DEPARTMENT OF ELECTRICAL
AND COMPUTER ENGINEERING

ÍRIS PASCOAL LISBOA
BSc in Electrical and Computer Engineering

EMOTIONAL ASSESSMENT BASED ON SINGLE-CHANNEL EEG AND EDA SIGNALS

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To myself.

Acknowledgements

I would like to thank my family for the support they gave throughout the years i was studying. This dissertation marks the end of a cycle in my life and the beginning of my freedom.

"I want so much that is not here and I do not know where to go." (Bukowski)

Abstract

As the interactions between humans and computers continue to grow, and technology takes more space in our daily lives, it's crucial for our devices to evolve and better serve us. Affective computing and Brain-Computer Interfaces have emerged as promising approaches to bring humans and technology closer together. These technologies aim to improve the machine's understanding of the human psychology and use it to provide personalized and efficient services. It could also improve the accuracy of facial recognition software, which often struggles with differentiating between similar emotional expressions. Identification of emotions can be achieved by self-report, physiological measurements or behavioral analysis. All these processes induce errors due to the subjective criteria in self-assessment and behavioural analysis, and the difficulty in identifying emotions from physiological measurements. Affective computing has mainly focused on EEG-based emotion recognition, EEG signals are directly related to brain activity and since emotions are the result of brain processes such measurements could offer value in identifying emotions. Combining the EEG signals with another physiological sensor could help improve emotion recognition and give a better insight of a user's emotional state, especially when dealing with single-channel or consumer grade EEG devices. Combining EEG with EDA sensors is gaining increasing interest. EDA sensors can measure changes in the skin's electrical conductivity, which can indicate emotional arousal. By analyzing both brainwave activity and changes in skin conductivity, researchers can gain a more complete picture of a user's emotional experience. This can be especially useful in fields such as psychology, where understanding emotional states is critical. Combining EEG and EDA sensors could improve accuracy in emotion recognition, as well as a more detailed understanding of emotional states. The proposed research aims to establish correlations between single-channel EEG and EDA measurements, and emotional self-assessment by promoting exposure of selected images in a trial with human volunteers.

Keywords: EEG, EDA, single-channel EEG, Affective Computing, Brain-Computer Interfaces, Emotional Assessment, Machine-Learning, BITalino (r)evolution Board

Resumo

À medida que as interações entre humanos e computadores continuam a crescer e a tecnologia ocupa mais espaço nas nossas vidas diárias, é crucial que os nossos dispositivos evoluam para nos servir melhor. A computação afetiva (affective computing) e as interfaces cérebro-computador (brain-computer interfaces) surgiram como abordagens promissoras para aproximar os humanos e a tecnologia. Tecnologias como estas visam melhorar a compreensão da máquina sobre o cérebro e a fisiologia humana e utilizá-la para fornecer serviços personalizados e eficientes, como a adaptação de listas de reprodução de música com base no estado emocional do usuário, ou melhorar a precisão de softwares de reconhecimento facial. A identificação de emoções pode ser alcançada usando auto-avaliação, medidas fisologicas ou avaliação comportamental. Todos estes processos teem falhas e induzem erros devido à natureza subjectiva das emoções. A Computação afetiva tem se focado principalmete em soluções à base de EEGs. Sinais de EEG estão diretamente relacionados com a actividade cerebral, visto que emoções são o resultado de processos cerebrais, equipamentos como EEGs podem tem bastante potencial na identificação de emoções. A combinação dos sinais EEG com outros sensores fisiológicos poderia ajudar a melhorar o reconhecimento de emoções e fornecer uma melhor compreensão do estado emocional de um utilizador, especialmente ao lidar com dispositivos EEG de um único canal. Os sensores EDA medem mudanças na condutividade elétrica da pele, o que pode indicar excitação emocional (arousal). Analisando a atividade das ondas cerebrais e as mudanças na condutividade da pele, os investigadores podem obter uma imagem mais completa da experiência emocional de um utilizador. Isto pode ser especialmente útil em áreas como a psicologia, onde a compreensão dos estados emocionais é crucial.

Palavras-chave: EEG, EDA, single-channel EEG, Affective Computing, Brain-Computer Interfaces, Emotional Assessment, Machine-Learning, BITalino (r)evolution Board

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Acronyms

AI Artificial Intelligence *(pp. 1, 2, 4, 20)*
ANN Artificial Neural Network *(pp. 1, 20, 22, 32)*
ANOVA Analysis of Variance *(p. 31)*
ANS Autonomic nervous system *(pp. 9, 10, 23)*

BCI Brain-Computer Interface *(pp. 3, 15, 16)*
BP Blood Pressure *(pp. 10, 23, 28, 29)*
BPF Band Pass Filter *(pp. 30, 51)*

CNN Convulutional Neural Network *(pp. 22, 32)*
CNS Central nervous system *(p. 11)*
CO Cardiac Output *(p. 10)*

DEAP Database for Emotion Analysis using Physiological Signals *(p. 20)*
DNN Deep Neural Network *(p. 22)*
DT Decision Trees *(p. 32)*
DWT Discrete Wavelet Transform *(pp. 20, 22)*

ECG Electrocardiogram *(pp. 20, 30, 36)*
EDA Electrodermal Activity *(pp. 5, 6, 10, 22, 23, 25, 26, 28–34, 36, 38, 40–44, 46, 47, 49, 52–54, 56, 62–64)*
EEG Electroencephalogram *(pp. 3–6, 11, 13–22, 30–34, 36, 37, 40–44, 46, 47, 49, 51–54, 56, 62–64)*
EEG Pet Electroencephalography Personal Efficiency Trainer *(p. 20)*
EMG Electromyography *(pp. 10, 11, 28, 30, 36)*
EOG Electrooculogram *(pp. 21, 22)*
ERP Event Related Potential *(p. 31)*

FD Fractal Dimension *(pp. 20, 22)*

FDA Fisher's Discriminant Analysis *(pp. 21, 22)*
FFT Fast Fourier Transform *(pp. 20–22, 31, 41)*
fMEG Facial Electromyography *(p. 29)*
fMRI Functional Magnetic Resonance Imaging *(pp. 8, 11)*

GSR Galvanic Skin Response *(pp. 22, 25, 26, 29, 30)*

HFD Higuchi's Fractal Dimension *(pp. 21, 31)*
HPF High Pass Filter *(p. 41)*
HR Heart Rate *(pp. 10, 23, 28, 29)*
HRV Heart Rate Variability *(p. 10)*

IADS International Affective Digitized Sounds *(p. 20)*
IAPS International Affective Picture System *(pp. 20, 34, 35)*
IBM International Business Machines Corporation *(pp. 2, 20)*
ICA Independent Component Analysis *(p. 31)*

KNN K-Nearest Neighbours *(pp. 21, 22, 30, 32)*

LPF Low Pass Filter *(p. 41)*

MDF Modified Universal Threshold *(pp. 21, 22, 30)*
MEG magnetoencephalography *(p. 11)*
ML Machine Learning *(pp. 1, 32, 33, 35)*

NB Naive Bayes *(pp. 30, 32)*

PAD Pleasure, arousal and Dominance emotional state model *(p. 7)*
PANAS Positive and Negative Affect Schedule *(p. 30)*
PEP Pre-Ejection Period *(p. 10)*
PSD Power Spectral Density *(pp. 31, 41)*

RBF Radial Basis Function *(pp. 42, 63)*
RF Random Forest *(p. 32)*
RNN Recurrent Neural Network *(pp. 22, 32)*
RWE Relative Wavelet Energy *(pp. 20, 22)*

SAM Self-Assessment Manikins *(pp. 9, 20, 21, 34, 47, 49, 50, 53)*
SCL Skin Conductance Level *(pp. 10, 24, 25)*
SCR Short-Duration Skin Conductance Response *(pp. 10, 25, 29, 32, 41, 42)*

SGF Savitzky-Golay Filter *(pp. 20–22, 30)*

STFT Short Time Fourier Transform *(pp. 21, 22, 31)*

SVM Support Vector Machine *(pp. 20–22, 29, 30, 32, 42, 62–64)*

SWT Stationary Wavelet Transform *(pp. 21, 22)*

TPR total peripheral resistance *(p. 10)*

V/A/D Valence, arousal and domiance dimentions of emotion *(pp. 8, 9, 33–35, 43, 47, 49, 53, 56)*

VR Virtual Reality *(p. 4)*

WCSS Within-Cluster-Sum-of-Squares *(p. 60)*

1

Introduction

Technological advancement has reached unprecedented levels never seen before. With emerging knowledge such as Artificial Intelligence (AI), Machine Learning (ML), Artificial Neural Network (ANN), and other so-called exponential technologies it seems that technology is becoming an extension of the Human being. To address such demand, research and investment are being poured each time more into advancing the Affective aspects of technology, so that technology can better serve it's users, and also adapt to each individuals needs.

Traditional scientific thinking and principles are derived from logic, rational thoughts, even though all of this comes from a sentient mind and body, emotions still have a stigma in science [66]. Much of the scientific work we have nowadays was propelled by fear and curiosity, those characteristics besides physical are intrinsic to humans, and, is the sum of all those contributing aspects that make us, sentient beings.

Emotions are part of the human decision-making process, and Affective Computing aims to provide better assistance to humans and better abilities to understand users on a psychological/emotional level. Studies on patients with frontal-lobe disorders show that they have a harder time making decisions compared to healthy patients. This is due to the inability to feel emotions to some extent due to damage in the frontal lobe. There is no pure reason in a person's thinking process [66].

There are several sensors and tools that have been used to study different physiological reactions to external stimuli and their relation with affective states. So, it is legitimate to question; is it possible for a machine to give accurate feedback and understand human emotion? If so, systems like these will be the future of computing; such as, there is a need to create standardize emotional assessment methods that allow for future studies on affective computing replicate and improve.

Smart devices are becoming a part of our daily lives, and, with the evolution of the industry within a competitive market, the tendency is to improve customer service by providing a service that adapts to the specificity of the client. Those services become more important the stronger the relationship between man and machine, or between people interfaced by technology. In the field of healthcare there are many examples where such relationship occurs, and tangible benefits could be obtained by such technological capabilities. Devices with affective capabilities may aid to access not only the patient's physical state but also the mental/psychological state. The interest in human aspects does not stand just for medicine, International Business Machines Corporation (IBM)'s Watson has developed a "Tone Analyzer" that can detect sarcasm and other emotions from writing patterns. This kind of development is an important step in human-computer interaction and puts AI one step closer to passing Turing's test [54]. At Ohio State University a team of researchers programmed a computer to recognize facial expressions of "complex emotions" such as "happily surprised" or "fearfully angry". Facial recognition software was already able to recognize different basic categories of emotions, and so are we humans. The groundbreaking thing in this study is that the facial recognition software was able to surpass humans and provide a more accurate evaluation of facial expressions. Most of us use the same facial muscles to indicate the same emotions [46], this combined with the superior processing ability of a computer makes the system surpass human ability.

Today, there are diverse devices aimed to support communications between individuals, some of those are also able to promote sensory stimulation in the form of audio (e.g. sound, music calls), video (e.g. movies, clips, video calls), symbols, avatars, emojis, etc. The first challenge is to identify the effect of sensory stimuli and how it affects the human being. The next challenge is to capture and analyze this information in a reliable way so that it can be used for study the impact of stimuli and the different sensations. Finally how we react and express our reaction to those stimuli vary from person to person. In face of such challenging aspects, it would be interesting to collect data from sources that provide us non-verbal information and that cannot be deceiving or influenced by a person's conscious body, such as facial expressions, heartbeat, brain activity or body temperature.

To collect sensory and physiological data, there are already several devices and biosensors that exist in the market or are being developed. This dissertation will focus on the correlation of brain waves and electrodermal activity with emotion.

1.1 Motivation

Research on affective computing is still in its early developing stages but already proves to have what is necessary to shape the evolution of how we interact with technology and with each other. Gartner, a global research and advisory firm for IT and communication predicts that by 2022, 10% of personal devices will have emotion related AI capabilities [30], this number was less than 1% in 2018. Affective computing and emotion tracking technologies can be introduced to many different industries, with endless applications.

Affective computing has been present in many different areas of research and in the most creative of ways. Figure 1.1 presents some of the areas of research.

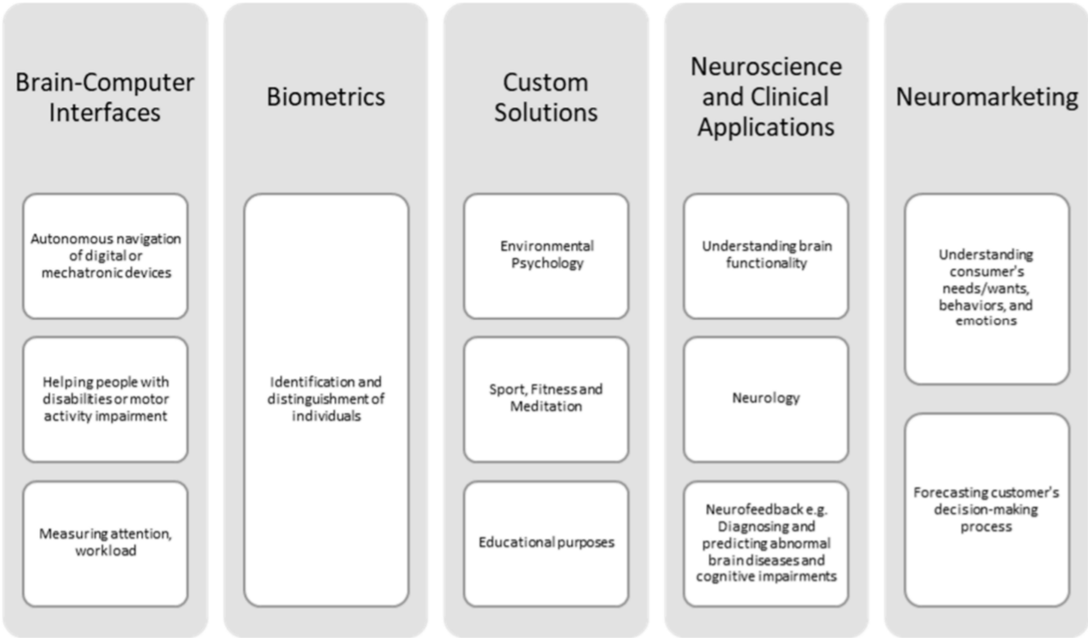


Figure 1.1: Some Affective Computing applications and areas of research

The areas of interest for affective computing solutions are constantly growing, as our everyday liver become more and more dependent of technological devices such as our smartphones or computers. Next, in the following items the author will dive into some emerging areas of research that have been contributing to the advancement of affective computing and the detection of affective states of a particular subject.

1. **Brain-Computer Interface (BCI):** Smart devices working with emotion tracking technology could bring a whole new lever of human-computer interaction. The joining of these two technological trends would bring into our daily lives devices that understand, and adapt to our own individual needs, always changing and learning [87] with them. BCIs can also be integrated into IoT systems such as home assistance or driver assistance, adds value and new opportunities in this area of research and development. Another underestimated application for BCIs is on the arts and performance fields, several installments based on biofeedback have already been created with beautiful results [6, 84, 21, 63, 62]. Taking art to another level where the object of admiration is customised to the viewer.

2. **Driver Assistance:** This is one of the most interesting applications regarding BCIs, automotive companies can embed technology on to their cars to track the driver's attention levels and, tiredness assessing the capabilities associated with a safer driving. This can be achieved with Electroencephalogram (EEG) sensors, microphones or even cameras. Nowadays, with more intelligent and autonomous cars that already have some sensors embedded, this reality is closer than ever [69, 31, 93].

3. **Environmental Psychology:** Businesses can track their employees' stress and anxiety levels or measure how much satisfaction they take from their respective task and workload. Unilever is one company that currently uses emotion AI to aid their recruitment process. Although beneficial to the company, the deployment of these techniques onto the company's staff brings ethical problems, as the monitoring of employees during their work hours, and the fact that with the current technology the emotion tracking might not be that accurate and it would make it unfair to judge the employee's performance solely on these measurements.

4. **Healthcare:** In the situation that we are living today, with a lot of medical appointments being made online or via telephone, an emotional tracking device would be most useful, not only to diagnose patients but also to evaluate their emotional condition, that way doctors can understand their patients mental state better, and without being in their presence. Patient care would also improve a lot for the same reasons, and in the future, maybe, intelligent care bots can, as well understand and care for the patients needs. One other major opportunity in health care is the potential that EEG has for helping people with disabilities or motor impairment. EEG reads brain waves, so it is also able to pick up waves that correlate with motor capabilities, such as the intent to move a certain limb, the intent to speak and in such cases, it is even possible to decipher the words [39, 58, 77]. Voice analysis can be helpful to doctors in the diagnostic of diseases like depression or dementia.

5. **Gaming:** Before releasing games, companies can use affective computing to test the gamer's engagement, thus making it easier for the company to make some last minute changes based on monitored reactions. Incorporating some form of biofeedback with gaming a new form of playing videogames arises as well, the adaptative gaming where the game adapts to the users emotional state. Also, with the rise of Virtual Reality (VR) games, there is a growing interest in incorporating emotional assessment with VR devices, giving the gamer an even more personalized experience and realness [34].

6. **Neuromarketing:** The era of information has always been a gold mine when it comes to spreading information about a product. It is no secret that the more data a company has over a certain population, the easier it is to appeal to that population, as it was seen with the Cambridge Analytica scandal. With access to EEG devices and emotion recognition software, businesses can analyze what engages their customers, measure emotional reactions and generate contents that are guaranteed to have success in a given population [43, 59, 33].

1.2 Research Questions

1. Is it possible to assess emotional states using single-channel EEG and EDA signals?

2. If so, can a framework that assesses emotional states establish a users' well-being?

1.3 Dissertation Outline

The dissertation outline begins, in the first chapter, with an introduction to the dissertation themes and the motivation and background that propelled this study. In this chapter the research questions that guide this dissertation are presented.

In the second chapter the author does a summary of the theory behind the research theme. Starting with a general description of what are emotions and how they have been studied. Followed by a detaled analysis of EEG and EDA technologies and processing methods.

The third chapter introduces the readers to the proposed system for emotional assessment, based on the knowledge acquired in the previous chapters, specifying the methods for the acquisition of data, filtering and classification of EEG and Electrodermal Activity (EDA) data.

The fourth chapter details the architecture for the data acquisition system. And the fifth chapter explains the experimental process in which the data acquisition system was used.

The sixth chapter presents the analysis of the data resulting from the conducted experimental sessions as well as the conclusions drawn from this analysis.

Finally in the last chapter the author makes some remarks on the dissertation work and some aspects that should have been included. The author also proposes some improvements and scenarios for future work.

2

Literature Review

This chapter provides a theoretical overview of the important concepts regarding the objectives of this dissertation. To assess emotional states based on EEG and EDA signals. First a general introduction to what are emotions, and how to evaluate them is presented. Secondly the state of art, potential applications, and theory involving EEG and EDA emotional assessment. Finally, the last section of this chapter presents a review on some methods used for processing and classification of physiological data.

2.1 Affective Computing

Different physiological and physical characteristics can transmit emotional details. While recognition and interpretation of emotional states comes easy to humans, this task is very challenging for a computer. Affective Computing is the field of computation born from these challenges to converge technology with human emotion [66]. Emotions are deeply rooted in Human communication; they are the foundation of what makes us sentient individuals. For hundreds of years, from the curious to researchers, time and effort have been dedicated to study and develop models that accurately represent emotions. Humans themselves have historically shown to intrinsically attracted to the expression of emotions and thoughts/ideas, most commonly seen in art, that has been with us since the dawn of our time. Nowadays we have various representative models of emotion, none of them can be said to provide a definite answer for what is emotion.

From a computational point of view, in an era that is ruled by digital communication, it is interesting to think about the possibility of these devices to become able to understand us, on a deeper level.

2.2 Emotions

"Emotions," wrote Aristotle (384–322 BCE), "are all those feelings that so change men as to affect their judgements, and that are also attended by pain or pleasure. Such are anger, pity, fear and the like, with their opposites."

To be able to address the challenge of capturing information about emotions it is important to define what are emotions, and if is possible for computers to classify/identify emotional ques from humans. Objectively speaking (because emotions are intrinsically subjective concepts), emotional states can be classified in a discrete or dimensional space. The most relevant discrete systematic approach was presented in 1992. Paul Ekman identified six basic emotional states: anger, disgust, fear, happiness, sadness, and surprise [24]. These emotional sates could be identified and differ in aspects such as expression, antecedent events, probable behavior response, physiology, etc... Ekman also states that these basic emotions have certain characteristics, such as: (1) emotions are born with humans, not learned; (2) a certain emotion occurs in the same situations that trigger them; (3) emotions are expressed in a similar way across humans; (4) similar physiological patterns appear when expressing the same emotions.

Another popular model of emotional states is the Plutchik's wheel (see figure 2.1), which is a discrete model that shows 8 basic emotions and their families: joy, trust, fear, surprise, sadness, anticipation, anger, and disgust based on their physiological purpose, according to this, emotions can be a combination of two or more primary emotions, and further, we get from the center of the wheel, less intensity we feel.

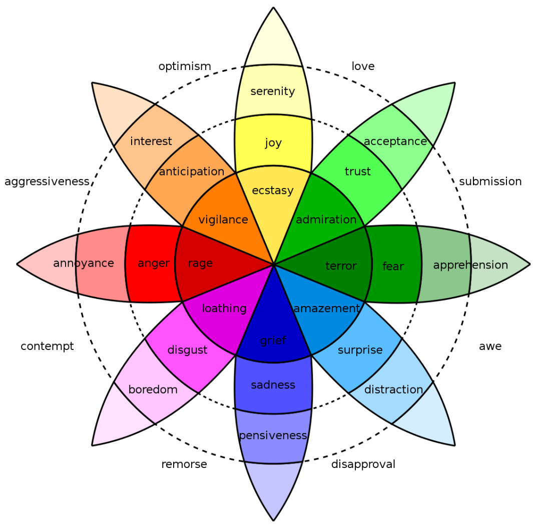


Figure 2.1: Plutchik's wheel of emotions.

Albert Mehrabian and James Russell [5] presented the Pleasure, arousal and Dominance emotional state model (PAD) in 1974 (see figure 2.2). This is a dimensional model that presents spatially three dimensions of emotion, Pleasure, Arousal, and Dominance that arise from the neurophysiological systems present in our brain.

