Anxiety detection from Electrodermal Activity Sensor with movement & interaction during Virtual Reality Simulation

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***Abstract*— Nowadays, Virtual Reality (VR) is bringing great benefits to Anxiety Disorder treatments, as well as to other brain cognitive dysfunctions. The advantage of VR is that it can provoke stimuli to the same degree as real-life situations. However, measurement methods of physiological changes caused by the aforementioned stimuli, which apply to VR Anxiety Disorder treatments, have not been examined extensively. As a result, clinicians who use biosignal sensors tend to ask their patients to remain motionless during simulations in order to achieve accurate measurements from the sensors. It is clear that this practice limits the level and range of benefits yielded when using VR simulation. As a consequence, the patients' experience is restricted and so is the potential of the sensors' application in the treatment methods. Furthermore, the data gathered from the sensors is handled using conventional analysis affecting the conclusions drawn about the patients' state. This study aims to emphasise the importance of interacting with the stimuli during the VR treatment through the proposal of an Electrodermal Activity (EDA) Sensor System architecture that can be combined with VR simulations while still allowing the patient to move and interact within the Virtual Environment, without compromising the sensor's measurements. Continuous Deconvolution Analysis is used to draw conclusions from the gathered biosensor data.**

I. Introduction

Anxiety disorders are common mental health disorders from which 19.1% of adults and 31.9% of adolescents in the US suffer, with 22.8% of them reported as serious cases [1]. Their cost is estimated to be as high as $42 billion per year in the US - approximately one third of the entire US health bill [2]. All different types of anxiety disorders share manifestations of excessive fear and anxiety as emotional responses to real or perceived threat [3]. This emotional build-up can result in the development of physical symptoms, such as muscle tension or panic attacks [4].

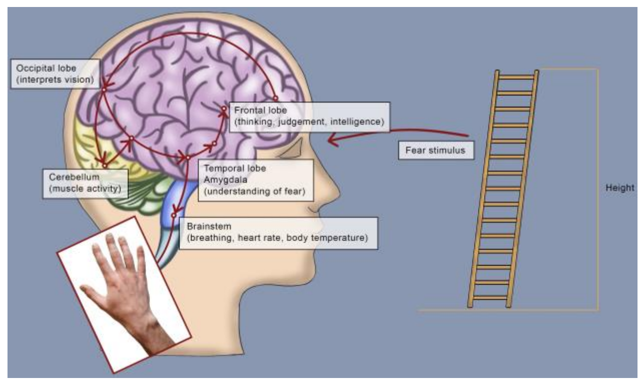

Figure 1: The process followed by the brain from the stimulus to the reaction

A widely-used treatment method is Exposure Therapy (ET); a cognitive behavioral technique [3] that aims to alter the patient's perception and behavior towards their phobia, by repeatedly exposing them to the avoided stimuli in a therapeutic manner [5] (Figure 1). Standard ET can be expensive and time-consuming [6], so, lately, it has successfully been enhanced with VR Systems, creating Virtual Reality Exposure Therapy (VRET) [7]. VRET can provide an equally realistic environment and make the user feel present to the same extent as Standard ET can [7]. The more VR systems improve in terms of presence and immersion, the more the chances to enhance ET and lead to more positive outcomes [5].

In the majority of VRET clinical trials, detecting the patients' emotional state and measuring the intensity of their anxiety is performed via questionnaires combined with electrophysiological biosignal sensors most of the time [8]–[10]. Biosignal sensors are mainly non-invasive wearable devices that can measure physiological changes which are regulated by the Autonomic Nervous System (ANS) and can provide a wide range of data. In general, the main purpose of VRET simulations is for the patient to perform tasks that are presumed to be stressful, with cognitive loads, resulting in physiological changes. So, biosignals collected during these tasks will reflect changes in the ANS and, therefore, the stress levels [11], [12].

