

Detecting Flow in Games using Facial Expressions

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Abstract— Many games use dynamic difficulty adjustment (DDA) to promote the achievement of flow and consequent positive affective states. However, performance based DDA assume a specific ludic attitude: that of the hard-core gamer. An alternative approach is to apply affective computing techniques to monitor players adjust difficulty to achieve the desired affective state directly. Such an emotion-controlled dynamic difficulty adjustment (EC-DDA) system might be more flexible and achieve better outcomes for a wider variety of players. Current approaches to monitoring affective state such as ECGs or EEGs can be very intrusive. However, monitoring affective state using facial expressions is non-intrusive, and can be done with minimal, generally existing hardware.

This paper presents a simple arcade styled game incorporating a webcam and COTS facial expression analytical software. It presents the results of a set of experiments investigating the issues involved in collecting and analyzing facial expressions to determine player affect. Results demonstrate the feasibility of using facial expressions as a mechanism for determining player affect, but also illustrate some of the difficulties inherent in the EC-DDA approach. Specifically, the affects observed are not consistent with a standard interpretation of flow as characterized by high arousal and positive affect. Instead, even in a state of flow, the affect expressed may be flat. In other instances, affect may be highly variable, expressing a range of transitory basic emotions. Preliminary findings support the notion of flow as a complex cognitive state resulting from a cycle of transitions between simple affective states such as frustration and joy.

Keywords— *flow; games; affective computing; emotion controlled dynamic difficulty adjustment;*

I. INTRODUCTION

The success or otherwise of computer games is highly dependent on the engagement of players with the game; on whether players achieve a state of ‘flow’. Engagement with a game is also of extreme importance in serious games (i.e. games intended for an educational purpose).

Flow in games is achieved through a careful balance between player skill and game challenge, both of which change dynamically throughout a game. Balancing the ‘progression of difficulty’ within a game to keep players ‘in the zone’ is one of the most important aspects of game design [1].

Many modern games attempt to avoid the pitfalls of a static progression of difficulty by using dynamic difficulty adjustment (DDA). However, current DDA systems use a performance based metric to decide on how to adjust difficulty. Use of such performance metrics ignores differences between player types,

and runs the risk of alienating casual gamers by making them work too hard, while insulting hard-core gamers by ‘nerfing’ difficult challenges.

An alternative approach to performance based DDA is to monitor player affect, adjusting difficulty to directly produce the desired affective state. Such an Emotion Controlled Dynamic Difficulty Adjustment (EC-DDA) approach offers the potential to dynamically adapt games to suit any type of player, providing them with the desired type of experience. However, the use of affective feedback to control game difficulty is in its infancy, and there are many issues and unknowns involved in implementing such a system.

The rest of this article is structured along the following lines. First, current knowledge regarding ‘flow’, its application in games, current approaches to dynamic difficulty adjustment, and techniques used in affective computing are briefly reviewed. Then, an experiment designed to investigate the issues involved in successfully utilizing affective biofeedback is explained. Finally, some preliminary results are presented and discussed.

II. BACKGROUND AND RELATED WORK

A. Flow

The concept of ‘flow’, is not new. Mihaly Csikszentmihalyi first coined and used this word to in the mid-1970s describe the feeling of complete and energized focus for a given activity with a high level of enjoyment and fulfilment [1]. Csikszentmihalyi theorized that several different elements were required to successfully achieve a state of flow, although not all elements are required at once, and the elements can appear in various combinations. The elements are:

1. Clear goals.
2. Direct and immediate feedback.
3. A balance between challenge and ability (the activity is knowingly achievable).
4. A sense of personal control over the situation or activity.
5. A high degree of focus on a limited field of attention.
6. Distorted sense of time.
7. The merging of action and awareness.
8. A loss of self-consciousness.

