



Department of Signal Theory and Communication

Biomedical Engineering Degree

Bachelor Thesis

**PHYSIOLOGICAL STRESS DETECTION
USING NEUROCOGNITIVE GAMES**

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Abstract

Stress has been defined as a reaction from a calm state to an excited state in order to preserve the integrity of the organism. This reaction is given by changes and pressures which provoke physical and physiological responses. Within description, stress occur in order to preserve the individuals integrity, and could appear in human signals such as heart activity, sweating or pupil dilatation. However, the presence of stress has been associated with a decrease in performance. Continuous daily stress can have negative effects on individuals' physical and mental well-being, being linked to chronic health risks, such as cardiovascular disease, hypertension, and coronary diseases.

The main goal of this Bachelor Thesis is to provide a system that determines different levels of stress using physiological signals. To achieve this goal, an experiment has been developed to induce stress to participants while their physiological signals were collected using wearable sensors.

The experiment consists on a set of cognitive tasks developed by *Lumosity Labs* that elicits different anxiety scenarios: attention, memory, flexibility, resolve tasking and speed. Three physiological parameters have been acquired aiming to classify different stress levels: heart rate, galvanic skin response and cortisol hormone. Three devices were used to measure physiological signals; *Q sensor*, *Garmin forerunner 310XT* and *Microsoft Band 2*, along with a cortisol test.

Finally, the classifier of stress reactions using physiological signals has been developed based on a linear regression. This complete method take into account four factors: individual performance, tasks that is been involved, chronic stress and real-time reactions. Results shows a individual scheme for different abilities played on the experiment. A characterization of Yerkes & Dodson curve is performed to evaluate his personal stress abilities using a linear normalization. Besides, features of electrodermal activity (area under the curve) and cardiac activity (ratio between low and high frequency) are selected as the ones that have more influence in terms of stress reactions.

The design obtains an individual performance characterization and determine the feature more relevant on the stress detection achieving the target expectations.

1 Introduction

Stress is a set of physiological responses to external stimulus that prepare the body to environment changes, usually generating an alert state. Within description, stress can be considered a positive survival mechanism of adaptation. Getting to know how the human body reacts under stressing situations is useful during certain activities that require a quick reaction time [1].

1.1 Motivation

Stress has effect on physical and psychological health. It wears oneself and leads to poor health, either physically or emotionally. It has been linked to numerous chronic health risks, such as cardiovascular disease, diabetes mellitus, obesity, hypertension, and coronary artery disease [2].

There is a relation between the performance during a task and the level of stress the individual is suffering [3]. This relation can be seen in situations where the individuals are subjected to high pressure levels. An example can be positions of responsibility, such as operators or air traffic controllers, where stress can pose a risk to the safety of other people.

This reaction given by environmental changes and pressures which brings on physical and physiological responses [4] can be characterized by means of physiological signals.

1.2 Objectives

The **main objective** of this Bachelor Thesis is classifying stress levels. 19 volunteers has participated in a experiment while their electrodermal activity and heart activity is being monitored. Sensors used to acquire data are the *Microsoft Band 2* from *Microsoft*, *Qsensor* from *Affectiva* and *Garmin forerunner 310XT* from *Garmin*. Chronic stress of each participant is determined by their level of cortisol. *IPRO Interactive cortisol test* has been selected to determine the cortisol values on real-time.

The **secondary objectives** pursued are:

- *To design of an experiment that elicits stress*: a set of cognitive tasks developed by *Lumosity labs* had been adapted to measure five aspects: speed, memory, attention, flexibility and problem solving abilities of the participants.
- *To process physiological signals*: different signal processing algorithms have been implemented to obtain information related to stress.

- *To obtain a correlation between the individual performance and the physiological responses:* relate the scores obtained in the experiment and the features extracted from signals.

This Bachelor Thesis has been divided in seven chapters. Chapter 3 will be the problem statement, where the experiment is proposed and explained, as how the data is acquired during the experiment. Signal processing as well as feature extraction and stress characterization are described on chapter 4. The results obtained from the stress characterization are presented next. Finally, in chapter eight the conclusions and future work are presented.

1.3 Social and economic framework

Stress is the second cause of heart diseases in developed countries, specially among positions of high responsibility, according to the World Health Organization (WHO) [5]. Pressure at the workplace is unavoidable due to the demands of the contemporary work environment. Pressure perceived as acceptable by an individual helps keep workers alert, motivated, able to work and learn, depending on the available resources and personal characteristics. However, when it becomes excessive or unmanageable it leads to anxiety states, damaging workers' health and business performance [6].

Possible applications of this work are reported in Section 7 along with the the planning of the work and a summary of the budget.

1.4 Regulatory framework

This work has been carried out in compliance with the "*Ley Orgánica 15/1999, of December 13, de Protección de Datos de Carácter Personal*". The principles established by current legislation and technical standards used on this project are reported in Section 6.

2 State of the art: stress detection

Stress is a set of physical and physiological responses caused by internal or external stimuli that generates an alert state on the organism. Those physiological responses can be classified as positive or negative human consequences. Positive stress or eustress is a cognitive and physical enhancer that increases individual performance while negative stress or distress produces an opposite reaction to the same stimuli [7]. Distress causes that an individual subjected to high pressure decreases his functionality and blocks against an affordable situation [8].

Stress responses are carried by the Autonomic Nervous System (ANS) which innervates the smooth musculature, cardiac musculature, secretory activity of glands, and neuronal regulation of internal milieu among other functions. This system is divided on two subsystems: Sympathetic Nervous System (SNS) and Parasympathetic Nervous System (PSNS). SNS is charge of stress response when an individual is subjected to a physical or emotional pressure. Those responses include the dismissal of anabolic processes and activation of the catabolic ones, as well as a rise on the secretion of neurotransmitters and cortisol. Meanwhile PSNS is active when an individual is out of pressure, controlling homoeostasis and energy balance [9].

However repetitive stress state is associated with chronic diseases and decrease on functionality. The relation between arousal and task performance has been studied by Yerkes and Dodson [10]. This study concluded that performance increase with arousal when an individual feel relaxed, then reaches its peak at the highest arousal level because the subject is involved in the task, and decreases when the individual feel in breakdown or anxiety situation. This model is shown on Figure 1.

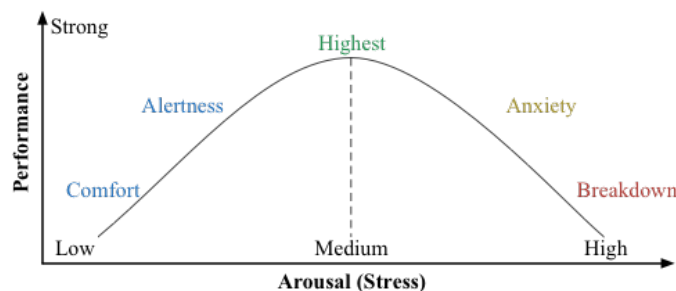


Figure 1: Yerkes-Dodson Law: relation between arousal and performance.

Stress reactions are different for each person, but present similar behaviours doing the same exercise. Several studies have been performed with

the purpose of characterize the physiological response against stressful situations. The most significant found on the literature have characterized different physiological signals on real-time, relating them to participant response.

One example is the experiment performed by Patrice Renaud and Jean-pierre Blondin [11], where 51 volunteers underwent a computerized version of the Stroop Colour-Word interference test. Heart rate and skin conductance were the physiological signals studied, recorded on a Grass Model 79D polygraph and the electrocardiogram signal, obtained by an R-wave detector. The study presented two types of stimuli: Stroop stimuli, which consisted on four colour names printed on incongruent colours and control stimuli, which were strings of four Xs printed in either one of the four colours used for the Stroop stimuli. The performance data reflected a longer response time and a larger rate of errors to Stroop stimuli, than to the control group, while the heart rate variability appeared in accordance with an effort account of the relationship between attention and cardiac activity. The study concluded that different aspects of task performance affect physiological and emotional responses to the Stroop task.

Noriyasu Takai et al. conducted another example found on the literature [12]. The aim of this experiment is to examine the effects of psychological stressor on salivary amylase and salivary cortisol, a proven biomarker associated with chronic stress. The subjects completed the trait version of State-Trait Anxiety Inventory (STAI) to assess the predisposition to personal anxiety. A 15 minutes video of corneal transplant surgery was used as stressor and a scenic beauty video viewing was used as the soother. Saliva samples were collected every 3 minutes throughout the session. The amylase level was significantly increased just after the beginning of the stressful video viewing, and immediately returned to the pre-stress level just after the end of the video viewing. The cortisol level was also increased, but to a lesser extent compared with that of amylase. The latency time to the peak level for cortisol was longer than that of amylase. The study concluded that amylase was more significantly increased than cortisol for shorter peak time while cortisol peaks appeared for a longer time.

Stress can be classified on three main groups attending to the intensity, duration on time and personal response to stress. Those reactions can be measured using different physiological signals that allows to approximate a model based on the Yerkes-Dodson Law described on Figure 1.

2.1 Chronic stress

Chronic Stress is the response to emotional pressure suffered for a prolonged period of time in which an individual perceives he or she has little or no control. This excitation results in widespread changes in both physical and mental profiles. Exposure to chronic stress is considered to accelerate or exacerbate several neuropsychiatric disorders including depression, mood and anxiety as well as a decrease on functionality [13]. This stress is resulting from repeated exposure to situations lead to the release of stress hormones. Salivary cortisol measurements can aid in identifying biomarker patterns associated with chronic stress [14].

Hormone cortisol

Cortisol hormone is a glucocorticoid produced on the adrenal cortex within the adrenal gland. It is released in response to stress and low blood-glucose concentration. Cortisol excess or insufficiency have been linked to endocrine disorders such as Graves' disease, obesity and diabetes mellitus along with stress derived disorders including post-traumatic psychological distress, chronic fatigue syndrome and other conduct disorders [15, 16].