Over the past years, there has been a continuous increase in the demand for portable and low cost electrophysiological

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biosignal sensors, like wrist-bands or ankle-bands which have numerous advantages including cost efficiency or portability [13], [14]. However, when the need arises for accurate data extractions for precise measurements and not for an approximation of the actual data that usually happens when calculating the average of a set of measurements, those sensors have some limitations and very specific usage instructions, with the main one being that patients need to remain still and seated during the measurements [15]–[20]. Therefore, therapeutic exercises suggested by the clinician for the patients' benefit that may cause sudden movements in the virtual space are restricted while the users are wearing the sensor. Currently, this restriction is necessary in order for the sensor to collect and measure the data accurately and correctly [21]. However, it contradicts the initial purpose; to include the biosensor in studies requesting more interactive exercises without minimising the patients' experience and interaction with the virtual stimuli, which interaction is considered beneficial and is mandatory for better treatment. As a support of this claim, it has been found in a wide range of studies in which questionnaires were the medium to measure the outcome of the treatment [22]–[24], the exercises that were assigned to the patients were much more interactive, like being requested to approach the phobic stimuli or to touch the phobic stimuli, rather than stay seated and observe the stimuli as is the case when sensors are currently used.

In this study, we present the need to raise these restrictions imposed by the use of biosignal sensors in VR simulations and by proposing a way to use them in VR systems that operate with an Electrodermal Activity Sensor System, at a cost of just about $70, so the patient can interact with the virtual environment, while improving Anxiety Disorder diagnoses & treatments.

II. Materials

Sweat is proven to be a key indicator of stress build-up [25], [26]. Electrodermal Activity sensors can measure continuous skin conductance changes, which are associated with sweat gland activity; the aforementioned activity relates to the activation of the sudomotor nerve, that is part of the ANS [3]. In the majority of the studies, the user is required to remain seated and immobile, because EDA sensors are

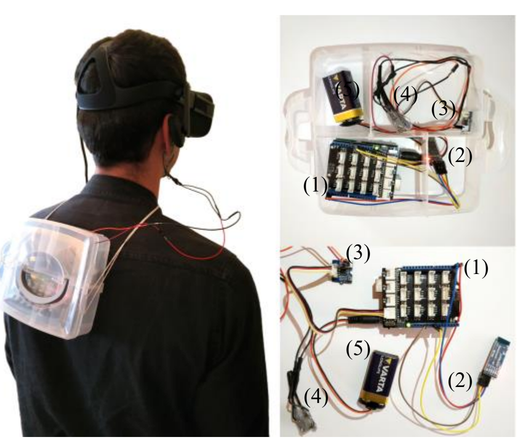

Figure 2: Electrodermal Activity Sensor Setup (a: Sensor System, b: Rift VR Headsets, 1: Arduino Uno, 2: Bluetooth Module, 3: Electrodermal Sensor, 4: Earlobe and Cables, 5: power-bank).

placed on their hands or feet. This is because users obviously perform activities with their limbs, so (a) sudden movements could detach the sensor from their body and cause unwanted noise in measurements and (b) sweat may be secreted due to physical exercise and not due to changes in the users' emotional state, yielding false data [8]–[10].

On the contrary, the system architecture proposed in this study is such that the user can move, while the sensor collects data of the same quality as in the studies in which they were immobile by minimizing the noise. This can be achieved if we attach the EDA sensor to the users' earlobes, instead of their limbs [27]. The earlobe may be a body part with high sweat burst, but no exercises are performed with it. Any motion usually happens when the whole head moves. This means that the movements produced by the earlobes are much smaller and fewer than other body limbs. So, the physiological signals obtained by the attached to the earlobe EDA sensor lead to less noise (Figure 2).

The components of the proposed system are: a desktop computer, which operates as the receiver and controller of the simulation, a sensor system which gathers information about the users' physiological state and transmits it wirelessly to the computer via Bluetooth, and a VR system to see and interact within the virtual environment.

The computer is an iMac computer with the following specifications: Graphics Card AMD: Radeon Pro 560, CPU: Intel i5, RAM: 8GB, Video Output: HDMI 1.3, Ports: 3x USB 3.0 and Bluetooth: 4. An Oculus Rift VR Headset, plugged into the computer, provides the virtual environment, while two Oculus Rift Touch Controllers, one for each hand, provide hand presence and interaction within it. Finally, the system includes two Oculus Rift Sensors which track constellations of IR LEDs to translate the user's movement within the VR environment. The Software tools used to create the VR environment are: Unreal Engine v.4.18 developed by Epic Games and Blender 3D Computer Graphics Software for creating 3D objects and animated visual effects.