Csikszentmihalyi characterized Flow as an affective state of high arousal and high concentration. He describes it as “a state in which people are so involved in an activity that nothing else seems to matter; the experience is so enjoyable that people will continue to do it even at great cost, for the sheer sake of doing

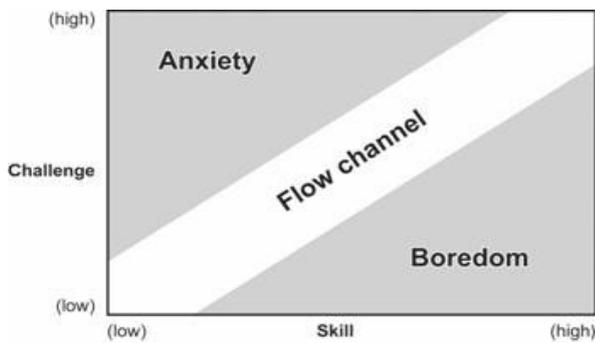


Fig. 1. The flow channel (from [1])

it.” [1]. The state of flow is encountered when a person is on the ‘edge of control’ and experiencing success while applying all their skills and knowledge to a task. “Flow is a constant balancing act between anxiety, where the difficulty is too high for the person’s skill, and boredom, where the difficulty is too low.” [1]. This is illustrated in Figure 1.

More recently, flow has been recognized as a learning-related or epistemic emotion, along with frustration, boredom, confusion, anxiety, curiosity, and delight [2]. In this context, the state of flow is conceived as an emergent state that results from small scale cycles of modest challenge and timely achievement. These cycles result in transitions between mild cognitive disequilibrium where a learner experiences confusion or even frustration, and cognitive equilibrium where the confusion is resolved [3]. As in other contexts, the learning-related flow state is associated with deep engagement.

B. Games and Flow

[4] argued that games provide an activity that forces players into an approximation of the flow state. Players generally start with relatively simple tasks that advance in complexity as familiarity and mastery increases. In a well-designed game this generates an ongoing cyclic balance between cognitive challenge and skill that allows flow to occur.

However, balance between challenge and skill is not the only factor that affects the achievement of flow in a game. Factors relating to other elements of flow (clear goals, immediate feedback, the merging of action and awareness, a loss of self-consciousness, and a sense of control) are also important.

Timely feedback is essential in promoting flow. Games do this in a variety of ways, ranging from direct visual cues, through immediate rewards, to ability upgrades and unlocking of new game levels [5].

Another critical factor in promoting flow is immersion. Immersion is the projection of the player’s awareness into the game world. It is promoted by game attributes that promote a rich mental model of the game world and that create consistency between elements of the game world [6]. These include multiple channels of sensory information, completeness of sensory information, a cognitively demanding environment, and a strong, interesting narrative or plot. Consistency is affected by believable behaviour of game elements (including NPCs and game physics), an unbroken presentation of the game world, and consistent interactivity with items in the game world. Other

factors that improve immersion include identification with the player avatar [7] and appropriate game audio [8].

Three distinct levels of immersion have been identified [9]. The first level is engagement in which a player invests the time and effort necessary to learn how to play the game. This is strongly affected by player preference. The second level is ‘engrossment’ in which the player can interact with the game without consciously thinking about the controls. The final level is ‘total immersion’ in which players feel present in the game and divorced from reality.

Player preference and hence engagement is affected by the player’s motivational attitude. It is commonly recognized that there are two types of players that respond differently to changes in difficulty levels. Hardcore players expect a challenge to overcome, while casual players are more interested in the game narrative and aesthetics. Casual gamers may respond negatively if difficulty is increased, whereas hard-core gamers may become bored if no sufficiently difficult challenge is presented [10].

Deep and continuous engagement with a game is the holy grail of game design. Achieving a state of flow in a game helps keep the player engaged longer during gameplay, and encourages the player to return to the game. A player is believed to be in flow if they meet at least two conditions of flow [11].

C. Dynamic Difficulty Adjustment

The most basic approach to maintaining a player in the flow zone is a static progression of difficulty. This is where the game increases in difficulty as a player progresses. Progression of difficulty recognizes that a player increases their skills through practice and that challenge must then rise to maintain player engagement in the game [12]. To promote flow, many modern games dynamically adjust difficulty to suit the player, generally based on a performance metric [13]. The concept was developed to provide a better gameplay experience avoiding both frustration (too hard) or boredom (too easy) [10, 14].

