An Immersive VR Game to Ascertain Pattern Recall in Virtual Reality

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***Abstract*—Virtual Reality is a rapidly growing form of media, with uses in entertainment, industry and education. By generating a real-time feedback loop based on a user's emotional state we can tailor experiences in such a way that it maintains the user's engagement, ensuring they learn more in an educational system, or play longer in a gaming scenario. Biosensors can be used to acquire physiological data from the user in real time, this data can then be used to determine the user's current emotional state. To determine whether creating such a feedback loop is viable in Virtual Reality we developed a simple pattern replication game for the Oculus Rift which uses two biosensor devices to read three different biosignals. We conducted a study with 53 total participants. We present some preliminary findings and a plan for the next phase of the study.**

***Index Terms*—VR, EEG, ECG, Secondary Input, Biosignals, Memory, Cognition, Education**

I. Introduction

The incorporation of biosensors and physiological signals into a Virtual Reality (VR) experience opens up the possibility of creating adaptive, dynamic and personalised experiences by generating a real-time feedback loop which tailors the player's experience, maintaining the user's engagement [1]. This would be particularly suitable to VR as the goal of VR is to immerse the user in a virtual environment where they can experience a sense of presence. Biosignals provide objective measures of a user's reactions to a system, event, or a set of events in real-time. These in turn can be used to dynamically change the VR experience to achieve the intended goals of the VR application, e.g. maintain concentration in an educational experience, keep the user focused on a task within a VR training environment, or maintain the complexity of a game to keep the user engaged [2], [3]. In order to implement such a feedback loop, it is important to first choose suitable physiological measures from which a user's emotional state can be determined. Following this, patterns in the biosignals must be identified which can be attributed to a particular emotional state, for example whether the user is bored or frustrated. Consideration must also be given to the ergonomics of wearing biosensors in a VR setting, the devices should not impede the user or detract from the experience. The Empatica E4 and Myndplay's Myndband were the biosensors chosen for this study; both are wireless devices which connect to the VR application via bluetooth. The Myndband utilises Neurosky technology to record and process data on the device. The Myndband is a single probe Electroencephalography (EEG) device which takes the form of a headband. The E4 is a wristwatch and can measure Galvanic Skin Response (GSR) and Heart Rate Variability (HRV). According to Wilson and Eggemeier [4] agreement between the different physiological signals strengthens the interpretation of the user's emotions and mental state. Where the system detects signs of anxiety, concentration, relaxation, frustration, etc. the appropriate response can be generated [5]. To test this approach a VR game was developed that required the user to memorise and replicate visual patterns of varying length (three to six items). The game had to be both simple and immersive, the latter being a very important requirement for Virtual Reality. The Oculus Rift headset was chosen, and the Oculus Touch controllers used as they allow for more natural movement compared with a traditional console controller. This paper focuses on the acquisition of data from biosensor signals taken while participants played the developed VR game. This data will later be used to the develop the feedback loop.

II. Biosignals

A biosignal is any physiological signal emanating from a living person which can be continuously measured. Examples of easy to measure biosignals include Heart Rate and temperature, however there are also subtler biosignals such as EEG and GSR. Biosignals are used to measure different aspects of a user's physiological response to stimuli, temperature for example can be used to identify if someone is ill. EEG, GSR and HRV are often used to determine a person's emotional state [4]. We use a number of different biosignals as it is believed the accuracy of the system in determining a person's emotional state will be increased [4]. Mental workload or attentiveness would first be determined by analysis of the EEG signals. GSR and Heart Rate Variability (HRV) could then be used to substantiate the conclusion provided by the EEG analysis.

A. EEG

Electroencephalography (EEG) [6] is the measure of electrical activity in the brain. When a neuron fires in the brain

Frequency Band	Range	Associated Cognitive States
Delta	$1-3Hz$	Deep Sleep
Theta	$4-7Hz$	Mental Workload
Alpha	$8-12Hz$	Relaxation
Beta	$13-30Hz$	Anxiety, Attentiveness
Gamma	$31-50Hz$	Higher Cognitive Functions

TABLE I
EEG FREQUENCY BANDS AND RELATED COGNITIVE STATES

a small electrical field is generated, however, the electrical response of a single neuron is too small to be detected. It takes hundreds of thousands of synchronised neurons firing at the same time to generate a detectable electrical field [7]. An array of EEG probes placed on the scalp can detect the strength of this field at different places on the head, this can be used to localise which parts of the brain are active at certain times. Conventionally this array consists of over 20 wet EEG electrodes, however recent developments have shown that it is feasible to use a singly dry electrode for non-medical purposes [8]–[10]. The raw EEG signal can be processed and broken into a number of frequency bands. In our case this processing happens on the Myndband itself. EEG frequency band data can be used to help determine a user's emotional state [11], [12]. Table I lists the frequency bands, the range represented by the band according to Neurosky [13] and Scheirer et al. [5], and the cognitive states they represent according to iMotions [14].