Cortisol measurement

Cortisol levels measurement are a diagnostic tool in certain stress-intensive activities. Several investigations have been carried out with the object of classifying chronic stress. The most significant ones have correlated the stress levels with salivary cortisol since this biomarker have been proved to present a proportional relation [17].

Cortisol levels fluctuate during the day having higher peak in the morning and lowest during the evening as can be seen on Figure 2. However, cortisol levels can be affected by dietary intake and circadian sleep cycles increasing the hormone level fluctuation. Experimental salivary cortisol tests should be performed under the most similar physical conditions in order to reduce the variability of the results.

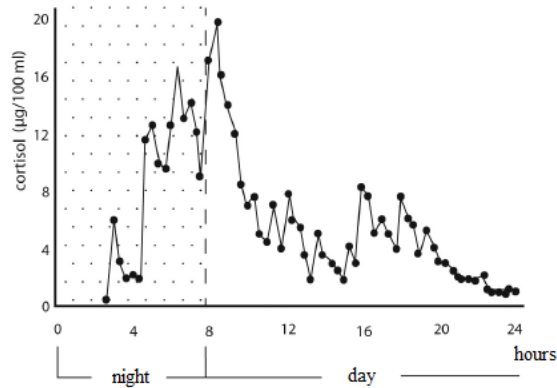


Figure 2: Twenty-four hour pattern of cortisol levels [1].

2.2 Real-time stress

Real-time stress correspond to the physiological response to an immediate stimuli that generates an alert state on the organism. This reaction known as “fight or flight” produces an increment on the heart rate, blood volume pulse and electrodermal activity. Stress reactions can be characterized on real time making use of signal processing. Those signals allow to extract information about the state of each individual and characterize their stress patterns [18].

Cardiac Activity

Cardiac activity can be measured using heart beats. Many factors influence the number of heart beats: genetics, ageing, regular exercise or medications are primary factors on resting heart rate. In stress situations, it is known that there are changes in the number of heart beats and on the blood pressure due to the action of the Sympathetic Nervous System [19]. This system innervates the contraction of the muscular wall of the vessels and increases the number of heart beats.

Blood Volume Pulse (BVP) signals represent the blood volume flowing through the blood vessels. Heart Rate can be extracted from those signals by analysing the distance between each maximum in seconds.

BVP signals are acquired by photoplethysmography (PPG). This process consist on applying a light source and measuring the light reflected by the

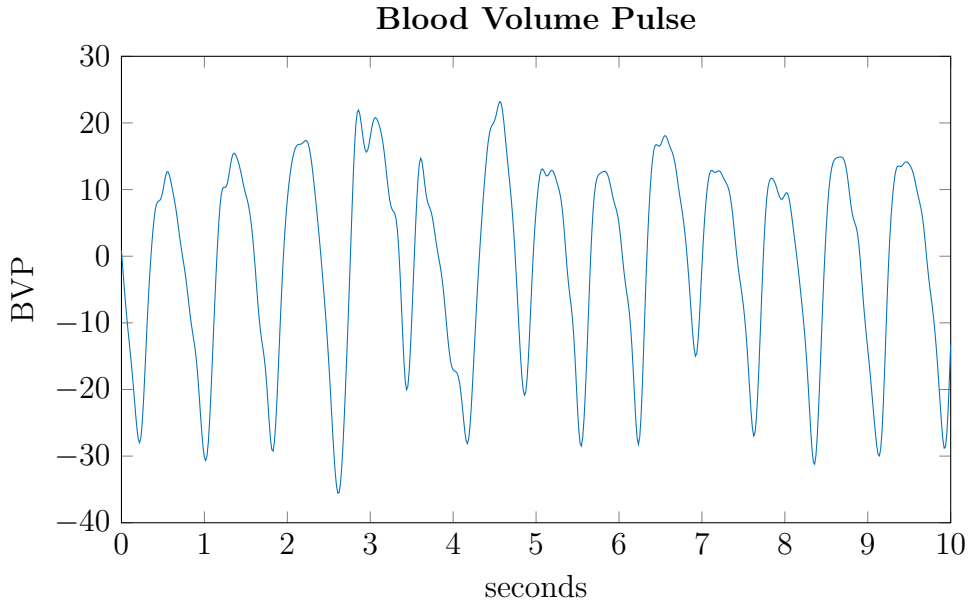


Figure 3: BVP signal example.

skin. At each contraction of the heart, blood is forced through the peripheral vessels, producing engorgement of the vessels under the light source, thereby modifying the amount of light the photo-sensor receives [20].

Electrodermal Activity

The term Galvanic Skin Response (GSR) refers to changes in the electrical properties on the surface of the skin in response to sweat secretions [21]. These secretions are due to an increment in sudomotor innervation, caused by the Sympathetic Nervous System (SNS), that results in changes in the GSR signals as the body responds to different daily circumstances: stress, temperature, anxiety, exertion situations, etc. [22]. Hence, the sympathetic activity can be measured by analysing the electrodermal signals, as already shown in [23]. For instance, this relation between SNS acts and the observed skin conductance, which determines the sympathetic innervation of the sweat glands [24], has been extensively used in stress detection applications.

GSR signals carry information about SNS activity, but are also influenced by other factors, like temperature changes or sweating due to aerobic exercise [25]. The challenge in analysing them is thus, to develop a method which is able to extract only SNS activity symptoms while avoiding other unrelated components. Indeed, GSR signals, which are usually denoted as, $s(t)$, can be expressed as a sum of two components [21]:

- The *tonic component*, $s_\ell(t)$, or Skin Conductance Level (SCL), which is the level of skin conductance in the absence of any particular environmental event or external stimuli. The tonic skin conductance level can slowly vary over time in an individual depending upon his or her psychological state, hydration, skin dryness, and autonomic regulation. The SCL is related to several non-SNS activity factors but also to the level of attention of the subject, even in the absence of instantaneous stimuli. Tonic changes in the skin conductance level typically occur in a large period, from ten seconds to even minutes.
- The *phasic component*, $s_p(t)$, also called Skin Conductance Response (SCR), which is the reaction to sporadic SNS stimuli. SCR measurements are typically associated with short-term events and occur in the presence of discrete environmental stimuli such as cognitive processes. The SCR, which is superimposed on top of the tonic component, includes higher frequency components and is a *sparse* signal, appearing only within specific time windows whose length typically lasts from one to five seconds.

Furthermore, SCRs can be modelled as the standard linear convolution between a sudomotor SNS innervation, $d_p(t)$, that corresponds to the *non-negative* unknown driver that causes the observable skin conductance response, and the response triggered by that driver, usually called as $r(t)$. Hence, GSR signals can be finally decomposed as [26],

$$s(t) = s_p(t) + s_\ell(t) = d_p(t) * r(t) + s_\ell(t). \quad (1)$$

A syntetic example is shown in the following Figures. First Figure (4) represents a GSR signal $s(t)$ over 90 seconds. If tonic component is removed, phasic component represent a pulse of a SNS reactions as is plotted in Figure 4. Finally, only the sparse driver, $d(t)$, can be obtained applying a non-negative deconvolution as [27] discussed in their method.

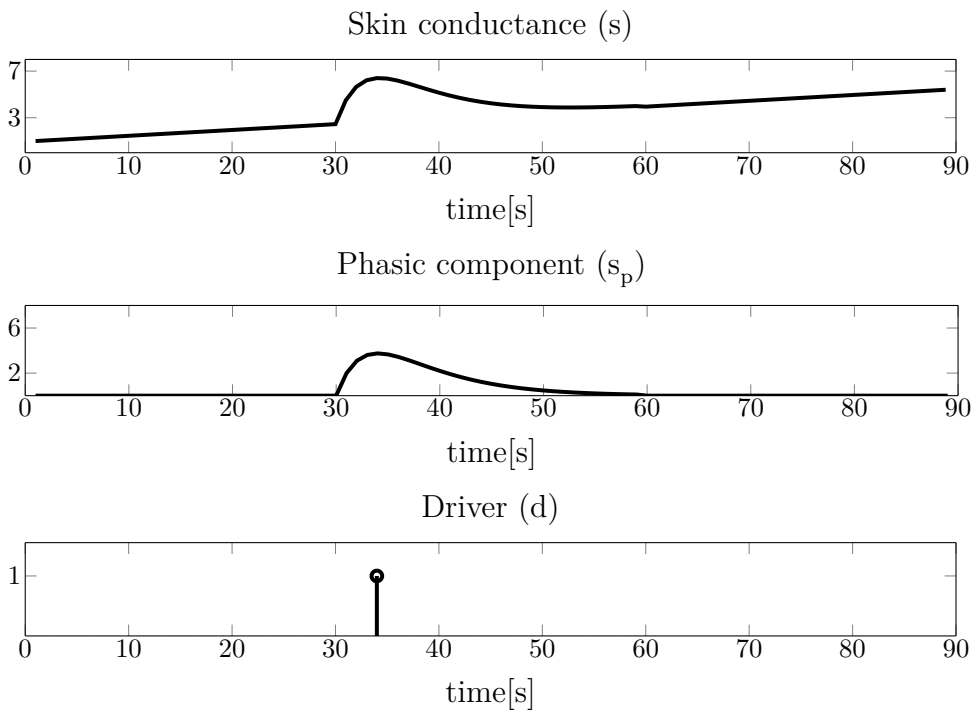


Figure 4: Skin conductance decomposition.

3 Problem description

The main objective of this work is to classify physiological reactions against different stress scenarios. This chapter describes the experiment designed, where different stress scenarios are produced to induce physiological stress on participants, as well as tools used along the work.

3.1 Experiment design

The experiment consist on a set of cognitive tasks that measure five aspects: speed, memory, attention, flexibility and problem solving abilities of the participants. Cognitive tasks are developed by *Lumosity labs* and this experiment is composed of two games of each category.

