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Emotional Error Signals in the brain
A BCI approach

Dissertação no âmbito do Mestrado em Engenharia Biomédica, orientada pelo Professor Doutor Gabriel Pires, pela Doutora Teresa Sousa e pelo Professor Doutor Miguel de Sá e Sousa Castelo Branco e apresentada ao Departamento de Física da Universidade de Coimbra.

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"It does not matter how slowly you go as long as you do not stop."

Confucius

EMOTIONAL ERROR SIGNALS IN THE BRAIN: A BCI APPROACH

Dissertation submitted to obtain the degree of master's in biomedical engineering

SINAIS DE ERRO EMOCIONAIS NO CÉREBRO: UMA ABORDAGEM BCI

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RESUMO

A monitorização de erro é um processo automático e altamente importante no nosso quotidiano, especialmente em situações que envolvam informação afetiva. As expressões faciais constituem um dos mecanismos de comunicação mais poderosos, informando-nos das intenções e emoções de quem as transmite. Em perturbações como o espetro do autismo, pensa-se que os processos de reconhecimento de expressões, e, consequentemente de emoções estejam afetados, o que dificulta a adaptação destes indivíduos em contextos sociais. Apesar destes dois processos já terem sido estudados separadamente, pouco se sabe sobre como eles interagem entre si.

O principal objetivo deste trabalho foi o de avaliar a viabilidade de uma interface cérebro-computador (BCI do inglês *brain-computer interface*) que permitisse modular os sinais de monitorização de erro no reconhecimento de emoções. Pretendia-se que pudesse ser utilizado como abordagem de treino cognitivo com feedback neuronal – *neurofeedback* – e em perturbações como o espetro do autismo. Para tal, desenvolveu-se uma aplicação BCI baseada no efeito de *Stroop* emocional, em que os participantes têm de reconhecer expressões faciais com etiquetas congruentes ou incongruentes. De forma a validar esta tarefa, adquiriram-se sinais eletroencefalográficos (EEG) de 10 participantes saudáveis, que realizaram sessões de calibração seguidas de sessões de teste. Posteriormente, avaliaram-se as respostas eletrofisiológicas assim como os resultados de classificação automática. As características dos potenciais EEG observados são similares às de potenciais evocados em tarefas de monitorização de erro presentes na literatura. Foi a primeira vez que uma tarefa de Stroop facial emocional obteve resultados classificáveis com base no efeito de congruência. Os resultados de classificação atingiram uma média de 67,8 ± 9,6%. Fizeram-se análises com base em diferentes condições, como a experiência em utilização de BCI, género e nacionalidade e mostrou-se que os sinais eletrofisiológicos não são significativamente afetados por nenhum destes fatores, no entanto os resultados de classificação foram superiores para participantes com experiência em BCI. Apesar de não serem muito elevados, os resultados de classificação obtidos são bastante promissores, permitindo validar a tarefa e deixando em aberto a possibilidade de utilizar o paradigma aqui desenvolvido numa abordagem de treino social e cognitivo em populações como o espetro de autismo.

ABSTRACT

Error monitoring is an automatic and highly important process in our daily life, especially in situations where affective information is involved. Facial expressions constitute one of the most powerful mechanisms of communication, displaying to us the intentions and emotions of those who convey them. It is believed that facial expressions, and consequently emotion recognition processes are altered in Autism Spectrum Disorder (ASD) individuals, which makes their adaptation in social contexts harder. Even though these processes have been studied separately, little is known about how they interact with each other**.**

The main goal of the present work was to evaluate the viability of a BCI that could modulate error monitoring signals in emotion recognition. The intention was that it could be used as a cognitive training approach with neurofeedback and in perturbations like ASD. For that purpose, we developed a BCI application based on the Emotional Stroop Effect, in which participants must recognize facial expressions with congruent or incongruent labels. To validate the task, we acquired electroencephalographic (EEG) signals from 10 healthy participants, who performed calibration sessions followed by test sessions. Subsequently, we evaluated the electrophysiological responses as well as the automatic classification results. The characteristics of the observed EEG potentials are similar to potentials evoked in other error monitoring tasks found in the literature. The classification results achieved an average result of 67.8 ± 9.6%. The waveforms were shown to be unaffected by conditions such as BCI experience, gender, and nationality, however, classification results were higher in participants with BCI experience. Although the classification results achieved are not very high, they are still quite promising, allowing the validation of the task and leaving open the possibility of using the paradigm as an approach to social and cognitive training in the population with ASD.

Keywords: BCI, Error Potentials, Emotional Stroop Effect, EEG.

List of Acronyms

ACC: Anterior Cingulate Cortex

ADHD: Attention Deficit Hyperactivity Disorder

ALS: Amyotrophic lateral sclerosis

ASD: Autism Spectrum Disorders

BCI: Brain-Computer Interface

CAR: Common Average Reference

CLIS: Completely locked-In State

CNS: Central Nervous System

EEG: Electroencephalography

ERN: Error-Related Negativity

ERP: Event-Related Potential

ErrP: Error-Related Potential

fMRI: functional Magnetic Resonance Imaging

OCD: obsessive-compulsive disorder

RL: Reinforcement Learning

$\boldsymbol{S_b}$: Spatial between class matrices

SNR: Signal to noise ratio

SP: Sustained Potential

SVM: Support Vector Machines

SVP: Serial Visual Presentation

$\boldsymbol{S_w}$: Spatial within class matrix

Pe: Error-related Positivity

PET: Positron Emission Tomography

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1. Introduction

In this chapter the motivation, hypothesis, main objectives and scientifical contributions of this work are made clear.

1.1 Motivation

Errors are part of human nature. We make them, most of the time without realizing so, and hope they can teach us how to better evaluate future situations. In decisions that might involve affective information, error monitoring – the process responsible for error awareness – is particularly critical. For example, the wrong identification of the expression of the person we are talking to might be detrimental to the outcome of the conversation. Therefore, being able to detect errors committed by ourselves or others and react accordingly is of utmost importance for social cognition.

The generation of facial expression is one of the most powerful means of communicating intentions and emotions, and it is intrinsically related, through action perception cycles, to emotion recognition – the process by which we can add meaning to facial expressions. It is an ability acquired early in age, with 6-months children already being capable of discerning between happy and sad emotional states (Walker-Andrews, 1998), which plays a key role when adapting to our surroundings. Such processes of decoding and understanding other people's emotions are thus key to creating and developing social connections.

Social interaction deficits are one of the hallmarks in autism spectrum disorders (ASD), along with difficulties in verbal and non-verbal communication (American Psychiatric Association, 2013). It is believed that altered emotion recognition processes are one of the reasons for such difficulties (García-Villamisar et al., 2010). Numerous studies aiming to understand the neurophysiological mechanisms behind emotion recognition have been conducted, pointing to the extended face processing system, which includes the amygdala, inferior frontal gyrus (IFG), precuneus, and superior temporal sulcus (STS) (Carr et al., 2003; van de Riet et al., 2009) as the core areas involved. However, the way these processes are integrated with error monitoring remains unclear (Hajcak et al., 2008). A potential approach to study the relationship between these two concepts/processes is the use of an emotional Stroop task to map the neural mechanisms underlying such integration through electroencephalography (EEG). The Stroop Effect, originated from the Stroop Task, is described as the increase in reaction time or error generation between congruent and incongruent stimuli. In the original form, which involves words and colors, congruent stimuli reflect words written in the correct color (e.g: 'green' in green), while incongruent stimuli reflect words written in an incompatible color (e.g: 'green' in blue)(Scarpina & Tagini, 2017).

A brain-computer interface (BCI) is a system that translates the user's brain signals, evoked by an internal or external factor, into action commands for a device or an interface (Schalk et al., 2008). Considered one of the most emerging technologies of the last decades, BCIs rely on machine learning algorithms and pattern recognition to achieve their goal (further information on this topic can be found in section 2.4). Initially developed to replace lost communication or motor abilities, BCI systems have expanded to passive BCIs (e.g., mental state monitorization) and advanced neurorehabilitation approaches (BCI-based brain training approaches usually known as neurofeedback).

The emotional Stroop effect has been used to study how the brain manages and reacts to emotional conflict, and many neuroimaging like functional magnetic resonance imaging (fMRI) (Feng et al., 2018) and EEG (Song et al., 2017) studies have been performed. However, to the best of our knowledge, there has not been an attempt to incorporate the responses evoked by this task in a BCI-based brain training approach. The positive response to previous EEG-based neurofeedback strategies for the autistic population (Friedrich et al., 2014) leads us to believe that the BCI approach developed here can be a great way of training the social and cognitive competences of these individuals.

1.2 Objectives

The principal goals of this work were:

- Design and validate a Facial *Emotional Stroop Task* that can be used to investigate cognitive processes related to facial emotion recognition and error detection.
- Analyze brain responses that occur in the light of the presence incongruence and compare them to error potentials.
- Characterize the neuronal responses evoked by the *Emotional Stroop task* and test if they are 'classifiable' enough to be used as targets in BCI.
- Design a neurofeedback-BCI system that could be used for cognitive training.

This masters' project was part of the interdisciplinary projects B-RELIABLE and BCI-CONNECT, which aimed at designing more natural forms of human-machine interaction and paradigms for neurofeedback intervention, by using automatic detection of error.

1.3 Developments and contributions

This work comprehended the following developments:

1 Design of a Facial Emotional Stroop Effect Paradigm (EFP) based on cue images (faces) expressing emotional expressions and stimuli (labels) congruent/incongruent with cue images.
2 Realtime implementation of the EFP in a Highspeed Simulink framework, based on previous implementations in (G. Pires et al., 2022) and (G. Pires, 2012), and respective methodological and technical validation.
3 Offline classification of recorded EEG data at a single trial level.
4 Integration of neurofeedback to the EFP, by adding online detection of error signals.
5 Neurophysiological analysis of error signals.
6 BCI validation of the overall system through systematic tests on healthy individuals.

On the scientific level, we have created a Facial Emotional Stroop task which allows for the study of error monitoring processes involved in the recognition of facial expressions. This task was inspired by the Facial Emotional Stroop tasks performed by authors such as Chen et al., 2016; Schreiter et al., 2018a; Shen et al., 2013), but modified to best serve our purpose. The study of

Error monitoring processes is of great importance in social cognition, consequently, this approach can be an interesting one. In addition, we have developed a novel BCI approach which uses a Facial Emotional Stroop paradigm to activate error monitoring mechanisms and that provides neurofeedback based on the users interaction.

At the technical level, we were able to produce a BCI approach based on error monitoring, perform the optimization of BCI systems applied to neurofeedback and provide a novel application of error potentials in BCI.

1.4 Dissertation organization

This dissertation is organized in seven chapters. Following this chapter, where an introduction of the work developed is made, we have chapter 2 which comprehends the theoretical concepts needed to understand the present work. The third chapter presents the state of the art of Emotional Stroop Studies and Electroencephalogram-Error related Potential based Brain Computer Interfaces. The fourth chapter describes the experimental task used to acquire the EEG data, the methods used to process and analyze the data as well as the techniques used to assess the viability of the BCI approach. Chapter five presents the results obtained. Chapter six comprehends the discussion and chapter seven the conclusions from the developed work.

2. Theoretical Background

This chapter describes the theoretical concepts needed to comprehend the work developed in this project.

2.1 Electroencephalography (EEG)

EEG is a widely used functional neuroimaging modality that measures the electrical activity of neurons through electrodes placed on the scalp. It can monitor the state of the brain in a continuous and non-harmful manner, and it allows for the realization of long-duration experiments. Although EEG has poor spatial resolution (up to 10 cm), it has a good temporal resolution in the order of the millisecond, and it is a portable and easy to set up equipment.

In the medical field, one of its most known applications has been in the identification and prediction of epileptic seizures (Slimen et al., 2020), but is also used in the diagnostic of several other pathologies such as the sleep-related ones. It has been also widely used in the neuroscience field to study the dynamics of various brain processes such as the ones underlying attention, learning, and memory (Gerě & Jaušcvec, 1999). The oscillatory activity measured by EEG comes from postsynaptic potentials generated by a group of neurons and reflects the summed activity of neurons oriented perpendicular to the surface of the scalp, aligned in such a way as to produce a dipole field (Coles & Rugg, 1996).

We can analyze EEG signals in two main domains: time and frequency. In the time domain, the signal is analyzed by considering amplitude and latency, usually locked to specific events in time. In the frequency domain, brain signals are known to be organized into several frequency bands. From the lower to the higher end of the spectrum we have delta (1-3Hz), theta (4-7Hz), alpha (8-13), beta (13-30,) and gamma (30-100Hz) (Schomer & Lopes da Silva, 2017). Each of these spectra is usually related to distinct mental states. For example, bands with a higher frequency are commonly related to activities that demand more focus and alert stage of consciousness while lower frequency waves such as delta are associated with sleep and relaxation (Doma & Pirouz, 2020; Marzbani et al., 2016; Nazari et al., 2012).

The EEG data is obtained by electrodes placed on the scalp according to a well-defined organization (Schomer & Lopes da Silva, 2017), with current EEG systems functioning with as few as 4 electrodes and up to 256, as detailed in the next subsection. EEG amplitude from the electrodes is measured in relation to a reference electrode, usually placed on the subject’s earlobe. Besides the reference electrode, there is also a ground electrode that is used for common mode rejection.

2.1.1 EEG Electrodes Positioning

There are diverse ways that electrodes can be distributed through the scalp, and the decision on which method to use depends on the requirements of the experiment being performed. In every system, each electrode is given a name and a position, forming a letter/site pair. The letter refers to the region of the lobe below the electrode. Fp, C, O, T and F, correspond to Pre-frontal, Central, Occipital, Temporal, and Frontal locations. While the “site” refers to which hemisphere the electrode is on. Sites are represented by the letter “Z,” even, or an odd number. “Z” sites correspond to electrodes placed in the middle of the skull, right above the corpus callosum, and do not represent any of the hemispheres, whilst even and odd numbers correspond to electrodes placed on the right and left side of the head, respectively.

In the 10-20 international system, the distance between electrodes is either 10 or 20% of the total distance (front back or right-left) of the skull. This electrode organization system was initially developed to use up to 21 electrodes, however, the need for an increasing number of electrodes led to the development of new systems. The 10-10 (Schomer & Lopes da Silva, 2017) system is an adaptation of the original 10-20 and adds electrodes to the already existing electrode positions. In recent years, a new system, which can use up to 345 locations, has been proposed. It is called the 10-5 International System.

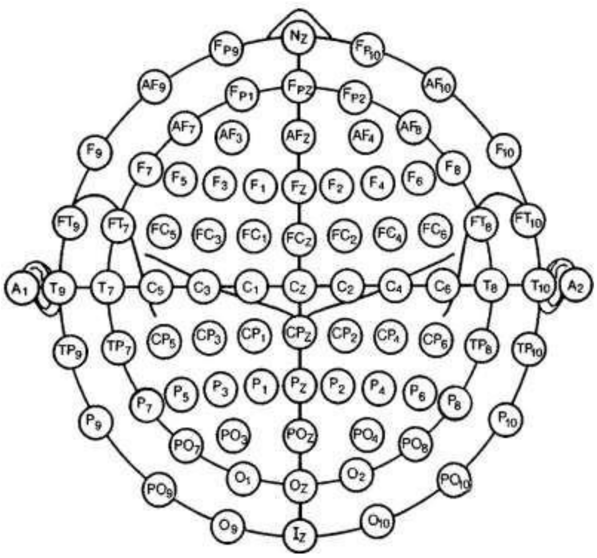


Figure 2.1: A Representation of a 10-10 electrode system extended with anterior and posterior electrodes in the inferior chain respectively (Figure from (Seeck et al., 2017)).

2.2 Event-Related Potentials (ERPs)

The EEG response that occurs in the presence of an event or stimulus in the time domain is called and Event Related Potential (ERP). It contains the overall voltage changes throughout time, from the moment the stimulus appears. There are several well-studied ERP components varying in magnitude and topographical distribution (Vallabhaneni et al., n.d.). They are represented by a letter P (positive) or N (negative), according to the voltage difference in relation to reference, and a number, indicating the order of the peak as a function of the temporal distance from the stimulus onset (increasing numbers represent a bigger distance).

Several ERP components have been described in the literature, and most of them are evident in specific EEG locations, during certain periods, and in the context of well-established paradigms such as oddball, Flanker task (L. Pires et al., 2014) Go/No go task (Kiefer et al., 1998), and Stroop Effect (Sahinoglu & Dogan, 2016).

In Bradley & Keil, 2012, a brief explanation about the origin of ERPs and their different components is made. For illustrational purposes, we decided to use Figure 2.2, adapted from Bradley & Keil, 2012, to showcase some ERP components. The ERP presented in Bradley & Keil, 2012 has no direct correlation with any task.

Following a temporal sequence, first, we have P1, a positive waveform appearing after 80-120 ms post-stimulus in occipital sites and one of the earliest components regarding basic visual processing. Next, we have P3, which is one of the most well-known ERP components. It commonly occurs in the context of an oddball paradigm and is seen as a positive wave occurring 300 ms after the event onset. One common P3 application is the BCI Speller, in which the P3 signal is used to communicate with a spelling interface (Cuntai Guan et al., 2004). After, we have the N1, a large negative deflection usually associated with any unpredictable auditory stimulus in the absence of task demands (Rollnik, 2019). It is thought to measure early perceptual processing and is commonly examined in relation to schizophrenia. The LPP is a positive going-component beginning at around 500 ms after the onset of a stimulus and usually provides a measure of emotional processing (Hajcak et al., 2011).

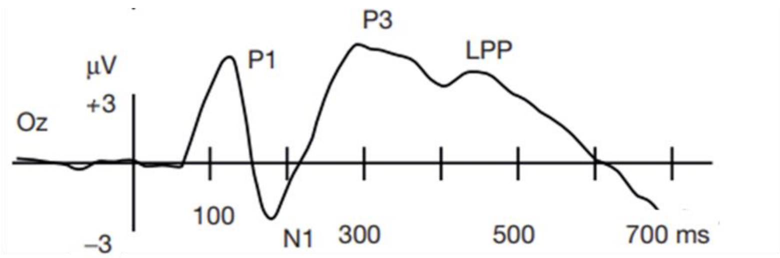


Figure 2.2:Representation of several ERP components (P1, N1, P300 and LPP). The component is presented by the pair letter/number (Figure adapted from **Bradley & Keil, 2012**).

For many years, ERPs resultant from error trials in experiments were discarded, as they did not provide any useful information about the task being analyzed. However, when scientists compared the responses given in correct trials with the ones where subjects committed a mistake, they noticed a negative-going deflection at frontal and central electrodes site. These would be coined as Error Related Potentials (Falkenstein et al., 1991).

2.2.2 Error-Related Potentials (ErrPs)

Error Related Potentials were found in the 90's in the context of cognitive psychology, where subjects committed errors when performing a response task (Falkenstein et al., 1991). They are characterized by a negative deflection, Error related Negativity (ERN) or Ne, occurring between

50-100 ms after the perception of an erroneous response and, in most cases, a subsequent centroparietal positive deflection (Pe), which usually appears between 200-500 ms.

These two components are thought to represent different components of the error monitoring system. It has been proposed that the Ne is associated with unconscious reflection and error processing (Krigolson et al., 2008), while the Pe most likely reflects conscious error perception since it is increased in cases where the subject is aware of the error made (Nieuwenhuis et al., 2001). Depending on the task the subject is performing, different types of ErrPs can be elicited, namely:

- **Response ErrP:** Happens when the subject is forced to respond as quickly as possible and commits an error in that process. It's mostly studied in reaction time tasks where the subjects must press a button (Falkenstein et al., 1991). In this type of task, the *Ne* occurs at 80 ms and the *Pe* between 200-500 ms after the press of the button.
- **Feedback ErrP**: Occurs when the subject is aware that there is an error based on the feedback provided by the task. The *Ne* appears around 250 ms after feedback during a task (Holroyd & Coles, 2002).
- **Observation ErrP:** Is elicited when the subject recognizes an error performed by a machine or an external device by which he has no control and exhibits a medial frontal negative peak around 260 ms. (Chavarriaga & Millan, 2010).
- **Interaction ErrP**: Proposed by Ferrez & del R. Millan, 2008 the interaction ErrP occurs when the subject is interacting with a machine that does not respond expectedly. Its waveform has differences from the above ErrPs, having a small positive peak around 200 ms, a negative peak at 250 ms, another positive peak at about 320 ms, and lastly another negative peak at 450 ms. These latencies and peaks can all exist or not, depending on the paradigm being used to elicit the ErrP (Iturrate et al., 2013).

ErrPs have gathered considerable interest in the last few decades for their use in BCI and neurofeedback applications.

2.3 Brain-Computer Interfaces

"*A BCI system is a system that measures Central Nervous System (CNS) activity and converts into an artificial output that replaces, restores, enhances, and supplements the natural CNS output*" (Wolpaw, 2013). The BCI realizes the user's intent by decoding the brain signals and converting them into command to control a machine or an interface.

In situations where people lose their motor communication abilities, a BCI can help these people recover their functions. In patients with amyotrophic lateral sclerosis, the use of invasive and non-invasive BCIs has allowed patients to control robotic hands, wheelchairs, and spelling systems (Kübler & Neumann, 2005; Sellers et al., 2010). More recently, the use of a BCI has enabled a patient in Completely Locked-In State (CLIS) to communicate (Chaudhary et al., 2022). BCI systems have started being used on patients with mental conditions, such as attention deficit hyperactivity disorder (ADHD) and ASD, as a way of assessing and training cognitive impairments. In ADHD, BCIs have been shown to increase the attention span of the population, by recurring to strategies like training games (Lim et al., 2012), while in ASD attempts at improving joint attention of these individuals have been (Amaral et al., 2018). Given their portability and temporal resolution, most BCI approaches obtain their information through EEG.

2.3.1 BCI Components

A BCI system is usually comprised of the following components: signal acquisition, pre-processing or signal enhancement, feature extraction, classification, and interface control.

