the game to playing types or styles can increase playing satisfaction and motivation [6], and efficacy of playing [7]. Like the game adaptation according to learning style, it can bring better learning outcomes [8].

For achieving style-based adaptation in video gameplay, player’s style should be recognized with an accuracy sufficient for the adaptation purposes. Static approaches for style estimation apply calculation of playing styles from self-report before entering the game [5], whereupon the player is not aware of the process. In contrast to self-reports, automatic recognition of playing style during the play is much more promising, because it infers the style of the playing person by analyzing individual player interactions and achieved results. They apply analysis of player’s behaviors at run time in an implicit way for the player and provide a basis for dynamic style-based adaptation of various features for both games for entertainment and applied games.

The present paper describes an emotionally-adaptive video game named “Rush for Gold” and designed for implicit in-game assessment of individual ADOPTA (ADaptive. technOlogy-enhanced Platform for eduTAinment) playing styles [9] - Competitor, Dreamer, Logician, and Strategist or, as well, of Honey and Mumford’s learning styles [10] – Activist, Reflector, Theorist, and Pragmatist. Style assessment applies multiple linear regression over specific gameplay metric metrics such as task effectiveness, efficiency and difficulty [11]. Further, estimated styles are used for content-based adaptation in educational maze games. For a more effective and efficient style estimation, affective adaptation of gameplay was introduced with dynamic adjustment of game dynamics and aesthetics according to player’s emotions and arousal inferred by facial expressions and electrodermal activity, respectively. There was conducted an experimental study with participation of 30 master students and University lecturers, who played game sessions with “Rush for

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Gold” and online post-game survey using the Game Engagement Questionnaire [12].

The paper presents a short overview of related works, explanation of adaptive game design including learning scenarios, assessment of emotions and arousal using facial expressions and electrodermal activity of individual player, and the mechanism of affective adaptation. Next, it outlines and discusses some experimental results concerning player's engagement assessed implicitly during the game session and, as well, by a post-game self-report. Finally, concluding remarks about affective adaptation and attained player's engagement are provided including some directions for future work.

2. BACKGROUND

This section outlines previous works related to the present study and concerning emotionally-based adaptation in video games, recognition of arousal and emotions, and measuring engagement in digital games.

2.1 Emotional Adaptation of Video Games

Main goal of each one game is the entertainment, but different people enjoy themselves in different way. Therefore, since the very beginning of their appearing, games try to adapt their scenarios to the player's preferences. Most frequently game adaptation is performed according to the player skills and depending on it change the level of difficulty. The balance between performance and difficulty is crucial for keeping up players immersion and flow and it can be achieved using emotional adaptation in video games [13]. Furthermore, affective adaptation can be used to increase the motivation for learning (when the positive arousal grows) in entertainment and applied games [5].

There are two main approaches for detection of player's emotional states. First of them takes into account the level of presence of basic emotions like happiness, sadness, engagement, angry, fear, etc. and it could be recognized based on facial expressions of players in game time. Second method for emotional state detection uses physiological data of players like skin conductivity and/or heart rate variability and depending on their changes increasing/decreasing of emotional arousal can be reported.

In implementation of the presented here applied game we used both approaches since the first one depends on the facial expressions, but not everyone expresses sufficiently clear his/her emotions on his/her face and, on the other hand, the second method can detect increasing/decreasing of emotional arousal, but it cannot define whether this arousal is positive or negative. Next section describes ways for emotions and arousal recognition according to the mentioned above approaches.

2.2 Recognition of arousal and emotions

Emotional arousal can be detect using different physiological signals such as electrodermal activity (EDA), skin temperature, heart rate, electroencephalogram, electromyogram, etc. [14]. EDA is one of the most reliable and usable psychophysiological parameter of the human body for monitoring of emotional state. The signal reflects changes in sympathetic nervous system based on changes in the electrical skin conductance caused by different eccrine gland activity. EDA consists of two components - a tonic component known as skin conductance level (SCL) (having low frequency) presenting the emotional background and

characterized by minor deviation and a phasic component known as skin conductance response (SCR) (having higher frequency than tonic) presenting last changes in the emotional state of an individual in response to external stimuli [15]. Arousal inference based on EDA measurement was used by Drachen et al. [16] and Tijs et al. [13] for measuring psychophysiological arousal and has proven strong content validity [17]. EDA was used in many affective games [4] like in a car racing game for adapting visibility, steering, and speed on the road [18] or in a Pong game for adjusting ball speed and paddle size [19].

