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EEG and ECG nonlinear and spectral multiband analysis to explore the effect of videogames against anxiety

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Pedro Rodrigues Ribeiro

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EEG and ECG nonlinear and spectral multiband analysis to explore the effect of videogames against anxiety

Thesis presented to Escola Superior de Biotecnologia of the

Universidade Católica Portuguesa to fulfill the requirements of Master of Science degree in

Biomedical Engineering

by

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July 2022

Dedication

This thesis, as well as every academic achievement I have garnered to this date, and those in my future, deserve to be dedicated to my parents, who have supported me, not only during the writing of this paper and the course of this project, but also during my entire academic journey, supporting me financially throughout my studies, and helping me along the way with constant words of encouragement and inspiration.

Resumo

Atualmente, o uso de videojogos tem propósitos que vão além do entretenimento e tem vindo a ganhar destaque na área da saúde. Nesse sentido, foi formulada a hipótese de que é possível discriminar sinais biológicos, nomeadamente os sinais eletrocardiográficos e eletroencefalográficos, recolhidos de diferentes participantes estimulados através de três videojogos comerciais diferentes, *Tetris*, *Bejeweled* e *Energy*. Para testar esta hipótese foi desenvolvido um protocolo com o *Trier Social Stress Test* para induzir e dosear o stress nos sujeitos para níveis semelhantes antes de cada sessão de jogo, de forma a observar os efeitos dos três jogos de teste (3 grupos de estudo) a nível fisiológico. Recolhidos inicialmente a 2000 Hz, os sinais foram reamostrados a 500 Hz e filtrados utilizando um filtro passa-baixo de *Butterworth.* Após filtragem dos sinais, recolheram-se várias características representativas dos sinais de estudo. Estas características consistiram numa série de métricas não lineares, como o expoente de *Lyapunov* e a Dimensão de Correlação, métricas de auto similaridade como o exponente de *Hurst* e a análise de flutuação com *trends* removidas, dimensões fractais - como as dimensões fractais de *Katz* e *Higuchi* - e métricas de caos e atividade dos sinais, como a energia dos sinais, a entropia Logarítmica e a entropia de *Shannon*, e uma série de métricas espectrais para o sinal EEG, que devem ser capazes de ajudar a identificar qualquer diferença na resposta ao stress. Como resultado final obteve-se uma precisão de discriminação de 100% para discriminar os três grupos de estudo, utilizando as 20% das melhores características selecionadas pela técnica de F-score, recorrendo ao classificador *coarse K Nearest Neighbor*.

Palavras-chave: EEG; ECG; Métricas Não-lineares; Videojogos; Ansiedade; Distúrbio de Ansiedade; Inteligência Artificial.

Abstract

Currently, the use of video games has purposes that go beyond entertainment and has been gaining prominence in the health area. In this sense, it was hypothesized that it is possible to discriminate biological signals, namely electrocardiographic and electroencephalographic signals, collected from different participants stimulated through three different commercial video games, *Tetris, Bejeweled and Energy*. To test this hypothesis, a protocol was developed with the *Trier Social Stress Test* to induce and dose stress in the subjects to similar levels before each game session, in order to observe the effects of the three test games (3 study groups) at the physiological level. Initially collected at 2000 Hz, the signals were resampled to 500 Hz and filtered using a *Butterworth* low-pass filter. After filtering the signals, several representative features of the study signals were collected. These features consisted of a series of nonlinear metrics such as the *Lyapunov* exponent and Correlation Dimension, self-similarity metrics such as the *Hurst* exponent, and detrended fluctuation analysis, fractal dimensions - such as the *Katz* and *Higuchi* fractal dimensions - and metrics of signal chaos and activity, such as signal energy, Logarithmic entropy and *Shannon* entropy, and a number of spectral metrics for the EEG signal, which should be able to help identify any differences in the stress response. As a final result, a discrimination accuracy of 100% was obtained to discriminate the three study groups, using the top 20% of features selected by the F-score technique, using the *coarse K Nearest Neighbor* classifier.

Keywords: EEG; ECG; Nonlinear; Videogames; Anxiety; Anxiety Disorder; Artificial Intelligence.

Acknowledgements

I would like to express my deepest appreciation for Infinity Games.io for their support in this project. From providing material like the smartphone and tablet used in the data collection protocol to providing technical support and guidance in the use of their game, Energy. Their help has been invaluable, with a special mention to João and Muhamad, who were the main points of contact with the company.

I could not have undertaken this project without the help of the Human Neurobehavioral Laboratory which took me in to the GAIN (Games Against Anxiety Inquired through Neuroscience) project and involved me in every step of the process. I am not only thankful for their help and guidance, but also for the opportunity to work on this project, an opportunity which has been one of deep personal and professional growth.

I am extremely grateful to my supervisors, Dr. Pedro Miguel Rodrigues and Dr. Patricia Oliveira-Silva. Their guidance throughout this project was extremely important, I felt supported at every step of the way. They enabled my work while providing clarification for any and all questions I needed answered.

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Symbols and Abbreviations

AD - anxiety disorder

BMI – Body Mass Index

COFSG - commercial off-the-shelf videogames

ECG - electrocardiogram

EDA - electrodermal activity

EEG – electroencephalogram

fNIRS - functional near infrared spectrography

RSP - respiratory pattern

SNS – Simpathetic Nervous System

TSST – Trier Social Stress Test

1. Introduction

Untreated anxiety disorder (AD) constitutes a major public health crisis, since it can lead to increased risk of suicide, psychiatric hospitalization, disability, decreased compliance with medical treatments, and a significantly higher usage of health services. AD comorbidities can also increase the risk for chronic and recurrent form of illness. There are factors that cause the lack of treatment of anxiety, namely those divided into three categories: Acceptability, Availability and Accessibility [1].

The rise of Covid-19 has been reported to have harmed mental health in many populations across the globe. That along, with the fact that the pandemic allowed for major developments in telemedicine, as well as the fact that personalized medicine solutions are on-demand, have increased the desirability for remote anxiety management, prevention, and treatment. It has, therefore, become necessary for this sort of equipment to become an extension of the medical team remotely [1].

Some researchers have suggested that commercial off-the-shelf videogames are a suitable at home stigma free treatment alternative for general anxiety disorders [2], [3]. A few of these videogames have been directly studied for their stressing [Tetris, [2]] and stress reducing effect [Bejeweled, [2]].

It would be an interesting prospect to be able to classify the effects of these types of games for their biological response in the user by applying several machine learning classifiers. This could be achieved by extracting various metrics representative of the signals collected from the user, like nonlinear metrics and spectral metrics, because those contain useful information about the autocorrelation, self-similarity, fractal dimension, energy, entropy, and distribution of power over the frequency spectrum.

To this thesis work, three games were selected for testing, two of which had their effects on stress-tested in previous works. One of them is Tetris, which would work as a stressor. The other one is Bejeweled 2, which would work as a stress reducer [2]. Finally, the test game (Energy, Infinity Games) is a game in which the effects on stress had not yet been empirically proved but has had received indication from users of its propensity for perceived stress reduction effect, according to the game's publisher.

To achieve this purpose, a protocol was developed meant to test the neuroaffective effects of each game, in particular their effect on a subject's physiological stress level. The protocol had two phases, the pre-laboratory phase, and the laboratory phase, the first of which involved obtaining the participants' informed consent, some socio-demographic information, and some information regarding the presence of state or trait anxiety. The second phase consisted of a visit lab in which the actual testing of the games' effects was tested. During the developed protocol, biosignals were collected, namely cardiac, electrocardiography, and cerebral signals, electroencephalography.

The signals collected through the protocol underwent a signal processing procedure to obtain the necessary features for classification. The signals were resampled and filtered before the features could be extracted.

The features collected were then put through a feature selection algorithm to search for the best combination of features for classification. After feature selection the datasets were fed to several different types of classification algorithms, by using MATLAB's® Classification Learner application for pre-training and then fully trained through the generated functions for each algorithm.

This study could have wide reaching implications both in the videogame industry since it provides a template for the evaluation and classification of the neuroaffective effects of particular videogames, this same method could aid the manufacture of videogames geared specifically towards tackling AD and other psychophysiological disorders.

2. Literature Review

In 2021, M. Kowal and colleagues [3] published a 2021 paper detailing the possibility of using commercial off-the-shelf videogames (COFSG) to mitigate anxiety. The researchers point out that the COFSG have been shown to have cognitive benefits in terms of attention control, cognitive flexibility, and information processing. Additionally, there is the promise of using COFSG for a purpose beyond simple entertainment, such as for the prevention and treatment of anxiety and other mental health problems. The COFSG can address the symptoms while being internationally available, effective, accessible, and free of stigma. Also, COFSG could be an alternative mitigation technique in the absence of, or as an addition to, common therapeutic treatments.

To date, many studies have shown the effectiveness of casual COFSG as tools to mitigate state anxiety, such as the games like Bejeweled II, Peggle, among others, which have been shown to cause reduced trait anxiety by decreasing levels of general anxiety [2]. Additionally, this hypothesis is supported by EEG evidence. For instance, in Russoniello's paper [2], all three reported games had different effects on mood-lifting, although these effects did complement each other. Bejeweled, for example, showed a decrease in left alpha brain waves, which could be associated with a decrease in withdrawal and depressive-type behaviors. The same authors stated that the use of casual video games, like Bejeweled, in mitigating stress-related phenomena, could be helpful since they are engaging, challenging and could increase compliance with the prescribed treatment.

Other researchers suggest that games can be designed to increase their stress relief effects by modulating certain variables like the music or the graphics to improve their attractiveness, such as the visual, interactive, and immersive experience. There is also evidence that music can be used to induce a state of relaxation. For example, it has been suggested that Meditative Binaural Music may contribute to a state of relation, although this might be age-dependent [4]. Background music to improve mood has also been tested, for the induction of a state of relaxation in non-patient hospital attendants [5], with other reports of similar relaxation effects in medical and surgical patients [6]. Finally, vibroacoustic stimulation has been correlated to stress reduction, as verified by a sharp reduction in skin conductance level [7].

On the other side, authors like Reinecke [8] have defended that people with high levels of work-related fatigue will often use videogames as a mean of recovery from stress. The same can be verified, however, less strongly, on people who experienced recent stressful situations, or who are routinely exposed to daily hassles, and, finally, those who have low levels of social support.

Nevertheless, not all games have a stress reducing effect, as seen in several papers that use games such as Tetris [9]. Cannon was the first to introduce the notion of stress as the Fight-or-Flight (FoF) response [10]. The concept evolved further under Selye's General Adaptation Syndrome (GAS) description. Initially, the focus was on describing the physiological reaction to various stressors. In Selye's work, this physiological response has three stages: alarm, resistance, and exhaustion stages [11]. The evolution of stress theories has continued more recently with the introduction of a cognitive evaluative component into the stress mechanism. This addition accounts for intra-, inter-subject variability related to stressors and induced stress levels [12]. The different types of stressors are presented in Table 1.

