Non-invasive Player Experience Estimation from Body Motion and Game Context

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***Abstract*—In this paper, we investigate on the relationship between player experience and body movements in a non-physical 3D computer game. During an experiment, the participants played a series of short game sessions and rated their experience while their body movements were tracked using a depth camera. The data collected was analysed and a neural network was trained to find the mapping between player body movements, player in-game behaviour and player experience. The results reveal that some aspects of player experience, such as anxiety or challenge, can be detected with high accuracy (up to 81%). Moreover, taking into account the playing context, the accuracy can be raised up to 86%. Following such a multi-modal approach, it is possible to estimate the player experience in a non-invasive fashion during the game and, based on this information, the game content could be adapted accordingly.**

I. Introduction

Interconnecting the player and the game in a closed affective-loop has the potential to open several new directions for game design and game development. A computer game that is able to evaluate the player's experience and directly influence it could adapt to the player's to induce specific player's reactions. In their paper, Yannakakis and Togelius [1] envision, among other things, a form of design in which the game designer would instruct the software to generate the game content according to some target affective states. Yannakakis and Togelius encapsulate the principles of affective computing [2] within a framework, in which the computer senses several aspects of the player experience and searches an optimal configuration of the game content to gear the current experience towards a desired state.

The main objective of affective computing can be described as the successful realisation of the affective loop [3]. This means that, during the interaction, a machine should be able to detect the user's affective state and consequently adapt its behaviour. Detecting and understanding the user's state is a challenging task [4]: the number of necessary modalities is very large, many useful modalities are quite invasive — e.g. BCI or Gaze Tracking — and the emotional response might differ from user to user. In a human-computer interaction and especially in computer games, the invasiveness of the detection method is crucially important as it might alter the user's experience. Relatively non-invasive devices such as a finger biofeedback signal sensor [5] or the Emotive EPOC[1] affect the interaction — e.g. by reducing mobility — and might appear cumbersome and introduce a bias in the affect detection outside of a laboratory environment.

An interesting opportunity to overcome this limitation comes for the recent introduction of devices such as Microsoft Kinect [2], which allow to wireless estimate the user's movements and her pose. Pose has been analysed as a possible estimator of affect by several researchers [6], [7], [8]; we propose an approach to affect detection and, in general, player experience evaluation based on a combination of behavioural cues coming from both the real world postural movements and the virtual world context. Furthermore, our approach analyses the changes in posture rather than the absolute body position with the purpose to build models more robust across different users.

We believe that the combination of multiple modalities along with the use of a posture motion allows to build more accurate models which are also more robust across different users and applications. The objective of this research work is to explore the relationship between postural movements, in-game behaviour and reported player experience and investigate if it is possible to estimate player experience from the first two. This work is aimed at providing a less invasive and more effective way to capture player experience for the purpose of game content adaptation/generation within the framework of Experience-Driven Procedural Content Generation [1].

For this purpose, we conducted an experiment to evaluate the ability of our approach to predict users' reports on their experience. A number of players played a series of short game sessions with different challenges and levels of difficulty while their pose was recorded trough a depth camera. In the game employed in the experiment, the participants interact with the game using a game controller, so their posture has no active role in the game-play. After each couple of experiences, the users reported their feedback on the experiences in forms of pairwise preferences. Based on these data, we built 6 models of corresponding to 6 different aspects of player experience; the models are built to predict the users' reported preferences using preference learning [9]. The results show that through the proposed approach we are able to predict aspect such as reported challenge with an 81% accuracy and reported anxiety with up to 86% accuracy.

[1] http://www.emotiv.com/epoc/

[2] http://www.microsoft.com/en-us/kinectforwindows/

(a) Fight (b) Jump (c) Collect

Fig. 1. User interface of the game for the three different tasks with on screen instructions. The UI shows a short text explaining what the player should do (bottom left), the time remaining (top left), the number of items collected (top right) and the controls (bottom right).

II. Related Work

Players' emotional response to a gaming experience is an important aspect of player experience [10] and developing robust methods to measure such a response is a key step towards goals such as adaptive game-play or procedural content generation [1]. Researchers have investigated different modalities, spanning from facial expressions to electrocardiography (ECG), to estimate the player's affective state from her physiological responses.