The experiment has been completed on a set of 19 participants with age interval from 20 to 59. The mean age of the group was 29.16 years, with a standard deviation of 33.21 years. All subjects have undergone the experiment on a voluntary basis. As the “*Ley Orgánica 15/1999 de Protección de Datos de Carácter Personal*” establishes, any personal data used for research purposes needs the consent of the involved individual and does not allow the publication of any personal information. For that reason each participant is assigned with an identification number at the beginning of the experiment.

Different family test are decribed below.

3.1.1 Speed tests

The games on this category have an intended primary skill target of brain processing speed and participant reaction time.

River Range Overdrive

The objective of this game is to identify rapidly the disappearing object that has previously appeared. It increases the difficulty with performance by showing similar shape and colour objects for a shorter time. This game develops the cognitive task of identification, making use of the brain attribute of information processing.

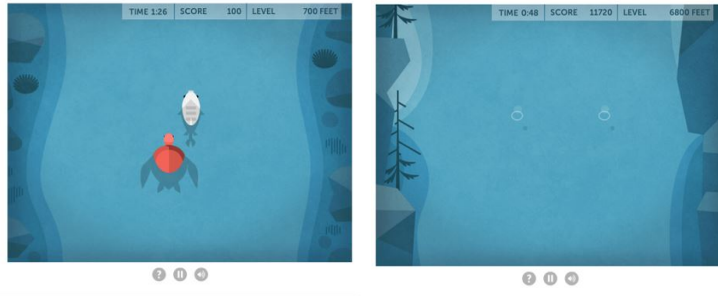


Figure 5: River Range Overdrive test: Luminosity speed task.

Splitting Seeds

The participant is expected to quickly determine how many objects occur on either side of a dividing line. The game increases its difficulty with time by changing the reference system. This game is intended to train the cognitive tasks of estimation, subtilizing, counting and spatial orientation, all of them based on brain attribute of information processing.

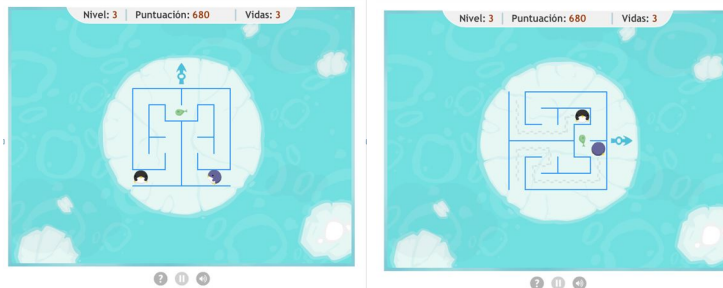


Figure 6: Splitting Seeds test: Luminosity speed task.

3.1.2 Memory tests

These games set is categorized under memory brain area focusing on short-term memory.

Memory Matrix

The general task of the game is to remember and indicate the location of blocks on a grid. The number of blocks is increased or decreased with participant performance. This game works the cognitive task of visuospatial memory, based on spatial recall brain attribute.

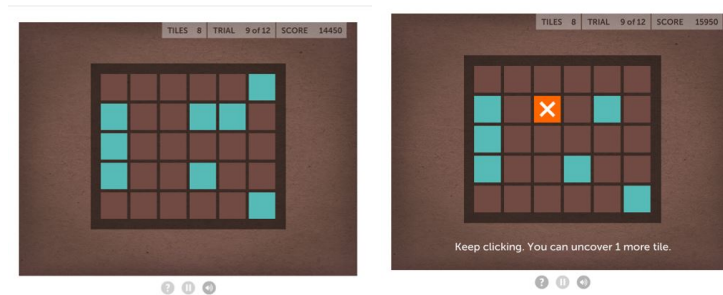


Figure 7: Memory Matrix test: Lumosity memory task.

Pinball Recall

The aim of the participant is to observe and remember the location and orientation of bumpers and predict the path of a ball that travels through them. This game is intended to train the cognitive task of spatial working memory, related to working memory brain attribute. The difficulty is increased by the number of bumpers that needs to be remembered, in order to adapt the game to the participant abilities.

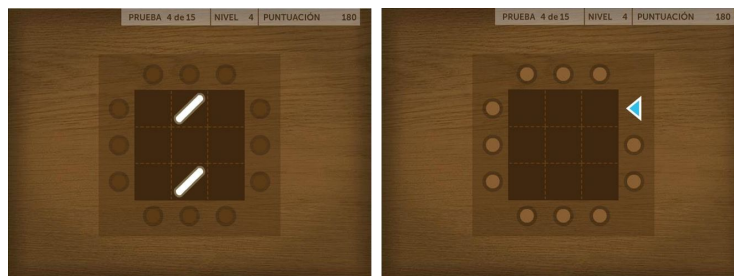


Figure 8: Pinball Recall test: Lumosity memory task.

3.1.3 Attention tests

The basic underlying tasks of these games are selective attention combined with multitasking.

Star Search

The objective of the game is to find the unique object between a set of similar ones. The complexity of the game increases with time by adding different objects and patterns. This game is proposed as operation for visual search cognitive task, based on selective attention brain attribute.

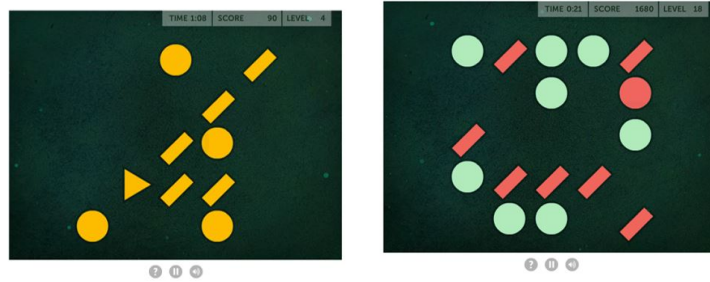


Figure 9: Star Search test: Lumosity attention task.

Trouble Brewing

The goal of the game is to lead trains to different stations by switching track pieces. The difficulty of the game increases by augmenting the number of trains at the same time on the train tracks. The game contemplates many cognitive tasks: multitasking, divided attention, sustained attention, planning and working memory. All of them are within brain attribute of divided attention.

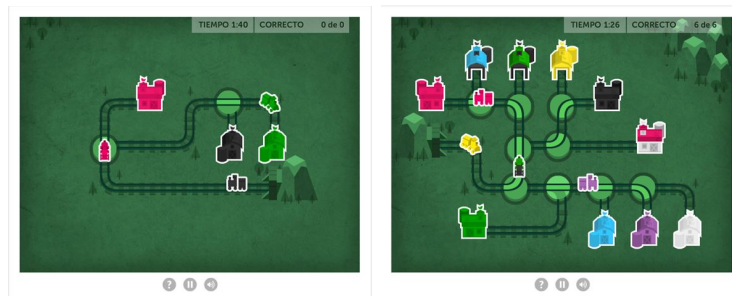


Figure 10: Trouble Brewing test: Lumosity attention task.

3.1.4 Flexibility tests

Flexibility games are meant to determine mental skills to process multiple tasks simultaneously and ability to switch between them.

Colour Match

The participant should indicate whether the colour of a word matches rather than the meaning of the word. The game level is maintained during the test, the participant must complete as many correct words as possible on the given time. The cognitive task driven on this game is semantic interference, related to response inhibition brain attribute.

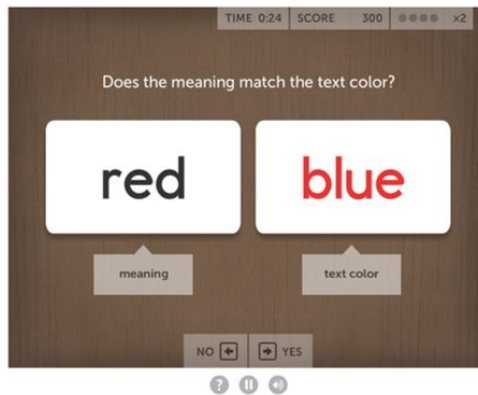


Figure 11: Colour Match test: Lumosity flexibility task.

Brain Shift

The objective of the game is to indicate whether a letter is a vowel or not and whether a number is even or not. The game does not increase the difficulty with performance, the participant is expected to complete as many correct cards as possible on the given time. The cognitive tasks measured on this game are classification and task switching, with a related brain attribute of task switching.



Figure 12: Brain Shift test: Lumosity flexibility task.

3.1.5 Problem solving tests

On this game set the participant is expected to work through the details of a problem to reach a solution.

Raindrops

The general task of the game is to respond to addition, subtraction, multiplication, and division problems to prevent raindrops from hitting the water below. The number of raindrops is increased with participant performance. The cognitive task developed by this game are arithmetic and sustained attention, making use of numerical calculation brain attribute.

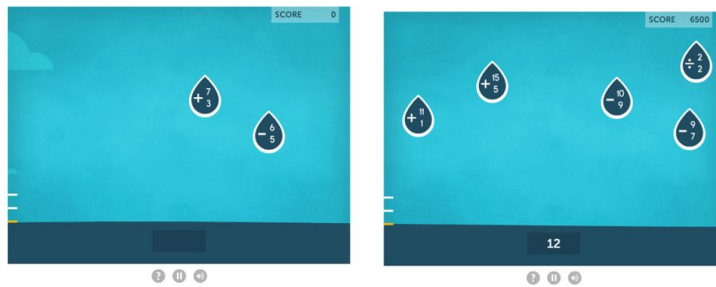


Figure 13: Raindrops test: Lumosity problem solving task.

Pet Detective

Plan and execute a route to pick up and deliver passengers with a limited number of movements. The game increases its difficulty by adding different routes and stops. This game is intended to train the cognitive tasks of route planning and resource management, making use of the brain attribute of planning.



Figure 14: Pet Detective test: Lumosity problem solving task.

Experiment structure

This software modifies automatically the different parameters of the games in order to adapt to the participant performance. The experiment has been

structured on two stages that are performed on consecutive days. This format allows the collection of data from two different situations and the prediction of individual performance.