Table 1 Types of Stressors[1]

Stressor type	Description and examples
Physical	Strenuous physical activity, sleep deprivation, tiredness, painful stimuli, acute injury or medical emergency.
Environmental	Extreme temperature conditions, high level of humidity, low oxygen/high carbon dioxide (or other noxious gas) levels, high levels of noise, earthquake in the surrounding area.
Mental/task related	Task demands and conditions taxing the person's cognitive capacities inconsistent reward/reinforcement schedule, rapidly changing or conflicting task instructions.
Social	Disturbances in social interactions, undesirable social roles, criticism, self-criticism, unfair treatment.
Psychological/emotional	Disturbances in personal life (e.g. break up/divorce, death of important person, job loss), intense emotional states, mental disorder affecting daily function.
Chronic	Severe financial difficulties, poor living conditions, job insecurity, chronic disease or disability in self or family, marriage difficulties.
Traumatic	Memory of past traumatic experience that intrudes into consciousness and still affects the psycho-emotional state of a person.

[1] Adapted from Giannakakis et al [13]

Under the Lazarus model, there are two types of appraisals: primary, relating to commitment to personal goals, and secondary, relating to responsibility and coping resources. Another perspective proposed by Rahe was that critical life events could cause changes that lead to stress syndromes [14]. Further studies indicated that there might be differences in stress response while others infer differences in personality as well as social presence, empathy, independence, and intellectual efficiency, among other traits, are more stress-prone [15]. It is suggested by personality theory that a type A personality may make the decision to be in a more demanding environment, tending to overreact to it, therefore being more stress-prone [16].

The physiological stress response, i.e., the body's reaction when in contact with stressors, can be of many types. Table 1 shows the reactions responsible for processing the potential stressor and preparing an adaptative response, such as mobilizing the myoskeletal system (so it can prepare and execute motor functions and prepares the body in case it sustains injuries as well as for increased metabolic demands) [17]. In other words, in a state of stress, there is an enhancement of cardiac output and respiration, while blood flow is redirected to irrigate the brain better and allow the highest perfusion to this area. In turn, the brain focuses on the threat being perceived and stimulates behavior to allow the body to react to it. The Autonomic Nervous System (ANS) is active in mediating this response. This demonstrates the passing of control to the Sympathetic Nervous System (SNS) [1], [18], [19].

Regarding the nature of stressors, they could be exogenous or endogenous stimuli, all of which are categorized in Table 1. Stress is multidimensional and can be subdivided into three main categories, these being psychological, physiological, and behavioral. The analysis of these is subjected to multidimensional measurement errors and response bias. There is, therefore, bias in the methods available for assessing the individual experience of stress, which can be aided using biosignals analysis [17].

There are two categories to be considered in the personal perception of stress: eustress, or positive stress (eu- is a Greek prefix meaning positive) and distress, or negative stress [17]. There is also evidence that the arousal level on personal performance follows Hebb's curve (see Figure 1) [20].

Although the concepts of stress and anxiety overlap there isn't a clear consensus on their meaning, but some researchers suggest anxiety may be one of the emotional effects of stress [22]–[24].

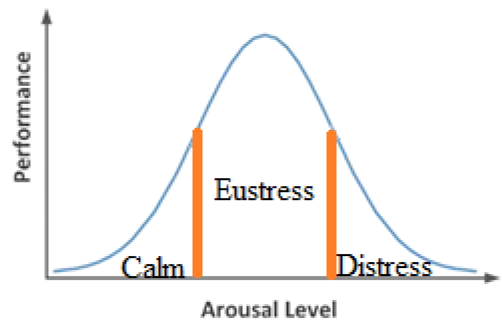

Figure 2 Hebb's curve [2]

[2] Adapted from Hebb [21]

Any biosignal features of stress-related processes will be largely involuntary and, therefore, mediated by the ANS. Therefore, the ANS's pattern of response is a good source of data relating to the individual's objective stress response and it can be sought within the cardiac activity of electrocardiogram (ECG), electrodermal activity (EDA), respiratory pattern (RSP), eye activity and speech recordings, just to cite a few examples.

All these signals refer to bodily processes heavily susceptible to ANS-SNS responses. Other studies, mentioned further in this study, have used brain activity acquired via electroencephalogram (EEG), as this will be a window to understand neural activity directly related to stress response and the secondary effect of stressor/stress experience [17].

From a perspective of evolutionary biology, the physiological response to stress described here may well serve homeostasis by regulating body functionality, namely in terms of the body's temperature, cardiac activity, blood pressure, respiration and glucose levels, all of which are essential to survival in situations of rapid environmental change. This flow of physiological processes constitutes the stress response [17], [25].

Stress response begins in the brain, with three main regions being active, the hippocampus [26], the amygdala and the prefrontal cortex [27].

Stressors related to audio-visual stimuli begin their processing in the thalamus and are subjected to two pathways, one with low-level analysis passing through the amygdala and prescinding higher cognitive function, being called the fast pathway, and another, passing through the prefrontal cortex, appraising the situation with a higher level of cognition, named the slow pathway [28].

Two pathways paralleling the stress response can be identified: the Hypothalamus-Pituitary-Adrenal axis and the Sympathetic-Adrenal Medullary system. The HPA pathway will terminate on the release of adrenocorticotropin into the bloodstream, which in turn stimulates the release of epinephrine, norepinephrine and cortisol, the three primary stress hormones. This hormonal process fulfils the function of providing an increased level of glucose to facilitate the adaptation to the stressful environment [17].

For the purposes of identifying the many biosignals discussed in the literature, these will be divided into two categories, physical signals, those pertaining to the deformation of the human body due to muscle activity, and physiological, those signals directly related to the vital functions of the body.

EEG analysis pertaining to stress response has been heavily linked to power spectrums or relative power indices, with these measurements being particularly helpful in linking the intra-individual adaptations to the intensity of stress response [29]–[31]. The EEG signal can be divided into several different frequencies, of which the most significant appear to be the α [8-13 Hz] and β [13-30 Hz]. This is because the α frequency seems to be prevalent during relaxation and conditions of minimal cognition or emotional strain. On the other hand, a state of elevated alertness can be associated with higher frequencies, like the relative β power [17], [32]. Several studies have used different EEG features to detect stress, these are shown in (see Table 2).

Although there is wide reporting of α and β variability, debate exists on how these values are altered under stress, although the general consensus appears to be a decrease of α activity, as mentioned earlier [13], [33]–[35], this frequency band has more activity under a state of relaxation or low cognition and an increase in β frequency activity [18], [35]. Other studies have considered a specific β sub-band [18-22 Hz] to be correlated with emotional intensity [36]. A measure of both β and α frequencies is the β to α power ratio, which is a great measure of cognitive load and dimension of the arousal [37].

Stress has been positively linked with beta power in the anterior temporal lobe [17], whereas the temporal lobe seems to experience more activity in the high-beta waves [38], [39]. Figure 2 demonstrates the placement of electrodes for EEG asymmetry and optimal stress detection.

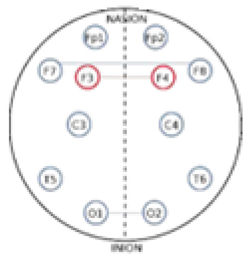

Figure 2 EEG electrode placement for optimal stress analysis [3]

[3] Adapted from Giannakakis et al [13]

As stated earlier, the cardiac system is highly responsive to SNS activation [1], [40] state the importance of HRV in this relationship between the cardiac system and the SNS and others who have denoted the rise in heart rate during interaction with stressors [1], [19], [41].

The initial objective of this study was established to be the study of the stress effect of different COFSGs in the subjects' stress response. To accomplish the objective of inducing this stress response in subjects within a laboratory setting the protocol described in the following chapter was developed. A study of specific metrics that could be used to characterize these signals, namely nonlinear and spectral metrics was then undertaken, with the selected metrics explained in the following chapter. To prove that these COFSGs invoke different reactions from the subjects, the main task of this study became attempting to successfully classify the subjects' response to each COFSG.

3. Materials and Methods

A protocol was developed to test the stress response of subjects when in contact with each of the selected COFSGs. This protocol included the induction and dosage of stress using the Trier Social Stress Test (TSST) methodology, which the subjects were exposed to before being exposed to each of the COFSGs. Biosignals were collected during the protocol, with those signals then having been analyzed and prepared for metrics extraction. The metrics extracted were then organized into data matrices and fed to classification algorithms.

3.1. Sample

We recruited 58 participants, including 43 females (74.13%) and 15 males (25.86%) with an average age of 21.34 years (*SD* = 4.44). Concerning their academic training, 87.93% were enrolled in university courses, and only 12.06% were only working. The exclusion criteria were having any current cardiac or neurological clinical condition (any participant reported being currently diagnosed with any clinical disorder).

Regarding their previous videogame experiences, 43.10% of participants reported having previous experience with videogames. The most common game mentioned was Clash of Clans, with 20.68% of subjects mentioning they played the game.

3.2. Materials

Sociodemographic data. The sociodemographic form was conceived to collect data regarding the participants' age, gender, height and weight (biosignal irregularities could be explained by the BMI), literary qualifications, marital status, profession, presence of eye sight problems (more significant stress could be experienced as a consequence of poor visibility of the screens), presence of hearing impairment (could influence the subject's response to auditory stimuli), cardiovascular problems (could affect the cardiac signal), photosensitive epilepsy (could affect the biosignals collected), whether or not the day of the session was a typical day (could explain outliers in the data), whether or not the previous night was a typical night (could explain outliers in the data), level of tiredness (could explain outliers in the data), nootropics' ingestion over the previous hours (could affect both the subject's stress level and the biosignals collected), alcohol ingestion over the earlier hours (could affect both the subject's cognitive ability and the biosignals collected), psychopharmaceuticals' ingestion (could affect the subject's response to stressors), the time passed since their last meal (subject could become more impatient due to the long duration of the protocol), the nature of their most significant entertainment and experience with videogames (a greater training effect derived from interaction with the games under study), and screen-time increase during COVID-19. All these questions are formulated to extract data that could explain irregularities in the subject's response concerning the larger group, as well as irregularities in biosignal responses, but also to help gather a more complete and realistic picture of the subjects before participation in the study.

Anxiety Inventory. Also, the *State-Trait Anxiety Inventory* (STAI) was administered in this study to assess the participants' anxiety level. This provides a useful grouping of subjects for later exploration of the collected data, while also being useful to determine if deviations in a subject's scoring are effects of state or trait anxiety. The instrument is based upon the work of [43], translated to Portuguese by Diana Moreira and colleagues [44], consisting of 40 items for self-report on a 4-point Likert scale, used to measure two types of anxiety, state anxiety (STAI-S) and trait anxiety (STAI-T). One subscale is called STAI-S, assessing the state or how the participant feels at that moment. The other one is called STAI-T, assessing the trait or how the participant feels regardless of the current moment, a more constant measure of stress.).

Stress Test. The Trier Social Stress Test or only TSST is based on [45]. It is a reliable way to induce stress in a research participant. The TSST exploits the vulnerability of the stress response to the social evaluative situation. In this case the participant is exposed to the evaluative component of the program that procedurally generates equations and checks whether the subject has answered them accurately, while the social component comes from the researchers present in the room. The application of this procedure three times along the protocol is meant to induce a stressful state in the subject. The achievement of this stressful state will then allow for comparison of the subject in the stressed state at the start of the games under study and at the end of the study where the games will have had a neutral effect, a stress reducing effect or a stress increasing effect. Three different applications were developed for the TSST, corresponding to the three modalities presented to the user. The first modality had two phases, the first of which showed the user ten equations that they should solve without function, producing an answer in the form of an integer or a decimal. This first phase did not have a time limit. The second phase of the first modality asked the user to solve the same equations in half the time it took them to solve these the first time. The other two modalities were similar, increasing the difficulty by a small amount. The second modality gave the user several equations to solve, which should take no more than 15 seconds, with equations being given to the user until 5 minutes had passed. The third modality reduced the time limit to 8 seconds per equation, with equations being given to the user until 5 minutes had passed. These applications were developed in a Linux environment since the time limit timer required file locking, and Linux's native system was used. Since the computers available in the laboratory were running Windows, Replit was used to host the applications. All programs were built on Python 3.9.9 using the IDE Pycharm Community Edition, by Jetbrains. The web-based IDE Replit was used to host the Linux based programs for the TSST. The Python based GUI platform Pygame was used to make every GUI. Figure 3 presents the GUI for the TSST applications.