- **Signal Acquisition:** In this phase, the activity of the user is captured through several sensors (for example, EEG electrodes).
- **Pre-Processing:** The Pre-Processing stage aims to erase unwanted signals or artifacts from the raw EEG data. The most common pre-processing techniques include high-, low- and band-pass filters and other techniques such as Common Average Reference (CAR) (Ilyas et al., 2015) or EOG Correction (Croft et al., 2005), which are commonly used when there is an overlapping of signals (Sweeney et al., 2012).
- **Feature Extraction:** This stage aims at finding relevant discriminative information (features) from the recorded brain signals. It usually assumes a transformation of the signal.Time, Frequency, and Spatial domain are popular techniques for feature extraction (Nicolas-Alonso & Gomez-Gil, 2012). Not all information is usually relevant to the problem being solved, so there are different methods that intend to reduce the dimensionality of data to improve classification. The rule of thumb in machine learning should be followed which says that the amount of training data should be much larger than the number of features being used for classification. Feature selection, as explained below, is also a form of reducing the dimension of feature vectors.
- **Feature Selection:** Comprehends methods that automatically select the best N features (N is usually decided by the BCI designer by trial-and-error or tuned automatically checking the classification accuracy). There are two main categories of methods (Lotte, 2014):

1. *Univariate* Methods: Evaluate the discriminatory power of each feature and select the best N features. *R*-square and t-student tests are included in this category. Although these methods require low computational power and are extremely fast, they are sub-optimal.
2. *Multivariate* Methods: Evaluate a subset of features and then pick the subset that possesses the best N features. These techniques consider complementarity between features and redundancy impact, but they are computationally heavier.

- **Classification:** This step intends to assign the data into a class. Classification algorithms can be used in offline or online contexts. Even though offline classification can be especially useful for testing methods, the BCI goal is to use a classifier that works in real time. The classifier is usually evaluated on its accuracy, although other methods are used (greater accuracy means that the classifier will predict the user's intent with higher confidence). Numerous classifiers have been proposed in the literature, such as support vector machines (SVM), Neural Networks, Linear Discriminant analysis (LDA), Bayesian Classifiers, and Deep Learning methods like Convolutional Neural Networks (CNN). Usually, to obtain a good BCI performance, a calibration process must be done before the online operation to fit the classification model to the current session and participant. This is due to a big EEG variability between subjects and between sessions.

Figure 2.3: Schematic representation of a BCI pipeline

2.3.2 ErrPs in BCI Applications

The perception of an erroneous action by the user can elicit an ErrP. If the BCI system can decode this ErrP, it can use it to alter the BCI detection and replace it with another likely user intention. This approach was shown effective by Cruz et al., 2018 and Artusi et al., 2011. In other situations, the ErrP can be used to update the system, so it becomes more accurate at detecting future errors, for example adapting the classification models. These strategies may follow approaches based on reinforcement learning (Luo et al., 2018).

Still, the use of the ErrP has limitations. Their low signal-to-noise ratio (SNR), decay in the classification throughout sessions, and difficulty in generalization of classification across subjects call for recalibration sessions every time the user utilizes the BCI, limiting the BCI usability (Kübler & Neumann, 2005). Even though there are findings that classification remains stable in recordings separated by weeks or even months (Chavarriaga & Millan, 2010), in most cases classification rates tend to decrease throughout time (Iwane et al., 2016). To counterbalance these issues, several approaches that intend on increasing the generalization of the use of these potentials, such as transfer learning techniques, (Cruz et al., 2022) have been proposed.

ErrPs have been observed in younger (Torpey et al., 2009) and older subjects (Reuter et al., 2018) and have also been shown to be modeled by the patient's fatigue (Boksem et al., 2006), motivation (Pailing & Segalowitz, 2004) and anxiety (Takács et al., 2015). Due to the effect these characteristics have on the ErrP, they have been used to study several mental disorders such as ADHD, obsessive-compulsive disorder (OCD) (Gehring et al., 2000), Depression (Chiu & Deldin, 2007), and other anxiety traits (Carrasco et al., 2013).

2.4 Emotional Stroop Effect

When assessing what things are important during a given activity or task in our everyday life, we need to account for and repress errors that might occur due to the ambivalence of our surroundings. An accurate representation of the above description is the Stroop Task. First developed by John Stroop (Stroop, 1935), the task consisted of participants naming the colors of words written on a table (Figure 2.4).

Figure 2.4: Schematic Representation of the original Stroop Task. Words that match their color are congruent stimulus whereas words who don't have their matching color are an incongruent stimulus.

In words where the color would enter in conflict with the word itself, there was a delay and sometimes a mistake in saying the correct color, which might indicate allocation of attention to the irrelevant attribute of the stimuli. This is because reading is a highly automatic process (Ivnik et al., 1996) making it hard to inhibit. The delay and mistake that occurred in the light of the incongruence between the color and word was therefore coined the Stroop Effect. The Stroop task assesses the ability to inhibit cognitive interference, which occurs when the processing of one of the stimulus attributes impedes the simultaneous processing of a second stimulus attribute

(Scarpina & Tagini, 2017) and forces the human brain to develop coordination and decision-making strategies to perform successfully. Besides measuring the capacity to inhibit cognitive interference, it allows to study processes like attention, processing capacity, cognitive flexibility, and working memory.

The Emotional Stroop Task, a variance of the original Stroop Task, started being employed in the late 1980's. Emotional Stroop Tasks have been used to investigate the effect of the emotional content when participants must answer to the non-emotional content of the task. The first and most common variation uses emotional and neutral words. Emotional words are usually related to specific emotional states or disorders. For example, for a participant with arachnophobia, emotional words could be spider, web, and tarantula.

Emotional Stroop Effect (ESE) tasks have been employed in a series of mental conditions, including Post-Traumatic Stress Disorder (PTSD), Body Dysmorphic Disorder, Schizophrenia, ASD, Depression, and other anxiety disorders (see section 3.1).

Particularly in the case of Autism, the Stroop Effect has been used to understand if these individuals possess intact inhibitory capacities. In opposition to neurotypical individuals, Autistic individuals show dysfunctions in several elements of the executive function (Hill et al., 2004). Even though much research has been conducted in this field, there is still some uncertainty as to whether these individuals possess inhibition deficits. Since the beginning of its use, the Emotional Stroop Effect has undergone different variations, and studies with emotional words, auditory stimuli (Wurm et al., 2004), pictures, and facial expressions (Ovaysikia et al., 2011) have been employed (see section 3.1 for more details on the conducted studies).

2.4.1 ERPs in Stroop Effect

In its earliest days, the Stroop Effect was only measured in terms of reaction time (RT). In Stroop Tasks, incongruent trials show longer RT in comparison to the congruent trials, due to the interference caused by the incongruence. However, RT is only a performance measure, not providing information about the underlying neural processes. More recently, neuroimaging studies started to provide a deeper understanding of what brain processes underlie this effect (MacDonald et al., 2000).

The original Stroop task requires participants to say aloud the colors of words printed on a table (Stroop, 1935). However, because facial movements can produce artifacts in EEG recordings, most EEG Stroop Tasks require participants to press a button corresponding to the color of the word presented on a screen. As previously explained, the two attributes of the stimuli (color and meaning of the word) can be congruent or not. The neuronal responses are recorded from the moment the stimulus appears.

Different ERP components can be elicited by Stroop tasks, and their appearance and modulation can vary from task to task. Here we will present the components more frequently identified throughout the studies.

First we have the N2 (Figure 2.5), described as a negativity component appearing 180-280 ms after stimulus appearance. There are various theories surrounding the mechanisms behind the modulation of this component. Some argue that the N2 is modulated by top-down attention; others speculate that is regulated by the emotional content in Emotional Stroop Tasks (that emotional content might elicit a stronger response); while others refer to it as a conflict monitoring component and even claim that it can be the same as the Ne/ERN component elicited in error monitoring, due to their similar distribution (Folstein & van Petten, 2007). This component is often elicited in Eriksen Flanker Tasks (Gehring et al., 2000; KOPP et al., 1996).

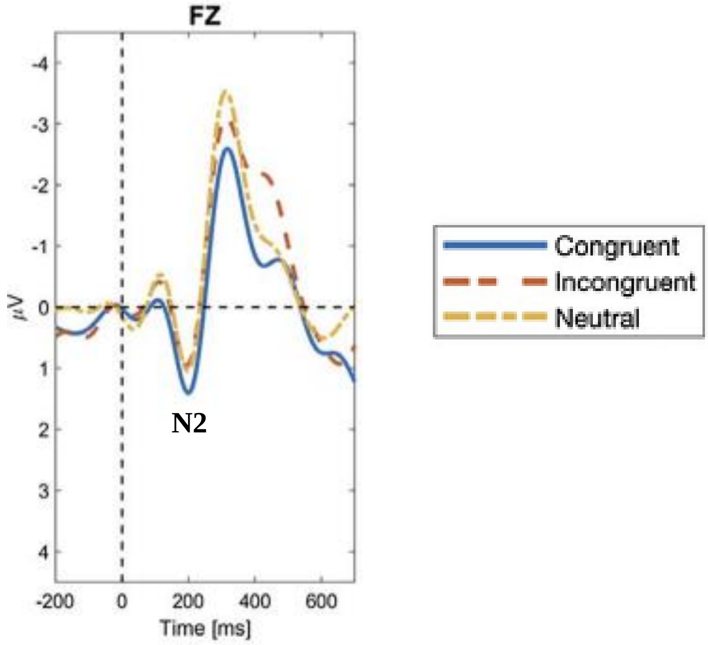


Figure 2.5: N2 (shown in bold) modulated by the congruency of a numerical Stroop Task at channel Fz. Adapted from Huang et al., 2021.

Secondly, we have the N450, which is described as a negativity around 450 ms and is shown to be more negative on incongruent trials in comparison to congruent and neutral trials as has been described in most Stroop Tasks (Liotti et al., 2000; Markela-Lerenc et al., 2004; McNeely et al., 2003; West, 2004; West & Alain, 2000). This component is thought to represent an index of conflict elicited by this task, which represents the activity of neural generators located in the ACC. (Figure 2.6)

Besides the N450, researchers have found another component, the sustained potential (SP). This component is also often called the conflict slow potential (CSP). The SP is a sustained centro-parietal positivity that follows the N450, starting at around 500 ms (Larson et al., 2009; West & Alain, 1999, 2000) or later, peaking between 600-800 ms after the stimulus onset, and is increased in incongruent trials. The increased positivity in incongruent trials is thought to reflect the increased recruitment of cognitive control resources needed to resolve conflict and subsequent compensatory adjustments for accurate task completion. This component is not found in all studies (Qiu et al., 2006). (Figure 2.6)

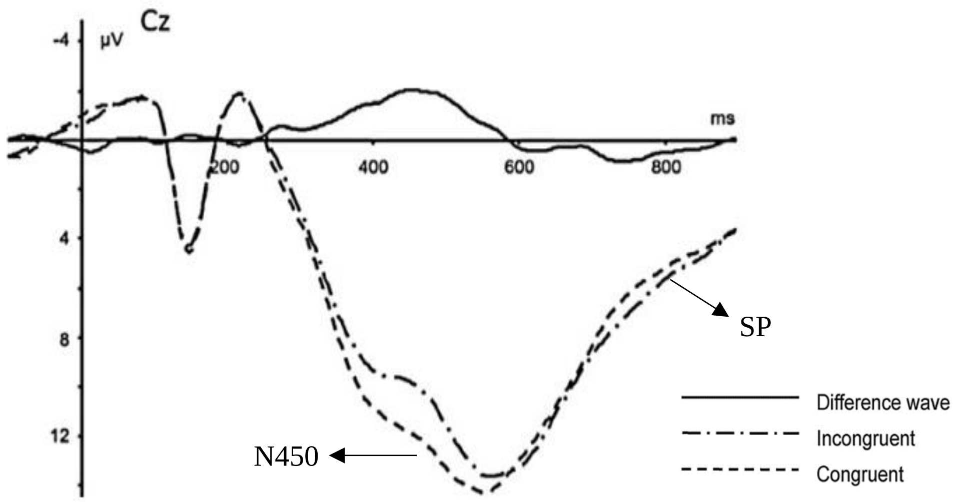


Figure 2.6: Example of the neural time course of a Facial Word Stroop Effect Paradigm. In this task only the N450 and SP (identified by the arrows) were shown to be modulated by congruency. Adapted from Shen et al., 2013.

2.4.2 Emotional Stroop Signals as Error Potential

Considerable experimental evidence suggests the ACC is the neural locus for detecting conflict, both at level of stimulus processing and at the level of response (Etkin et al., 2011). This is compatible with results of the Stroop task, in which incongruent trials show stronger activation in the ACC when compared to congruent trials (Bush et al., 1998; MacLeod & MacDonald, 2000; Pardo et al., 1990). However, the ACC has also been implicated in detecting the occurrence of errors. Studies using ERPs have established that the ERN is originated at this region (Orr & Hester, 2012). The apparently different conflict detecting, and error-detecting activities of the ACC can be reconciled if we consider the following example: labelling a happy face as a sad face will be considered an incorrect association between the expression “happy” and its label. The conflict monitoring loop in the brain will therefore produce an ErrP when it tries to do the association between the face and its label (Parashiva & Vinod, 2022).

3. STATE OF THE ART

3.1 Event Related Potentials in Stroop Tasks

3.1.1 EEG Facial Emotional Stroop Studies

In recent years, Facial Emotional Stroop Tasks have been employed to try and understand the impact of emotional conflict. In EEG Facial Emotional Stroop Tasks, faces with superimposed words (congruent or incongruent with the facial expression) are presented and participants are asked to indicate the facial emotion of the picture presented as fast and precisely as possible, by pressing a button that is correspondent to that facial expression, while ignoring the superimposed label. The Stroop Effect comes from the difficulty in indicating the facial expression (attribute 'one' of the stimulus) while ignoring the superimposed label ('second' attribute of the stimulus).

This kind of task was researched by Shen et al., 2013. The authors conducted an EEG study to find the electrophysiological correlates of emotional conflict control by performing a Facial Emotional Stroop task. In this study, red labels (Chinese characters), were superimposed across the happy and fearful facial expressions. The labels could be congruent or incongruent with the facial expression. The study revealed a negative ERP component between 300-550 ms (N450), which was more negative in incongruent trials than in congruent trials, and a positive deflection in the 700–800 ms time window (P700–800) over the posterior parietal scalp. (Figure 3.2)

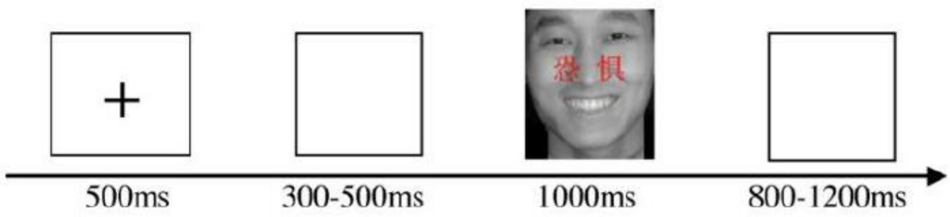


Figure 3.1 : Schematic Representation of the Task used by Shen et al., 2013. First, the participant has 500 ms of staring into a cross. After, a blank screen appeared for a variable time of 300-500 ms. Next, the stimulus (face with congruent/incongruent label on top) appeared for 1000 ms, and participants had 1500 ms to answer. The last blank screen was used as a break between trials.

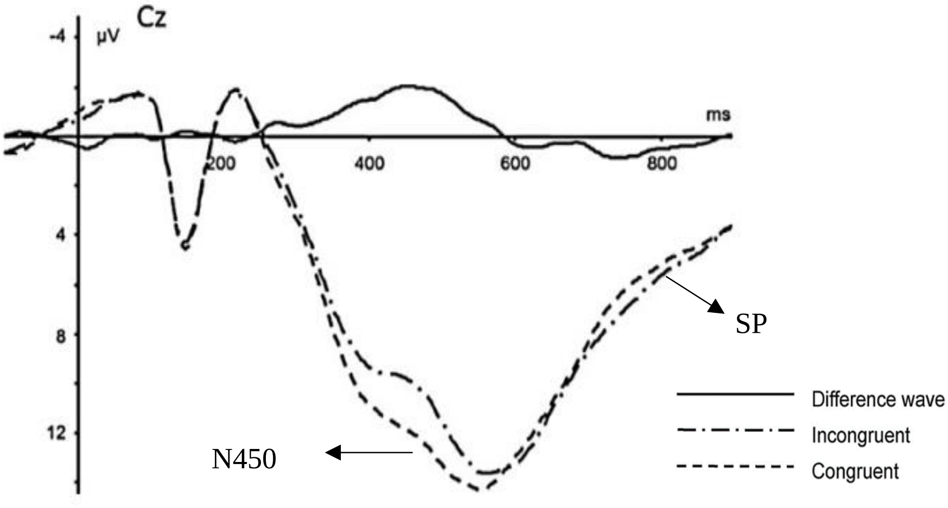


Figure 3.2: Grand Average ERPs for the difference wave, congruent and incongruent trials of the Facial Emotional Word Stroop Task performed by Shen et al., 2013. N450 and SP are identified by the arrows.

Equivalent results were obtained by Fan et al., 2016 and Xue et al., 2016. Xue et al., 2016 utilized the same type of task as Shen et al., 2013. Besides evaluating the responses between congruent and incongruent trials, it also analyzed how previous trial congruency affected the ERP, for example, if having an incongruent trial followed by a congruent trial or vice versa had any impact on the neurophysiological responses. The results showed that N450 is affected by previous trial congruency, with the amplitude of the N450 more attenuated in the incongruent-incongruent trials than in the congruent-incongruent trials.

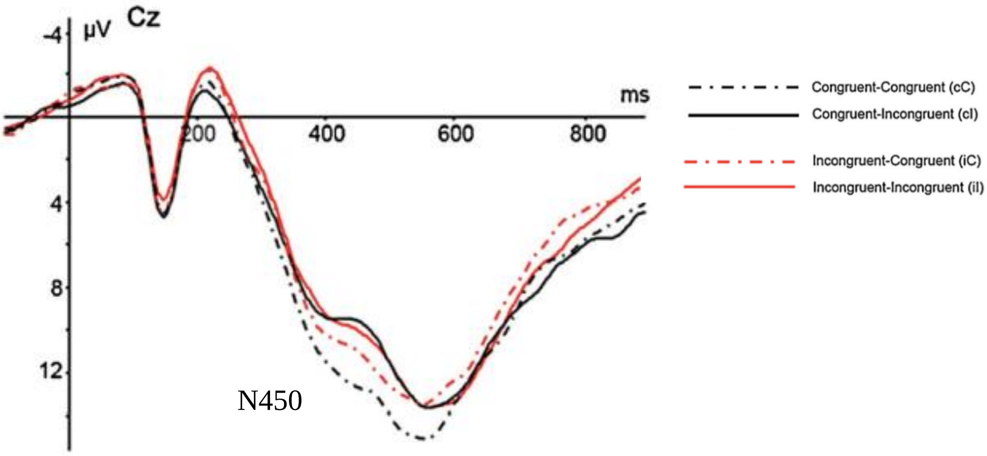


Figure 3.3: Grand average ERPs for channel Cz representing the waveforms for the pairs congruent-congruent, Incongruent-Incongruent, Congruent -Incongruent, Incongruent-Congruent trials. Adapted from Xue et al., 2016.

Fan et al., 2016 utilized the same task and besides evaluating the neurophysiological responses in congruent and incongruent trials, also did a second version of the task where the words were presented in the participant's second language (English) (Figure 3.4).

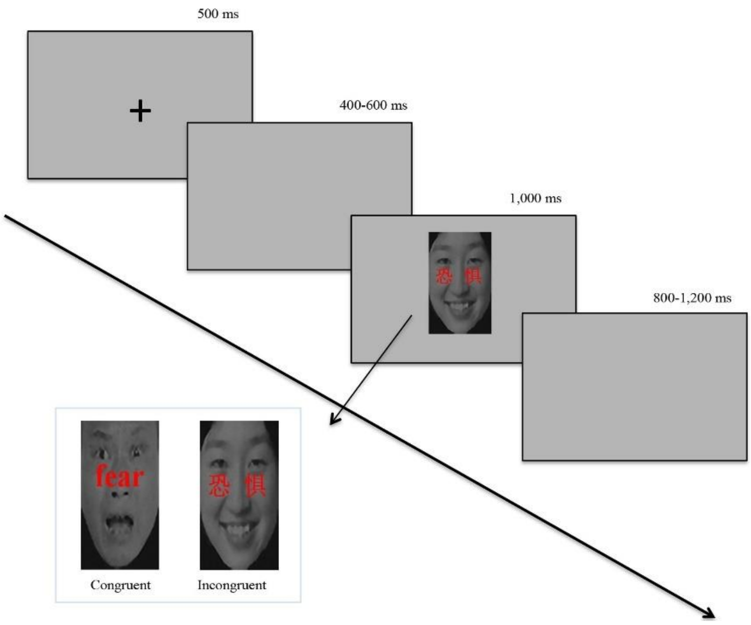


Figure 3.4: Schematic representation of the task performed in Fan et al., 2016. The pictures on the third screen reflect the type of task. The picture with words in chines reflects the task in native language while the pictures with words in English were utilized for the task with the nonnative language.

ERPs showed there was not a significant Stroop Effect when the labels were in the participant’s second language, leading to the conclusion that words in a second language are less automatic to emotional content (Figure 3.5).

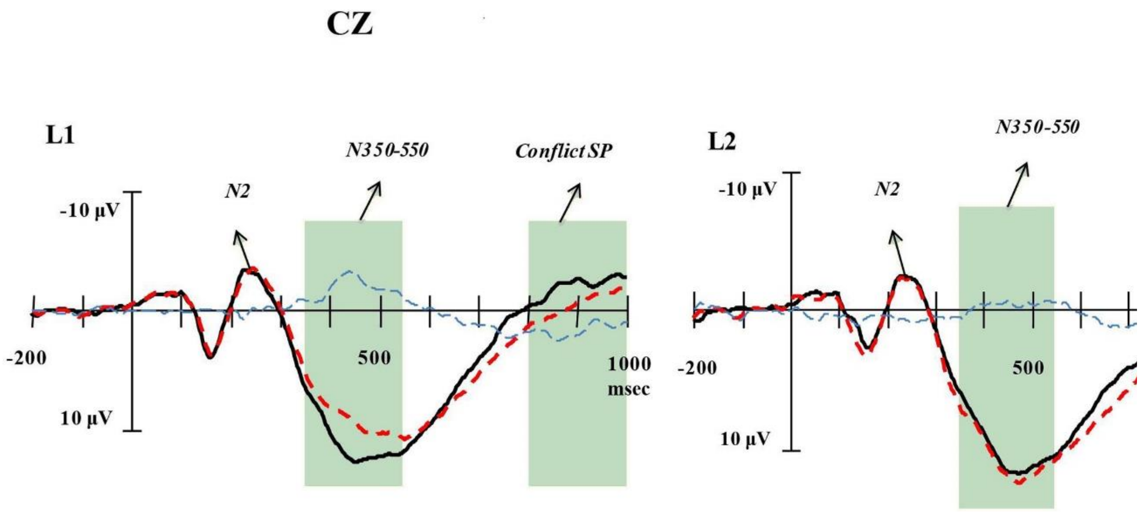


Figure 3.5: Grand Average ERPs for the Incongruent(red) and Congruent (black) trials and difference waveform (blue) at channel Cz, for native language (L1) and for the second language(L2). We can see there is no difference regarding the N450 in the participants second language between congruent and incongruent trials. (Fan et al., 2016)

A study performed in 2016 (Maier et al., 2016) interpreted the signal elicited in the incorrect responses of the Facial Emotional Stroop Task as an ErrP. They did so because conflict monitoring processes and emotional processes both have an origin in the anterior midcingulate cortex (aMCC). In this way, they consider that the aMCC integrates information about affect, pain, and the need for cognitive control to implement behavioral adjustments that intend to optimize performance. The Facial Emotional Stroop Task was like the ones described above, where participants had to press the button corresponding to the emotions presented. In this task, the superimposed words were presented in Italian, the participants native language. Besides the Facial Emotional Stroop task, participants were confronted with another variation of the task, where the labels superimposed on the pictures were related to the gender of the pictures, and they had to identify the gender of the face presented with superimposed (congruent/incongruent) gender labels.