The final structure of the experiment is the following one:

Experiment structure	
Duration	Process
2'	Cortisol test
8'	Sensor calibration
2'30"	Relax time
7'	Speed task: River Range Overdrive
2'30"	Relax time
7'	Memory task: Memory matrix
2'30"	Relax time
10'	Attention task: Star search
2'30"	Relax time
7'	Flexibility task: Colour match
2'30"	Relax time
7'	Problem solving task: Raindrops
2'30"	Relax time
2'30"	Take of the sensors and stop measurement
2'	Cortisol test
5'	Questionnaire

Table 1: Experimental structure: Stage I.

First stage of the experiment is composed of five games, each one corresponding to a cognitive aspect. Experiment starts taking a saliva sample in order to measure the cortisol value. Different sensors used to capture physiological signals are set to start signal acquisition. Signal acquired before the start of the stress inducing test will be discarded on the results analysis, as this data will correspond to sensors calibration. Stress inducing test will start after 10 minutes. The test consists on an alternating set of games followed by a 2'30" of participant relax. Right after finishing the stress inducing test another saliva sample is taken for cortisol measurement.

Participants are asked to fill a questionnaire about the sensations perceived during the experiment in order to complete the information about the induced stress on the subject. This survey provides information about the stress, performance, effort and frustration felt by the individual on each of the tasks and makes a comparative between the two sessions of the experiment.

Experiment structure	
Duration	Process
2'	Cortisol test
8'	Sensor calibration
2'30"	Relax time
7'	Speed task: Feed the penguin
2'30"	Relax time
7'	Memory task: Pinball recall
2'30"	Relax time
10'	Attention task: Trouble Brewing
2'30"	Relax time
7'	Flexibility task: Brain shift
2'30"	Relax time
7'	Problem solving task: Pet detective
2'30"	Relax time
2'30"	Take of the sensors and stop measurement
2'	Cortisol test
5'	Questionnaire

Table 2: Experimental structure: Stage II.

The second stage of the experiment presents the same structure as the first one. It is composed of five cognitive games of the same duration as their analogues of the first stage. Each experiment session has a total duration of one hour. It has been previously exposed that cortisol values fluctuate during the day following a given pattern, so in order to archive the maximum accuracy it is mandatory to perform the experiment following the set timetable.

3.2 Individual performance

Every person has different responses in presence of stress situations, but present similar behaviours performing the same activity. In this work, individual performance is simulated from different scores obtained on games with the given time. Those scores are calculated attending to the reaction time and to the correct answers of the games. Having into account the participants performance along the two sessions of the experiment, a yield curve is obtained. This curve corresponds to Yerkes-Dodson Law previously described previously on Figure 1.

Chronic stress measured with cortisol test indicates the starting point of each participant while individual performance and number and intensity of

physiological features will describe the shape of the curve. Those parameters are extracted from the measured signals.

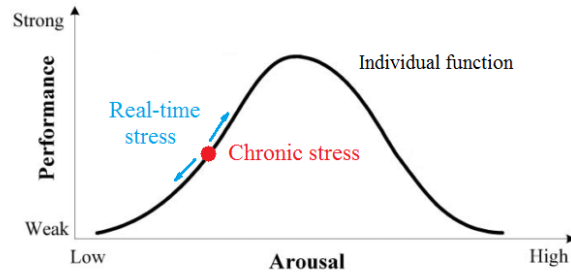


Figure 15: Stress parameters in Yerkes-Dodson Law.

3.3 Data acquisition

Three devices were used to measure physiological signals, along with a cortisol test. Signals should be obtained on the less intrusive possible way in order to avoid any interference with the experiment development. The three devices selected have been chosen from a wide range of available commercial sensors due to their reliability and small size.

3.3.1 Heart rate

Heart rate signal have been acquired with two different sensors *Garmin forerunner 310XT* and *Microsoft Band 2*. Those sensors are shown respectively on Figure 16 and Figure 17. Both sensors have been used to acquire data simultaneously on opposite wrists to avoid data loss.

Garmin forerunner 310XT [28] consists on a compact wristband and an elastic band placed around the thorax. It allows obtaining information about heart rate by connecting the two parts of the sensor via bluetooth. Data is extracted from the device connecting the sensor to the computer through a bluetooth device, and uploading it to the *Garmin* server using *Garmin Express* Software. This server allows to download the different sessions on a *tcx* format.



Figure 16: Heart rate sensor: Garmin forerunner 310XT.

Microsoft band 2 [29] is also a compact wristband that allows obtaining data about electrodermal activity, heart rate, R-R interval, device position and angular velocity. This device generates three csv files that contain data of electrodermal activity, heart rate and R-R interval respectively.



Figure 17: Heart rate and EDA sensor: Microsoft Band 2.

3.3.2 Galvanic Skin Response

Galvanic Skin response have been acquired with two sensors *Microsoft Band 2* mentioned before and *Q sensor* [30] simultaneously.

Q sensor consists on a metallic case that contains all the sensors and an elastic band that can be adjusted to the participant wrist as it is shown on Figure 18. It allows the measurement of electrodermal activity through two silver electrodes placed on the base of the sensor and the device position by means of a three-axis accelerometer. Data extraction from *Q sensor* is done through USB connection using the software *Q of Affectiva*, that provides a csv file.

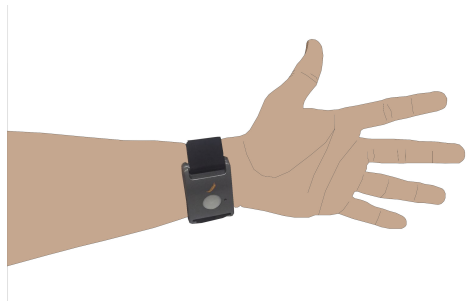


Figure 18: EDA sensor: Q sensor.

3.3.3 Cortisol

*I*PRO *Interactive cortisol test* has been selected to determine the cortisol values on real-time without laboratory equipment. Although this product was originally addressed to determine an athlete's relative stress level in a run, the same technique can be used for this experiment. The test was carried out by adding a saliva sample to a buffer. This mixture is placed on a sample pad, where the reader measures the line intensity and obtains the cortisol concentration, expressed in nM. The experiment starts with a real-time saliva analysis to obtain the original cortisol level unaffected by induced stress and finishes with another saliva analysis. The results allows to characterize the saliva cortisol level of each individual and compare them with the reference pattern.



Figure 19: Cortisol test: Buffer bottle and Swab.

4 Signal processing

This chapter describes the complete system developed in order to characterise individual stress reactions. It contains a brief explanation of the preprocessing carried out for signal synchronization, feature extraction and feature selection. This process has been done with the **MATLAB** tool.

4.1 Synchronization

Signals must be synchronized in time in case of using different sensors. Each sensor start and calibration times do not allow this process to be performed manually. For this reason, it has been established a global start time and a duration for the experiment to obtain same length sessions. All the data recorded outside this period is discarded. The final result of this process is illustrated on Figure 20.

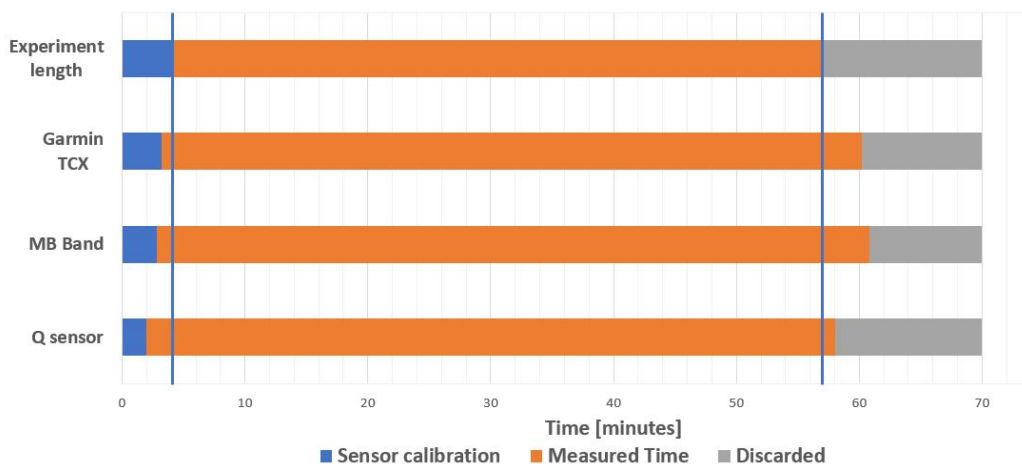


Figure 20: Schedule synchronization for different sensors.

Signals are scaled according to their sampling frequency, in order to correctly represent these data. In the case of the *Microsoft Band 2* the sampling frequency is not continuous and data needs to be manipulated with the purpose of facilitate information process. Since the sampling frequency is close to 1Hz, it has been calculated the total number of samples collected at that frequency and a screening has been performed attending to three possible cases:

- *Excess of samples*: To solve this problem the surplus data has been discarded. In order to avoid a temporary displacement of the signal,

the measurement times have been rounded off and the data of repeated times has been eliminated. This suppose a data loss around 5% but having into account the sampling frequency it does not affect the final shape of the signal.

- *Missing samples*: The presence of voids in the signal has been solved by making a polynomial approximation between the extreme values of the artefact.
- *Coincidence between estimated and obtained samples*: On this case the signal does not need any type of screening.

It is not necessary to perform this type of sift for the rest of sensors, since they have constant sampling frequencies. Once all the signals are scaled to the sampling frequency of their sensor, they are synchronized in time, beginning on the starting time determined on the experiment. This pre-processing generates clean signals from which physiological characteristics can be extracted.

4.2 Feature extraction

Characteristics obtained from biological signals are those that allow to determine different levels of stress. These characteristics are extracted from cardiac activity and electrodermal activity. Another extra feature obtained from the experiment is the cortisol level of the participant.

The duration of each experiment session is 53 minutes. Each feature is extracted during one minute to simplify the database development. This seems that following formulas are calculated for a period of 60 seconds denote with letter i . Each feature is identified using a integer number [Feature X].