- **Pleasure (Valence)** represents how much pleasure a person feels and the direction of the emotion, for example, joy is classified as a pleasant emotion whereas anger is classified as an unpleasant emotion.

- **Dominance** represents how much control and dominance, or submission and controlled a person feels. Feelings such as anger trigger dominance, while boredom is mostly non-dominant.
- **Arousal** measures the intensity of the feeling. For example, boredom and rage are both unpleasant feelings, but boredom has a low arousal value while rage has a higher arousal state, because the former is a calmer feeling, and the latter is more a more exciting one.

In 2004 Anders [2] exposed volunteers to a set of emotional pictures and took verbal ratings of valence and arousal for each, while the volunteers were being monitored with Functional Magnetic Resonance Imaging (fMRI). The analysis revealed a correlation between brain activity and the Valence, arousal and domiance dimentions of emotion (V/A/D) of a stimulus, thus proving that the brain reacts to visual stimuli.

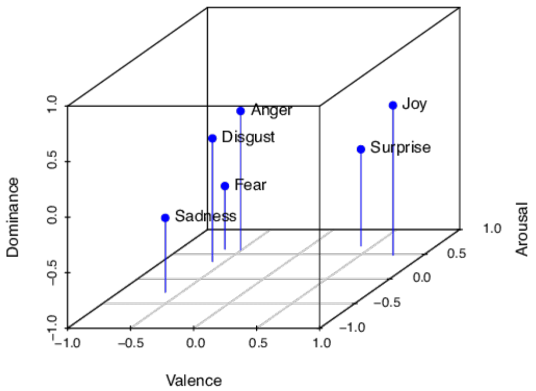


Figure 2.2: Affective space spawned by valence, arousal, and dominance.

2.2.1 Techniques to collect emotional Information

To create a model for human emotion detection an extensive amount of data needs to be collected so that there is a possibility to infer an certain emotional state a person might be feeling. Even with great amounts of data and state-of-art hardware and software, these days there isn't a reliable technique that can precisely evaluate a person's emotion and it's depth. In this dissertation, given the resources and material available, the expected results are but a fraction of the complexity human emotion can have.

Emotions are a human characteristic, although sometimes it is hard, from an outside point of view, to identify which emotion someone is experiencing in other manner then known face expressions or verbal expression. Emotions are also transmitted through speech patterns, writing patterns, heartbeat, galvanic skin response, brain waves, or other biometric measurements [25].

Emotion detection must be objective, unobtrusive and non-invasive,with no need for special expertise in a specific language or culture. This means that independent of the culture/language/nationality of the subject similar stimulus should elicit similar responses.

There are three major areas we can consider when evaluating emotions:psychological evaluation, behavioral and physiological [45].

2.2.1.1 Psychological evaluation

The Psychological evaluation of one's emotions is a subjective measurement, and not very precise. It is dependent on the self-awareness of the individual and also, sometimes, on the interpretation of the person delivering. This is due to the different levels of insight each subject shows, and their ability to show inner feelings. Within the psychological tools to evaluate the affective state of a subject, the most common is through self-report, whether it being through the help of a psychologist or simply the subject reporting and emotion when faced with and emotion eliciting stimuli.

Self-report can be used to acquire emotional responses according to the chosen emotional model. The type of self-report plays a key role in the validity of the test, as reports of current emotional states are more likely to be true than reports of emotional states felt in the past. Dimensional models such as the one presented in section 2.2 are much more likely to have a higher accuracy because of the discrete nature of these models.

Mehrabian and Russell proposed the differential scale for self-report of emotions, a tool to measure 3-dimentional structure objects, a collection of 18 bipolar adjective pairs (e.g., unhappy-happy, annoyed-pleased, unhappy-satisfied, etc.), each pair belonging to a 9-point scale with an adjective pair at each extreme. This method results in a large database and is difficult to apply to non-English speakers it is not widely used nowadays. The Self-Assessment Manikins (SAM) test was proposed as an alternative, a picture-oriented instrument that directly evaluates the V/A/D (Bradley and Lang, 1994). This model, presented in figure 2.3, is picture oriented so that the self-report measurements can be understood across different cultures, languages, countries. Although being a subjective measurement, psychological evaluations can be very useful when complemented with other forms of emotional evaluation, such as physiological assessment.

2.2.1.2 Physiological assessment

Physiological assessment is based in the notion that when a person experiences some emotional state, the body triggers involuntary physiological changes, these can be increased heart beat, sweating, blood pressure, etc.... These changes in the body can be measured using dedicated sensors. With physiological assessment there are numerous focal points from where to draw some kind of emotional response, because the body itself is always aware of our surroundings, whether we are conscious of it or not.

- **Autonomic measures of emotion** focus on measuring responses from the Autonomic nervous system (ANS) responsible for peripheral functions. The ANS consists of the sympathetic and the parasympathetic nervous branches. The ANS measures

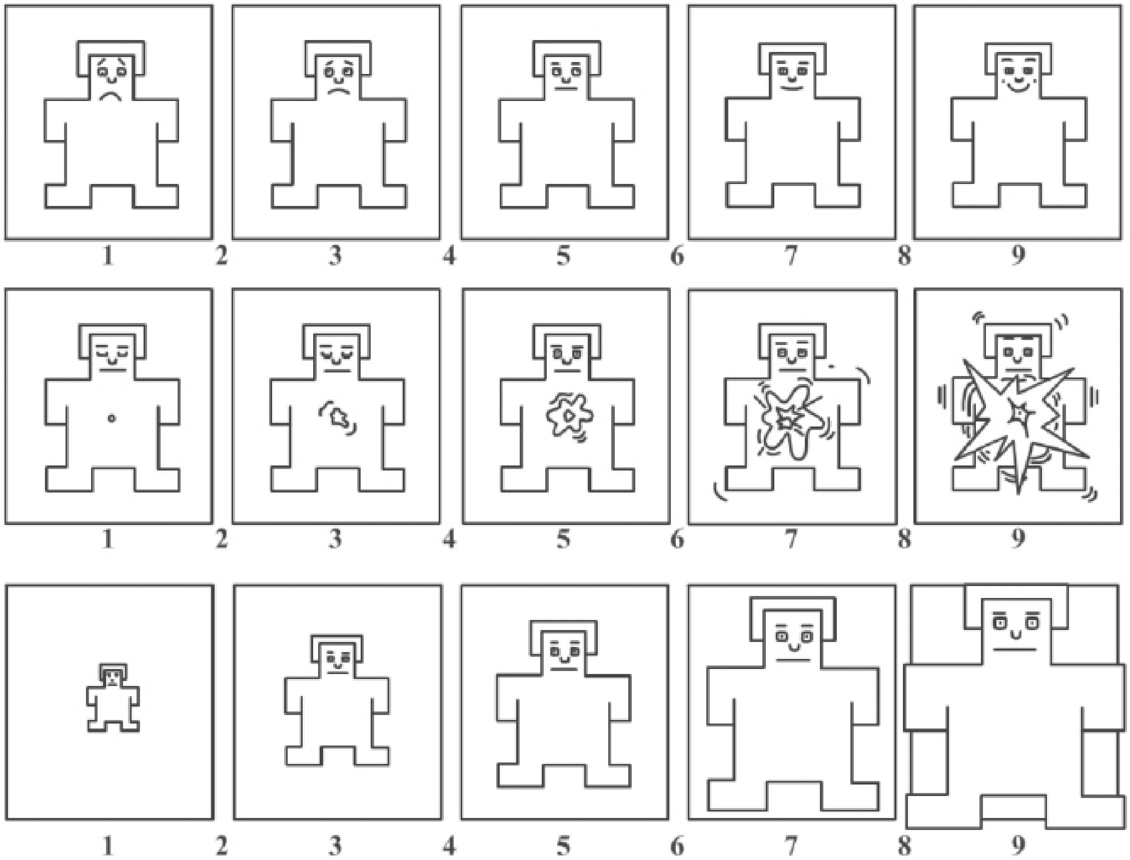


Figure 2.3: Self-Assessment Manikins. Valence (top panel), arousal (middle panel), and dominance (bottom panel)

are controversial because it is not clear whether the activity in this system is a consequence of emotional responses, or just part of other processes in the system [56]. The ANS activity is often assessed from EDA, which can be used to measure Skin Conductance Level (SCL) or Short-Duration Skin Conductance Response (SCR)s. Cardiovascular activity is also used for autonomic assessment, the most common used cardiovascular measurements are Heart Rate (HR), Blood Pressure (BP), total peripheral resistance (TPR), Cardiac Output (CO), Pre-Ejection Period (PEP), and Heart Rate Variability (HRV). Several studies point to the relation between arousal and the increase in SCL values [56].

- **Startle response magnitude** uses Electromyography (EMG) to measure involuntary reflexes such as eye blinks and muscle flexing specifically in the neck or back or face. When EMG is usually recorded, using visual and auditory stimulus that vary in valence, the readings tend to be smaller when presented with pleasant stimuli, and larger when presented with unpleasant stimuli [11].

- **Brain states as measure of emotion** have been used based on the notion that expressions of emotions must be more likely to be found in the brain itself rather than peripheral responses [12]. Directly assessing the structure in the brain from which an emotional state emerges, neuroimaging techniques such as fMRI, magnetoencephalography (MEG) and EEG are among the most used.

2.2.1.3 Behavioral assessment

Behavioral assessment consists on the observation of changes in behavioral patterns of a person to infer it's emotional state. The behavioral analysis consists on the observation of behaviour a person conveys outwards, and is capable of being observed by other humans without any major technique or apparatus. Behavioral assessment we do everyday, observing and analysing a persons body language, facial expressions or vocal characteristics. Nowadays, with emerging technology, behaviour analysis doesn't need to be performed by a human observer as there are technologies able to monitor facial expressions and body movements, for example through EMG [56].

2.3 EEG

The analysis and assessment of the human emotions and behaviour requires a deep understanding of the brain, the core component of human functions and behaviours. The brain contains approximately 85 billion neurons, responsible for the majority of communication within it. Synapses between neurons function as gatekeepers for excitatory or inhibitory activity, transmitting information across neurons that can cause the release of neurotransmitters such as dopamine, epinephrine, or acetylcholine, which can alter the cell's voltage. This synaptic activity can also create an electrical field known as a postsynaptic potential that usually lasts tens to hundreds of milliseconds.

EEG sensors use electrodes placed on the subject's scalp to measure neuron activity. It is one of the most adaptable brain imaging methods currently available and is frequently used in medicine to diagnose sleeping disorders, epilepsy, brain damage, and even some mental illnesses. The human brain is the main organ of the Central nervous system (CNS), and is composed by:

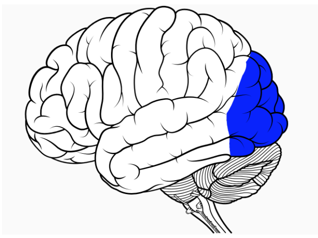
1. **Cerebrum**, the most significant portion of the human brain, known as the Cerebrum, is responsible for higher cognitive processes such as perception and awareness. The largest part of the cerebrum is the cortex, which is divided into two hemispheres and connected by the corpus callosum. The cortex is further subdivided into four lobes, namely the occipital, temporal, parietal, and frontal lobes. 2.4.

    a) **The Occipital Lobe** Processing of visual information is carried out by the occipital lobe, such as color discrimination and motion perception. It plays a central role in visual perception and processing. Damage to this region of the brain can result in hallucinations, color or motion agnosia, or even blindness.

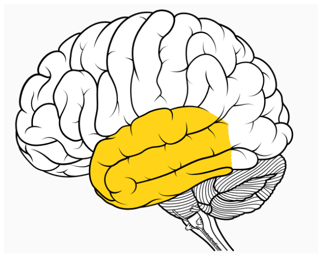
b) **The Temporal Lobe** is responsible for long term memory, and the comprehension of written and spoken language. It processes sensory input using visual memories, language and emotional association.

c) **The Parietal Lobe** is responsible for the integration of information coming from external sources as well as internal sensory sources (muscles, limbs, eyes, head, etc...) into a representation of how we relate to the environment around us and the other way back. Coordination, and our navigation in the world is managed from the parietal lobe, eye-hand coordinated task would be impossible without the parietal lobe.

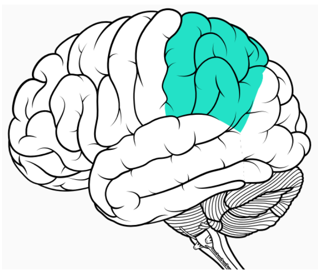
d) **The Frontal Lobe** Dopamine-sensitive neurons are abundant in the frontal lobe, which is important since the dopamine system regulates a variety of cognitive functions, including motivation, planning, short-term memory, attention, and reward. This region of the brain is also responsible for conscious thought and decision-making. The Frontal Lobe is widely recognized as a core component of our personality, and damage to this area can result in profound changes in personality, social behavior, and control of actions.



(a) Occipital Lobe



(b) Temporal Lobe



(c) Parietal Lobe

(d) Frontal Lobe

Figure 2.4: Four lobes of the brain cortex

2. **The Cerebellum** is located in the back of the head, under the cerebrum. Additionally, it has two hemispheres, which help to regulate and manage little motions, posture, and balance. The cerebellum and other brain regions connect with the spinal cord sensory system to modify motor activity in order to maintain balance.

3. **The Brainstem**, is the oldest portion of the brain, sometimes known as the reptilian brain, is made up of the midbrain, pons, and medulla. Controls autonomic functions like the heartbeat, bladder function and sense of equilibrium.

4. **The Limbic System**, the thalamus, hypothalamus, and amygdala make up this structure, which is in charge of the survival instinct in humans. It is frequently referred to as the emotional brain since it triggers fight-or-flight scenarios.

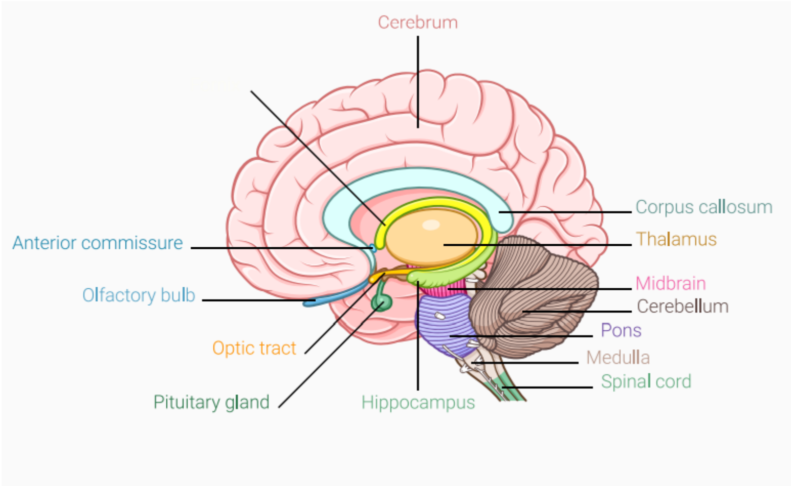


Figure 2.5: The Structure of the brain.

Studies have shown that external tools, such as the EEG, can mainly measure the synchronized activity of pyramidal neurons located in the cortical brain area. The occipital, temporal, parietal, and frontal cortices are only a few of the areas that contain these neurons, which are organized perpendicular to the cortical surface. The perpendicular arrangement of these neurons allows for the generation of a stable electrical field with a specific orientation. In contrast, deeper brain structures lack a specific orientation, resulting in electrical fields that spread in multiple directions and cancel out instead of projecting towards the scalp surface in a stable manner [13, 38].

The creator of EEG, Hans Berger, was also the first person to identify that there are different waves present in the brain and that these are affected by the performance of

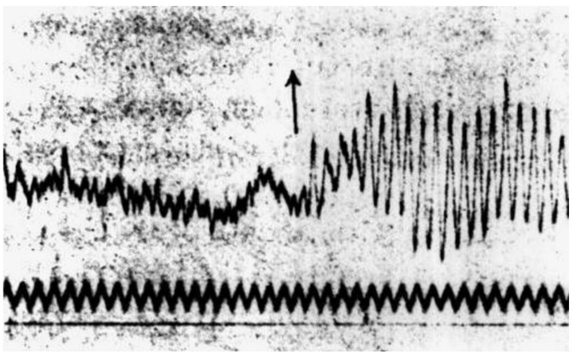


Figure 2.6: An early EEG recording performed by Hans Berger. The presented signal belongs to a subject asked to perform a mental arithmetic task, prior to the arrow. After the mental task is performed the brain response returns to normal, as observed in the figure, after the arrow.

Table 2.1: Brain wave frequency bands [48]

Wave	Frequency(Hz)	Psychological state
Delta(δ)	<4	Is the slowest and the wave with the highest amplitude. Usually present in the deep non-REM sleep state of adults. These are used as a basis for studies on sleep patterns and therapy, the stronger the delta rhythm the deeper the sleep. Movement can produce artificial delta waves. Deep sleep is associated with memory consolidation, so delta waves are important in the organization of memory, acquired skills and learned information. Delta waves have also been associated with some kind of physical healing, mainly tissue repair and regeneration. The true beauty sleep brain wave
Theta(θ)	4-7	These are the waves that manifest when we first fall asleep, in a meditative/focused state or creative inspiration. Studies correlate theta activity with the difficulty of mental operations, this means theta wave rhythm increase with increasing task difficulty. Theta waves can be triggered by emotional stress, frustration, or disappointment. High levels of theta waves are not considered normal in adults.
Alpha(α)	7-12	It is the main wave of the normal relaxed adult brain.Alpha waves can help reduce stress and anxiety since they are mostly present in states of relaxation, daydreaming and meditation. Positive states of mind. A strong alpha wave is connected to a mental and physical relaxation. Alpha waves are related to sensory, motor and memory functions. Low alpha band activity is often associated with sates of mental activity and engagement, for example focused attention towards any stimuli [65]. Alpha bands are usually monitored for studies on attention, meditation and relaxation
Beta(β)	12-30	These waves are related to a state of mental activity usually anxious thinking, alertness, focus or concentration. Normally associated with engagement on problem-solving or mentally challenging tasks. These waves when in an healthy pattern and with dominant activity can signal a healthy memory and cognitive performance, and are associated with concentration on mental effort tasks.
Gamma(γ)	30-50	Associated with joy and alleviation of stress. Together, beta and gamma waves have been linked to cognition, perception, and attention.

different tasks. EEG is a low-cost, non-intrusive, and passive recording method. The brain activity measured by the EEG can be visualized in its raw, unprocessed format, but the signal is actually composed of several different overlapped frequencies that are considered to reflect certain cognitive, affective or attentional states. The main waves identified in the brain and often used in research are presented in Table 2.1.

2.3.1 Applications of EEG

EEG technology has become quite accessible including the general public, thus becoming more then a device for observation of brain waves or medical studies. In 2014, a paraplegic person kicked off the World Cup in Brazil using an exoskeleton controlled by his own brain waves. While early research in the neuroprosthetics field required to collect brain signals previously, this one merely uses electrodes to pick up the signal and give real-time feedback. This was a major breakthrough in the field. The robotic exoskeleton is the achievement of the Brazilian neuroscientist Dr. Miguel Nicolelis alongside a team of more then 150 researchers. In 2003, Dr. Nicolelis also presented a study on the movement of virtual arms controlled by monkeys, proving that it is possible for monkeys to control a virtual arm using their brain activity [55].

Making art may be one of the most ancient and pure manifestations of Humans trying to express inner feelings and thoughts. Throughout history there have been times where art meets technology, the most obvious example being cinema. With BCIs human and computers became closer, so it's logical that some artist took inspiration from the technology. The merging of EEG and art gives artists the opportunity to explore a more intimate form of the human nature. New York-based visual artist Lia Chavez along with a multidisciplinary team have created a BCI, The Octave of Visible Light: A Meditation Nightclub art installation [16, 62]. Allows the audience to wear EEG headsets while being guided through a meditation. The EEG headset records the brain waves in real-time, then transfers them to a processor that will manipulate the colors and sounds, immersing the audience in a reflection of their own brain patterns and intensity. "Viewers can witness the interrelation between their own brainwaves and the vibrations that create sound and light" [84]. Other articles on art and brainwaves can be found in [6, 84, 21, 63].

Figure 2.7: The Octave of Visible Light: A Meditation Nightclub art installation

In sports, research has been made using EEG testing to learn the long-term and short-term effects of head trauma or multiple concussions [85, 27, 53]. And sleeps studies have been using EEG to track the effects of various qualities of sleep [61, 29].

Neuromarketing has been using biometric data such as eye movement, facial expressions, and brain waves to determine the effectiveness of pieces of media, to improve the advertisement success [67]. The examples presented are just some of the areas EEG and BCIs have spread, communication, education, entertainment and gaming are some other fields that are advancing in this area. As the cost of hardware decreases EEG will become more easily available to the consumer and more applications will surface with endless potential. Of course that there are still challenges and and drawbacks that can make the advancement of EEG and EEG related technologies have a slower advancement. The quality and resolution of the readings are still a challenge. Users must be very static, for a accurate reading, and any hair strands need to be removed from under the electrodes. Eye blinks, muscle movement or external noise are also picked up by the EEG. In short, the general of EEG devices is very unstable when it comes to situations that are dependent on very accurate readings, and reliable data [81, 50].

2.3.2 EEG Sensors

EEG devices monitor brain activity through the placement of electrodes in the scalp, these pick up electric potentials generated by the human brain. The design and cost of the EEG headset vary in a lot of aspects. The number and type of electrodes placed on the scalp that affects the quality and resolution of the readings. The more electrodes the headset has, more spatial resolution will exist in the readings, but, increasing spatial resolution means decreasing ease-of-use and comfort while also increasing the cost [73], devices like this are mainly found in Hospitals or in research labs with big budgets.

The NeuroSky's MindWave, NeuroVigil's iBrain, the Emotive headset or Bitalino's (r)evolution board are some consumer grade products available in the market, although more accessible in therms of cost, these devices may lack in the quality of technology, because of the reduced number of electrodes, or in general quality of the components. This kind of products, more accessible to the general public are very important to accelerate the development of new ideas and applications in the Affective computing area. Consumer grade EEG devices are often mobile and wireless, making them more ergonomic and more comfortable for a day-to-day use. If the objective is to create technology to better assist Humans in their daily lives, and that is able to better understand and act on affective states, then seems logical to think that conducting more research and improving consumer grade EEG sensors that are easy to use is the next important step in Affective computing. This way research is not only limited to the great institutions and labs with big budgets. Figure 2.8 presents some variations of common EEG headsets, as reviewed by [47].