They compared the Ne/ERN and Pe of correct (trials where the participant guessed the correct facial expression) and error (trials in which the participant incorrectly identified the facialexpression) trials, and separately, they evaluated N450 of Incongruent and Congruent trials, for individuals with high and low Alexithymia, a condition where individuals are not capable of feeling or detecting emotions. The results showed clear Ne/ERN, starting at 50 ms and lasting until 100 ms, maximal at channel FCz, with more negative peaks for error trials than for correct trials, with the biggest difference between error and correct trials appearing in channel FCz. They also found the Ne/ERN to be larger in the Facial Emotional Stroop task set (labeling emotions) than in the neutral task (labeling faces regarding their gender), which means that error monitoring activity was increased by presenting task-irrelevant (Congruent/Incongruent labels) affective (emotions) information. (Figure 3.6)

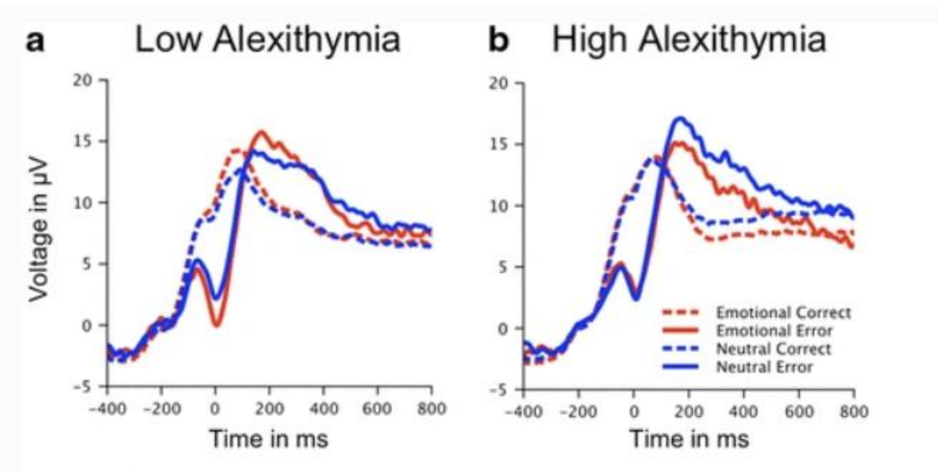


Figure 3.6 : Grand average of all Correct and Error trials, divided by the emotional neutral task set for participants at channel FCz with a) Low Alexithymia and b) High Alexithymia. (Maier et al., 2016)

Participants with high Alexithymia did not show significant differences between the Facial Emotional Stroop Task and neutral task. This indicates that individuals who show problems regarding emotion perception are less likely to show enhanced error monitoring activity in emotional contexts.

The Pe - defined as the 200-400 ms time window after the given answers - was more positive for errors than correct answers, and the difference was maximum for channel Pz. (Figure 3.7)

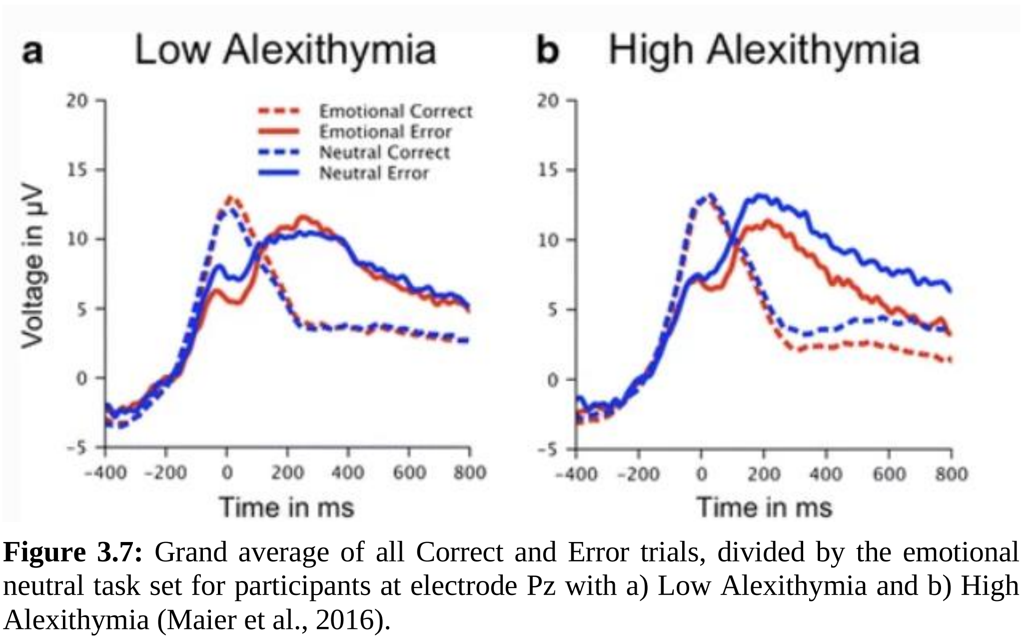


Figure 3.7: Grand average of all Correct and Error trials, divided by the emotional neutral task set for participants at electrode Pz with a) Low Alexithymia and b) High Alexithymia (Maier et al., 2016).

Regarding the N450 (Figure 3.8), waveforms were more positive for congruent than incongruent stimuli, and participants with High Alexithymia. The authors also concluded that congruency of the task did not modulate the N2 component.

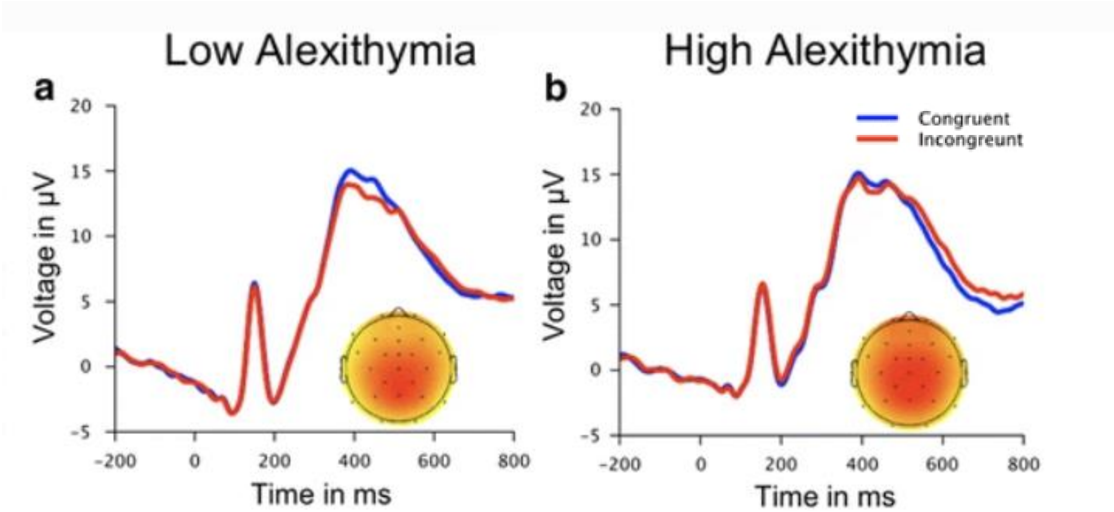


Figure 3.8 : Grand average of all Congruent and Incongruent trials at electrode Pz for participants with a) Low Alexithymia b) High Alexithymia (Maier et al., 2016).

Schreiter et al., 2018b employed a Facial Emotional Stroop Task much like the ones described above, however, this time the labels were in German. They used 3 facial expressions (happy, disgust, and anger) and evaluated the impacts of emotional conflict on these emotions.

They found that the N2, a conflict-related component that can be modulated in other Stroop and conflict tasks (section 3.2) was not modulated by congruency in this task (Figure 3.9), claiming that the task might be too complex to allow that. Results also showed modulation of CSP (conflict SP or just SP as it is usually referred to in other tasks) regarding emotion, with negative emotions showing stronger amplitude when compared to positive emotions, and stronger amplitudes for incongruent trials, but only for the faces displaying a happy

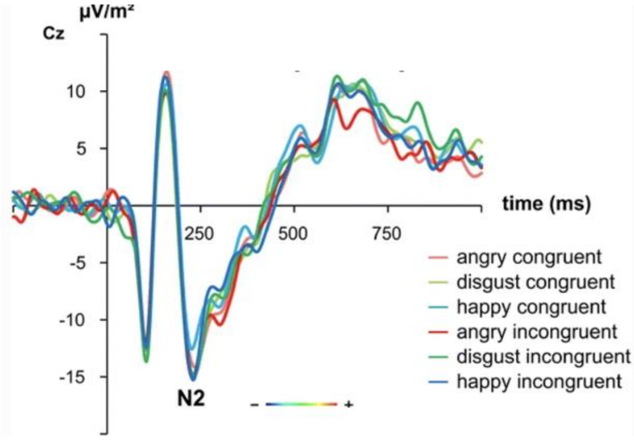


Figure 3.9 Grand average of Congruent and Incongruent trials of the Facial Emotional Stroop task divided by the three emotions displayed (happy, angry, and disgust), at channel Cz. N2 component is showed in bold (Schreiter et al., 2018b).

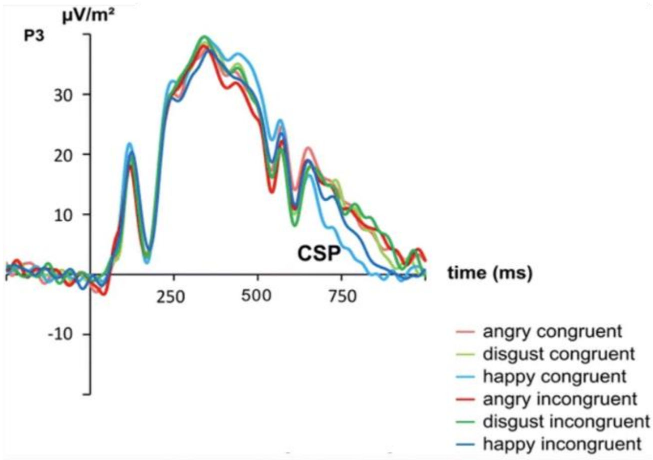


Figure 3.10: Grand average of Congruent and Incongruent trials of the Facial Emotional Stroop task divided by the three emotions displayed (happy, angry, disgust), at channel P3.CSP waves are shown in bold (Schreiter et al., 2018b).

One thing to be noted, for all the studies reviewed, is that both attributes of the stimuli (face and word) are presented at the exact same time to the participant.

3.1.2 Clinical Stroop Studies

The original Stroop Task has been performed on people with different clinical conditions and has allowed for interesting conclusions. Studies comparing young with older adults (Agustí et al., 2017) have shown a decrease in the interference effect of older adults, as well as a delayed response to the stimulus, which can be accounted for the diminishing capacity in monitoring interference as we age (Kray et al., 2005). A Stroop Task performed with schizophrenia patients (McNeely et al., 2003) showed a reduction in their Stroop effect, as their N450 was reduced when compared to controls and their SP was nonexistent. These findings agree with studies that reveal that patients with schizophrenia have functional disruption of the ACC and prefrontal cortex, areas associated with conflict processing (Cui et al., 2015).

3.2 Application of Error-related Potentials in BCI

Error Potentials have been applied in BCI throughout the last two decades in different fields. A review of the use of ErrPs in BCIs was made by Chavarriaga et al., 2014, so only some studies will be presented. As explained in section 2.3, a BCI can transform the user's intention into action commands, by decoding the user's brain signals. Different techniques can be used to measure brain activity, however, EEG is the most widely used technique. Still, EEG-based BCIs have limitations, due to their low SNR and fallibility in detecting the user's intent.

They can be used to automatically detect, and correct errors committed by the BCI. This is the case of Cruz et al., 2018; Iturrate et al., 2013; Salazar-Gomez et al., 2017; Yousefi et al., 2019, where the error potentials elicited by the tasks were used to correct the system, allowing it to perform the pre-established operation in case a correct response was given or revert the outcome if an ErrP was detected. Cruz et al., 2018 went as further as using a double ErrP to improve the performance of a BCI speller. In this approach, featuring 9 able-bodied subjects and a patient with Multiple Sclerosis (MS) with slight hand movements, the proposed letter would be shown to the user, who would provide error or correct feedback. If a correct potential was detected, the verification process would stop. Otherwise, the second most likely character would be delivered to the subject. If this decision elicited positive feedback, the second letter would be chosen, however, if the second letter elicited another error potential, then the previous letter would be chosen. The results showed a 5% increase in classification rates.

ErrPs can also be used to help the system learn and adapt until it reaches optimal behavior using Reinforcement Learning (RL) algorithms. Such approaches have been described by Artusi et al., 2011; Iturrate et al., 2015; Kim et al., 2017. In Iturrate et al., 2015, 12 subjects monitored the actions of 3 different external agents (1D cursor, stimulated robot, real robot arm) while these tried to reach a target defined by the user. If an ErrP was evoked, (the robot performed an action the user considers wrong to obtain his goal) then the signal was delivered to a RL algorithm that improved the behavior of the neuroprosthesis. After a short training period, all subjects were able to operate the neuroprosthesis and reach the desired target. Online error detection reached an accuracy of 70%.

3.2.2 Signal processing and classification

The first step of a BCI system involves acquiring the EEG signal. Even though there is no guide for how many electrodes should be used, most studies use a low number of electrodes (2-12) (Artusi et al., 2011; Cruz et al., 2018; Ferrez & del R. Millan, 2008; Iturrate et al., 2010, 2015; Salazar-Gomez et al., 2017; Spüler et al., 2012), mainly focused on the frontal and fronto-central area of the brain (eg: FCz, Cz, FC1, FC2), which have shown to be more activated in error detection, with some parietal electrode locations (e.g.: P3, P4, POz, Oz). However, some authors decided on 32, or even 64 electrodes (Kim et al., 2017; Kim & Kirchner, 2013) to record the signal.

One of the most important parts of ERPs detection is the division of the entire signal into smaller time frames (epochs). These windows must be big enough to capture the full error potential but not too great to capture irrelevant signal. ErrPs, in specific, tend to occur between 100-800 ms after stimulus onset, so the period used to analyze the ErrP usually lies between those values. There are some studies where authors choose wider time frames for ErrP detection (Yousefi et al., 2019). Yet, most of them tend to choose a period of 1 second or less (Cruz et al., 2018; Ferrez & del R. Millan, 2008; Iturrate et al., 2010, 2015; Spüler et al., 2012). There are also studies where the temporal window starts before the stimulus onset (Kim et al., 2017).

The pre-processing stage intends to highlight the components of interest for feature extraction. It includes filtering the signal and using techniques to remove any artifacts that might affect the data. In many of the cases, the studies conducted only apply filtering methods. The range used for filtering differs between authors, but many decide to low pass the data at 10 Hz, since it has been found that the ErrP lies between the 1-10 Hz range. After filtering, artifact removal algorithms such as ICA are sometimes applied (Yousefi et al., 2019) or CAR (Iturrate et al., 2010; Iwane et al., 2016; Spüler et al., 2012). There is no rule as to how extensively the signal should be processed, but there should be some caution not to over-filter or remove important components of the ErrP.

Feature extraction is probably the most important part in processing of EEG signals. If chosen correctly, the selected method can maximize the potential of the classification stage. Here, the goal is to reduce the dimensionality of the data without losing any key information, and, if possible, improve the SNR of the signal. This is the most heterogeneous step as numerous techniques can form the feature vector. Even though no specific technique has been considered ideal, the studies presented relied on spatial filters like xDAWN (Kim et al., 2017; Kim & Kirchner, 2013; Salazar-Gomez et al., 2017) or FCB (Cruz et al., 2018), downsampling (Ferrez & del R. Millan, 2008; Iturrate et al., 2010, 2013, 2015) and spectral features (Artusi et al., 2011; Yousefi et al., 2019).

If the vector from feature extraction already has a small size, it can be used for classification. However, in most cases, a dimensionality reduction must be made to improve classification performance and reduce computational time. Feature selection methods are varied and can be computationally demanding, but their rationale is similar, aiming to remove redundancy between features while retaining the ones with the most discriminative power. *R*-square is one of the preferred methods to obtain the most discriminating features (Cruz et al., 2018; Iturrate et al., 2010, 2015). There are, however, many cases in which the feature vector is obtained directly from feature extraction without requiring the feature selection step (Ferrez & del R. Millan, 2008; Kim et al., 2017; Kim & Kirchner, 2013; Spüler et al., 2012).

After all the stages above, it is expected that the feature vector allows for the distinction between correct and error signals. The data collected during calibration are used to train a classification model and then applied in real-time to decode the error signal. Regression (Salazar-Gomez et al., 2017) but mostly classification models are typically used. The most common methods are surveyed in Bashashati et al., 2007; Lotte et al., 2007. One of the most used classification methods is the SVM (Artusi et al., 2011; Iturrate et al., 2010; Kim et al., 2017; Kim & Kirchner, 2013; Spüler et al., 2012). Another popular classification method is LDA (Iturrate et al., 2013, 2015; Yousefi et al., 2019), which has extremely low computational requirements, making it optimal for an online BCI system. Both algorithms usually present good and equivalent results, so what appears to matter the most is the features chosen to describe the EEG signal.

4. METHODS

4.1 Facial Emotional Stroop Task

In this chapter, we describe in detail the proposed Facial Emotional Stroop Paradigm task. Six different images of actors performing a happy or sad expression are shown, and each image has a label on the "T" Zone of the forehead, with the letter "T" (*Triste* in Portuguese, sad in English) or "F" (*Feliz* in Portuguese, happy in English). The superimposed letter can be congruent (sad face with a “T” label / happy face with an “F” label) or incongruent (happy face with a “T” label/ sad face with an “F” label) with the facial expression. Participants must acknowledge facial expressions presented with a superimposed label detecting whether they are congruent or incongruent.

4.2 Experimental Protocol

The experiment based on the Facial Emotional Stroop task was divided into two parts: a calibration session and an online session. The EEG recorded during calibration is labeled according to events (cue image and congruent/incongruent labels) and used to create a classification model for the online session. The length of the experiment, including preparation, was around 120 minutes. Between each block of the session, there was a 1-minute break, and between the two sessions a 10-minute break, both to reduce eye fatigue and to ensure that participants focused as much as possible.

4.2.1 Calibration

The calibration session consisted of ten blocks, and every block was comprised of thirty trials (9 incongruent and 21 congruent trials) randomly distributed. In each trial, participants were asked to evaluate the facial expression presented with the superimposed label, which can be congruent or incongruent with the facial expression (Figure 4.1). The main goal is to mentally acknowledge if the facial expression presented matches the label. Each trial begins with 500 ms of staring into a red cross, followed by the presentation of the facial expression, which lasts for 800 ms, and lastly the facial expression with the label on top, which is presented for 1500 ms. We used the red cross as a focal point for the participant, to minimize eye movements and artifacts when the stimulus appears. Each session block lasted for 94 seconds (30 trials + a 10-second waiting period at the beginning of the session). The acquired calibration dataset for each participant (if all data were used) is composed of 90 target epochs (incongruent) and 210 non-target (congruent) epochs, which were used to train the classifier for the online task.

4.2.2 Online Task

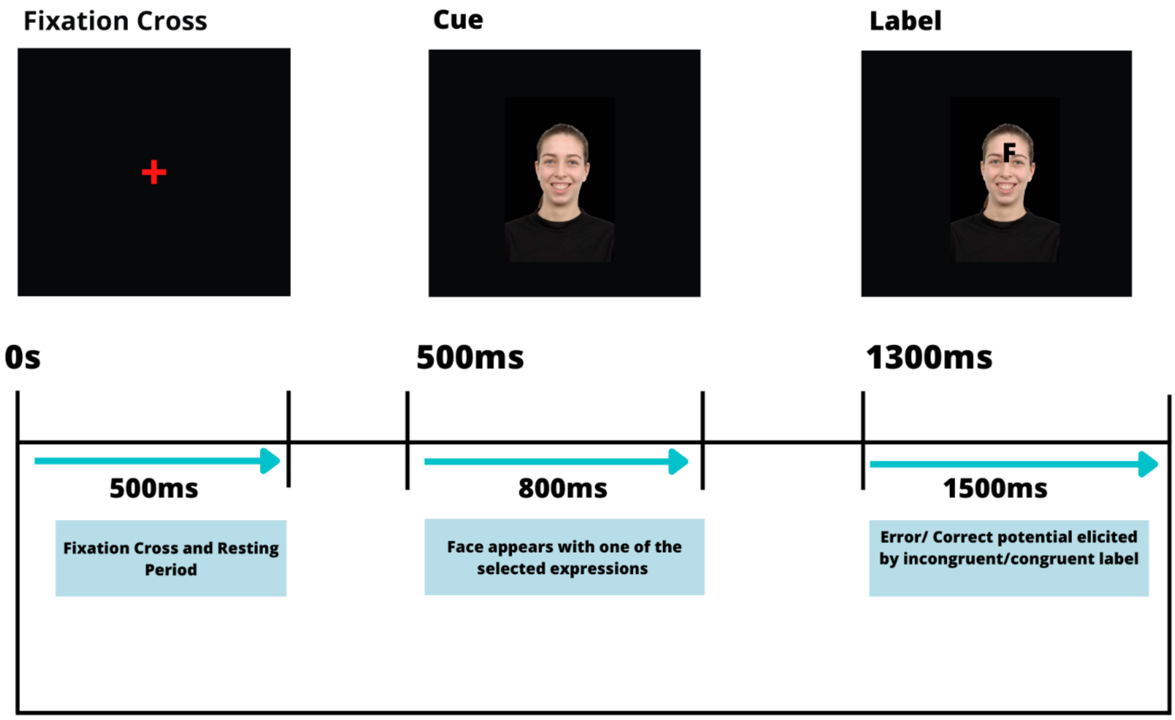


Figure 4.1: Schematic representation of the trials of the calibration task. The blue arrows determine the duration of each stimulus. Each trial begins with a red cross, followed by the facial expression and lastly the presentation of the label on top of the face, which is expected to elicit the participant's error/correct potential

The Online session consisted of 5 blocks, and every block was comprised of thirty trials (9 incongruent and 21 congruent trials) randomly distributed. Figure 4.2 shows the scheme of the online task. Each trial can be "divided" into 3 parts. The first part of the trial is the same as in the calibration task, starting with the red cross, for 500 ms, then, the facial expression for 800 ms, and lastly 1.5 seconds of the facial expression with the label on top. In the second part of the task, the system presented feedback on the facial expression based on the automatic detection. The words "SYSTEM DETECTED: FELIZ/TRISTE" were presented to the participant depending on the identification. Here it was expected to obtain Interaction-ErrPs when the detection of the BCI was wrong. Figure 4.3 represents the labeling process regarding the interaction potential. If the detection corresponds to the actual facial expression, then we label the trial as correct, otherwise, we will label it as an error. This is inferred from the congruence/incongruence detection of the algorithm which is prone to failure if classification accuracy is low. In the last part, the BCI presents the question "Ok?" to the participant, regarding its detection, asking for 'agreement.' If the detection is correct, the user must press the left mouse button, otherwise, he/she does nothing. This served to disambiguate whether the participant correctly detected the congruence/incongruence. Every trial had a duration of 5.8 seconds. The number of incongruent and congruent trials (including the three parts) per block was the same as for the calibration session, however, the number of blocks was only 5 to reduce the duration of the experiment.

