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Desarrollo de un Sistema de Identificación de Estrés Académico Usando la Técnica de Fotopletismografía Remota

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Development of an Academic Stress Identification System Using Remote Photoplethysmography Technique

by

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Abstract

Stress is the disease of our society. Mental health has become a key priority in private and public sectors. Some governments are becoming to consider stress, a public health affair. Costs associated to stress are quantified in millions of US dollars every year and it's impacting in economic development, productivity, health and well-being.

When stress is presented at school or as a result of any academic activity, such presence of stress, called academic stress, becomes of fundamental relevance due to the consequences that academic stress triggers in some students. From low academic performance to critical mental affections, academic stress has been studied profoundly, due to ultimately fatal consequences.

The fundamental question is if there is any novel way to provide academic stress levels using video recordings and demographics data by using anxiety as the body response to stress and become the predictive label for machine learning classifiers.

In chapter 1, the background of stress, all techniques and tests associated to stress detection and the problem statement is described in order to provide a framework for the research. The hypothesis is enunciated and the scope and limitation of the research is defined.

In chapter 2, a deep description of the different methods, techniques, technologies and innovations are described. An initial overview on how stress can be detected using physiological responses is presented and then is deeper analyzed to understand technologies and innovations from the state-of-the-art to finally provide the theoretical framework to go deeper into the selected technologies to be used for solving the problem.

In chapter 3, the proposed methodology to gather data and finally solve the problem, is described. One of the main goals of the research is to produce a non-invasive, low-cost tool that can used in the academic environment with no special setup. The methodology provides the theoretical elements to implement this tool and obtain the expected results.

In chapter 4, a summary of the research article is presented and a number of recommendations based on the methodology are described. For further information, the reader might consult the research article, where all detailed information is described in detail.

Finally, in chapter 5, the discussion, results and conclusions are presented, where the reader will be able to understand that the proposed methodology lead to accept the hypothesis, with similar or better results provided using other methods.

Chapter 1

Introduction

In agreement to *"Reglamento de Estudios Avanzados"* of *Universidad Autónoma del Estado de México*, articles 59 and 60BIS, the modality to obtain the master degree is via a research article on indexed publication. A summary of the article can be seen on Chapter 4.

1.1 Background

Stress is one of the most common affections of our society. Stress signs can be observed from little children to elders, in school homework and personal financial management. According to Putwain [1] *"Academic Stress is defined as to all of the work conducted in school lessons, the homework and preparation for the SATS as well as the examinations themselves"*. Also, Kitsantas [2] research shows that up to 75% of students present some sign of stress during the first year, whereas Ros-González [3] has shown that stress causes up to 50% of the school dropouts during the first year. In an interview done in September 2018 to Alejandro Gutierrez Cedeño, CESPI Director, Behavior Sciences School at Universidad Autónoma del Estado de México, said that *"...suicide and homicide are really close between them. The igniting factor is stress"*

Stress prognosis is not new and has been researched from different angles and using different perspectives. Cedeño also suggests that stress should be summarized as follows [4]:

1. Stress can be catalogued as a set of observable physiological signs such as sweating, accelerated heart rate and breathing, facial gestures or quick eye blinking. Other signs not necessarily observable but measurable can be muscle tension, heart rate variability and brain signals.

2. There is a set of psychological symptoms derived from stress, which are diagnosed by the specialist via standard tests such as anxiety levels tests, distress or depression. In general, any test that provides indications of the psychological state derived from stressful activities.

3. The behaviors from stress are one of the main areas of study, mainly when these are affecting individual's life or the society surrounding him or her. Commonly in academic environments, these

behaviors are associated to sleep or nutrition disorders but also others like evasion or aggressiveness. These behaviors can also be correlated by using results from specific anxiety levels tests for instance.

These facts and research papers lead us to several questions around stress and more specifically to academic stress and the means to prevent it by using technology:

- Is academic stress a result of a particular activity?
- What are the underlaying causes of academic stress?
- Can academic stress be measured?
- Is it possible to quantify academic stress and provide metrics of the "amount of stress" of an individual?
- And more importantly, by using these metrics and their interpretation can we provide tools that helps specialists to anticipate and eventually manage stress?

1.1.1 Psychological tests associated to stress level assessments

Anxiety was defined by Freud as *"something felt"*. It might be considered as an emotional state accompanied of nervousness, distress, feelings of apprehension, tension, and worry accompanied by an increase of physiological behaviors and potentially, body responses. Freud also observed that anxiety was a response to certain stressful situation that led to a behavior that individuals showed in threatening situations. In most of the known psychiatric disorders, intense anxiety was present, but not only present on those individuals with such disorders, but also present in other situations, where individuals were under stressful situations. Cattell (1966) showed the importance of measuring anxiety properly: as a response to a specific condition, called an emotional state, or as part of a personality trait [5].

The proposed research is focusing on the stress derived from academic activities, thus stress as a consequence. By proposing a non-invasive tool that correlates anxiety with a physiological sign, it will be able to provide information from observable physiological signs in order for the specialist to identify stress signs and be able to provide management and potential treatments.

As such, anxiety and other behaviors associated to stress and depression have been studied mainly after the second half of the twentieth century. There are a number of existing tools such as psychological scales and tests as well as devices and sensors that focus on specific observable signs such as anxiety, distress or depression.

In 1960, Max Hamilton [6] published a paper briefing on self-assessments ratings for measuring mental disorders for war veterans. This scale consisted of 17 variables, which included anxiety stages, including depression. The Hamilton Scale of Depression, is one of the very first psychological tests were developed to diagnose stress using anxiety as the lead factor. Today, there are many other psychological tests that are used for stress prognosis, derived from his work.

The most common test to measure anxiety is the Spielberger State-Trait Anxiety Inventory (STAI) [7]. It is a reliable and useful scale that provides both state and trait anxiety measures. Its popularity has meant that researchers are able to compare their results with those of others. The one drawback, however, with the STAI test is its length, being 40 items long, compared to other stress tests or scales, which are shorter. The test consists of two questionnaires of 20 items each. The first questionnaire measures state anxiety −how one feels at a specific moment or after doing a stressful activity− whereas the second, trait anxiety− measures how an individual generally feels−. In particular, this scale measures the anxiety that a person has developed since chilhood and it is associated to a personal characteristic or trait. There are two versions STAI questionnaires: one produced in 1970 (Form X), the other in 1983 (Form Y) [8]. Respondents fill in the answer forms, responding to the questions depending upon if state is assessed as how he or she feels at an specific situation, or how generally she or he feels. Higher scores are positively correlated with higher levels of anxiety.

A second test is the Adult Manifest Anxiety Scale (AMAS), which is an assessment used to evaluate the level of anxiety experienced by individuals across the lifespan, developed by Reynolds, Richmond and Lowe [9]. AMAS test battery consists of three instruments: the AMAS-A (Adult), AMAS-C (College) and AMAS-E (Elderly). The AMAS-C (College) are intended for use in screening and evaluating anxiety in college students. The AMAS-C has four anxiety scales and one validity test: worry and oversensitivity scale (WOS), physiological anxiety scale (PHY), social concerns stress scale (SOC) and test anxiety scale. It also provides a validity or lie scale for proper results correlations of the main four scales.

Finally, there is the Sheldon Cohen Perceived Stress Scale (PSS) [10], which is the most widely used psychological instrument for measuring the perception of stress in the work environment. In general, this instrument pretends to measure the situations, internal or external to any activity, school or workplace, on how an individual perceives the related activities associate to its own life, if they are unpredictable, uncontrollable and how much overloading might influence respondents' lives. PSS scale assess the individual's time span over the last 30 days, so it can analyze potential tasks or situations affecting current individual's performance. In each case, respondents are asked how often they felt a certain way. Table 1.1 shows a high level comparison of the described stress tests commonly used.

Comparison of Common Stress Tests	State-Trait Anxiety Inventory	Adult Manifest Anxiety Scale	Perceived Stress Scale
Main Measurement	Anxiety	Anxiety	Stress
Time span	Lifespan (Trait) Event (State)	Lifespan	4-8 weeks
Use for Undergraduate Students	Yes, recommended	Specific Test (AMAS-C)	Yes, requires at least junior high-school
Correlation of Trait and State	Yes	No	No
Scales	State anxiety scale Trait anxiety scale	Worry/Oversensitivity Scale, Physiological Anxiety Scale, Social Concerns/Stress Scale and Test Anxiety Scale	Perceived Stress Scale
Response time	10-20 minutes for both tests	10-15 minutes per scale	5-7 minutes

Table 1.1: Comparison of commonly used tests to assess anxiety as a measurable factor for stress.

For the purpose of this research, STAI - State Trait – Anxiety Inventory (it will be referenced from the Spanish test as *IDARE - Inventario de la Ansiedad Rasgo-Estado*) will be used due to the widely use and

availability of the test. *IDARE* scales help to understand student both trait and state anxiety levels and are used to detect anxiety after a particular stressful event.
As described in the introduction, stress is the sum of observable physical responses, psychological responses and behavior patterns to an stimulus. The focus of this work is to help behavior specialists in diagnosing quicker stress behaviors by providing a non-invasive tool that correlates a physical sign measure to a psychological pattern response.
According to Norman Endler stress response may include anxiety but not necessarily so [11]. Stress is commonly understood in one of three ways:

a As a stimulus such as a critical event, for example a "stressor". In the academic scenario, this could be a final exam. In this case, anxiety follows the critical event, for example in the form of a post-traumatic disorder (Keane, Taylor, and Penk, 1997).

b As a response to such an event (symptoms). In the academic scenario this might be on a form of high-blood pressure response or bad sleep patterns. In this case, anxiety is part of the response pattern.

c As a transactional encounter between a person and a situation. In this case, anxiety is an accompanying emotion. In the academic case, this can be the emotion after failing an exam or test.

1.1.2 Physiological techniques associated to anxiety and stress measurement

Regarding tools and sensors, which correlates physiological signals with stress conditions, there are a number of them that we will be referencing throughout the research, such as:

- **Electrocardiography (ECG)** [12] – a technique used to measure electric signals from the heart muscle, that correlates and provides heart rate measurements.
- **Oxygen saturation (SO2)** [13] – is a technique that measures the percentage of hemoglobin binding sites in the bloodstream occupied by oxygen. There are different methods that measure oxygen saturation.
- **Electroencephalography (EEG)** [14] – is an electrophysiological monitoring method to record electrical activity of the brain.
- **Electrodermal Activity (EDA)** [15] – Electrodermal activity measures electrical activity on the surface of the skin or originating from within the skin.
- **Electromyography (EMG)** [16] – is an experimental technique that measures physiological variations on the muscle fiber, coming from the exciting of myoelectric signals.
- **Photoplethysmography (PPG)** [17] is an optical technique that uses blood volume changes in superficial capillary veins and arteries from the skin. It is particularly interesting for this research the study and use of this technique and related State-of-the-Art work, given is possible to use low-demand computing resources, potentially mobile and from a low-cost video feed.