Each game genre has its own way of adjusting difficulty. A puzzle games may drop a hint or reduce/increase game difficulty based on how long a player takes to resolve a puzzle. A first-person shooter may analyse a player’s shooting accuracy versus death ratio to evaluate player performance. For a generic game a global difficulty scale could be modified for each success and fail event in the game, increasing difficulty on success and lowering it on failure [15].

A good dynamic difficulty adjustment system should be transparent and non-intrusive to avoid detection from the player. The game risks losing immersion, or even offending the player if the player notices the game’s difficulty level changing dramatically over a short period [16].

D. Affective Computing

Affective computing is the term used to describe AI computing technology that can detect, simulate, or affect a human user’s emotional state [17]. Entertainment oriented games may be considered an almost pure expression of an affective computing application, since they exist for no purpose other than to affect players’ emotions. However, there has been

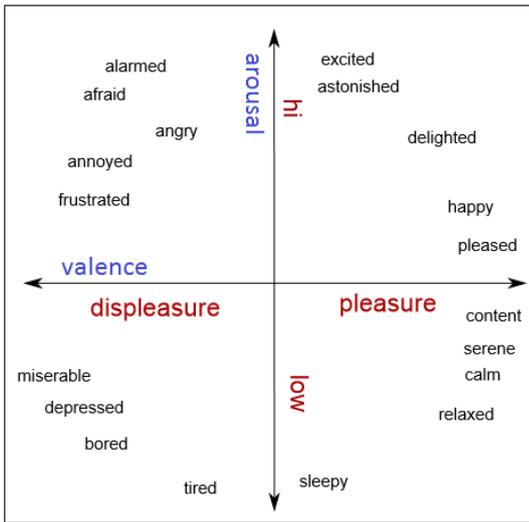


Fig. 2. Circumplex model of affective state (from [19])

little application of the emotional detection aspect of affective computing in games to date.

Basic affective states are fear, joy, excitement, disgust, or anger [18]. Affective states have also been described using a ‘circumplex model’ where affective states are categorized using hedonic valence and physiological arousal [19, 20]. Valence represents the pleasantness or unpleasantness of a mood and arousal is the strength of that mood. Affective states corresponding to varying valence and arousal are shown in Figure 2. Figure 2 shows that boredom is characterized by moderately low valence and low arousal, while frustration is characterized by low valence but moderately high arousal. Flow is not recognized as a basic affective state. Csikzentmihalyi’s suggested it to be associated with high valence and high arousal [1]. However, Graesser and D’Mello suggested that it may be a more dynamic state that emerges from transitions between other more basic affective states [2, 3].

Player valence and arousal can be measured at runtime and mapped to affective state [12]. This affect information can be used directly to modify the game difficulty, to implement an Emotion Controlled Dynamic Difficulty Adjustment system (EC-DDA), EC-DDA would allow a game to be tailored automatically to suit all player types.

[21], [22] and [23] applied affective computing to modify game difficulty. [21] used ECG signals to modify difficulty in both a puzzle game and a game of Pong. [22] used EEG signals to modify difficulty levels in a Tetris like game. [23] describes using skin conductance, heart rate, and two types of facial electromyography measurements as input to a system that generated events intended to keep player interest and arousal high. A common feature of all these approaches is the rather intrusive sensor setup (the ‘borg’ approach).

Another approach to detecting affective state is through the analysis of facial expressions. One non-game study demonstrated that this approach could produce better results than generated using an EEG sensor [24]. Xiang used this approach to control the difficulty of a Tetris game, and reported that it improved the player experience [25]. Facial expression

recognition software has improved greatly in recent years [26]. High performance facial recognition toolkits are now available as CoTS software components [27].

E. Summary

Enhancing flow is important to a games success. Performance based DDA has been used to achieve this, but it may be that an approach using affective computing has advantages. Affective computing inputs have been experimented with in a few instances, but generally involve an intrusive sensor setup. Monitoring facial expressions in real time could offer a non-intrusive mechanism to implement an EC-DDA system. This technique would allow the affective computing approach to be extended very widely since no specialized sensors are required and webcams are available for almost all gaming hardware.