The online session therefore involves the three following parts. The first one is correctly identifying the facial expression so that the interface can make an accurate guess, the second is receiving feedback from the detection of the interface and mentally acknowledging whether this feedback is correct or not, and finally, providing mechanical feedback by clicking on the left button of the mouse cursor.

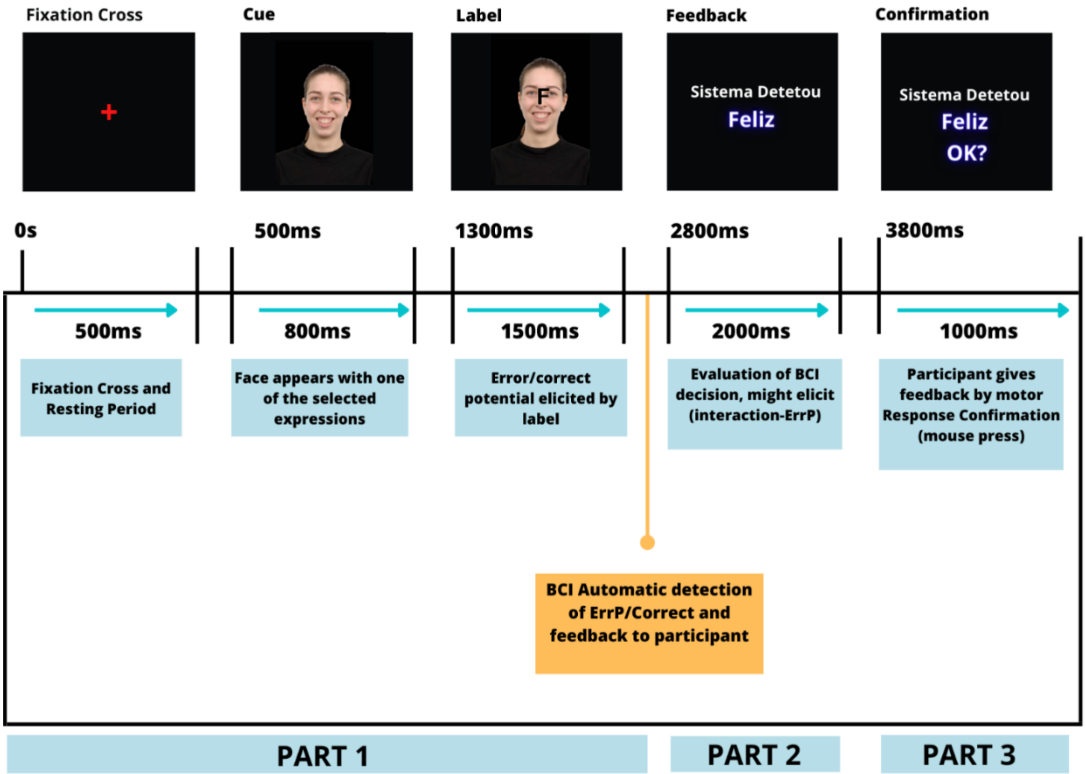


Figure 4.2: Schematic Representation of the trials in Online Task. The blue arrows indicate the duration of each section of the trials. Part 1 includes the recognition of facial expression and acknowledgement of a congruency/incongruency between the face and the label. Part2 represents the feedback given to the participant regarding the detection of the facial expression. Part 3 represents the feedback.

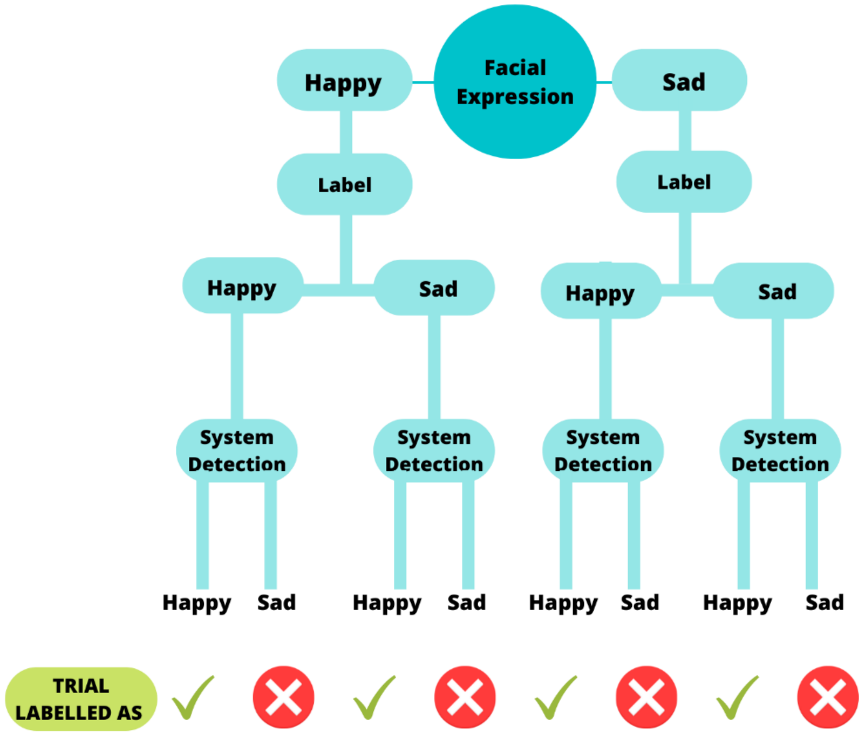


Figure 4.3: Schematic Representation of the labelling scheme for the Interaction Error Potential**.** If the emotion detected by the classifier matches the emotion displayed, then we label a trial as correct, otherwise, we will label it as an erroneous trial.

4.3 PARTICIPANTS

Ten subjects, six women and four men, between the age of 20 and 32, mean age (25 ± 3) ,participated in this study. All participants had normal to corrected-to-normal vision and had university education. All participants gave informed consent after we explained the study. Ten participants performed the calibration session (S1-S10), and six participants performed the online session (S2, S5, S6, S7, S8, S10). After acquiring data for participant S1, we realized a malfunction with the synchronization block had happened, so it meant that the results obtained were not reliable. Participants S3 and S4 had to leave the laboratory and hence they did not perform the online session. Participant S9's data had many artifacts and so this subject did not perform the online session.

4.4 FACIAL EXPRESSIONS

The facial images used in the experiments were obtained from the Radboud Faces Database (RaFD) (Langner et al., 2010). We chose six actors, three females and three males, all Caucasian adults, and with distinct prominent facial expressions. Two images were used per actor, representing the emotions "Happy" (Figure 4.4), and "Sad" (Figure 4.5), with a frontal gaze. We edited the pictures to have a black background using Adobe Photoshop 2022.

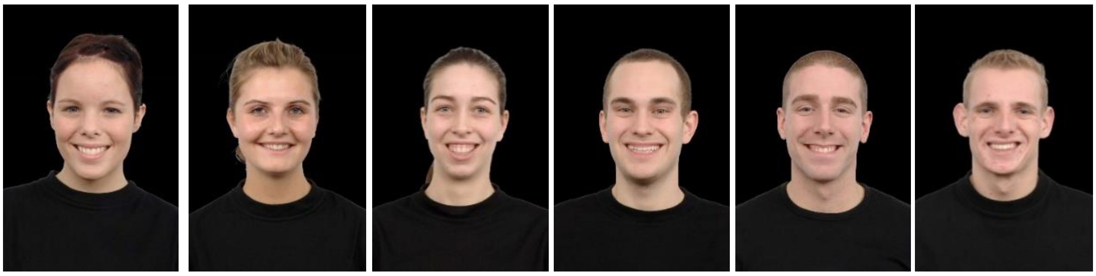


Figure 4.4: Happy facial expressions used in the visual paradigm.

Figure 4.5: Sad facial expressions used in the visual paradigm**.**

The pictures observed had 9.86 cm in height and 6.56 cm in width, and were observed at 70 cm, which corresponds to a visual angle of 8.01° (height) x 5.4° (width). The pictures were all at eye level, so that no movements had to be made to fully acknowledge the whole face. An example of the stimulus is presented in Figure 4.6. The labels 'F' and 'T' were superimposed on the forehead of the image, consequently creating a new image. This was done using MATLAB's Computer Vision Toolbox (insertText function).Figure 4.6 shows the new image formed.

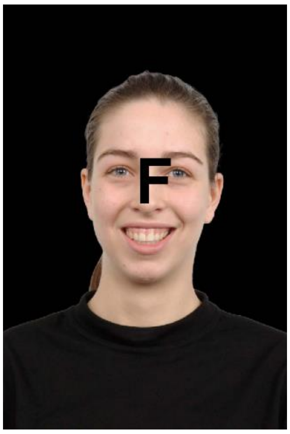


Figure 4.6: Stimulus presented in the Facial Emotional Stroop Paradigm (face with label on top). This is the representation of a congruent stimulus (happy face with "F" label).

4.4 Experimental Setup

All the experiments were conducted at the laboratory of Robotics and Mechatronics at the Institute of Systems and Robotic (ISR). We used a 22,9" LCD BENQ Monitor to perform the experiments, with a 60 Hz refresh rate and, 1920 x 1080 resolution (Figure 4.7). The participant sat at 70 cm from the screen (distance measured at eye level). Participants were asked to avoid talking, blinking or performing facial movements during the blocks, to reduce bioelectrical artifacts that could compromise the acquired data. Early pilot studies revealed a delay of approximately 160 ms and jitter of ≈ 20 ms, in the presentation of the stimulus to participants. This delay and jitter meant that the data analyzed did not correspond to the exact moment the participant saw the stimulus. To overcome this issue, a photodiode (light sensor Thorlabs SM1PD1A) was used to obtain the precise timestamp of the stimulus onset on the screen. The photodiode was placed in the left bottom corner of the computer and captured the appearance of a white square, which appeared at the same time as the stimulus (face with label) (Figure 4.7). The photodiode covered the square in a way that it was not a distraction for the participant.

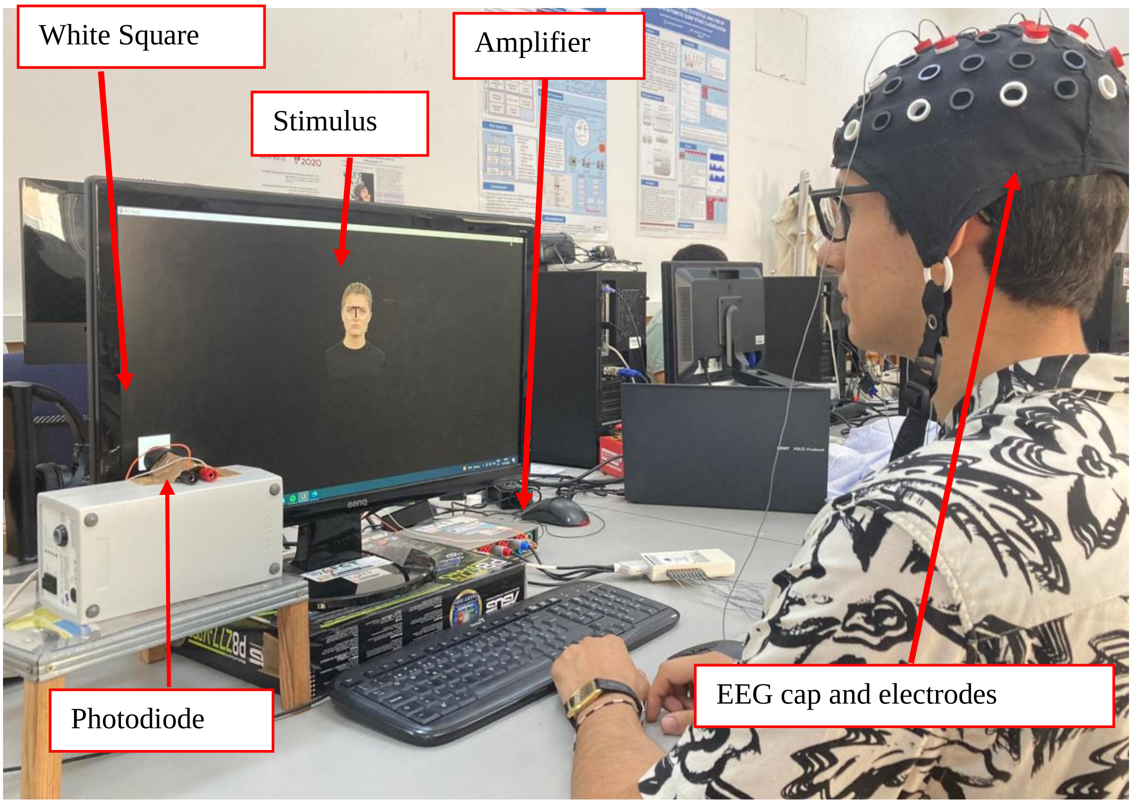
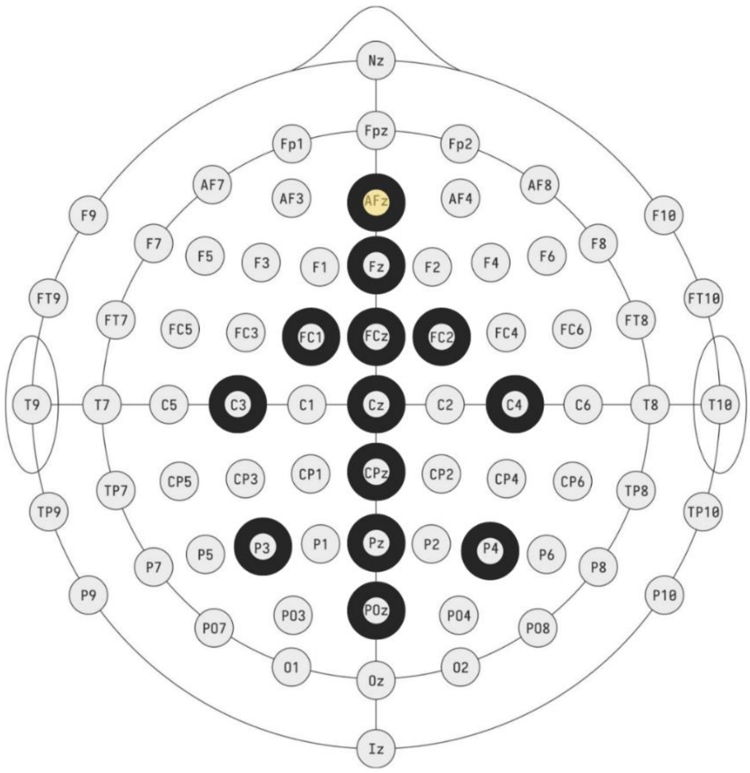


Figure 4.7: Photograph of the setup used to perform the experiments. The table and box placed next to the computer are used to hold the photodiode in place, with tape.

4.5 EEG Recordings

EEG was recorded with a g.USBamp bio amplifier, from electrodes Fz, FCz, FC1, FC2, CZ, C3, C4, CPZ, PZ, P3, P4, and POZ using the extended 10–20 standard system. We placed the reference electrode in the right earlobe and the ground electrode at the AFz position. For acquisitions, we used active Ag/AgCl electrodes. Firstly, we placed the EEG Cap, making sure that the Cz electrode was at the center of the skull. After placing the cap, we scrubbed the head through the holes of the cap, as well as the chosen ear for reference electrode with an abrasive gel, to remove all dead skin. Next, we applied the gel to the previously scrubbed electrode locations. This gel allows for a low impedance and good conductivity during the experimental period. After that, we assured that the electrodes were well connected. The EEG signal was sampled at 256 Hz and pre-processed using a notch filter at 50 Hz in gUSBamp bioamplifier. Throughout the experiment, we plotted the recordings of the sessions, to track how well the experiments were going and to check the stability of the signal.



4.6 BCI Framework

All the code used to perform the experiments was done using MATLAB and Highspeed Simulink (Mathworks 2021a ; G.HIsys-g.USBamp), based on implementations in G. Pires, 2012; G. Pires et al., 2022. The main Simulink blocks are represented in the Simulink model (Figure 4.8) and described below.

"Acquisition driver" block: Provides a graphical interface to the g.USBamp hardware, and allows the tuning of parameters such as filtering, notch, channels used, sampling rate, etc. The EEG signal enters the computer through a USB connection. the g.USBamp driver provides a hard real-time clock through a hardware interrupt that drives the whole Simulink model.

"Preprocessing" block performs the 256 Hz sampling and applies a 50 Hz notch filter. In the Online Session

"Synchronization" Block: The Synchronization block was created to resolve the synchronization issues described in section 4.4. This block transforms the analog signal provided by the photodiode into digital. This signal is sent to the Event block as a trigger and is used to extract the epochs related to the observed stimulus and provide the trigger classification.

"Event Generation and Classification" Block: Implements the event generation, data buffering, and implements the algorithms for EEG signal processing and classification (detailed below).

"Key Press" Block: Saves the time points in which the user pressed the mouse.

“Visual paradigm” Block implements the visual Emotional Stroop Effect paradigms (calibration and online). The timestamps and duration of the events required for the “Event Generation and Classification” block were fully parametrized. The online classification was embedded in the ’Event Generation and Classification’ block, which was implemented with minor changes of the offline classification models obtained from calibration data. The event and classification information controlled the items shown in the “Visual Paradigm” block**.**

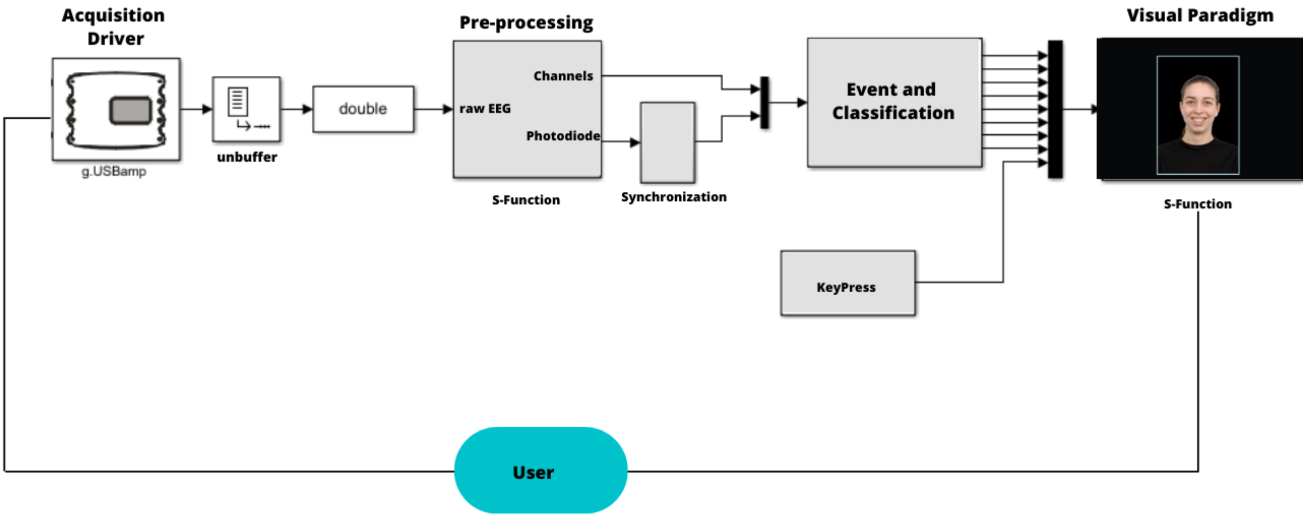


Figure 4.8: Schematic Representation of the Software Framework and user in the BCI loop.

4.7 Online Task: pre-processing and model creation

In the online part of the task, a classifier performs real-time detection of Correct/Error Potentials. Before the online task, a model, based on the training data is generated. Due to the variability between subjects, each subject has its model. Before the creation of the classification model, a brief analysis of the sessions is performed to check whether they contain artifacts. If artifacts are presented some blocks may be discarded, meaning that the calibration models can be trained from a different number of trials. This changes from participant to participant. The scheme for data pre-processing for model creation can be seen in Figure 4.9.