The cost of EEG systems can vary based on a variety of elements, including the quantity and quality of electrodes, the communication mechanism, the kind of electrodes used, the resolution, and the device's sample rate. Systems with greater sample rates typically cost more than those with lower sampling rates. See table 2.2 for a comparison

Figure 2.8: EEG headsets [47]

between EEG devices regarding their density and electrode type, as reviewed by [47]. Some characteristics of EEG sensors that can affect their cost include:

- **Single-channel vs Multiple-channel headset:** The ideal number of electrodes for EEG investigations is not known. The type of experiment being conducted and the desired outcomes will determine how many electrodes are used and where they are placed. A 64-channel reading may be used for a deep view of the brain signals. In some cases 32-channel or less devices are enough for the experiment parameters, and increase the ease-of-use, nonetheless for this dissertation using a single channel EEG benefits the research, is enough for it's requirements and decreases the complexity of the work and time spent placing electrodes and denoising multiple channels [38]. Multi-channel EEG recording devices provide better spacial understanding and more detailed measurements from the brain signals, but it also increases the cost of the device and decreases ease-of-use. Most medical-grade devices are multiple-channel devices, the great drawback of multiple channel reading is that the EEG device is also more complex, and more complex to set-up, usually are very uncomfortable. Single-channel EEG devices are cheaper because of the decreased number of electrodes, normally 2 or 3 electrodes are used, one for reference and the others for collecting data.

- **Communication Type:** EEG devices transfer data to a computer via either wireless connection or wired connection. Wired connections limit movement but usually can establish more stable connections and can transfer more data at a given time. On the other hand, wireless connection often use Bluetooth, a drawback is that although the user has more freedom of movement, the connection can be lost and no data is recorded. The aspect of the wireless connections also reveals a new challenge for

EEG sensors and technology in therms of filtering and collecting clean EEG data, the gained freedom of movement allows for multiple advancements in the area, but also means less reliable readings. Despite the freedom of movement, brain wave readings need to be as clean as possible so the user will have to remain very still, regardless of the connection type [80].

- **Electrode Types:** The electrodes present in the EEG device need to be continuously connected to the scalp of the user for a reliable reading. The main electrode types used are saline solution based, soft-gel based or dry electrodes. The **saline solution** technique is usually used in EEG caps that cover the entire head and have more electrodes, so usually found in professional studies, the saline solution is placed in each of the electrodes to aid the connection between the electrode and the scalp. The **soft-gel** electrodes connect to the scalp via a adhesive-type of electrode that allows for the gel to have direct contact with the skin. The soft-gel can also be applied in EEG caps, where the gel is inserted inside an electrode pocket. The two electrode types mentioned above are considered wet electrodes. The most common wet electrode type is made of silver (Ag) with a thin layer of silver chloride (AgCl) – Ag/AgCl electrodes. **Dry** electrodes are usually the cheapest electrodes found in the market, because there is no need for preparation of the skin, but also these electrodes, in some cases, don't provide reliable contact with the skin. EEG devices with these type of electrodes are usually found in consumer/cheaper grade products. Dry electrodes are faster and easier to apply, as most of the time the electrode makes contact with the scalp only through applied pressure, and no adhesive is involved. However, these are more prone to motion artifacts when comparing to the wet electrodes that are applied though adhesive or an electrode cap, ensuring continuous contact with the scalp [38].

The placement of the electrodes cannot be arbitrary, the most common way of standardizing electrode placement along the scalp is the 10-20 system, provided by the American Encephalographic Society (1994) as well as Oostenveld and Praamstra (2001). Electrodes are positioned at 10% and 20% positions along longitude and latitude lines in the 10-20 system. The Figure 2.9 shows a depiction of the electrode placement system.

2.3.3 EEG and Emotions

As stated in the sub-section above 2.3.2, there are available in the market several devices that perform EEG readings, and in section 2.3.1, the potential of EEG regarding its integration in our daily lives was discussed. In the field of affective computing many studies of emotion recognition are conducted using EEG technology. Although affective computing recurring to EEG shows a lot of promise, it still has a lot to go, a deeper understanding of emotion processes and its neurophysiologic responses is needed.

Table 2.2: EEG devices comparison of channels and electrode type [47]

System(manufacturer)	Density(channels)	Electrode Type
MindWave (NeuroSky)	1	Dry (stainless steel)
ENOBIO 8 (Neuroelectrics)	8	Wet(gel)
BR8+ (BRI)	8	Dry (spring, foam)
Epoch (Emotiv)	14	Wet (saline)
g.SAHARA (G.Tec)	16	Dry (pins, metal)
B-Alert X24 (Advanced Brain Monitoring)	20 (+ 4 auxiliary)	Wet (gel)
Smarting (mBrainTrain)	24	Wet (gel)
Trilobite (Mindo)	32	Dry (spring, foam)
eego sports (ANT Neuro)	65	Wet (gel)/ Dry (polymer)
Mobile-128 (Cognionics)	64/128 (+ 8 auxiliary)	Wet (gel)
BITalino EEG sensor	1	Wet (gel)

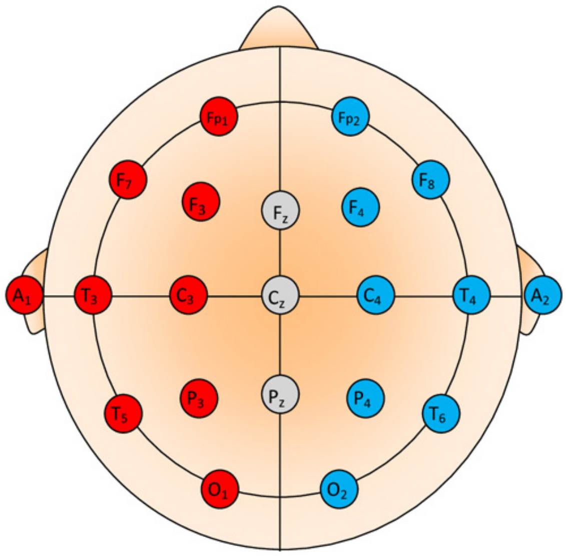


Figure 2.9: 10-20 EEG electrode placement

As mentioned before, EEG devices can range from medical grade to consumer grade, while medical grade technology offers great precision and quality of signal it lacks in operability and ease-of-use. Consumer grade devices are more mobile and accessible, so a lot of interest is being put in these, with recent studies showing its positive results. Although showing promising results the relatively low data quality and lack of spatial perception make the pre-processing of raw EEG rather difficult. A lot of denoising algorithms rely on spatial information, which is not feasible with a reduced number of channels. As such, there is no standardized de-noising pipeline for EEG data collected with commercial grade devices, making it more difficult to compare results and evaluate its validity across different studies [37]. Additionally the conclusions about EEG and emotional states do not often clarify their results in terms of repeatability of results over time and their effect on different populations, with very few studies on direct replications of former studies [37].

Below some studies focused on EEG and emotions are reviewed, the EEG devices, denoising methods and processing vary across studies for a better understanding of the possibilities and challenges regarding the processing and analysis of EEG data.

- **[91]:** This study focuses on the identification of emotions using brain signals and facial expressions, for a defined period of time. The EEG readings used came from an online Database for Emotion Analysis using Physiological Signals (DEAP). For the feature extraction of EEG readings **Wijeratne** uses Relative Wavelet Energy (RWE) Calculation and Discrete Wavelet Transform (DWT), for the emotion classifications an ANN is used, with 1-hidden layer and 20 neurons. For the facial feature extraction, the Active Shape Model is used along with Support Vector Machine (SVM) for classification.

- **[71]:** Focuses on using a single-channel EEG device for emotion detection. The data is read, saved, and processed using Matlab, for the study of the signal's features the IBM SPSS Modeler is used. This modeler is composed of a set of tools for data mining and the development of predictive models, it's methods range from automated learning, AI and statistics. In the experiment, subjects are shown 60 pictures from the International Affective Picture System (IAPS), each picture being evaluated using the SAM test as the experiment evolved. A Matlab software was then developed to show the images, record the EEG readings and place time marks for the EEG epochs. For the signal preprocessing, the difference between the maximum and minimum sample value (MinMax), a lowpass Savitzky-Golay Filter (SGF) filter (order 2 and length 35) and finally, the total energy of the signal were calculated. For the signal processing, Squared Fast Fourier Transform (FFT) is applied to each segment to obtain the energy bands, the Fractal Dimension (FD) is also calculated, a total of 5 values per epoch were obtained. The average accuracy obtained was 81%, this result is comparable to results from studies with multi-channel sensors for emotion detection, and one of the best results for studies using the NeuroSky's MindWave.

- **[49]:** This study focus on the recognition of emotions, from brain signals measured with the BraInquiry Electroencephalography Personal Efficiency Trainer (EEG Pet) device, five electrodes of which 2 are used for an Electrocardiogram (ECG) and the remaining 3 to the measurement of brain signals (EEG). The subjects were exposed to a set of pictures and sounds (IAPS and International Affective Digitized Sounds

(IADS)). A bandpass filter, from EEGLab for Matlab, was applied to extract specific frequency bands. Beta and alpha ratios and power were calculated to pass on to a binary linear Fisher's Discriminant Analysis (FDA) to predict the emotions. Different ratios with different electrode placements were tested, and the mean average between them is calculated. The average result was 80%.

- **[75]:** This paper focuses on how to record and process raw EEG signals, using the MindWave MW001, developed by NeuroSky. The author also presents how to connect and communicate with the device via the ThinkGear library and Matlab and presents an efficient algorithm such as the FFT to convert the signal to frequency domain.

- **[40]:** This study aims to classify two different emotional states, a state of relaxation and a state of fright. The experiment consisted in 19 subjects exposed to video clips that evoked the emotional states, while being recorded by a single-channel EEG. The subjects were then asked to give a score between 0-10 referring to the level of relaxation and fear during the recording session.Stationary Wavelet Transform (SWT) and Modified Universal Threshold (MDF) were applied during pre-processing to reduce artifacts from the signal. The study achieved 92% accuracy using a SVM classifier.

- **[90]:** This paper focuses on the characteristics of EEG features for emotion classification and techniques for tracking the trajectory of emotion changes. A 62-channel EEG device was used to identify positive and negative emotional states, a set of movie clips were shown to 6 subjects and these were asked to rate them using the SAM test. To remove artifacts from the signal an Electrooculogram (EOG) was also recorded and used to identify blink artifacts and later manually removed. Three features were used to evaluate the emotional sates, namely, power spectrum, wavelet, and non-linear dynamical analysis along with SVM as a classifier. The best average accuracy obtained was of 91,77%.

- **[94]:** This study aims to identify brain states such as, Focus, Normal, Sad and Shocked, using the single-channel NeuroSky's MindWave. For the feature extraction and classification FFT and K-Nearest Neighbours (KNN) with K=15 were used. Accuracy in each emotional state was performed using a confusion matrix, the average accuracy results were of 83,33%.

- **[8]:**This study uses 15 participants, in which the participant's brain waves are recorded using a single-channel EEG, the MindWave. The selected stimuli of video clips that evoke calm, neutral and fearfull emotional states. The signal preprocessing was performed using SWT, a Garrote threshold and SGF. The features selected for classification were the Short Time Fourier Transform (STFT), to determine the frequency and amplitude of the signal at each interval of time, Higuchi's Fractal

Dimension (HFD), used for detection of changes in human EEG alpha rhythm from wakefulness to drowsiness. The classifiers chosen were SVM with a custom designed kernel, a Deep Neural Network (DNN) and a Recurrent Neural Network (RNN), the accuracies resulted in average 55,407%, 68,675%, and 75% respectively.

- **[23]:**This study proposes an emotional classification framework based on Convulutional Neural Network (CNN). Three emotions were classified here, fear, fun and sadness. The EEG signal was mapped into a time-frequency function to extract features using STFT then the spectrogram of the signal was obtained by the squares of the STFT coefficients. The average accuracy was of 84,69% using a CNN.

Below in table 2.3 a comparison of the processing and classification methods used in the mentioned studies above. A more in depth analysis of these methods and results will be made in section 2.5.

Table 2.3: Comparison of EEG processing and classification methods

Author	**Channels**	**Denoising**	**Feature Extraction**	**Classification**	**Accuracy(%)**
[91]	—	—	RWE and DWT	ANN	91.7%
[71]	1	MinMax Difference, SGF	FFT for power spectrum and FD	C5.0	80.71%
[49]	3	Band-Pass Filtering	Alpha/Beta wave ratios and power bands	FDA	80%
[40]	1	SWT and MDF	STFT for power spectrum	SVM	92%
[90]	62	EOG	Power spectrum, wavelet, and non-linear analysis	SVM	91.77%
[94]	1	—	FFT for power spectrum	KNN	83.33%
[8]	1	SWT and Garrote threshold	STFT and FD	SVM, RNN, RNN	55.41%, 68.67%, 75%
[23]	1	—	STFT for spectrogram analysis	CNN	84.69%

2.4 EDA

Galvanic Skin Response (GSR), also known as skin conductance or EDA, refers to the changes in the electrical conductivity of the skin that occur when we are exposed to arousing stimuli. The sympathetic nervous innervation of the skin produces an "electro-dermal"signature of EDA [26]. This can be measured on the skin surface. The secretory channels of the sweat glands are subject to the activity on the sudomotor sympathetic nervous system. This implies that with the increase of sweating and high levels of porosity in the skin lead to increased electical conductance [60]. As a result, stimulation in the nervous system causes variations in the electrical properties on the skin surface through the activation of the sweat glands. The most common way to measure EDA is through conductance since the higher the activity of the sweat glands, the greater the skin conductance, making it easier to interpret the signal.

The peripheral nerve system's ANS controls uncontrollable physiological functions like respiration, digestion, sexual desire, and HRand BP among others.

The ANS is divided into:

- **Sympathetic nervous system:** Responsible for the body's quick, automatic response to threatening, stressful conditions. Increased sympathetic activity is connected to physical signs of autonomic arousal like increased HR, BP, and sweating.
- **Parasympathetic nervous system:** Also referred as the "rest and digest" system as it regulates the body's natural activity and relaxes the body once an emergency has passed, decreases arousal.

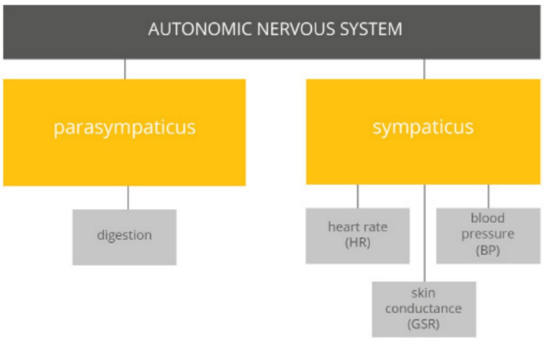


Figure 2.10: Autonomic Nervous System Structure

The EDA originates from the autonomic nervous system's activation of the sweat glands in the skin, triggered by emotional stimulation. The skin has three primary layer (Epidermis, Dermis, and Hypodermis), these are responsible for three major roles in the Human body:

- **Immune system:** It functions as a protective barrier from the outside environment.
- **Thermoregulation:** The temperature of the body is regulated by the skin through the sweat glands, piloerection(goosebumps) and blood circulation.
- **Sensing and perception:** The skin contains a network of nerve cells that detect changes based on the activity of pain, temperature, and pressure receptors.

The sympathetic and parasympathetic nervous systems operate independently of our conscious body, but their responses affect both the behavior of the body and the brain. Based on the unconscious responses from the sympathetic and parasympathetic nervous systems the brain can trigger learned behaviours in response to the environment. The body produces a trained autonomic reaction when a frightening stimulus is present in the environment, such as an accelerated heart rate or perspiration. The brain uses these learnt responses as a cue to direct conscious behavior and respond accordingly. The body's autonomic response could be regulated and made normal through later responses. Anxiety disorders are frequently characterized by an inability to control these emotions [64].

The importance of the peripheral nervous system for mental functions and emotional regulation has been extensively studied over the years. The James-Lange theory of emotion [92] (see figure 2.11), one of the earliest and most significant theories of emotions, suggests that physiological variations like expression of behavior, facial expressions (crying, smiling), and peripheral visceral responses (heart rate, emotional sweating, etc.), precede emotions in time. Thus, emotions may be partially an interpretation of the body's peripheral changes. However, one major criticism of this theory is that visceral responses may be too slow to allow for rapid responses to the environment. Walter Cannon presented an alternative model to this theory [14], the Cannon-Bard theory of emotion, illustrated in figure 2.12.

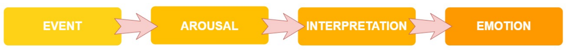


Figure 2.11: James Lange Theory of Emotion - Emotional responses are a result of the body's interpretation of the surrounding environment or stimuli.

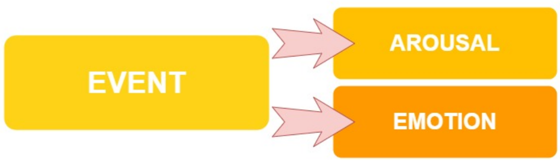


Figure 2.12: The Cannon-Bard theory of emotion - The bodily response and cognitive evaluation are independent from each other and occur at the same time.

According to the Cannon-Bard model, a person's emotional state includes their peripheral responses. This implies that the physical reactions serve as indicators of the emotions experienced, according to Christopoulos [18]. As a result, one might draw the conclusion that bodily reactions are an almost necessary component of the experience that may affect cognition and, in turn, behavior.

Two main component have been identified in GSR signals:

- SCL also known as tonic level is constantly changing within an individual subject on a time scale of tens of seconds to minutes depending on the hydration, skin dryness or autonomic regulation. Due to its inconstant nature, and the fact that the tonic level differs significantly across individuals some researchers consider that the SCL is not an informative value when used on its own [38].

- The phasic response, also referred to as SCR, exhibits much quicker changes compared to the SCL. These variations are manifested as peaks in EDA and are particularly responsive to emotionally arousing stimuli. Typically, these bursts occur between 1-5 seconds after the stimulus onset. It has been observed that SCR peaks also can occur spontaneously approximately at an interval of 1-3 minutes [38]. EDA SCR peaks are linked to emotionally arousing stimuli across all sensory modalities including vision, hearing, taste, smell, and touch [28].

EDA patterns have been studied thoroughly and reliably linked with human behaviour and emotion. For example, anxiety has been observed to correlate with specific SCR patterns [20].

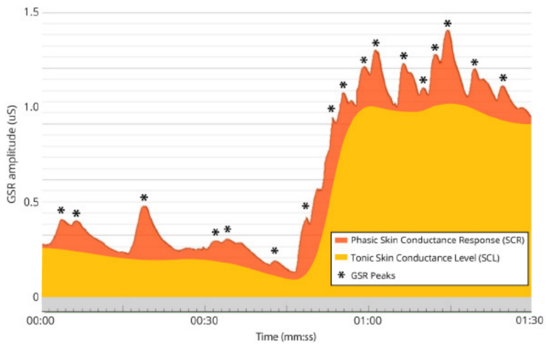


Figure 2.13: SCL and SCR responses in the skin over time [38]

SCRs can be interpreted as direct measures of arousal and engagement. The SCR activity of EDA signals can be computed into four features, peak amplitude, number of peaks, and latency of the SCR peaks as seen in figure 2.14:

- Latency: The time interval between the onset of the stimulus and the start of the phasic burst is known as latency. SCRs often appear 1 to 5 seconds after the stimulus begins. The time at which the GSR curve surpasses a minimum amplitude criteria (0.01 or 0.05 S, respectively) is commonly referred to as the onset.

- Peak amplitude is the difference between the onset of the SCR burst and it's peak amplitude;

- Rise time is the duration from the SCR's onset to it's peak;

- Recovery time is the duration from peak to 100% recovery. Usually the recovery time of a burst is much longer then the duration of the rise time.

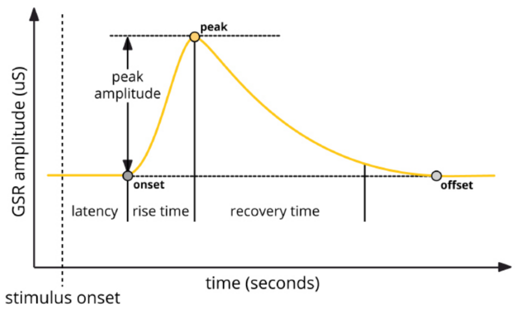


Figure 2.14: Event-related SCRs [38]

2.4.1 Applications of EDA

- **Psychological research:** GSR can be used to identify how humans respond emotionally to different stimuli and how its different characteristics affect our behavior.

- **Clinical Research:**Patients with some mental disorders are shown to have a higher fear response and emotional arousal to trauma triggers. In therapy GSR can be used to asses the severity of the disease, measure the physiological arousal, and train relaxation techniques.

- **Consumer Neuroscience and Marketing:** GSR can be measures to track emotional arousal towards specific products and market them accordingly.

2.4.2 EDA Sensors

Skin conductance is recorded in a non-invasive manner, using only electrodes places on the skin and very basic equipment to process the data. Compared against other physiological sensors the EDA is easier to use and more comfortable since almost no preparation time is needed, and most sensors are portable. Generally, the sensors are made of Ag/AgCI (silver/silver chloride) and are placed on the skin with the aid of Velcro straps or with a adhesive sticker, the latter requires the use of conductive gel.

EDA sensors typically consist of two electrodes, an amplifier (to boost signal amplitude). Some devices are wireless for communicating with another party, using for example Bluetooth.

Although sweat glands are located all over the human body, palms, fingers, and the soles of our feet respond to stimulation better than other body parts, making them a more dependable recording location. The experimental set-up, the type of electrodes accessible, and the level of intrusion the participants are comfortable with all influence where the electrodes should be placed. The table 2.4, according to [19], shows some electrode placement recommendations, as well as the recommended electrode type [10].

Other devices feature EDA electrodes rigidly fixed in wrists or elastic straps, while some devices allow almost arbitrary sensor placements in any of the previously described

Table 2.4: Recommended Electrode Placement [19]

Body Location	Sweat glands density	Electrode Type	Intrusiveness	Recommended for
Palm	High	Pre-gelled disposable and wet/dry reusable	Low	Stationary/mobile studies where the hand with electrodes will not be used
Fingers	Mid	Wet/dry reusable	Low	Stationary/mobile studies where the hand with electrodes will not be used
Feet	High	Pre-gelled disposable and wet/dry reusable	High	Stationary studies where both hands will be used
Shoulder	Mid	Pre-gelled disposable and wet/dry reusable	High	Stationary/mobile studies where both hands will be used

locations.