Separately or in addition to emotional arousal detection based on physiological signals there can be used automatic approaches for emotion recognition based on observational methods such as voice intonation, gestures, and facial expressions [4]. The main goal of these methods is through high-resolution cameras automatically (and remotely) to identify and measure level of presence of at least six emotions - happiness, sadness, surprise, fear, anger, and disgust. These emotions are introduced by Paul Ekman and are accepted to be universal since they are culturally, geographically and ethnically independent [20]. Emotional inference based on facial expressions was used in the Portal 2 game [21] for recognizing joy, surprise, and anger, and neutral expressions; FILTWAM [22]; Feed The Fish [23], and the game library framework Koko [24].

2.3 Measuring Engagement in Video Games

While player motivation concerns “reasons why people begin to play”, the concept of engagement is related to aspects about playing situations such as flow [25], immersion, pleasure, and fun, and deals with “what makes people want to continue playing” [26]. Video games are supposed to provide deep engagement in playing as a must for an enhanced overall game playability and, in the case of games applied for education, for better learning outcomes.

The player engagement process can be presented as a model linking player objectives (intrinsic or extrinsic), activities (exploring, solving, sensing, experimenting, destroying, etc.), accomplishment (achievement, completion, and progression) and affect (positive, negative, and absorption) [26]. Similarly, Brockmyer et al. [12] used engagement as “generic indicator of game involvement”. They proposed and validated the Game Engagement Questionnaire (GEngQ) created using psychometric techniques in order to assess by self-reporting the subjective experience of engagement in video games (mainly in violent games) as a combination of immersion, presence, flow, and absorption. Unlike other similar questionnaires such as Game Experience Questionnaire (GEQ) including a core module about experiences during game session, a social presence module, and a post-game experience module [27], GEngQ is rather shorter and contains only 19 items, which makes is appropriate for fast online conduction.

3. ADAPTIVE GAME DESIGN

The design of the “Rush for Gold” emotionally-adaptive video game was focused on implicit assessment of individual ADOPTA playing styles [9] or Honey and Mumford's learning styles [10] by means of applying multiple linear regression over specific gameplay metric [11]. The metrics are tracked dynamically during completion of game tasks embedded in game scenarios.

3.1 Game Scenarios

The game scenarios of “Rush for Gold” are about collecting of 12 gold bars in a 3D Egyptian temple. They comprise four types of explicit tasks concerning and challenging player’s knowledge and intellectual abilities including synthetic, analytical and practical skills, as follows:

- Groups A: shooting tasks – the player has to hit and collect at least two and no more than six of the gold bars flying near the ceiling of the temple (fig. 1); for doing it, he/she has to shoot at a bar of gold by choosing appropriate position for shooting and, next, to press on the fallen gold bar in order to collect it;
- Groups B: discovering tasks – the player has to discover and collect at least two and no more than 6 of the gold bars hidden in secret places at the temple;
- Groups C: solving tasks – the player has to solve at least two and no more than 6 of the logic puzzles shown at the pedestals of statues at the temple; after giving the right answer, a gold bar appears over the pedestal and the player has to click on it in order to collect it;
- Group D: planning and monitoring tasks by maintaining a Strategy Management Table (SMT) with three rows for planning number of gold bars of Groups A, B and C, whereupon their total number should equal to 12. As well, SMT provides data about average efficiency of performance of tasks of each group in order to be used when planning. If no SMT planning is done by the player, then each successfully collected bar of gold of given group provokes appearance of a new bullion of the same group until reaching the allowed maximum of bullions. In the end, the game estimates the playing styles by applying linear regressions over gameplay metrics (completion time, result, efficiency, and task difficulty), writes them down to a log file together with all other session data, and shows the styles to the player.