1.1.3 Framework

Dupéré in [18] states that, without a doubt, academic stress is one of the main reasons of school dropout, mainly in high-school and undergraduate programs. Stress observed in students under different conditions and situations are handled in different ways. Also, Dupéré suggests that within the same observed group of students, under the same conditions, a few of them have complications to deal with stress derived from school work, whereas the majority is able to manage stress effectively. From the perspective of students, academic stress is seen as workload derived from homework, school related activities and examinations. Derived from academic stress, consequences are observed such as distraction, low or lack of attention, lack of focus, bad sleep patterns, fatigue and anxiety.
Thus, the arising question is if it will be feasible to provide a non-invasive tool with an acceptable level of accuracy using a simple protocol compared to psychological tests such as *IDARE*, on a way that the behavior specialist can make proper and quicker decisions from within the academic environment, instead of waiting for the test interpretation, without depending on subjects responses and associated bias and outside of the real academic environment.
In summary, the development of a non-invasive system, that uses physiological signals derived from academic stress present in anxiety levels will provide analytical information that will be used to correlate these physiological signals with the psychological test results from *IDARE* tests.

1.2 Problem description

From a general point of view, stress occurs when an individual response to external factors is affecting its performance at work or at school and is potentially affecting its health, presenting some disorders such as sleep habits or nutrition. Cohen's states that operationally, stress focus either on the occurrence of environmental events that *"are consensually judged as taxing one's ability to cope or on individual responses to events that are indicative of this overload, such as perceived stress and event-elicited negative affect"* [19]. Academic stress, as defined previously, refers to all the workload derived from academic activities such as classes, assignments, scholar work and most specifically the tests and examinations. But it makes sense to go the next level down. When behaviors want to be measured, for instance, assess the anxiety leves via a psychological test like *IDARE*, it is time consuming, not readily available and also subject to individual response bias. Once stress is clearly appreciated and observed by third parties, it might be at advanced levels. When the student is already under a heavy burden, can be too late to prevent a crisis. Under this context, a crisis might be a chronic fatigue, insomnia or even deteriorated health conditions. In extreme situations, it might lead to eating disorders or depression [20].
For the purposes of this research, academic stress is composed of:

- A set of observable signs, this is what we can see physically, can be measured and compared with others as well as with other physical states.
- A set of symptoms, this is more to what we feel and it might result of a physical response to an stimulus like anxiety, distress or depression.

- A set of behaviors, or the psychological responses to specific situations such as loneliness, nutrition or sleep disorders.

When the problem is analyzed in detail, some challenges are found. Figure 1.1 describes at a high level what it's being discussed.

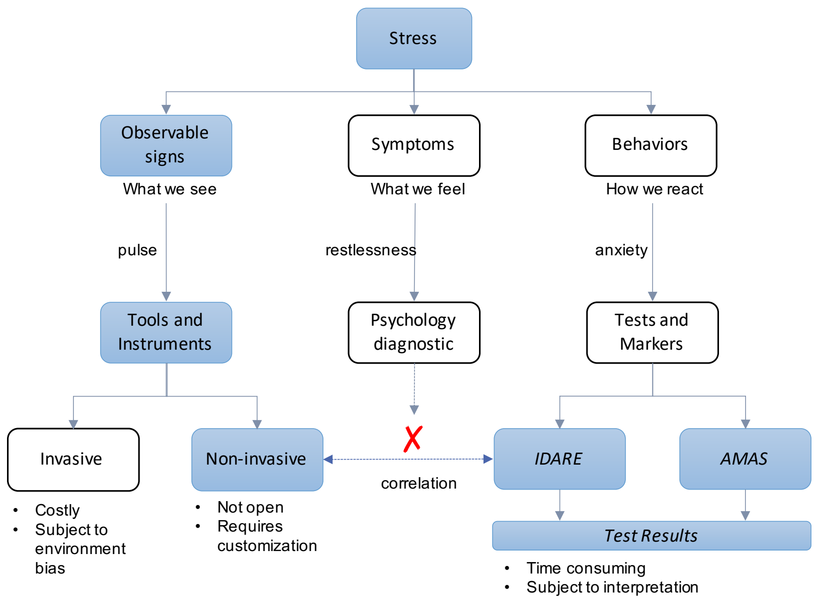

Figure 1.1: Stress as a sum of observable signs, symptoms and behaviors.

These three perspectives have its own set of measures: heart rate, anxiety levels and test psychological responses, for instance. Each of these perspectives are using its own references to measure. Some research papers are starting to discuss the correlation between heart rate with a particular anxiety level or a skin galvanic response with a depression level. However, there are even other observable signs that are evident enough such as skin allergies, skin color changes, nails bitting or sweating that are not researched and correlated to academic stress. This lack of prompt correlation between physiological signs and psychological states makes harder, almost impossible, to make quicker decisions in advance to prevent a stress crisis. Stress detection systems are not new, including those on academic stress detection. Current systems and techniques are mostly either low-cost intrusive or non-intrusive but at higher costs [21]. Research on correlations between anxiety levels and heart rate, oxygen saturation or skin galvanic response have been researched as well leading to acceptable results [22], however these tests have not been applied in academic environments. Most of the observations and tests have been conducted in research labs, where environment itself might lead to a stressful activity *per-se*. There is a very interesting research conducted by Alberti, Aztiria and Basarab, who ran a series of detail tests to measure stress in a multimodal environment [23] with impressive results using different types of sensors and techniques. Unfortunately, these tests can not be extended to a real academic environment due to the complexity and because are subject to a lab environment. However, these results provide a solid background to extend the research to the academic environment. On the other hand, there are very few stress detection systems which provide feedback mechanisms to the user. In 2007, Taelman suggested a ECG shirt which was able to provide some feedback to the user, when high heart rate signals where detected [24] correlating mental workloads. Feedback systems are complex, expensive or non-practical for a simple use [25] [26].

Based on the evidence from observations to a group of 32 undergraduate students from the School of Engineering, UAEMex, who were subject to a stress inducing protocol [27], it was noticed that the environment was leading to a stressful activity: to answer a 20-minute test, it was necessary about 40 minutes for the setup. Between the time to setup and all sensors, connectivity and instructions, some students develop a form of stress before the actual stress test even started.

Overall, all of these systems, invasive and non-invasive, even though have demonstrated good results on stress identification, like Alberdi summarizes in his research [23] they are not suitable to measure academic stress properly in the actual student environment: the classroom.

1.2.1 Proposed solution

The proposed research work will be focused on three main aspects:

- The identification of observable physiological signs using Remote Photoplethysmography (rPPG) non-invasive technique.
- The development of a non-invasive system that is able to correlate to heart rate from video recordings with the psychological responses from the current available tests (*IDARE* specifically) before and after stress test.
- The assessment of the best classifiers, based on the anxiety level correlation to video recordings and the predictive label to *IDARE* scale results within a short period of time after application.

The proposed solution, shown in Figure 1.2, consists on the use of, but not limited to, a low-cost camera, such as a computer webcam, which will be used as the sensor to detect the physiological signals from the subject. The camera will get images from the subject's face, they will be processed and filtered to obtain plethysmography heart rate signal and other facial signals using a technique known as Photoplethysmography (PPG), which is a technique used to non-invasively determine blood volume changes by measuring the absorption of light [17] in skin superficial capillary veins. It is proposed to use a modified PPG technique called Remote Photoplethysmograpgy (rPPG), which makes use of optical imaging sensors, in this case the computer webcam, to measure subtle skin-color changes resulting from blood volume changes in near-surface vessels [28]. Using this technique in combination with the video imaging patterns filters, it will be able to analyze the data in order to identify the main features that can be correlated with a student stress level, for example, skin color changes, heart rate, heart rate variability and others.

As for the stress test, it is suggested to apply the *IDARE* tests, both trait anxiety(SXR) and state anxiety(SXE) before the actual academic stress test and measure the anxiety physical response from rPPG signals. See Figure 1.3 below. It potentially can be applied anytime before academic stress and it is desirable that the student is in low to none academic stress test, in order to clearly separate academic stress from any other stressful activity leading to anxiety. The student will be subject to the academic stress test

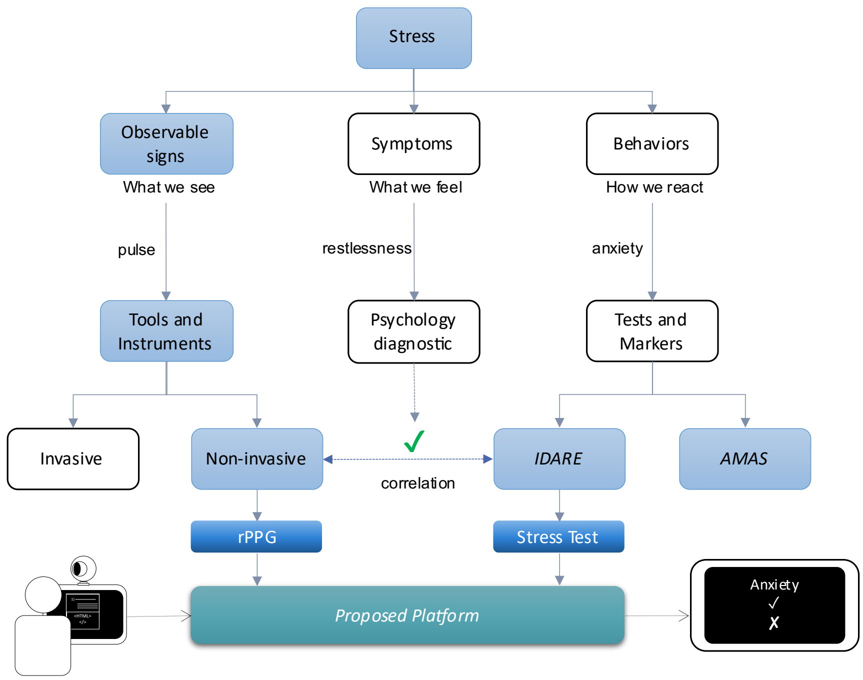

Figure 1.2: Proposed solution.

that emulates academic stressful activities such as homework, readings, test preparation and actual tests. Immediately after this test, it will be applied the *IDARE* state scale, in order to find anxiety levels derived from stressful academic activities. It will be expected to find higher values on these test results, thus, higher physiological anxiety responses from the rPPG signals.