B. GSR

Galvanic Skin Response (GSR) is the measure of the electrical conductivity of skin, which changes due to the autonomic activation of sweat glands. While sweating is usually associated with exercise, it also occurs more subtly as a result of changes in a person's emotional state. Emotions such as nervousness, frustration or excitement can cause a physiological response and trigger sweating [15]. Previous studies, such as those by Yu Shi et al. [16] and Nourbakhsh et al. [17] have shown that GSR is a valid and useful measurement of task difficulty, or stress caused by performing a task.

C. Heart Rate Variability

Heart Rate Variability (HRV) is the measure of the variation in time interval between heartbeats. A number of methods can be used to measure HRV, these include photoplethysmography (PPG) and electrocardiography (ECG). PPG uses a high precision light sensor to detect the volume of blood flow and uses this to derive HRV. ECG records the electrical activity generated by heart muscle depolarisations, which propagates in pulsating electrical waves towards the skin. As noted by Appelhans and Luecken [15], an increased HRV usually indicates physical or physiological stress, while a reduced HRV can be an indicator of stability of calmness [13].

III. METHOD

A. Study Design

Experiments were carried out to investigate the feasibility of using biosignals in a VR memory game. 53 participants took part in the study, each participant was asked to fill out a pre-experiment demographic survey, and post-experiment questionnaires. Each subject wore the same biosensors and VR equipment. Subjects played the same memory game, although with a randomised set of visual patterns ranging from 3 to 6 items. Ethics approval (2019-036) for this experiment was granted by UCC's Social Research Ethics Committee.

B. Virtual Environment and Tasks

The VR experience was developed in the Unreal Engine 4 (UE4). The biosensors were integrated into the VR game, allowing for the time-stamping and logging of GSR, HR and EEG data, as well as timestamped in-game events, which could be analysed post-game. The virtual environment consists of two scenes, the first being a tutorial designed to familiarise a user with VR and to teach them the control scheme used for the game. In this tutorial section aural instructions provide information on how to use the Oculus Touch controllers. The tutorial consists of two rooms, designed to look like a warehouse. In the first room the player learns the basics of using the controllers in VR, they then move through a corridor to the second room. The second room (fig. 1) features two guns which the player can use to shoot holographic targets. When the player is ready to play the pattern game they can move to a designated area in the room where they are teleported to the second scene. The purpose of this scene is to condition subjects to VR and the control scheme employed. It also serves as a baseline for comparing the biosignals from the memory game scene.

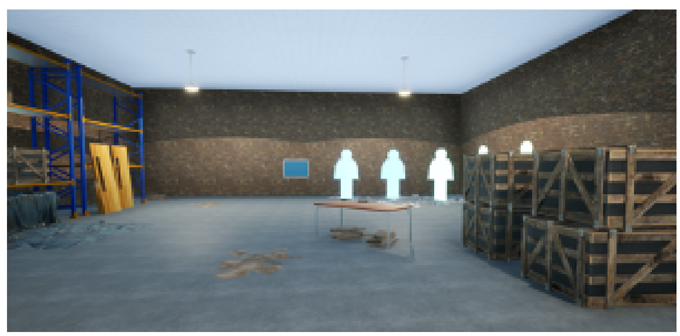

Fig. 1. Tutorial Scene

The second scene features a simple pattern replication game (the memory game). The player has to memorise a colour pattern displayed on a screen in one room, move to a second room and replicate the pattern on that room's screen (fig. 2). The player performs this task four times. Patterns are generated randomly, with each subsequent pattern longer than the previous, therefore increasing the difficulty in recall and cognitive load.

C. Measures

Several questionnaires were used to measure various aspects of the VR experience, as well as the user's perceived performance. Each participant was asked to fill out four

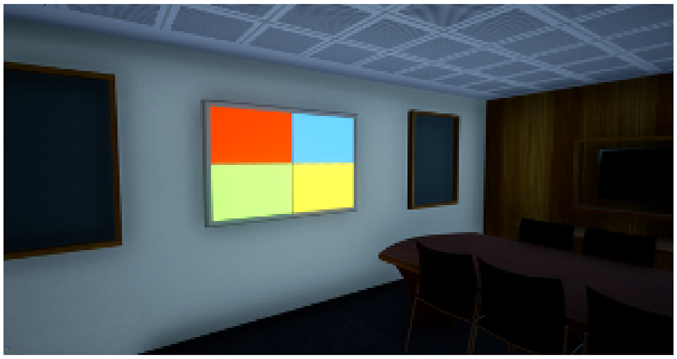

Fig. 2. Pattern Replication Screen

questionnaires; the System Usability Scale (SUS) [18]–[20], a NASA Task Load Index survey (TLX) [21]–[23], the iGroup Presence Questionnaire (IPQ) [24], [25] and a demographic questionnaire. The SUS was used to measure the usability of our developed system. The purpose of the IPQ was to determine the participants' subjective level of presence within the virtual environment. The TLX was employed to measure the difficulty of the task given to the subject, in this case the pattern replication game. The TLX is a multidimensional measure of the required mental workload to complete the given task.