Mandryk et al. [11] have investigated how multiple physiological measurements, such as skin conductance or hearth rate, correlate with some aspects of the players' affect while playing a sport game. Barreto et al. [12] pursued the same objective but concentrated their research in estimating user's stress using machine learning techniques — i.e. Decision Threes and Support Vector Machines. Their results show how machine learning an physiological data can be lead to very high accuracy in stress prediction. More recently, Tognetti at al. [13] and Martinez at el. [14] have investigated player experience estimation and modelling through a combination of physiological features and preference learning.

While the results presented by the aforementioned works are very solid, their main limitation lies in the invasiveness of their measurement methods. Capturing signals such as galvanic skin response or heart rate requires the player to be wired with some on-body sensors, potentially introducing some interference in the player's experience. Pedersen et al. [15], have investigated the possibility of estimating various aspects of player experience only based on a combination of features extracted from the players' in-game behaviour. Other researchers have, instead, investigated less invasive means of measuring the player's physical response, such as body posture and motion.

Savva et al. [16] investigated the usage of multiple motion sensors attached to the players' body to estimate their affect during full-body game play sessions. A number of studies [17], [18], [7], employed different forms of chairs featuring a matrix of pressure sensors to estimate postural activity and predict aspects such as frustration or engagement; however, these studies focus primarily human-to-human or human-to-agent interaction — i.e. the player interacts "face-to face" with an artificial agent — which limits the applicability of the results to a computer games in which there is no such type of interaction. Moreover, both in these studies, as well as in the work by Savva et al. [16], the measurements require a custom hardware combined, in some cases, with other physiological sensors, making them complex to be employed for player experience estimation in commercial games.

A further approach to non-invasive estimation of affect and cognition employs computer vision to detect different aspects, such as head pose [19] or facial expressions [20]. Shaker et al. [21] extended their initial work on head pose by including game contextual information and and visual reactions, demonstrating an increase in the prediction accuracy when multiple modality are combined. In this research work we employ a similar approach to testing whether body posture can be used along with game contextual information to achieve similar or better results.

III. The Experiment

The goal of this study is to investigate whether body motion can be used along with player in-game statistics to estimate player experience. For this purpose, we conducted an experiment with 26 participants playing six pairs of short game sessions (maximum 30 seconds each) with different virtual camera settings and with different tasks. Each participant is seated in front of a computer and is asked to hold an *Xbox 360* [3] game controller; after this, the participant is guided through the experiment by on-screen instructions. As depicted in Figure 1, the controls for the characters where organised according to the following configuration: left thumb-stick for avatar movements, *A* button for jumping and *B* button for punching. The participant plays initially three pairs of games, each pair features a different game task and the two games in the pair differ only by the way the camera behaves. During the second phase of the experiment, the participant plays the same initial three pairs, but the order of the camera settings is inverted to minimise the effect of the order of play. For each pair, the player has to compare her experience between the two games on a set aspects — e.g. frustration or engagement.

The game employed in this study is a reduced version of Lerpz Escape, a three-dimensional platform game by Unity Technologies[4]. Similarly to the original game, it features an alien-like avatar trapped in a futuristic 3D environment made of floating platforms and containing collectible items and non-player characters. The game world is composed by one area in which each player has to complete the assigned task; the area contains different elements depending on the task to be performed. The tasks that the each player has to perform in the three games are the following:

[3]http://www.xbox.com/en-GB/xbox360/
[4]http://www.unity3d.com

Fig. 2. Map of the game level with the position of the elements. A points at the spawn location of the avatar, B indicates the spawn position of the enemy during the fight task, D is the target location of the jump task and $C1$ to $C4$ indicate the position of the collectible items during the collect task.

- **Fight**: the player has to fight with an enemy and destroy it.
- **Collect**: the player has to collect a number of items.
- **Jump**: the player has to reach a specific area of the game level.

The game environment is composed by a large circular 3D platform containing a small building and a series of crates as shown in Figure 2. In the "fight" scenario, the environment includes an opponent which spawns near the centre of the main platform (position *B* in Figure 2) and chases the avatar controlled by the player. The player can punch the opponent, which in turn will try to push the player out of the platform. In the "collect" scenario, the player needs to collect 4 items placed as shown in Figure 2. In the "jump" scenario, the player needs to jump over the small platforms shown to reach the top of the building (position *D* in Figure 2).