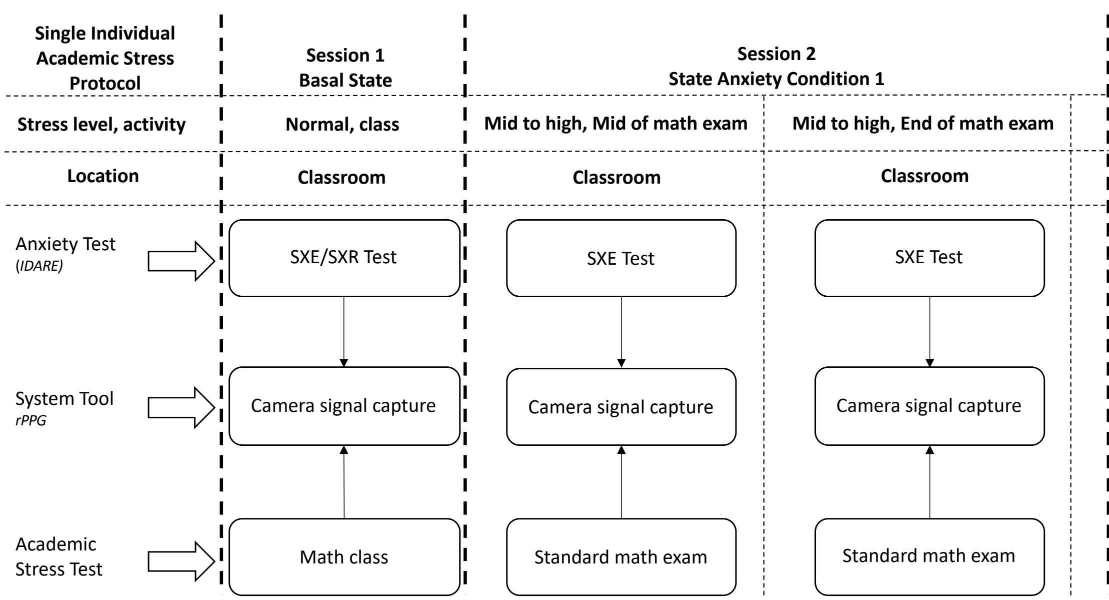

Figure 1.3: Academic stress test protocol framework.

1.3 Justification

Academic stress has already been defined as well as stress perspectives in order to build the research framework. It was also discussed the fact that current stress detection techniques, sensors and systems are lacking of a particular feature: either are accurate but high priced or low-cost but invasive or non-invasive but biased on the way the test is done. Also, we have learned that there are few research works that provides any correlation between physiological signal with presence of stress. Currently, the best way to obtain stress levels is subject to the different tests and scales that measures anxiety, such as *IDARE* scales, which provide a metric that relates anxiety to stress levels. The biggest disadvantage of such scales is the fact that its interpretation takes time and it is subject to the specialist time and objectiveness.

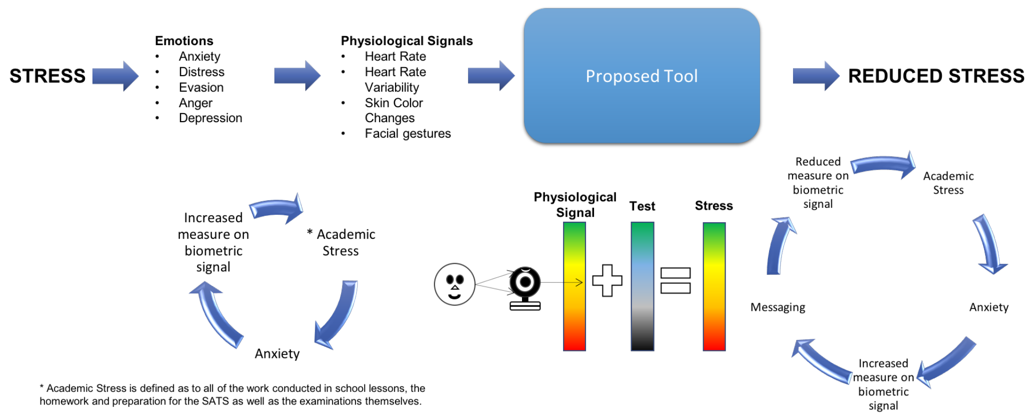

Figure 1.4: By identifying physiological signals, it is possible to provide a messaging mechanism to inform academic stress levels.

When the student is subject to academic stress, collateral effects are observed such as anxiety or distress. These behavioral responses can then be easily measured via physiological signals such as heart rate, heart rate variability or skin color variations. See figure 1.4 to understand at a high level, the research proposal and how would be impacting in student's academic stress management. By using remote photoplethysmography technique it is possible to get biometric signals from a live video imaging and in combination with other computer vision techniques to detect other facial patterns. By using this technique, it will be possible to provide a non-invasive tool which will be able to provide an snapshot of stress presence associated to anxiety biometric measures, which, later, can be correlated to anxiety levels on the proper scales. As this tool is near real-time, messaging can provide information for either other systems to use it as feedback or for specialists as a way to calm down the student, even using standard stress-management strategies [29]. This work might even be used for external systems such as panic buttons or any similar mobile applications.

The main goal of this work is to provide a non-invasive tool that provides enough information to the specialist in order for him or her to early detect stress presence in students. The tool pretends to be a companion while the test results are ready. Providing an acceptable degree of accuracy to standard stress tests. will help the specialist to make proper decisions.

The target community that will be immediately benefited from the implementation of this solution is the school of engineering, Universidad Autonoma del Estado de Mexico (UAEMex) and its community of students, but can be extended easily to other schools.
This research is in collaboration with the School of Behavior Sciences from the UAEMex and with the CESPI (from the Spanish *Centro de Estudios y Servicios Psicológicos Integrales*) in order to get assistance and feedback to develop the tool with the proper specifications for a broader use. Prototypes and test runs will also be in collaboration to validate the results.

1.4 Hypothesis

Using a webcam from a mobile device or computer is possible to calculate the heart rate and correlate with academic stress levels from standard stress tests based on anxiety body responses by using Remote Photoplethysmography technique.

1.5 Objectives

1.5.1 Main objective

Propose a non-invasive tool to detect academic stress in undergraduate students using the remote Photoplethysmography technique in order to obtain physiological signals from a live video feed and correlation to anxiety levels.

1.5.2 Particular objectives

1.1 – Review and document State-of-the-Art.

2.1 – Design and validate an academic stress test protocol using the suggested scales for anxiety detection.

2.2 – Review and validate current libraries and software techniques for video pattern recognition for heart rate detection.

3.1 – Design, implement and test an initial prototype to include video recording and an interactive platform for testing (scales and stressor). Validate scale results.

3.2 – Research, design and develop a classifier that labels heart rate signals with anxiety levels from academic stress tests results. Identify key features for the classifier.

4.1 – Run a first experiment with a group of students and document results, including validation with anxiety scales.

5.1 – Upgrade the prototype based on initial group findings

5.2 – Run a second experiment with a group of students and document results, including validation with anxiety scales.

6.1 – Document results on a scientific article.

1.6 Scope and limitations

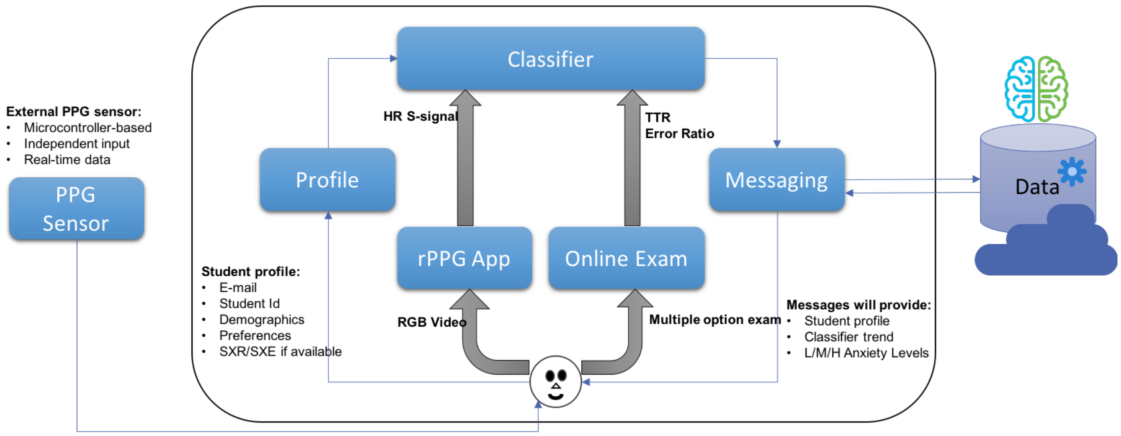

Figure 1.5: Proposed academic stress system architecture.

The proposed tool architecture is described in Figure1.5. A local rPPG sensor, the stressor protocol and the anxiety scale will be assessed using a web portal. Results will be stored locally and according to the described methodology. The proposed messaging mechanism might be extended to use a cloud-based API open system, which will send messages on anxiety level

1.6.1 Scope

Based on the current proposed architecture, the tool and system has the following scope:

- The system will consist on three components:
  - A local rPPG software sensor that will provide hear rate signal based on video input, either live or from a video recording.
  - Anxiety scale test will be available on a web portal.
  - Academic activity will be in any of these forms: class, exam or presentation. During class, students will be assessed their SXE/SXR scales. During exams, students will be asked to answer SXR scales during and at the end of the exam. Alternatively, students might be asked to present an be assessed on the SXR scale. These activities will be video recorded, using a local computer and local web cam.
- Video feed will be provided from a standard camera on a local computer. Remote PPG technique will be implemented locally using the webcam as the sensor.
- All development will be done using available public and open software frameworks and tools. Initially Python 3.7 will be used.

1.6.2 Limitations

Based on the current status and research work, the following limitations have been identified:

- The proposed system will be available only on a local computer with all necessary software installed. Performance will depend on actual computer characteristics, that includes non-real time performance.
- Given the time to deliver the project,most of the web development will be based only on available platforms such as Google Cloud Platform tools and API's. It is not expected to develop any web portal or web-based system, but instead a prototype to provided full functionality.
- The proposed computer platform will be based on MAC OSX as well as all the associated software and hardware dependencies.