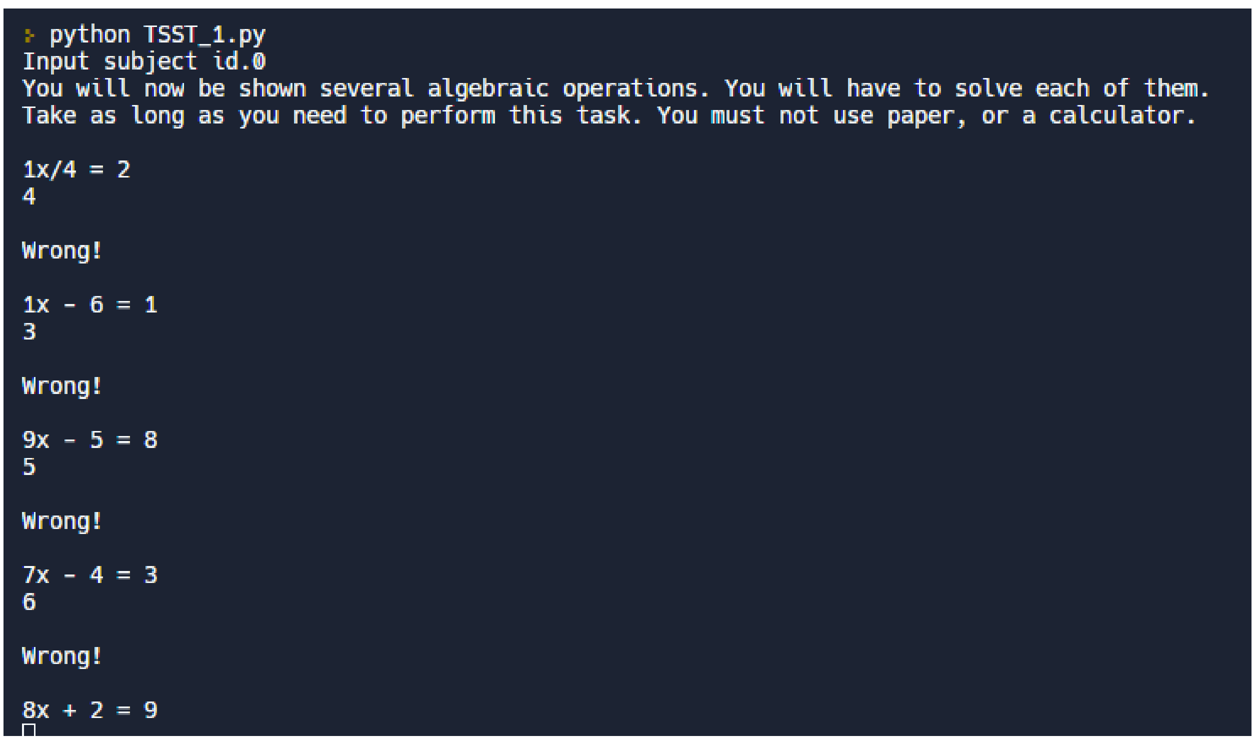

Figure 3 Screenshot of the TSST applications in progress

Tetris. Two versions of Tetris were made, a tutorial version which has no difference between itself and the stock version of Tetris other than the fact it is played on the computer and controlled via the arrows on a keyboard, and a test version of the game which differed from the tutorial version in terms of difficulty, since the velocity the pieces fell on the game increased by a factor of 2 every time the user broke a horizontal line, as well as semi randomly after a few minutes of gameplay. Restarting the test version of the game did not reset the velocity of the falling pieces. This was maintained until the application was shut down and its variables cleared from memory. Figure 4 presents the GUI for the Tetris applications.

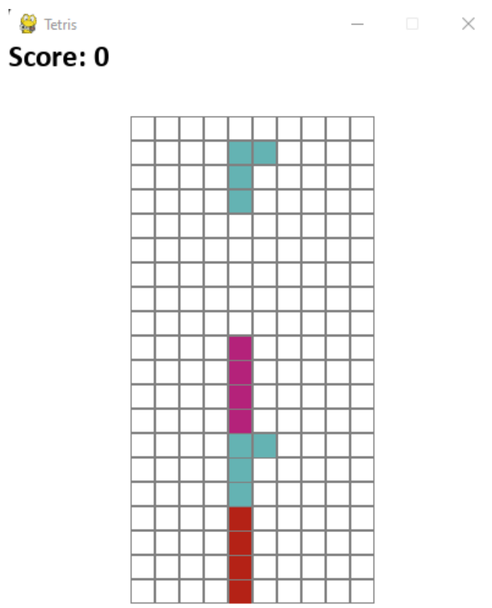

Figure 4 Graphical interface for the Tetris applications developed

Neurophysiological Data Collection. The data collection procedure counted on the use of the Biosignals Plux V2 and V1 devices (PLUX), which were used to record the participants' biosignals during the protocol. The application of electrodes was conditioned by the material available. Good, clean signals were achieved by using the following configurations:

Cardiac Data Collection

The ECG signal was obtained by forming Einthoven's triangle with a three-pronged cable containing a positive pole, a negative pole and a reference pole. To achieve a clean signal, Einthoven's triangle was formed in two possible configurations to be used depending on the subject's body, both of which place the poles directly over the heart, the negative pole at the right, relative to the subject's point-of-view, and the positive pole to the left, relative to the subject's point of view, as far spread out as the cable would allow it. The positioning of the reference electrode was the one variation between the two configurations used. The preferred configuration placed the reference below the subject's breast, over the ribs, as far down and far away from the polarized electrodes as the cable allowed for, while the alternative configuration placed the reference over the sternum, as far up and far away from the polarized electrodes as the cable would allow for (see Figure 3).

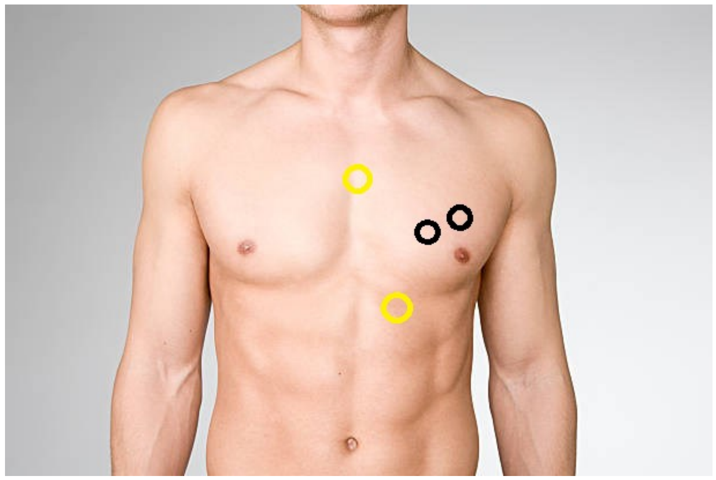

Figure 5 ECG electrode placement (black - polarized; yellow) [4]

[4] Adapted from DPG Media Privacy Gate [46]

EEG Data Collection

The EEG signal was collected via two three-pronged cables. The positioning of the electrodes followed one configuration, in which the polar ends of the cable were placed laterally relative to the sagittal plane over the subject's forehead, superior to the subject's eyebrows, inferior to their hairline, proximal to the Nasion, while the reference electrodes were placed over the Mastoid process to each side of the subject's head. Figure 6 presents this configuration.

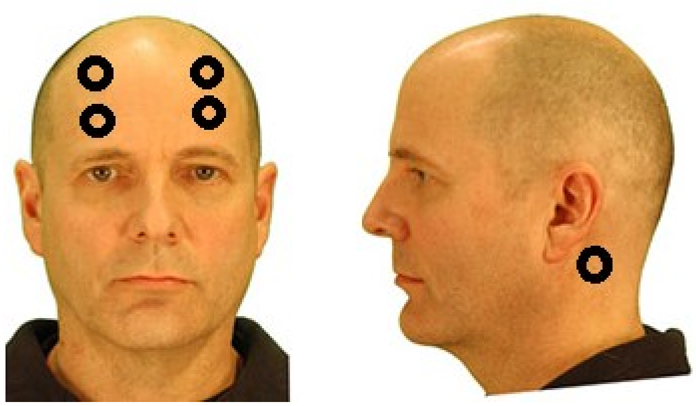

Figure 6 EEG electrode placement [5]

[5] Adapted from Modeling Nurbs Head [47]

Baseline Task. The baseline task was developed to be a low demanding task and measure the participants' baseline reactivity level or default functioning pattern [48]. It was conceived not to stress or overly excite the subject, but rather simply hold their attention for the duration of the required time. The baseline in this case runs for 2 minutes, regardless of the subject's speed in identifying the requested shape and was designed built in python, using the pygame library, where the participant is asked to click one of four random shapes (triangle, rectangle, parallelogram, and circle), placed in one of four random positions on the screen (top left, top right, bottom left and bottom right) with a five second time limit. An application was developed where the user was presented 4 shapes (rectangle, parallelogram, circle, and triangle) placed within four random positions on the screen. Figure 7 presents an example of a possible window for this application.