Game tasks difficulty was dynamically adapted according to player’s affective state including both emotions and arousal.

3.2 Assessment of Emotions and Arousal

“Rush for Gold” applies EDA measurement for assessing player’s arousal using a RAGE¹ arousal asset. The RAGE software asset (Real-Time Arousal Detection Using Galvanic Skin Response Asset) is a software component receiving raw EDA signal from a custom device using exosomatic method for EDA measuring (fig. 1) and processing it in real time in order to infer player arousal. More precisely, the asset applies high and low pass software filters in order to extract background tonic SCL reflecting general long-lasting (tens of seconds to tens of minutes) changes in autonomic arousal and phasic changes known as SCR produced by sympathetic neuronal activity. The asset applied and returns phasic arousal level (set from 1 to 10), tonic arousal level (set from 1 to 10), moving average of the raw EDA signal, phasic activity represented by amplitude of skin conductance response, SCR rise time, SCR ½ recovery time, response peaks/second, average area under the curve per second, and tonic activity represented by slope of tonic activity and amplitude of skin conductance level. Phasic arousal level is applied to adjust difficulty of the shooting and discovering tasks (together with the emotions inferred on facial expressions). Tonic arousal level is not

applied to adapt difficulty of any tasks because it indicates long-lasting changes in autonomic arousal of the player [28].

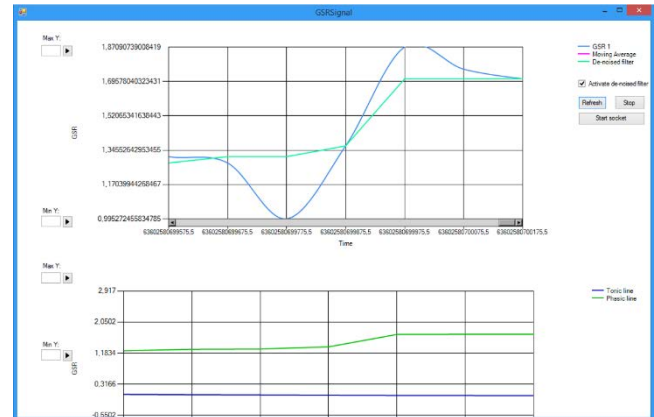


Figure 1. Raw and filtered EDA signal (over) and tonic and phasic EDA components (below)

“Rush for Gold” embeds an emotion recognizer applying facial expressions for emotion recognition using Affectiva SDK². It estimates player’s emotion levels (in percentage) by means of face expressions analyzed 15 or 30 times per second. The emotion recognizer is built as a client side application using the video stream produced by the Web camera of the laptop. Data about the six basic emotions (sadness, disgust, anger, surprise, fear and joy) together with some psychological states (engagement, attention, and eye closure) are averaged within a moving window of 10 seconds and, together with player arousal, are applied for controlling emotional adaptation of game mechanics, dynamics, and aesthetics [29].

3.3 Emotional Game Adaptation

Affect-based adaptation of gameplay was introduced into the game with the hypothesis that it will result in shorter playing time and better efficiency and higher difficulty of completed tasks compared to the non-adaptive gameplay. The “Rush for Gold” video game applies a positive affective feedback loop for dynamic adjustment of task difficulty and, as well, of ambient light intensity.