The current research uses facial expressions to detect affect in a simple game. The game is then used to investigate some of the issues involved in implementing a viable EC-DDA system.

III. EXPERIMENTAL APPROACH

A. Technical Framework

A simple arcade game was constructed using the Affectiva Affdex SDK to monitor facial expressions. Affdex is an emotion aware artificial intelligence platform built using deep learning [27]. The software can detect 7 emotions and 15 highly nuanced facial expressions, as well as provide metrics for valence and arousal (although they refer to arousal as engagement).

Affectiva measures accuracy of facial expression recognition using the area under a Receiver Operating Characteristic (ROC) curve to generate a score varying between 0 and 1, where 1 represents complete accuracy. They claim an ROC score for their emotion classifiers of over 0.8 with expressions of joy, disgust, and surprise the most accurately classified. Expressions such as anger, sadness, and fear were classified less accurately.

The game was developed using the Unity game engine. Unity facilitates rapid game development and the availability of the Affdex SDK Unity Plugin made integration with facial expression analysis very easy. The Affdex SDK integrates with Unity in the following way. An Affdex Detector is registered with a Unity Scene, and a callback method onImageResults is registered with the Detector. During the game, Unity creates Frame objects from a camera feed and supplies them sequentially to the Affdex Detector. The Affdex Plugin then analyses the supplied image and invokes the callback method with the results. Results are communicated via a data structure that contains metrics for all facial expressions and emotions specified to the detector. Results are stored in a timeline for use by the EC-DDA system, and for output to a log file on completion of the game.

Only valence and arousal values are used in the current work, although other data were collected to support further research.

A webcam and the Windows 10 OS are the only external requirements needed for the game. Although facial expressions are monitored, no video of players is recorded or stored. All



Fig. 3. Gameplay screen showing difficulty adjustment parameters

facial and emotional expressions are converted into game traces of the recorded metrics and stored as csv files for later analysis. A game trace is a time series of observations of a feature during gameplay.

B. Game Design

The game is a variant of the game Star-Surf [28]. It requires the player to move the mouse up and down to control a cartoon avatar on the screen. The player must maneuver the avatar through gaps in an infinite series of red block gates to collect small white pellets (or 'orbs') from the centre of the gaps. If the player hits a gate they are pushed back towards the left side of the screen until they maneuver the avatar to escape through a gap. The player then moves slowly to the right with each successful traversal of a gate. Health is represented by the distance of the avatar from the left side of the screen. The game ends when the avatar hits a gate and is pushed off the left side of the screen before it can escape through a gap. A screen shot of the game screen is shown in Figure 3. The game mechanic is easy to understand but difficult to master.

The design allows difficulty to be adjusted in a controlled way. There are three parameters affecting difficulty change:

1. **Varying gap width.** As difficulty increases the width of the gap within each gate decreases.
2. **Varying gate interval.** As difficulty increases the interval between each gate decreases.
3. **Varying gate speed.** As difficulty increases, the speed of each gate from right to left increases.

In the current implementation, all three difficulty factors are treated as one. In the easiest mode (where the difficulty scale is set to zero), gates move slowly, gaps are wide, and there is a long interval between gates. At the most difficult setting (when the difficulty scale approaches one), gates move quickly, gaps are tight, and gates are spawned frequently.

The performance based DDA engine simultaneously modifies each game difficulty control linearly between minimum and maximum values based on three game performance events, as shown in Table 1.

C. Experimental Design

Two sets of experiments were carried out with the experimental game. The first round comprised a set of informal trial runs to determine if the EC-DDA approach was feasible. The results of these trials were unexpected and a second set of experiments was developed. The second set undertook a much more detailed investigation of the mechanics for detecting flow during gameplay using facial expressions. It is the results of this second set of experiments that is reported on in detail here. However, some explanation of the first set of experiments is warranted since it sets the context for the second.