If the task is not completed in 30 seconds, the experiment continues to the next game in the pair or to the next pair. These three tasks represent the basic mechanics of a 3D platform game and have been separated in order to collect a finer feedback about the effects of the different camera behaviours. The dependent variables that are measured during the experiment are the players' reported states and their in-game performance. Furthermore, each game sessions is recorded using a Microsoft Kinect, to collect information about the players' posture motion. The independent variables of this experiment are the game tasks and the camera behaviour.

A. Camera Behaviour

The virtual camera behaviour changing across the different game sessions is the main difference in the stimuli used in the experiment. For this reason, in order to ensure replicability of the experiment, in this section, we describe the cinematographic conditions employed.

Based on previous articles describing the impact of camera behaviour on player experience [5], the different camera configurations are designed to maximise such impact, ranging from very close shots to aerial view. The camera is instructed to produce the following 6 types of shot: bird's eye, fixed, long shot, mid shot, over the shoulder, and point of view. These shots offer a range of different visual experiences of the same game ranging from a very detached and distant one for the bird's eye and fixed shots to a very close and claustrophobic experience in the point of view shot. Results of a study conducted in parallel to this work [22] — the study was conducted using the same game for the purpose of investigating the impact of virtual cinematography on player experience — show a strong impact of the aforementioned camera configurations on the player experience, which ensure presence of a wide range of emotional and cognitive responses connected to the different stimuli.

In all experimental conditions, the camera is controlled by an automatic camera controller, which ensures the shots maintain the required properties while the avatar and, when present, the enemy move around the environment. The implementation of the camera controller is based on the architecture proposed in one of the authors previous work on virtual cinematography [23]. The instructions given to the controller to generate the shots are the following:

- **Bird's eye**: The avatar should be visualised at the centre of the screen from a high vantage point.
- **Fixed**: The camera stands above the level visualising the entire scene from a fixed perspective.
- **Long Shot**: The avatar is shown on screen from behind and the camera keeps at and appropriate distance so that its body is completely visible.
- **Mid Shot**: The avatar is shown on screen from behind and the camera keeps at and appropriate distance so that only the upper part of its body is visible.
- **Over The Shoulder**: The camera stands above the left shoulder of the avatar — which is partially visible — and points towards the enemy or the nearest item to collect.
- **Point Of View**: Similarly to a first person game, the viewpoint is placed by the side of the head of the avatar.

B. Player Experience

Six features have been selected to describe player experience: *challenge*, *frustration*, *fun*, *anxiety*, *engagement* and *attention*. They describe both aspects of the player's affective and cognitive states, which have shown signs of dependence on the way the virtual camera moves — i.e. the independent

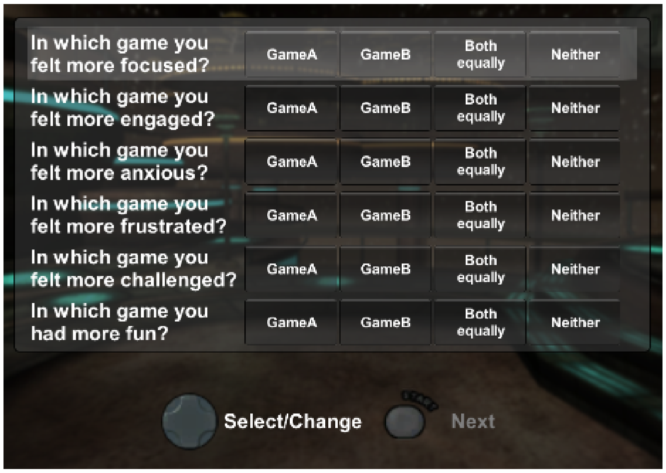

Fig. 3. 4-AFC questionnaire on player experience filled out by the player every pair of games played.

Fig. 4. Depth image captured through Kinect with locations of head and torso.

variable of this experiment [5], [22]. Furthermore, the first four features allow a comparison with previous works on affect detection for procedural content generation such as [5] and [15]. Attention and Engagement are included as a further development of one of the authors' previous study on attention based camera control [24], with the purpose of investigating the possibility of estimating these two features for on-line virtual camera adaptation.