¹ <http://rageproject.eu/rage-ecosystem/>

² <http://www.affectiva.com/>

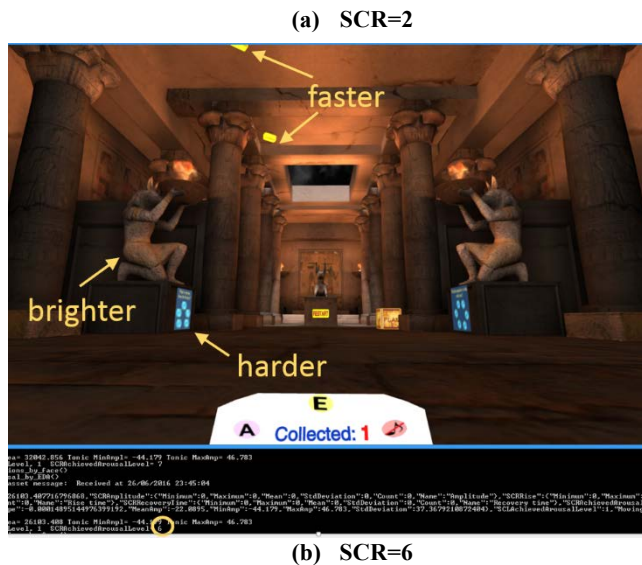


Figure 2. Adaptation of flying bullions' velocity, puzzle difficulty, and ambient light for lower (a) and higher (b) phasic arousal

Dynamic level content adjustment [30] was chosen as most appropriate dynamic difficulty adjustment (DDA) method for activities with game items for player interactions, like shooting and discovering tasks. According to player's skill acquisition within the context of specific task, it adapts dynamically level of task difficulty set initially on the base of player's performance applying specific threshold values. Thus, hidden bars of gold appear to be more difficult to be discovered with increase of player's positive emotions or arousal (they are moved to more hidden places). The same goes for flying bullions – when affectation level becomes higher, they change their velocity and acceleration set initially according to player's performance. In contrast to shooting and discovering tasks, puzzle solving tasks are not subject to dynamic affect-based adaptation, because DDA of a shown puzzle means replacing it by another having different difficulty that would be rather embarrassing for the player. For this reason, puzzle solving tasks apply affect-based adaptation statically, when selecting new puzzle to be shown in the game.

Besides DDA of shooting and discovering tasks, the game introduces an affective adaptation of visual effects. According to player's affect (both emotions and arousal) ambient light intensity is adapted using thresholds of emotion or arousal level. Dynamic adjustment of difficulty of tasks and illumination (light intensity) according to player's affectation level (comprising emotions or arousal) is done using execution efficiency of last accomplished task, whereupon both task difficulty and ambient light intensity change if affectation level passes specific thresholds. Fig. 2 presents dynamic adaptation of velocity of flying bullions, puzzle difficulty, and ambient light for lower (a) and higher (b) phasic arousal assessed by the level of SCR signal. When applying positive feedback loop [31], in cases of lower phasic arousal, puzzles are easier, flying bar velocity is slower, and ambient light is darker, and vice versa. "Rush for Gold" provides a panel for changing both the direction of the feedback loop and strength of adaptation [29].

4. EXPERIMENTAL STUDY

The section describes the experimental study applying the "Rush for Gold" emotionally-adaptive video game for implicit

assessment of individual playing or learning styles, with focus on the engagement of players assessed implicitly in the game and by post-game self-report.

4.1 Experimental Setup

For conducting the experiment a single gamer laptop was used. On this laptop following software/hardware components were installed and configured:

- "Rush for Gold" applied video game - it was applied for implicit recognition of playing and learning styles, which next were communicated to an educational maze game with learning content about strategic business management adapted to the recognised individual style. Both "Rush for Gold" and the maze video game were developed by means of the Brainstorm eStudio platform using music, textures and 3D visual objects specially designed for this purpose;
- RAGE arousal asset – it is external software applications for measuring player's arousal. This component is integrated in "Rush for Gold" by means of a TCP socket. The asset receives the raw EDA signal sent by the custom device and processed it in real-time in order to calculate current tonic and phasic arousal level;
- Custom client side application for emotion recognition – it is based on facial expressions using Affectiva SDK. As well as the RAGE arousal asset this component is integrated in "Rush for Gold" by means of a TCP socket. It estimates player's emotion levels by means of face expressions analyzed 15 times per second using video stream produced by the Web camera of the computer/laptop. Data about six basic emotions are averaged within a moving window of 10s, together with data about more complex emotional states such as engagement, attention (based on eye fixation), and eye closure. After finishing the game session, engagement and attention are compared to those extracted from post-game self-reports;
- Custom device for EDA measuring – it is connected to the laptop by USB port and send EDA data of individuals to the RAGE arousal asset.
- Web camera of the laptop – it was used from the component for emotion recognition based on facial expression.