In the first set of experiments, the difficulty was varied based on a straight-forward interpretation of Csikzentmihalyi's concept of flow: if frustration was detected (high arousal, low valence), difficulty was reduced. If boredom (low arousal, neutral valence) was detected, difficulty was increased. However, during game-play, difficulty varied erratically, going unchanged for long periods, rapidly becoming more difficult, and then just as rapidly becoming extremely easy. When players realized the control mechanism, they manipulated the difficulty of the game by making exaggerated facial expressions to increase or decrease difficulty.

Clearly, a naïve mapping of valence and arousal metrics onto presumed affective state and a direct use of this to determine game difficulty was insufficient for effective EC-DDA. It became obvious that a much more detailed understanding of how players' facial expressions related to their experience during gameplay was necessary. This led to the design for the second round of experiments.

In the second round of experiments, an attempt was made to place players into known states of boredom, frustration, or flow, and then to observe their facial expressions during gameplay while in these states.

In these experiments the game is manually set to one of three game modes each of which was intended to produce one of the affective states of interest. These game modes were:

1. **Boring Mode.** The game is set to the lowest difficulty level and never changes throughout gameplay.
2. **Frustrating Mode.** The game is set to the highest difficulty level and never changes throughout gameplay.
3. **Dynamic Mode.** The difficulty level is dynamically adjusted depending on player's performance to keep the player on the 'edge of control'.

During gameplay, logs of the facial expression metrics were accumulated. Logs of game difficulty levels were also kept for the dynamic difficulty mode. Upon completion of the entire playing session, these logs were written out to a CSV file and collected for later analysis.

Following each round of the game, players were asked to respond to a set of statements designed to distinguish whether they felt frustrated, bored, or achieved some form of flow during the game round. This was intended to act as validation for players achieving the intended state. Responses to these statements are graded on a five point Likert scale associated with the following numeric values: -1.0: Strongly Disagree, -0.5: Disagree, 0.0 No Opinion, 0.5: Agree, 1.0 Strongly Agree.

The statements were the following:

- I found this round challenging
- I felt in control
- I lost track of time while I was playing
- I could ignore what else was happening

Players experiencing flow were expected to respond positively to all statements. Bored players were expected to respond positively in relation to control, but negatively in terms of challenge, time sense, and distraction. Frustrated players were expected to respond positively regarding challenge, but negatively regarding control. We were uncertain how frustrated players would respond in terms of time sense and distraction.

D. Data Collection

A pilot study to assess the experimental framework was conducted. Fifteen computer science students participated, each completing several (3-7) rounds of each game mode. Students volunteered in response to a flyer advertising the experiment placed outside the programming laboratory. Preliminary results providing useful insight into the implementation of an EC-DDA system were obtained.

The experiment was run in CSU’s programming laboratory, using 27 inch 2012 iMacs equipped with 3.4GHz i7 processors, and 8GB RAM. The iMacs are also equipped with high resolution webcams. Images were captured at a resolution of 1024x1024 pixels.

IV. RESULTS

A. Questionnaires

The questionnaires were intended to provide an instrument that would allow classification of game traces in non-controlled settings.

Figure 3 shows the results of the post-game questionnaire in terms of challenge and control responses for each of the different game modes. The figure shows that perceptions of challenge and control were broadly in line with expectations, although there was some overlap between frustrating and dynamic (flow-inducing) game modes.

The results of the post-game questionnaire were subjected to discriminant analysis (DA), using the game mode (Boring, Frustrating, or Dynamic) as the classification variable and the

responses to the questions as the predictive variable to check whether the questionnaire was effective at distinguishing between the affective states of interest. The results of DA are presented in Table 2 and illustrated in Figure 4.