Each state is expressed as a comparison between two games through 4-alternative forced choice (4-AFC) questionnaire scheme. As show in Fig 3, the preference questionnaire includes four alternative choices: Game A, Game B, Neither or Both Equally. This scheme has been chosen over a rating scheme for a number of advantages, including the absence of scaling, personality, and cultural biases as well as the lower order and inconsistency effects [25]. Moreover, a 4-AFC scheme, opposed to a 2-AFC scheme, accounts also for cases of non-preference. Moreover, the scheme has been successfully employed for player experience recording in previous procedural content generation works for aspects such as view-point adaptation [5] or platform game level generation [15].

Finally, for each player, we asked to quantify his/her gaming experience, age and gender, and we recorded the duration of each game session.

C. Posture Movements

While different libraries for skeletal tracking can be used in conjunction with the Kinect, in order to acquire the maximum possible information about the participants' body, we decided to record raw data from the depth and the RGB sensors of the Kinect. For this analysis, we have processed the date through a fast and simple marker-less body posture tracking method to monitor the user's body motion during the gameplay. The method uses only the depth images [26] provided by a Microsoft Kinect and tracks a 2-point (head and torso) skeleton in a user seated mode as shown in Figure 4.

The first part of the algorithm performs a *slicing* of the depth map in which each layer represents the existence of objects of a specific depth range. The slicing is performed by dividing the original values from the map with the constant value of 4000, which transforms the depth map to sixteen layers. In the layered depth map, the algorithm is using a morphological filtering to cover any depth holes and a connected components method to track the seated user in each frame. The algorithm continues by applying a connected components method. By this method, we track the person in each frame, which defines our region of interest. We consider the first "point of interest" to be the "torso point", which is equivalent to the centroid of the area tracked.

To find the head joint, a temporary calculation is made between the known torso point and the top extrema points of the region of interest. Then, we use the y coordinate of this temporary head point and crop a line. From that line we find the minimum and the maximum coordinates, which are calculated by finding the positions of the first and the last bit in that binary line. From that we obtain the minimum and maximum y-coordinates of the head. The mean distance between these head points is used to re-coordinate the central head point to a more stable and accurate head centre. After this, from the given depth frame, the depth values (z-coordinates) of the head and the torso points are calculated.

Finally, a post-processing method is applied in order to improve the results of the detected points and deal with a salt and pepper-like noise. This noise was noticed on the results and is produced by a small shift of the depth scene which derives from the depth generation algorithm of the RGB-D camera. This shift produces some changes in the x,y coordinates of the detected 2 points of the head and torso, which should not be accepted. To this goal, we apply a simple median filtering to alleviate the data from this particular noise.

From the two points representing the head and the torso, six features are extracted to describe the overall body movement during each game session:

- **Side and front lean shift**: these features describe how

		Att.	Eng.	Anx.	Frustr.	Chall.	Fun
Side Lean Shift	ϕ	-0.07	-0.12	0.10	0.01	0.19	-0.08
	p	0.54	0.26	0.43	0.91	0.09	0.44
Front Lean Shift	ϕ	-0.04	0.01	-0.12	-0.04	-0.04	0.04
	p	0.76	1.00	0.36	0.82	0.74	0.70
Side Lean Motion	ϕ	0.01	0.17	0.00	0.14	**0.25**	0.01
	p	1.00	0.13	1.00	0.22	**0.03**	0.88
Front Lean Motion	ϕ	-0.01	0.10	0.08	0.11	0.09	0.01
	p	1.00	0.36	0.57	0.42	0.42	0.90
Head Motion	ϕ	-0.03	0.04	0.05	0.16	0.12	0.07
	p	0.84	0.76	0.73	0.21	0.28	0.50
Body Motion	ϕ	-0.01	0.06	0.03	0.16	0.12	0.04
	p	1.00	0.61	0.91	0.21	0.28	0.75

TABLE I. CORRELATIONS — I.E. ϕ COEFFICIENTS — BETWEEN THE PLAYERS REPORTED STATES AND THEIR MOVEMENTS. THE FIRST TWO FEATURES DESCRIBE THE SHIFT BETWEEN THE PLAYER'S LEAN ANGLE AT THE BEGINNING OF EACH SESSION AND AT THE END OF IT, THE THIRD AND FOURTH FEATURE DESCRIBE THE OVERALL LEANING MOTION PERFORMED BY THE PLAYER, THE LAST TWO FEATURES DESCRIBE THE OVERALL DISTANCE COVERED BY THE PLAYER'S HEAD AND BODY DURING EACH SESSION. THE ONLY SIGNIFICANT CORRELATION IS HIGHLIGHTED IN BOLD.

much the player changes his/her position during the game session. It is calculated as the difference between the body angle at the end of the session and at the beginning.