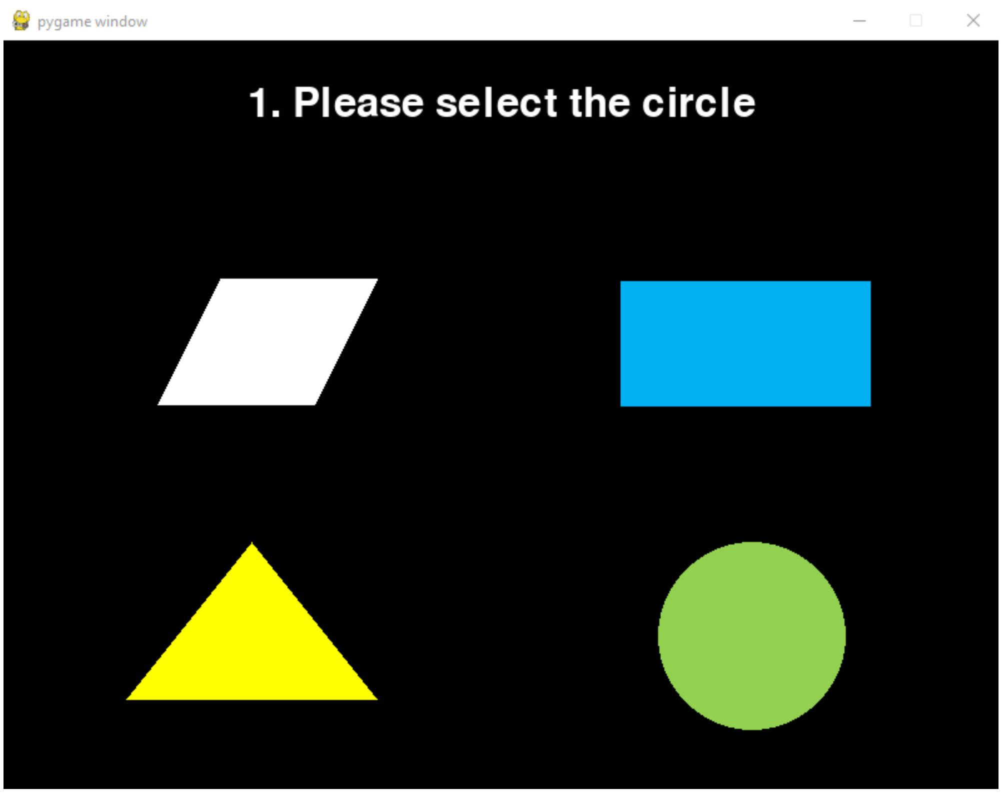

Figure 7 Screenshot of the Baseline application developed

Behavioral Task. To allow the subject to play the COFSGs, the mobile phone model TCL 20L+ was used. A tablet was used to allow the subjects to play the tutorials for the COFSGs, the tablet model Alcatel 1T. Another table device was used for the consent, sociodemographic and STAI forms was the Lenovo M10 HD X306F, which was later used for the collection and visualization of the biosignals. The electrodes used for the collection of biosignals were the from Meditronic. The games used as testing subjects were Bejeweled Classic, by Electronic Arts, and Energy, by Infinity Games. The version of Tetris used was made specifically for this project. This version of Tetris increased the speed at which the pieces fall on the screen by a factor of 1.5 every time a horizontal line is filled with Tetris pieces.

3.3. Data Collection

The data collection was carried out in the Human Neurobehavioral Laboratory.

3.3.1. Protocol

A protocol was devised to test the above-formulated hypothesis. As previously reported, two games were chosen from the literature to compare with the third game, which will be called from now on, the test game. These games were Tetris [9], which would act as a stressor game, and Bejeweled 2 [8], which would act as stress reducer. In order to test the effects of these three games in a comparable manner, the following process was applied to willing participants.

1. **Phase 1 (Pre-laboratory)**
   a. Forms – The subjects filled out three forms meant to get their informed consent, some social-demographic information as well as the anxiety level.
      i. Reading and signing of a consent form
      ii. Filling out a social-demographic form
      iii. Filling out STAI forms
   b. Tutorials – The subjects were shown the objective and mechanics of each of the games under study and follow the sequence below:
      i. Test Game – The participant was told to play the game up to and achieving the level 10.
      ii. Bejewelled 2 – The participant was told to play only a fraction of the first level of the game on classic mode, until they feel comfortable with the mechanics and understand the objective of the game.
      iii. Tetris – The participant played a version of the game with reduced difficulty and was asked to fill one horizontal line with Tetris pieces.

c. The subjects were moved to the laboratory for the next phase of the procedure: neurophysiological data collection.

2. **Phase 2 (Laboratory)**
   a. The laboratory was disinfected for each data collection and the participants were also asked to proceed to self-sanitize.
   b. The electrodes for the ECG and the EEG data were placed according to guidelines [13], [49] and the participants received a short explanation about the equipment and data collection procedure.
   c. Baseline task – A request was made to the user to press one of the four shapes, with the target shape being selected at random from the four. The subject then had five seconds to select the shape. Even if the user selected the shape before the end of the five seconds, the application would wait until the end of that period to move on to the next prompt. This process was repeated 24 times. This task lasted around 2 minutes and was performed screen placed in front of the participant. At the end of the task, the participants were asked to fill in the stress self-report form consisting of a ruler going from 0 to 10 to indicate their stress level at the end of the game. All participants reported a low level of stress (lower than 3).
   d. TSST 1 – The first instance of TSST was built in two phases. In the first phase the participant is asked to solve ten procedurally generated equations without any time limit, while in the second phase the participant is asked to solve those same equations again with half the time it took them to solve them in the first phase. At the end of the task, stress self-report form was filled in.
   e. Test game – The participants continued playing the test game from the point they left off in the tutorial. The participants played the game for ten minutes while timed by the researchers. The participants were asked to audibly warn the researchers when they finished a level. The stress self-report form was again administered.
   f. TSST 2 – The second instance of TSST, consisted in asking the participant to solve procedurally generated equations for 5 minutes, with each equations having a time limit of 15 seconds. Then, the stress self-report form were presented.

g. Stress reducer game – The participant was asked to play the game for 10 minutes, timed by the researchers, warning them when they finished a level. At the end of the specified time, the participants were asked to fill in the stress self-report form.

h. TSST 3 - The second instance of TSST, consisted in asking the participant to solve procedurally generated equations for 5 minutes, with each equations having a time limit of 8 seconds. Then, the stress self-report form.

   i. Stressor game - The participant was asked to play the game for 10 minutes, timed by the researchers, warning them when they finished a level. At the end, the final stress self-report form was presented.

   ii. Once the procedure was completed, the electrodes were removed, the material was disinfected, and the participant was debriefed and accompanied to the exit.

The application of self-report measures for every stage of the protocol will allow for a control of the subject's stress level throughout the protocol and allow for a comparison of perceived stress.

3.4. Data Analysis Procedure

The data analysis procedure used MATLAB®, along with its Signal Processing and Machine Learning toolboxes. The app Classification Learner was used to perform the pre-training and generate the training functions for each algorithm.

3.4.1. Biosignal Processing

The processing of Biosignals was done in two stages. The first was the pre-processing of the data, consisting on the translation of the timestamps collected throughout the protocol, the subsequent splitting of the biosignals through the timestamps, through which the signals referring to each phase of the protocol (Baseline, TSST 1, Test Game, TSST 2, Stress Reduction Game, TSST 3 and Stressor Game), the resampling and filtering of each signal, and, finally, the extraction of the several metrics that will be used by the classification models, namely the non-linear and spectral metrics, which will be described below. The second stage of Biosignals processing was the classification of the signals based on the collected metrics.

3.4.2. Resampling and filtering of the signals

The biosignals were collected with a sampling rate of 2000 Hz to ensure that all of the relevant frequencies were captured. To facilitate the analysis of the data, all of the signals were resampled to one quarter of the sampling frequency, 500 Hz.

After resampling the function, a second order Butterworth filter [50] was applied to each Biosignal, with the only difference between each application being the frequency range imposed on each signal. The Butterworth filter was chosen due to its frequency response being as flat as possible within the passband. The Butterworth filter has a monotonic amplitude response within the stop and passbands, a quick roll-off around the cutoff frequency, improving with increasing order, a slightly non-linear phase response and a largely frequency-dependent group delay [51]. Figure 8 presents the Butterworth filter's frequency response.

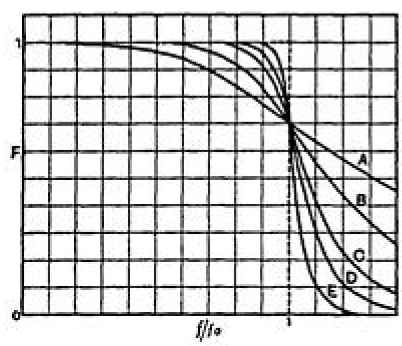

Fig. 3.

Figure 8 Frequency response of a Butterworth Filter [6]

[6] Adapted from Butterworth [50]

The Butterworth filter has its cutoff frequency normalized within the limits of 1 radian/second. The frequency response of the Butterworth filter can be modelled through equation 1:

$$G(\omega) = \frac{1}{\sqrt{1+\omega^{2n}}} \qquad (1)$$

Where the Gain is given as a function of the angular frequency, ω, given in radians per second. n is the number of poles in the filter.

Has stated before, the frequency response of the Butterworth filter is maximally flat within the passband, then rolling off towards zero in the stopband. For the purpose of these Biosignals processing a second order, Butterworth filter was used, since it decreased at -12 dB per octave. Another advantage of the second order filter is the worsening of the considerable overshoot and the ringing in the step response at higher orders [51].

Digital Butterworth filters often use either the bilinear or the matched Z transforms. The digital implementation used to process the Biosignals was the standard matlab Butterworth filter function, *butter()* [52].

Using this implementation, the ECG signals were filtered between 1 and 50 Hz, while the EEG signals were filtered between 1 and 40 Hz.

3.4.3. Windowing and Wavelet Transform

The signals were windowed to guarantee its stationarity and stability. The windowing process was achieved by creating windows of size T as described in equation 2:

$$T = t * Fs \qquad 2$$

Where t is the time window for each window and Fs is the sampling frequency. Since the time period defined for each window was 1 second, and the sampling frequency was 500 Hz, each window contained 500 samples.

A wavelet series represents a square integral by an orthonormal series [53]. A wavelet transform is based on the principle of allowing changes only is time extension, not shape. This is affected by the function chosen to create the transform. The base function determines the impulse response of the system. A wavelet transform informs about the time and frequency of the signal [54], [55].

After the windowing process, the signals were then processed through wavelet decomposition. The wavelets chosen were the Symlet 4 wavelet for the ECG signals, and the Biorthogonal 3.5 wavelet for the EEG signals.

The Symlet 4 wavelet transform was applied to the ECG signal due to its long-standing use in literature. The Symlet 4 is an altered version of the Daubechies wavelet transform which down samples the original ECG signal, reducing the number of samples but retaining the QRS complex. The Symlet 4 yields noise free signals, with a threshold that is 60% of the maximum value. The resulting values which are above the threshold are R-peaks [56].

For the EEG signals a Biorthogonal wavelet was applied which can be used to decompose and recover function, similarly to Orthogonal wavelets [57].

All signals were decomposed in six levels. Levels D3, D4, D5, D6, and A6 were analyzed to retrieve the nonlinear and spectral metrics explained in next points.

3.4.4. Nonlinear Metrics

Silva et al [58] describe a set of nonlinear features which are used within this project to feed a classification system. The metrics described were applied to every relevant level of the previously described wavelet decompositions of the biosignals.

Nonlinearity introduces a set of physical characteristics to signal dynamics, among which are chaotic dynamics, while providing the methodologies to analyze the predictability and determinism of a signal. The dynamics of a system are described within the phase or state space, whose dimension is given by the number of dependent variables. In an experimental setting, a variable is usually measured as a function of time and its state space is typically an unknown. The way to arrive at a system's state space attractor was first given by [59] with the first application of a state space reconstruction [60] later proved that it is feasible to reconstruct a diffeomorphically equivalent state space from a scalar time series which can then be analyzed through deterministic nonlinear dynamics, in order to obtain, among other things, its Lyapunov exponents [61]. Within the state space, curves or trajectories can be formed over periods of time. When observed for long periods of time these trajectories describe geometric structures called attractors. These attractors' evolution over time can be verified through the Lyapunov exponents. The largest exponent for each state x_i is estimated by getting the state x_j which presents the minimum distance between x_i and x_j in such a way that the absolute value of $i - j$ is larger than the mean period. This estimate can then be given by equation 3:

$$\lambda(i) = \frac{1}{M+2} \sum_{k=1}^{M} \frac{1}{kT_s} ln \frac{||x_{i+k} - x_{j+k}||}{||x_i - x_j||} \qquad 3$$

With T_s being the sampling period. The largest Lyapunox Exponent estimation is then given by the slope of the best linear approximation of $\lambda(i)$ [58].