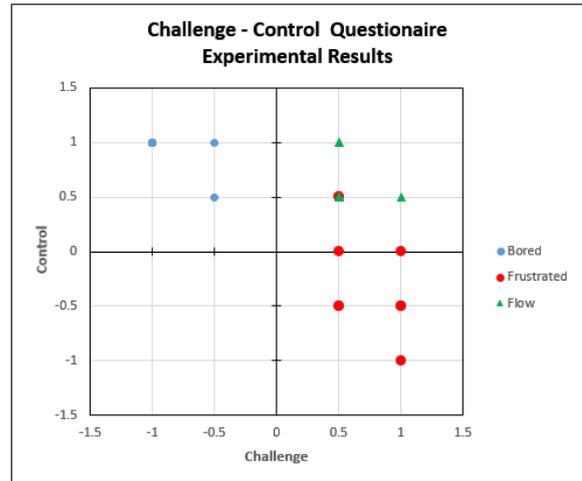


Fig. 3. Challenge – Control Responses for different game modes

TABLE II VARIABLE / FACTOR CORRELATIONS

Variables	Factor 1	Factor 2
Challenge	0.988	-0.151
Control	-0.414	0.691
Time-sense	0.177	0.947
Distraction	0.681	0.003

TABLE I. DDA SCALING PARAMETERS

Event	Description	Difficulty Adjustment
Wall Hit	When the player collides with a red block wall.	-0.03f (-3%)
Orb Missed	When a white pellet goes off the left side of the screen.	-0.01f (-1%)
Orb Collected	When the player intercepts one of the white pellets.	0.01f (1%)

Table 2 shows that the first explanatory variable is very highly correlated with the perception of challenge, and to a lesser extent the ability to ignore distractions. This factor discriminates between boring games and both other game types. The second explanatory variable is strongly associated with distortion of time-sense, and to a lesser extent the feeling of being in control. This factor discriminates between frustrating and flow inducing games.

The following generalizations can be made:

1. It was very easy to distinguish between boring games and other game modes. This is largely based on whether players felt challenged or not. The ability to ignore external distractions was also strongly associated with the sense of challenge.
2. It was much more difficult to distinguish between whether a player felt frustrated or achieved some type of flow. The primary factors distinguishing these states appeared to be the loss of time-sense and whether the player felt in control. The sense of challenge and the

ability to ignore distractions was similar in both frustrated and dynamic game modes.

B. Game Traces

The valence/arousal and attention game traces for several examples from each of the game modes (boring, frustrating, and dynamic) are shown below in Figures 5a through 5g.

All figures show valence, arousal, and attention in terms of ‘Z-Scores’. These are calculated by extracting the mean and standard deviation of each measurement during a game run, and then expressing the measurements as deviations from the mean scaled by the standard deviation. This is intended to allow different measurements to be shown on the same graph using the same scale.

Figure 5a and 5b show example traces from ‘boring’ games. They are characterized by generally neutral values of valence and arousal. They also show strong negative excursions in the attention metric, generally just before the game was terminated. All ‘boring’ games were deliberately terminated by the player, since in this game mode it was difficult to lose. Also noticeable