- **Side and front lean motion**: these features describe how much the player moves during the game sessions. It is calculated as the accumulated angular distance that is covered by the player's body during the game. These measures, combined with the previous two, give a description of the type of motion performed by the player — e.g. if a player has high lean motion and low lean shift, it means that he oscillated back an forth during the game.
- **Head and body motion**: these two features describe the overall motion of the head and body independently. The are calculated as the accumulated linear distance covered by the point describing the head position and the one describing the torso position.

IV. RESULTS AND ANALYSIS

All 26 participants played 6 pairs of games generating a total of 312 recorded game sessions. For each game session, the recorded data contains information about the player movements, the type of stimulus and the game-play statistics. We first study the correlation between the player expressed states with a set of features describing the game context and the body movements.

The calculated correlation ϕ, which is reported in table I, is calculated by converting body motion features and the preferences into dichotomic variables: each preference assumes value 1 when the first game is chooses and value 0 when the second game is chosen; likewise, the body motion features assume value 1 if the first game has a higher numerical value and value 0 if the second game has a higher value. The ϕ coefficient and its significance are calculated through a chi-square test conducted on a reduced set containing only pairs in which a preference was expressed, which covers, depending on the feature, from 85% to 65% of the answers.

	Att.	Eng.	Anx.	Frustr.	Chall.	Fun
Age	1.02	0.63				
Experience						
Duration					1.03	
Game Type			0.28			
Side Lean Shift				-0.20	0.16	
Front Lean Shift	-0.17			0.20		
Side Lean Motion		0.60		3.30	0.34	
Front Lean Motion	1.05		0.32		-1.08	
Head Motion	0.06		0.25			0.28
Body Motion	1.47		0.54			0.69
Accuracy	65%	59%	76%	68%	81%	66%

TABLE II. PREDICTION ACCURACY OF THE SINGLE LAYER PERCEPTRONS TRAINED TO ESTIMATE THE PLAYERS REPORTED STATES. THE INPUTS OF EACH PERCEPTRON HAVE BEEN SELECTED USING SEQUENTIAL FEATURE SELECTION AND THEIR WEIGHT IS DISPLAYED IN THE TABLE. THE ACCURACIES DISPLAYED IN THE LAST LINE HAVE BEEN ASSESSED THROUGH A LEAVE-ONE-OUT CROSS-VALIDATION.

The only significant correlation, in this first analysis, emerges between the *Side Lean Motion* — i.e. the total amount of side-wise motion that the player performed during the sessions — and the reported challenge. This results indicate that such a feature might be a good predictor of perceived challenge and, intuitively, this is reasonable in a game which involves the control of a virtual, human-like, avatar. However, the correlation is not extremely strong, suggesting the concurrence/mediation of other features.

A. Single Layer Perceptron

For a more in-depth understanding of the relationship between body motion and expressed emotions, it is necessary to analyse the interplay of all the features combined and the participants' answer to the questionnaire. For this purpose, we analyse the data using machine learning; more specifically, to identify the combined relationships, we employ a single layer perceptron trained using evolutionary preference learning. Based on the methodology proposed by [27], the fitness function $f(\vec{x})$ used in the neuro-evolutionary process is given by:

$$f(\vec{x}) = \frac{1}{k}\sum_{i=0}^{k} \epsilon_i(\vec{x}) \quad (1)$$

where k is the number of pairs of game sessions in the data-set and $\epsilon_i(\vec{x})$ is equal to 1 if the configuration of the network given by the weights $\vec{x}$ matches the reported preference in the dataset and 0 otherwise. For this analysis, the preference data is classified in three categories for each feature — i.e. GameA, GameB and "Neither" with "Both Equally" — so a 3-class classification is performed. The class including both the "Neither" and the "Both Equally" answers represents non-preference cases. Finally, we employ sequential feature selection to isolate only the features that have a relevant impact on the models' prediction. This allows us to discern the relevant features from the irrelevant ones.