Table 2.5: Comparison of EDA devices

Manufacturer	Device	Electrode Type	Communication	Location(s)	Portable
Mindfield Biosystems	eSense Skin Response	Velcro electrodes (dry), adhesive (wet) or finger clips	Cable connected to phone audio jack	Figers, palms	Semi-portable
BITalino	BITalino EDA sensor	adhesive (wet)	Bluetooth, BluetoothLE	Fingers, palms, feet, shoulders	Semi-Portable
EMPATICA	E4 Wristband	SUS03 stainless steel (standard) or Silver (Ag) plated with a metallic core	Bluetooth or USB	Wrist	Portable
movisens	EdaMove	Adhesive (wet)	Bluetooth, Micro-USB	Wrist, ankle	Portable
shimmer	Shimmer3 GSR+ Unit	Velcro straps (dry)	Bluetooth	Fingers	Portable
fitbit	sense2	Wristband (dry)	Bluetooth	Wrist	Portable

If the experiment doesn't require the subject to move a lot and the hands can be static then the fingers are the best spot to place the electrodes - For example this happens if the experiment requires the participants to watch a video- If the participants have to use both hands, then the electrodes can be placed in the palm of the hands or wrists, this way the hands are free for limited movements. If the participants must perform more complex movements, and the hands need to move a lot, then, the feet or shoulders are the recommended spot for electrode placement. In this particular case, the electrodes are attached to the inner side of the foot.

2.4.3 EDA and Emotions

There are several studies that show a relation between emotional states and changes in EDA activity. Bellow the author will briefly examine some research that associate EDA signal with emotional states.

- [1] This study sought to examine the relationship between self-reported emotional experience and physiological responses to various odorants associated with basic emotions (happiness, fear, sadness, disgust, and anger), including skin potential, skin resistance, skin temperature, skin blood flow, and instantaneous heart rate and respiratory frequency. Participants were exposed to five different odorants: vanilla, menthol, eugenol, methyl methacrylate, and propionic acid. The findings revealed a significant association between verbal reports and the estimated emotions based on physiological responses. Specifically, the pleasant odorants were mainly associated with happiness and surprise, while the unpleasant ones evoked mainly disgust and anger.

- [35] Twenty-seven female undergraduate participants completed three tasks aimed at eliciting four emotions (happiness, sadness, anger, and peacefulness). The first task involved feeling these emotions, the second task involved expressing them without trying to feel them, and the third task involved both feeling and expressing the emotions clearly. Participants were instructed to press a button when they reached the required emotional state, and the latency from emotion cue to button press was recorded. Physiological measures including HR, skin conductance, and EMG were also recorded, and self-reports were collected after each trial. Results indicated that feeling and expressing emotions together, as in task 3, was the most effective method for eliciting emotions. Additionally, the self-generation method was shown to reliably induce emotional reactions and was recommended as a useful technique for eliciting various emotional states in laboratory settings.

- [86] The participants' BP, HR, respiration rate and EDAs were measured. The subjects were told that they would be participating in a cooperative study with a physician to examine the physiological state during a memory task. After performing the task the physician would provide the patients with a false medical diagnosis creating a fear eliciting scenario. Increased general levels of EDA ere correlated with the sensation of fear.

- [4] The participants were informed that they were partaking in a study that aimed to investigate physiological differences between individuals with and without hypertension. They were instructed to lie down on a bed and listen to music for approximately an hour, with a 25-minute break between stimuli. Unknown to the participants, the actual purpose of the study was to measure their reactions to stimuli designed to elicit fear and anger. The fear-inducing stimulus involved gradually increasing intermittent shocks to the little finger, never reaching a level of intensity that would cause pain. Once the participant reported feeling the shock, the experimenter would pretend shock and exclaim, "This is a dangerous high-voltage short circuit!". Following the fear stimuli, the anger stimulus was created by simulating an unprepared polygraph operator who made the participants' lives difficult during the study. This experimentation successfully generated an atmosphere of alarm and confusion, and the results indicated an increase in EDA activity in response to the fearful situation.

- [15] A study was performed with the objective of eliciting anger in the study's subjects while measuring the EDA activity, HR, and Facial Electromyography (fMEG). A faulty intercom and an annoyed sound researcher were used. In parallel another set of subjects were subdued to a different experiment where using brain imaging and GSR, participants were asked to recall memories associated with anger. The results showed that the GSR levels were significantly increased in the first experiment. The GSR levels in the second experiment were also significantly higher that the neutral GSR condition.

- [42] On how they would respond to upbeat or depressing music, a group of volunteers was examined. Participants were instructed to concentrate on the stimuli while listening to a collection of sound tracks that ranged in mood from cheerful to sad. The participants were asked to verbally judge whether each stimulus was happy or sad after hearing it, as well as to score the valence and arousal of the sound. Throughout the experiment the HR, BP, respiration rate, skin conductance, zygomatic and corrugator muscles activity were recorded. Regarding the eletrodermal activity researchers found that happy excerpts evoked more SCRs than sad excerpts.

- [51] The e-Health Sensor Platform V2.0 was used to acquire EDA signals, which were then denoised using a wavelet function and normalized to remove individual differences. From the normalized data, 30 features were extracted, and a covariance-based feature selection method was used to obtain optimized features. The SVM algorithm was applied for emotion recognition classification. The experimental results showed that the recognition accuracy was more than 66.67%.

- [78] The article introduces a method for detecting emotions using GSR data. The study involved exposing participants to audio-visual stimuli and asking them to rate the stimuli as positive, neutral, or negative using the Positive and Negative Affect Schedule (PANAS) method. The EDA data was then classified using SVM, Naive Bayes (NB), and KNN algorithms. The accuracy of the proposed approach was evaluated using the Receiver Operating Characteristic curve and accuracy measurement. The results showed that the SVM classification achieved the highest accuracy of approximately 75.65%, with a receiver operating characteristic of about 0.8019. Therefore, the proposed method offers a satisfactory and well-performed approach to detecting emotions.

- [88] A model was developed to classify an individual's level of stress using EDA data. The study induced stress by either performing mathematical operations or deep breathing exercises. The model was able to accurately classify stress levels with an accuracy of up to 76.56%

2.5 Processing and Classification of Physiological data

In general physiological sensors are prone be sensitive to external noise and movement. The data denoising and feature extraction stages are the most important stages in the analysis of physiological signals. Finding the prominent features that map signals and data into ensuing emotional states is the primary goal of feature extraction. There is no algorithm capable of assessing whether data is poorly recorded. EEG electrodes pick up electrical activity from other sources in the environment and in the subject itself, muscle activity like EMG or cardiac functions, ECG, eye movements or blinks are the major sources of artifacts coming from the sensors. But the movement of the electrodes in the scalp, line noise or too much movement in the EEG device also create severe artifacts in the signals. Strong drifts in EDA data caused by vigorous breathing and excessive inhaling and exhaling can potentially be mistaken for changes in arousal.

Physiosignal analysis is not a easy task. There are several possible approaches to the processing and filtering of the raw signals, each one with it's advantages and drawbacks. Artifact removal and feature extraction are important in the processing of physiological signals to improve the quality of the data and extract relevant information from the signals. The process of feature extraction and the extracted features directly affects the accuracy of the classification of the data.

Common artifact removal methods for physiosignals are [82]:

- Filtering to remove unwanted frequency components of the signal. This can be achived using Band Pass Filter (BPF)s, SGF or MDFto remove unwanted high and low frequency components. Notch filters can be applied to remove specific frequency components of the signal [71, 49, 40, 8, 36, 76].

- Independent Component Analysis (ICA), separates the signals into independent components and identifies those that represent noise. These components can then be removed or filtered out [57].

- Wavelet Denoising, uses wavelet analysis to decompose the signal into different frequency bands. It then removes noise from each band separately, and reconstructs the signal to remove the noise [40, 8, 91, 92, 17].

The analysis of physiological signals for feature extraction can be done in the time domain, the frequency domain or time-frequency domain [50].

- Time-domain analysis: Analyses the characteristics of the signal over time. Time domain feature extraction usually focuses on the statistical parameters of the signal. Some features that can be extracted from the time-domain are mean and standard deviation, root mean square, zero crossing rate, slope sign change or peak-to-peak amplitude [3]. EEG features extracted in the time domain include histograms, statistical characteristics [3] , Hjorth parameter [72], HFD [71, 8] or Event Related Potential (ERP). For EDA signals most of the time domain features are statistical values, for example mean amplitude and standard deviation [76], or SCR peaks and amplitude.

- Frequency-domain analysis: Frequency-domain analysis breaks down time-domain signals into frequency-domain signals to extract characteristics. The FFT technique is the most popular way to break down a signal into its frequency domain. Common extracted features from frequency analysis are Power Spectral Density (PSD) [76] and spectral entropy. For EEG the most common features extracted are PSD [71, 90, 94] and average band power [50].

- Time-frequency analysis: combines information from both the time and frequency domain, allowing for the combined analysis in both domains at the same time. The STFT is often used, which applies a fixed window function to the time signal. Non-stationary signals can be analyzed as a series of short-time stationary signals. Common methods for time-frequency analysis include STFT and Wavelet analysis, as mentioned in several studies [8, 23, 40, 90, 91].

Any combination of features and types of analysis can be used in the feature space for emotion classification. Some studies perform a feature selection stage in addiction to the feature extraction. "Feature selection is the process of selecting a subset of features to optimize performance and reduce the dimensions of the feature space" [41]. This is done so that the complexity and computational cost of the system can be reduced. Feature selection can be made using statistical analysis, for example the Analysis of Variance (ANOVA) [41].

Several ML methods that have been used have been used for the classification of EDA signals to assess emotions. These algorithms, including including SVM, Decision Trees (DT), ANNs, and Random Forest (RF), use various features of the EDA signal, such as the number of SCR peaks, average SCR peak amplitude and onsets. The accuracy of these algorithms can vary depending on the specific dataset and classification task. However, studies have shown that machine learning algorithms can achieve high accuracy in classifying EDA signals.

Among the studies mentioned in sub-section 2.4.3, the KNN, NB and SVM classification algorithms were compared for the classification of EDA data in [78]. The highest accuracy score was obtained using the SVM, with 75.65%. The KNN and NB achieved an accuracy of 58.02% and 54.78% respectively.

A systematic review of fifty-nine scientific studies on EDA signals for arousal classification [76], concluded that SVMs and ANNs stand out within supervised learning methods given their high-performance values. According to [76] in contrast, unsupervised learning is not effective in detecting arousal through EDA. The use of EDA for detecting arousal is widespread, with particularly good results in classification with the ML methods found.

In [51], referenced in sub-section 2.4.3 an SVM algorithm was applied to recognize human emotions based on EDA signals, achieving a recognition accuracy of over 66.67%.

For the classification of EEG signals, the most popular ML methods are SVM [40, 90, 8], KNN [94], RF, and NB, according to the study made in [89]. Traditional ML algorithms in this study show a classification accuracy ranging from 57.50% to 95.70%, with SVMs being the most popular classification algorithm. Deep learning methods have also gained more attention in recent years, showing classification accuracy ranging from 63.38% to 97.56%, with CNNs, RNNs, and ANNs being the most prominent methods due to their ability to handle more complex data analysis.

3

Proposed system for EEG and EDA Emotional Assessment

This dissertation aims to study the assessment of emotional states in a subject, when exposed to visual stimulus, based on brain activity and electrodermal activity responses. The analysis and classification of physiological data typically involves multiple components that play vital roles in processing the data, as shown in Figure 3.1. Building on the research in the previous chapter 2, this chapter will introduce the technologies and methods employed to meet the objectives of this dissertation. First an brief introduction to the proposed data acquisition system, the chosen sensors, stimuli and tools used are discussed. Followed by a review on processing and features extraction techniques for EEG and EDA signals and what should be the most appropriate method for this dissertation objectives. Finally the classification method for the EEG and EDA data is presented.

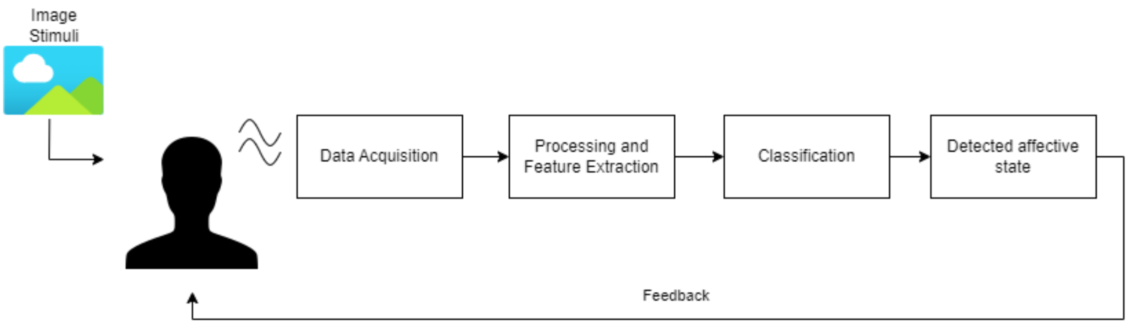


Figure 3.1: Emotional assessment process from EEG and EDA data

3.1 Data Acquisition

ML algorithms can be trained on a database of EEG and EDA signals with known V/A/D ratings to learn patterns in the signal features that correspond to different emotional responses. These algorithms can then be applied to new EEG and EDA signals to predict their emotional content. In order to train a ML algorithm capable of evaluating physiological signals first a sufficient amount of data needs to be collected. A database of EDA and EEG signals associated with a corresponding affective state (V/A/D). For this intent a data acquisition system for acquiring EEG and EDA data was created where subjects are asked to self-assess their affective states when exposed to images from a database, all while recording their brain activity and electrodermal activity. The data acquisition process is performed through a series of experimental sessions detailed in chapter 5.

To meet the goals for the data acquisition:

1. A reliable method for measuring the affective content of an image must be chosen. The self-report with the SAM test was ruled the most appropriate along with EEG and EDA signal data.

2. Select a sample of images diverse enough to elicit different affective states.

3. Using the selected methods, have a large enough group of subjects rate the selected images while having their EEG and EDA activity recorded.

4. Based on the values of V/A/D the affective reaction to each picture and their corresponding physiological reaction can be associated, regarding each subject in the group individually. Creating a database of raw EEG and EDA measurements with known V/A/D values.

5. Based on the mean values of V/A/D the image database can be characterized and validated.

6. Based on the individual self-assessment each subject in the group made regarding each image, a corresponding EEG and EDA signal can be associated to a V/A/D rating.

3.1.1 Stimuli

"One of the most important aspects of emotion recognition is determining what stimuli should be used to elicit the assessed emotions". According to the review of stimuli done in [41], the most common type of stimuli used to trigger emotional reactions are visual stimuli, specifically images. Video clips are the second most commonly used stimuli.

There are numerous available databases for emotion elicitation, based on different types of stimuli. For example the IAPS is one of the most widely used databases for affective studies. This database contains a large set of pictures with their own ratings for V/A/D which were averaged from a large sample of participants.

In the reviewed studies on emotional assessment for EEG and EDA signals, in sub sections 2.3.3 and 2.4.3 respectively, visual stimuli is the observed preferred method to evoke emotional responses on subjects. In [91, 40, 90, 8, 23, 78] short videos or movies were used as stimuli. In [71, 49] pictures from the IAPS were used. And finally in [94, 4, 15, 42] the authors used auditory stimuli to evoke different emotions. Mental and physical tasks can also be used to induce stress, calmness or anger, as seen in [35, 86, 88, 1].

The chosen stimuli for this dissertation is picture-oriented visual stimuli, as mentioned in the referenced studies above, pictures have shown to be effective in eliciting emotional responses. Images are an immediate stimuli, that unlike videos or music are stationary and produce an almost instant reaction. Videos or music take too much time to change an emotion and that change will be progressive and slow. It is also easier to collect a broaden the range of emotional responses though pictures because of the visual richness that images can get [79].

Automated methods, such as ML algorithms, can predict the affective state elicited by an image on a subject. If a database with known values of V/A/D (such as the IAPS database) is available, these values can be paired with other methods of collecting emotional information to predict affective states.

For this dissertation a database of 120 images was created composed of 60 random images from the IAPS database and 60 images collected randomly, and selected specifically for this experiment to broaden the range of elicited emotions. The affective content of the database is unknown, this means, the V/A/D values for each image are not established. The decision to create a custom database was made because other available image databases were deemed inappropriate and not relatable for a scenario where the population of study would be Portuguese young adults. To complement and create a broad database that is relatable for the experiment subjects, the author and the advisor concluded that other images should be included in the database, images that would be relatable for a Portuguese population, as well as images that could elicit stronger emotions. This is achieved, for example, with pictures of recent events or cultural references for Portuguese people.

The affective content of the database in unknown. Thus, the created database needs to be analysed and categorized in affective content. For this purpose it was decided that the self-assessment values collected during the experimental phase are going to serve two purposes. 1 - To label the corresponding raw signals with a V/A/D measurements, using self-report; and 2 - To study the affective content in each image of the database by analysing the overall self-assessment values for each image across different subjects.

To properly classify a database like this the images have to be presented to a large population, in a controlled environment where everyone is subject to the same conditions and regulations, thus creating a reliable source of data. For this purpose the Professors from UMinho helped to create regulations and an experiment guide so that all experiment sessions are subject to the similar conditions. The experimental process will be discussed in chapter 5.

See Annex IV for the 120 selected images that compose the database.

3.1.2 Physiological sensors

Commercial and lower grade EEG devices often lack in precision and accuracy, so it is beneficial to pair them with other biosensors for more accurate classifications. The EDA signal alone has been associated with arousal in humans, but it lacks when determining what kind of arousal a subject might be feeling since an EDA peak is equal for a frightening experience or a happy one. When complementing the EDA with the EEG a new depth of information is reached. The EEG is able to collect more complex data regarding a persons emotional state because of the different brain waves decomposed from the raw signal. The chosen sensors for the data collection for this dissertation are the EEG and EDA sensors from BITalino. These sensors can be connected to a dedicated board, the BITalino (r)evolution Board, easing the process of data collection and synchronizing.

3.1.2.1 BITalino (r)evolution Board

The Bitalino (r)evolution Board is a all-in-one hardware device for biosignals data collection. The board can be connected simultaneously to several sensors and actuators to make the data acquisition system. The actuators are: LED and Buzzer. And the sensors are: EDA, ECG, EMG, EEG, Light, Push button and an Accelerometer.

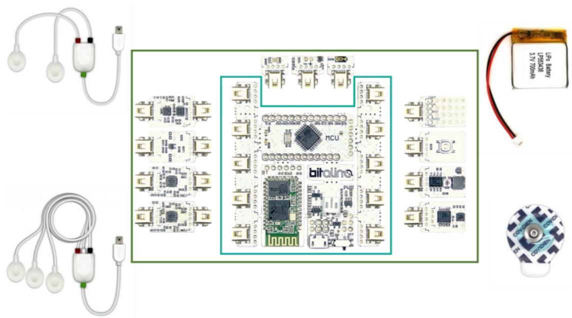


Figure 3.2: Bitalino (r)evolution board kit

This board is available as a kit that comes with all accessories needed for an experimental setup, including battery, cables, and electrodes. The Bitalino Board also gives access to the OpenSignals (r)evolution, a free software designed to perform the data collection, this software also provides a series of add-ons to extract statistical, temporal, and spectral parameters. See table 3.1.

See [68, 83, 32, 22, 7] for more information about research on Bitalino devices, as well as some projects.

The toolkit can be used for a variety of purposes, such as Biomedical device prototyping, biofeedback or human-computer interaction.

3.1.2.2 BITalino EEG Sensor

The EEG sensor is designed for both classic and localized EEG measurement, it is a great replacement for the traditional EEG cap. The sensor has a bipolar configuration, meaning

Table 3.1: Bitalino Board technical specifications

Communication	Bluetooth 2.0 + EDR or Bluetooth 4.1 BLE
Resolution	10-bit (A1-A4) + 6-bit (A5&A6)
Digital Ports	2 INPUT (1-bit) + 2 OUTPUT (1-bit), CMOS 3.3V compatible
Sensors	EMG; ECG; EDA; EEG; ACC; LUX; BTN
Actuators	LED; BUZ
Battery	700 mA 3.7V LiPo (rechargeable)
Operating Voltage	3.3V
Input Voltage Range	3.0-5.5V
Sampling Frequency	1, 10, 100 or 1000Hz
Analog Sensor Ports	4 in (10-bit) + 2 in (6-bit) + 1 auxiliary in (battery) + 1 out (8-bit)
Size	65mm x 108mm x 2mm (Board); 65mm x 56mm x 2mm (Core)
Consumption	~65mA

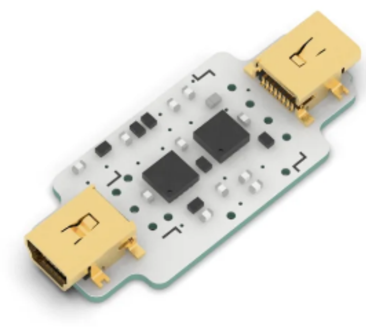


Figure 3.3: Bitalino EEG sensor

Table 3.2: EEG sensor technical specifications

Gain	41782
Range	±39.49 μ V with VCC = 3.3V
Bandwidth	0.8 - 48 Hz
Consumption	~ 3mA
Input Voltage Range	1.8 - 5.5 V
Input Impedance	>100 GOhm
CMRR	100 dB

that it has two measuring electrodes that detect the electrical potentials in the specific scalp area, with respect to the reference electrode. The difference between the two measuring electrodes is the generated raw signal. The sensors design allows for discrete placement and versatile for the various scalp regions [74].

Although the sensor uses 3(two for measuring, and one for reference) measuring electrodes this EEG is a single-channel sensor [74].

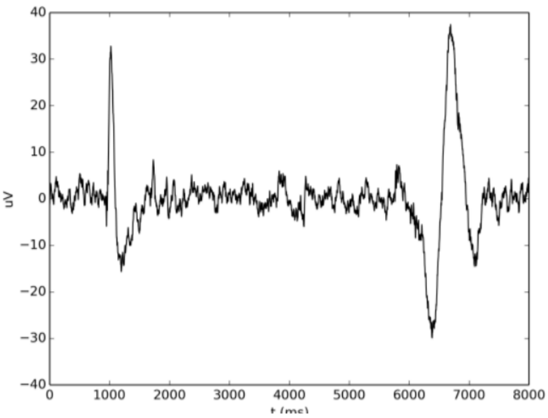


Figure 3.4: Typical raw EEG data (acquired with BITalino (r)evolution) showing the influence of eye blinking (left spike) and eye movement (right spike).