Besides the software/hardware setup a 92 items questionnaire was prepared including a version of GEngQ adapted to educational video games. Questions in it were related to demographic data, previous gaming experience of participants and their playing and learning style.

4.2 Procedure and Participants

The experiment was conducted in two weeks in June 2016, at the Faculty of Mathematics and Informatics at Sofia University, Bulgaria. The experimental procedure included:

- participants selection (students and lecturers) - by means of email announcement, there were selected 30 volunteers (average aged near 31, with gender balance 18 men and 12 women);
- pre-gaming session - before gaming sessions, a consent form (translated in Bulgarian) was signed by each individual participant and short demonstration of the game was performed;
- gaming sessions' appointment and performance - they were scheduled in Doodle and took in average about 90 minutes each. To avoid pressure artefacts, participants were

instructed not to use these fingers while playing. At the beginning each participant was asked to spend two minutes in relaxation, with the electrodes placed on his/her fingers, while listening to calm music and watching playing instructions. The player was asked to perform a short assisted training session playing “Rush for Gold” followed by two game sessions in random order – one without and another with affective adaptation control. After playing “Rush for Gold”, the participant was automatically transferred to an educational maze game with learning content adapted to the recognised individual style of the participant. No background music was played during the sessions other than game music and event-related sounds such as at shooting at hitting;

- post-game session – after the gaming session, each player was asked to fill in a self report by filling online a 92 items questionnaire including the Game Engagement Questionnaire and the participant was asked to share his/her personal impressions of all the phases of the experiment.

The experimental results concern the effect of affective (i.e., emotionally-based) adaptation over the players’ assessment and, on other side, on game session time, task’s effectiveness, efficiency and difficulty due to affectively adaptive gameplay.

4.3 Results

As explained over, six basic player’s emotions and three psychological states were inferred by facial expressions taken from video stream, while player’s arousal was recognized by means of tonic and phasic EDA signal components. Fig. 3 and 4 represent box plot graphics of the value distribution (averaged for the whole game session) of the six emotions (fig. 3) and the three psychological states (fig. 4) all inferred by facial expressions. Excluding joy, disgust, and partially surprise, all other emotions show very low average values. Hence, we can conclude joy and disgust are manifested by facial expressions much more than the other emotions and, therefore, are appropriate for emotion-based adaptation. The same goes for engagement and attention (fig. 4).

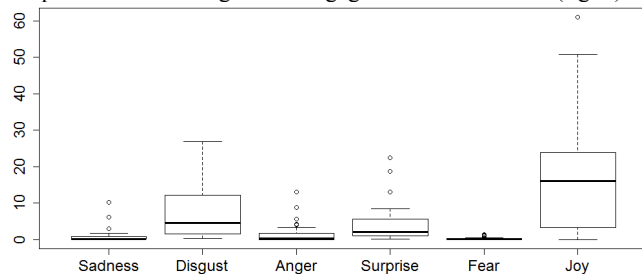


Figure 3. Box plots of player’s average emotions inferred by facial expressions

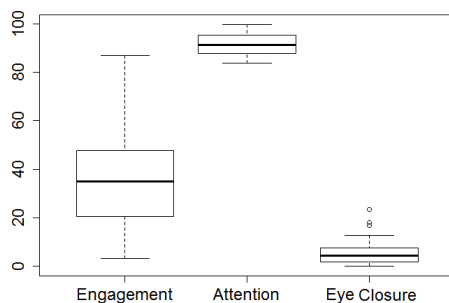


Figure 4. Box plots of player’s average psychological states extracted from facial expressions

It is interesting to note that the other, not well manifested, emotions (sadness, anger and fear) and state (eye closure) have very low median but outliers above upper whisker providing evidence for few but very emotional players.