Table II displays the prediction accuracy of the models built using this methodology and the weight of the connection between the features selected and the input of the perceptron. The presence of a weight in the table, indicates that a certain feature has been identified, through sequential feature selection, as significantly related to the predicted preference. The weight of that feature expresses the kind and magnitude

	Fight	Jump	Collect
Age			
Experience			
Duration	0.66		
Game Type			
Side Lean Shift			
Front Lean Shift			-0.16
Side Lean Motion			
Front Lean Motion	-0.53	0.45	0.47
Head Motion	0.56	0.38	1.36
Body Motion		0.59	
Accuracy	72%	85%	86%

TABLE III. PREDICTION ACCURACY OF A SINGLE LAYER PERCEPTRON TRAINED TO ESTIMATE REPORTED ANXIETY ON SEPARATELY FOR EACH GAME MECHANIC. THE ACCURACY IS ASSESSED THROUGH A LEAVE-ONE-OUT CROSS-VALIDATION.

of the relationship, much like a correlation; however, the relationship can be analysed only in relation with the other features that compose the model's input, as they all contribute together to the model's accuracy — i.e. the values are not absolute coefficients but define the contribution of a feature in proportion to the other ones.

The accuracy obtained in the prediction of *anxiety* and *challenge* both exceed 75% suggesting a strong relationship between the selected feature set and the reported player experience aspect. The highest score is achieved in the prediction of the reported challenge (81%) and the selected features include the game session duration and three aspects of the body movements: side lean shift, side lean motion and front lean motion. The positive relationship between challenge and the game session duration can easily be explained by the fact that there is a good chance that people will report as more challenging a game which takes more time to complete. Furthermore, it is interesting to see how side and front lean motion have an opposite effect on challenge. Side lean motion seems to have moderately positive relationship with reported challenge, confirming the results of the correlation study. On the other hand, front lean motion appears to have a negative relationship, suggesting that the player that felt challenged in the game moved moderately sideways, but performed very little forward and backward leaning.

Reported anxiety appears to have a positive relationship with most form of body motions and it seems to depend also on the type of game that the player plays. For this reason, we evaluate the anxiety reports employing three different perceptrons, one for each game type. Table III shows that, following this approach the prediction accuracy for anxiety increases up to 86%. This result highlights the importance of mediating the body motion modality through the game context to achieve the most accurate modelling of the player experience.

Furthermore, the overall results on *anxiety* and *challenge* prediction are even more significant if compared with the results on the same prediction in previous research works using the same approach [5], [15]. A direct comparison is not possible as the games employed for these studies are different as well as the number of participants in the experiments; however, the improvements in prediction accuracy suggest that body posture movements give a significant contribution in the estimation of these two states compared to both game-play data and physiological data.

V. CONCLUSIONS

In this article we explore the interplay between player experience, body motion and game context. During an experiment, 26 participants played a series of short game sessions with different settings while their body movements were recorded using a depth camera. For each pair of games, the player reported their preference between the games on a series of features describing the player experience. The collected data has been analysed using machine learning to predict the reported states given information about the game context and body motion.

The results of the analysis show that it is possible to predict aspects of player experience, such as perceived challenge or anxiety, with accuracy up to 86%. Such results demonstrate the potentials of motion detection based on computer vision as non-invasive and robust modality for implicit interaction and player experience estimation. In light of these results, we believe that it would be important to further investigate this modality, especially at a single event level and in relationship with other modalities, in order to have an robust and responsive feedback on the player's reactions to game events. Such a methodology can be applied to drive a procedural content generation process to generate in real-time the game content depending on the current state of the player — e.g. to control the level of anxiety of the player in an horror game.

Overall, we believe that the combination of postural movements and in-game behaviour for the prediction of reported player experience shows promising results and provides a non invasive and robust mean for player experience estimation. At the same time, it is more accurate than pure game-play based estimation and less invasive than physiology or EEG/EMG based approaches. Furthermore, the proposed solution relies on inexpensive and widespread hardware, making it easy to integrate in the game development process.

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