Chapter 2

State-of-the-Art and Theoretical framework

2.1 State-of-the-Art

As could be seen in Figure 2.1, the focus of the research is in the tools and instruments used to assist on academic stress detection and diagnostics. Even though the project pretends to develop a non-invasive tool, makes sense to do a deeper analysis on the different options, alternatives, research work and in general, identify the State-of-the-Art on the matter, scope and limitations.

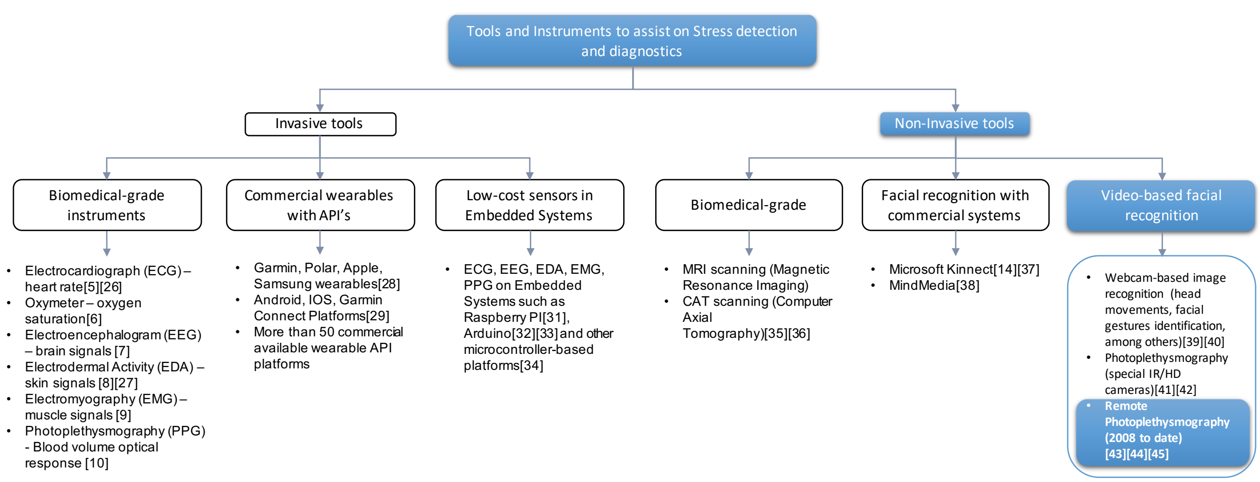

Figure 2.1: Tools and Instruments to detect stress can be divided in invasive and non-invasive tools.

2.1.1 Techniques to obtain physiological signals

Discussion and analysis of the current techniques used to obtain physiological information, are described below:

- Electrocardiography (ECG) - Cardiovascular system activity can be measured through various physiological signals. Blood volume pulse (BVP) and electrocardiography (ECG) are the most frequently employed signals. The ECG signal provides heart electrical activity measurements through electrodes placed on the chest. ECG is more robust against movement in general, but they must be placed in user's chest and in direct contact with the skin. This is unpractical and could be uncomfortable for some users. However, they provide a very good signal quality of the heart rate. Heart rate can easily be calculated from BVP or ECG signals by counting the number of peaks per minute [30].

- Oxygen saturation (SO2) - Respiration rate is influenced by changes between calm and excited states and it is also strongly related to cardiovascular system activity. The respiratory signal can be recorded using an elastic band placed on a subject's chest at the breastbone. More complex setups employ two elastic bands placed on a subject's chest and abdomen. Differences in breathing can lead some individuals to produce more abdominal distention, making a belt placed on the chest insensitive to breathing. Using two bands, however, can increase discomfort. Other technique used to detect Oxygen Saturation is using sensors directly attached to the nose, which provides the volume of oxygen when the subject inhales versus the amount of exhaled CO2. Another technique used in the pulse oxymeters is by detecting the finger's PPG signal from blood volume changes detected by a light emitter and a light receiver. Heart rate variability, detects the oxygen volume on the blood stream [31].

- Electroencephalography (EEG) - EEG measures brain waves via electrodes placed on the subject's head. However, EEG can measure only the activity of the cortex region in the brain, and it is vulnerable to noise. According to Elsayed [32], EEG has the advantage of relatively easy signal acquisition and high resolution. Even though EEG signals provide a very detailed behavior of the brain zones to get stress information, it is complex to get and then processed them due to the amount of data, plus the necessary setup. By using EEG signals, the level of accuracy to get stress signals is around 65% according to Elsayed research.

- Electrodermal Activity (EDA) - Electrodermal activity (EDA), or the galvanic skin response, has been shown to be associated with emotions since the late 1800s (Féré, 1888) [33]. Even though the relevance of the electrodermal signal, its use was limited to in-lab tests. With the rise of new wearable non-intrusive sensors, cognitive state can be tracked in real time using portable EDA sensors [34].

- Electromyography (EMG) - Muscle activity can bee measured using electromyography (EMG), which detects the electrical discharges caused by contractions of muscle fibers. The different facial muscles such as the ones located in the cheeks, the forehead and around the eyes, are responsible for smiling, frowning, blinking and winking, and contracting when smiling. These muscle contractions help distinguish between positive and negative emotions related to excitement and stress, respectively [30].

- Photoplethysmography (PPG) - Heart rate (HR) signal might be obtained from measuring the heart volumetric change as the number of contractions per minute. HR measurements such as ECG, requires direct skin contact. In this context, measuring electrical changes on the skin derived from the heart rate [35], requires a sensor directly attached to the subject's skin. The type of photoplethysmogram (PPG) available on wearable devices such as smart watches, uses skin contact to obtain a plethysmogram optically, by using the optical reflection on the vessels to calculate the amount of blood in a period of time. This technique is particularly useful for those scenarios where the subject has a delicate skin like baby borns or burnt subjects. As explained in the ECG technique, getting HR data provides good information on stress levels.
- Remote Photopletysmography (rPPG) - A new alternative technique being researched lately is a variant of PPG. Whereas standard PPG might use of low-intensity infrared (IR) light, this means light and light sensor detects the changes in blood flow as changes in the intensity of light. Remote PPG uses the same light absorption principle but instead of using an IR sensor, it uses a color space provided by a digital camera, for example, the red, green, and blue (RGB) color space, where pixels from the image are able to provide subtle changes on skin pixels, which actually bring a pulse signal and can be obtained from a distance of up to several meters [35].

All of these techniques are used on both, invasive and non-invasive tools and systems can range from biomedical instruments to simple low-cost sensors in low-cost open source systems. The same technique is used. Precision, accuracy and resolution will vary as well as costs, mobility and deployment models. Typically, one system supports a combination of different techniques. While biomedical instruments are able to provide simultaneously heart rate, heart rate variability and oxygen saturation data with high precision and accuracy, costs of acquisitions are high. On the flip side, one low-cost sensor connected to a embedded system can provide an acceptable precision and accuracy data.

2.1.2 Invasive tools

For this set of tools, we found three main categories:

1. **Biomedical-grade instruments** - these are systems that have high-precision and high-accuracy of measurements using any of the described techniques in the Background section. These systems are complex electronic hardware and software-based solutions, which are used in hospitals and research institutions, where high accuracy is needed. Even though there are smaller wearable systems like the one used by Sandulescu, Andrews, Ellis, Bellotto and Martínez-Mozos work [36], from a sample of 200 individuals they were able to correlate heart rate and electrodermal activity physiological signals with the Trier Social Stress Test (TSST), which is a popular psychological test to detect stressful activites.The system they used is a Nomadix module from Biopac, model BN-PPGED, which can be considered as biomedical-grade. There are also military-grade biomedical systems that have been proposed like the Wearable Biomedical Measurement System [37], where a combination of wireless biomedical-grade sensors, fabric sensors and wireless telecommunications are used to create a military grade system for combatants in order to measure mental stress. This system is able to

provide Galvanic Skin Response (GSR), body temperature, ECG data among others in real time in combination with speech analysis. In this research, they collected 10 out of 244 ECG features to get to a 23.72% error rate in their stress test protocol. These systems are in the ranges of USD $50,000-$100,000 and are sold and maintained by healthcare suppliers such as Siemmens or GE. The biggest advantage is the quality, accuracy and precision of data, however its main disadvantages are the cost of acquisition and maintenance, as well as the lack of portability.

2. **Commercial wearables with Application Programmable Intefases (API's)** - these systems offers an adequate level of precision and accuracy, without going all the range to be a hospital-grade solution at a acceptable cost of acquisition. Normally, the cost of maintenance of these systems is low and its in a form of a software-subscription to keep up-to-date the software. They normally use a combination of ECG, EDA or PPG via a wearable at the wrist or with the use of a sensor band attached to the chest. In the work presented by Suo and Kun [38], they were able to demonstrated the use of a Garmin chest band and its monitor with a Galvanic Response Sensor and a Accelerometer to detect stress in a group of 20 individuals. They reported good results but they conclude that these tests have to be personalized. These are niche offers and typically are in the sports or medical sport consumer segment. Most advanced systems like Garmin, Polar or Apple offers a good set of Software API's and SaaS-based services (Software as a Service from the cloud) which complement data gathering from the sensor to powerful cloud-computer algorithms that are able to provide correlations such as heart rate with maximum oxygen saturation to derive peak performance of an athlete with nice GPS maps. In the United States currently 15% of consumers uses wearable technology, including smart watches or fitness bands. By 2015, around 20 million of fitness wearable devices were sold. By end of 2018, sales grew to 110 million [39]. Lang and Maslove [40] compared a FitBit wrist band with a Polar Chest/Monitor system. They tested ten healthy volunteers from a large university in Singapore during a month to gather daily data. Participants wore one Fitbit Charge HR activity tracker and one Polar H6 heart rate monitor. They concluded that Fitbit devices detected 52.9% of heart rate zone correctly and Fitbit trackers are affected by significant systematic errors. The big advantage of these sensors is the relative low cost of acquisition, which is in the USD $500 to $2000 range plus software subscription of USD $100-300 per year. The main disadvantage of these systems is the dependency of the API's, which are not necessarily offering the data breadth and accuracy and also, might have some privacy risks associated to the commercial aspect of these brands.