The Sensor System is wearable and consists of: an Arduino Uno, a Galvanic Skin Response Sensor, a Bluetooth module (HC-06 model) and a battery to supply energy. The Sensor System is stored in a box and placed on the back of the patient. The sensor attached to the earlobe consists of jumper cables and a hair-clip to keep them attached to the earlobe (Figure 2). We used Arduino licensed software for the measurement collection program (at 20Hz) and python for data acquisition via the computer Bluetooth port.

III. Method

The goal of this study is to compare the effectiveness of previous VR systems, during which the user had to remain motionless during the simulation, with the proposed VR system, during which the user is allowed to move and interact within the virtual room. The comparison process took place in the Biomedical Engineering Laboratory of the National Technical University of Athens (BEL of NTUA). The simulation was focused on Anxiety Disorders and acrophobia, a specific fear of heights. Acrophobia is a common anxiety disorder, with one in twenty people meeting its diagnostic criteria. Individuals suffering from acrophobia

Figure 3: sub-session A (s-sA). The participant is outside while holding the balcony bar of a real balcony and he wears the portable biosensor on his ear at the same time.

Figure 4: sub-session B (s-sB). The participant watches a VR video while seated without moving or interacting and he wears the portable biosensor on his ear at the same time.

Figure 5: sub-session C (s-sC). The participant holds the virtual bar of a virtual balcony with the Hand Controllers and he wears the portable biosensor on his ear at the same time.

typically avoid height-related situations such as stairs, terraces, apartments, being in high buildings, elevators, on bridges or even go on plane trips [4], [28], [29].

The participants in this study were five individuals who claim to feel uncomfortable when in places of a certain height but have not been officially diagnosed with acrophobia. This trial was approved by the Ethics Committee of the National Technical University with protocol number #64185. Taking into consideration the goal of our study and the fact that the participants are not diagnosed acrophobic patients, our study is not a clinical trial, but a system trial. Each user participated in a fifteen-minute session, divided into three-minute sub-sessions, with two-minute breaks between sub-sessions. More specifically:

- **sub-session A (s-sA)**: the user is exposed to a height in the physical world; specifically standing on the balcony of the building (Figure 3).
- **sub-session B(s-sB)**: the user is exposed through a virtual reality video to the height of a balcony, remaining seated and still, without being able to interact within the VR environment (Figure 4).
- **sub-session C (s-sC)**: the user is exposed to the height of a balcony placed in a virtual reality environment, and has the ability to interact within the virtual environment (i.e. walk in the virtual room) (Figure 5,6,7).

In sub-sessions A and C, the user has to complete the same task, which is to approach the balcony, touch the rails and stay in this position for two minutes; then walk away from it. In the case of sub-session B, the user does not need to do any of the above. Instead, the user watches a demonstration video of the same task performed by an avatar in the VR environment. The video was recorded before the beginning of the tests. The man appearing in the photographs is not one of the five participants, but a member of our team.

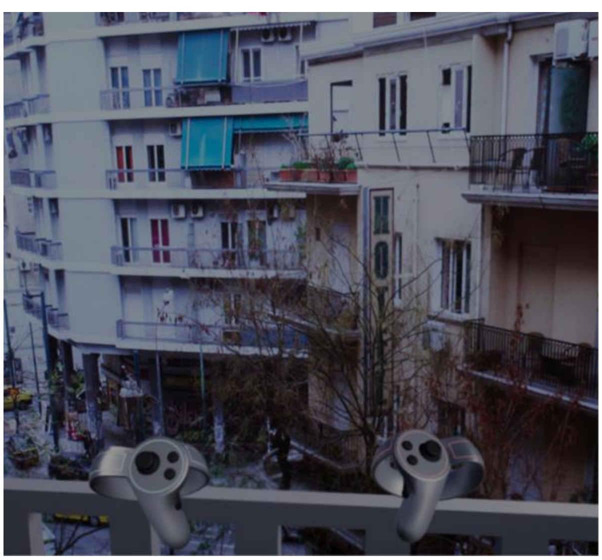

Figure 7: Virtual Reality environment of the acrophobic simulation, out on the balcony

Figure 6: Virtual Reality environment of the acrophobic simulation, inside the room overlooking the balcony.

