A QoE Assessment method based on EDA, Heart Rate and EEG of a Virtual Reality Assistive Technology System

Débora Pereira Salgado
Faculty of Engineering & Informatics
Athlone Institute of Technology
Ireland
d.psalgado@research.ait.ie

Felipe Roque Martins
Faculdade de Engenharia Elétrica
Universidade Federal de Uberlândia
Brazil
felipe.rmartins@outlook.com

Thiago Braga Rodrigues
Faculty of Engineering & Informatics
Athlone Institute of Technology
Ireland
t.brodrigues@research.ait.ie

Conor Keighrey
Faculty of Engineering & Informatics
Athlone Institute of Technology
Ireland
c.keighrey@research.ait.ie

Ronan Flynn
Faculty of Engineering & Informatics
Athlone Institute of Technology
Ireland
rflynn@ait.ie

Eduardo Lázaro Martins Naves
Faculdade de Engenharia Elétrica
Universidade Federal de Uberlândia
Brazil
eduardonavesufu@gmail.com

Niall Murray
Faculty of Engineering & Informatics
Athlone Institute of Technology
Ireland
nmurray@research.ait.ie

ABSTRACT

The[1] key aim of various assistive technology (AT) systems is to augment an individual's functioning whilst supporting an enhanced quality of life (QoL). In recent times, we have seen the emergence of Virtual Reality (VR) based assistive technology systems made possible by the availability of commercially available Head Mounted Displays (HMDs). The use of VR for AT aims to support levels of interaction and immersion not previously possibly with more traditional AT solutions. Crucial to the success of these technologies is understanding, from the user perspective, the influencing factors that affect the user Quality of Experience (QoE). In addition to the typical QoE metrics, other factors to consider are human behavior like mental and emotional state, posture and gestures. In terms of trying to objectively quantify such factors, there are wide ranges of wearable sensors that are able to monitor physiological signals and provide reliable data. In this demo, we will capture and present the users EEG, heart Rate, EDA and head motion during the use of AT VR application. The prototype is composed of the sensor and presentation systems: for acquisition of biological signals constituted by wearable sensors and the virtual wheelchair simulator that interfaces to a typical LCD display.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**; • **Human-centered computing** → Virtual Reality

KEYWORDS

QoE, Virtual Reality, Assistive Technology, Physiological Metrics

ACM Reference format:

D.P. Salgado, F.R. Martins, T.B. Martins, C. Keighrey, R. Flynn, E.L.M. Naves, and N. Murray. 2018. SIG Proceedings Paper in word Format. In *Proceedings of ACM Multimedia System conference, Amsterdam, Netherlands, June 2018 (MMSys'18)*, 4 pages

MMSys'18, June 12–15, 2018, Amsterdam, Netherlands

ACM ISBN 978-1-4503-5192-8/18/06.
https://doi.org/10.1145/3204949.3208118

1 INTRODUCTION

In recent years, new metrics and methodologies have been proposed with the purpose of developing QoE models that best suit the evaluation of new multimedia systems. The literature, for example in [1], reports categories of influencing factors (IFs) such as Human IFs (HIFs), System IFs (SIFs) and Context IFs (CIFs). As outline in [1], IFs frequently overlap and together have a mutual impact on QoE. Such IFs are complex and strongly interrelated, and due this fact, still needs continuous studies to establish which factors influence QoE given the context. Traditionally, the SIFs and CIFs were considered most important for QoE, but the HIF have gained significant interest and importance in more recent years.

In this context, the proposed demo presents a framework which captures a number of implicit metrics from the user continuously as they experience an immersive multimedia training application. Traditionally, the user's assessment in this context was via self reporting post the experience (e.g. questionnaires, which do provide valuable insight into the user perceived QoE). Such methods of evaluation are used to determine an overall mean opinion score (MOS). However, these types of evaluations are not without their flaws. They are often limited to the specific application scenarios [2-3]; they are often considered expensive; time consuming; inflexible and sometimes the number of subjects is not enough to represent the aim population of the study [3].