Fig. 5 shows a box plots of player’s average tonic and phasic arousal levels from 1 (lowest) up to 10 (highest) inferred by EDA. As expected, average player’s arousal is low (with level 3 for tonic arousal and level 2 for phasic one) though their whiskers are high (6 and 5.5, respectively). There was found only one outlier with higher average arousal.

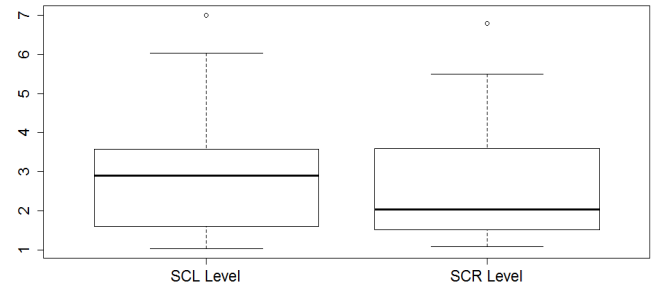


Figure 5. Box plots of player’s average arousal levels inferred by EDA

Next, fig. 6 provides box plots of the GEngQ terms measured using the 5-level Likert scale. The post-game survey results show very high player’s average immersion (with median values near 4.5 and with no whiskers) and rather high presence in the video game environment, which is prove of both the attractiveness and overall playability of the game. Absorption, flow, and engagement have moderate values but are above the middle.

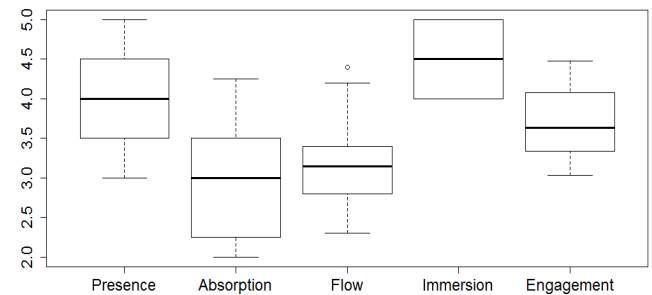


Figure 6. Box plots of measured GEngQ terms

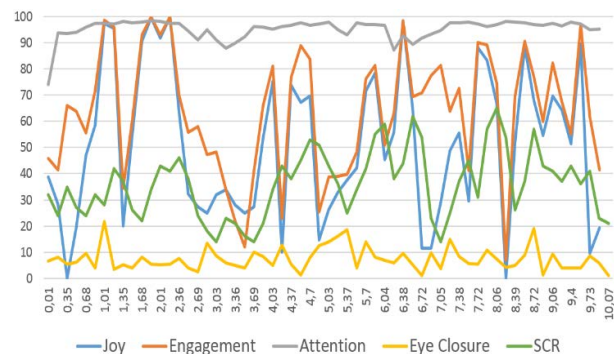


Figure 7. Player’s joy, engagement, attention, eye closure, and SCR measured for 10 minutes game playing

Table 1. Extract from the game event log file

Time	Event	Success	Difficulty
0.43	Plan Change	Yes	n.a.
1.20	Shot	Yes	1
2.29	Shot	Yes	2
2.71	Solving	No	1
2.87	Solving	Yes	1
3.54	Solving	Yes	2
3.79	Solving	No	3
3.89	Solving	Yes	2
4.43	Discovered	Yes	2
5.29	Solved	No	1
6.40	Discovered	Yes	1
6.93	Plan View	Yes	n.a.
7.26	Shot	No	3
7.46	Shot	No	3
7.56	Shot	No	2
8.26	Shot	No	3
8.47	Shot	No	2
8.57	Shot	No	3
8.77	Shot	No	3
9.33	Discovered	Yes	3