Another possible metric extracted from a reconstructed attractor is the estimation of the distribution of the attractor points, the correlation dimension, which reflects the complexity of the system. The correlation dimension of a system is given by equation 4:

$$D_2 = \lim_{r \to 0} \frac{\log C(r,M)}{\log(r)} \quad 4$$

Where $C(r, M)$ is given by equation 5:

$$C(r,M) = \frac{2}{M(M-1)} \sum_{i=1}^{M} \sum_{j=1;j!=i}^{M} \theta(r - \left\| x_i - x_j \right\|) \quad 5$$

The long-term memory measures of the signal are an analysis of long-range statistical dependence of a signal, as well as its self-similarity. The Hurst exponent and the Detrended Fluctuation Analysis are good long-term memory measures.

The Hurst Exponent analyses the long-range statistical dependence of a time-series, which can be used to appraise its smoothness, correlational properties and self-similarity. The Hurst Exponent is the slope of the best linear approximation of the logarithm of the rescaled range (R/S) as a function of the logarithm of N. The irregularity of a signal is inversely proportional to the Hurst Exponent, meaning that the more irregular the time series is, the closer its Hurst Exponent will be to 0. The Hurst exponent is, therefore, given by equation 6:

$$H = \frac{\log(R/S)}{\log(N)} \quad 6$$

The detrended fluctuation analysis provides a way to quantify a nonstationary time-series' self-similarity. The cumulative deviation series ($y(k)$) relative to time series $x(n)$ is calculated through equation 7:

$$y(k) = \sum_{i=1}^{k} [x(i) - \bar{x}] \quad 7$$

For each m-long segment of the cumulative deviation series a linear approximation is calculated ($y_m(k)$). The time series' average fluctuation as a function of m ($F(m)$) is defined by equation 8:

$$F(m) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_m(k)]^2} \quad 8$$

The correlation properties of the time series are calculated through the slop of the best linear approximation of $F(m)$, denoted by the scale exponent Δ.

Fractal analysis can be helpful in analyzing the biosignals as well. A fractal, described by its creator Mandelbrot, is a fragment for which the Hausdorff-Besicovitch dimension, a measure of a signal's roughness, exceeds the topological dimension, which can be used in applied mathematics in rugged, indeterminate systems through the extension of classical dimensional analysis to include a fractional number which describes the ruggedness of the system within the space covered by the N number of dimensions, N being an integer, which encompasses its fractal magnitude. The fractal dimension (D) is an indication of the ability of a fractal to fill its Euclidian space. This fractal dimension provides a quantitative description of a given system. In more certain terms, the fractal dimension is the measurement of a signal's irregularity of the object in a mathematical sense. A system is self-similar when each fractal is geometrically similar to the whole in shape and in the generating mechanism of the shape's details, with this mechanism being called the cascade. A system is self-similar when transformations to each direction of the Euclidian space are the same, otherwise, if the transformations to each direction are not the same, then the system is self-affine [62].

Within waveforms, fractal dimensions are a useful tool for the detection of transient events, since this metric can be calculated directly from the time series without having to reconstruct its attractor. The added benefit is that the fractal dimension's computational complexity is not as high as other chaotic measures. The two fractal measures used to analyse the biosignals were the Higuchi algorithm, which is described by the slope of the best linear approximation of $\ln(L_k)$, with L_k being described in equation 9 through 12:

$$L_m(k) = \frac{N-1}{[a]k} \sum_{i=1}^{[a]} |x(m+ik) - x(m+(i-1)k)| \qquad 9$$

where:

$$a = \frac{(N-m)}{k} \qquad 10$$

with [a] representing the closest integer equal to or less than a.

$$L_k = \sum_{m=1}^{k} \frac{L_m(k)}{k} \qquad 11$$

for $k = 1 \ through \ k_{max}$ 12

And the Katz algorithm, described by the slope of the best linear approximation of FD_k, described in equation 13:

$$FD_k = \frac{log(\frac{L}{a})}{log(\frac{d}{a})} \quad 13$$

where L is the sum of successive distances of the time series, a is the average distance between successive points and d is the greatest distance between $x(1)$ and the remaining points of $x(n)$.

The energy of the signal might be a useful metric since the stressing and relaxation of the subjects implies the transfer of power back and forth between the α and β frequencies in the EEG. The energy of the biosignals is given by equation 14:

$$EN = \sum_{n=1}^{N} |x(n)|^2 \quad 14$$

The entropy of a time series describes the disorder or uncertainty of the system. The measures of entropy used to analyze the biosignals were Shannon entropy (ET_S) and the Logarithmic entropy (ET_L), which can be calculated through equations 15 and 16, respectively:

$$ET_S = -\sum_{n=1}^{N} |x(n)|^2 log\,[|x(n)|^2] \quad 15$$

$$ET_L = \sum_{n=1}^{N} log[|x(n)|^2] \quad 16$$

3.4.5. Spectral Analysis

The analysis of the power distribution over the frequency spectrum may provide useful metrics. As explained before, the main effect to be expected from the stressing and stress reduction of the subject is the transfer of power between the α and β frequencies in the EEG [13], [18], [33]–[35]. Spectral analysis can, therefore, provide invaluable data about the biosignals, especially in the case of the EEG.

To begin the spectral analysis, the signals' power spectral density was calculated. Firstly, a fast Fourier transform was applied. The data was then selected through equation 17:

$$n = \frac{1}{\left(\frac{N}{2}\right)+1} \quad 17$$

Equation 18 was then applied to the Fourier transform of the signal ($xFFT$):

$$PXX = \left(\frac{1}{Fs*N}\right) * |xFFT|^2 \quad 18$$

The power spectral density was then calculated through equation 19:

$$PXX = \frac{PXX}{\sum_{i=1}^{n} PXX} \quad 19$$

Finally, the power spectral density was normalized through equation 20:

$$PXX = \frac{PXX}{\sum_{i=1}^{n} PXX} \qquad 20$$

Spectral features were extracted from the normalized power spectral density using the algorithm from Araújo et al [63].

3.5. Classification

The results provided by the data multiband analysis were saved into *.xlsx files. These results were then reimported into MATLAB®. After being imported, the results were stripped to data pertaining represented the first 8 minutes of the time series, this would ensure that every subset would have the same number of data features samples extracted from the 8 minutes non-linear and spectral multiband analysis of the signals , which is important for the classification process, and then segmented into binary classification-ready subsets, these subsets were Test Game vs Stress Reduction Game (TvR), Test Game vs Stressor Game (TvS) and Stress Reduction Game vs Stressor Game (RvS). Each comparison subsets suffer a normalization by z-score algorithm before classification step.

After the creation of the subsets, the data was labeled. Label 0 pertained to data from signals taken during the Test Game period, label 1 pertained to data from signals taken during the Stress Reduction Game period and label 2 pertained to data from signals taken during the Stressor Game period.

After labeling, the data was submitted to the feature selection f-score algorithm provided in [64]. The algorithm was used to find the best 5% of features, then 10% and then in 10% steps until 100% classification accuracy was achieved.

The prepared data was then submitted to MATLAB®'s Classification Learner app for discrimination. All the classifications have been done within a leave-one-out-cross validation procedure. The types of machine learning algorithms used are explained bellow:

a. Neural Networks: System capable of adaptation which learns using interconnected nodes in a layered structure that resembles the human brain. The network works by breaking down the input features into layers of abstraction. The success of the neural network is based on the connections between features and the strength, or weight, of said connections. The weights are adjusted until the network performs the task required of it correctly [65].

b. Support Vector Machine (SVM): System whose objective is to find a hyperplane capable of separating one class from another to the best degree possible. In this scenario, “best” can be defined as the hyperplane with the largest possible margin, or the maximum width of the slab parallel to the hyperplane that has no interior data points, between the two classes. A SVM can only find the best hyperplane for linearly separable problems. Support vectors are defined as a subset of the training observations which identify the location of the separating hyperplane [66].
c. Naive Bayes: naive Bayes classifiers are based on the application of Bayes’ theorem, which describes the probability of an event based on prior knowledge of related conditions, with strong, or naive, independence between the features. These classifiers are highly scalable and requires several parameters with a linear number of variables in a learning problem [67].
d. Decision Trees: A tree can be a leaf node labeled by classes or a structure consisting of a test node linked to two or more subtrees. The test node can compute the outcome based on the features of an instance, where a possible outcome is associated with one of the subtrees. An instance is classified by beginning at the root node of the tree. If this node is a test, the outcome for the instance is determined with the process then continuing by using the appropriate subtree. The construction of a decision tree can involve a divide and conquer strategy, meaning that if instances belong to different classes and a single lead with a single class as label, other strategies can be used until the algorithm can fulfil the classification task [68].

4. Results

4.1. Self-Report

The central tendency measures obtained from analysis of the self-report data indicated, at first glance, a similar mean value for the Test Game vs TSST 1 and Stress Reduction Game vs TSST 2 datasets, while also indicating that the mean value for Stressor vs TSST 3 was higher than these values. The variance was higher in the Test Game vs TSST 1 subset. The minimum value for perceived stress variation was found in the Stress Reduction Game vs TSST 2 and Test Game vs TSST 1 subsets at -9.000, while the maximum value for perceived stress variation was found in the Stressor Game vs TSST 3 subset at 5.000.

Having applied an independent samples t-test between the Test Game vs TSST 1 and Stress Reduction Game vs TSST 2, no significant difference was found, therefore not being able to reject the null hypothesis. The same was not true for the comparison between the subsets of Test Game vs TSST 1 and Stress Reduction Game vs TSST 2 with the Stressor Game vs TSST 3 subset, as there is a significant difference between these sets of data.

4.2. Classification

The abbreviations of the classifiers are based on Araújo et al [63].

For the purposes of this analysis, a classification accuracy of 80% or higher will be considered a good result, while anything bellow will be considered a poor classification accuracy.

While using the 5% best combination of features, the classification algorithm was unable to obtain a good classification accuracy for the TvS and TvR datasets, obtaining a maximum classification accuracy of 55.76% on the TvS dataset and 71.15% of the RvS dataset. The TvR dataset obtained a classification accuracy of 80.76%. The highest classification accuracy for the TvR subset was obtained through the quadratic SVM algorithm, while the highest classification accuracy for the TvS and RvS subsets was obtained through the coarse Tree algorithm. The average classification accuracy for the TvR subset was 53.73%, while the average classification accuracy for the TvS subset was of 19.17%, and the average accuracy for RvS subset was 24.79% (Figure 9).