As a result, the QoE community has begun to explore alternative methods of evaluation [4-7]. More specifically in terms of implicit metrics, a body of work is emerging which aims to monitor and evaluate physiological signals as parameters to evaluate the user behavior [8]. This is now possible due to the availability of a new generation of wearable devices. Smart watches and activity trackers observe heart rate (HR), GPS position, and step count to provide feedback on the wearers fitness levels. More advanced devices are also available which provide the opportunity for users to monitor electrocardiographic signal (ECG), blood volume pressure (BVP), galvanic skin response (GSR, also known as electrodermal activity or EDA), body surface temperature, accelerometer, respiration rate, encephalography signals (EEG) and other physiological signals [9]. Even within the traditionally expensive EEG equipment companies such as Muse®, Emotiv®, OpenBCI® and Neurosky® offers options of low-cost EEG devices.

Recent advances in display technology are changing how we experience multimedia. The entertainment (gaming and movie) industry now focuses on the development of 360 degree immersive multimedia content which can be viewed on head mounded displays (HMD). This virtual reality (VR) experiences can be displayed on consumer available devices such as the Oculus Rift ® and HTC Vive®. These VR systems allow human-machine interaction (HMI) where the user can interact, navigate and reproduce real situations without risk [10]. In other words, it becomes accessible to simulate and visualize actions that would be impossible to be perceived in the real word. Hence, VR systems are applicable not only to gaming, being feasible for training, rehabilitation and education [11]. One such area where VR systems can be applied is in Assistive Technology.

According to the World Health Organization (WHO), assistive devices and technologies are "those whose primary purpose is to maintain or improve an individual's functioning and independence to facilitate participation and to enhance overall well-being. They can also help prevent impairments and secondary health conditions." [12].Within this scenario, this paper presents a prototype of an Assistive Technology system in VR; a wheelchair simulator. The assessment task was implemented in VR environment and a number of physiological metrics: EEG signal, GSR/EDA, body surface temperature, accelerometer, HR and BVP were captured to provide an objective analysis while the individual is operating the wheelchair simulator.

2 RELATED WORK

There are many studies related to the Autonomic Nervous System (ANS) to observe the human behavior [13]. The ANS is divided into the sympathetic nervous system (SNS) and parasympathetic nervous system (PNS) [14]. When a person experiences excitement or anticipation of an important event, the SNS is activated. This means the body is under stressful conditions, as result, it increases heart rate, respiration activity and sweat gland activity, etc. After the stress has passed the PNS is activated, when the body needs to relax and slow down. Hence, the PNS reverses the stress response. Since the ANS controls the heart, measuring the heart activity is an alternative for evaluating the state of the ANS. If we want to analyze the sympathetic activation separately, the GSR/EDA must be monitored, and to evaluate the parasympathetic activation the alternative is extracting the high frequency component of this heart rate variability [9].

The electroencephalogram measurement is widely used to investigate mental states, which is most certainly a difficult task considering the complexity of the human brain. The work of Duncan et Al. [1], [15], mentions that while recording relevant information about the brain activity, significant noise or unwanted information can also be captured, e.g. motion artifacts (e.g. eye and facials movements), and also effects of electromagnetic interference. There are standard guidelines used in a clinical setting to appropriately collect and analyse EEG signals. However, some of the practices used to measure the EEG may affect critical IFs on the user's QoE. For example, to use a wet/gel electrode, the participant's scalp needs to be properly prepared. As a result, the time consumed in the process of preparation can exhaust the user before a test or experiment. In addition, the freedom of movement of the user is reduced because they need to avoid the moving their body. To address these issues as outlined in [1], [16], low-cost EEG devices, e.g. Emotiv-EPOC and NeuroSky Mindewave headset, are capable to retrieve useful information in the context of QoE research. In [10], the features provided by Emotiv-EPOC device were used and the authors have applied the system to draw the inference of frustration from human observer caused by the quality of the played audiovisual excerpt. This demo will employ the low cost NeuroSky MindWave EEG headset which is minimally invasive.

Our approach captures and presents EDA and Heart rate, blood volume pressure, the hand surface temperature, xyz-acceleration

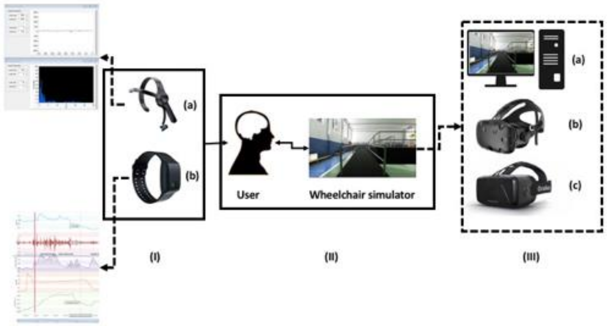

Figure 1: Prototype System Framework. I. Physiological wearable sensors used to capture data. (a) Neurosky mindwave® device. (b) Empatica E4® wristband. II. Representation of user interaction with the wheelchair simulator. III. The compatibles displays. (a) Common screen. (b) Oculus Rift® HMD device. (c) HTC Vive® HMD device.