VCC	3.3V
G_EEG	41782
EEG(V)	EEG value in Volt (V)
EEG(μ V)	EEG value in microvolt
ADC	Value sampled from the channel
n	Number of bits of the channel

The transfer function of the sensor is:

$$EEG(V) = \frac{(\frac{ADC}{2^n} - \frac{1}{2})xVCC}{G_{EEG}} \tag{3.1}$$

$$EEG(\mu V) = EEG(V)x1x10^6 \tag{3.2}$$

3.1.2.3 BITalino EDA Sensor

Figure 3.5: BITalino EDA Sensor

The electrical characteristics of the skin can be precisely measured by the Bitalino EDA sensor. Even the weakest electrodermal skin response events can be detected with

Table 3.3: EDA sensor technical specifications

Range	0-25μ S (with VCC = 3.3V)
Bandwidth	0-2.8Hz
Consumption	±0.1mA
Input Voltage Range	1.8 - 5.5V
CMRR	100 dB

VCC	3.3V
EDA(μ S)	EDA value in micro-Siemens (μ S)
EDA(S)	EDA value in micro-Siemens (S)
ADC	Value sampled from the channel
n	Number of bits of the channel

the best performance possible thanks to the low-noise signal filtering and amplification circuit design. The (r)evolution board is attached to this sensor. [9].

The sensor transfer function is:

$$EDA(\mu S) = \frac{\frac{ADC}{2^n} - \frac{1}{2}xVCC}{0.132} \quad (3.3)$$

$$EDA(S) = EDA(\mu S)x1x10^{-6} \quad (3.4)$$

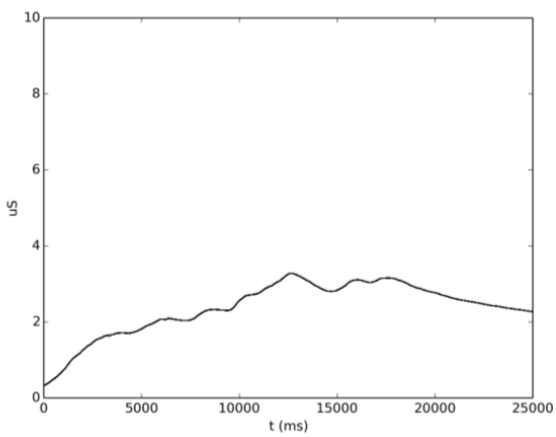


Figure 3.6: Typical raw EDA data (acquired with BITalino (r)evolution)

3.1.3 Design

Different approaches were considered for the data collection system. The BITalino Board has Bluetooth features, so it can be connected to a computer or processor. The communication is made through COM port. The BITalino products have a GitHUb page, the BITalinoWorld GitHub Page where users can access several API's built by the BITalino community, data samples as well as some tutorials, this page has been a source of tools and materials useful for this dissertation. BITalino also has a free software (OpenSignals) that handles connection to the sensors, data collection and synchronization. Although this software records, timestamps, and synchronizes the sensor data, not all of its features are free, and lacks in tools for experimental research with stimuli association.

For the interfacing of the sensors output the Bitalino API was used BITalino (r)evolution Python API from the APIs avaliable in the BITalinoWorld GitHub Page. The BITalino (r)evolution Python API is a python-based API that provides the necessary tool to interact with a BITalino (r)evolution Board.

Using **PsychoPy**, an open source Python package, the entire data gathering process for the training and categorization of EEG and EDA data is carried out. An alternative to MatLab for doing experiments in Python is the open-source tool known as PsychoPy. It enables free and straightforward stimulus presentation and control packages, which are frequently used in experimental psychology, psychophysics, and cognitive neuroscience. The key advantage that led to the decision of using PsychoPy was its Builder interface to guide experiment creation with minimal coding and wide variety of available stimuli formats(images, text, ratings, random dots, noise, movies, sounds). PsychoPy has a builder interface, as seen in figure 3.7 that allows for the creation of separate routines that follow one another. In each routine a list of different components is possible to be added, text, images for stimuli, forms and buttons for responses, another key component in the builder is the possibility of adding custom code in each of the routines created.

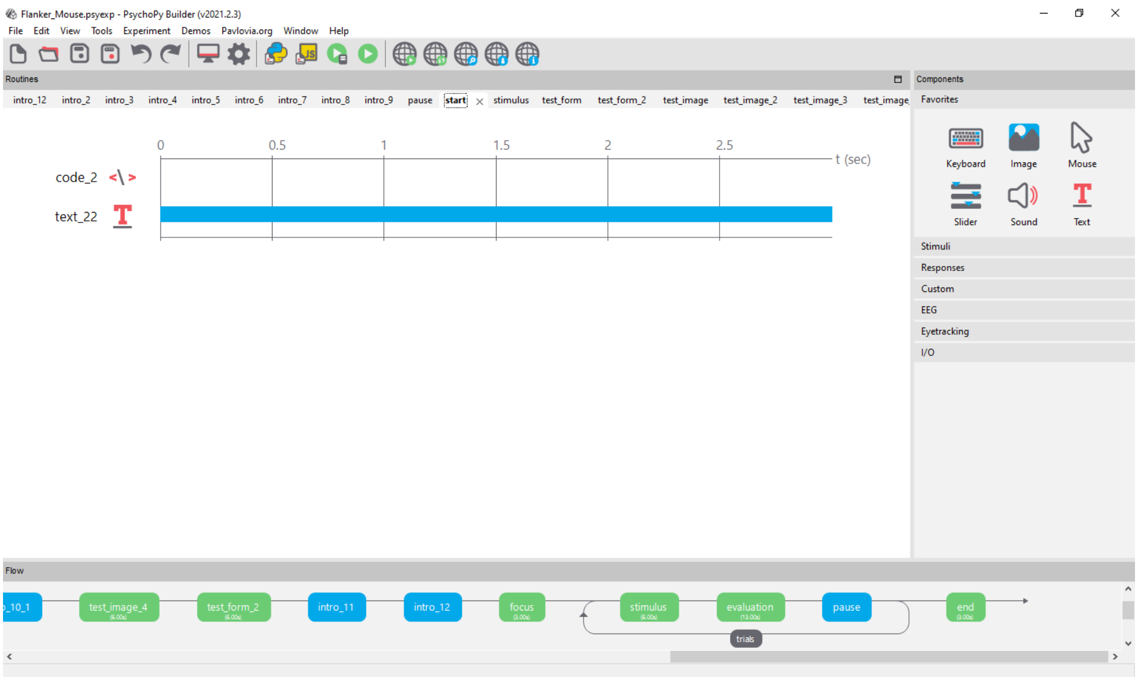


Figure 3.7: Psychopy Builder interface with created routines and custom components

3.2 Signal Processing and Feature Extraction

Both the EEG and EDA sensors are extremely sensitive to external noise. Artifacts can arise from muscle movement, or even external sources, mainly from electrical appliances. Unwanted data needs to be removed from the signals for the extraction of features with the best quality possible. Muscle artifacts, eye-blinks and power line noise are some of the main sources of noise in EEG and EDA signals. For example, in EEG signals, eye-blinks and heart functions appear in the signal, usually bellow 4Hz. On the other hand, muscle artifacts affect the 30Hz spectrum. Noise originated from external sources like power lines appear around 50-60Hz.

The artifact removal of the EEG and EDA signals was made using a Low Pass Filter (LPF) and a High Pass Filter (HPF). The HPF allows the high-frequency components of the signal to pass through while blocking the low-frequency components. It removes the low-frequency noise from the signal and keeps only the high-frequency information. The LPF allows low-frequency components of a signal to pass through while blocking the high-frequency components. It removes the high-frequency noise from the signal keeping only the low-frequency information.

To reduce noise and artifacts in the EEG signal, a 16 order Butterwoth HPF with 4 Hz cut-off frequency and LPF with 40 Hz cut-off frequency were applied delimiting the signal to its frequencies of interest (Gamma, Beta, Alpha, and Theta). The raw EDA signal goes through a similar denoising process first using a Butterworth LPF of order 4 and cutoff frequency of 5Hz. The signal is then smoothed in order to remove high frequency noise, making the analysis of the signal easier.

The features extracted from the raw EEG and EDA signals are the average power in the Theta (4-8)Hz, Alpha low (8-10)Hz, Alpha high (10-13)Hz, Beta (13-25)Hz and Gamma (25-40)Hz frequency bands from the EEG signal. The filtered EEG and EDA signals.

FFT is used to calculate the PSDof the EEG signal. The PSD represents the distribution of power across different frequency bands in the signal. Once the power spectral density is calculated, the signal is divided into several frequency bands, the average power in each of these frequency bands is then calculated by integrating the PSD within each band. This yields the total power in each band.

Finally, the average power in each band is calculated by dividing the total power in each band by the bandwidth of that band. This accounts for the fact that some frequency bands are wider than others.

The EEG average band powers were computed using a FFT with a window size of 0.25 seconds with 50% overlap, the used kernel was a Hann kernel. The average band power from the signal frequency bands is then computed by averaging the power of each frequency range within the defined time window.

For the feature extraction of the EDA filtered signal the Kim-Bang-Kim method [44] to extract the SCRs onsets, peaks, and amplitudes. This method identifies the peaks and onsets of each SCR by finding the maximum value of the differentiated signal within each zero-crossing interval, and calculating the SCR amplitude as the difference between the peak and the previous zero-crossing.

The artifact removal and feature extraction of both signals was computed using the BioSSPy python toolbox, this toolbox bundles together various signal processing and pattern recognition methods geared towards the analysis of biosignals, supports analysis for both EEG and EDA signals.

In total 7 features used: the average powers in the Theta, Alpha low, Alpha high, Beta and Gamma frequency bands, and the filtered EEG and EDA signals.

3.3 Data Classification

Based on the research made throughout this dissertation, in section 2.5, the author analyses classification methods used in previous researches.

Among the classification algorithms presented in 2.5, SVM was ruled the most appropriate. Showing overall better results in the classification of both EEG and EDA data. SVMs have been widely used in the field of biosignal processing. This classification algorithm is often used, and has shown good results when dealing with EEG and EDA signals.

One advantage of SVMs is their ability to handle high-dimensional datasets, which is important for EEG and EDA signals that have many variables. One other reason for choosing the SVM is its good performance on small datasets and its versatility. SVMs work by finding a hyperplane that maximizes the margin between the different classes in the data. This hyperplane can then be used to classify new data points based on their distance from the hyperplane this is implemented using a kernel. A kernel transforms an input data space into the required form. SVM kernels include linear, polynomial, and Radial Basis Function (RBF) kernels, to handle different types of data distributions, a custom kernel can also be used.

In conclusion, SVMs have been shown to be effective in the classification of both EEG and EDA signals and have been used in a number of studies to predict different physiological states based on several biosignals.

The pyton Scikit-learn library for machine learning was used to employ the SVM classification.

4

Methodology

This dissertation, aims to study the possibility of assessing emotional states, EEG and EDA physiosignals, using visual stimuli to elicit a bodily response. This section describes the methodology used in to implement the emotional assessment process defined in the previous chapter 3. The author will explain the data acquisition system and it's main components. The detailed data acquisition system is used in the experimental procedure, described in chapter 5, to collect the necessary data for the emotional assessment process.

4.1 Data Acquisition

This section will explain the created system for the data acquisition and it's resulting data. The objective of this data acquisition system is to collect EEG and EDA responses from a subject, as well as their self-assessed V/A/D values, regarding 120 different images with unknown affective content (V/A/D values). The data acquisition system described in this section is designed to be used in the experimental procedure in chapter 5, in order to collect the necessary data for the emotional assessment process.

Figure 4.1 shows the designed data collection system. In chapter 3, sub-section 3.1.2 it was defined that the chosen hardware for the data acquisition would be the BITalino (r)evolution Board paired with the EEG and EDA sensors from the same brand. The BITalino board is interfaced and the sensor outputs are handled by a custom python script, the BitalinoLib.py, as shown in figure 4.1. This script stores the raw output from the board into a .csv file, and saves the timestamp for the start_time of the experiment. Most of the data collection is handled by the experiment process created in a PsychoPy environment. PsychoPy is responsible for the presentation of the stimuli, the storing of the self-assessment values regarding each image and the storing of the timestamps of each stimuli.

4.1.1 BitalinoLib.py

The **BitalinoLib.py** is a custom python code created for the handling of the sensors and recording of their output. Using the BITalino (r)evolution Python API, this API allows for

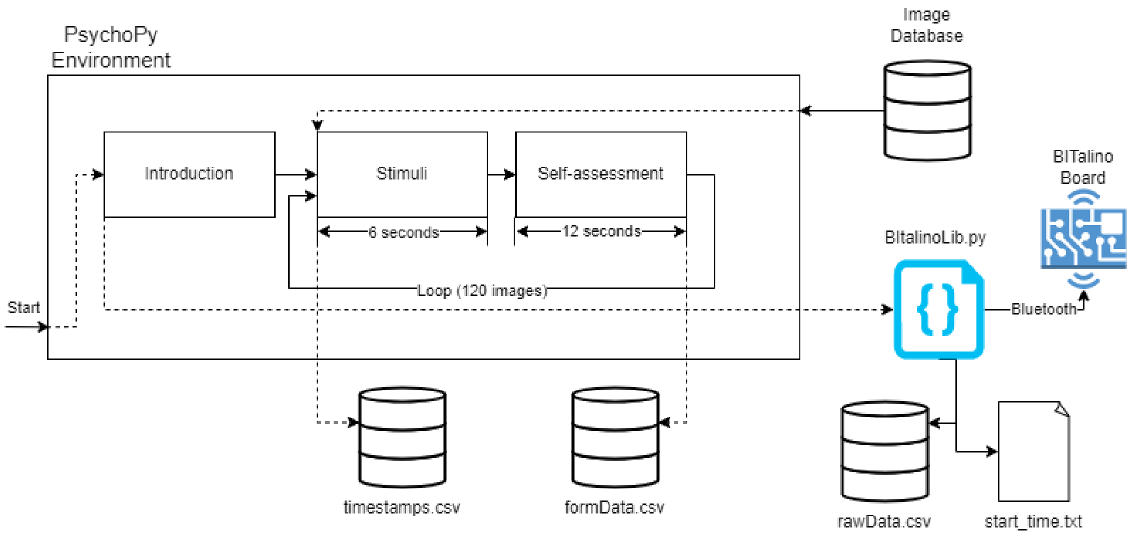


Figure 4.1: Block diagram of data collection framework

communication with the board through COM port or MAC address, creating an instance of a BITalino device. Once the device is connected the data collection starts, using the method **def start(self, SamplingRate, analogChannels)** from the BITalino API, allowing to set the sampling rate for the analog channels of the BITalino device, and select the channels themselves, in this case only two channels are needed, one for the EEG and one for the EDA. To acquire the samples read from the device, the **def read(self, nSamples)** where the number of samples to draw at a time is defined. The established sampling rate for the sensors is 1000Hz.

The BitalinoLib.py custom code is responsible for:

- The connection to the BITalino Board through COM port.
- Setting the sampling rate of the EEG and EDA sensors to 1000Hz.
- Creation of the rawData.csv file and storing the raw output from the sensors.
- Registering of the start time of the data acquisition.

The relevant functions, from the BITalino API library, used in this code are:

- **def start(self, SamplingRate, analogChannels)**: Sets the sampling rate and starts acquisition in the analog channels set. The possible SamplingRate values are 1, 10, 100 or 1000 Hz. The analog channels correspond to the channels analog channels A1 trough A6 of the BITalino board.
- **def read(self, nSamples)**: Where nSamples represents the number of samples to acquire.
- **def stop(self)**: Stops the acquisition.

- **def close(self)**: Closes the Bluetooth serial port.

Listing 4.1: BitalinoLib.py

```python
import bitalino
import numpy as np
import time
import sys
import csv

current_time = time.localtime()
time_string = time.strftime("%H:%M:%S", current_time)
extension = ".csv"
location = 'C:/Users/irisp/Desktop/iris/FCT/5ÂžANO/bitalino_lab/
MultiModal_MultiSensory_Flanker_Task-master/stream/rawData_'
file_name = location + time_string.replace(":", "_") + extension

f = open( file_name, 'w', newline='')
writer = csv.writer(f)

timestamp_file=open('C:/Users/irisp/Desktop/iris/FCT/5ÂžANO/
bitalino_lab/MultiModal_MultiSensory_Flanker_Task-master/stream/
start_time_' + time_string.replace(":", "_") + '.txt', 'w')

# Windows
macAddress ="COM10"#"88:6b:0f:f1:94:1b"
while True:
    try:
        print("connecting to device")
        device = bitalino.BITalino(macAddress)
    except:
        print("Device not found...")
    else: break
time.sleep(1)

srate = 1000
nframes = 1
writer.writerow(['nSeq', 'D1', 'D2', 'D3', 'D4', 'EEG', 'EDA'])

try:
    #channel 0 will be EEG channel 1 will be EDA
    device.start(srate, [0,1])
```

```
    print ("START")
    t = time.time()
    start = time.time()
    timestamp_file.write(str(time.time()))
    timestamp_file.close()
except:
    print("Sampling rate or analogue channels not valid...")

try:
    while True:
        t = time.time()
        raw = device.read(nframes)
        #print(raw)
        writer.writerows(raw)

except:
    print("lost communication with device...")
finally:
    print ("STOP")
    f.close()
    timestamp_file.close()
    device.stop()
    device.close()
```

4.1.2 PsychoPY

The data collection system was designed in the PsychoPy builder environment, introduced in the previous chapter, section 3.1.3.

In figure 4.1, once a data collection session starts the Bitalino.py script (see Listing 4.1) is launched through the PsychoPy environment. This happens during the "Introduction"phase, which will be further discussed in the next chapter. This phase exists mainly to brief and accustom the subject to the set-up, is not relevant for the inner workings of the system. The BitalinoLib.py script connects the BITalino Board to the working computer and immediately starts saving the EEG and EDA sensor output. The timestamp corresponding to the exact time the BITalino board started recording the EEG and EDA signals is also registered to later be used for the synchronization of the signals with the image presentation timings.

The stimuli presentation and self-evaluation are in a loop, so that each of the 120 images from the database can be presented only once and in a random order. The data collection loop is the focal point and the most important phase of the experiment session. In the figure above 4.1, each image is shown for 6 seconds, afterwards the participants are asked to perform a SAM test regarding the affective impact of the presented image. A timestamp marking the beginning of the presentation of the stimuli is registered for each loop. Like so, the self-assessment answers of V/A/D are also registered for each image.

In short the experiment created in PsychoPy is responsible for:

- Launching the **BitalinoLib.py** script, responsible for the interfacing of the Bitalino hardware to the computer, the recording of the raw EEG and EDA data, and registering the timestamp corresponding to the beginning of the recording;
- Registering the timestamps corresponding to the beginning of the presentation of each image in the database;
- Registering all the answers from the subjects in the V/A/D domain to each of the images in the database.

The resulting files from one experimental session (one subject), as shown in figure 4.2 should be:

- formData.csv - File containing 120 V/A/D values resulting from the self-assessment the subject made regarding each image in the database. The resulting file has 120 rows labeld by image id, and three columns corresponding to the V/A/D measurements (see figure 4.2a).
- timestamps.csv - File containing 120 timestamps, each row corresponding to the start of the presentation of an image (see figure 4.2b).
- rawData.csv - File containing the raw output from the BITalino Board at 1000Hz. The first column is a sequence number of the output, the next 4 columns correspond to unused digital channels in the Board. The last two columns contain the raw EEG and EDA data respectively (see figure 4.2c).
- start_time.txt - Start time of the BITalino Board recording. With the timestamps file along with the start_time file the continuous raw data in the rawData.csv file can be synchronized with the timing of the images presentation. This way the signals can be separated into 120 samples of 6 seconds, each sample corresponding to the respective image.

Image	Agradabilidade	Ativação	Controlo
ImageFile/53.jpg	6	5	
ImageFile/2375.2.jpg	4	6	5
ImageFile/5.jpg		6	3
ImageFile/31.jpg	3	5	5
ImageFile/42.jpg	4	5	5
ImageFile/2352.2.jpg	3	6	4
ImageFile/35.jpg	6	3	6
ImageFile/2055.2.jpg	6	5	5
ImageFile/9295.jpg	3	6	3
ImageFile/18.jpg	7	3	6
ImageFile/7361.jpg	3	6	5
ImageFile/10.jpg	5	5	5
ImageFile/44.jpg	6	5	
ImageFile/9186.jpg	4	4	5
ImageFile/6250.jpg	5	5	
ImageFile/7380.jpg	3	7	4
ImageFile/2045.jpg	7	2	6
ImageFile/9810.jpg	2	7	3
ImageFile/20.jpg	3	7	3

(a) formData.csv excerpt

Column1
Timestamp
1661555981.8910997
1661556000.8324451
1661556017.4458895
1661556036.4728727
1661556051.3999293
1661556065.2860053
1661556083.5496857
1661556098.623456
1661556113.559057
1661556128.4384081
1661556146.714952
1661556164.7795155
1661556176.4303732
1661556195.4451902
1661556212.0841765
1661556231.0944352
1661556244.0507882
1661556262.722968

(b) timestamps.csv excerpt

Column1	Column2	Column3	Column4	Column5	Column6	Column7
nSeq	D1	D2	D3	D4	EEG	EDA
0.0	1.0	1.0	0.0	0.0	508.0	311.0
1.0	1.0	1.0	0.0	0.0	516.0	311.0
2.0	1.0	1.0	0.0	0.0	523.0	312.0
3.0	1.0	1.0	0.0	0.0	529.0	312.0
4.0	1.0	1.0	0.0	0.0	535.0	312.0
5.0	1.0	1.0	0.0	0.0	536.0	312.0
6.0	1.0	1.0	0.0	0.0	531.0	311.0
7.0	1.0	1.0	0.0	0.0	527.0	312.0
8.0	1.0	1.0	0.0	0.0	518.0	312.0
9.0	1.0	1.0	0.0	0.0	508.0	312.0
10.0	1.0	1.0	0.0	0.0	491.0	311.0
11.0	1.0	1.0	0.0	0.0	481.0	311.0
12.0	1.0	1.0	0.0	0.0	470.0	311.0
13.0	1.0	1.0	0.0	0.0	459.0	311.0
14.0	1.0	1.0	0.0	0.0	456.0	311.0
15.0	1.0	1.0	0.0	0.0	464.0	311.0
0.0	1.0	1.0	0.0	0.0	475.0	311.0
1.0	1.0	1.0	0.0	0.0	487.0	311.0

(c) rawData.csv excerpt with the EEG and EDA raw values

Figure 4.2: Generated files from one experimental session

5

Experimental Procedure

This chapter describes the experimental procedure used to collect the EEG and EDA raw signals and self-report ratings regarding the images in a database created for this dissertation. The experimental procedure architecture and framework design follow the guidelines discussed in the previous chapters 3 and 4 respectively.