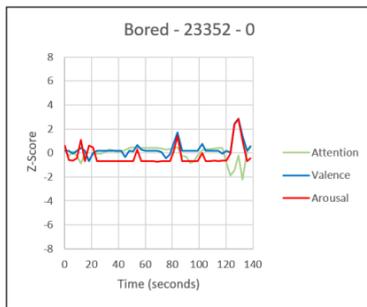


Fig 5a

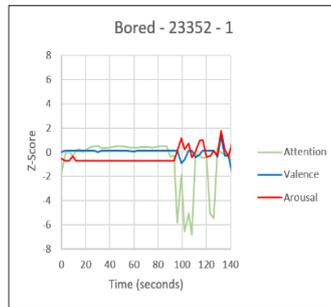


Fig 5b

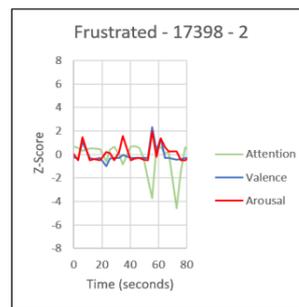


Fig 5c

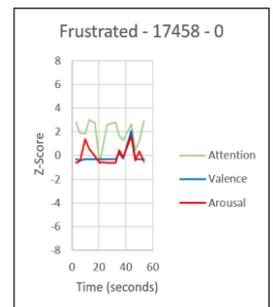


Fig 5d

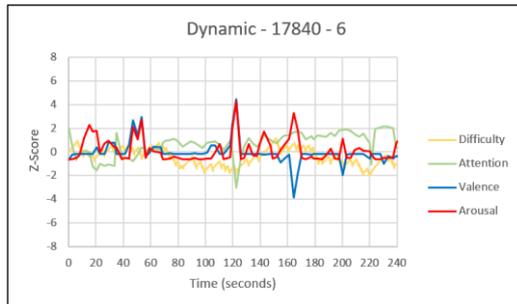


Fig 5e

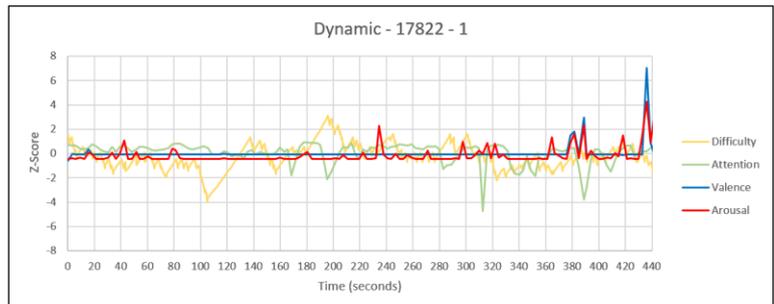


Fig 5f

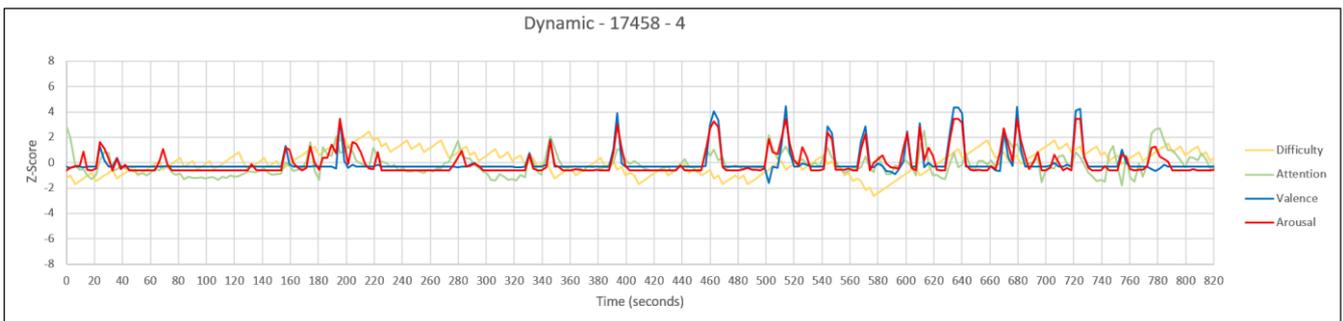


Fig 5g

Fig. 5. a-g Game traces of Attention, Arousal and Affect during experimental runs.

is that players terminated boring games at around the 2-minute mark.

Figures 5c and 5d show example traces from ‘frustrating’ games. The traces in these figures are made up from several games since in this game mode the player generally ‘lost’ (i.e. the avatar was pushed off the left-hand side of the screen) within a few seconds. The traces are made up from several sequential attempts players made at this game mode during the same overall game session. They are characterized by generally higher attention levels with spikes of arousal. However, the expected negative valence was not observed. Instead, spikes of positive valence were associated with spikes of arousal.

Figures 5e, 5f, and 5g show example traces from dynamic sessions intended to generate flow. The most noticeable difference is the lengths of the games. Dynamic games generally lasted over 3 minutes and sometimes much longer. Traces are much more variable than from either the boring or frustrating games, but show long periods of neutral valence and arousal. Similarly to the frustrating game traces, valence and arousal both show positive spikes, and there is very little negative valence displayed. More variability in arousal and affect seems to be displayed in the later stages of dynamic games.