3. **Low-cost sensors in Embedded Systems** - these systems are based on open-source or vendor-specific ecosystem solutions, which are in the range of USD $30-300 acquisition cost. Normally they don't involve any maintenance cost, but it is possible to acquired maintenance contracts in case of mission-critical developments. In this segment we can find solutions such as Raspberry Pi [41] or Arduino [42], which offers a broad catalogue of solutions and sensors, that can deliver basic ECG, EDA, EMG or PPG functionality complemented with computer software that runs on a desktop or laptop computer for quick prototyping and testing. In the work developed by Santos and Boticario [43], they presented a list of different systems using Arduino-based embedded systems to get physiological signals. There are other research papers using similar systems, whose objective is

to get biometric signals using low-cost systems, like the one done by Gupta, Bera and Mitra [44], where they used a low-cost microcontroller connected to Matlab to get ECG data via RS-232 serial port. There are also hardware-specific vendor solutions such as JETSON CUDA from nVidia or Nucleo from ST Microelectronics. These solution are more targeted to the scientific or mission-critical quick development and prototyping, but fundamentally offers the same ecosystem solutions. The biggest advantage of these solutions are the low-cost of acquisition and also the relatively easy way to develop a solution from zero to prototype, which typically is in the order of days or a few weeks. The biggest disadvantage is the accuracy and precision of data, if we compared to biomedical-grade instruments, plus the gap to go from prototype to productization.

2.1.3 Non-Invasive tools

For this set of tools, we found three main categories:

1. **Biomedical-grade instruments** - as in the invasive tools case, these systems are able to provide biometric data using any of the discussed techniques such as ECG, EEG, or PPG with the difference that any of these systems are not using direct sensors over the subject. These systems are using either sound or ultrasound or any form of electromagnetic fields or radiation to get information from the different human organs with a lot more detail from the specific organ. More specifically, we are referring to systems using MRI or CAT scanning (Magnetic Resonance Imaging and Computer Axial Tomography). For example, a CAT scanning instrument is able to provide a detailed image in real-time of the heart muscle. Given the cost of these systems, which is on the range of USD $100,000-250,000, the use for stress detection using any physiological signal is rare and not used for this specific matter, unless any organ anomaly is found, where stress can deteriorate subjects health, such as the risk of a heart or brain stroke, derived from stressful situations. As a result, Its maintenance costs are also expensive due to the complexity of the systems. They are extremely accurate and precise and provide a very detailed data source that is analyzed in complex software systems, that outputs very nice interpretations of the different phenomena occurring in an organ. A report from the American Heart Association published in 2006, details how stress can be a risk factor for men older than 65 years old when calcium has been detected in arteries, leading to heart diseases using ECG in a Class IIa CAT Screening [45]. Even though they are not invasive, one biggest disadvantage is that the subject requieres some preparation for the study. It is very unlikely to use any of these systems to diagnose stress, however, in some extreme cases, these are used to diagnose complex psychological behaviors. Other interesting research was done by Poltavsky [46], where they used a commercially available low-cost wireless EEG device from NeuroSky (MindSet), very convenient and ease-of-use due to the software and data information gathering.

2. **Facial recognition with commercial systems** - this is a non-invasive commercial solution that uses different video imaging and pattern recognition techniques to build a 2D or 3D computer image. Systems like Microsoft Kinetic [47] are able to offer a good accuracy when building these computer images and provide a good set of API's and other interfaces to get full view of raw data, which later

can be post-processed and filter to develop further information or data. In the work done by Aigrain, Spodenkiewicz, Dubuisson, Detyniecki, Cohen and Chetouani [22], they used a Microsoft Kinect to get the video of the whole body as well as the skeleton. They also used a Nexus-10 portable device (MindMedia B.V.,The Netherlands) to measure EMG, GSR, skin temperature, respiration, BVP and HR, and also used a HD Camera for face recording. They were able to get 101 features from the 3 sources and correlate physiological signals with facial and body postures. The cost of acquisition is in the order of USD $300-800, which makes very attractive to use in stress diagnosis. The biggest disadvantage of Microsoft Kinetic is the dependency on Microsoft and their software reliability plus the integration of other systems that helps with data correlation. DeepBreath, recognizes people's psychological stress level from their breathing patterns [48]. Using a low cost thermal camera, breathing patterns as temperature changes, is possible to detect. They analyzed spectrograms from the breathing patterns and by using a Convolutional Neural Network (CNN) they are able to recognize stress. They used cognitive tasks with sessions of different difficulty levels to trigger stress. The CNN reaches 84.59% accuracy in discriminating between two levels of stress and 56.52% in discriminating between three levels.

3. **Video-based imaging recognition** - this is one of the most current advances in developing non-invasive tools to get physiological data using video imaging and pattern recognition [35]. The baseline is the use of very low-cost cameras or even reuse embedded cameras on mobile phones or computers. The key factor for these advances lies on the computer power available on mobile phones and computers, but also on the fact that for most of the training models are created using cloud computing resources, which later are deployed on end user devices, but still can be retrained or updated because these devices are still connected to the cloud. We can find different systems, solutions and even algorithms that are written using these premises of design. For the particular interest of the research, these three models were studied:

   - Systems that are using webcam-based imaging to detect head movements and correlate with biometrics such as pulse rate or respiration [49] [50].
   - Systems that are using high-fidelity webcams with infrared and high-speed frame detection to implement PPG algorithm and correlate heart rate and heart rate variability [51] [52].
   - Systems that are using low-cost and mostly embedded mobile or computer cameras to implement a modified PPG technique, called Remote PPG [53], which uses video frames and face recognition to reproduce the same finger PPG LED/LRD optical reflection data using pixel analysis on a region of the subject's face. With this data, heart rate signal, heart rate variability and oxygen saturation can be found and correlate with facial gestures to identify anxiety levels, thus determine a stress state. Other systems using rPPG are proposing the use of SVR [54] or different color schema to RGB such as Chrominance [55]. The research will be developed around the chroma-based rPPG technique, its computer algorithm and associated techniques further on.

2.2 Theoretical framework

This section explains the theoretical background behind the proposed solution. In particular, first section discusses the use of anxiety inventories and scales from *IDARE* test as the baseline for identifying anxiety levels and be able to classify presence or absence of anxiety. This is fundamental to select the sample to be used for the system tests. The second section describes the technical background behind the *PPG* signals, the analysis of the resultant wave and the process to obtain it as an introduction of *rPPG* algorithm and the resultant signal obtained from RGB a sequence of digital images, i.e, a digital video stream.

2.2.1 *IDARE* anxiety scales

Anxiety is one of the physical signs resulting from stress. Different mechanisms and tests have been developed to measure anxiety levels. Particulary, *STAI* or *IDARE*, has been the defacto anxiety scale due to its spread use, its references in the research world but more importantly, because it has been translated, customized and validated to Mexico's population, including the use for academic undergraduates. The *IDARE* scale provides all technical background on the validity and includes a description of the test scales and results.

IDARE consists on two self-evaluation scales that are used to measure two different anxiety dimensions:

1. Trait Anxiety (*A-trait*)
2. State Anxiety (*A-state*)

Even though the scale was originally developed to research anxiety phenomena in normal adult subjects, this means, without psychiatric symptoms, it has been demonstrated that it is also useful to measure anxiety in high-school and undergraduate students as well as in neuropsychiatric patients, both medicated and post-surgery [5].

The *A-trait* scale inventory is based on twenty statements which ask to the individual how they feel generally. *The A-state* also has twenty statements, but the instructions require that the individuals provide answers based on how they feel at a very specific moment or after a particular situation. This is particularly useful when dealing with academic stress. In *IDARE* manual [56], a detailed analysis is provided on how instructions affect the responses of *A-Sate* when students are in basal state or after an exam.

The *A-trait* scale can be used as a research instrument in the selection of subjects that vary their inclination to response to psychological tension with levels of intensity different to A-state. On the other hand, A-state can be used to determine real levels of intensity of A-state produced by tension experimental procedures, such as a stressful situation.

This is particularly useful as a trend analysis for sample selection of individuals. According to the *IDARE* user's manual [56], a low, medium or high anxiety level will be a trend for the subject under certain stressful scenarios, meaning that a high-anxiety level *might* trigger a high-anxiety *state* as a result of that event.

The *IDARE* inventory was designed to be self-applied and can be applied to an individual or a to a group. The inventory does not have a time limit but typically the subject will be answering based on the first response of how he or she feels after a particular situation described on the question. A normal response time

of each of the inventories is of less than 5 minutes, unless the subject has certain education level or mental illness, which is not the case in undergraduate students.
The way to apply the inventory is first responding to the *A-State* (from now on will be referred as SXE) and the the *A-Trait* (from now on will be referred as SXR), when both scales are applied.
The SXE inventory can be applied standalone in order to get the actual *state* of an individual as a response to a particular scenario (the instruction to respond the inventory).
The SXRE and SXE scales score vary from 20 points to a maximum of 80 points. The subject responds to each of the questions assessing themselves in a 4-point scale.
For SXE the point scale is:

1. Not at all
2. A few
3. Enough
4. All the time

For SXR the point scale is:

1. Never
2. A few times
3. Frequently
4. Always

The scales are designed on way that some questions assess a high level of anxiety whereas other questions assess a low level of anxiety. When the high level of anxiety is assessed then the scale goes from 1 to 4 (direct scale), whereas a low level of anxiety goes from 4 to 1 (inverse scale). Scales are balanced to have a similar number of direct and inverse scales. Appendix A of *IDARE* user's manual [56], describes the scoring and qualification process used to get the anxiety levels.
In order to determine the low, medium and high anxiety levels, the *IDARE* user's manual uses a table to set the proper levels, being low an score of less than 30 point, greater or equal than 30 but lower or equal than 45 as medium and greater than 45 as high.

2.2.2 Photopletysmography

The technique called Photopletysmography or *PPG* is an optical technique, which is able to provide some vital signs, like pulse rate, respiratory rate, and blood oxygenation, first described in the 1930s [57].It is very popular because of simplicity: a light emitter, a light receiver and a bandpass filter with amplification. Essentially, *PPG* detects the optical absorption variations of the human skin due to the blood volume variations during the cardiac cycle [58].

The resulting signal produces a periodic signal called cardiovascular pulse wave, that can be analyzed in order to obtain the heart rate beat or frequency. The *PPG* signal reflects the blood movement in the vessel, which goes from the heart to the fingertips and toes through the blood vessels in a wave-like motion [59]. Common implementation for a *PPG* diagnostic system consists of the following stages:

1. Signal acquisition.
2. Signal filtering using bandpass filter.
3. Signal extraction stage to detect the PPG signal.
4. Data extraction from signal for classification and diagnosis.

It makes sense to analyze two fundamental aspects of the described system. Initially, the amplified signal has to be filtered in order to obtain the desired cardiovascular signal.

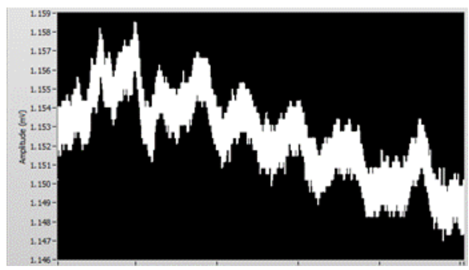

Figure 2.2: Adapted Unfiltered Heart Rate Signal. Picture adapted from NI [60].