5.1 Method

20 random participants were exposed to 120 images and asked to self-assess their affective response to the image in therms of V/A/D, using the SAM test.

The data collection sessions were conducted in the Department of Psychology of the University of Minho in the Gualtar Campus.

Before any data collection, participants are asked to read the experiment Briefing (Annex II), in order to fully understand what will be happening during the session, and be familiarized with the concepts of valence, arousal and dominance, so that the self-assessment of the images is as reliable and true as possible. After being briefed about the experiment the subject can sign the Informed consent(Annex I) if the subject agrees with the use of their information and with the experiment guidelines. Once the subject is briefed and has signed the informed consent the set-up can begin. The skin must cleared and the EDA and EEG electrodes placed in their respective places. Once everything is set-up the data collection begins.

The complete guide used to standardize the data collection experimental sessions can be consulted in Annex III.

5.1.1 Stimuli

The selected stimuli for this experiment is images. Visual stimuli has been often used in experiments like this, and proven to be effective in provoking emotional responses on the subjects.

The database consists of 120 images chosen by the author of this dissertation. As mentioned before in chapter 3 in section 3.1.1, the affective content of the database in unknown, this means that images in the database have no associated affective category whatsoever.

Thus the collecting of SAM values from as many subjects possible is imperative for the statistical study of the database. The process of classifying the database is be conducted separately from the processing of the biosignals, because it will only serve to study the statistic nature of the database for later to serve as reference for the classification of the biosignals and label the signal samples according to the conclusions drawn from the analysis of the database.

To properly classify a database like this the images have to be presented to a large population, in a controlled environment where everyone is subject to the same conditions and regulations, thus creating a reliable source of data. For this purpose the Professors from UMinho helped to create regulations and an experiment guide so that all experiment sessions are subject to the similar conditions.

5.1.2 Material

- Bitalino (r)evoltion board
- Bitalino EEG sensor
- Bitalino GSR sensor
- 2-Lead Electrode cable (for the EDA sensor)
- 3-Lead electrode cable (for the EEG sensor)
- 5 Gelled self-adhesive Ag/AgCl electrodes
- Headband
- Computer
- Chair
- Table
- Rubbing Alcohol
- Cotton pads

5.1.3 Participants

20 subjects participated in the experiment. The average age of the participants is of 22,4 years, with a standard deviation of 3,4 years. The majority of the participants were female, 15 to be exact, with an average age of 21,6 years and standard deviation of 2,6 years. The rest of the participants were male, which means 5 participants, with an average age of 24,8 years and standard deviation of 4,8 years.

Figure 5.1: Material for the data collection

ID	Age	Sex
1	20	F
2	21	F
3	23	F
4	18	F
5	18	F
6	20	F
7	33	M
8	22	F
9	23	F
10	28	F
11	25	M
12	22	F
13	19	F
14	21	F
15	21	F
16	21	M
17	22	M
18	24	F
19	24	F
20	23	M

Figure 5.2: Subjects age and gender

Total	
Average Age:	22,4
Standard Deviation:	3,4

(a) Total subjects

Females	
Average Age:	21,6
Standard Deviation:	2,6

(b) Female Subjects

Males	
Average Age:	24,8
Standard Deviation:	4,8

(c) Male Subjects

Figure 5.3: Mean and standard deviation of the experiment subjects' ages

5.1.4 Set-up

To set up the sensors, the EEG sensor should be connected to the A1 port of the Bitalino Board and has three electrodes, one for reference and two for measurement. The measuring electrodes (IN+/-) should be placed above the left eyebrow in the FP1 position with a distance between the electrodes not exceeding 3cm, while the reference electrode is placed on the bone behind the ear. A BPF with a range of 0.8-48Hz is applied to eliminate unwanted signals. It is crucial to note that the EEG sensor has high amplification gain, making it susceptible to noise from electromagnetic and motion sources. Therefore, it is recommended to acquire data in a noise-free environment.

On the other hand, the EDA sensor uses two measuring electrodes placed on the palm of the left hand on the thenar area. Participants should be seated comfortably in front of the computer screen before beginning the data collection.

The PsychoPy experiment ensures that all sensors are connected and recording. A more detailed description of the set-up can be consulted in Annex III

Sleeve Color	Red	Black	White
Electrode Cable	+	-	reference

Figure 5.4: EEG Electrode color code

5.1.5 Procedure

Before the start of the experiment each subject is asked to read the experiment briefing and sign the informed consent. The subject is informed of the duration of the experiment, the sensors that would be used and their placement. See Annex II for more details on the experiment briefing. After the briefing is read and understood, the subjects are asked to fill the informed consent form in order to authorize the use of their data see Annex I. The experimental sessions were conducted in portuguese.

Once the briefing is done and the informed consent is signed the experimental procedure can begin as detailed in Annex III. The first step is to prepare the skin for the sensor set-up, the skin is cleaned and any strands of hair are removed. The EEG sensor has 3 electrodes, one for reference that is placed behind the left ear, and 2 measuring electrodes, that are placed above the left eyebrow. The EDA sensor only has 2 electrodes that are placed in the palm area of the left hand right by the wrist.

Once the subject is seated comfortably and the sensors are set the experiment can begin. The participants are warned to keep their body movements to the minimum, only moving when its necessary to minimize unwanted noise in the signal.

Figure 5.5 shows a block diagram of the experimental process timeline. The first portion of the experiment is an introduction phase where the subjects are presented

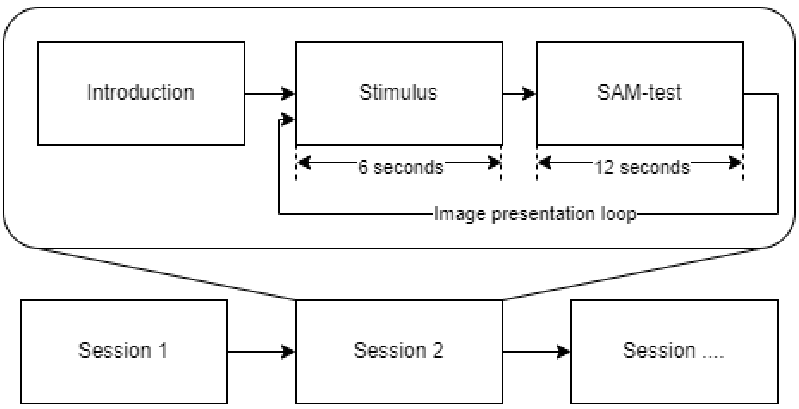
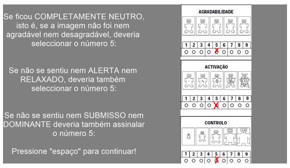


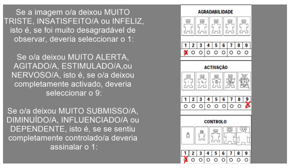
Figure 5.5: Block diagram of the experimental process

again with a brief simulation of the experiment for the subjects to get familiar with the setting and relief any stress and anxiety related to the experiment itself. And to, once more review the concepts of valence, arousal and dominance. Figure 5.6 shows several slides from the experimental process corresponding to the introduction phase.

(a) Slide introducing the format and images of the experimental process



(b) Slide explaining the valence, arousal and dominance concepts



(c) Slide explaining the valence, arousal and dominance concepts

(d) Slide introducing the self-assessment form

Figure 5.6: Slides from the introduction phase of the experimental procedure

The stimulus presentation only begins when the subject feels ready, by pressing the 'space' key. Once again the subjects are reminded to anwer honestly and to keep body movements to a minimum. Entering the data collection loop. Where each of the 120 images are presented randomly appearing for 6 seconds each (see annex IV for the images used in the experimental procedure). After, each image the subject is asked to self-assess their affective state regarding the presented picture. The self-assessment is based on the SAM test, a picture oriented three dimensional 9 point scale of V/A/D (see figure 5.7). The subject has 12 seconds to answer the form or else the next image is presented.

5.2 Results

For the analysis and selection of successful experimental sessions the collected raw EEG and EDA signals were plotted to manually analyse the quality of the signal. Any saturated

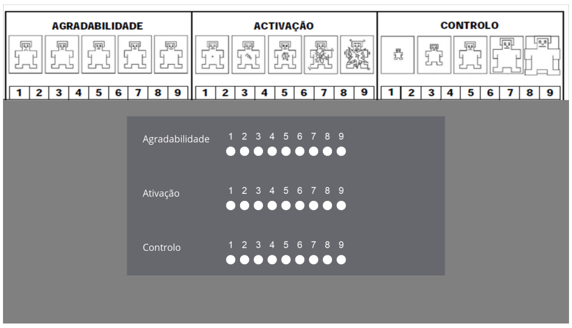


Figure 5.7: Self-assessment test presented after each picture

signal, or signal with too much noise had to be excluded. Only sessions with valuable EEG and EDA pairs were considered.

Regarding the 20 conducted experimental sessions sessions, only 6 resulted in usable EEG and EDA signals. The majority of the EDA signals collected were relevant and usable, with little to no outliers and small amounts of noise, resulting in 20 good data samples. Figure 5.10 shows a sample of a collected EDA signal. On the other hand the EEG signals collected had too much noise, and the majority of the signals were saturated, only 6 data samples are usable(see figures 5.9 and 5.8). This results in only 6 pairs of signals (3 males and 3 females).

The type of results observed, especially with the EEG signals were expected. As explained in previous chapters, EEG sensors are particularly sensitive to external noise, muscle movements, eye blinks, etc... The characteristics of the device also play a major role in the data quality. The number of channels, type of electrodes, and overall quality of the technology greatly affect the results. So when dealing with a single channel, commercial device the data collection becomes even more unreliable and difficult. The BITalino EEG sensor electrodes are placed in the FP1 region, just above the left eyebrow, this location is also very sensitive, because any facial movements or eye blinks will definitely be picked up by the sensor.

For the classification of emotions only the data collected from 6 subjects is used, the remaining were ruled inappropriate. For the categorization of the database of images and analysis of the affective content of the database, the self-assessment values from all 20 conducted sessions are used.

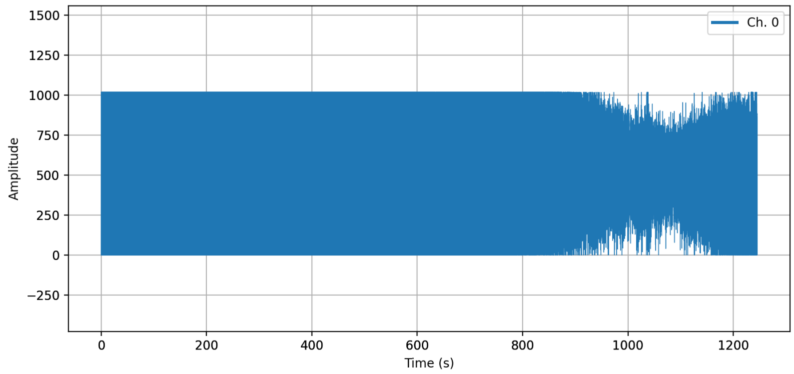


Figure 5.8: Saturated EEG signal

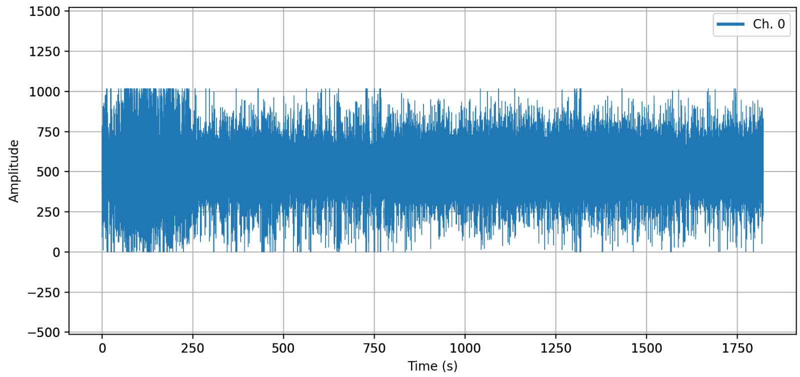


Figure 5.9: Good EEG signal

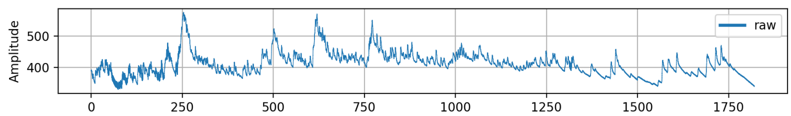


Figure 5.10: Good EDA signal

6

Results and Analysis

This chapter reports the results and conclusions from the analysis of the collected data in the experimental sessions detailed in the previous chapter 4. Raw EEG and EDA data were collected from each subject as well as their self-assessment of the presented images.

6.1 Image Database

The collected V/A/D values for each image will serve two purposes: 1 - To study the characteristics of the of the images in the database in order to identify and categorize the images into different affective groups. This will be achieved by analysing the spread of the valence and arousal values across a 2 dimensional affective space. 2 - Based on the results from the analysis of the image database, label each EEG and EDA signal according to the corresponding valence and arousal values.

The analysis of the created database in therms of the affective dimensions of V/A/D is important to gain insights into the emotional content of the visual stimuli presented to the different subjects. The collected self-assessment values from each of the 20 subjects that participated in the experimental session will be used to categorize each of the 120 images in the database. The categorization will be made using a basic k-means clustering algorithm to group the image data into distinctive groups that represent the number and type of affective states this database triggers.

Valence refers to the positive or negative valence of the emotion elicited by an image, arousal refers to the intensity of the emotional response, and dominance refers to the degree of control felt by the viewer over the emotional response.

The conducted experimental sessions collected 20 self-assessment ratings for each of the 120 images in the database created for this dissertation. In other words, each image in the database has 20 different V/A/D measurements.

During the experimental sessions the author observed that the dominance metric wasn't properly understood by the subjects and often left unanswered, so the decision to only consider the images in the 2 dimensional space of valence and arousal was made. After eliminating any data entries with missing valence and arousal values the data set was left with 2366 valence-arousal measurements each labeled with their respective image id.

The calculated mean and standard deviation for the valence and arousal of all images in the database are:

1. Valence mean: 4.232
2. Arousal mean: 5.649
3. Valence Max: 8.1
4. Arousal Max: 8.0
5. Valence Min: 1.1
6. Arousal Min: 3.7
7. Valence standard deviation: 2.219
8. Arousal standard deviation: 0.994

For the analysis of the affective characteristics of the images in the database, the mean and standard deviation of the valence and arousal measurements were calculated according to their respective image ID (see figure 6.1).

ID	Val-M	Val-SD	Arou-M	Arou-SD	Dom-M	Dom-SD
1.0	2.05	1.3562719801759993	6.5	1.4327007988227578	3.7	1.8666040089734595
2.0	1.8	0.894427190999916	6.7	1.2607433062326867	3.4	2.036508880671192
3.0	6.631578947368421	1.3420765964144055	4.473684210526316	2.0376571801031034	6.052631578947368	1.4709665835968129
4.0	6.2105263157894735	1.7819760370137494	5.315789473684211	1.5294382258037453	5.842105263157895	1.572795031314098
5.0	1.894736842105263	0.9941348467724342	7.105263157894737	1.1496249070460265	3.526315789473684	2.318246968260274
6.0	1.65	0.9880869341680844	6.6	1.2732056517228263	3.6	1.930366749991743
7.0	5.25	1.1180339887498945	4.95	1.5035046776746235	5.35	1.5312533566021211
8.0	5.6	1.0462967275611939	4.7	1.0310954828418375	5.85	1.3869694338832113
9.0	5.75	1.164157703189193	4.5	1.3572417850765923	5.0	1.654340383737022
10.0	6.2	1.7651599003161755	5.4	1.6351404253232553	5.7	1.8381913307436342
11.0	1.45	0.8870412083230169	7.35	1.1367080817685318	3.15	2.345768867332706
12.0	3.85	1.3088765773505315	5.0	1.1239029738980328	4.6	1.6670175069329813
13.0	7.05	1.4317821063276355	4.45	1.4317821063276355	5.2	1.9628121608924705
14.0	2.1	1.0208355710680808	6.55	1.234376040972246	2.95	1.4680814547887786
15.0	6.45	1.9324105480761042	5.15	1.6944180805158295	5.65	1.7851728502481652
16.0	6.65	1.5312533566021211	4.65	1.8144159564878983	5.85	2.0072237962970276
17.0	4.5	1.9056702094980709	5.5	0.9459053029269174	4.8	1.852452144420584
18.0	7.05	1.2763022245616642	4.4	2.087557121815378	5.65	1.725200217213551

Figure 6.1: Mean and standard deviation for the first 18 images of the database

As stated in the items above, the average valence rating across all 120 images of the database is of 4.23 with standard deviation of 2.22, which is very close to the neutral point of the valence metric, with a minimum and maximum values of 1.15 to 8.1.

The arousal has an average of 5.65 which indicated that the majority of the images in the database aroused the participants moderately with a minimum and maximum values of 3.7 to 8, this means that the image database arousal has a tendency to high arousal, with no registered mean values below 3.7.

The standard deviations for valence and arousal indicate that the ratings of the participants varied widely for each dimension, with standard deviations of 2.21 and 0.995, respectively. This suggests that the images elicited different emotional responses in different participants, with the valence having more weight in variance of values.

The mean values for each images in the database can be plotted into a two dimensional space where the x axis is the mean valence and y is the mean arousal. The results are shown in figure 6.2, where each image is represented by a dot with size proportional to the standard deviation of valence.

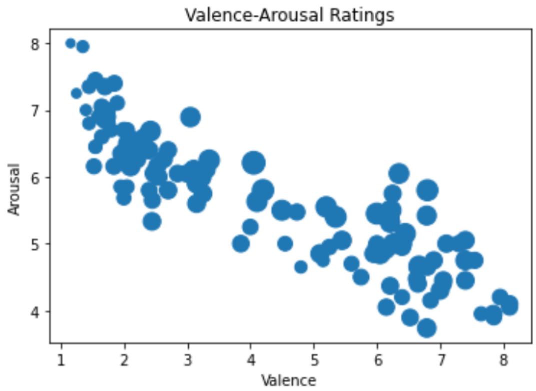
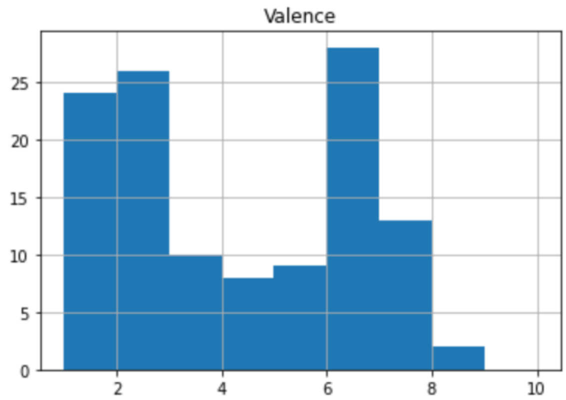


Figure 6.2: Average valence and arousal scatter plot of image database where each image in represented by a dot with size proportional to the standard deviation of valence

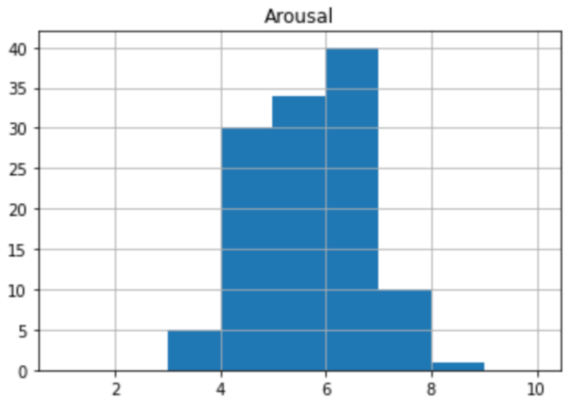
To better understand the distribution of values across the valence and arousal axis, three histograms were calculated. One dimensional histograms for the valence and the arousal axis and a 2 dimensional histogram, or heat map for the combined valence-arousal dimensional space. The histograms for the valence and arousal dimensions are as presented in figure 6.3.

The distribution of the average valence of the images in the database shows that most images have a mean valence rating between [6-7[, as seen by the peak of the histogram in figure 6.3a. The distribution of ratings has more density in the lower range of the histogram, with more then 50% of valence scores between [1-5[(77 values). There are no registered values for a valence of 9. The histogram is slightly symmetrical, with most values tending to the both extremes of the average valence scale and fewer neutral values. The analysis of the valence histogram is compatible with the average valence of the database of 4.23 and standard deviation of 2.21 calculated above. Overall the distribution of the average valence values of the database suggests that the images in the database have an overall large range of valence values with more images on the negative spectrum of valence (below 5), but most common valence score is 6.

As seen in figure 6.3b, the average arousal ratings have a range from 3 to 8. The histogram has a peak in the 6th bin which indicates most images in the database have arousal values from 6 to 7. This suggests that the database is generally moderately aroused. It is also observable there are no values with arousal levels below 3, and very few values with arousal levels above 8. This suggests that extreme arousal levels are less common in the database. Overall, the histogram shows a relatively symmetrical distribution, with a peak



(a) Valence Histogram



(b) Arousal Histogram

(c) 2-dimensional histogram for valence and arousal, or heat map where each tile presents the sum of images within the respective interval

Figure 6.3: Histograms

in the middle and fewer values at the extremes. The average arousal of the database is of 5.6 and standard deviation of 0.99. The density of arousal values in the database tends to neutral valence ratings with a slight positive tendency.

Analysing the distribution of the average valence-arousal ratings in the heat map of figure 6.3c there are data points across all bins of the valence axis. As stated before the average arousal values range between 3 and 8, and have the highest concentration between the 4 and 6. The heat map in figure 6.3c appears to have a bigger concentration of data points in the lower right corner of the graph, with peak concentration of points around average valence between 6 and 7, and average arousal between 4.5 and 5.5. This concentration of points has moderately high valence and and mostly neutral values of arousal.