V. DISCUSSION

A. Effectiveness of the Framework.

The Affectiva toolkit integrated easily with the Unity game engine, and could analyse images in real time to provide arousal and valence feedback to the game. It was also able to provide metrics for other potentially useful variables of interest such as attention. Furthermore, the toolkit easily kept track of faces, losing track only for very short periods of time, and reacquiring tracking within a few seconds.

The initial run of experiments referred to briefly above demonstrated that a naïve direct application of valence and arousal values based on a straightforward interpretation of the circumplex model of affect was not appropriate to implement EC-DDA, even when valence and arousal measurements were averaged over period of several seconds. The second run of experiments illustrated some of the reasons why: the affect player’s display is not what was expected, and was subject to far more influences than just the in-game experience.

What was unexpected were the long periods of relatively flat affect displayed during boring and dynamic games. However, these periods do not reflect an inability of the toolkit to detect expression, rather they reflect the fact that for long periods in these games, players display flat affect. The toolkit did pick up facial expressions and correctly interpreted the valence and arousal of those expressions. In later stages of the dynamic games, players showed much more variation in valence and arousal.

While no definitive statements can be made based on small amount of data gathered in the pilot study, it is possible that the relatively flat affect shown by players for periods of the dynamic games might indicate that the game was less engaging than intended during those periods. The framework provided new information on how players express emotions during games, and

how they reacted to the game. This demonstrates that an affective computing approach to DDA based on facial expressions is feasible. Although as yet little can be said about the effectiveness of EC-DDA, considerable information can be extracted from the game traces.

B. Game Design

There is a clear need to make frustrating games longer. Frustrating games were so abruptly and overwhelmingly difficult that players did not experience frustration, merely surprise. There was no frustration (high arousal and negative valence), possibly because players never felt that success was even remotely possible. A common reaction was laughter. An automatic reset feature together with a number of lives would extend the length of the frustrating game, allowing players to get over any initial shock and to become truly annoyed at the difficulty of the game.

In regard to generating the conditions for flow, it would be useful to provide more feedback for negative game events, such as an annoying buzzer for hitting a gate or missing a pellet. This would encourage a greater focus on high performance.

Finally, in order to further engage the player, it might be useful to increase the cognitive load at higher levels of difficulty by providing alternate paths through the gates and providing a range of pellet types, each worth varying points. This would encourage the player to engage in some sort of strategic planning activity.

The salient point here is that it is possible to make useful inferences about player’s reactions (or lack of reaction) to the game based on the responses observed by the framework. In this case, the results clearly suggest that increasing challenge would be likely to improve the in-game experience.

C. Flow

While once again stressing that no definitive findings can be made based on the pilot study, some interesting features have been observed.

First, there are the long periods of flat affect during dynamic games. These are not consistent with the high arousal and high affect predicted by flow theory. Anecdotally, this is consistent with what is commonly observed in game players: high concentration and deep engagement associated with a ‘zombie face’. In the current study, the same affect pattern is seen in boring games, so this observation is ambiguous.

The other interesting observation was the high variability of arousal and affect seen in the later stages of dynamic games when a flow like state might be considered more likely. These transitory spikes in affect seem to support the interpretation of Graesser and D’Mello [3] of flow as an emergent state resulting from rapid transitions between more basic emotional states.

D. EC-DDA

The relationship between valence and arousal measurements and player’s in-game experience appears to be complex. Players often show positive affect when under pressure. However, flow theory and the circumplex model of affect suggest that they

should be showing anxiety which is associated with negative affect. Furthermore, facial expressions are transitory and players express a range of emotions within a short space of time. The decision-making algorithm associating actual displayed emotions with in-game experience requires considerable further research. A hybrid system using performance metrics to modify difficulty but observing the response to those adjustments via facial expressions might be a useful approach.

VI. CONCLUSIONS AND FURTHER WORK

This paper shows that it is possible to derive real-time affective feedback from facial expressions during gameplay. It has also developed and demonstrated a useful framework for recording and analyzing players' affective responses. Even at this preliminary stage the framework has provided useful insight which has been used to modify game design.

Results from the pilot study suggest that flow may not be a simple affective state characterized by high valence and high arousal. Instead, it may be a complex state arising from transitions between other simpler affective states.

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