4.2.1 Cardiac Activity

Cardiac Activity is analysed by means of the RR interval. It comprises the time elapsing between two consecutive R waves in the electrocardiogram. From this signal, it is possible to extract the Heart Rate Variability (HRV). HRV analyses the physiological phenomenon of the oscillation in the interval between consecutive heart beats [31]. It is a measure of neurovegetative activity and the autonomous function of the heart [32]. The HRV measurement is done on both time and frequency domain.

Time Domain

On time domain, the standard HRV measurements, are related to the variance of RR intervals. The following have been selected for feature extraction.

- [Feature 1]: standard Deviation of all NN intervals (SDNN).

$$SDNN = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (RR_i - \overline{RR})^2}$$

- [Feature 2]: the square root of the mean of the sum of the squares of differences between adjacent NN intervals (RMSSD).

$$RMSSD = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (RR_{i+1} - RR_i)^2}$$

- [Feature 3]: number of pairs of adjacent NN intervals differing by more than 50 ms in the entire recording divided by the total number of all NN intervals (pNN50).

$$pNN50 = P(|RR_{i+1} - RR_i| > 50ms)$$

Frequency Domain

In the frequency domain high and low frequency components of HRV and its ratio has been calculated. The LF_{HRV} band in HRV, 0.04-0.15 Hz, is thought to reflect the activity of the sympathetic nervous system (SNS) and the baroreflex (blood pressure), while the HF_{HRV} band, 0.15-0.4 Hz, is believed to correspond to the activity of the parasympathetic nervous system (PNS).

- [Feature 4]: ratio of the power in the LF_{HRV} and HF_{HRV} frequency bands reflects the degree of sympathovagal balance with a higher ratio representing dominant sympathetic activity and a lower ratio indicating an increased vagal modulation [33].

$$LF/HF \text{ ratio} = \frac{\int_{0.04Hz}^{0.15Hz} f(\lambda) d\lambda}{\int_{0.15Hz}^{0.40Hz} f(\lambda) d\lambda}$$

4.2.2 Electrodermal Activity

This work use the method developed for F. Hernando and free available at <https://github.com/fhernandogallego/sparsEDA>. This algorithm allows to extract two GSR components (features) that should be interesting for SNS studies:

Tonic component (SCL): The slope is related to the level of attention of the subject. If the patient is concentrated and/or involved in a task, an increasing slope should be observed [34]. Otherwise, the SCL slope should either decrease or remain constant.

Phasic component (SCR): This is the indicator of SNS reactions. The proposed method allows us to extract both their locations and durations. Furthermore, the sparsity of the resulting signal enhances its interpretability, whereas the post-processing stage allows to avoid false alarms.

Features obtained from GSR signal components are the following for each minute represented as $i - th$ interval:

- [Feature 5]: SCL slope.

$$m_i = \frac{SCL_{i+1} - SCL_i}{t_{i+1} - t_i}$$

where SCL are the values of the slope for the $i - th$ interval and t is the time lapsed (in this case are always 1 minute).

- [Feature 6]: SCR peaks on an interval.

$$SCR_i = \sum(d_i > 0)$$

where d is the driver obtained for each $i - th$ interval.

- [Feature 7]: area under the curve (AUC).

$$AUC_i = \sum d_i$$

and finally the values of the driver for each $i - th$ interval are summed.

4.2.3 Cortisol

- [Feature 8]: a cortisol test is performed by the participant right before and after of the experiment realization. The difference between obtained values provides a feature of the stress levels subjected by the participant during the experiment.

4.3 Linear Regression

Linear regression (LR) is a statistical tool that allows to regress a variable as a function of the extracted characteristics. LR attempts to model the relationship between several variables by fitting a linear equation to observed data. One variable is considered to be an explanatory variable, and the other ones are considered to be dependent variables. The LR systems assign different weights to each of the input variables depending on the information provided by each one.

Firstly, a linear model is created to apply machine learning techniques and extract conclusions,

$$SCORE = f(\text{individual performance, test, chronic stress, real-time stress})$$

where each of the functions are calculated using parameter saved on the dataset:

- Individual performance is drawn by means of the linear regression with the scores of the 10 tests carried out by each participant.
- Cortisol function is obtained from the initial and final cortisol levels.

$$f(\text{chronic stress}) = \frac{\text{cortisol}_{final}}{\text{cortisol}_{initial}}.$$

- Test function is given by the increment in difficulty of the games provided by *Lumosity Labs*.
- Stress function is calculated with the features extracted from the signals and their applied weight.

$$f(\text{real-time stress}) = \sum_{i=1}^n (w_i * x_i),$$

where n is the number of features.

4.4 Stress Characterization

Each participant achieve different scores despite the experiment has the same structure. The goal of this characterization is to normalize the scored obtained and then, simulate a possible Yerkes & Dodson curve for each subject.

Scores are normalize for each test over the mean of all of them. This division seems an global overview for each test. Finally, a histogram for each task is obtained to know the performance.

4.5 Feature Selection

The selection of the real-time features is calculated using the Mean Square Error (MSE) between the normalized scores and the linear regression obtained.

$$MSE_i = \sum_{i=1}^N (\text{score} - w_i * x_i)^2$$

where i is the iteration of the $i - th$ feature leave out of the MSE and N is the number of features. The MSE is calculated using the method Leave One Out (LOO) so this work find the minimum MSE obtained to know with parameters are more/less important in the regression.

$$\min_{x_1, \dots, x_N} MSE_i$$

5 Results

This chapter presents the results of different level stress classification using physiological signals. The study has been performed on nineteen participants, but for simplicity, only the results of a random participant are presented.

The analysed signals of EDA and HR for the selected participant are shown in the following Figure 21, as well as the obtained results for the first part of the experiment. Each of the signals have been captured with two different sensors to avoid data loss on the case that one of the sensors does not acquire the signal properly. Both signals had been correctly acquired in most cases. Given this situation, it has been chosen to select the signals obtained by the *Q sensor* and *Garmin forerunner 310XT* for EDA and HR signals respectively, since they present higher resolution.

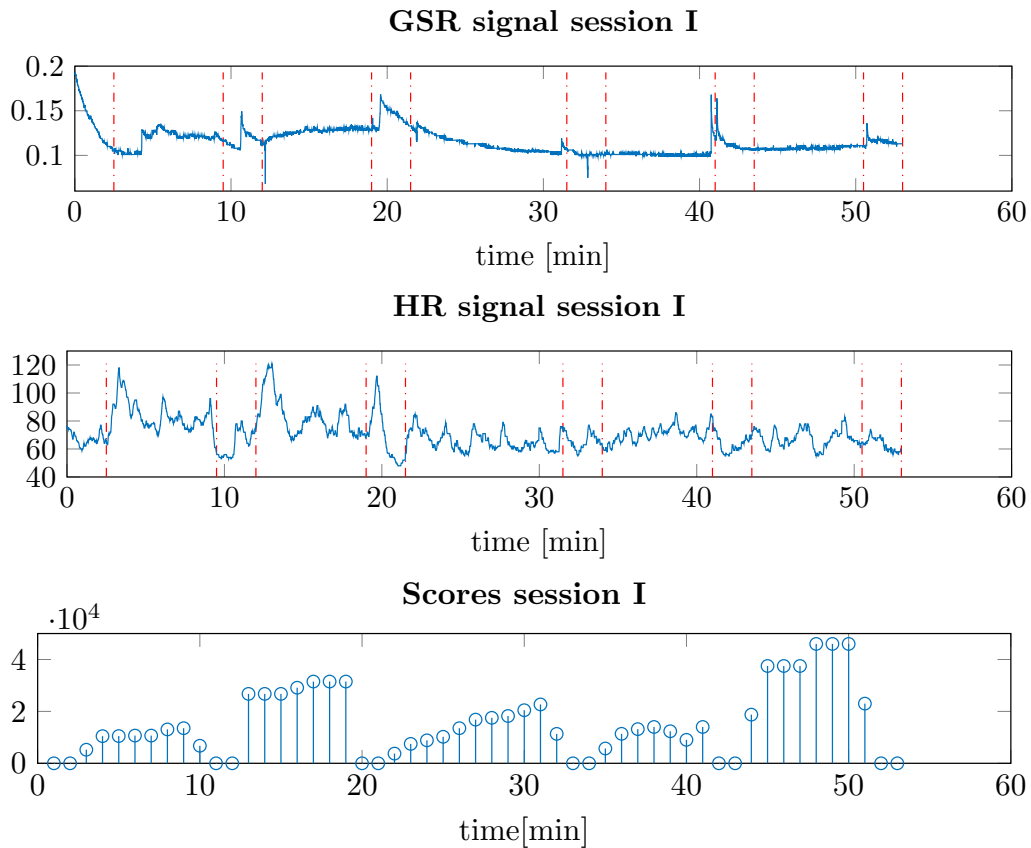


Figure 21: Data collected for the first session of the experiment.

5.1 Individual characterization

A linear regression has been performed with the obtained scores of each participant to obtain a regression fit line that allows to normalize them. An example of the scores obtained for the first task and its regression fit are shown on Figure 22. Once the linear regression of each game is obtained, the normalization of the different scores is carried out for each participant by the mean of all of them.

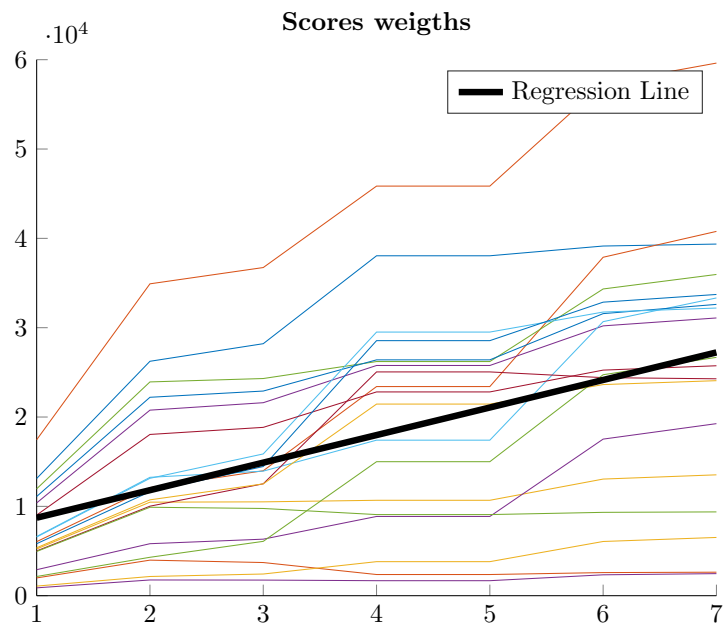


Figure 22: Scores Linear Regression.