Another observable concentration of values is in the upper left corner of the 6.3c graph, with its peaks concentration in the lower valence values (1 and 2) and arousal between 5.5 and 7.5. The overall figure 6.3c suggests that there is a correlation between high valence levels and neutral arousal, and low valence levels with high arousal levels.

The mean valence-arousal ratings of each image were subjected to a k-means clustering technique in order to determine whether the photos in the database may be divided into various affective states. K-Means divides the unlabeled data into several groups based on shared characteristics and trends. By calculating and comparing the mean distances of each data point inside a cluster from its centroid, one can determine how many groups or clusters there are in the data. By employing the Within-Cluster-Sum-of-Squares (WCSS) approach to minimize the distance between the data points and the centroid of the clusters, the elbow method's ideal number of clusters may be easily determined. The sum of the squares of the distances between each cluster's centroid and each data point was determined using this method. The process is iterated until a minimum value for the sum of distances is reached. Figure 6.4 shows the plot between WCSS values and the respective number of clusters K. The sharp point of bend in the graph is considered the best value of k [70].

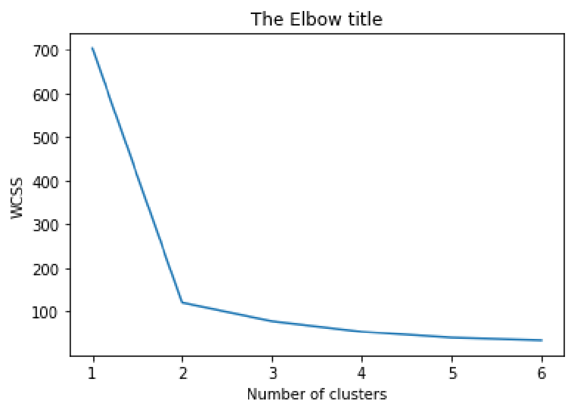


Figure 6.4: Plot of WCSS values and their respective number of clusters

As seen in the plotted graph 6.4 the best values for k, which means, the optimal number of clusters is 2. Based on the heat map in figure 6.3c, the result for the number of clusters was expected as it can clearly be observed in the heat map the two areas with higher density. The first cluster with label 0 has 6.42±0.9 valence and 4.7±0.5 arousal with 56 images, the second group, with label 1 has 2.31±0.7 valence and 6.40±0.6 arousal with 64 images. Figure 6.5 shows the resulting clusters.

The 2 dimensional affective space is shown in figure 6.6. The centroid of group 0,

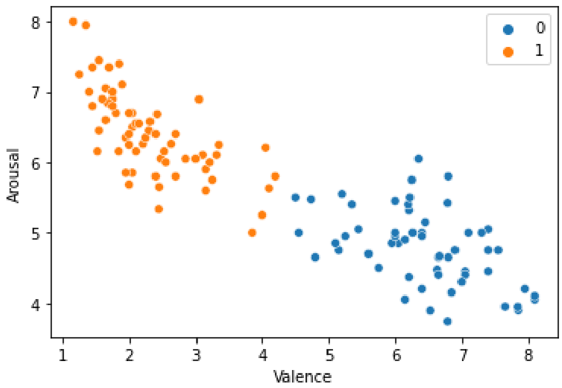


Figure 6.5: Images of the database mapped into their mean valence and arousal values. The blue points correspond to the first cluster of images and the orange points correspond to the second cluster of images

6.42±0.9 valence and 4.7±0.5 arousal, is located in the positive spectra of the valence scale, and in the neutral area of the arousal scale. The images from group 0 fall mostly on the 1st and 4th quadrants of the valence-arousal affective space with the arousal around the neutral line. Based on figure 6.6 the group 0 of images can be said to elicit positive affective states with moderate arousal. The centroid of the group 1 is centered in 2.31±0.7 valence and 6.40±0.6 arousal which falls on the 2nd quadrant of the valence-arousal affective space, associated with negative emotions.

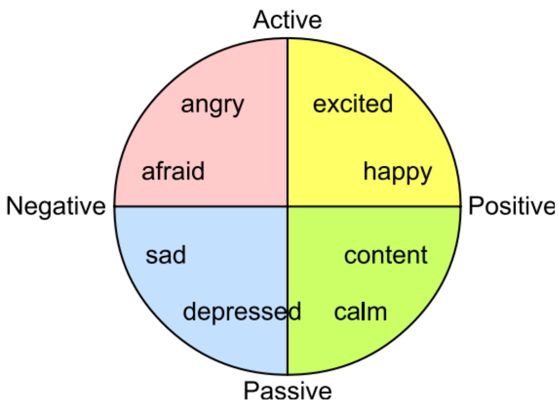


Figure 6.6: 2 Dimentional affective space with valence in the x axis and arousal in the y axis

In conclusion the created image database for this dissertation, was labeled based on the valence and arousal scores collected from a population of 20 subjects. Resulting in two different groups of images, the first group, eliciting positive emotional states, consists of 56 images with mean valence and arousal of 6.42±0.9, 4.7±0.5 respectively. The second group elicits negative emotional states, with mean valence and arousal of 2.31±0.7, 6.40±0.6 respectively, and has 64 images. See annex V for the resulting average and standard deviation of each image in the database, as well as the corresponding label, calculated in this section.

6.2 EEG and EDA signals

The results presented in this section regard the Emotional classification process introduced in chapter 3.

The experimental procedure in chapter 5 resulted in 6 usable EEG/EDA signals.

For the assessment of emtoional states, first, the EEG and EDA signals are synchronized with the images presented and separated into 6 second samples of data, by calculating the difference between the images timestamps and the start time of the experiment. Each 6 second signal sample is associated with a valence and arousal value, given by the experiment subjects, as seen in the experimental procedure detailed in 5.

After being filtered, relevant features for each of the EEG and EDA signal pairs are calculated. The average band power in the theta (4-8)Hz, lower alpha (8-10)Hz, higher alpha (10-13)Hz, beta (13-25)Hz and gamma (25-40)Hz frequencies, the downsampled filtered EEG signal and the downsampled filtered EDA signal are the extracted features for classification. This results in 7 features for each 6 second signal samples. Each containing 47 data points, which results in 329 features for training.

Before the SVM classification process, the signals need to be labeled according to their valence and arousal values resulting form the self-assessment each participant took regarding the presented images.

For the labeling of the signal samples, and using the conclusions from the previous section 6.1. Each image was labeled according to the two different affective states identified above, positive(label 0) and negative(label 1). The images in the database associated with positive affective states have mean valence and arousal of 6.42 ± 0.9, 4.7 ± 0.5 respectively, and the images associated with negative affective states have mean valence and arousal of 2.31 ± 0.7, 6.40 ± 0.6 respectively. By using the trained k-means clustering algorithm in 6.1, each valence/arousal rating is labeled accordingly, resulting in 396 instances for the positive affective state and 316 instance for the negative affective state.

The final dataset used for training the SVM classification algorithm contains 712 samples each with 329 features associated with the EEG and EDA signals. 396 samples for positive affective states and 316 for negative affective states. Table 6.1 shows a simple description of the resulting data structure used for classification.

Table 6.1: Mapping of the used features for classification

Filtered EEG	Theta	Alpha High	Alpha Low	Gamma	Beta	Filtered EDA
F1 - F47	F48 - F94	F95 - F141	F142 - F188	F189 - F235	F236 - F282	F283 - F329

The SVM classification with 'rbf' kernel achieved a classification accuracy of 57.01%.

7

Conclusions

The research work, presented in this dissertation, aims to study the use of single-channel EEG and EDA signals for the assessment of emotional states, and the possibility of establishing the well-being of a person based on the assessed emotional state. This study is relevant because with the rise of artificial intelligence and the growing trend towards personalized and customized services, businesses and organizations are seeking ways to better understand their customers and clients' emotional states to provide better services.

To achieve these goals, and based on the knowledge acquired during the research, the author proposed and implemented a three-phase process to assess two emotional states, positive and negative. The first phase involved data acquisition, followed by processing and feature extraction, and finally classification. The experimental sessions were conducted using the data acquisition system created to collect data for emotional assessment, and the database of images created for this dissertation was categorized into two different groups of affective states, positive and negative.

The developed data acquisition system was used to conduct experimental sessions to collect data for emotional assessment and the categorization of the database of images created for this dissertation. Out of the 20 subjects that took part in the experiment, only 6 had valuable EEG and EDA signals. The author identified that when a subject is connected to the sensors, if the subject touches the computer with their bare hands, the EEG sensor output gets overloaded and saturates the signal. This could explain why only 30% of the sessions were successful. The experimental process needs further improvement to avoid mistakes like this, which could compromise the data collection.

In conclusion, the designed acquisition system and the experimental procedure used showed good results and was successful in the collection of data, but the experimental process needs further improvement and have a larger population of study.

The analysis and categorization of the image database was successful, and the classification of the EEG and EDA signals into the two identified affective groups, using a SVM algorithm with RBF kernel reached an accuracy level of 57.01%. Although this is not the best result compared with similar studies, it shows that emotional assessment based on single-channel EEG and EDA signals is possible.

The proposed emotional assessment process in this dissertation is unique because of the methods used to characterize the image database and label the EEG and EDA signals. However, there are still several aspects that need improvement or require further study.

7.1 Future Work

Although the general objectives of this dissertation were accomplished there are several aspects that should be improved or are of interest for further studies.

The experimental procedure should have had a verification phase where the output from the sensors was verified in order to see if there was no saturation in the signal. Regarding the population of study, it is of interest in future studies to collect data from a larger population and also even the female/male ratio. The more data samples collected more accuracy the classification algorithm will have.

Future work should explore different denoising and feature extraction techniques for better data classification. A feature selection method should be applied to the selected features to identify the most relevant ones. The SVM classifier could also be tested with different parameters to find the best results and accuracy of the prediction. Finally, the trained SVM should be validated using a series of statistical tools and new data.

It was not possible to complete all the objectives of this dissertation. To evaluate whether it is possible to establish a user's well-being based on their emotional state using the proposed system, another experimental procedure should be conducted using the trained SVM to give real-time feedback on the assessed emotional state and act accordingly. This could be used in a number of applications, such as controlling ambience lighting based on the user's affective state.

For future work, the emotional assessment system could be improved to have real-time feedback on a person's emotional state. This could be achieved by automating the data acquisition and feature extraction processes. Furthermore, the trained SVM algorithm could improve classification accuracy in real-time by repeatedly retraining the algorithm using new data. These improvements are considered relevant for the advancement of emotional assessment and interfaces that act according to the user's affective state.

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I

Annex 1 - Informed Consent

NOVA SCHOOL OF SCIENCE & TECHNOLOGY

Nome:____

Idade:_____ Sexo:__________

Declaro ter sido informado e sinto-me esclarecido sobre os objetivos do estudo , em que aceito participar.

Aceito igualmente os métodos utilizados sabendo que não prejudicam a minha saúde e estou ciente de que tenho toda a liberdade para interromper a participação no estudo a qualquer altura, se assim o desejar.

Autorizo pois, a utilização dos dados obtidos, apenas para efeitos científicos ou educacionais, salvaguardando sempre a minha identidade e a confidencialidade de todos os lados.

Assinatura:___________________________ Data:____________

II

Annex 2 - Briefing

Obrigada pela sua participação!

Neste estudo procuramos conhecer como as pessoas reagem a imagens que retratam diferentes acontecimentos/situações que ocorrem na vida.

Durante cerca de 30 minutos, ser-lhe-ão apresentadas um conjunto de imagens projetadas, que deverá avaliar de acordo com a forma como elas o/a fizeram sentir enquanto as estava a observar.

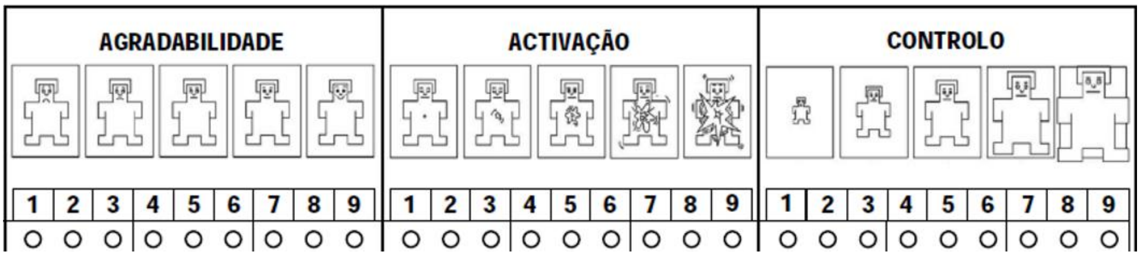
Não existem respostas verdadeiras ou falsas. **Por favor, responda o mais sinceramente possível.**

Todas as informações recolhidas durante este estudo são **confidenciais** e serão usadas apenas para fins estatísticos. **Os resultados individuais são absolutamente confidenciais.**

Este é um exemplo das imagens que irá observar e avaliar:

E como o irá fazer?

Este é um exemplo do formulário que terá que responder depois de cada imagem apresentada.



Cada imagem será apresentada durante 6s, quando visualizar as imagens deverá concentrar-se apenas no ecrã, **minimizando qualquer movimento ocular, expressão facial ou motora.**

Observando em mais detalhe a escala de resposta, verificamos que ela considera **3 dimensões** (**AGRADABILIDADE**, **ACTIVAÇÃO** e **CONTROLO**) materializadas numa **série de figuras** que procuram facilitar a avaliação de cada imagem **pela materialização dos diferentes estados emocionais que elas podem provocar**.

Repare que, cada dimensão, contém:

- **5 figuras**;
- **E uma escala de 9 pontos** para a sua resposta (com valores intermédios entre as figuras):

Vejamos novamente a imagem:

Agradabilidade:

- Se a imagem apresentada o/a deixou **FELIZ, ALEGRE**, **SATISFEITO/A**, **CONTENTE** ou **OPTIMISTA**, isto é, se para si foi **muito agradável observar a imagem**, deveria assinalar o **valor 9** na sua folha de respostas.

Ativação:

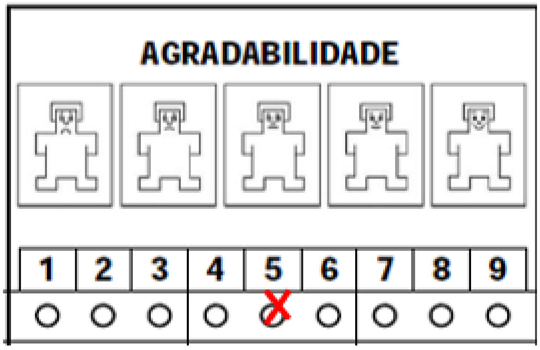
- Se, por outro lado, a imagem o/a deixou **RELAXADO/A**, **CALMO/A**, **TRANQUILO/A** ou **POUCO ACTIVADO/A** deveria avaliá-la com o **número 1**.

Controlo:

- Finalmente, se a imagem o/a fez sentir **DOMINANTE**, **INFLUENTE**, **IMPORTANTE**, **AUTÓNOMO**, isto é, se o/a fez sentir **completamente "em controlo"** deveria assinalar o **número 9** da escala de resposta

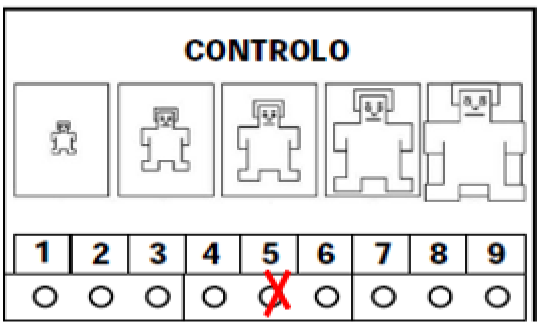
Vejamos agora outros exemplos:

Se ficou **COMPLETAMENTE NEUTRO**, isto é, se a imagem não foi nem agradável nem desagradável, deveria selecionar o **número 5**:



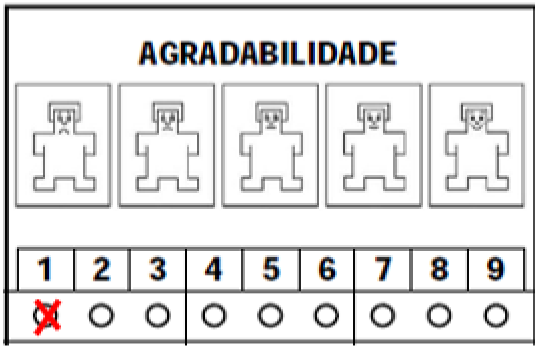
Se não se sentiu **nem ALERTA nem RELAXADO**, deveria também selecionar o **número 5**:

Se não se sentiu **nem SUBMISSO nem DOMINANTE** deveria também assinalar o **número 5**:

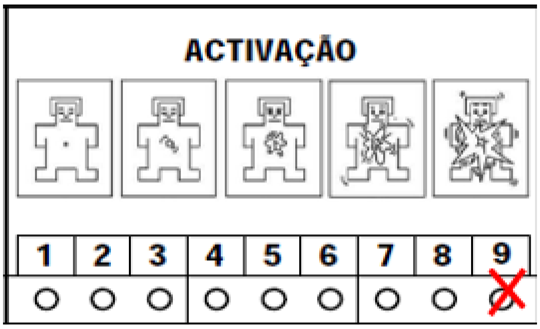


Mais um exemplo de imagem:

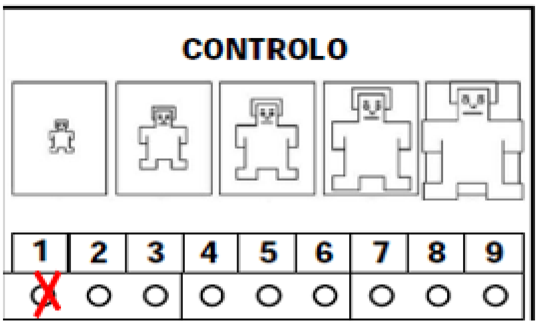
Se a imagem o/a deixou **MUITO TRISTE**, **ABORRECIDO/A**, **INSATISFEITO/A** ou **INFELIZ**, isto é, se foi muito desagradável de observar, deveria selecionar o **número 1**:



Se o/a deixou **MUITO ALERTA**, **VIGILANTE**, **AGITADO/A**, **ESTIMULADO/A, INQUIETO/A** ou **NERVOSO/A**, isto é, se o/a deixou completamente ativado, deveria selecionar o **número 9**:



Se o/a deixou **MUITO SUBMISSO/A**, **DIMINUÍDO/A**, **NFLUENCIADO/A** ou **DEPENDENTE**, isto é, se se sentiu completamente controlado/a enquanto a estava a observar deveria assinalar o **número 1**:



Por favor, avalie cada uma das imagens que lhe serão apresentadas de seguida de acordo com aquilo que **verdadeiramente sentiu**. Se não conseguir avaliar alguma das imagens apresentadas deixe, por favor, a linha correspondente em branco.

Repare que as escalas de resposta permitem também **classificações intermédias entre as figuras** (**2**, **4**, **6** e **8**) que podem refletir melhor o que verdadeiramente sentiu enquanto observava as imagens.

Cada imagem será apresentada por **6 segundos**. De seguida terá **13 segundos** para responder. Após este tempo será apresentada a imagem seguinte.

Durante a apresentação é extremamente importante que **se concentre na imagem**, mantendo nela o seu olhar. **Evite qualquer distração, movimento desnecessário ou expressão facial**.

Não se esqueça de desligar o telefone, os aparelhos com que estamos a trabalhar são extremamente sensíveis a sinais exteriores.

Alguma dúvida? Qualquer dúvida deve ser esclarecida neste momento.

III

Annex 3 - Lab Guide

NOVA University

NOVA School of Science and Technology

NOVA SCHOOL OF
SCIENCE & TECHNOLOGY

LABORATORY PROTOCOL

Emotional Assessment with single channel EEG and EDA

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01/05/2022

1 Introduction

The present protocol is intended to provide a detailed step-by-step procedure of the recording of EEG and EDA signals with image stimuli for emotional assessment.

2 Equipment

Recording Equipment

- Bitalino (r)evolution Board Kit;
- BITalino EDA sensor;
- BITalino EEG sensor;
- 2x UC-E6 to UC-E6 sensor connection cable;
- 5 self-adhesive disposable electrodes;
- Headband

Table 1: Materials

Component	**Quantity**	**Link**	**Price**
Bitalino (r)evolution Board Kit	1	https://www.botnroll.com/pt/varias/2682-bitalino-r-evolution-board-kit-bt-kit-de-desenvolvimento-biom-dico.html https://www.pluxbiosignals.com/collections/bitalino/products/bitalino-revolution-plugged-kit-ble-bt	177€ 257€
UC-E6 to UC-E6 sensor connection cable	2	https://www.pluxbiosignals.com/collections/bitalino/products/bitalino-sensor-cable	12.30€ per cable
Self-adhesive disposable electrodes	300	https://safeprint.pt/produto/eletrodo-fiab-pg10c/	30
Headband	1	https://www.decathlon.pt/p/fita-de-tenis-tb-100/_/R-p-165595?mc=8166945&c=PRETO	3

Clean up Equipment

- Rubbing alcohol
- Cotton Pads

Extras

- Table
- Chair
- Computer
- Computer mouse

2.1 Bitalino (r)evolution Board Kit

The Bitalino (r)evolution Board is a all-in-one hardware device for biosignals data collection. The board can be connected simultaneously to several sensors and actuators to make the data acquisition system. The actuators are: Light Emitting Diode (LED) and Buzzer (BUZ). And the sensors are: Electrodermal Activity (EDA), Electrocardiography (ECG), Electromyography (EMG), Electroencephalography (EEG), Light (LUX), Pushbutton (BTN) and the Accelerometer (ACC). This board is available as a kit that comes with all accessories needed for an experimental setup, including battery, cables, and electrodes. The Bitalino Board also gives access to the OpenSignals (r)evolution software designed to perform the data collection, this software also provides a series of add-ons to extract statistical, temporal, and spectral parameters.