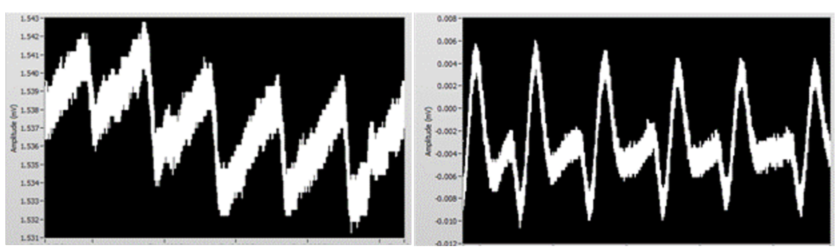

Figure 2.3: Filtered Heart Rate Signal using 1st order band-pass filter (left) and the 2nd order band-pass filter (right). Picture adapted from NI [60].

The raw data that is acquired from the signal acquisition stage has inherent noise due to the low magnitude of the signal, thus signal amplification is needed. Once the signal is amplified, results evident that noise is amplified as well. So signal filtering must be performed in order to obtain a usable and clean signal that represents the heart rate. The unfiltered, noisy signal as shown in Figure 2.2 demonstrates visible high frequencies, noise in the signal, as well as a DC offset that causes the peak to fluctuate. On the other hand, Figure 2.3 shows the same signal after filtering is performed, using a first and second order bandpass filter. In order to eliminate this high frequency noise and the DC offset, it is necessary to understand the HR frequency spectrum, so proper frequency bands are provided.

Average person's heart rate is 40 beats per minute (bpm) at rest (known as bradycardia [61]). The peak's heart rate is of 220 bpm (known as supraventricular tachycardia [62]). During vigorous exercise, an average adult heart rate increases considerably with a peak of about 160 to 175 bpm. The frequency of this signal would then be around 1 Hz (60 bpm) for an idle heart rate and 3 Hz (180bpm) for an active heart rate of an active healthy adult. There can be cases where the adult is at lower levels of 60 bpm but no less than 40 bpm or at higher levels of 180 bpm but no more of 220 bpm.
This is the reason why the recommended bandpass filter for an *PPG* signal is between 40 bpm or 0.67 Hz and 220 bpm or 3.67 Hz. Figure 2.4 shows a filtered and amplified signal also known as *plethysmogram*.

Figure 2.4: Amplified heart rate signal.

The last step is of particular interest for the research as this is the most important one for obtaining the heart rate frequency, which is the physiological signals will be used to correlate with anxiety levels. The more anxiety, a higher heart rate frequency will be obtained.
There are fundamentally two methods to identify the frequency of the filtered and amplified plethysmogram:

- Time-domain analysis
- Frequency-domain analysis

2.2.3 Time-domain analysis

In order to understand the time-domain analysis is important to understand the plethysmogram wave.
PPG pulse signal is commonly divided into two phases: the anacrotic phase is the rising edge of the pulse, whereas the catacrotic phase is the falling edge of the pulse [59] as shown in Figure 2.5. The first phase is primarily concerned with systole, and the second phase with diastole and wave reflections from the periphery. A number of features based on the PPG have been described in literature:

1. The pulse width in the PPG wave is shown in Figure 2.5. Some authors used the pulse width as the pulse width at the half height of the systolic peak. They have suggested that the pulse width correlates with the systemic vascular resistance better than the Systolic amplitude.

2. The pulse area is measured as the total area under the PPG curve.

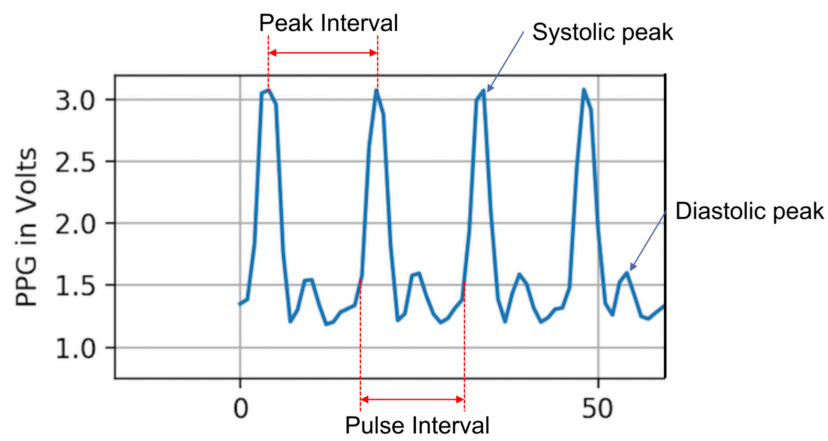

Figure 2.5: Plethysmogram analysis and components.

3. The distance between two consecutive systolic peaks will be referred to as Peak-Peak interval. The Peak-Peak interval has been used to detect the heart in PPG signals.

4. The distance between the beginning and the end of the PPG waveform, as shown in Figure 2.5.

Based on the analysis it is concluded that the best way to obtain the heart rate frequency is using the pulse interval when there is a a quick gradient change after a diastolic peak. This method is frequently used in microcontrollers or dedicated circuits that are used to detect a raising edge after a sudden gradient change.

2.2.4 Frequency-domain analysis

An alternative method top obtain the heart rate frequency is by using a frequency-domain analysis.
In this case the described plethysmogram in 2.5 is now analyzed as a resultant frequency and power of that intensity using Fourier Transform. Figure 2.6 shows the resultant PPG in the frequency domain. As can be seen, the location of heart-rate is identified where the power of that frequency is the highest among the resultant frequency transformation. It is also seen that there are 2 harmonic frequencies.

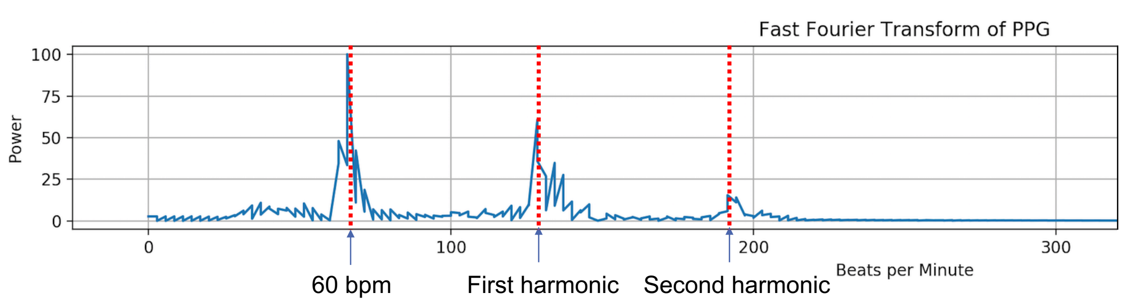

Figure 2.6: Plethysmogram in frequency domain using Fourier transform.

The use of Fourier Transform is particularly useful when analog acquistion of the signal is done via an ADC, where the resultant signal is a digital vector, so that a Fast Fourier Transform from these discrete signals can be done.

2.2.5 Remote photoplethysmography

In 2008, Verkruysse, Wim and Svaasand [63] demonstrated that color skin variation as a result of a external light source could also provide a similar plethysmogram signal. It can also be measured at a distance leading to *remote Photoplethysmogram (rPPG)* algorithms and research [64], [65]. Since then, several publications have even shown successful rPPG using a regular color video camera under ambient light conditions [63] [66] [67] [68].
In general terms, Remote Photoplethysmography (rPPG) can be defined as the technique that enables non-invasive, contact-less monitoring of human heart rate by detecting the pulse-induced subtle color variations on human skin surface using a RGB camera [63]. In recent years, several core rPPG methods have been proposed for extracting the pulse-signal from a video. These include:

1. Blind Source Separation (e.g., PCA-based [67] and ICA-based [69]), which use different criteria to separate temporal RGB traces into uncorrelated or independent signal sources to retrieve the pulse;

2. CHROM [58], which linearly combines the chrominance-signals by assuming a standardized skin-color to white-balance the images;

3. PBV [70], which uses the signature of blood volume changes in different wavelengths to explicitly distinguish the pulse-induced color changes from motion noise in RGB measurements; and

4. 2SR [71], which measures the temporal rotation of the spatial subspace of skinpixels for pulse extraction.

The essential difference between these rPPG methods is in the way of using, combining and pattern identification of RGB-signals to get a pulse-signal.
Methods described in (1) are temporal-based and require a heuristic calculation of parameters depending upon ambient light and color screen. For each setup, a new set of parameters has to be calculated.
Methods (3) and (4) are data-driven and even they are accurate, they require more compute power.
Method (2), Remote Photoplethysmography using Chroma difference has shown a good level of accuracy but also, it is suitable to run on a regular computer with a standard web cam, plus the fact that ambient light and skin colors are compensated in the algorithm.
The Robust rPPG algorithm developed by DeHaan [58] is based on what is referred as the skin reflection model, which is a mathematical model of the skin response to external light conditions and how the reflected light can be interpreted as a signal carrying heart rate information. Wang, den Brinker, Stuijk, and de Haan, in 2017 made a mathematical analysis of the different existing rPPG algorithms at that time concluding that skin reflection is a function of specular reflection and difuse reflection [72]. Figure 2.7, taken from their article, shows this conceptual idea.

In order to understand the principles for pulse extraction in rPPG methods, De Haan *et al.* defined a rPPG model that considers optical and physiological properties of skin reflection.
Consider a light source illuminating an area of human skin tissue, for example the face, which contains heart rate pulse information and a color camera recording this image. That light source has a constant spectral composition but the reflected light will vary its intensity, for example, when the subject is moving or due to external reflections. The intensity of the pulse signal will depend on the distance from the light source to the skin tissue and to the camera sensor.
The resulting light intensity measured in the skin has color intensity and variations over time, due to the motion induced intensity or specular variations and pulse-induced subtle color changes. These temporal changes are proportional to the luminance intensity level [72]

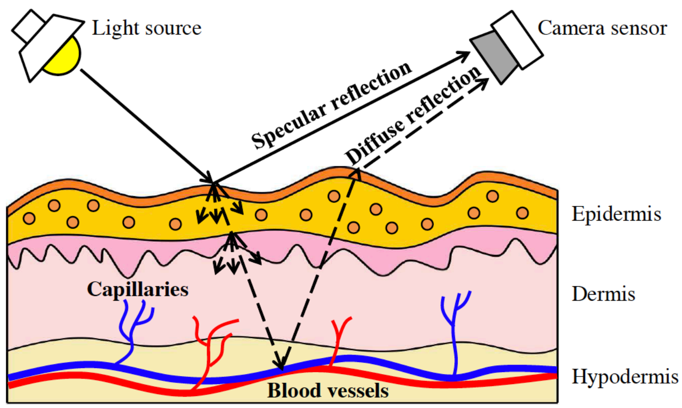

Figure 2.7: Skin reflection model as defined by Wang, den Brinker, Stuijk, and de Haan [58]

$$C_k(t) = I(t) \cdot ((v_s(t) + v_d(t)) + v_n(t) \tag{2.1}$$

where:
$C_k(t)$ denotes the RGB channels of the k-th skin-pixel;
$I(t)$ denotes the luminance intensity level, which absorbs the intensity changes due to the light source as well as to the distance changes between the light source, skin tissue and camera;
$I(t)$ is modulated by two components in the dichromatic model: specular reflection $v_s(t)$ and diffuse reflection $v_d(t)$. The time dependency is due to the body motion and pulsatile blood; the last component $v_n(t)$ denotes the quantization noise of the camera sensor [72].