The normalized scores obtained by one participant for both sessions of the experiment are shown in Figure 23. Additionally, on Figure 24 the different normalized skills measured by the experiment are appreciated on a performance histogram.

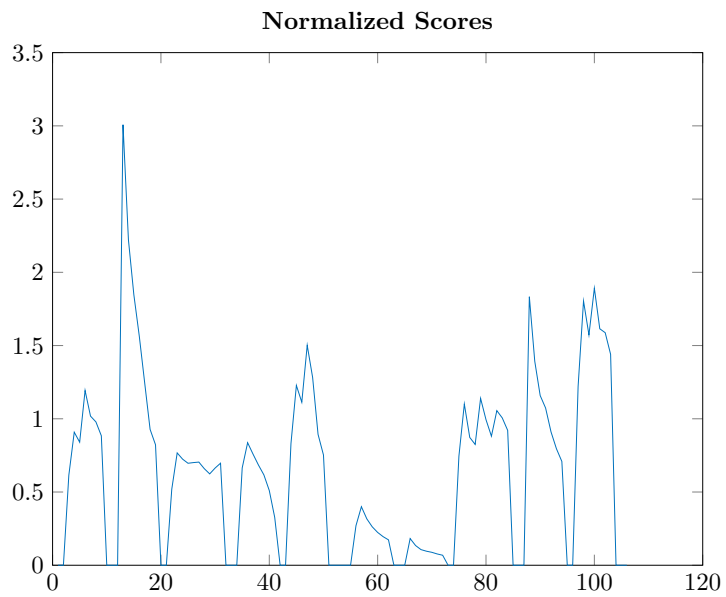


Figure 23: Normalized Scores.

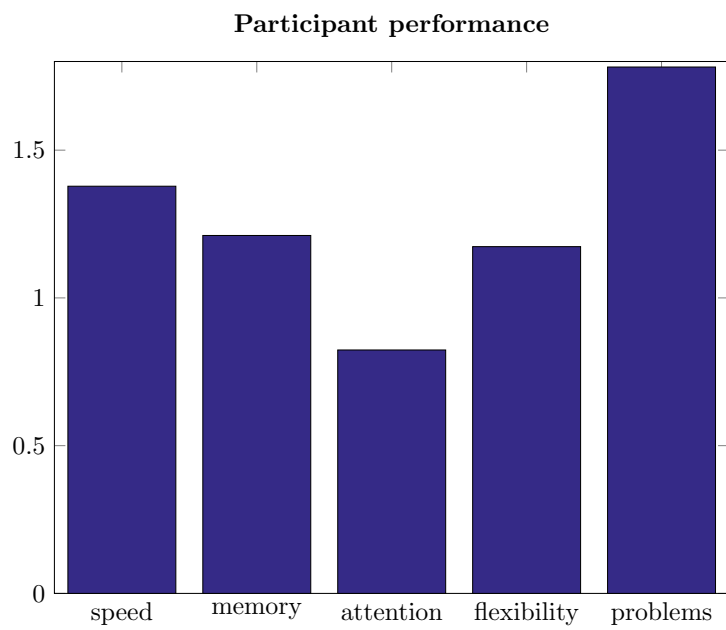


Figure 24: Performance Histogram.

From these data an approximation has been made to the Yerkes and Dodson curve shown on Figure 25.

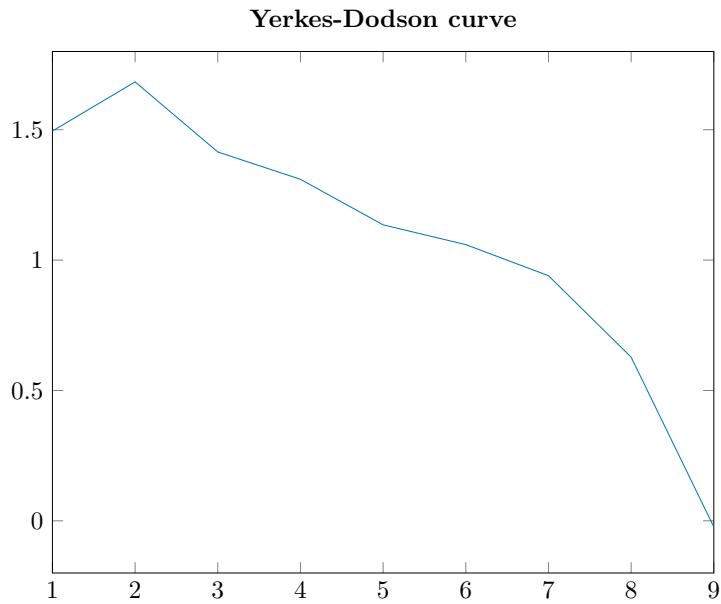


Figure 25: Yerkes-Dodson curve.

5.2 Feature extraction

Features extracted from EDA and HR that allow the characterization of the participant are shown on Figure 26 and Figure 27 respectively.

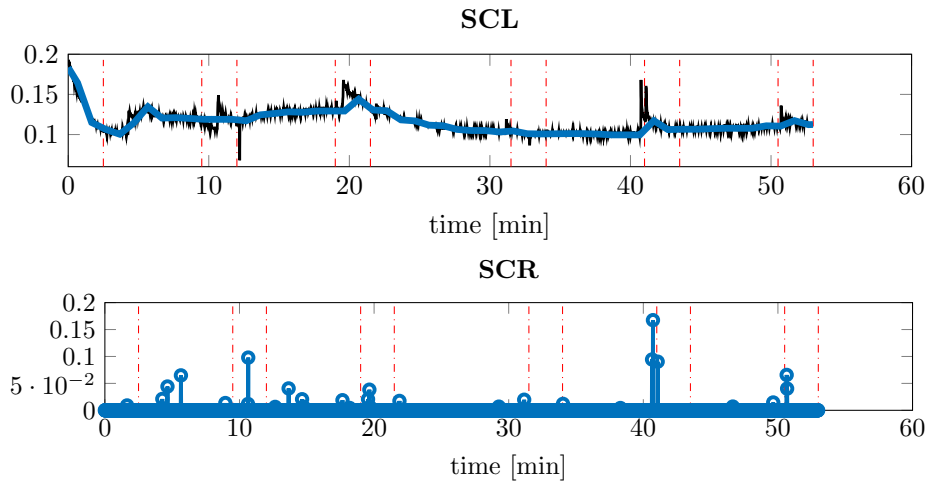


Figure 26: EDA features, in black is represented the signal, the first one shows in blue the slope and the second one the driver extracted. Vertical lines in red difference tests and relax slots.

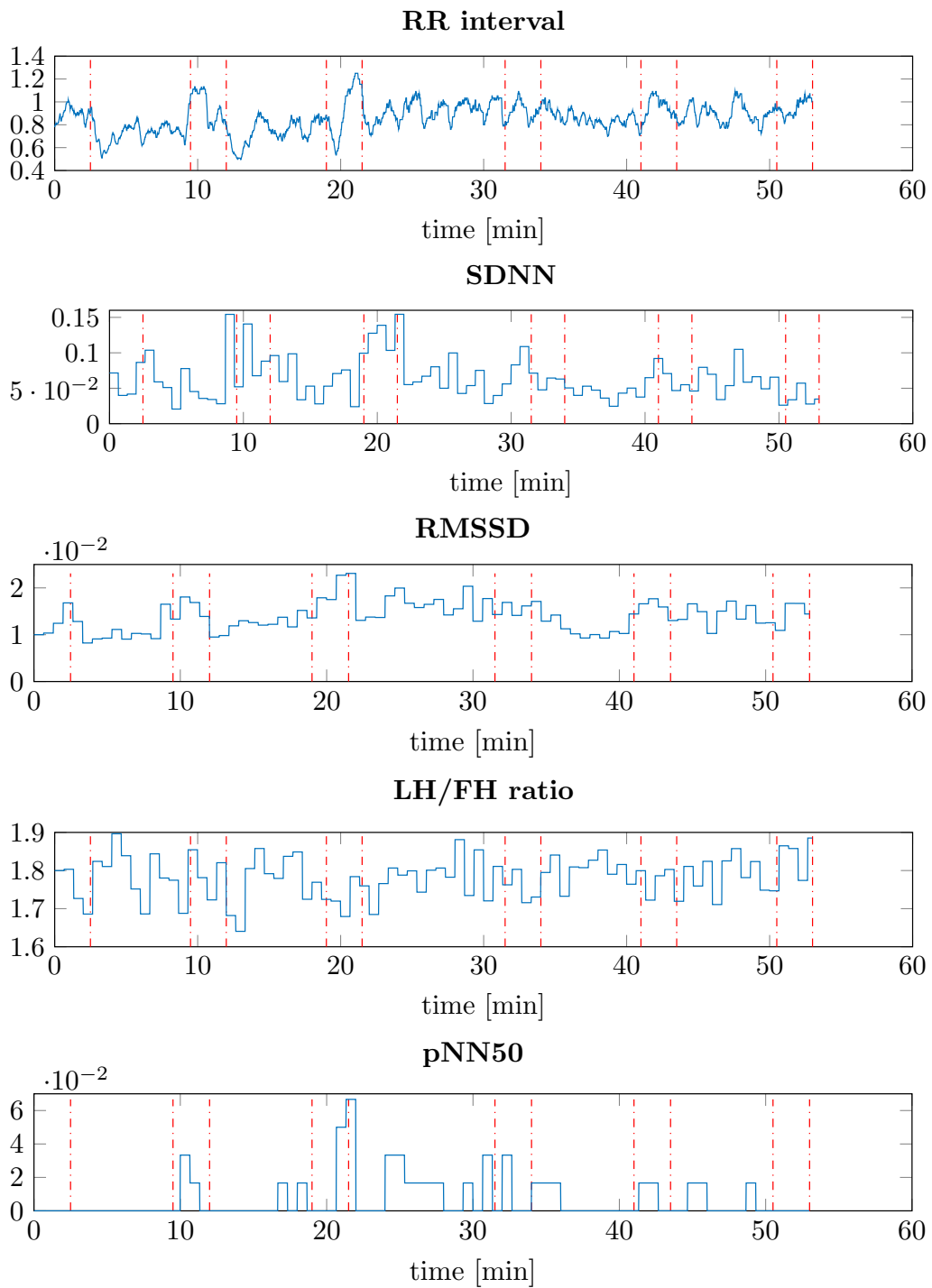


Figure 27: HR features.