2.1.1 Specifications

- Sampling rate: 1, 10, 100 or 1000HZ
- Analog Ports: 10-bit (A1-A4) + 6-bit (A5 and A6) + 1 auxiliary on battery + 1 out (8-bit)
- Digital Ports: 2 in (1-bit) + 2 out (1-bit)
- Communication: Bluetooth or BLE
- Range: up to 10m (in line of sight)
- Sensors: EMG; ECG; EDA; EEG; ACC; LUX; BTN
- Actuators: LED; BUZ
- Size: 100x65x6mm
- Battery: 500mA 3.7V LiPo (rechargeable)
- Consumption: 65mA
- Accessories: 1x 3-lead cable; 1x 2-lead cable; 5x Electrodes

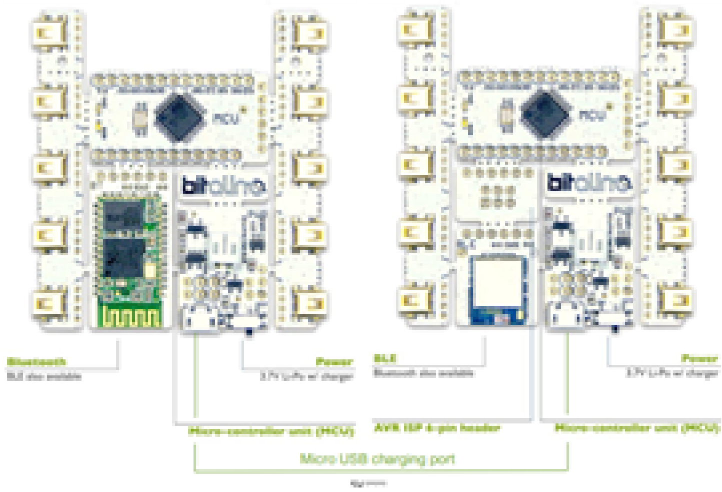


Figure 1: Bitalino (r)evolution board

2.2 EDA sensor

The BITalino EDA sensor is capable of accurately measuring the electrical properties of the skin which changes. These changes are caused by alterations in sweat secretion and sweat gland activity because of changing sympathetic nervous system activity. The low-noise signal conditioning and amplification circuit design provide optimal performance in the detection of even the most feeble electrodermal skin response events. This sensor is connected to the (r)evolution board.

2.2.1 Specifications

- Range: 0-25µS(VCC)
- Bandwidth: 0-3Hz
- Consumption: ±0.1mA
- Input Bias Current: ±70pA
- CMRR: 130dB
- Measurement: continuous
- Current: DC

2.2.2 Transfer Function

The analog sensor signals acquired with BITalino devices are converted into digital values ranged between 0 and 2 n -1 (n=sampling resolution, usually 6-bit or 10-bit) and streamed in the raw digital format.

$$EDA(\mu S) = \frac{\frac{ADC}{2^n} \times VCC}{0.12} \tag{1}$$

$$EDA(S) = EDA(\mu S) \times 1 \times 10^{-6} \tag{2}$$

Valid sensor range: $[0\mu S, 25\mu S]$

with:

$EDA(\mu S)$	EDA signal in microsiemens (μS)
$EDA(S)$	EDA signal in siemens (S)
ADC	Value samples from the sensor/channel (digital value)
n	Sampling resolution (default: 10-bit resolution (n=10), although 6-bit may also be found)
VCC	Operating voltage (3.3V when used with BITalino)

2.2.3 Sensor Placement

The EDA sensor uses two measuring electrodes. The following image shows some examples of different body locations in which the skin conductance has been compared in previous studies.

2.3 EEG sensor

This EEG sensor has been especially designed for both classic and localized EEG measurement. The sensor has a bipolar configuration, with two measurement electrodes detects the electrical potentials in the specific scalp region with respect to a reference electrode (placed in a region of low muscular activity). The resulting signal is the amplified difference between these two leads, eliminating the common unwanted signals. Its convenient form factor enables a discrete placement in regions such as the forehead, occipital, and others.

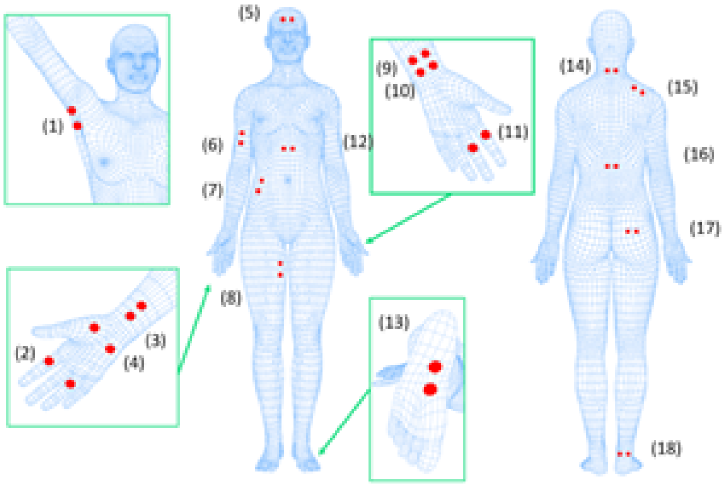


Figure 2: Electrode position examples over the body to measure and compare electrodermal activity: armpit (1), fingers (2,11), wrist (3,9,10), hand palm (4), forehead (5), arm (6), abdomen (7), thighbone (8), chest (12), foot (13), neck (14), shoulder (15), back (16), buttock (17), and calf (18).

2.3.1 Specifications

- Gain: 41782
- Range: ±39.49 (with VCC = 3.3V)
- Bandwidth: 0.8-48Hz
- Consumption: 3mA
- Input Voltage Range: 1.8-5.5V
- Input Impedance ¿100GOhm
- CMRR: 100dB
- Channels: 1

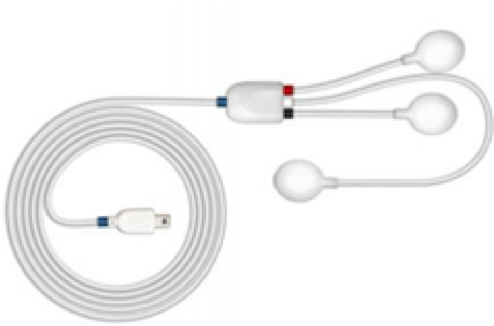


Figure 3: EEG sensor

2.3.2 Transfer Function

The analog sensor signals acquired with BITalino devices are converted into digital values ranged between 0 and 2 n -1 (n=sampling resolution, usually 6-bit or 10-bit) and streamed in the raw digital format.

The sensor has a high amplification gain, which causes it to be particularly sensitive to noise resulting electromagnetic and motion sources. It is recommended that data acquisition is done in an appropriate environment. Power supplies, lighting and other common household elements are prone to introduce parasite signals.

$$EDA(\mu S) = \frac{\frac{ADC}{2^n} \times VCC}{0.12} \quad (1)$$

$$EDA(S) = EDA(\mu S) \times 1 \times 10^{-6} \quad (2)$$

Valid sensor range: $[0\mu S, 25\mu S]$

with:

$EDA(\mu S)$	EDA signal in microsiemens (μS)
$EDA(S)$	EDA signal in siemens (S)
ADC	Value samples from the sensor/channel (digital value)
n	Sampling resolution (default: 10-bit resolution (n=10), although 6-bit may also be found)
VCC	Operating voltage (3.3V when used with BITalino)

2.3.3 Sensor Placement

The EEG measured signal is s the amplified difference between the two measuring signals which is bandpass filtered by 0.8-48Hz to eliminate the common unwanted signals. Two measuring electrodes (IN+/-) should be placed above the electrode position for example FP1 (international 10-20 system) with a distance between the electrodes that is not bigger than 3cm. The reference electrode is placed in a neutral region such as on a bone behind the ear.

Sleeve Color	Red	Black	White
Electrode Cable	+	-	reference

Figure 4: EEG sensor color codes

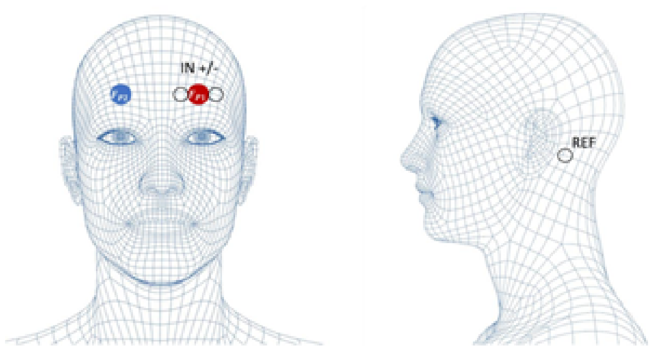


Figure 5: Electrode Placement

3 Methodology

3.1 Participants

- 30 male.
- 30 female.

3.2 Stimuli

The stimuli consists of 60 images displayed in a random order.

3.3 Procedure

Prior to Arrival:

1. Send reminder email 1-2 days before the study. Include date, time and location of the session, as well as information about the general testing procedure (e.g. what to expect, how long it will take, appropriate clothing, etc...).
2. Charge the Bitalino device
3. Lay out the material that will be used for the recording session before the subject arrives.
4. Assemble the electrodes.
5. Assemble the BITalino hardware withe the EEG sensor connected to the A1 port and the EDA sensor connected to the A2 port.
6. Prepare the software.

Sensor setup:

1. Present document explaining the complete procedure.
2. Obtain consent to collect the subject's data
3. Sit the subject in the chair

4. Collect subject data(e.g.Name, age, sex, dominant hand)
5. Apply rubbing alcohol on the forehead, back of the left ear and palm of the non-dominant hand.
6. Place the EDA electrodes on the inside of the wrist side-by-side to each other and with no more than 1cm apart.
7. Place the white EEG electrode on the back of the left ear.
8. Place the red EEG electrode on the right side of the left eyebrow, above the eyebrow, almost in the middle.
9. Place the black EEG electrode on the left side of the eyebrow, above the eyebrow.
10. The distance between the red and black electrodes should be no more then 3cm.
11. Prepare the software.
12. Turn Off cellphones and electric equipment.

Data Collection:

1. Tell the subject to sit comfortably so that during the experiment their movement are minimal.
2. Remember the subject to focus on the computer screen at all times, minimizing fidgeting.
3. Ensure the subject comprehends the concepts of "Agradabilidade", "Ativação" and "Controlo".
4. Start recording.
5. Make sure the BITalino device is blinking as data is being collected.

3.4 Time Taken

- Experiment briefing - 15min
- Informed consent - 5 min
- Sensor setup - 5 min
- Data collection - 25 min
- Sensor clean up - 5 min

The total time of the experiment will be of 1hr

4 Anticipated Results

The software created for the data collection will originate 3 data files. The files are:

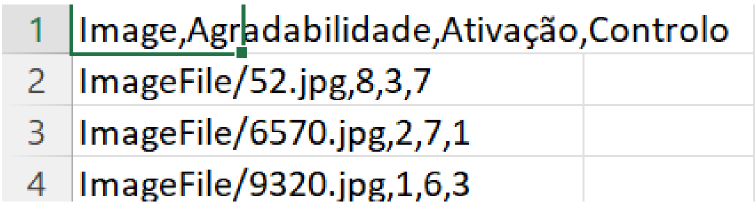
- timestamp - File containing the time where each image is presented during recording.
- rawData - A file containing the raw EEG and EDA data
- formData - Contains the "Agradabilidade", "Controlo" and "Ativação " levels given to each image by the participants.

1	1651179121.2921011
2	1651179142.2558534
3	1651179163.2423866
4	1651179184.2538462
5	1651179205.2458355
6	1651179226.2183204
7	1651179247.2141309
8	1651179268.251986
9	1651179289.258986
10	1651179310.257348

Figure 6: Timestamps file

1	nSeq,A1,A2,A3,A4,EEG,EDA,D1
2	0.0,1.0,1.0,0.0,0.0,429.0,1020.0,2.0
3	1.0,1.0,1.0,0.0,0.0,347.0,1020.0,3.0
4	2.0,1.0,1.0,0.0,0.0,259.0,1019.0,2.0

Figure 7: Raw Data file



1	Image,Agradabilidade,Ativação,Controlo
2	ImageFile/52.jpg,8,3,7
3	ImageFile/6570.jpg,2,7,1
4	ImageFile/9320.jpg,1,6,3

Figure 8: Form Data

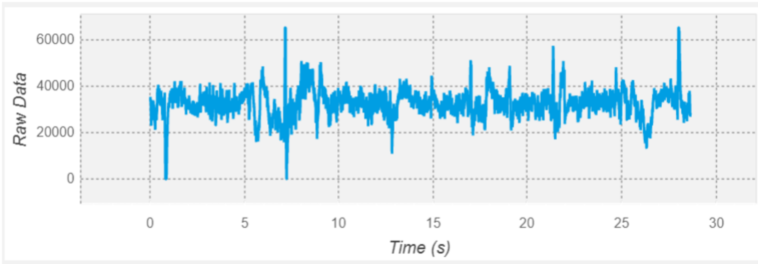


Figure 9: Raw EEG data

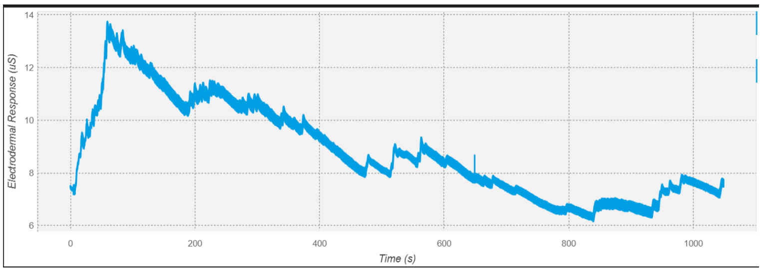


Figure 10: Raw EDA data

5 References

[1] Bitalino revolution user manual https://bitalino.com/storage/uploads/media/bitalino-revolution-user-manual.pdf.

[2] EDA sensor user manual https://bitalino.com/storage/uploads/media/electrodermal-activity-eda-user-manual.pdf.

[3] EDA sensr datasheet https://support.pluxbiosignals.com/wp-content/uploads/2021/11/Electrodermal_Activity_EDA_Datasheet.pdf.

[4] EDA sensor home guide https://bitalino.com/storage/uploads/media/homeguide4-eda.pdf

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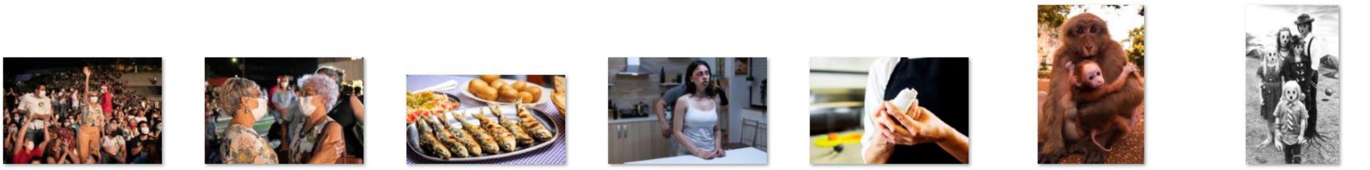
[6] EEG sensr datasheet https://bitalino.com/storage/uploads/media/revolution-eeg-sensor-datasheet-revb.pdf.

[7] EEG sensor home guide https://bitalino.com/storage/uploads/media/homeguide3-eeg.pdf

IV

Annex 4 - Image Database

1 2 3 4 5 6 7



8 9 10 11 12 13 14

15 16 17 18 19 20 21

22 23 24 25 26 27 28

29 30 31 32 33 34 35

36 37 38 39 40 41 42

43 44 45 46 47 48 49

50 51 52 53 54 55 56

57 58 59 1111 1274 1303 1340

1441 1510 2045 2050 2053 2055.1 2055.2

2095 2110 2154 2156 2158 2306 2345.1

2345 2352.1 2352.2 2375.1 2375.2 2730 3008

3069 3071 3102 3103 4071 4085 4534

4550 4690 4692 4693 6250 6570 7359

7361 7380 8640 9182 9183 9184 9185

9186 9187 9295 9300 9301 9302 9320

9321 9322 9325 9326 9330 9700 9800

9810

V

Annex 5 - Image Database Statistics

ID	label	Val-M	Val-SD	Arou-M	Arou-SD
1.0	0	2,50	1,38	6,67	1,75
2.0	0	1,50	0,84	6,67	1,03
3.0	1	7,00	1,79	3,83	2,71
4.0	1	5,33	0,52	4,67	1,86
5.0	0	1,83	0,75	7,17	1,33
6.0	0	1,67	1,21	7,17	1,17
7.0	1	4,83	0,41	4,33	1,63
8.0	1	5,33	0,52	5,00	0,00
9.0	1	6,17	0,98	4,00	1,67
10.0	1	5,33	1,86	4,33	1,63
11.0	0	1,00	0,00	7,50	1,05
12.0	0	3,50	1,64	5,33	0,52
13.0	1	7,67	1,51	4,17	1,47
14.0	0	1,83	0,75	6,67	1,37
15.0	1	6,83	1,83	5,67	1,21
16.0	1	6,33	1,75	4,50	1,22
17.0	1	4,67	2,42	6,00	0,89
18.0	1	6,17	1,60	5,17	2,23
19.0	1	7,17	0,98	3,17	1,60
20.0	0	3,00	2,10	6,17	0,75
21.0	1	8,17	0,75	3,33	1,51
22.0	1	7,83	0,98	5,00	1,10
23.0	0	4,00	2,10	6,17	0,75
24.0	0	3,17	2,71	6,33	1,03
25.0	1	6,33	1,97	4,33	2,16
26.0	0	3,50	1,64	5,50	0,55
27.0	1	4,33	1,63	5,00	0,00
28.0	0	2,17	1,33	6,17	1,17
29.0	1	7,67	1,21	2,83	1,72
30.0	1	4,67	1,03	5,83	0,98
31.0	0	2,17	0,41	5,33	2,66
32.0	0	2,33	1,21	6,17	0,98
33.0	0	2,83	1,47	5,00	1,26
34.0	1	8,67	0,82	3,33	2,16
35.0	1	5,67	0,82	3,50	1,76
36.0	1	5,83	1,60	4,83	0,41
37.0	0	2,00	1,26	6,50	1,22
38.0	1	7,33	2,34	5,83	0,41
39.0	0	1,83	0,75	6,83	0,75
40.0	0	1,67	0,82	6,17	0,75
41.0	1	6,60	1,52	3,60	1,95
42.0	0	2,83	1,17	6,17	0,98
43.0	1	6,00	1,10	4,00	1,67
44.0	1	6,00	2,37	5,00	2,19
45.0	1	6,67	1,86	6,17	0,75
46.0	1	4,83	0,41	5,00	0,00

47.0	0	3,83	2,14	5,67	0,82
48.0	1	6,00	1,67	4,50	2,17
49.0	1	8,67	0,52	3,33	2,25
50.0	1	7,00	1,67	4,17	1,33
51.0	1	6,33	1,03	5,50	1,22
52.0	1	7,00	1,67	3,83	2,23
53.0	0	2,17	1,17	5,83	0,98
54.0	0	4,00	2,00	5,17	0,75
55.0	0	3,50	1,38	6,00	1,26
56.0	1	7,17	1,83	4,50	1,97
57.0	0	2,17	1,17	6,33	1,03
58.0	1	8,67	0,52	3,00	2,76
59.0	0	2,83	0,98	6,00	0,63
1111.0	0	2,17	1,17	6,50	1,38
1274.0	0	2,33	1,21	6,33	1,21
1303.0	0	3,50	1,38	6,00	1,41
1340.0	1	8,00	1,10	4,33	1,51
1441.0	1	8,33	1,03	3,33	2,16
1510.0	1	7,17	0,41	3,83	1,94
2045.0	1	6,67	2,58	5,50	1,52
2050.0	1	7,17	1,94	5,50	1,64
2053.0	0	2,50	1,05	6,33	1,03
2055.1	0	2,50	1,52	6,17	1,17
2055.2	1	4,83	2,71	5,33	2,58
2095.0	0	1,67	0,82	6,50	1,22
2110.0	0	4,00	1,26	5,00	1,90
2154.0	1	7,50	1,05	4,67	2,25
2156.0	1	7,67	1,03	3,83	2,23
2158.0	1	6,83	1,94	4,17	2,04
2306.0	1	7,00	1,55	5,83	0,75
2345.0	1	7,17	1,47	5,33	1,51
2345.1	0	1,83	1,33	7,00	1,67
2352.1	1	7,00	1,79	5,00	1,79
2352.2	0	1,33	0,82	7,33	0,82
2375.1	0	2,67	1,03	5,83	0,75
2375.2	1	5,33	1,03	4,17	1,60
2730.0	0	1,83	0,98	7,17	0,75
3008.0	1	4,67	0,82	4,33	1,75
3069.0	0	1,00	0,00	7,80	0,45
3071.0	0	1,83	1,33	6,67	0,82
3102.0	0	1,17	0,41	7,33	1,03
3103.0	0	2,00	0,89	6,67	0,52
4071.0	1	6,00	1,10	4,17	1,83
4085.0	1	5,83	1,17	4,33	1,75
4534.0	1	6,17	1,17	5,00	1,26
4550.0	0	3,67	1,86	4,83	2,23
4690.0	1	5,83	0,75	4,50	1,52

4692.0	1	5,83	0,75	4,50	2,43
4693.0	1	5,50	1,05	5,17	1,33
6250.0	0	3,00	1,79	7,33	0,52
6570.0	0	2,83	1,60	6,67	0,52
7359.0	0	2,50	1,22	6,00	0,63
7361.0	0	1,33	0,52	7,50	1,22
7380.0	0	2,00	0,89	6,50	1,05
8640.0	1	5,50	0,84	5,00	1,26
9182.0	0	2,17	1,47	7,00	0,89
9183.0	0	1,17	0,41	8,17	1,17
9184.0	0	2,50	1,52	6,50	1,64
9185.0	0	1,33	0,82	7,33	0,82
9186.0	0	1,50	0,55	6,33	1,03
9187.0	0	1,17	0,41	6,83	0,75
9295.0	0	1,67	0,82	5,17	2,14
9300.0	0	1,50	0,84	6,17	1,47
9301.0	0	1,33	0,82	6,33	1,03
9302.0	0	1,50	0,55	5,83	1,33
9320.0	0	1,33	0,52	6,00	1,10
9321.0	0	1,67	0,82	6,67	1,03
9322.0	0	1,50	0,84	6,00	0,89
9325.0	0	1,50	0,55	6,50	0,84
9326.0	0	2,00	0,89	6,17	0,41
9330.0	0	2,50	1,64	4,67	0,82
9700.0	0	4,17	1,60	5,17	0,41
9800.0	0	1,67	1,21	6,83	0,75
9810.0	0	2,83	1,72	5,83	2,48

2023 Emotional Assessment based on single-channel EEG and EDA signals Íris Lisboa

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