2.2.6 Robust photoplethysmography

The selected method for *rPPG* is the chrominance model, also known as X-αY. It uses a color space based on Chrominance and Luminance information from pixels. The method is based on the fact that skin color information related to blood changes is a difference of intensity [58].
The best way to get this difference is to interpret each RGB pixel as an individual sensor that carries information of *PPG* signal and interprets the skin color difference separating specular reflection from difussed

light, where the later carries the heart rate blood volume information. In order to compensate the specular reflection coming from skin-color differences, it uses a skin-color parametrization, independent of light source so that Heart Rate signal can be obtained without any special illumination setting [58].
This Chrominance-based mathematical model is described as follows:

$$C_i = I_{C_i}(\rho_{C_{dc}} + \rho_{C_i} + s_i) \tag{2.2}$$

Where:

I_{C_i} – Intensity of light of channel *i*
ρC_{dc} – Reflection coefficient of the channel *i*
ρ_{Ci} – Pulsation information coming from channel *i*
s_i – Additive specular reflection

Being a channel, a color channel in a color space such as RGB.
In practical terms, the algorithm shall be able to separate the reflection coefficient and additive specular information from the actual pulsation information, independently of motion related changes on light intensity. The following subsection describes the algorithm implemented,

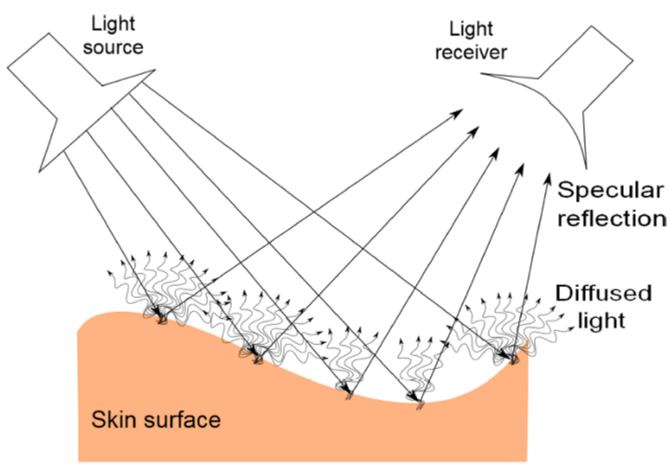

Figure 2.8: Each skin pixel will be used as a independent heart rate sensor by obtaining the pulse-related information contained in the specular reflection signal.

The fundamental theoretical use of color intensity difference relies on two facts:

- Any digital video recording encodes analog signals in digital domains known as color spaces, which provides discrete information of the moving image as a sequence of motion pictures encoded with these color spaces.
- Red, Green, Blue or RGB color space is the default encoding algorithm for digital video recording and even the pixels contain information associated to intensity, obtaining the difference in each color channel results computational expensive and impractical from a implementation point of view.

Based on these facts, De Haan suggests to do a color space transformation adjusting values to provide a better approximation of specular reflection. These color space transformations will provide color intensity instead of individual color channel information. The suggested color space transformation is based on CIE XYZ color model, which provides a unique color space independently of the device and also, for this case, will be adjusted to provide only X and Y wavelengths, corresponding approximately to red and green wavelengths [73].
As also described in the De Haan article, skin color shall not affect the intensity of each pixel, hence the color space transformation will require specific constant values for X and Y channel spaces. Equations 2.3 and 2.4 describes these color space transformations:

$$X_s = 3R_n - 2G_n \tag{2.3}$$

$$Y_s = 1.5R_n + G_n - 1.5B_n \tag{2.4}$$

As noted in Equations 2.3 and 2.4, RGB channels are referred with a *"n"* subindex, indicating that this channel is not the actual RGB channel, but instead, a normalization of each channel. The constant values correspond to the skin-color and non-white light compensation provided by DeHaan.
After careful analysis and verification of the state-of-the art references, channel normalization implies that an interval shall be used to determine these values. De Haan article does not describe how to calculate normalization, instead it provided a time interval, which will be used for these normalizations during the implementation described in the research article.
RGB channels to be normalized, will need to be calculated over a period of time. According to De Haan, 1.2 seconds will be enough to calculate a pulse rate signal within this time period. Once each channel has been normalized, then these values will be used to calculate Equations 2.3 and 2.4. After channel transformation is done, the S heart rate signal can be calculated using Equation 2.5

$$S = X_f - \alpha Y_f \tag{2.5}$$

where X_f and Y_f are the passband filtered versions of X_s and Y_s, and α is the ratio of the standard deviation of $\frac{\sigma(X_f)}{\sigma(Y_f)}$.
As noted, X and Y signals have a *"f"* subindex, indicating that these matrices are filtered in the range of 0.67Hz and 3.67Hz or 40bpm to 220bpm. Filtering the X and Y matrixes refer to the fact that it is necessary to eliminate any noise that each pixel does not correspond to the pixel bringing pulse information.
For the purpose of the research, a Butterworth digital filter of 3rd order is used with these parameters:

- A low cut frequency of 40 bpm equivalent to 0.67 Hz.
- A high cut frequency of 220 bpm equivalent to 3.67 Hz.

The next step is to perform a convolution of S_f vector by a Hanning window in order to smoothen and filter the signals in the temporal space.
50% overlapping signals are summed after Hanning window is applied in order to obtain the *S* heart rate signal.

Finally, a *Fast Fourier Transform* is applied to the resultant S_f signal in order to get the highest peak of the first harmonic, which contains the actual HR value of the interval.

Chapter 3

Proposed methodology

As described in Section 1.2.1, the goal is to provide a non-invasive tool that is able to identify physiological signs of anxiety response to stress levels.
The proposed methodology consists on 4 major steps and it's shown on figure 3.1:

1. Define the academic stress protocol.
2. *IDARE*, student profile and video recording automation in the academic environment.
3. Obtain heart rate (HR) signal from video recordings.
4. Classification of anxiety.

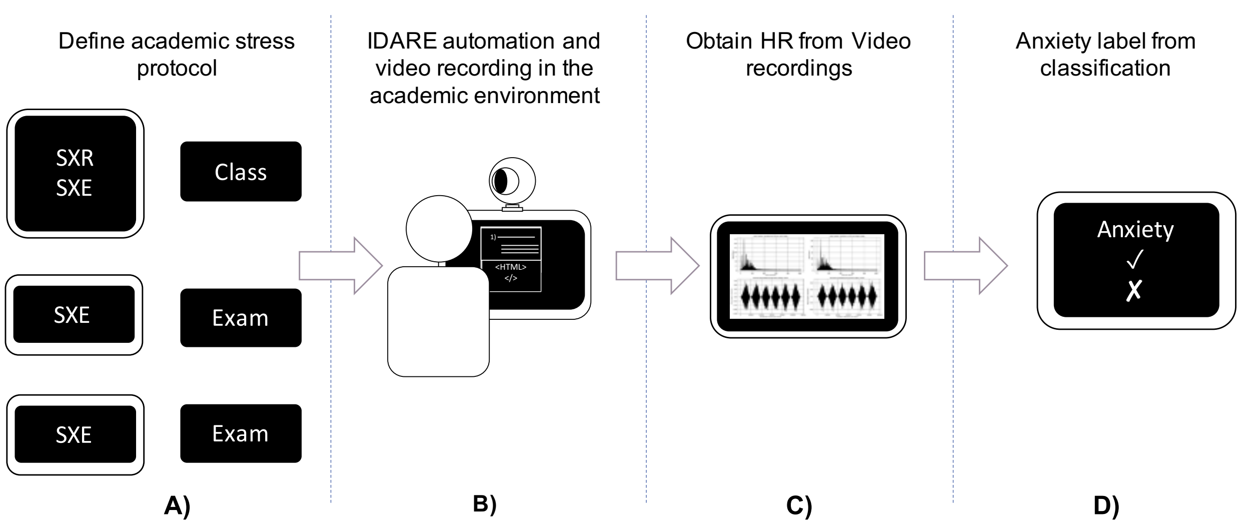

Figure 3.1: Proposed methdology A) Define academic stress protocol. B) *IDARE* automation and video recording in the academic environment. C) Obtain HR from video recordings. D) Anxiety label from classification.

3.1 Implementation

The implementation of the system consists on a web-based interface, which will be able to obtain the student profile and anxiety levels using the standard *IDARE* tests [74]. Student's video imaging from the integrated webcam will be recorded all the time during tests.

The platform will be based on standard laptops, which will allow student's profile to be answered on-line, as well as video recording using a python script so that all data can be saved in a cloud drive for further analysis. Standard *IDARE* tests are answered within the same setup. One monitor laptop is used to validate data from the test laptops and their cloud storage. All the computers are connected to Internet in a local network. Complete setup is as follows:

- 2 Test Laptops branded as Asus G750JZ laptops with 4-socket Intel Core i7-4700HQ at 2.40GHz with 16 GB RAM running Windows 10 Professional.
- 1 Test Laptop branded as Lenovo X10 with Intel Intel i7-8665U at 1.9GHz with 16 GB RAM running Windows 10 Professional.
- 1 Monitor Laptop branded as Mac Book Pro 2015 with 2.6 GHz Intel Core i7, 16 GB 2400 MHz DDR4.
- 1 Meraki Wireless Router MX64W with 4 Ethernet Ports, 1 Internet uplink and Wireless Access Point capability
- Google Cloud Platform was used as the dataset repository

Up to 3 students are able to be measured simultaneously, decreasing the time to get data and also making the experiment more cost-effective (instead of using a computer room and condition each machine for our purpose).