IV. DATA ANALYSIS

After completing the data collection from the five participants, we used JupyterLab to process it, with the Neurokit Python library used to process EDA signals. The implemented signal analysis process is based on Continuous Deconvolution Analysis (CDA), according to which the skin conductance signal is decomposed into its tonic and phasic driver data [25]. It is based on an explicit biophysical model, and its parameters are optimised for each individual dataset. The decomposition process comprised of three different steps: the preprocessing phase, in which the signal is filtered to reduce the noise, the deconvolution process in order to obtain the phasic and tonic driver data, and the optimization stage to improve the estimation of the parameters of the impulse response function. Finally, the features we extracted from the phasic signal are Mean, Variance and Energy. The data we collected from the users are in Table I.

The statistics (Mean & Std. Deviation) of each feature and session group are shown in Table II. The formulas we used for the *Mean*, *Variance* and *Energy* are the following:

$$Mean = \frac{1}{n}\sum_{i=1}^{n} a_i \quad (1)$$

$$Variance = \frac{1}{n}\sum_{i=1}^{n} (a_i - Mean)^2 \quad (2)$$

$$Energy = \frac{1}{n}\sum_{i=1}^{n} (a_i)^2 \quad (3)$$

For the statistical analysis, repeated measures were performed with ANOVA within sub-sessions A, B & C, with alpha level set at a=.05. As expected, the phasic signals *Means*, *Variances* and *Energies* of the sub-sessions differed significantly from each other: *Means* ($F(2,8)=145.48$, $p<.001$, $n^2=.97$), *Variances* ($F(2,8)=90.37$, $p<.001$, $n^2=.95$), *Energies* ($F(2,8)=8332417364554.063$, $p<.001$, $n^2=.97$). Subsequently, a paired-sample t-test, with alpha level set at a=.05 was performed on each pair signal. As shown in Table III, the features of phasic signals from sub-sessions A and B are significantly different by a high factor. However, the features of the phasic signals of sub-sessions A and C are not significantly different (only the Variance is significantly different by a low factor). So, from those measurements we conclude that the sense of fear that emerged from the virtual stimuli with interaction s-sC was at a similar level as the sense of fear that emerged from the real-life stimuli s-sA. On the contrary, during the s-sB in which the participants were seated and could not interact with their phobia, the sense of fear was much lower than the real-life stimuli. SPSS (version 25) was used for the statistical analysis.

TABLE II.

EDA Freq. Data	Phasic Skin Conductance Signal		
	M (SD) ***Mean***	**M (SD)** ***Variance***	**M (SD)** ***Energy***
s-sA	11.10 (1.80)	96.98 (17.36)	736811.19 (143651.47)
s-sB	.94 (.49)	.66 (.37)	1818.75 (469.57)
s-sC	9.83 (1.05)	67.42 (10.39)	677186.08 (120813.872)

The signal screenshots appeared in Figures 8, 9 & 10 from a randomly selected participant. We can easily observe that the exported signal from virtual reality simulation with interaction s-sC (Figure 10) is quite similar to the signal from the real-life simulation s-sA (Figure 8), while the signal exported during the virtual reality simulation without interaction s-sB (Figure 9) is quite different from the other two. Moreover, the variation of the phasic signal from the s-sB does not exceed 2 mV, compared to those of s-sC and s-sA in which the phasic signals exceed 20 mV. However, from Figure 8 we observe a gradual increase of phasic signals in real-life simulation s-sA, in contrast with the two virtual simulations s-sB and s-sC in which there is greater variation of phasic signals (Figure 9, 10). So, even if the similarities between the real-life simulation and the virtual reality with interaction simulation prove that the interaction and confrontation are key factors for the better stimulation of a *fear* feeling, the participants understand that the virtual simulations are not real so there is more variation of their sweating and consequently of the measured signals.