A regression of the extracted characteristics of the signal to the normalized scores is fulfilled. On Figure 28 can be appreciated an example of how the weights of the different features adjust to the normalized scores, appearing rise during the performed tasks and falls during rest periods.

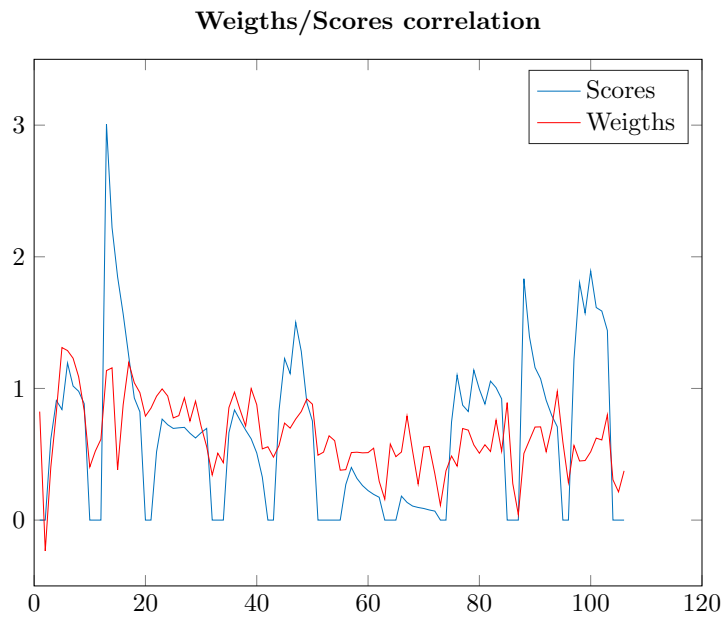


Figure 28: Weight /Scores Correlation.

For the selection of characteristics, the MSE between the normalized scores and the linear regression has been used. This adjustment to the error provides the weight of the different characteristics extracted from the signals. By minimizing the error, the characteristics with higher weights are obtained, and by maximizing it, the ones that provides less information.

On Figure 29 can be seen that the features that provides less information about the stress state of the participants are SCR and SDNN. On the other hand, Figure 30 shows the most relevant ones for the characterization of stress, that are LF/HF ratio and AUC.

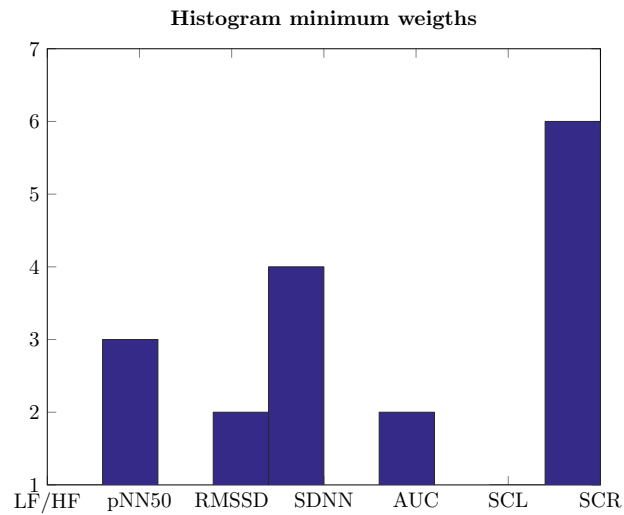


Figure 29: Maximized MSE: Minimum Weights.

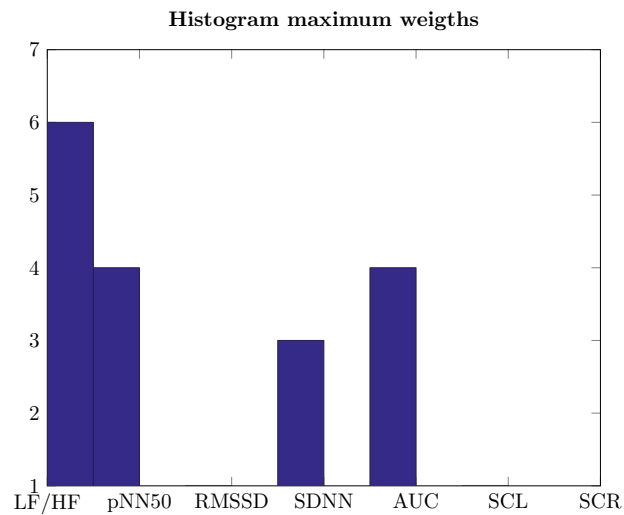


Figure 30: Minimized MES: Maximum Weights.

6 Regulatory framework

6.1 Applicable legislation

This work analyses a physiological signals database from a set of 19 participants that have accepted to participate free and selflessly on a voluntary basis. As the “*Ley Orgánica 15/1999, of December 13, de Protección de Datos de Carácter Personal*” establishes, any personal data used for research purposes needs the consent of the involved individual and does not allow the publication of any personal information. On that basis all participants have been informed of the current legislation as well as the possibility of exercising their rights to access, rectify, cancel and oppose any personal data, and have signed a consent document of data transfer.

The main principles the “*Ley Orgánica 15/1999 de Protección de Datos de Carácter Personal*” establishes are the following:

- The purpose of any study that uses the data must be informed and consented by the participants.
- The data must be updated and deleted when no longer useful.
- Before the data is used by third parties, the individuals must be informed and asked for consent.

6.2 Technical standards

The following software have been used:

Experiment

The experiment has been carried out using Lumosity games developed by *Lumosity labs*, a brain training and neuroscience research company. A research license is necessary in order to use this software on academic studies since it is not an open source. The license includes 100 research accounts designed to use one per study participant.

Free access software from different sensors have been used for data extraction. This software includes: *Q of Afectiva*, *Microsoft Band 2* and *Garmin Express*.

Data processing

Signals have been subjected to manipulation in order to improve its quality and facilitate the information processing. The developed software for this

end as well as the process of the statistical data have been created with **MATLAB**.

6.3 Intellectual property

All the data obtained on this experiment as well as the developed software are stored on a secure server of the *Department of Signal Theory and Communications* on *Universidad Carlos III de Madrid* in order to guarantee the security of the data and the personal information of the participants.

Future applications of this work go through the design of a complete system of stress detection on real time. For that purpose the *Microsoft Band 2* can be used as measuring device. Obtained data are sent to a computer that uses the developed software to give a stress value and returns a real time result to the MB band.

7 Socio-economic framework

Throughout this chapter, the planning of the work and a summary of the necessary budget for the complete accomplishment of the work are described, as well as the socio-economic impact of the obtained results.

7.1 Work planning

This project has been developed as a continuation of the internship practices carried out in the *Department of Signal Theory and Communications*. For that reason, it has required a larger time inversion.

The project has been divided on five different phases: documentation, design, experiment conduction, results and memory composition. Duration and composition of each of the phases are described on Table 3.

Phase	Task	Time (h)
1.Documentation	Literature study	14
	Sensors familiarization	8
	Tools familiarization	8
2.Design	Experiment design	18
	Prototypes testing	15
	Scripts development	50
3.Experiment	Experiment performance	48
	Results preprocessing	22
4.Results	Data processing	80
	Feature extraction	14
	Algorithm optimization	20
5.Memory	LaTeX environment familiarization	8
	Memory composition	72
	Memory review	8
	Presentation	15
TOTAL		400

Table 3: Project planning: Description of the Bachelor Thesis.

7.2 Budget

The budget for the realization of the project can be divided in two parts: material costs and personal costs.

Personal costs

For the calculation of the personal costs it has been taken into account the Official College of Telecommunication Engineers fees table. It establishes a 150 €/hour rate for a project director and a 60 €/hour rate for a junior engineer. This last statistic have been employed as an approximation for the rate of a biomedical junior engineer since there is no available information for this degree yet. The total personal cost of the project has been calculated having into account that the 15% of the 400 hours dedicated to the project have been shared with the tutor, resulting in **33.000 €**.

Material costs

For the calculation of the material cost it has been taken into account that the duration of the project has been of 5 months and that the amortization of the used computer, as well as the sensors, is of 5 years. Besides those costs, it is estimated that there exist a 20% of indirect expenses.

The total of the expenses are itemized on Table 4

Material	Total cost (€)	Project cost (€)
Computer	1500	150
MB	350	35
Qsensor	400	40
Garmin	300	30
Cortisol test	890	890
LFC reader	450	45
Indirect expenses (20%)		238
TOTAL		1.428

Table 4: Material cost detail.

After applying Value Added Tax (VAT), the total cost of the project is 34.670 € as shown in Table 5.

Concept	Cost (€)
Personal	33.000
Material	1.428
V.A.T. (21%)	7.299
TOTAL	41.657

Table 5: Breakdown of total project cost.

