

A System Architecture for Emotion Detection in Virtual Reality

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1. Introduction

As the applications of Virtual Reality (VR) technologies increase, and the adaptation of experimental protocols from diverse research disciplines with immersive technologies becomes prevalent, the need for emotion recognition in VR is evident. In emotion recognition, various affect assessment methodologies are investigated (see review by [2]). Experiment design utilising VR can offer controlled laboratory conditions while granting content resources and ecological validity [1]. Typically, a usual model utilised for measuring emotions is the two-dimensional space model, consisting of the dimension of arousal (activation levels) and valence (positive/ negative polarity levels) which are also considered as the basic quantitative dimensions of emotions [3]. Multiple studies in Human Computer Interaction (HCI) and Affective Computing have explored the link between self-rated emotional dimensions with the physiological and/or behavioural responses for emotion classification (e.g. [4]).

The study of emotions' elicitation and detection in VR however is still in early stages [5]. Although, the actions of the user can be tracked via numerous input and sensory modalities (e.g. motion tracking), the underlying emotions that instigated these actions and choices remain difficult to detect. There are numerous studies in VR in which the arousal levels of the users were investigated via physiological responses (e.g. [6]). There is however only a limited number of studies in which the valence polarity of the user's experience is being explored (e.g. [7], via questionnaires). We believe that the coalescence of both dimensions is required to evaluate the nature of the emotion elicited during an immersive experience.

According to previous valence detection research in, facial expressions (FE) are rich in valence information. However, the area of the face in VR is typically left unexplored since the Head-Mounted Display (HMD) is covering almost 2/3 of the face, including the most informative facial muscles. Common methods outside VR for detecting FE, are computer vision [8] and facial electromyography (EMG) [9,10]. These methods can be applied for continuous FE monitoring. As VR uses are increasing, it is fundamental to propose novel, specially designed approaches to measure emotions in VR.

2. Brief Overview of the Proposed System's Architecture

In 2016, we developed a novel interface prototype 'Faceteq™' [11]. The interface was designed to work as an intermediate layer between the HMD and the face of the wearer, consisting of eight electromyography (EMG) sensors, one electrocardiogram (ECG), a skin-conductance sensor (SC), two Photoplethysmographic (PPG) sensors and one inertial measurement unit (IMU) including gyroscope and accelerometer. We envisaged that by placing biometric sensors on the facial areas where the VR HMD covers already, could prove to be an easy-to-use, unobtrusive and non-motion-constraining solution for affect monitoring.

We designed a system where continuous physiological responses are simultaneously collected via the Faceteq™ interface. As you can see in Fig. 1, the raw data are recorded while participants are exposed to audio-visual stimuli with affective content and while they are also subjectively self-rating their levels of valence and arousal. This step is essential for acquiring information on the levels of emotional stimulation of every individual experiencing the content. Once the recordings are collected, they become subject to signal processing where they were denoised and divided into epochs of 512 seconds. Through feature extraction,

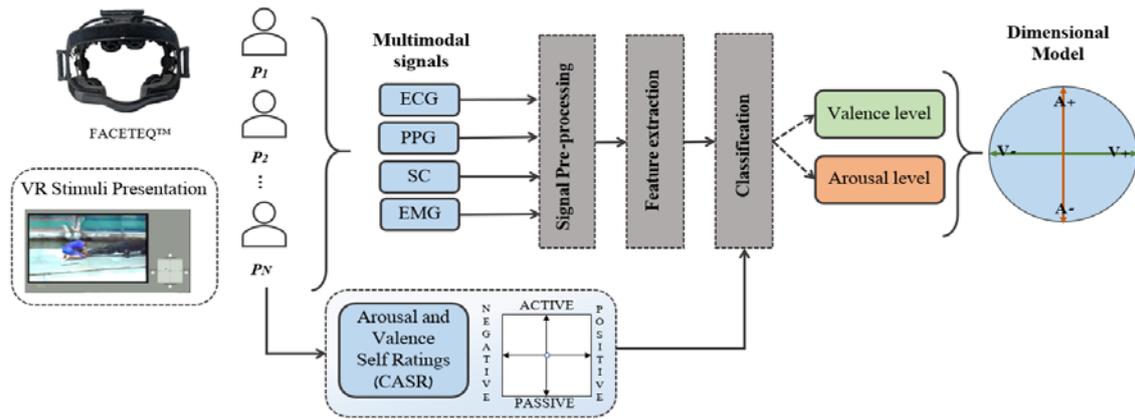


Figure 1. Brief Overview of the System's Architecture

various components of the signals are extracted. The features together with the participants' self-ratings are then sent to train a classifier, in order to classify the arousal levels from the participants' heart-rate responses to the stimuli. The outputs of the classifier in terms of valence and arousal levels can then be used to produce a two-dimensional representation of the user's state (based on the dimensional model of emotions).

To evaluate the system's architecture for off-line analysis we designed a feasibility study with 11 participants where physiological responses together with continuous self-ratings from each participant were collected. The reported results for binary arousal (low and high) from heart-rate metrics and binary valence (positive and negative) classification from EMG metrics using a C-Support Vector Machine (SVM) using a Gaussian kernel demonstrated the effectiveness of our approach [12,13]. We are currently analysing the remaining physiological signals including IMU and SC data, whilst we are also recruiting a larger sample size, and investigating additional regression approaches in order to detect finer-grained levels of the two emotion dimensions.

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