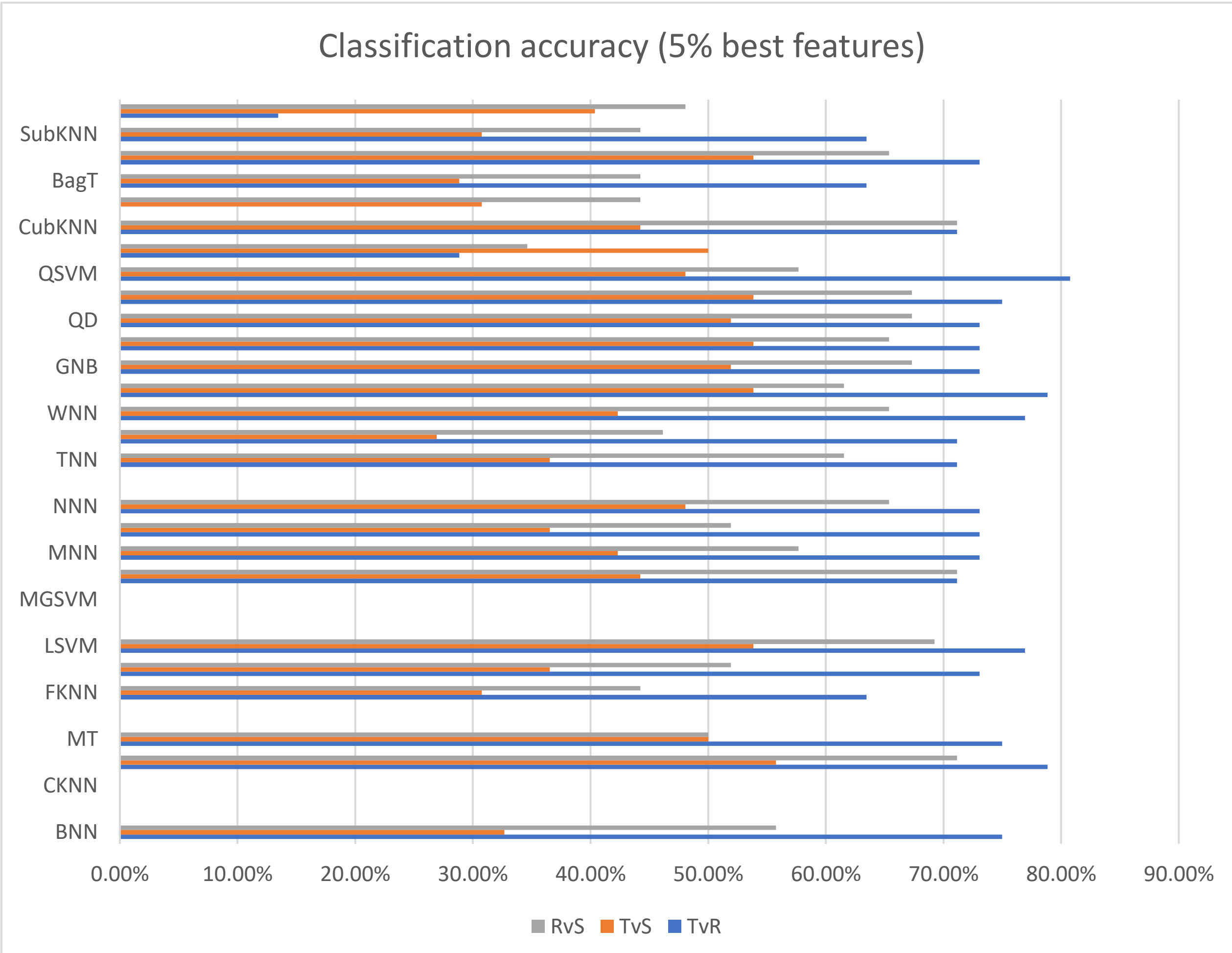

Figure 9 Classification results using 5% of features

While using the 10% best combination of features, the classification algorithm was unable to obtain a good classification accuracy for the TvS and TvR datasets, obtaining a maximum classification accuracy of 55.76% on the TvS dataset and 71.15% of the RvS dataset. The TvR dataset obtained a classification accuracy of 80.76%. The highest classification accuracy for the TvR subset was obtained through the quadratic SVM algorithm, while the highest classification accuracy for the TvS and RvS subsets was obtained through the coarse Tree algorithm. The average classification accuracy for the TvR subset was 53.48%, while the average classification accuracy for the TvS subset was of 35.39%, and the average accuracy for RvS subset was 46.94% (Figure 10).

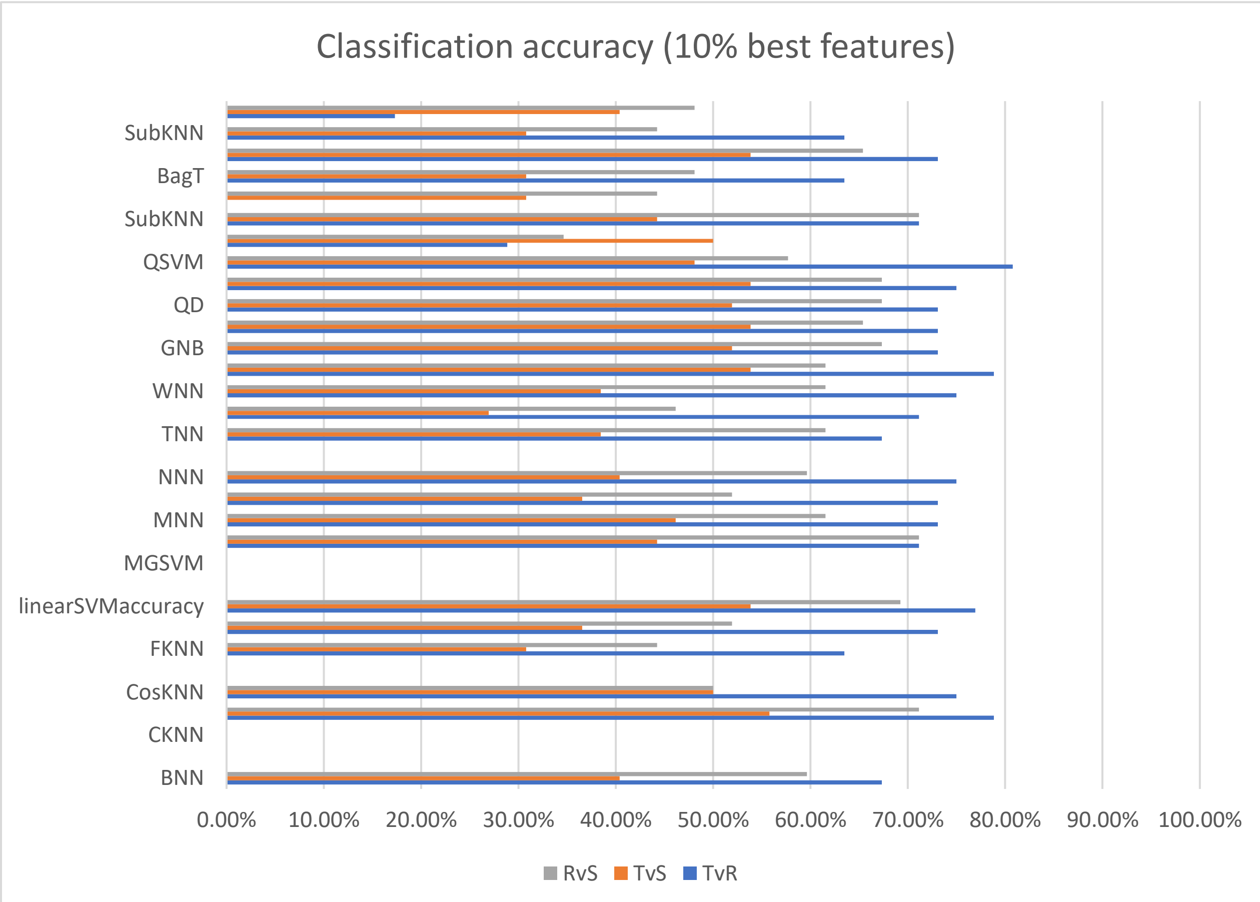

Figure 10 Classification results using 10% of features

While using the 20% best combination of features, the system obtained excellent classification results for every subset at 100% classification accuracy, through the coarse KNN algorithm. The average classification accuracy was also much improved for all subsets with 75% for the TvR subset, 77% for the TvS subset and 79% for the RvS subset (Figure 11).

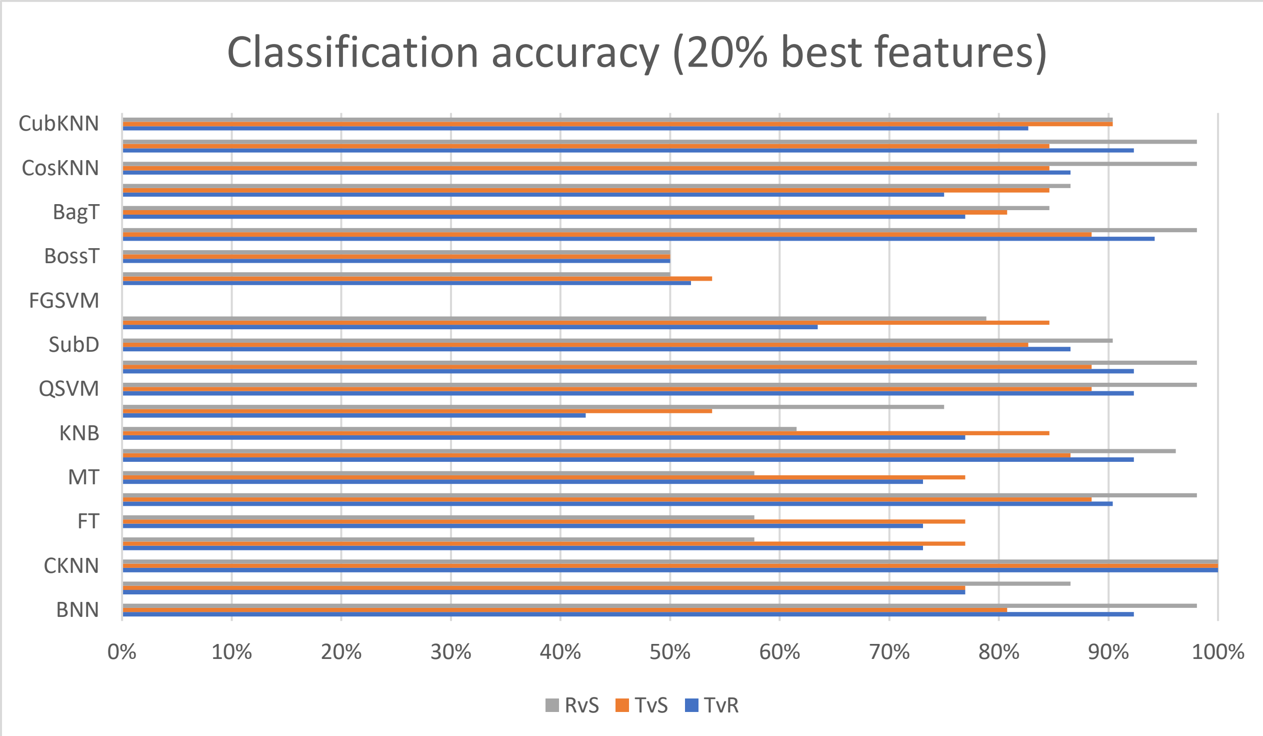

Figure 11 Classification results using 20% of features

The full tables are in Annex 2.

5. Discussion

For this study, a protocol was designed and validated to study the potential difference in the physiological stress response evoked by three different COFSG. This protocol involved using an adapted version of the TSST to provoke and dose stress in the study's subjects, who were then subjected to the three games (i.e., Bejeweled 2, Tetris, and Energy). During this protocol, EEG and ECG signals were collected. These signals were resampled, filtered, and subjected to wavelet transforms. The resulting data were then processed to obtain nonlinear metrics and spectral metrics. These metrics had the goal of characterizing he signals for its self-similarity, autocorrelation, energy entropy and power distribution throughout the frequency spectrum. These metrics were then fed to different AI classification algorithms. The results obtained in this study from signals classification seem to be highly accurate and discriminative, potentially due to several factors besides the analysis strategy, namely the quality of the metrics chosen, and the combination of metrics selected by the feature selection algorithm.