V. LIMITATIONS

A limitation of our study is that our sample consisted of only five users. This means that even though it outlines sufficiently the potential of our system, it limits the knowledge extracted from the results. Thus, we would like to include more people from different social groups and collect

TABLE III.

Paired Sample T-Test	Phasic Skin Conductance Signal	
	t-value	***Significance***
s-sA Mean & ssB Mean	12.99	.001
s-sA Mean & ssC Mean	1.71	.162
s-sA Variance & ssB Variance	12.46	.001
s-sA Variance & ssC Variance	3.27	.031
s-sA Energy & ssB Energy	11.46	.001
s-sA Energy & ssC Energy	2.57	.062

TABLE I.

EDA User's Data	Phasic Skin Conductance Signal								
	Mean			***Variance***			***Energy***		
	s-sA	**s-sB**	**s-sC**	**s-sA**	**s-sB**	**s-sC**	**s-sA**	**s-Sb**	**s-sC**
User 1	12.13	.61	9.36	99.91	.76	70.07	867004.97	1533.43	726777.08
User 2	9.41	.78	8.51	78.36	.45	56.80	568462.12	1697.71	557364.06
User 3	13.54	1.02	10.31	82.59	.96	82.25	889220.70	2582.94	857655.40
User 4	9.32	.53	9.69	102.30	.13	58.13	618465.28	1377.23	583844.09
User 5	11.14	1.76	11.32	121.78	1.02	69.85	740902.92	1902.44	660289.77

(a)

(b)

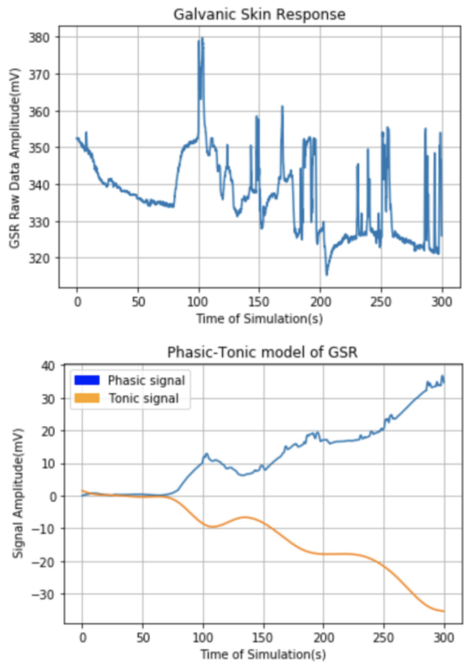

Figure 8: The measured signals from a randomly selected participant during the real-life simulation s-sA.

(a)

(b)

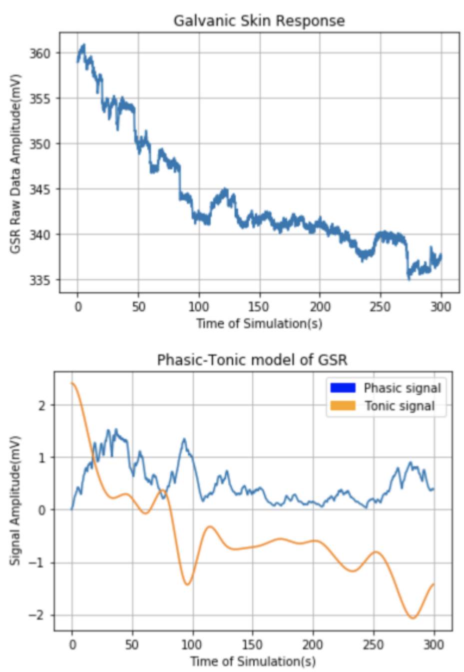

Figure 9: The measured signals from a randomly selected participant during the virtual reality simulation without interaction s-sB.

more diverse data about the effectiveness of the system. Additionally, our sample consisted of young people (23 - 28 years old), which could possibly affect the results since young people are more familiar with VR technologies and applications. As a result, they can easily comfort themselves that the phobic situation happening in the VR environment is not a real experience, which could affect their anxiety levels.