3.2 rPPG implementation

Remote Photoplethysmography algorithms (*rPPG*) [58] [70] [54] rely on the fact that light intensity variations coming from individual skin pixels, are able to provide a heart rate signal.

De Haan [58] algorithm called *chroma-based robust remote photoplethismography - rPPG*, provides all theoretical elements to go over the implementation. In summary, from a video recording, face recognition is needed to obtain the region of interest (ROI) where the signal will be analyzed. This ROI will be analyzed in chunks, this means, in fixed time intervals to first obtain the mean of that interval in order to normalized that interval. In other words, to obtain the average RGB values, which will be processed to a XY color space, chrominance and luminance, to obtain the signal S_f value corresponding to the heart rate in that interval for that ROI.

$$S_f = X_f - \alpha Y_f \tag{3.1}$$

This S_f value behaves as any other signal, so a passband filter is applied between 40 beats per minute, 0.67 Hz, and 220 beats per minute, 3.67 Hz. The proposed filter is a Butterworth filter. Filtered signals are 50%

overlapped and add them up to build the actual heart rate value of the interval using *FFT* to get the highest peak of the first harmonic. This procedure is repeated until the video is finalized or the designated time interval is reached. The use of different Python 3.7 packages and modular programming was fundamental to provide a simple and short code, which could be ported between platforms with no further changes. The detailed implemented algorithm is described below:

1. **Variables initialization**. It is necessary to initialize camera feed and Haar face cascade classifiers [75]from OpenCV 4.0 python package. Also, different frame arrays of 4 dimensions, are created to support rPPG implementation, frames per second determination based on video recording input, interval size in seconds, number of intervals, bandpass high and low cut frequencies as well as the desired order Butterworth filter.

2. **Frame interval generation**. It is necessary to get an interval of time for the video input, where the analysis of rPPG signal will be done. The resulting output of this step is an amount of raw RGB frames. The number of frames can be variable and depends on the camera frame rate and the time interval selected. Number of frames follows the recommendation by De Haan [58], which is of 1.2 seconds or 32 frames in a video recording at 30 frames per second.

3. **Frame by frame capture for analysis**. In the algorithm proposed by De Haan [58], it is mentioned that each color channel shall be normalized. It is needed to capture frame by frame, saved those frames, separate in individual color channels and then calculated the media value over those color frames in the interval. In order to do this, it is needed to capture temporally these frames for further analysis. A 4-dimension array was needed to index color channel RGB frames.

4. **Overlapping windows generation**. In the robust rPPG method it is mentioned that overlap-add windows is recommended on the interval for obtaining a quality signal that provides a better hear-rate from the images. The process to overlap-add requires memory to save three arrays: interval *i*, interval *i+1* and the overlap interval o_i between these two, meaning, half of interval *i* and half of interval *i+1* will be used.

5. **Run *X minus* α*Y* algorithm on each array**.The final step is to run the actual algorithm in each of the arrays: current interval, overlap-add interval and next interval. After all these calculations are done within the total intervals, S-signal can be generated.

6. **S vector processing in the temporal space**. Once S-vector is obtained, it is filtered using a Hanning window to smoothen the signal, then these filtered overlap-add signals are summed up to the filtered interval signals to obtain the HR signal, which is passband filtered in the temporal space between 0.67Hz and 3.67Hz to finally apply a *FFT* to get the HR of the interval, which corresponds to the highest peak of the first harmonic.

7. **HR value generation**. From each ROI, left and right cheeks, the process is performed until the video recording is completed and a vector of HR values is obtained. Left and right HR values are averaged

per Kwon ROI analysis recommendations [76] in order to obtain a HR of the interval. A 5-point average then is applied to the HR values dataset in order to obtain the HR trend of the interval. 5-point moving average represent the trend in 16.5-second moving segments using a 3.3-second interval.

Chapter 4

Research article

In this chapter, the manuscript sent for review and potential publication to *IEEE Transactions on Affective Computing* magazine (ISSN: 1949-3045) of IEEE Society. Such magazine has an impact factor JCR of 7.512 (2019) and SJR-SCOPUS of 1.32.
The methodology, experimentation, results and their analysis are be presented in the research article contained in the following section.
In general terms, the following methodology was used as described in Figure 3.1:

- Define academic stress protocol
- *IDARE* automation and video recording in the academic environment
- Obtain HR from video recordings using th rPPG technique
- Obtain anxiety predictive labels from classification methods

An experiment was run with 56 first-year undergraduate students, who provided their demographic data and their SXE scales during an exam, while they were video recorded. SXE scales were used to obtain the predictive labels, whereas the profile information from demographic data and the HR values, obtained from the rPPG technique, provide the feature vector for the classifiers. An algorithm applied to HR values was developed enhancing rPPG technique to clean the HR values and provide better performance for the HR signal. Four classifiers were selected to be used SVM, KNN, J48 and Random Forest

Chapter 5

Discussion and Conclusions

At the beginning of the research it was formulated the following hypothesis:

Using a webcam from a mobile device or computer is possible to obtain the heart rate and correlate with academic stress levels from standard stress tests based on anxiety body responses by using Remote Photoplethysmography technique.

In order to validate the hypothesis, 2 main experiments were performed:

Experiment 1 Standard *IDARE* paper scales and manual analysis to validate that academic stress is derived from pure academic activities.

Experiment 2 Automated video recordings with student's profile using a web-based platform while they were subject to academic stress during an exam. *IDARE* scales were taken during this activity. Using this data, different classifiers were used to provide predictive values based on video recordings. On this way, academic stress might be found using a low-cost (web computer) camera only.

The main goal of these experiments were to validate the academic stress protocol, in this case, academic stress activities such as classes, presentations, home work and examinations are, in fact, activities that might lead to anxiety, which is the way to measure stress. Another goal was to label anxiety levels to biometric measures, in this case, to heart rate values. And finally, be able to predict anxiety levels by using heart rate values from rPPG technique and student's profile.
An important aspect over the development of the project, was to obtain pertinent data from students under certain activities that led to anxiety. As discussed, the use of *IDARE* scale was fundamental to identify anxiety levels in students. It was necessary to, first, understand how *IDARE* scale works and second, to automate this test so that it was possible to take this inventory at scale, providing enough data from students in different moments.
An advantage of automating the methodology is the fact that all data is immediately available in the cloud for further analysis. Google Cloud Platform and Google Forms API's were used for this purpose. It was possible to generate more than 100 inventory scales in a few days and get actual anxiety results in minutes.

This is a contribution of the present work as hundreds of students can be tested in a matter of minutes and remotely.
The other important component during the development of the project is video recording gathering. Providing video recording at the moment of the academic-related activity to lead to anxiety was fundamental to effectively create a non-invasive tool.
In order to obtain HR values, rPPG technique was used. The input of the algorithm is a video recording from a laptop computer, but not limited, as long as the video is recorded at least at 20 fps and using a 720p resolution. The output of the algorithm is a file with HR values from the right and left student's cheeks.
These HR values are post-processed to obtain a single HR value vector. Right and left HR values are averaged and then a 5-point moving average is calculated in order to obtain HR value trend. After this processing, a zero-value and a faster adjacent values algorithm is applied to the HR 5-point moving average values, so a HR clean signal is obtained. This algorithm is another contribution to rPPG technique.
Finally, this signal and other 7 features coming from the student's profile are used as the entry to the classifier.
Three datasets were processed using these four classifiers – KNN, SVM, Random Forest and J48 – to find the classifier that provides the best accuracy to identify anxiety. Each classifier was tested with 10-fold cross-validation, using the toolset from Weka 3.8 software [77] with the default parameter settings.
These datasets were created and different features were used to classify based on predictive labels:

1. Dataset 1 - Demographic features only: age, gender, private or public school, sports practice, extra activities, family issues and failed tests. This dataset showed 60% to 65% accuracy for the 4 classifiers, with F-measure in the 0.60 to 0.63 range and Kappa in the range of 0.21 to 0.29. Detailed results are shown in Table 5.1.

2. Dataset 2 - HR CLEAN feature only, HR values in the interval. This dataset showed an accuracy in the range of 48% for SVM up to 60% for KNN with F-measure in the range of 0.41 for SVM and up to 0.60 for KNN, whereas Kappa was in the range of 0.03 for SVM up to 0.20 for KNN. Detailed results are shown in Table 5.2.

3. Dataset 3 - HR CLEAN and Demographic features: HR values,age, gender, private or public school, sports practice, extra activities, family issues and failed tests. This dataset showed enhancement in practically all classifiers and variables. SVM showed the worst accuracy, F-measure and Kappa with 66.85%, 0.66 and 0.33, respectively, whereas Random Forest showed the best accuracy with 96.45%, F-measure with 0.96 and Kappa with 0.92. Also interesting to see that KNN and J48 showed enhancements in the order of 96% for accuracy, 0.96. for F-measure and 0.92 for Kappa. Detailed results are shown in Table 5.3.

The motivation to create a new dataset with a cleaner version of HR values coming from rPPG technique was initially to assess if HR RAW values might be sufficient to provide correct classification and avoid any dataset post-processing. When the correction was done and tested in classifiers, not only accuracy enhanced but also the other variables: F-measure and Kappa. Hence, HR CLEAN dataset shown better results.

	Dataset #1 Demographic data		
Classifier	Accuracy	F-Measure	Kappa
SVM	63.88%	0.62	0.27
KNN	60.10%	0.60	0.21
J48	64.87%	0.63	0.29
RF	64.58%	0.62	0.29

Table 5.1: Dataset 1, demographic data only.

	Dataset #2 HR-CLEAN data		
Classifier	Accuracy	F-Measure	Kappa
SVM	48.44%	0.41	0.03
KNN	60.05%	0.60	0.20
J48	54.39%	0.48	0.08
RF	59.49%	0.59	0.18

Table 5.2: Dataset 2, HR Clean values only.

	Dataset #3 Demographic + HR-CLEAN data		
Classifier	Accuracy	F-Measure	Kappa
SVM	66.85%	0.66	0.33
KNN	96.03%	0.96	0.92
J48	96.03%	0.96	0.92
RF	96.45%	0.96	0.92

Table 5.3: Dataset 3, HR Clean values and demographic data.

Based on these results the hypothesis stated at the beginning of the research:

Using a webcam from a mobile device or computer is possible to calculate the heart rate and correlate with academic stress levels from standard stress tests based on anxiety body responses by using Remote Photoplethysmography technique.

has been verified, concluding that the development of a system to measure academic stress by using video recording is feasible.

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