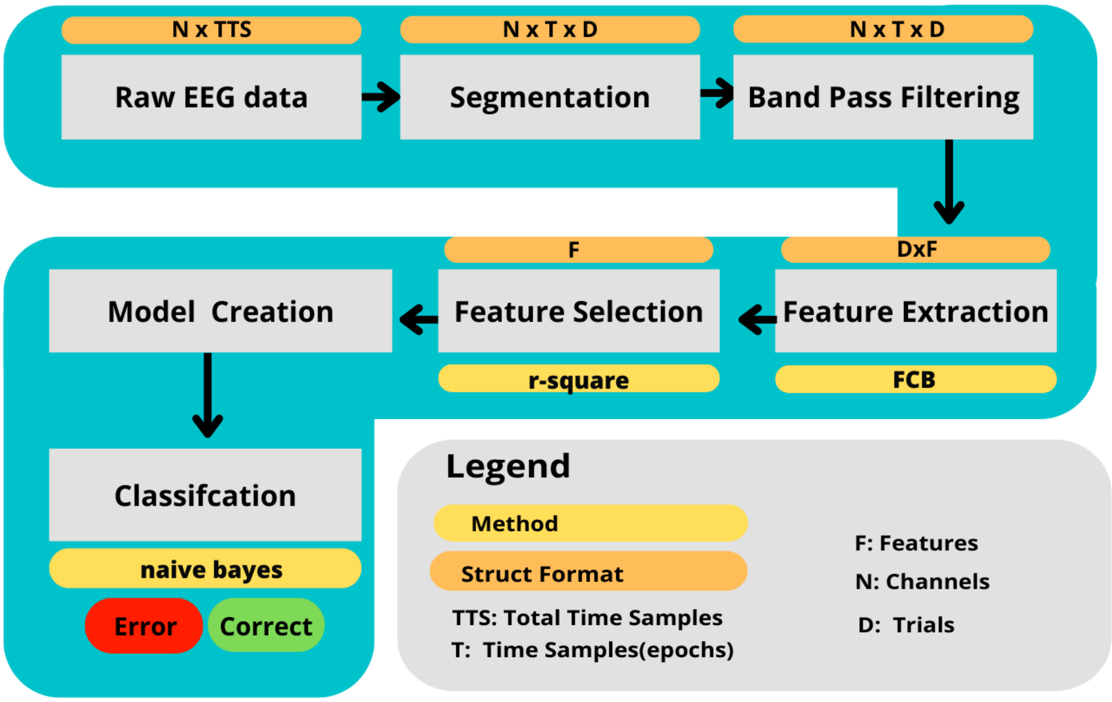


Figure 4.9: General Pipeline for classification model creation and Classification.

The Pipeline for Model Creation begins with segmentation, i.e., dividing the signal into the epochs of interest (congruent and incongruent trials). Segmentation produces epochs of 1000 ms, from the stimulus onset, for both congruent and incongruent trials. All stimuli for correct and wrong events are appended into a single structure. Next, a band-pass filter is applied to the Raw EEG Data, to remove all frequency components above 1 Hz and below 10 Hz. After filtering, feature extraction is performed, transforming our twelve channels into twelve new 'pseudo' channels with 256 samples each. Out of the twelve new 'pseudo' channels, the first two channels are selected for feature selection. We then select the best 150 features. The model based on these 150 features is then applied to the real-time EEG data from the online task and classification is performed.

4.7.1 General assumptions and notation

An EEG epoch representing an ERP is a series of temporal samples, $\boldsymbol{X} = [\boldsymbol{x}_{(t)}, \boldsymbol{x}_{(t1)}, \boldsymbol{x}_{(t2)}, \dots \dots \dots \boldsymbol{x}_{(T)} \dots]$, where T is the number of time samples and $\boldsymbol{x}_{(t)}$ is a column vector with dimension $\boldsymbol{N}$, in which $\boldsymbol{N}$ is the number of EEG channels. In our case, we have a 12 x 256 matrix, corresponding to 12 channels and 256 time-samples per channel.

4.7.2 Feature Extraction

To extract relevant features, we used a statistical spatial filter proposed in our lab termed Fisher criterion beamformer (FCB) (G. Pires et al., 2011). A spatial filter is a weighing vector that combines data from channels at each time instant. It transforms the original channels, into a new feature space of "pseudo" channels. The spatially filtered signal $y_j(t)$ $(j = 1..N)$ is generically obtained from the input signal x_i $(i = 1..N)$ multiplied by the coefficients of the spatial filter w_{ij} , according to:

$$\boldsymbol{y_j(t) = \sum_{i=1}^{N} w_{ij} x_i(t),\ j = 1, \dots, N} \tag{1}$$

In matrix notation, the spatial filter output is given by:

$$\boldsymbol{Y = W'X} \tag{2}$$

where W represents the spatial filters (with a dimension NxN), Y is the spatially filtered output with a dimension NxT and X represents the EEG signals with a dimension NxT. The " ' " symbol stands for transpose operator.

4.7.2.1 Fisher Criterion Beamformer

In particular, we used the Fisher Criterion Beamformer (G. Pires et al., 2011), which relies on Fisher's criterion and provides one projection that optimizes discrimination between two classes. The Fisher criterion is applied in the spatial domain increasing the separation between classes while minimizing the variance within a class. The following Rayleigh equation translates this criterion:

$$\boldsymbol{J(W) = \frac{W' S_b W}{W' S_w W}} \tag{3}$$

in which S_b is the spatial between class matrix, and S_w is the in spatial within class matrix. The filter that solves this problem is given by:

$$\boldsymbol{S_b W = S_w W \Lambda} \tag{4}$$

where Λ is the eigenvalue matrix and which is computed as an eigenvalue problem. The spatial filter chosen is the eigenvector with the higher associated eigenvalue. For a 2-class problem such as ours, the within-class matrix is defined as:

$$\boldsymbol{S_w = \sum_{i=1}^{2} \sum_{x_i \in C_j} (xi - m_i)(x_i - m_i)^T} \tag{5}$$

The between class matrix is defined as:

$$\boldsymbol{S_b = \frac{1}{K}\sum_i K_c(m_i - m)(m_i - m)^T} \quad (6)$$

where K is the number of total trials, K_c is the number of total trials in class c, m_i is the mean of epochs in class c and m is the mean of all epochs. They are computed from:

$$\boldsymbol{m_i = \frac{1}{K}\sum_{k=1}^{K_c} X_{i,k} \ and \ m_i = \frac{1}{K}\sum_{k=1}^{K_c} X_{i,k}} \quad (7)$$

The solution to the eigenvector problem can be regularized:

$$\boldsymbol{S_b W = [(I - \theta)S_w + \ \theta I]W} \quad (8)$$

where I is the identity matrix, and θ is a parameter obtained from training data.

4.7.3 Feature Selection

To select the most discriminating features between the spatial projections of the two classes, the *r*-square method was used, which returns values between 0-1 (the higher the *r*-square value the better). The r-square value can be obtained by the following equation:

$$\boldsymbol{r(X,Y) = \frac{\sigma_{X,Y}}{\sigma_X.\ \sigma_Y} = \frac{\sum_{k=1}^{K}(X_k - \bar{X})(Y_k - \bar{Y})}{\sqrt{\sum_{k=1}^{K}(X_k - \bar{X})^2}\ \sqrt{\sum_{k=1}^{K}(Y_k - \bar{Y})^2}}} \quad (9)$$

The *r*-square is applied to all the features previously extracted and used to rank the features from the highest to lowest relevance. As stated above (section 4.7) we defined 150 as the number of features being utilized for the models created.

4.7.4 Classification

The previous steps allow for the BCI to create a model that is user and session specific. The classifier used in our experiments was the $Naïve\ Bayes$ classifier, which is a usual and successful method used in our lab in this context, with offline and online implementations already available.

4.7.3.1 $\boldsymbol{Naïve\ Bayes}$

The naïve Bayes uses a probabilistic model to assign an instance to a class. It assumes that all features are independent from each other, which is a strong assumption and not always true, hence the name naïve. Given an independent set of features $\boldsymbol{X}$ = (x_1, x_2,…,x_n) and a class variable $\boldsymbol{y}$, the Bayes Theorem claims that:

$$\boldsymbol{P(y|X)} = \frac{\boldsymbol{P(X|y) * P(y)}}{\boldsymbol{P(X)}} \quad (10)$$

Where $P(y|X)$ is the posterior probability of class y , $P(X|y)$ is the conditional probability of class y given X and $P(y)$ is the prior probability of y. $P(X|y)$ can be further decomposed into:

$$\boldsymbol{P(X|y) = P(x_1, x_2, \dots \dots x_n|y)} \quad (11)$$

Because we assume independency of components, this can be simplified into:

$$\boldsymbol{P(X|y) = P(x_1|y) * P(x_2|y) * P(x_3|y) \dots \dots P(x_n|y)} \quad (12)$$

If we substitute equation 12 into equation 10, we are left with:

$$\boldsymbol{P(y|X)} = \frac{\boldsymbol{P(x_1|y) * P(x_2|y) * P(x_3|y) \dots\dots P(x_n|y) * P(y)}}{\boldsymbol{P(x_1) * P(x_2) \dots\dots * P(x_n)}} \quad (13)$$

The denominator is constant, therefore the posterior probability can be written as:

$$P(y|x_1, x_2, \dots \dots . x_n) \propto P(y) \prod_{k=1}^{p} P(x_k|y) P(y) \quad (14)$$

The class is detected following the maximum a posteriori decision rule:

$$\boldsymbol{\hat{y} = argmax_y\, P(y) \prod_{k=1}^{n} P(x_k|y)} \quad (15)$$

4.8 Neurophysiological Analysis

EEG data were analyzed using EEGLAB, v2022.0 (Delorme & Makeig, 2004), and routines were written in MATLAB R2021B (The MathWorks, Natick, MA).

EEG signals related to the Facial Emotional Stroop Task were analyzed from data collected during the calibration session. Signals were preprocessed as follows: first, a bandpass filter 1-10 Hz was applied to the data. After, 1-second epochs were extracted using the photodiode stimulus-based trigger. Then, components related to artifacts were removed by using ICA. Finally, we plotted each session as well as the *r*-square. By visual inspection, sessions with too many artifacts (blinks when stimulus appears, channels having exaggerated amplitudes when compared to others) were discarded from the analysis.

EEG signals related to the feedback of the detection algorithm (where Interaction ErrPs were expected in wrong detections) were analyzed using the same preprocessing of the Facial Emotional Stroop Task.

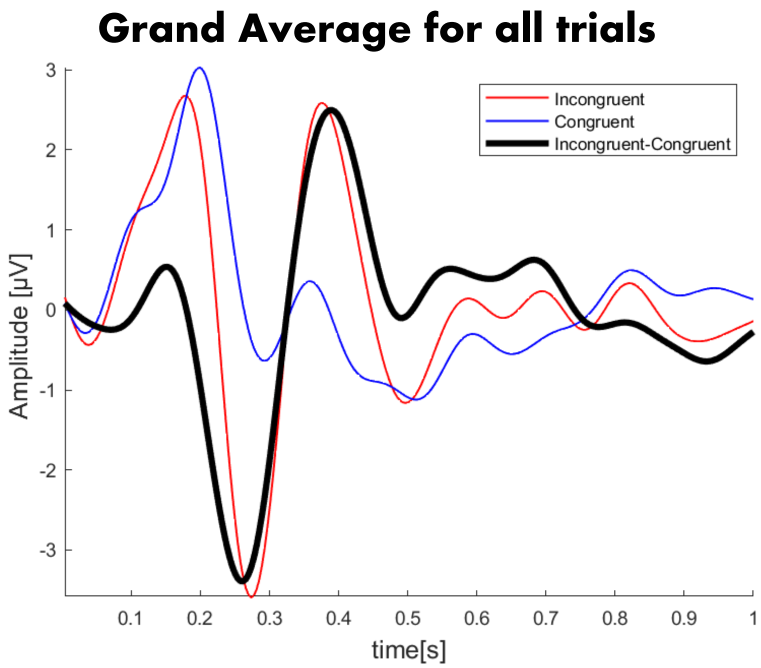
5. Results

In this chapter, we present the results of the developed work. Both neurophysiological and classification results obtained from data recorded in calibration and online sessions are presented. Reported results to congruent/incongruent ERPs and interaction ErrPs, showing group and individual analyses are made. The classifier's ability to detect such signals is also evaluated.

5.1 Neurophysiological analysis

5.1.1 Emotional Stroop Task – Group

In this section, we analyze the waveforms resulting from the incongruent and congruent event responses obtained during the Facial Emotional Stroop task. Considering the literature review carried out in chapter 3, we intend to analyze whether it is possible to identify the following ERPs: Ne/ERN, Pe of Error Potentials, N2, N450, and SP. The plots presented below were obtained using MATLAB after data was processed with band-pass filter of 1-10 Hz and inspection of Artifacts by visual analysis and ICA was performed using MATLAB and EEGLAB. The grand averages presented in Figure 5.1a) comprehend the 1-second responses after the onset of the stimulus (Face with an overlaid label, see section 4.1) and were obtained from the trials of all participants, excluding S9, at channel FCz. Participant S9 was excluded from all analyses due to the many artifacts present in EEG recordings.



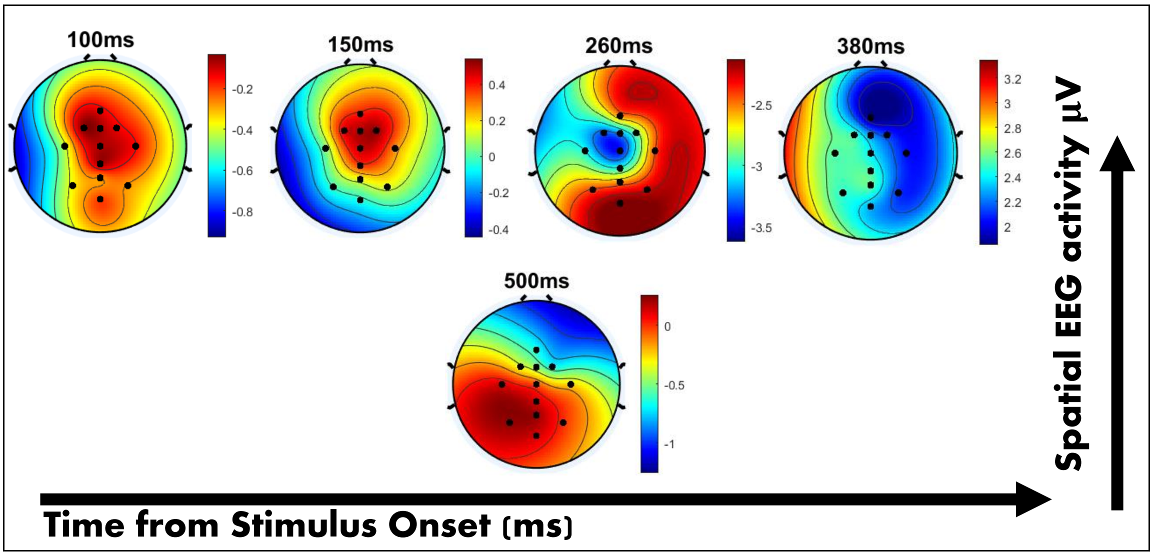


Figure 5.1: a) Average of all trials in all conditions, Incongruent (blue line), Congruent (red line), Incongruent-Congruent (black), at channel FCz. The components produced in the Incongruent-Congruent condition are due to the differences in processing Congruent and Incongruent trials b) Topographical maps of the average of all trials in the latencies (100, 150 ms, 260 ms, 380 ms, 500 ms) for the Incongruent-Congruent condition.

Figure 5.1b) shows the respective topographical maps for the peaks in the Incongruent minus Congruent (Incongruent-Congruent) condition. FCz channel was chosen based on its known association with processes involving error monitoring. In the time window of 220 to 320 ms following the stimulus onset, the waveforms were more negative for incongruent (-2.6948 µV SE= 0.8830 µV) than congruent (-0.39 µV SE=0,492 µV) trials, with a peak in Incongruent-Congruent trials at 260 ms, possibly being the Ne/ERN/N2. In the 380-430 ms time window following the stimulus, there is another clear difference between incongruent and congruent trials, with incongruent trials (1,62 µV SE= 0.25 µV) more positive than congruent trials (-0,43 µV SE= 0,26 µV) and a peak in the difference waveform at around 400 ms, which could be a Pe. In the 450–500 ms window, usually named the N450, we found a negative deflection, at around 480 ms, with incongruent trials (-1.49 µV SE= 0.40 µV) more negative than congruent trials (-1.28 µV SE= 0.08 µV). In the window of 550-750 ms, incongruent trials (0.15 µV SE= 0.4752 µV) were slightly more positive than congruent trials (-0.41µV SE=0.33µV). This time window is usually where SP occurs.

The topographical maps were obtained for the peaks 100, 150, 260, 380, and 500 ms. These maps were obtained with EEGLAB, after processing the signal with a 1-10 Hz passband filter and removing artifacts with ICA. There is a fronto-central distribution of activity in the analyzed peaks, except for the 500 ms peak, which presents a more parietal distribution. A fronto-central distribution is typical for processes involving error monitoring.

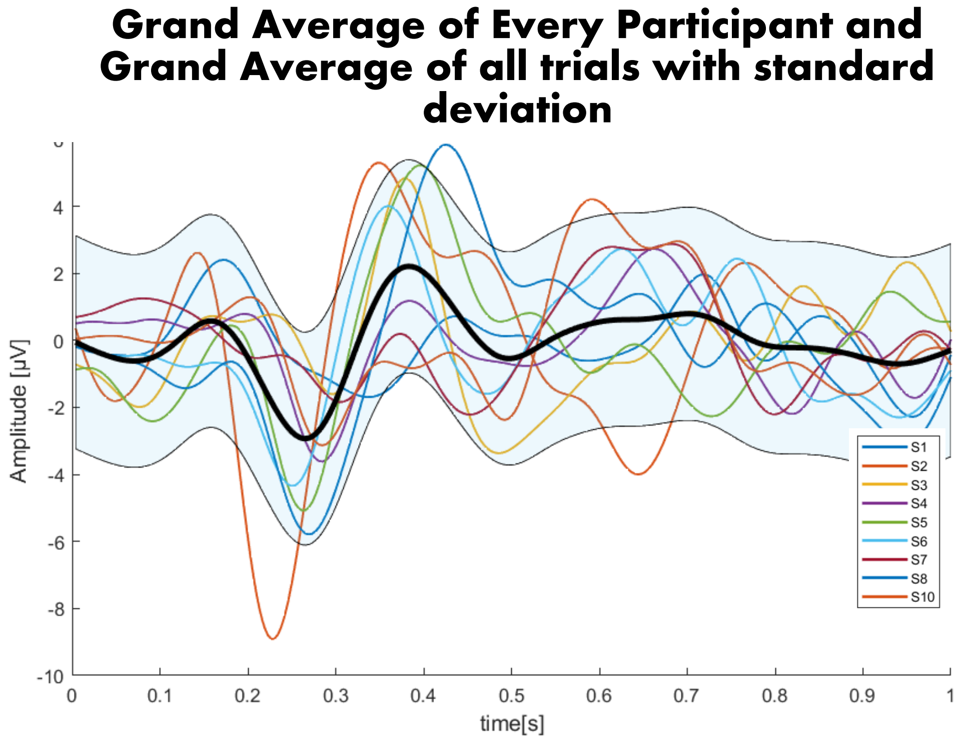


Figure 5.2 Grand average and individual averages of Incongruent-Congruent Trials at channel FCz. Black line represents the grand average of all participants, and the colored lines represent the individual grand averages. Shaded blue area represents the standard deviation.

Figure 5.2 presents all the average waveforms that comprehend the grand average waveform and the individual averages. Even though there is variability between subjects, it is possible to see that most follow the pattern of the grand average waveform. We computed the *r*-square (Figure 5.3) for Incongruent and Congruent trials and performed point-wise paired *t*-tests Figure 5.4) with an alpha of 0.01 between the two conditions. The *r*-square points to the 220-320 ms and 340-450 ms time windows as the ones presenting discrimination between Incongruent and Congruent trials. Those same time windows show an effect of congruency in the point-wise paired t-test and show a significant effect of congruency in the time window of 220-320 ms and the time window of 340-450 ms, which correspond to the time windows of the first and second peaks, respectively. The visual differences in the 450-500 ms and 550-750 ms time windows were not deemed statistically significant.

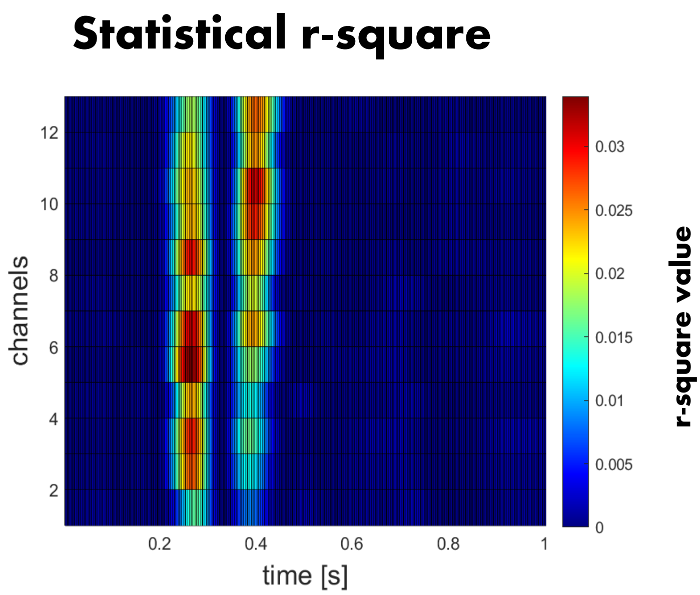


Figure 5.3: r square between Incongruent and Congruent trials for all twelve channels.