7.3 Socio-economic impact

According to the World Health Organization (WHO) [5], stress is the second cause of heart diseases in developed countries, specially among positions of high responsibility. As the WHO states, stress at workplace is not only a matter of health, but also a risk for the companies. Stress increases absenteeism and reduces the performance of the employees. It also causes accidents due to the lack of concentration in those employees who suffer stress.

The socio-economic impact of this project depends on the future design of a complete system of stress detection on real time. This application would allow the patient to obtain a stress value on a determinate scale as a function of his physiological responses. Stress level calibration would be done based on the data obtained on this project, being used as reference frame, and the software developed for signals feature extraction.

The target of this product would be people under a high physical and physiological pressure as well as people suffering from chronic stress that require continuous monitoring. Signal recording would allow posterior medical analysis of the data, making it available as an element of diagnosis.

8 Conclusions and future work

This chapter present the conclusions of the results obtained on the development of this work and shown in Chapter 5. In addition, possible future lines of research derived from this work are proposed.

- I. The main goal of this project was to classify different stress levels using physiological signals. For this purpose, it has been possible to develop a complete system of stress detection using cognitive games. This system allows to capture physiological signals in real time, for later characterization, while carrying out a series of cognitive tasks that elicit stress.
- II. With the purpose of obtaining the physiological signals, a series of biomedical devices have been manipulated, developing a precise synchronized measurement system. The devices used are non-intrusive and the results and the signal acquisition were satisfactory providing a feasible system.
- III. The physiological acquired signals had been EDA and HR, as well as the cortisol levels of the participants. Those signals had undergone a synchronization pre-processing and a feature extraction processing in order to be able to extract their characteristics.
- IV. Different methods of machine learning have been tested for the extraction and selection of characteristics. The 10-fold cross-validation model has provided suitable results for the developed method.
- V. Furthermore, a linear regression has been carried out to obtain the performance level according to three parameters: Individual characterization of the participant, task difficulty and physiological signals. This performance level has been adjusted to the different abilities of the participant on the tasks accomplished during the experiment.
- VI. Finally, it has been possible to obtain the most relevant features on stress classification and the approximation of a Yerkes and Dodson curve.

Taking this Bachelor Thesis as a reference, some future lines of research can be followed to improve the obtained results, and for the development of a complete system of stress detection on real time.

- I.** Increase the number of test subjects in order to improve the dataset, which would allow the system to use more training techniques.
- II.** Perform the experiment several times on the same participant in order to analyse the learning curve.
- III.** The completion of a questionnaire about the level of stress experienced by the participant throughout the experiment that allows to add a new characteristic to the system.

A List of Acronyms

ANS	Autonomic Nervous System
BVP	Blood Volume Pulse
EDA	Electrodermal Activity
GSR	Galvanic Skin Response
HFHRV	High Frequency Heart Rate Variability
HR	Heart Rate
HRV	Heart Rate Variability
LFHRV	Low Frequency Heart Rate Variability
LOO	Leave One Out
MSE	Mean Square Error
pNN50	Number of pairs of adjacent NN intervals differing by more than 50 ms
PPG	Photoplethysmography
PSNS	Parasympathetic Nervous System
RMSSD	Root of the mean of the sum of the squares of differences between adjacent NN intervals
SCL	Skin Conductance Level
SCR	Skin Conductance Response
SDNN	Standard Deviation of all NN intervals
SNS	Sympathetic Nervous System
STAI	State-Trait Anxiety Inventory
WHO	World Health Organization

References

- [1] E. D. Weitzman, D. Fukushima, C. Nogueira, H. Roffwarg, T. F. Gallagher, and L. Hellman, "Twenty-four hour pattern of the episodic secretion of cortisol in normal subjects," *The Journal of Clinical Endocrinology and Metabolism*, vol. 33, no. 1, pp. 14–22, 1971.
- [2] A. Ghosh, M. Danieli, and G. Riccardi, "Annotation and Prediction of Stress and Workload from Physiological and Inertial Signals," *2015 37Th Annual International Conference of the Ieee Engineering in Medicine and Biology Society (Embc)*, pp. 1621–1624, 2015.
- [3] A. Sinha, P. Das, R. Gavas, D. Chatterjee, and S. K. Saha, "Physiological Sensing based Stress Analysis during Assessment," 2016.
- [4] H. Selye, *The stress of life*. McGraw-Hill, 1984.
- [5] World Health Organisation, "Guidelines for the Management of Conditions Specifically Related to Stress," *Assessment and Management of Conditions Specifically Related to Stress: mhGAP Intervention Guide Module (version 1.0)*, pp. 1–273, 2013.
- [6] World Health Organization, "Work organisation and Stress," *Protecting Workers Health*, no. 3, pp. 1–27, 2003.
- [7] B. H. Chew, A. Zain, and F. Hassan, "Emotional intelligence and academic performance in first and final year medical students : a cross-sectional study," 2013.
- [8] Y. Alkahrer, O. Dahan, and Y. Moshe, "Detection of Distress in Speech," 2016.
- [9] C. L. Stephens, I. C. Christie, and B. H. Friedman, "Autonomic specificity of basic emotions : Evidence from pattern classification and cluster analysis," *Biological Psychology*, vol. 84, no. 3, pp. 83–93, 2010.
- [10] J. D. Yerkes, Robert M and Dodson, "The relation of strength of stimulus to rapidity of habit-formation," *Journal of comparative neurology and psychology*, 1908.
- [11] P. Renaud and J.-p. B. U, "The stress of Stroop performance : physiological and emotional responses to color word interference , task pacing , and pacing speed," pp. 87–97, 1997.

- [12] N. Takai, M. Yamaguchi, and T. Aragaki, “Effect of psychological stress on the salivary cortisol and amylase levels in healthy young adults,” pp. 963–968, 2004.
- [13] J.-x. Chen, J. Ding, Y. Liang, and H.-m. Rao, “Effect of Xiaoyaosan on Changes of Behavior in Chronic Immobilization Stress Rats,” no. 30672578, 2009.
- [14] A. H. Marques, M. N. Silverman, and E. M. Sternberg, “Evaluation of stress systems by applying noninvasive methodologies: Measurements of neuroimmune biomarkers in the sweat, heart rate variability and salivary cortisol,” *NeuroImmunoModulation*, vol. 17, no. 3, pp. 205–208, 2010.
- [15] S. Ranabir and K. Reetu, “Stress and hormones,” *Indian J Endocrinol Metab*, vol. 15, no. 1, pp. 18–22, 2011.
- [16] C. Touma, R. Palme, and N. Sachser, “Analyzing corticosterone metabolites in fecal samples of mice: A noninvasive technique to monitor stress hormones,” *Hormones and Behavior*, vol. 45, no. 1, pp. 10–22, 2004.
- [17] L. Luo, L. Xiao, D. Miao, and X. Luo, “The Relationship between Mental Stress Induced Changes in Cortisol Levels and Vascular Responses Quantified by Waveform Analysis: Investigating Stress-Dependent Indices of Vascular Changes,” *2012 International Conference on Biomedical Engineering and Biotechnology*, pp. 929–933, 2012.
- [18] B. Relaxation, “Sympathetic Nervous System Activity in Stress and Biofeedback Relaxation,” no. April, pp. 52–57, 2005.
- [19] S. Parvanehl, N. America, and K. S. Branch, “Impact of Mental Stress on Heart Rate Asymmetry,” pp. 793–796, 2015.
- [20] E.-H. Jang, B.-J. Park, M.-S. Park, S.-H. Kim, and J.-H. Sohn, “Analysis of physiological signals for recognition of boredom, pain, and surprise emotions.,” *Journal of Physiological Anthropology*, vol. 34, pp. 1–12, 2015.
- [21] W. Boucsein, *Electrodermal activity*. Springer Science & Business Media, 2012.
- [22] S. Taylor, N. Jaques, W. Chen, S. Fedor, A. Sano, and R. Picard, “Automatic Identification of Artifacts in Electrodermal Activity Data,” pp. 1934–1937, 2015.

- [23] V. G. Macefield and B. G. Wallin, “The discharge behaviour of single sympathetic neurones supplying human sweat glands,” 1996.
- [24] M. M. Bradley and P. J. Lang, *Handbook of psychophysiology*. Handbook of psychophysiology, 2000.
- [25] E. Hudlicka, “To feel or not to feel : The role of affect in human – computer interaction,” vol. 59, pp. 1–32, 2003.
- [26] C. L. L. U, C. Rennie, R. J. Barry, H. Bahramali, I. Lazzaro, B. Manor, and E. Gordon, “Decomposing skin conductance into tonic and phasic components,” pp. 97–109, 1997.
- [27] M. Benedek and C. Kaernbach, “A continuous measure of phasic electrodermal activity,” *Journal of Neuroscience Methods*, vol. 190, no. 1, pp. 80–91, 2010.
- [28] “Garmin forerunner 310XT Users manual.” <https://www.garmin.com/es-ES>.
- [29] “Microsoft Band 2 Experience Design Guidelines.” <https://www.microsoft.com/microsoft-band/en-us>.
- [30] “Q users manual.” <http://qsensor-support.affectiva.com/>.
- [31] Guidelines, “Guidelines Heart rate variability,” *European Heart Journal*, vol. 17, pp. 354–381, 1996.
- [32] M. Vollmer, “A robust, simple and reliable measure of heart rate variability using relative RR intervals,” *Computing in Cardiology*, vol. 42, no. 6, pp. 609–612, 2016.
- [33] T. Chanwimalueang, L. Aufegger, W. V. Rosenberg, and D. P. Mandic, “Modelling stress in public speaking : Evolution of stress levels during conference presentations. Theerasak Chanwimalueang , Lisa Aufegger , Wilhelm von Rosenberg , Danilo P . Mandic,” pp. 814–818, 2016.
- [34] J. Hernandez, I. Riobo, A. Rozga, G. D. Abowd, and R. W. Picard, “Using electrodermal activity to recognize ease of engagement in children during social interactions,” in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 307–317, ACM, 2014.