Further, we were interested to explore how individual player's emotions, psychological states and arousal advance with player's achievements during the game session. For this purpose, we confronted their values at given play time to the events logged at that time for the individual player. Fig. 7 presents individual joy, engagement, attention, eye closure, and SCR measured for 10 minutes game playing. The diagrams should be matched with the events done by the same individual and logged in a game event log file as shown in Table 2. The reader can juxtapose the peak values of joy, engagement, and SCR (tonic arousal) to the successful events listed within the extract from the game event log file. At the same time, falls in joy, engagement, and SCR clearly match non-successful events such as puzzle solving without success at time 2.71 and 3.79, or failing shot's sequence between time 7.26 and 8.77 provoking saw-tooth charts for the same charts with local minimums at times of unsuccessful shots and increasing slopes with hope for a better next trial. Note that the SCR signal follows with some delay (offset) the form of both the joy and engagement charts including their inflection points happening at right event times. This offset of the SCR chart is caused by the delay required for the perception of the event. As well, minimums of these charts depends on the difficulty of the problematic task. For example, the absolute minimum of both joy and engagement charts matches the failing shot at time 7.26 at a flying bullion with maximal difficulty (equal to 3). It is similar to the minimum at time 3.79 when the player tries to solve a puzzle with difficulty 3 without success. Both these minimums are resulted by the player's disappointment by having a task challenge greater than his/her knowledge or skills. On the other hand, the falls in engagement and joy sometimes may provoke falls in attention, however, player remains very attentive for the majority of the events. Its eye closures may have a peak or a fall for given

event depending on the individual perception of that event. As the reviewers suggested, if we could establish strong correlations between EDA input, emotion recognition and game input patterns, they may lead to future recognition of player emotional status indirectly from game input patterns only, without any additional hardware or setup.

Table 2. Correlations of psychological states inferred by facial expressions and arousal with GEngQ terms

State / arousal	Game Engagement Questionnaire (GEEngQ)				
	Presence	Absorption	Flow	Immersion	Engagement
Attention	0.3878	0.0645	0.1779	0.0139	0.1978
Engagement	0.0087	-0.0510	0.1870	-0.0532	0.0221
Eye closure	0.3818	0.0885	0.3711	0.1737	0.1554
SCL level	0.1341	-0.1312	0.0459	-0.1067	-0.0318
SCR level	-0.0119	-0.0558	-0.2177	0.1042	-0.0674

We looked for correlations of the psychological states inferred by facial expressions and arousal found by EDA with GEngQ terms, although they have different nature and are measured or reported at different times - psychological states and arousal are recognized dynamically during the game session, while GEngQ terms are reported after finishing the game session. Table 2 provides found Pearson correlations by presenting statistically significant ones ($p < 0.05$) in bold. Attention is correlated moderately but significantly with presence in virtual environment, and eye closure correlates moderately with both presence and flow having similar r values.

It was important to check how average psychological states and arousal correlate with emotions inferred by facial expressions. Table 3 shows statistically significant correlations for attention with disgust, engagement with surprise and joy (a very strong correlation), eye closure and SCL (tonic arousal) with surprise, and SCR (phasic arousal) with both disgust and joy. Therefore, these states/arousal types might be applied as indicators of emotions they correlate with.

Table 3. Correlations of psychological states and arousal with emotions inferred by facial expressions

State / arousal	Emotions					
	Sadness	Disgust	Anger	Surprise	Fear	Joy
Attention	-0.0226	0.3712	0.2329	0.1835	-0.1677	0.2040
Engagement	0.0782	0.7049	0.1653	0.4296	0.1013	0.8346
Eye closure	-0.1257	0.2293	0.0918	0.4657	0.1713	0.3196
SCL level	0.0226	-0.1484	-0.0759	0.3873	0.3007	-0.0027
SCR	-0.0275	0.3616	-0.0307	0.1285	-0.0959	0.4008

level						
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Table 4. Correlations of psychological states inferred by facial expressions and arousal with gameplay metrics

State / arousal	Gameplay metrics			
	Relative time	Average efficiency	Average normalized difficulty	Average normalized effort
Attention	0.1637	0.1753	-0.0669	-0.1693
Engagement	0.0019	0.1668	-0.0778	-0.1925
Eye closure	0.0759	0.3991	-0.1748	-0.0514
SCL level	0.4003	-0.1937	0.1399	0.1157
SCR level	0.2090	0.0274	0.0910	-0.0659

Finally, Table 4 presents correlations of average values of psychological states inferred by facial expressions and arousal with some gameplay metrics, such as:

- relative time (for collecting one bar of gold by solving a puzzle, shooting, or discovering it);
- average efficiency (successful trials divided by the total number of trials to solve tasks);
- average efficiency and difficulty both normalized to the maximal attained values – all in case of applying adaptive gameplay.