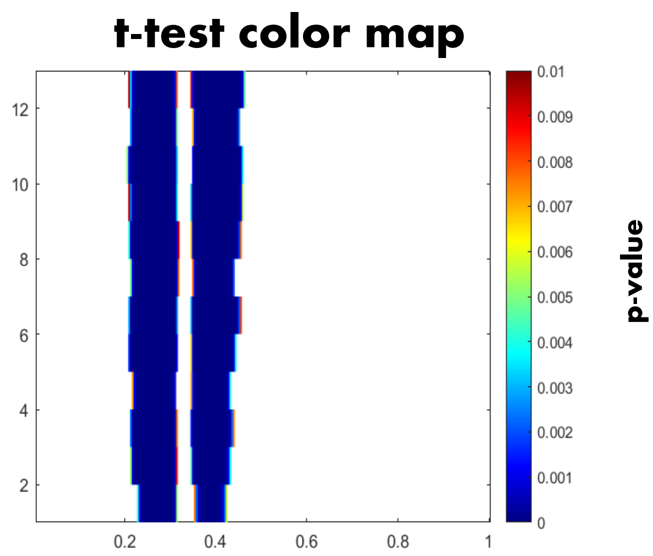
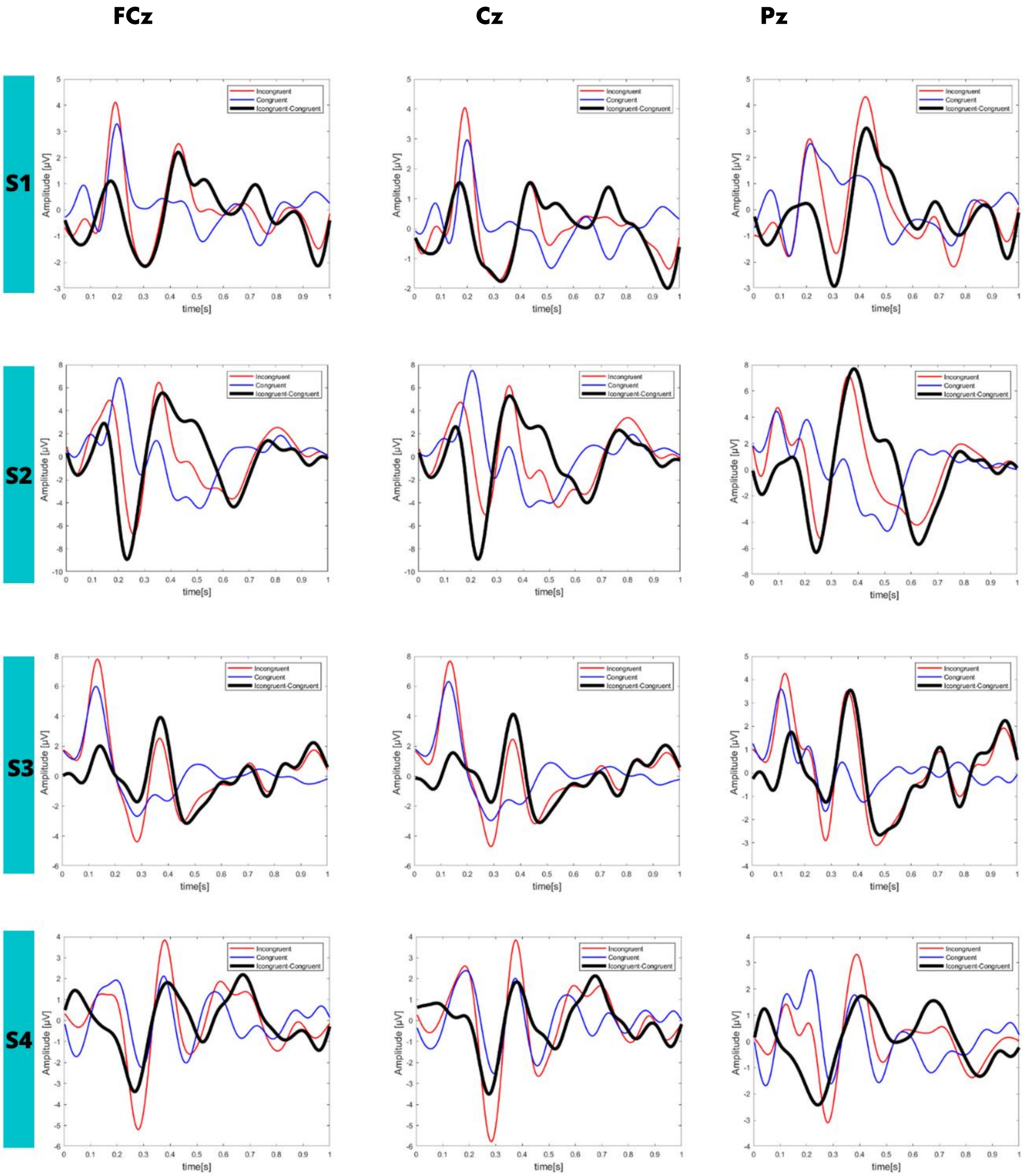
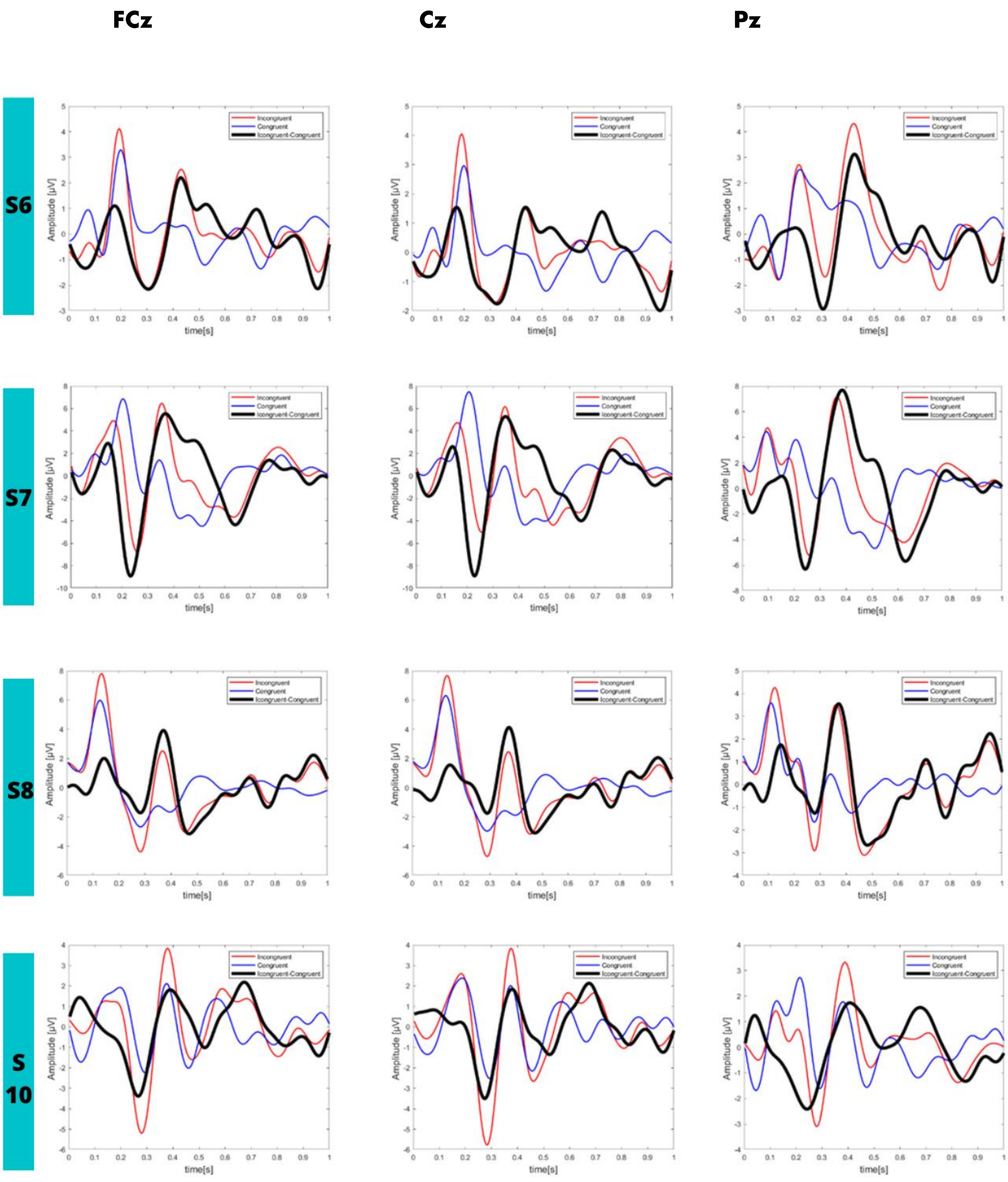


Figure 5.4: Color map of point-wise t-tests comparing Congruent and Incongruent potentials for the twelve channels. Significant differences appear in color for an alpha criterion ≤ 0.01.

5.1.2 Emotional Stroop Task – Individual Plots

Figure 5.5 presents the individual grand averages for all trials in the Incongruent, Congruent, and Incongruent-Congruent conditions, for channels Cz, FCz, and Pz. The averages were obtained using the same pre-processing of the group analysis.


FCz
Cz
Pz
S1
S2
S3
S4
Incongruent
Congruent
Icongruent-Congruent
Amplitude [µV]
time[s]


FCz
Cz
Pz
S6
S7
S8
S 10
Incongruent
Congruent
Icongruent-Congruent
Amplitude [µV]
time[s]

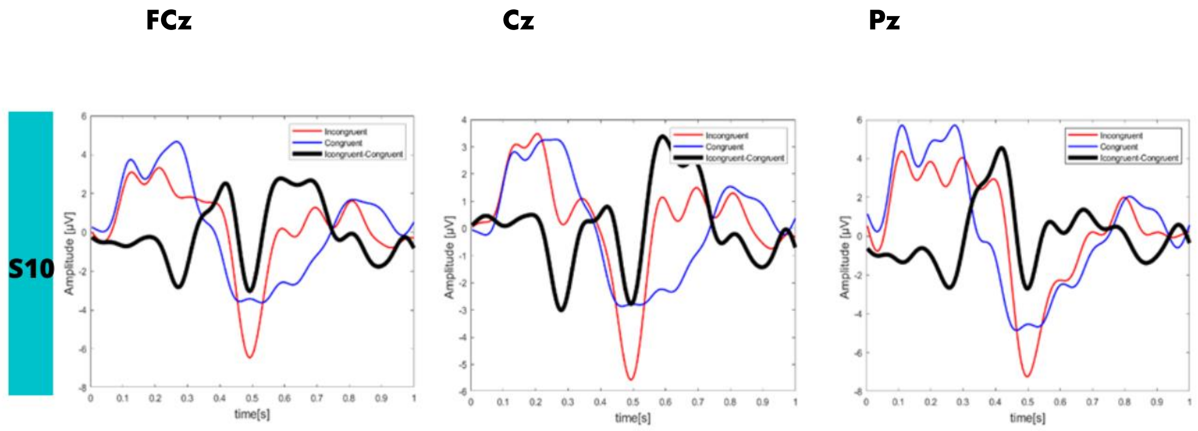


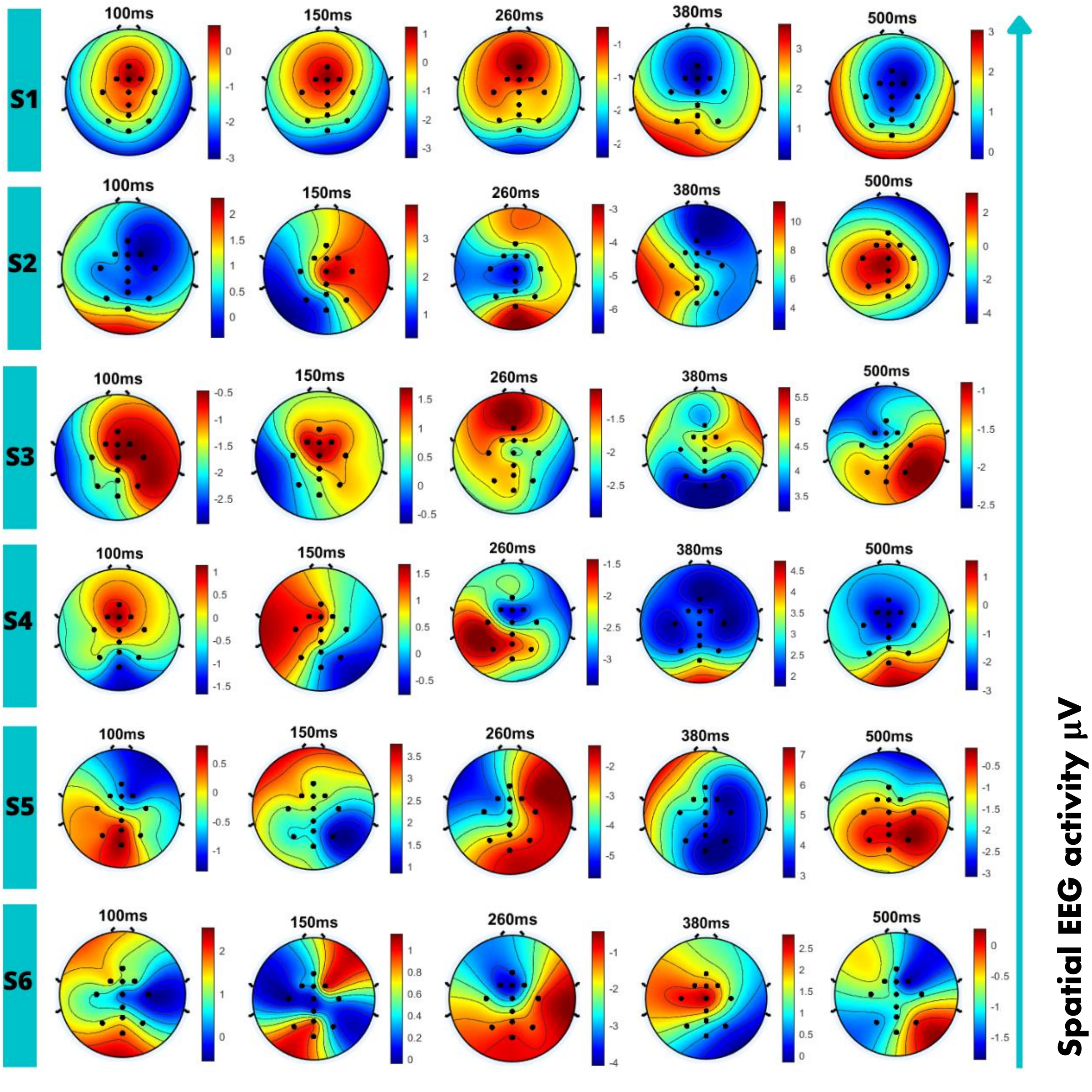
Figure 5.5 Potentials elicited by the Emotional Word Face Stroop Paradigm of 1 second post stimulus presentations, for Incongruent (red line), Congruent (blue line) and Incongruent-Congruent (black line) trials for participants S1, S2, S3, S4, S5, S6, S7, S8, and S10 at channels FCz,, Cz and Pz, respectively.

Since we are more interested in the globality of the results thorough individual analyses were not conducted, and as consequence, we will only highlight some relevant aspects of the above plots.

From the visual analysis of the above plots, we observe that most of the participants depict a similar waveform, with a first accentuated negative peak in the 200-300 ms time window, except for participant S10, in which it occurs in the 400 ms range. This peak is caused by Incongruent trials being more negative than congruent trials, most likely representing the Ne/Ern/N2. This peak is variable in amplitude, oscillating from -2 to -9 µV. This negative peak is followed by a positive peak, occurring at around 400 ms, except for participant S7 and S10, in which the peak occurs at around 600 ms. This peak might represent the Pe. After this positive peak, the waveforms greatly differ across participants. The windows in which there is bigger discrimination between Incongruent and Congruent trials are presented in Annex A. *R*-squares for participants S7 and S10 show different discriminatory time windows in comparison to the other participants.

5.1.3 Emotional Stroop Task – Individual Topographical Maps

Figure 5.6 presents the individual topographical maps for each participant, in the same latencies as those of Figure 5.1.


S1
S2
S3
S4
S5
S6
100ms
150ms
260ms
380ms
500ms
Spatial EEG activity µV

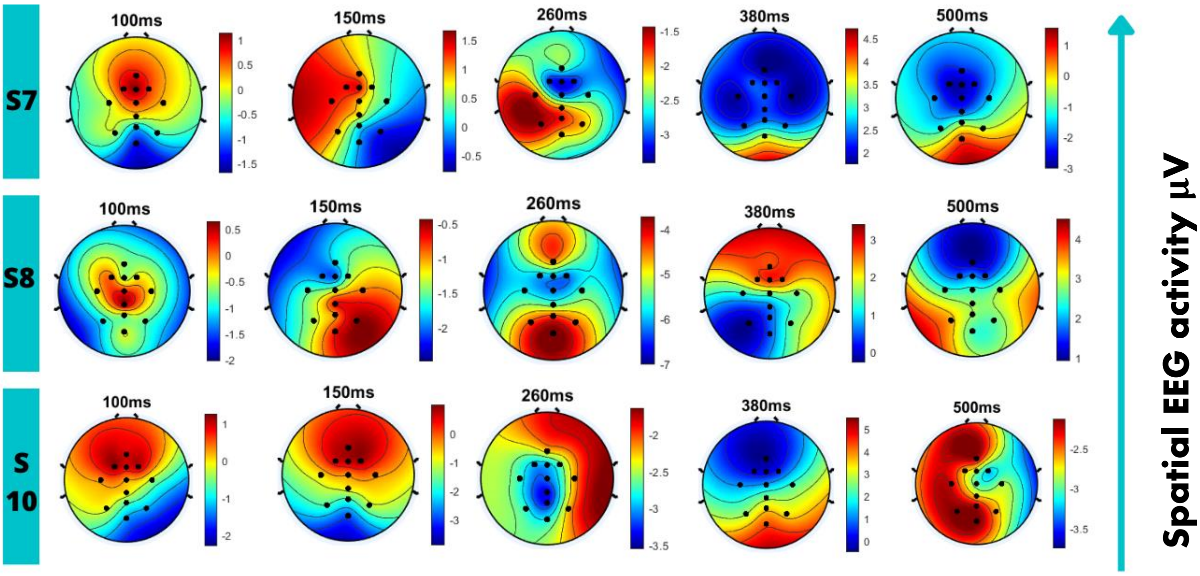


Figure 5.6: Topographical Maps of the Difference (Incongruent-Congruent) trials at 100, 150, 260, 380 and 500 ms, for participants S1, S2, S4, S5, S6, S7, S8 and S10. The bar next to the plots corresponds to the spatial EEG activity (μV).

The topographical maps show the distribution of the EEG spatial activity for the same latencies as those of Figure 5.1. Generically, it is possible to see that most participants present a frontal to fronto-central distribution of EEG activity, characteristic of Error Potentials.

5.1.4 Effects of Condition

Besides the main analysis, we wanted to understand if some factors regarding the participants and their experience had any influence on the potentials. We decided to take the following factors into account: BCI experience, Gender, and native language, in a preliminary approach. We also decide to evaluate if experimental conditions had any impact on the results achieved. We performed an exploratory analysis on the influence of the facial emotion in the responses, as well as the gender of the faces being presented. Figure 5.7, Figure 5.8, and Figure 5.9 represent the grand average ERPs regarding BCI experience, gender, and nationality, respectively. We analyzed amplitude differences regarding the first negative (220-320 ms) and second positive (340-450 ms) peaks.

BCI experienced users vs BCI naïve users

One of the main aspects to consider when creating a BCI application is its usability for first-time users. We assume that users with BCI experience have a bigger "ease" at modulating potentials, however, our goal is to make the experience work for all users. This analysis intends to evaluate if there is any group bias, i.e., if users who have no experience have the capacity of recruiting other selective attention mechanisms beside error monitoring mechanisms. Out of the 9 participants used to conduct this analysis, 3 had previous BCI experience and 6 had no previous BCI experience (naïve). The plots below were obtained through MATLAB.

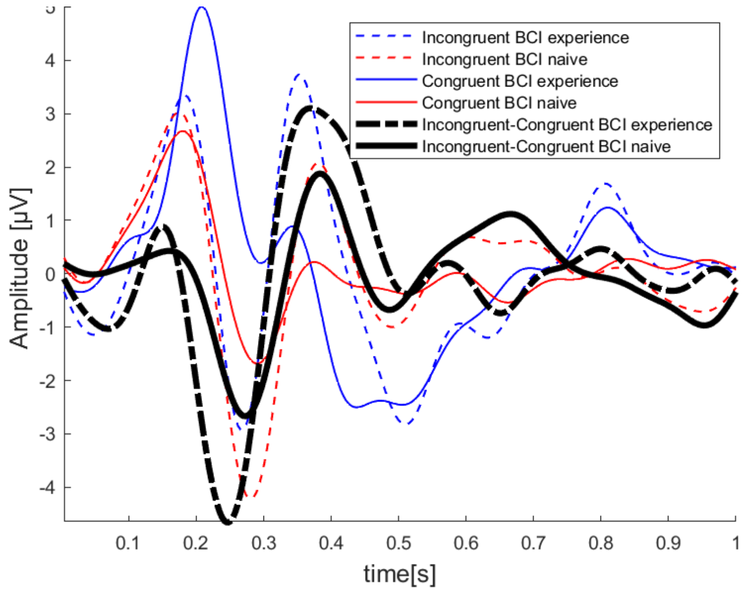


Figure 5.7: Grand Average of all trials for the Emotional Stroop Task, for BCI experienced (n = 3) and BCI naïve group (n = 6), at channel FCz. Blue Lines represent congruent trials, red lines represent incongruent trials and black lines represent the difference waveform (Incongruent-Congruent).

The difference waveforms of BCI experienced users vs BCI naïve users have visible differences in the amplitudes and latencies of the first negative peak and second positive peak. BCI experienced users have smaller latency for the first peak and, as for the Pe, the latency is similar, however, BCI experienced users exhibit a bigger amplitude. A 2 (Group: BCI experienced x BCI naïve) × 2 (Congruency: Incongruent, Congruent) repeated measures ANOVA was conducted. There was no main Effect of Group ($p > 0.05$) for the time windows analyzed.

Gender Effects

Even though there are several studies and paradigms that involve the use of error potentials, studies that aim to find differences between cognitive processes based on gender have not produced any conclusive results. This analysis intends to compare differences, in case they exist, on the potentials evoked by men and women. Of the nine participants used to perform this analysis, 4 were men and 5 were women.

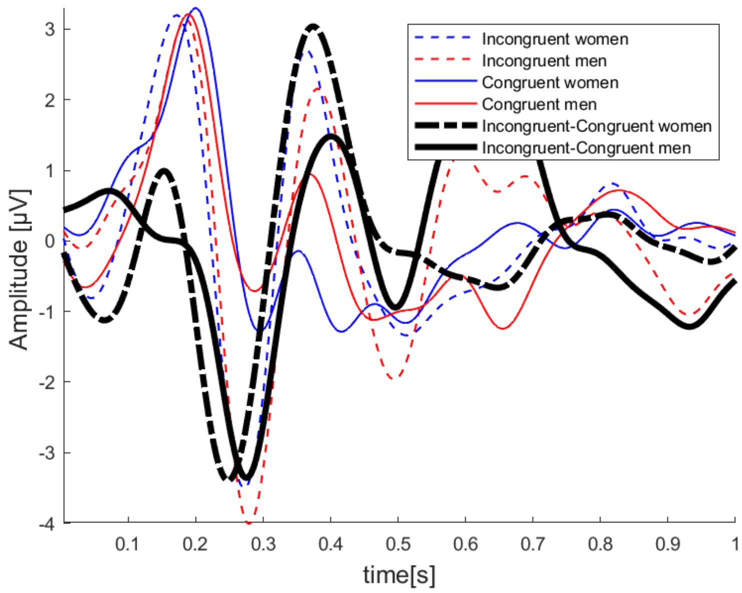


Figure 5.8: Grand Average of all trials for the Facial Emotional Stroop Task, for Women (n=5) and Men (n=4) group, at channel FCz. Blue Lines represent congruent trials, red lines represent incongruent trials and black lines represent the difference waveform (Incongruent-Congruent).