and EEG. The ultimate aim is to understand any correlations or inference between these metrics and the user's QoE. Although recently literature, Keighrey et al. [4], used the wearable sensors, PIP® and Fitbit®, to capture heart rate variability and GSR/EDA activity in order to assess a user's QoE objective data; very few works are as exhaustive as the proposed system. The motivation is that analyzing these physiological metrics can give a good indication of the ANS activation.

3 EXPERIMENTAL SETUP

This section provides details of the technologies employed in the prototype system framework as shown in Figure 1.

3.1 Virtual Reality Display Technologies

The simulator can operate with two types of HMD, the Oculus Rift Development Kit 2 (DK2) and HTC Vive. These two HMD options were added to the simulator for future comparative experiments between these models. Each of these respective devices has proprietary controller systems. In this demo, users control movement in the virtual environment using a USB joystick or keyboard. However, the simulator can support different forms of control of the wheelchair such as using electromyographic signals from facial muscles and eye tracking. As such, users with severe motor disabilities can still operate the wheelchair. However, for the purposes of the current research, only the default joystick controller is used. The objective of this is to provide a similarity with the controls of a real electronic wheelchair.

3.2 Wheelchair Simulator – The Assistive Technology application

The virtual environment used in this research was developed using the Unity 3D game engine [17-20]version 2017.2.0f3 (64-bit). The simulation was developed as a training tool, providing inexperienced users of electric wheelchairs a method to learn operation skills in a safe environment. In the current version, three

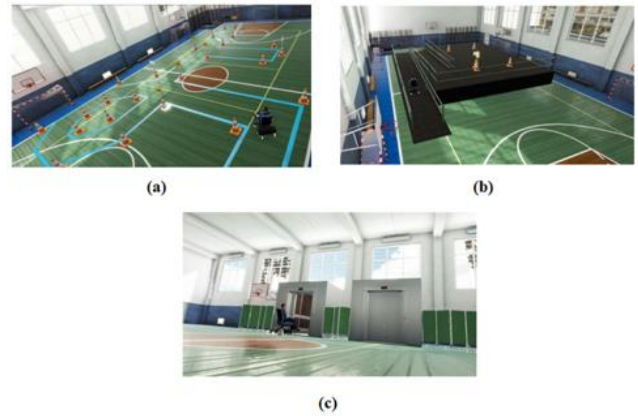

Figure 2: Current training courses included in the Wheelchair Simulator. (a) Obstacle course for training basic maneuvers. (b) Navigation in accessibility ramp. (c) Navigating the wheelchair in elevators.

different training scenarios are available for users (Figure 2). These were designed to reproduce situations that are commonly found by wheelchair users during a normal navigation routine: (A) an obstacle course (to introduce the user to basic maneuvers); (B) navigation of ramps; (C) the complex task of maneuvering within elevators.

3.3 Objective Metrics – Physiological Data

To capture the physiological metrics such as EDA/GSR, HR, BVP, temperature, accelerometer and EEG, two non-invasive and dry wearable devices were used. The sensors selected for the demo are the Wristband E4 from the company Empatica, and Mindwave Mobile from Neurosky, as shown in Figure 1 (I). The Mindwave is one channel EEG device, the electrodes are dry type, its bandwidth is between 3 to 100 Hertz (Hz), with 12 bits of resolution, sample rate is 512 Hz and the transmission is made via Bluetooth. The Neurosky device already includes factory data processing of the EEG signals, to provide an indicative of the user's level of attention and meditation. However, these algorithms are private and are still not scientifically validated. As an alternative, it is possible to access the raw EEG signal that can then be processed. In the EEG module, the demo focuses not only on the acquisition of brain signals, but also on the signal processing to identify and quantify cognitive states such as stress, sleepiness, and attention. EEG signals are composed by a range of different frequencies (1-100Hz) that can be related to the beginning of a mental state. For example, delta waves (1-4Hz) can be related with the relaxed, unconscious state, while theta waves (4 – 7 Hz) are related to REM sleep, cognitive tasks, intuition, creativity, and dream. Alpha waves (8-12 Hz) refer to a relaxed but awake state. Beta waves (13 – 40 Hz) represent alertness, agitation and emotional influence, and gamma waves (40 – 100 Hz) are related to motor functions and higher mental activity [21]. Different methods need to be used to acquire the brain signals, which are commonly classified into groups depending on the equipment used.