Another limitation is the number of sessions, which in this case happen to be limited to just one, as well as the lack of variety in virtual environments. Every user would react

(a)

(b)

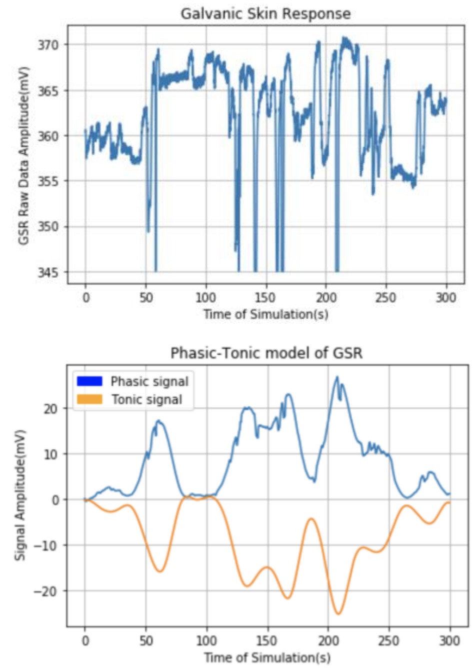

Figure 10: The measured signals from a randomly selected participant during the virtual reality simulation with interaction s-sC.

differently during the task, so it would be very informative to collect as many reactions as possible. In future, we would like to expose our users to a variety of environments, in order to test the level and range of their fear and form a more detailed analysis about it. For example, some people are only afraid of more extreme acrophobic situations like airplane flights, while others cannot even stand on a first-floor balcony. This might help in diagnosing even the most rare and difficult types of acrophobia and choose the most appropriate treatment for each user.

VI. Discussion

Interaction within the virtual system is very important and reflects more accurately the possible situations that actually occur in real life. The architecture we propose serves the VRET to a good extent as it provides mobility and interaction within the virtual environment, enhancing the sense of reality for the user. As proven above, remaining in a fixed position limits the stimuli the user could encounter, and, therefore, their experience in the virtual world. Our five users responded immediately to the task given, and the information gathered from the results actually confirm our hypothesis. The proposed system yields better results not only in identifying an anxiety disorder, which in this case happens to be acrophobia, but also in suggesting and designing a better treatment for the user. Actually, the effectiveness of this system is based on the user's ability of movement and interaction within the VR environment, which increases the sense of reality in the user's experience compared to the systems with no interaction throughout the tasks.

Furthermore, in this study, we used a simple biosignal sensor, the electrodermal activity sensor. In the future, we propose that the system would be tested with more sensors aiming to collect more detailed biometrical data, in order to gather even more information about the user's behavior during the tasks and obtain more accurate knowledge on the effects of anxiety disorders on the human body, while always seeking for more effective methods of identifying and treating anxiety disorders.

Last, it is worth mentioning that even though the proposed EDA Sensor System architecture provided measurements with less noise, looking at the time graphs which are presented in Figures 8, 9 & 10 there are some spikes during the assignments [Figures 8 (a) & 10 (a)]. Those spikes are motion artifact, they are sparse, and they are individual data points that could be easily removed by a bandpass filter which in our study were removed during our data analysis phase. Nevertheless, we chose to present the unfiltered form of those signals in order to propose topics for further study, and the development of VR sensor systems with better movement freedom, without any reduction in accuracy, due to the need to interact within the virtual environment.

VII. Conclusion

In a variety of studies from sentiment and emotion analysis to medical monitoring, or, as is the case here, to treat anxiety, the biosensors are the main tool for physiological data extraction, but in those studies, the participants are requested passively to observe images or videos to stimulate emotion. Our main purpose in this study is to emphasize that sentiment stimulation is a lot more increased, in any way if this can be achieved, when the participant has an active role when it comes to the stimulus and as a consequence the biosignal measurements are different, probably more informative, from those when the participant does not interact. So, we propose the studies using electrophysiological means to consider, as an important factor, the interaction with the stimuli.

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