This study represents another piece of evidence that spectral metrics may be one of the best choices of metrics for this analysis. It is known that stress implies a transfer of power between the α and β frequencies [13], [18], [33]–[35], so the results obtained from our analysis approach may be related to changes in the subject's stress level. Such a conclusion needs to be supported by the perceived stress of the subjects, which, in fact, is shown that participants tend to show a change in perceived stress level between the test and stress reduction games and the stressor game.

It can be suggested that the difference found by the classification algorithms between the test and stress response games does not lie in the stress response, but within the degree of self-similarity in each. Although both are puzzle games, it could be suggested that Bejeweled has a much more linear approach than Energy in terms of gameplay, since it has a less expansive range of moves and a steady difficulty, while Energy can present different patterns of complexity over the duration of the play time. While Energy's puzzles form different shapes and could arguably demand greater special awareness and greater cognitive effort on some levels than others. Another differentiating factor between the two games could be the subjects' response to the games' soundtracks, which are different and, consequently, unparalleled. Literature has vastly exposed that music can have an effect on a subject's state of mind [4]–[7].

The placement of the EEG electrodes might be a contributing factor since the literature suggests the most common placement for electrodes is in the F3 and F4 zones (Figure 2) while the placement used for this project was in the Fp1 and Fp2 zones (Figure 2) [13], since it was the configuration that allowed for the optimal attachment of the electrodes. It is expected that the stress response involves the pre-frontal cortex since this is one of the three main active regions [68], [69]. The good results with this electrode placement could also be indicative of which stress response pathway was activated during the game sessions, since the slow pathway passes through the prefrontal cortex, involving higher cognition, which was to be expected, since the possible stress induced in the subjects should have a high cognitive component for every stimulus used.

The cardiac signal seems to be an accurate stress index since the onset of stress is usually linked to an increased HR as a consequence of the ANS activation and hormonal changes [70]. Also, the HR represents a good metric of the cognitive effort underlying the emotion regulation attempt due to the activation of the parasympathetic nervous system (PNS), which also influence the cardiac activity [71]. When experiencing a physical or psychological stress state, an individual's SNS will be predominant activated to increase the arousal level and support adaptation and appropriate response to the stressor, resulting in an increase in HR. By contrast, after a stress response, the PNS will be in charge of reducing the arousal level and, consequently, the HR. To measure this change pattern, the HR seems to be the best peripheral neurophysiological index.

Other physical indicators could have been explored to evaluate the effects of the SNS on the subjects during the game sessions. The cardiovascular system is highly sensitive to neurobehavioral processes [18], making it an excellent indicator of AD. In turn EDA measures (the electrical changes in the conductivity of skin), which increases and decreases as a function of stress [18] and is, therefore, a useful metric. RSP could also be useful since the respiratory system has complex response pattern to a variety of psychological variables, including emotions and stress. Respiration is, therefore, a useful indicator of AD, since physical exertion and emotional arousal reportedly cause faster and deeper respiration, but sudden stressors may cause momentary cessation of respiration [18].

Overall, it can be considered that most of the physiological metrics could have had an impact on the success of the classification algorithms, and it can also be considered that the choice of metrics, which was substantiated by the literature review, could provide a good blueprint for future similar neuroaffective studies.

6. Conclusion

In this study the principal objective of analyzing the potential differences in stress response caused in subjects by the interaction with different COFSGs. To accomplish this goal a protocol was developed where this effect is provoked in subjects. The protocol included the induction and dosing of stress with the TSST methodology before each of the selected COFSGs. The COFSGs selected were Bejeweled Classic, Energy and a modified version of Tetris. Throughout this protocol biosignals were collected, namely EEG and ECG. Nonlinear and Spectral metrics were selected through literature review. An algorithm was then created to pre-process the signals and collect the selected metrics. The metrics were then organized in a data matrix. Three subsets of data were created, these were Test game vs Stress Reduction game, Test game vs Stressor game, and Stress Reduction Game vs Stressor Game.

It was then decided to attempt to find a suitable binary classification algorithm using machine learning to distinguish between each pair of subsets. This task was successfully completed, as 100% classification accuracy was achieved for every pair of subsets, while using the top 20% best features. This success can be attributed to the choice of metrics retrieved from the biosignals collected, as the several nonlinear metrics provide a good idea of how each signal's self-similarity, autocorrelation, fractal dimension, chaotic properties and metrics from reconstructed attractors, and the spectral metrics provide a good idea of how the energy of the signal is distributed throughout the frequency spectrum, which is particularly helpful, since it allows the classification system to take stress response into account.

Future works are required to explain the classification results fully, namely deeper analysis of the stress response could be very useful. The cerebral response also merits some further studies, as it could be useful to have a complete analysis, including some idea of the activation of the different areas of the brain, this would allow the creation of inferences about which cognitive processes are being activated by each game. In other words, the classification task has been concluded with excellent results, proving the usefulness of the nonlinear and spectral metrics, as well as of the cardiac and cerebral signals to discriminate different physiological signals underlying a stress response.

It can be considered that this study contributes to the notion that the creation of video games could be improved by the introduction of neuroaffective study procedures, which could ultimately help inform the developers of the real, evidence-based effects. Gameplay, music and storytelling aspects of the game could help the developers more adequately induce the emotion intended in the users, making for better gaming experiences overall.

From a healthcare perspective, this study adds to the idea that different games can have different effects on the user and could, therefore, provide an interesting treatment option for several neuroaffective disorders. Having a classification tool for the neuroaffective effects of COFSGs may provide the necessary impetus for the use of these games as a remote treatment option for anxiety disorders, like has been mentioned throughout this paper. The necessity of these remote treatment options has intensified with the COVID-19 pandemic, so studies like this one, which present new protocols to test several different COFSGs for their stress reduction effects are important. This tool could help game production make specific COFSGs for the treatment of anxiety disorders, which could be used in conjunction with prescribed treatments and medications to reduce stress in specific situations.

7. Future Works

It is recommended that future studies explore other aspects which could not be added to the paradigm used in this paper. For instance, other modalities of biosignal, namely the EDA and RSP indices. Also, more central measures, such as the functional neuroimaging techniques could be targeted to investigate the activation of the different brain areas during the game sessions. This approach could provide a complete picture of what reflex arcs that are being activated for each game and would allow for better inferences to be made about what cognitive processes are being activated, and by extension, it would allow for a more complete analysis of each game's cognitive demands. This analysis could be done effectively within the laboratory by adding fNIRS, functional near infrared spectrography, measurements, although a combination of the fNIR data with a full cap EEG analysis could provide the complete analysis possible.

Still focusing on the peripheral measures, it would be beneficial to complete the analysis of the stress response of each game by adding more SNS dependent metrics, like the different metrics extracted from the EDA (skin conductance level or skin conductance frequency) since those metrics will allow to detect subtle changes throughout the session [70]. This, in addition to the ECG measurements, would provide the tools for a more complete analysis of the stress response to each game. We believe that a more complete picture of the stress response would help explain the classification results obtained in this paper.

Finally, it is essential to explore the effects of the music in the background of the games divorced from the effects of the respective games. This could provide some clarity on the effects of the music and allow the choices of pieces of music which would allow a better experience, as well as provide a possible explanation for the classification accuracy between the two subsets.

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9. Annex

Annex 1

Informed Consent, Sociodemographic form and SATI forms

Start of Block: Consentimento Informado

Informed consent We are inviting you to take part in this study. This form contains information about the study and the questionnaire. Further questions can be addressed to the contact details at the end of this form. You may choose not to participate in this study if you wish so. If you decide to participate, you are asked to review and agree to the terms in this consent form before you can start completing the questionnaire.

Why am I being asked to take part in this study?

This study aims to explore the relationship between certain mobile phone video games and altered stress levels in players. To do this we need people who can test the videogames in an experimental setting. We welcome your contribution to this study!

Why is this study being conducted?

The main aim of this study is to explore the relationship between certain mobile phone video games and altered stress levels in players, using self-report measures, peripheral and central neurophysiological measures.

What will I be asked to do?

If you decide to participate in this study, please read this informed consent and, if you agree with the terms presented, we ask you to firstly complete the following questionnaire, to answer some socio-demographic questions and some questions about how you feel in general and how you feel at the moment. It is also planned for this first moment, the tutorial of the three video games that will be tested. In a second moment, we will measure heart rate variability, as well as spectral characteristics of electroencephalography, while playing the test video games.

How long will my participation in the study require?

The first moment, which comprises reading the informed consent, completing the questionnaire and the video game tutorials, requires approximately 30 minutes.
The second moment, which encompasses the testing of the different video games, as well as the completion of a self-report instrument, lasts approximately 40 min.
The total duration of participation in the study, in a laboratory context, is estimated at one hour and ten minutes.

Are there any risks or discomfort caused by participation in this study?

There are no anticipated risks or discomfort that may result from your participation in this study. You may choose not to answer any questions if you wish so.

Will I get any benefit from participating in this study?

There are no benefits of any kind anticipated from taking part in this study. However, the information gathered will contribute to a better understanding of the possible relationship between playing certain video games and altered stress levels; and also to expand scientific knowledge on the topic.

Who will have access to the information I have provided?

The data collected through the questionnaire, the electroencephalogram and the electrocardiogram are coded so that no information can be used to identify participants. The data collected will be further be analyzed by the researchers associated to the project, in order to ensure the privacy and confidentiality of the participants. Only researchers associated with this project will have access to the raw data collected through this questionnaire. When these data are used for scientific publications, they will not include any information that could identify the participants. Given the data coding process, which we use to ensure the anonymity of the participants, it will not be possible to exercise the right to delete or rectify the data.

Can I discontinue my participation in this study at any time?

Participation in this study is entirely voluntary. You do not have to participate if you do not feel like it and you can refuse to answer any question or stop the data collection process. Even if you have already started filling in the questionnaire or collecting data, you can withdraw at any time.

Who can I contact if I have any questions or problems?

If you have any questions about this study, please feel free to contact the researchers responsible for the project Pedro Ribeiro and Miguel Ferreira, through the following emails: p.ribeiro.engenheiro@gmail.com; s-mimaferreira@ucp.pt .

Who can I contact about my rights as a participant?

If you have any questions about your rights as a participant in this study, you may contact the investigators responsible for the project, Pedro Ribeiro and Miguel Ferreira, through the following emails: p.ribeiro.engenheiro@gmail.com; s-mimaferreira@ucp.pt .

Will I be remunerated for participating in this study?

Participation in this study is voluntary and does not imply any form of compensation for the participants.

Will there be any costs for participation?

There are no costs associated with participation in this study.

○ I agree with the terms presented in this document and a consent to participate in this study

○ I do not agree with the terms presented in this document and i do not agree to participate in this study.

End of Block: Consentimento Informado

Start of Block: Identificação

Email address

____

Write the first letter of all your names (e.g., Ana Carolina Costa Ferreira = ACCF)

____

End of Block: Identificação

Start of Block: Questionário Sociodemográfico

*

Please indicate your age (years)

____

Indicate your gender

- ○ Female
- ○ Non-Binary / Third Gender
- ○ Prefer not to say
- ○ Male

*

State your height in cm (e.g., 179). Only write the numbers.