The E4 has four sensors: photoplethysmography, electrodermal activity, 3-axis accelerometer and optical thermometer. These sensors are used to determine the blood volume pressure with a sample rate of 64 Hz, inter beat interval (IBI), electrodermal activity in a sample rate of 4 Hz, xyz raw acceleration with a sample rate of 32 Hz and the skin temperature with a sample rate of 4 Hz. The commonly analyzed components of the EDA signal are the rapid change skin conductance response, which corresponds to short-term external stimuli, and the conductance of the skin changing more slowly (after several seconds or longer), which reflects long-term emotional changes regardless of external stimuli [22-23]. Exposure to stress also results in changes in skin temperature in various parts of the body. In the distal region the temperature decreases, for example, in the surface of the hands, and the temperature of the skin remains in proximal regions, such as the core area [24]. The Heart Rate variability refers to the beat-to-beat variation. This analysis can be categorized into time-domain and spectral-domain analysis, when the HR increases may relate that the user is under stressful conditions.

3.4 Demonstration

For the demo, participants can experience all user scenarios and the physiological data will be presented. In the meantime, if it is in the interest of the user the system can monitor the EDA, HR, EEG and temperature values in real time. After the completion of the demo, the performance results (e.g. time of the experiment, number of commands and collisions) and the physiologic data will be presented. Demonstration setup for the attendees will be using a conventional PC monitor, and the simulator with the VR Headset will be shown in video format.

4 CONCLUSIONS

This demo will solicit an experimental and theoretical discussion on the use of physiological data as indicators of QoE. Our system allows the user to experience immersive multimedia training in a safe environment. The system allows us to conduct many experiments and can provide enough data for deep analysis of the obtained results. To correlate the measurements and experience regular statistics will be applied facilitating the future development of an informative model of QoE.

ACKNOWLEDGMENTS

The work presented in this paper has been supported by the Government of Ireland, CAPES, FAPEMIG and CNPq.

REFERENCES

[1] S. Möller and A. Raake, "Quality of Experience - Advanced Concepts, Applications and Methods", pp. 55-132, 2013.

[2] M. Suznjevic, M. Mandurov, and M. Matijasevic, "Performance and QoE assessment of HTC Vive and Oculus Rift for pick-and-place tasks in VR", *2017 9th Int. Conf. Qual. Multimed. Exp. QoMEX 2017*, pp. 3–5, 2017.

[3] T. Hossfeld *et al.*, "Best practices for qoe crowdtesting: Qoe assessment with crowdsourcing", *IEEE Trans. Multimed.*, vol. 16, no. 2, pp. 541–558, 2014.

[4] C. Keighrey, R. Flynn, S. Murray, and N. Murray, "A QoE evaluation of immersive augmented and virtual reality speech & language assessment applications", *2017 9th Int. Conf. Qual. Multimed. Exp. QoMEX 2017*, 2017.

[5] N. Murray, Y. Qiao, C. keighrey, D. Egan, D. P. Salgado, G. M. Muntean, C. Timmerer, O. Ademoye, G. Ghinea, and B. Lee, "Evaluating QoE of Immersive Multisensory Experiences". In IEEE MMTC Communications Frontiers, Special Issue on "QoE Evaluation and Control in Immersive Multi-modal Multimedia Applications" (vol. 13, no.1), January 2018.

[6] C. Keighrey, R. Flynn, S. Murray, S. Brennan, and N. Murray "Comparing user QoE of AR and VR applications using physiological and interaction measurements". In 25th ACM International Conference on Multimedia (ACM MM 2017).

[7] D. Egan, S. Brennan, J. Barrett, Y. Qiao, C. Timmerer, and N. Murray, "An evaluation of Heart Rate and Electrodermal Activity as an Objective QoE Evaluation method for Immersive Virtual Reality Environments". In 8th International Conference on Quality of Multimedia Experience (QoMEX 2016) June 2016, in Lisbon, Portugal.