Comparing the difference waveforms of women vs men, we can see differences in the amplitude of the first negative peak and second positive peak and amplitude differences in the second positive peak. Women have smaller latencies for both peaks and bigger amplitudes for the second positive peak. A 2 (Group: Women x BCI naïve) × 2 (Congruency: Incongruent, Congruent) repeated measures ANOVA was conducted. There was no main Effect of Group ($p > 0.05$) in the time windows analyzed.

Foreign Vs Portuguese

In the current study, we had 3 foreign participants (who know some words in Portuguese) vs 7 Portuguese participants. Our study includes letters that correspond to the Portuguese word for the used facial expressions (F for “Feliz” and T for “Triste”). Since we did not change the letters to those that correspond to the emotions in the participant’s native language, we will try to analyze if thinking in a non-native language has any implication on the evoked potentials.

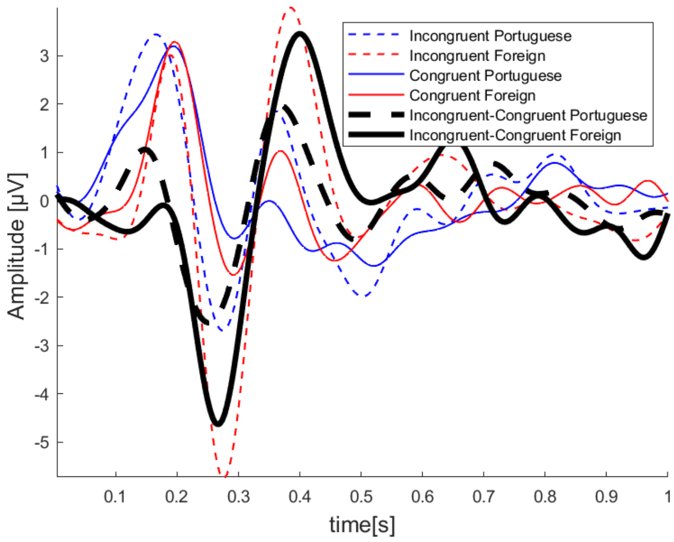


Figure 5.9: Grand average of all Incongruent and Congruent trials and difference waveform for Portuguese (n=6) and foreign group (n=3), at channel FCz. Blue Lines represent congruent trials, red lines represent incongruent trials and black lines represent the difference waveform (Incongruent-Congruent).

Comparing the difference waveforms of the Portuguese and foreign group we can see differences in the amplitude and latency of the main peaks. The foreign participants present (on average) longer latencies and higher amplitudes for both peaks. A 2 (Group: Portuguese x Foreign) × 2 (Congruency: Incongruent, Congruent) repeated measures ANOVA was conducted. There was no main Effect of group ($p < 0.05$) in the time windows analyzed.

Stimulus emotion and gender

Figure 5.10 and Figure 5.11 present the grand average of all trials for the Incongruent and congruent conditions, respectively concerning the two facial emotions and regarding the gender of the faces. Both Figure 5.10 and Figure 5.11 lead us to believe that the experimental conditions have minor impact on the results produced. In Figure 5.10 we analyze the influence of the emotion presented (happy, sad). The analysis of the significant time windows (220-320 ms) (340-450 ms) reveals an overlap between both congruent lines and a small difference in incongruent waveforms regarding time and latency. In incongruent trials, sad emotions produce waveforms with smaller latencies, and, regarding the second positive peak, their amplitude is bigger. Two point-wise paired t-tests were performed, one for each condition (incongruent happy x incongruent sad) (congruent sad x congruent happy) and neither test revealed statistically significant differences between emotions ($p>0.01$). Figure 5.11 tells us what effect of the gender of the facial expressions was. Visually, there are some differences in amplitude and latency, especially for the incongruent condition, however, as for Figure 5.10, the point-wise t-tests performed for both conditions (Incongruent female expression X Incongruent male expression), (Congruent female expression X Congruent male expression) reveal no significant influence of the gender of the facial expression used. ($p>0.01$)

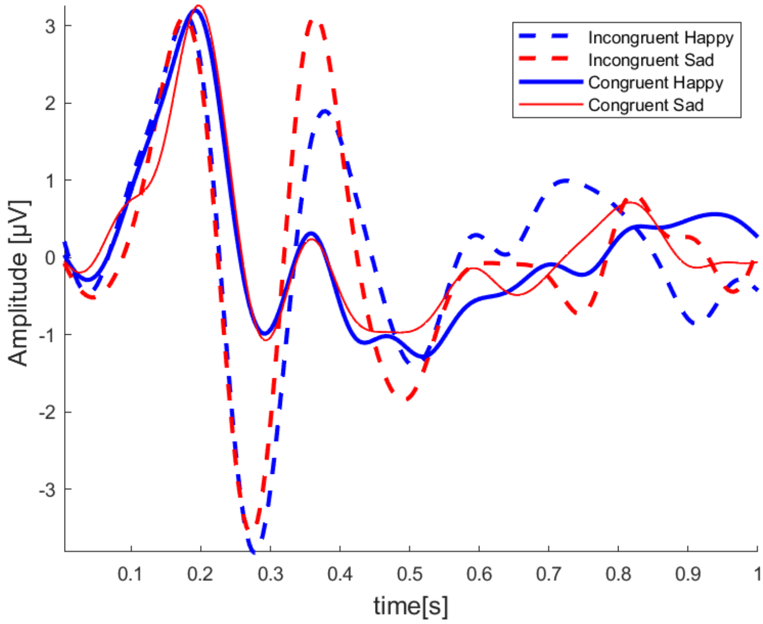


Figure 5.10: Grand Average of Congruent and Incongruent trials for the Facial Emotional Stroop Task, for both facial expressions, at channel FCz. Blue Lines represent a happy facial expression while red lines represent a sad facial expression.

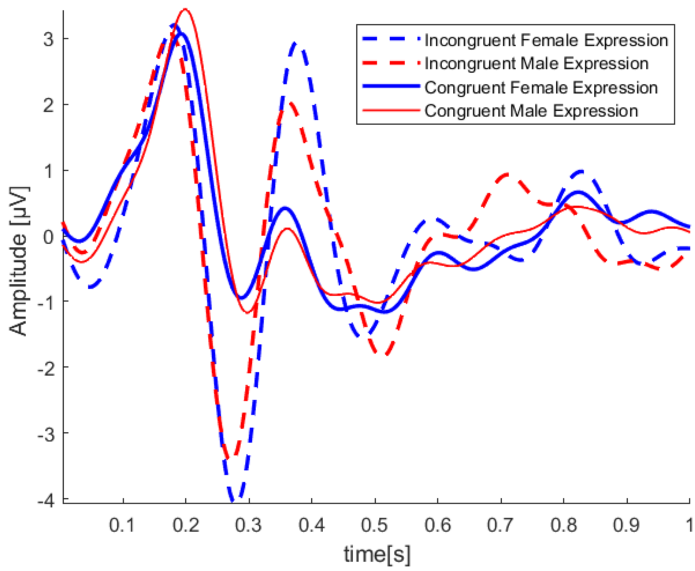


Figure 5.11: Grand average of all trials for the Facial Emotional Stroop Task, for both facial expressions, at channel FCz. Blue Lines represent the female facial expressions while the red line depict the male facial expressions.

5.1.5 Interaction ErrPs

In this section, we analyze the waveforms of the Interaction ErrPs elicited from the trials we labeled as correct or incorrect (as explained in section 4.2). We hoped an Interaction Error Potential would occur when the feedback provided by the BCI did not match the user's expectation, i.e., when the face detected by the interface was not the same as the face identified mentally identified by the participant.

Only six participants performed the online session. After acquiring data for S1, we realized that a malfunction with the synchronization block had happened, so it meant that the results obtained were not reliable. Analyses for this part of the task were conducted for all participants that took part in the online except for participant S2 due to issues regarding the photodiode. The plots presented below were obtained in Matlab after bandpass filtering at 1-10 Hz and artifact rejection using ICA (EEGLAB). The topographical maps were obtained through EEGLAB.

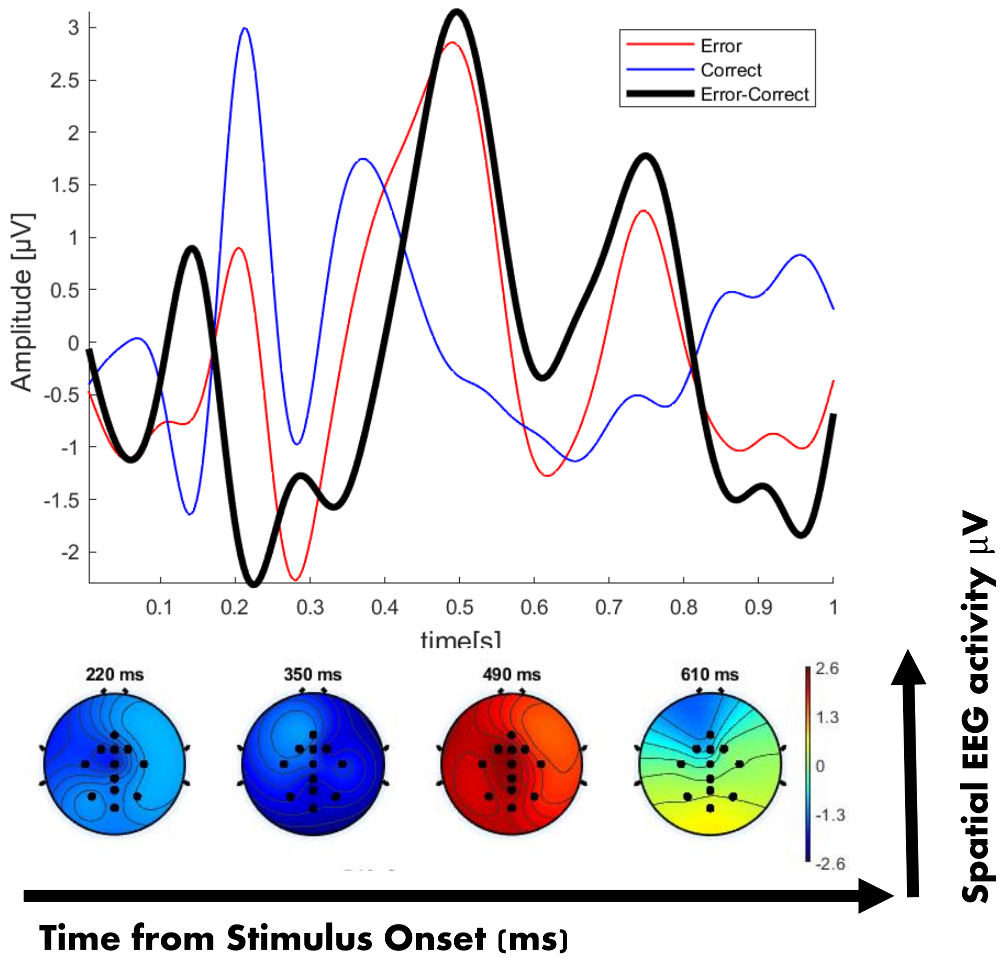


Figure 5.12: a) Average of all trials in all conditions, Error (blue line), Correct (red line) and Incongruent-Correct (black), at channel FCz. The labelling of correct/error events was done according to section 4.8. b) Topographical maps in the peaks (220 ms, 350 ms, 490 ms and 610 ms)

Figure 5.12 presents the ErrP comparison and shows the grand average of all error, correct and error-correct trials. The blue line represents correct trials, the red line represents error trials (both according to section 4.9), and the black line depicts the difference waveform between error and correct trials. The difference waveform had fronto-central positive and negative peaks. A first more accentuated negative peak occurs at 220 ms (-2.29 μV), possibly representing the Ne. We believe the Pe (3.14 μV) to be the peak occurring at 490 ms. Between the Ne and the Pe, there is a minor negative (290 ms) and positive peak (350 ms).

Looking at Figure 5.13, which shows the individual grand averages, we observe great variability between subjects (especially if compared to the results of the Emotional Stroop Task). As we did for the Emotional Stroop Task, we found the *r*-square between the error and correct trials and applied a point-wise paired t-test for the two conditions. Statistical significance is found between the correct and erroneous trials in the colored time windows of Figure 5.14 ($p<0.01$). The analysis of the topographical maps of the difference (error-correct) shows that there is no focal point for the origin of the ErrP. For that purpose, we also generated the topographical maps for the error and correct trials, separately. Those topographical maps can be seen in Figure 5.17. The visual inspection shows a similar and even distribution of EEG activity in error and correct Trials.

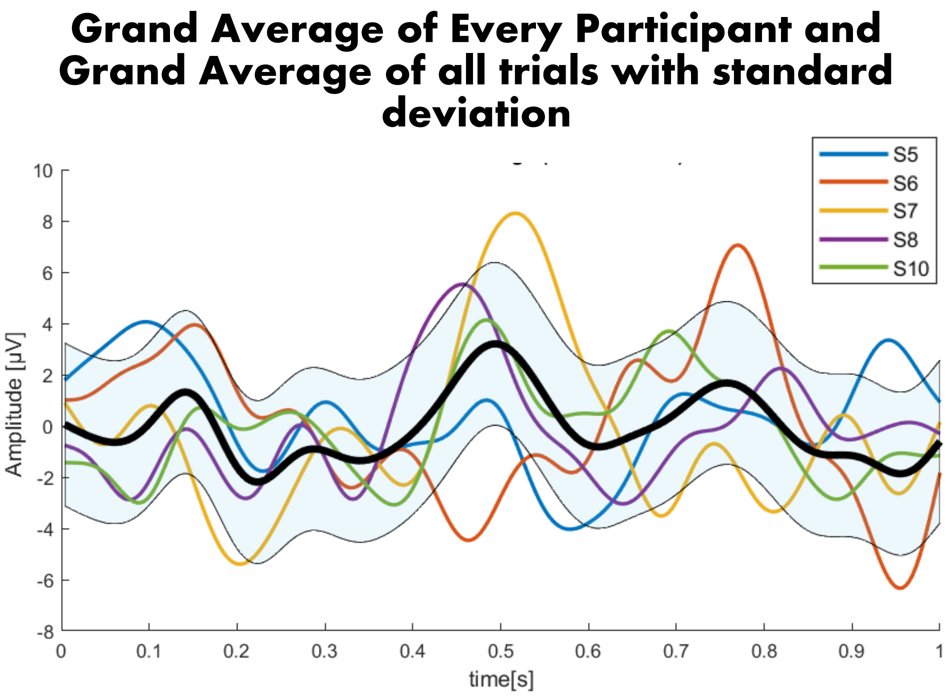


Figure 5.13: Grand averages of Incongruent-Congruent trials with standard deviation and grand average (Incongruent-Congruent) of all participants for the interaction part of the task, at channel FCz.

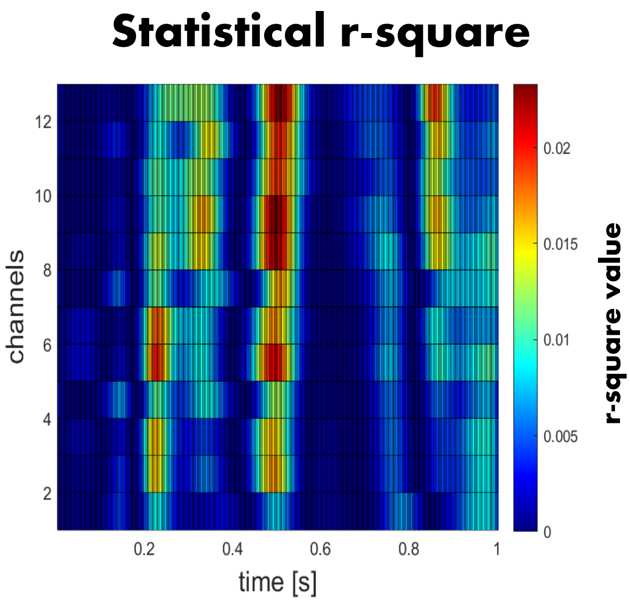


Figure 5.14: Statistical *r*-square between Incongruent and Congruent trials in the Interaction part of the task.

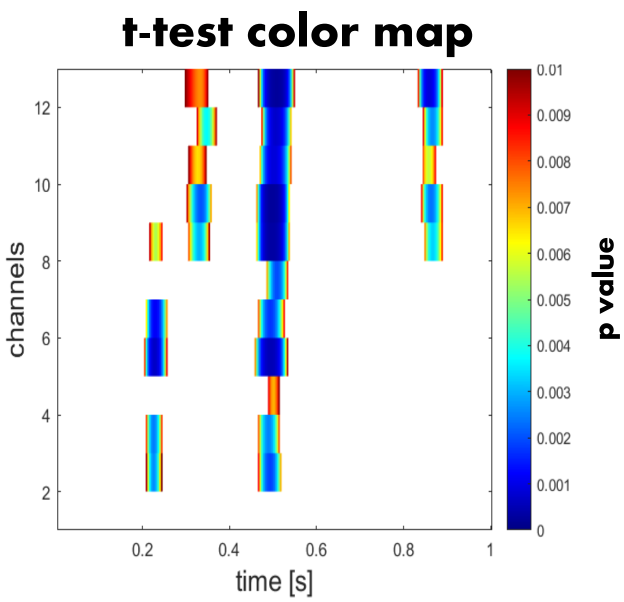


Figure 5.15 : Color map of point-wise t-tests comparing Error and Correct potentials for the twelve channels. Significant differences appear in color for an alpha criterion ≤ 0.01.

The number of error and correct trials used in the analysis directly depended on the performance of the ErrP detector. As seen in Figure 5.16, it was quite variable across participants, which may have had an impact on the analysis.

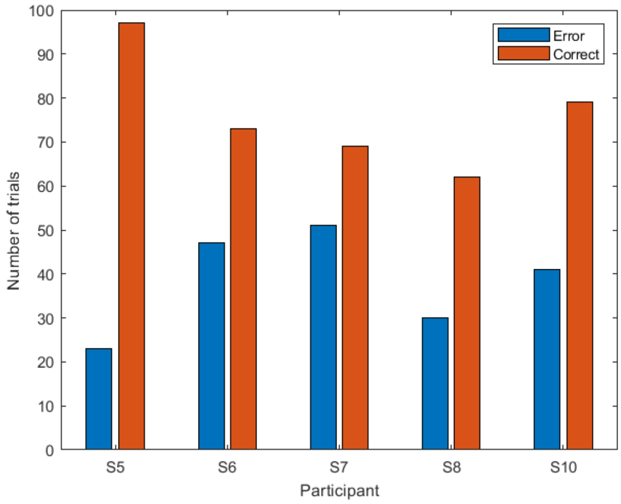


Figure 5.16: Number of Correct and Error Trials utilized to plot the grand averages of the Interaction Error Potential. The red bars represent the correct trials, and the blue bars represent the error trials.

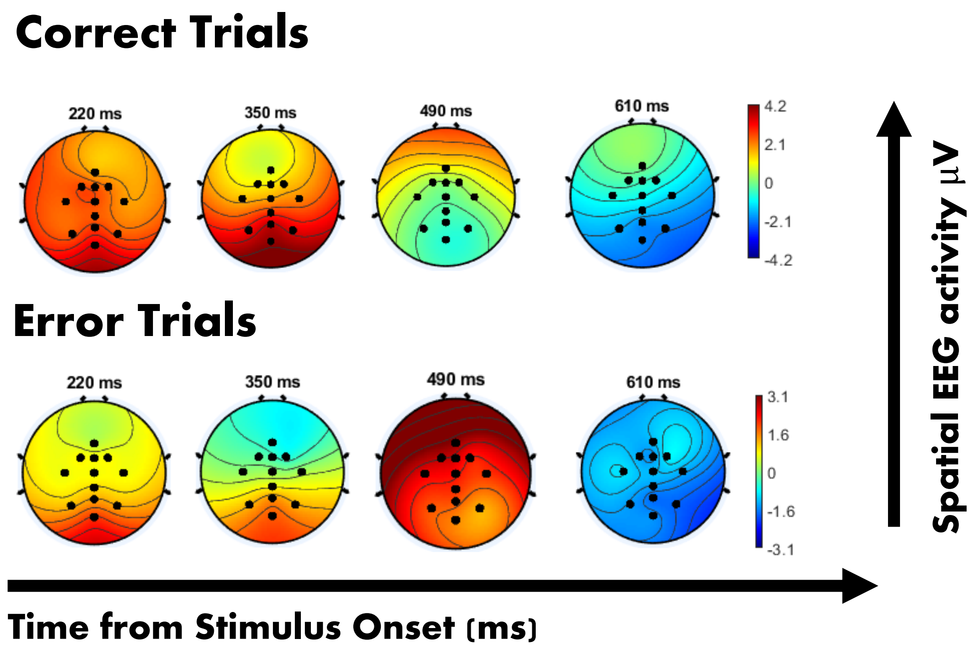


Figure 5.17: Topographical Maps for Error and Correct Trials in the Interaction part of the Task at the latencies of 220, 350, 490 and 610 ms.

5.2. Classification Results

5.2.1 Emotional Stroop Task

This section presents the results for individual offline and online classifications regarding the Incongruent and Congruent Trials, classified at a single trial level. The metric used to evaluate the results was Balanced Accuracy, which considers the imbalance between congruent and incongruent trials. Balanced accuracy is calculated as:

$$Balanced\ Accuracy = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) \tag{16}$$

We considered True Positives (TP) and Trues Negatives (TN) respectively as Incongruent correctly classified and Congruent Trials correctly classified. False negative (FN) and False positive (FP) are congruent and incongruent trials incorrectly classified, respectively.

5.2.1.1 Offline Classification

Table 1 shows the Specificity, Sensitivity, and Balanced Accuracy obtained for all the subjects using calibration data. The results were obtained through n-fold cross-validation (7<n<10). The cross-validation performed served to provide robustness to the classification results obtained. The offline classification was obtained using the same preprocessing that was used online.

Table 1: Results from offline classification from the calibration sessions for all participants, obtained using a n fold cross validation, n being the number of sessions kept for each subject.