____

*

State your weight in kg (e.g., 75 or 77.5). Only write the numbers.

____

Please indicate your academic qualifications

- ○ Primary education
- ○ Secondary Education
- ○ University Attendance
- ○ Bachelor’s Degree
- ○ Master’s Degree
- ○ PhD or higher
- ○ Other ____
- ○ Prefer not to say

Please indicate your marital status

- ○ single
- ○ Married
- ○ Divorced/Separated
- ○ Widower

Please indicate your profession (e.g., student, salesman, psychologist, engineer, etc.)

____

Do you have any vision problems?

- ○ Yes, please state which ____
- ○ No

Do you have a hearing problem?

- ○ Yes, please state which ____
- ○ No

Do you have a cardiovascular problem?

- ○ Yes, please state which ____
- ○ No

Do you have photosensitive epilepsy?

- ◯ Yes
- ◯ No

Was today a typical day?

- ◯ Yes
- ◯ No, please state why ____

Last night was a typical night?

- ◯ Yes
- ◯ No, please state why ____

From 0 to 10, how would you rate the level of fatigue you are experiencing at the moment? (0 - No fatigue; 10- very high levels of fatigue).

	0 1 2 3 4 5 6 7 8 9 10
fatigue level	

Have you had coffee or a caffeinated drink today (e.g., Tea, Redbull, Monster and other caffeinated soft drinks)?

- ○ Yes, please state which ____
- ○ No

Have you had any alcoholic drinks (e.g., wine, beer, cider) in the last few hours?

- ○ Yes, please state which ____
- ○ No

Today, have you taken some psychotropic drug such as anxiolytics (e.g., Diazepam, Clanazepam, Nitrazepam) or antidepressants (e.g., Agolematine, Paroxetine, Fluoxetine)?

- ○ Yes, please state which ____
- ○ No

How many hours ago was your last meal? Slide the indicator approximately to the number of hours since your last meal.

0 5 10 14 19 24 29 34 38 43 48

Hours since last meal	

What is the most significant nature of your entertainment?

- Audio
- Music
- Video
- Videogames
- Board Games
- Physical exercise
- Other, please state which ______________________________

Do you have experience with video games?

- ◯ Yes. Please state which ones you usually play ____
- ◯ No

During the pandemic by COVID-19 did you increase your screen time?

- ◯ Yes. Please indicate how many minutes per day this increase was (e.g., 20 min) ____
- ◯ No

End of Block: Questionário Sociodemográfico

Start of Block: STAI-Y1

Instructions

A number of statements which people have used to describe themselves are given below. Read each statement and then circle the appropriate number to the right of the statement to indicate **how you feel right now**, that is, **at this moment.** There are no right or wrong answers. Do not spend too much time on any one statement but give the answer which seems to describe your present feelings best.

	Not at all	Somewhat	Moderately	A lot
I feel calm	○	○	○	○
I feel secure	○	○	○	○
I am tense	○	○	○	○
i feel strained	○	○	○	○
I feel at ease	○	○	○	○
I feel upset	○	○	○	○
I am presently worrying over possible misfortunes	○	○	○	○
I feel satisfied	○	○	○	○
I feel frightened	○	○	○	○
I feel comfortable	○	○	○	○
I feel self-confident	○	○	○	○

I feel nervous	○	○	○	○
I am jittery	○	○	○	○
I feel indecisive	○	○	○	○
I am relaxed	○	○	○	○
I feel content	○	○	○	○
I am worried	○	○	○	○
I feel confused	○	○	○	○
I feel steady	○	○	○	○
I feel pleasant	○	○	○	○

End of Block: STAI-Y1

Start of Block: STAI-Y2

Instructions

A number of statements which people have used to describe themselves are given below. Read each statement and then circle the appropriate number to the right of the statement to indicate **how**

<u>you generally feel</u>. There are no right or wrong answers. Do not spend too much time on any one statement but give the answer which seems to describe **<u>how you generally feel.</u>**

	Almost Never	Sometimes	Often	Almost Always
I feel pleasant	○	○	○	○
I feel nervous and restless	○	○	○	○
I feel satisfied with myself	○	○	○	○
I wish I could be as happy as others seem to be	○	○	○	○
I feel like a failure	○	○	○	○
I feel rested	○	○	○	○
I am “calm, cool, and collected”	○	○	○	○
I feel that difficulties are piling up so that I cannot overcome them	○	○	○	○
I worry too much over something that really doesn’t matter	○	○	○	○

I am happy	○	○	○	○
I have disturbing thoughts	○	○	○	○
I lack self-confidence	○	○	○	○
I feel secure	○	○	○	○
I make decisions easily	○	○	○	○
I feel inadequate	○	○	○	○
I am content	○	○	○	○
Some unimportant thought runs through my mind and bothers me	○	○	○	○
I take disappointments so keenly that I can't put them out of my mind	○	○	○	○
I am a steady person	○	○	○	○

I get in a state of tension or turmoil as I think over my recent concerns and interests	○	○	○	○

End of Block: STAI-Y2

Annex 2

5% of features

Table 2 Classification accuracy using 5% of the best features

dataset	BNN	CGSVM	CKNN
TvR	75.00%	0.00%	0.00%
TvS	32.69%	0.00%	0.00%
RvS	55.77%	0.00%	0.00%
dataset	CT	MT	FGSVM
TvR	78.85%	75.00%	0.00%
TvS	55.77%	50.00%	0.00%
RvS	71.15%	50.00%	0.00%
dataset	FKNN	FT	LSVM
TvR	63.46%	73.08%	76.92%
TvS	30.77%	36.54%	53.85%
RvS	44.23%	51.92%	69.23%
dataset	LRK	MGSVM	MKNN
TvR	0.00%	0.00%	71.15%
TvS	0.00%	0.00%	44.23%
RvS	0.00%	0.00%	71.15%
dataset	MNN	MT	NNN
TvR	73.08%	73.08%	73.08%
TvS	42.31%	36.54%	48.08%
RvS	57.69%	51.92%	65.38%
dataset	SVMK	TNN	WKNN

TvR	0.00%	71.15%	71.15%
TvS	0.00%	36.54%	26.92%
RvS	0.00%	61.54%	46.15%
dataset	WNN	KNB	GNB
TvR	76.92%	78.85%	73.08%
TvS	42.31%	53.85%	51.92%
RvS	65.38%	61.54%	67.31%
dataset	LD	QD	LR
TvR	73.08%	73.08%	75.00%
TvS	53.85%	51.92%	53.85%
RvS	65.38%	67.31%	67.31%
dataset	QSVM	CSVM	CubKNN
TvR	80.77%	28.85%	71.15%
TvS	48.08%	50.00%	44.23%
RvS	57.69%	34.62%	71.15%
dataset	BossT	BagT	SubD
TvR	0.00%	63.46%	73.08%
TvS	30.77%	28.85%	53.85%
RvS	44.23%	44.23%	65.38%
dataset	SubKNN	RUSBT	
TvR	63.46%	13.46%	
TvS	30.77%	40.38%	
RvS	44.23%	48.08%	
dataset			
TvR	max	75.00%	
TvS	max	32.69%	
RvS	max	55.77%	
dataset			
TvR	avg	25.00%	

TvS	avg	10.90%	
RvS	avg	18.59%	
dataset			
TvR	std	43.30%	
TvS	std	18.87%	
RvS	std	32.20%	

10% of features

Table 3 Classification accuracy using 10% of the best features

dataset	BNN	CGSVM	CKNN
TvR	67.31%	0.00%	0.00%
TvS	40.38%	0.00%	0.00%
RvS	59.62%	0.00%	0.00%
dataset	CT	CosKNN	FGSVM
TvR	78.85%	75.00%	0.00%
TvS	55.77%	50.00%	0.00%
RvS	71.15%	50.00%	0.00%
dataset	FKNN	FT	LSVM
TvR	63.46%	73.08%	76.92%
TvS	30.77%	36.54%	53.85%
RvS	44.23%	51.92%	69.23%
dataset	LTK	MGSVM	MKNN
TvR	0.00%	0.00%	71.15%
TvS	0.00%	0.00%	44.23%
RvS	0.00%	0.00%	71.15%
dataset	MNN	MT	NNN
TvR	73.08%	73.08%	75.00%
TvS	46.15%	36.54%	40.38%
RvS	61.54%	51.92%	59.62%
dataset	SVMK	TNN	WKNN
TvR	0.00%	67.31%	71.15%
TvS	0.00%	38.46%	26.92%
RvS	0.00%	61.54%	46.15%

dataset	WNN	KNB	GNB
TvR	75.00%	78.85%	73.08%
TvS	38.46%	53.85%	51.92%
RvS	61.54%	61.54%	67.31%
dataset	LD	QD	LR
TvR	73.08%	73.08%	75.00%
TvS	53.85%	51.92%	53.85%
RvS	65.38%	67.31%	67.31%
dataset	QSVM	CSVM	SubKNN
TvR	80.77%	28.85%	71.15%
TvS	48.08%	50.00%	44.23%
RvS	57.69%	34.62%	71.15%
dataset	BossT	BagT	SubD
TvR	0.00%	63.46%	73.08%
TvS	30.77%	30.77%	53.85%
RvS	44.23%	48.08%	65.38%
dataset	SubKNN	RUSBT	
TvR	63.46%	17.31%	
TvS	30.77%	40.38%	
RvS	44.23%	48.08%	
dataset			
TvR	max	0.673076923	
TvS	max	0.403846154	
RvS	max	0.596153846	
dataset			
TvR	avg	0.296153846	
TvS	avg	0.223076923	
RvS	avg	0.303846154	
dataset			

TvR	std	0.334361088	
TvS	std	0.20738938	
RvS	std	0.283091032	

20% of features

Table 4 Classification accuracy using 20% of the best features

dataset	BNN	CGSVM	CKNN
TvR	92%	77%	100%
TvS	81%	77%	100%
RvS	98%	87%	100%
dataset	CT	FT	LSVM
TvR	73%	73%	90%
TvS	77%	77%	88%
RvS	58%	58%	98%
dataset	MT	NNN	KNB
TvR	73%	92%	77%
TvS	77%	87%	85%
RvS	58%	96%	62%
dataset	LR	QSVM	CSVM
TvR	42%	92%	92%
TvS	54%	88%	88%
RvS	75%	98%	98%
dataset	SubD	SubKNN	FGSVM
TvR	87%	63%	0%
TvS	83%	85%	0%
RvS	90%	79%	0%
dataset	RUSBT	BossT	WNN
TvR	52%	50%	94%
TvS	54%	50%	88%
RvS	50%	50%	98%
dataset	BagT	WKNN	CosKNN

TvR	77%	75%	87%
TvS	81%	85%	85%
RvS	85%	87%	98%
dataset	TKNN	CubKNN	
TvR	92%	83%	
TvS	85%	90%	
RvS	98%	90%	
dataset			
TvR	Maximum	1	
TvS	Maximum	1	
RvS	Maximum	1	
dataset			
TvR	avg	0.897435897	
TvS	avg	0.727564103	
RvS	avg	0.758547009	
dataset			
TvR	std	0.117501941	
TvS	std	0.245056413	
RvS	std	0.236837836	