[8] L. Han, Q. Zhang, X. Chen, Q. Zhan, T. Yang, and Z. Zhao, "Detecting work-related stress with a wearable device," *Comput. Ind.*, vol. 90, pp. 42–49, 2017.

[9] F. Sun, C. Kuo, H. Cheng, S. Buthpitiya, P. Collins, and M. Griss, "Activity-aware Mental Stress Detection Using Physiological Sensors," *Mob. Comput. Appl. Serv.*, vol. 76, pp. 1–20, 2012.

[10] E. F. Damasceno, A. Cardoso, and E. A. Lamounier, "An middleware for motion capture devices applied to virtual rehab," in *Proceedings - IEEE Virtual Reality*, 2013, pp. 171–172.

[11] R. Skibba, "Virtual reality comes of age," Nature, vol. 553, no. 7689. pp. 402–403, January 2018.

[12] "WHO | Assistive devices and technologies," *WHO*, 2017. [Online]. Available: http://www.who.int/disabilities/technology/en/. [Accessed: 03-Mar-2018].

[13] M. Moghtadaei, E. Langille, S. A. Rafferty, O. Bogachev, and R. A. Rose, "Altered heart rate regulation by the autonomic nervous system in mice lacking natriuretic peptide receptor C (NPR-C)," Sci. Rep., vol. 7, no. 1, 2017.

[14] Ludwig, Kip, Erika Ross, Nicholas Langhals, Doug Weber, J. Luis Lujan, and Dmitrios Georgakopoulos. "The Autonomic Nervous System." In *NEUROPROSTHETICS: Theory and Practice*, pp. 12-39. 2017.

[15] C. C. Duncan *et al.*, "Event-related potentials in clinical research: Guidelines for eliciting, recording, and quantifying mismatch negativity, P300, and N400," *Clinical Neurophysiology*, vol. 120, no. 11. pp. 1883–1908, 2009.

[16] A. N. Moldovan, I. Ghergulescu, S. Weibelzahl, and C. H. Muntean, "User-centered EEG-based multimedia quality assessment," in IEEE International Symposium on Broadband Multimedia Systems and Broadcasting, BMSB, 2013.

[17] Borges, L. R.; Martins, F. R; Naves, E. L. M. Electric-powered wheelchair control using eye tracking techniques. In: International Journal of Innovative Research in Computer and Communication Engineering, v.4, p.16690-16695, 2016.

[18] Borges, L. R.; Martis, F. R.; Naves, E. L. M.; Bastos, T. F.; Lucena, V. F.. Multimodal system for training at distance in a virtual or augmented reality environment for users of electric-powered wheelchairs. In: IFAC-PAPERSONLINE, v.49, p.156-160, 2016.

[19] Salgado, D. P.; Martins, F. R.; Borges, L. R.; Naves, E. L. M.. Realidade Virtual e tecnologia assistiva: ambiente seguro para treinamento de cadeirantes controlado por sinais eletromiográficos. In: IX Simpósio em Engenharia Biomédica, 2016, Uberlândia. Anais do SEB 2016, p.86-89, 2016.

[20] Martins, F. R.; Salgado, D. P.; Naves, E. L. M. Sistema de controle multimodal para cadeiras de rodas motorizadas: uma alternativa ao joystick. In: XXV Congresso Brasileiro de Engenharia Biomédica, 2016, Foz do Iguaçu. Anais do XXV Congresso Brasileiro de Engenharia Biomédica, p.1486-1489, 2016.

[21] L. F. Nicolas-Alonso and J. Gomez-Gil, "Brain computer interfaces, a review," Sensors, vol. 12, no. 2, pp. 1211–1279, 2012.

[22] E. Kuijpers, H. Nijman, I. M. B. Bongers, M. Lubberding, and M. Ouwerkerk, "Can mobile skin conductance assessments be helpful in signalling imminent inpatient aggression?", Acta Neuropsychiatrica., vol. 24, no. 1, pp. 56–59, 2012.

[23] B. Kikhia et al., "Utilizing a wristband sensor to measure the stress level for people with dementia," Sensors (Switzerland), vol. 16, no. 12, 2016.

[24] C. H. Vinkers et al., "The effect of stress on core and peripheral body temperature in humans," Stress, vol. 16, no. 5, pp. 520–530, 2013.