Participant	Specificity (%)	Sensitivity (%)	Bal Accuracy (%	Fold
S1	38.6	60.4	49.5	10
S2	77.9	89.7	83.8	10
S3	44.8	73.9	59.4	10
S4	19.1	81.1	50.1	10
S5	57.1	71.6	64.4	7
S6	47.5	59.9	53.7	7
S7	45.9	54.2	50.1	7
S8	58.6	81.5	70.0	8
S10	62.5	79.0	70.8	9
Mean ± STD	50.2 ± 15.6	72.4 ± 11.2	61.3 ± 11.2	

Table 1 shows the offline classification results. The average accuracy, sensitivity and specificity were 61.3± 11.2 %, 72.4 ± 11.2%, and 50.2± 15.6%, respectively. Averaging the results of BCI experienced users the accuracy, specificity and sensitivity rates are 73.0%, 80,1% and 65.8%, respectively, against 55.5%, 68.5% and 48.4% for naïve BCI users. Participant S1 did not surpass the 50% mark (accuracy= 49.5%). Balanced Accuracy rates between men (61.1%) and women were equiparable (61.4%). Sensitivity rates (mean average= 72.4%) were significantly higher than Specificity rates (mean average = 50.2%) for all subjects, which in part can be from the fact that the amount of training samples of congruent trials were double the size of incongruent trials. Not all models were trained with the same number of trials, as some sessions contained artifacts, which could influence the overall accuracy results.

5.2.1.2 Online Classification- Single Trial

The results obtained from the single trial detection can be found in Table 2. The results are presented for the 6 participants that completed the online task (participants S2, S5, S6, S7, S8, and S10). The decoded and classified ERPs represent the responses to the incongruent and congruent stimulus (face with incongruent and congruent label on top). One of the trials of participant S8 was shorter in time, therefore the total number of single trials was lower.

Table 2: Results from Online Classification (4 best sessions). Sub= Subject; Bal Acc= Balanced Accuracy; Spec= Specificity; Sens = Sensitivity. We considered incongruent trials to be positive and congruent trials as negative.

	Sens (%)	Spec (%)	Bal Acc (%)	TP	FP	FN	TN
S2	86.0	70.2	78.2	31	5	25	59
S5	88.8	77.4	83.1	32	4	19	65
S6	52.8	64.3	58.5	19	17	30	54
S7	58.3	57.1	57.7	21	15	36	48
S8	55.2	73.0	64.1	16	13	17	46
S10	52.8	77.4	65.1	19	17	19	65
Mean $\pm$SD	65.7$\pm$15.5	69.9 $\pm$ 7.3	67.8 $\pm$ 9.6				

By looking at table 2, we can see that single trial classification with different rates of success was achieved. The balanced accuracy was, on average, 67.8 ± 9.6%, and sensitivity and specificity rates were 69.9 $\pm$ 7.3% and 65.7$\pm$15.5%, respectively. Participant S5 had the best performance (balanced accuracy = 83.1%), while participant S7 had the worst performance (balanced accuracy= 57.7%). Participant S7 was also the one who performed worse in the Calibration Task, so it was expected he would provide weaker results. Participants S2, S8 and S10 decreased their performance in comparison with the calibration session, while participant S5 increased its performance.

5.2.2 Interaction ErrP

In this part of the analysis, we evaluated if the mental responses given when feedback is presented (‘System detection: Feliz /Triste’) could be classified. As it happened in section 5.1.2, analyses for the ‘Interaction Error Potential’ were made for all participants that completed the online part of the task, except for participant S2, who had issues regarding the photodiode. Table 3 shows the classification results obtained doing 4-fold cross-validation. For each participant, the total number of error and correct trials were different, since these were dependent on the classification of the BCI. The highest accuracy value was 67.9%, while the worst value was 54.68 %. Specificity values are much higher than Sensitivity Values, which is reflected by the number of Correct Trials. The worst Sensitivity value (21.7%) corresponds to the participant who had the lowest number of error trials while the best (56.9%) belongs to the participant who had the highest number of error trials. The best specificity values (87.63 % and 79.7%) are representative of the number of correct trials used (97 and 79 respectively).

Table 3 Results from Offline Classification for subjects S5, S6, S7, S8 and S10 using a 4x fold cross validation.

Participant	Sensitivity (%)	Specificity (%)	Accuracy (%)
S5	21.7	87.63	54.68
S6	53.2	53.4	53.3
S7	56.9	69.6	63.2
S8	56.7	79.0	67.9
S10	31.7	79.7	55.7
Mean $\pm$ STD	43.6 ± 9.4	74.1 ± 13.6	58.8 ± 6.8

5.2.3 Feedback

Table 4 presents the mechanical feedback given by participants regarding the detection of the system. The percentage presented corresponds to the percentage of trials in which the participant agrees with the feedback given by the interface. We could not obtain feedback from participants S2, S5 and S6. Participants said they could not concentrate properly doing it, so after one block they asked if it would be okay not to perform that part.

Table 4 Mechanical feedback provided by the participants, in percentage. The percentages correspond to the percentage of trials in which the user considered the feedback of the system to be correct**.**

Participant	S7	S8	S10
Feedback (%)	55	57.5	65.8

By looking at the rates for the mechanical feedback for all participants, we can see they are like the rates of balanced accuracy of the Facial Emotional Stroop Task. This means that the user was attentive during the first part of the task and could compare the facial expression identified with the one detected by the system and that the error in detecting the actual facial expression can be considered a flaw of the system.

6. Discussion

In this chapter, the results of the project work will be discussed. This chapter is divided into four sections. First, a comparison with other studies in the literature will be performed. Section 6.2 describes the significance and utility of the online results. In section 6.3 the results obtained for the Interaction Error Potential are debated and finally, section 6.4 presents the main limitations of the Study and potential future directions.

6.1 Emotional Stroop Task

Emotional Stroop Effect Studies

First, we will make a comparison with other Stroop Tasks (section 2.4). Our ErrP presents a first negative component at 260 ms. In most emotional Stroop tasks and conflict detecting studies, this component is found to be modulated by conflict. Some facial Emotional Stroop Studies (Schreiter et al., 2018b, 2018a, 2019) have not been able to find a modulation of this component regarding congruency (side by side comparison in Figure 6.1) claiming that the lack of N2 modulation might be because emotional expressions require deeper processing and therefore, conflicts are not detected in the time window of the N2 (Figure 6.1). Our results prove otherwise and agree with Chen et al., 2016, as there were statistically significant differences regarding the time window where N2 is present.

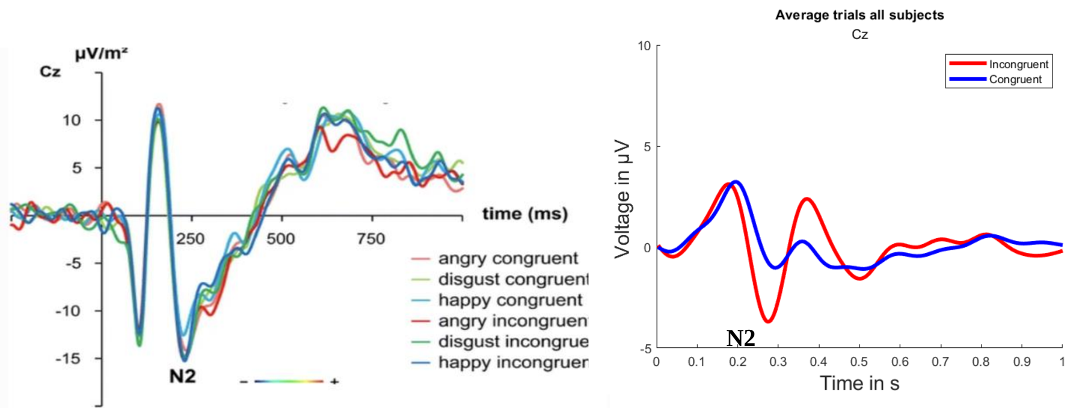


Figure 6.1: Left side) Stimulus-locked grand average waveforms at electrode Cz for congruent and incongruent trials (Schreiter et al 2018). Right side) Stimulus-locked grand average waveforms at electrode Pz for congruent and incongruent trials (our results). For both figures the N2 component is shown in bold.

In the time window of 450-550 ms, usually associated with the N450, we found a small component with a negative deflection due to incongruent trials being more negative than congruent trials.

In the time window of 500-750 ms, where the SP (linked to conflict resolution) is usually reflected, incongruent trials showed an increased positivity compared to congruent trials.

Most Stroop Studies have reported statistically significant differences between Congruent and Incongruent trials for the N450 (Fan et al., 2016), SP(Chen et al., 2016), or both (Ma et al., 2016; Xue et al., 2016). However, our results do not show statistical significance for any of these components.

The differences in components obtained between our study and other studies might be derived from the two differences between our and other Facial Emotional Stroop Tasks. All the Facial Emotional Stroop studies found (Chen et al., 2016; Fan et al., 2016; Huang et al., 2021; Ma et al., 2016; Maier et al., 2016; Schreiter et al., 2018b, 2018a, 2019; Xue et al., 2016) required participants to perform an extra activity beyond thinking, whether this is pressing a button or performing a physical movement to identify the facial expression. Besides that, all the studies show the two attributes of the stimuli (face and word) at the same moment, while we first present the face and shortly after present the face with the label on top. The act of first identifying the face and then comparing it to an additional label has a different effect than looking at two distinct stimuli (face and label) and identifying them at the same time. Nevertheless, we consider this to be a positive characteristic of our task, the ability to study neuronal processes involved in error monitoring without interferences of motor response.

We also found another positive component, in the time window of 350-450 ms, reflective of the bigger amplitude of incongruent trials in relation to congruent trials, however, this component has not been reported on any other Stroop Task.

Error Potential Studies

The difference waveform for the difference (Incongruent-Congruent) is comparable to those obtained in Chavarriaga & Millan, 2010; Iturrate et al., 2015; Spüler et al., 2012.

Chavarriaga & Millan, 2010 performed a task in which users had to monitor the action of an external agent. The error potentials elicited by the task possessed a first negative peak at 260 ms, the Ne, followed by a positive peak at 330 ms, the Pe. Our neurophysiological responses have a first negative peak at 260 ms, followed by a positive peak at 380 ms. Our topographical maps of the difference waveform show a central and fronto-central focus for the peaks. In the literature, these are the regions associated with error monitoring.

Altogether these findings lead us to believe that our first peak might represent the Ne/ERN, while the consecutive peak may represent the Pe and that we can classify our signals as Error Potentials. The exploratory analysis made regarding participants (Gender, BCI experience, Nationality) and experience characteristics (Emotions used, Gender of the faces presented) seem to suggest that error signals produced are not influenced by any of these conditions.

The results regarding participants BCI experience reveal that any new (typically developing) user can carry out this task, although BCI experience might have influenced the results.

Studies that have compared neural correlates of the presentation of female and male faces tasks have not drawn definite conclusions on the topic. Our results seem to agree with those who claim there are no electrophysiological differences between error potentials as a function of gender (Larson et al., 2011; Li et al., 2009).

The analysis we performed based on the nationality of the participants (Portuguese x Foreign) did not reveal any significant differences between groups. (Fan et al., 2016) used a similar task and varying the language used to produce incongruence (Participant's mother language vs second language) discovered that the second language was less automatic to the activation of emotional content. Since we only used foreign participants' second language, we cannot draw any direct conclusions. In our task, we only used the first letter of the two chosen emotions, as opposed to the full word. Even though it still requires foreign users to make an association between the letter and the facial expression, it facilitates the task.

Taking all of this into account, our results suggest that the Facial Emotional Word Stroop Task proposed here can elicit Error Potentials, provoked by differences in congruency. EEG correlates during an emotional task are of great interest for investigating both error and emotional processing. We also found that the Stroop component N2 possessed the same distribution and latency as the error-monitoring component Ne/ERN. This leads us to believe that they may represent the same component.

6.2 Significance of the online results

The online results show that single-trial error detection is possible using an Emotional Stroop Task. Parashiva & Vinod, 2022 used a rapid serial visual presentation, with incorrect associations between objects and audio, and text labels and obtained similar classification results. To our knowledge, this is the first time a potential elicited by a facial Emotional Stroop Task can be classified on a single-trial basis.

Most Participants performed similarly between tasks, (difference< 8%), however, participant S5 showed a substantial increase from Calibration to the Online Task. This can be explained by habituation to the task (and therefore bigger automaticity in doing the associations). As expected, participants who performed better in the Calibration Task had higher performances in the Online Task. BCI users (S2, S5, S10) performed better than non-BCI users, which might have to do with the ability to focus for extended periods, something that is needed for this type of task. Congruent and Incongruent trials were detected at a similar rate (Incongruent= 65.7%, Congruent=69.9 %), however, specificity was higher than sensitivity for every participant except participant S6. This is expected as the number of Congruent (correct) trials used to create the classification model was much larger than the number of Incongruent (incorrect) trials. One approach to overcome this issue could be increasing the number of errors used during the calibration task, however, 15-30% are the error rates of studies that have shown successful results (Ferrez & del R. Millan, 2008; Iturrate et al., 2013). Also, Stroop Studies involving different rates of congruent and incongruent trials claim that there are stronger responses to incongruent trials when there is a larger proportion of congruent trials (Chen et al., 2016). Another approach would be increasing the number of sessions in calibration, however, this could result in a bigger loss of focus and decrease the quality of the signal, as the calibration task is already tiresome.

The results obtained are far from those seen in other tasks that use ErrPs as a means of communication (Cruz et al., 2018; Kim et al., 2017). As seen in section 3.2 the ErrPs evoked in these tasks can successfully control and or correct the performance of machines used in real-time. Even though our results cannot reliably achieve that goal, they prove error signals evoked in emotional contexts are classifiable. The development of a BCI that makes use of error signals elicited in an emotional context might prove very useful in improving social cognition. Social Cognition includes various competences and cognitive skills required to recognize social stimuli and react accordingly. ASD subjects, as previously said, present deficits regarding functions of

SC, so, tasks that can help improve and reinforce ‘positive’ behaviors are potentially helpful. The approach developed here could be turned into a gamified BCI application, where to successfully “play” the game, participants must be focused and correctly evaluate the presented stimulus.

6.3 Interaction Potential

One of our secondary goals was to understand if an Interaction Error Potential would occur when the BCI feedback was not the one expected by the user (error of the BCI). If the evoked answers in the ‘Interaction’ part of the task (the moment when the feedback of which face the interface detected is presented to the user) could be classified, they could help in two separate ways. First, they could help us understand if a correct evaluation of the facial expression (presented in the first part) was made. For example, if the participant considers the facial expression presented to be happy, but the system detects a sad facial expression, then it is presumed that an error response, time-locked to the moment of the presentation of the feedback, occurs. If that does not happen, then that might indicate that there are alterations regarding the participant’s emotion recognition system. Besides working as an indicator of emotion recognition, the results given could help improve the accuracy of the classifier and reinforce the error-monitoring system. Yet, the low classification accuracy of congruent vs incongruent detection derails this purpose, providing the user with misclassifications, which may have affected users’ evaluation of feedback. Waveforms of Interaction-ErrPs were very oscillatory and variable between subjects. Although not the same, our Interaction-ErrP shows some resemblances with the Interaction Potentials obtained by (Ferrez & del R. Millan, 2008). These were characterized by a first positive peak at 200 ms, a first negative peak at 250 ms, a second positive peak at 320 ms, and a second negative peak at 450 ms. We have a first positive peak at around 150 ms, a first negative peak at 220 ms, a second positive peaking at 490 ms and after it a negative peak at 610ms. We have however a negative peak occurring at 220 ms and a third positive peak occurring at 750 ms, for which we could not find any direct correlate.

Other reasons can be pointed out to the untypical waveform of the interaction-ErrP, namely, the way the feedback is shown may be confusing about what the participants should do, and on the other hand the long trial with a sequence of several cognitive processes.

The distribution of EEG activity obtained from topographical maps still leave us uncertain regarding the focal point of the potentials. This could mean that the participant did not understand that the feedback provided was related to the facial expression recognition, and therefore he did not make a mental distinction between error and correct trials. However, the mechanical feedback given by participants, which in percentage was the same as the number correctly reported, revealed that they were able to relate the facial expression observed (the participants clicked the mouse in every successful single trial). Given the results achieved, it was not possible to be sure that the participants identified the system’s incorrection as an error. Perhaps, altering the way we provide feedback could clarify this issue. The classification results were worse when compared to the ones obtained with the Error Potentials of the Calibration Task. This is not a surprise given that the number of trials in every subject is much smaller when compared to those of the calibration task.

The overall results show us that there is still progress to be made regarding the BCI feedback, and that to provide more concrete results, more experiments ought to be made.

6.4 Limitations and Future Directions

The fulfillment of this study with a bigger number of participants would provide more sustainable conclusions. There were also some technical issues related to the photodiode which led to the loss of data. It required successive check-ups during the experiment, to ensure that it was properly attached to the monitor. Besides affecting data, this issue caused some experiments to take longer than expected. The experiment is already quite long, so further delays only make increase tiredness in participants, which then can be reflected in their performance. The next step could encompass the usage of another software for stimulus presentation.

For this first version of the paradigm, we only used two emotions, and very expressive ones. Future iterations could encompass more subtle facial expressions as well as other emotions, to compare the differences with the evoked results. A paper by Sexton, 2015 discussed the importance of using rewards of social stimuli to participants engaging in BCI tasks. Taking this into account, one of the modifications involved could be displaying the feedback of the interface with pictures instead of words. As a first demonstration of the proposed paradigm, we have made use of a very straightforward classification approach. In the future, other approaches could be used to increase the performance of the BCI, reduce calibration time and increase usability.

7. Conclusion

The main goal of this work was to implement a neurofeedback BCI system, which could be used to train social and cognitive skills in ASD. For that purpose, we designed a Face Word Emotional Stroop Task, to investigate the cognitive processes related to Facial Emotion Recognition and error detection. For validation of that paradigm, we tested the task on ten healthy subjects and used the responses to train a classification model. Finally, we implemented that classification model in an EEG-based BCI and obtained results for single-trial detection of the evoked potentials.

The results obtained show that the Face Word Emotional Stroop Task designed produces specific responses regarding congruent and incongruent trials that can be decoded in real-time with different rates of success, validating the task. The neurophysiological evidence obtained by this paradigm is similar to those of studies involving error monitoring tasks, which leads us to believe that these can be considered Error Potentials. When compared to the responses of other Facial Emotional Stroop Studies, our results fail to display the existence of some its most recognizable components (N450, SP). Regarding the interaction error potential (resulting from the BCI performance evaluation by the user), we were able to detect differences between Error and Correct Trials, suggesting that an ErrP is elicited. However, offline analyses failed to show successful classification of these signals, leading us to reconsider the design of this part of the task.

In sum, the conducted experiments conducted show the feasibility of using an emotional context to elicit an intuitive brain pattern (error potential) and lay the possibility of using the paradigm proposed in a social cognition training approach.

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9. ANNEX A

The following figure (Figure 9.1) presents individual r-squares for the calibration session of the emotional Stroop Task.

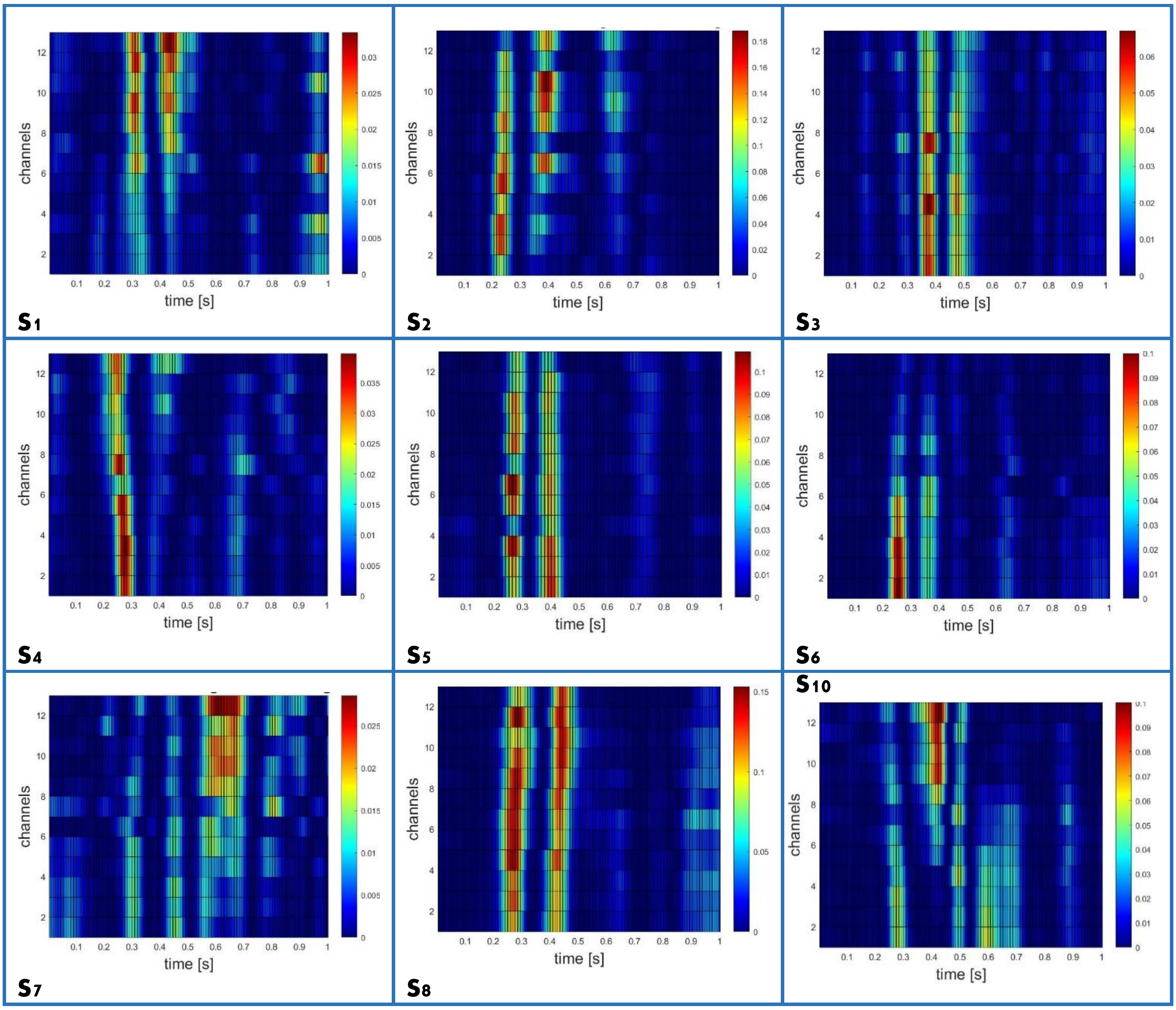

Figure 9.1: R square for Incongruent and Congruent trials of all twelve channels, for participants S1, S2, S3, S4, S5, S6, S7, S8, S10, respectively.