Users' physiological responses to the VR experience and memory game were captured using biosensors. The Empatica E4 recorded GSR and HR while the Myndband recorded EEG. All biosignal data was timestamped and recorded in a csv file for analysis following the experiments. User generated events, such as the successful or unsuccessful entering of a pattern, are also recorded and timestamped.

D. Procedure

Subjects participated individually, one at a time. Upon arriving the participant was welcomed, given an information sheet, and asked to fill out a consent form and the pre-experiment demographic questionnaire. A brief explanation of the biosensors was given and the biosensors were then applied. The participant was then brought to the VR area where the headset and controllers were shown and a basic description of the experience was given. The participant was then asked to put on the VR headset and given the Oculus Touch controllers. The VR experience would then begin.

Following the VR experience, the controllers, VR equipment and biosensors were taken from the participant. The participant was then asked to fill in the IPQ, TLX and SUS, in that order. Finally, the participant was thanked for taking part in the experiment.

E. Participants

53 participants took part in our experiment (38 male, 14 female, 1 other). These participants (aged between 20 and 61) were recruited through the University's student and staff mailing. Most participants stated that they used a desktop or laptop daily, and that they were comfortable using technology. 28 participants said they regularly played video games. 29 participants had prior VR experience, however of these, 17 had tried VR only once before.

IV. Findings

The experiments have recently been completed. We are currently encoding the responses, and preparing the data for proper analysis. From our experience conducting the experiment and a cursory view of the data we can see the following. Of the 53 completed experiments, 34 were completely successful. Of the remaining 19 experiments two were ended early due to time constraints. A further 14 were partially successful, meaning that the data obtained from either the E4 or Myndband was considered bad, however data from the other device was good. In one experiment no data was obtained from either the E4 or Myndband. Incorrect application of the biosensor devices was the most common source of bad data. One subject could not complete the experiment, or post experiment surveys, due to motion sickness. One participant could not partake in the experiment as the headset would not fit over their spectacles. Most users enjoyed the experience and found it engaging. It was noted during experiments that most participants entered each pattern successfully on their first attempt. It is believed that this can be attributed to the use of both audio and visual cues in the memorisation stage of the experiment. This indicates that VR would be an effective tool for learning and would achieve similar results to a real world tool. Analysis of the NASA TLX indicates that the task was moderately difficult, scoring a mean of 50.58% on Mental Demand. Subjects did not find the task particularly frustrating (mean of 27.31%) and most felt that their performance of the task was good (mean of 72.31%). As a source of biosignal data, HRV derived from a wearable wristband PPG sensor is less reliable than the other sensor data, which may be attributed to motion artefacts. Signals from a single dry electrode EEG sensor can suffer from motion artefacts, poor placement, and physical interference by the Head Mounted Display. Overall the GSR data is consistent and reliable, and appears to be the most promising of the biosignals.

V. Conclusion

This experiment was designed to explore the feasibility of using a memory game in VR. Our long term goal is to use acquired biosignal data to aid in the generation of a real-time feedback loop which could alter the difficulty of the game. This study consisted of a simple colour pattern memorisation game where players were presented with a pattern in one virtual room and asked to replicated it in a second virtual room. Two Biosensor devices were employed, the Empatica E4 (GSR, HR) and the Myndplay Myndband (EEG). Both of these devices were implemented into the VR experience in order to acquire physiological readings. Experiments were carried out using the VR experience, the biosensors and a number of surveys (Demographic questionnaire, TLX, SUS, IPQ). 53 experiments were carried out and subjects were of a wide range in age and technical experience. In total 34 of the experiments were completely successful. The next phase will be to formally analyse the data from these experiments with the long term goal of implementing a real-time feedback loop which can improve the player's levels of engagement with the experience.

It is important to consider the additional constraints caused by the biosensor devices when designing a VR experience. It was found that some noise in the biosignals could be minimized by careful design of the VR game. Movement noise was especially detrimental to both the EEG and GSR signals, however this could be minimized by allowing the controllers to both move and rotate the player. Improper application of the biosensor devices also resulted in avoidable noise.

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