All these game metrics are improved statistically significantly ($p < 0.001$) by the adaptive gameplay [11]. However, only the relative time and the average efficiency are found to correlated with $p < 0.05$ with SCL and eye closure, respectively.

5. DISCUSSION

The experimental results presented over prove the “Rush for Gold” emotionally-adaptive video game applied for implicit assessment of individual ADOPTA playing styles or Honey and Mumford’s learning style appeared to be appealing and engaging for students. First, player’s engagement and especially attention inferred using facial expressions have rather high average values. For all the participants in the experiment, average attention varies between 86.76% and 99.63% and has mean value $M=91.85$, while mean engagement is 36.10%. On the other hand, there are three emotions manifestation player’s behavior in adaptive gameplay – joy, disgust, and surprise. Second, results obtained from post-game online administration of GEngQ questionnaire prove again the “Rush for Gold” emotionally-adaptive video game invokes great immersion ($M=4.5000$) and high presence ($M=4.0167$) and engagement ($M=3.6563$) at players, while absorption ($M=...$) and flow ($M=3.1667$) remain above the moderate.

The study found some statistically significant correlations of psychological states and arousal with the following:

- Some GEngQ terms;
- Some emotions inferred by facial expressions;
- Some gameplay metrics.

Some of these correlations interesting dependences between values extracted by facial expression analysis or by EDA during the game session and self-reported terms. Others allow us to use emotions instead psychological states or vice versa in order to control the adaptation process.

Obviously, further analysis is needed for revealing correlations with other gameplay metrics. It requires to overcome some limitation of the study, such as the relatively small number of participants ($N=30$) and applying more psychophysiological indicators for confirmation of inferred arousal such as player’s temperature or hearth rate [4].

6. CONCLUSIONS

The present article described a novel approach embedded in the game “Rush for Gold” for automatic assessment of individual ADOPTA playing styles and/or Honey and Mumford’s learning style. It experimented gameplay adaptation based on player’s performance together with affect-based adaptation. Player’s affect was recognized by applying arousal level detected through EDA measurements and, as well, by emotional state inferred according to facial expressions. For a flexible control of the affective loop, the game provided a graphic interface for assessment of affective adaptation and setting its strength and direction.

The conducted experiment investigated the correlation between emotional arousal states from one side and from another side game engagement, current player emotions and gameplay metrics. Results from it found statistically significant correlations between attention and presence, eye closure and presence, eye closure and flow, engagement and surprise, engagement and joy, SCL arousal level and surprise, SCR arousal level and joy, eye closure and average efficiency and between SCL level of arousal and relative time. This encourage us in looking for strong correlations between EDA input, emotion recognition and game input patterns, which would allow future recognition of player emotional status from game input patterns only, in an indirect way and without applying additional setup.

Recognized playing and/or learning styles are appropriate for implementation of style-based adaptation not only of didactic content in educational games [7, 8], but for adjusting various features of mechanics of other applied games according to personal style and traits of the player, as well. On the other hand, studies of Fairclough and Gilleade [31] and Yannakakis and Paiva [3] have proved affect-based adaptation is able to increase playing outcomes and, as well, to enhance overall game playability. Therefore, style-based adaptation is preferable to be applied not in isolation, but together with methods for affective adaptation of gameplay using inference of player emotional state based on efficient, accurate and non-obtrusive techniques.

As future improvements, authors plan to implement “Rush for Gold” by means of a game platform such as Unity 3D [32] allowing it to be installed on a Web server and hence to be accessed by multiple players simultaneously. Moreover, the presented game generally can be extended for recognition not only of ADOPTA playing styles and/or Honey and Mumford’s learning style, but also for other families of playing and learning styles.

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