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EEG Functional Connectivity Measures for Emotional Processing Analysis

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A thesis submitted in partial fulfillment of the requirements for the degree of
Doctor in Electronic Engineering

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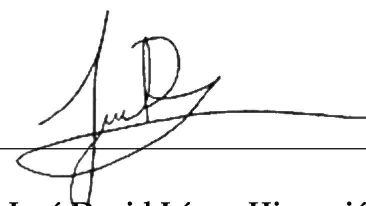
This thesis entitled "EEG Functional Connectivity Measures for Emotional Processing Analysis" prepared and submitted by Andrés Quintero Zea in partial fulfillment of the requirements for the degree of Doctor in Electronic Engineering has been examined and recommended for final defense.



José David López Hincapié
Advisor

Declaration of Authorship

I, Andrés Quintero Zea, declare that this thesis entitled, 'EEG Functional Connectivity Measures for Emotional Processing Analysis' and the work presented in it are my own. I confirm that:

- This work was done wholly while in candidature for a research degree at this University.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
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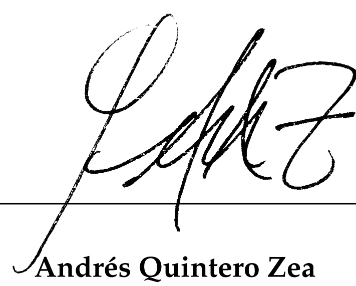

Andrés Quintero Zea
February 22nd, 2019

To my family and friends.

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Abstract

Emotional processing (EP) is necessary for the analysis of everyday situations and for the expression of social cognition and behavior (SCB) patterns. In ex-combatants, EP is affected by chronic exposure to violent events. For a successful reintegration into society, it is necessary to characterize their brain responses to emotional stimuli, as a first stage to develop interventions in mental health. In the present work, we present three approaches to assess emotional processing and its relation with SCB dimensions, such as aggression and social skills, in a sample of 50 subjects, 30 ex-combatants from illegally armed groups in Colombia and 20 controls without combat experience. To achieve this objective, we use EEG data from an emotion recognition task for faces and words. In the first approach, we implement a SVM classifier using features extracted from event-related potentials. Classification rate is improved by incorporating SCB features. For the second approach, we extract features from functional connectivity network (FCN) to discriminate the neural reorganization in ex-combatants from controls. In this approach, we use a feature fusion scheme based on canonical correlation analysis for integrating SCB scores. Finally, we perform a canonical correlation analysis to explore relations among FCN and behavioral variables related to performance in the task. In general, the proposed approaches provide new empirical knowledge on the atypical EP in ex-combatants elicited by a neural reorganization.

Keywords

EEG, Emotional processing, Ex-combatants, Functional connectivity, Social cognition.

List of acronyms

CCA	Canonical correlation analysis
CCDF	Canonical correlation discriminant features
COH	Coherency
D	Diameter of the MST
DDR	Disarmament, demobilization, and reintegration
EEG	Electroencephalography
EOG	Electrooculography
EP	Emotional processing
ERP	Event-related potentials
ERT	Emotion recognition task
FC	Functional connectivity
FCN	Functional connectivity network
fMRI	Functional magnetic resonance imaging
G-RBF	Gaussian radial basis function
GSSS	Global social skills score
GTA	Graph theoretical analysis
ICA	Independent component analysis
iCOH	Imaginary part of coherency
ISI	Interstimulus interval
LF	Leaf fraction of the MST
M	Mean value
MD	Maximum degree of the MST
MEG	magnetoencephalography
MST	Minimum spanning tree

NIMH	National Institute of Mental Health
RDoC	Research Domain Criteria
RFE	Recursive feature elimination
ROI	Region of interest
RPQ	Reactive-Proactive Aggression Questionnaire
SCB	Social cognition and behavior
SD	Standard deviation
SEM	Standard error of the mean
SSS	Scale of social skills
SVD	Singular value decomposition
SVM	Support vector machine
SVM-RFE	Support vector machine recursive feature elimination

Notation and symbols

Notation

$a, b, c, \alpha, \beta, \gamma$	Scalars
$\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}$	Vectors
$\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C}$	Matrices
a_{ij}	ij-th element of matrix $\boldsymbol{A}$
$\boldsymbol{A}^\top$	Transpose of matrix $\boldsymbol{A}$
$\boldsymbol{A}^{-1}$	Inverse of matrix $\boldsymbol{A}$
$\langle \boldsymbol{x}, \boldsymbol{y} \rangle$	Inner product of $\boldsymbol{x}$ and $\boldsymbol{x}$
$k(\boldsymbol{x}, \boldsymbol{y})$	Kernel function among $\boldsymbol{x}$ and $\boldsymbol{x}$
$(\boldsymbol{x}, y)$	Training instance tuple
$\mathbb{R}^n$	n-dimensional vector space of real numbers
$\mathbb{R}^{n \times m}$	nm-dimensional vector space of real numbers
$\lvert \cdot \rvert$	Absolute value
$\lVert \cdot \rVert$	Euclidean norm
$\mathrm{Im}\{\cdot\}$	Imaginary part of a complex number
$\mathrm{sgn}(\cdot)$	Signum function
$\min(\cdot)$	Minimum value
$\mathrm{rank}(\boldsymbol{A})$	Rank of matrix $\boldsymbol{A}$

Symbols

N_a, N_b	Number of features before performing CCA
N_c	Number of electrodes
N_p	Number of participants (or instances)
$S_{ii}(f)$, $S_{jj}(f)$	Autospectral density from electrodes i and j, respectively, at frequency f
$S_{ij}(f)$	Cross-spectral density from electrodes i and j at frequency f
T	Threshold value

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Chapter 1

Introduction

Colombia is an upper-middle-income country that has been challenged by the adverse effects of internal conflict for more than six decades (Denissen, 2010). A central challenge in definitely bringing internal conflicts to an end is the reintegration of illegal combatants into civilian life. Recently, the Reincorporation and Normalization Agency (ARN)[1] has been leading disarmament, demobilization, and reintegration (DDR) programs with illegal armed groups in Colombia (Kaplan and Nussio, 2015). Previous studies in ex-combatants have informed that DDR programs involve at the same time social, political and economical (Denissen, 2010; Thorsell, 2013) risks.

Recidivism is among the related social problems in DDR programs. Multiple reasons to return to violent and illicit behavior have been identified, such as social cognition impairments, unstable family liaisons, lack of educational attainment, and the presence of illegal groups (Kaplan and Nussio, 2016). Combatants have a high possibility of developing aggressive behavior traits (Baez et al., 2017; Weierstall et al., 2013) elicited by their exposure to numerous forms of extreme violence (Köbach et al., 2015). Several studies have found aggression traits to be highly correlated with recidivism of ex-combatants, and profoundly affect their overall experience of reintegration into Colombian society (Kaplan and Nussio, 2016; Rodríguez López et al., 2015). Moreover, ex-combatants exhibit atypical modulation of the emotional processing (EP) during valence recognition lead by adaptive mechanisms elicited by chronic exposure to war experiences (Tobón et al., 2015; Trujillo et al., 2017b).

EP as part of social cognition is associated with the evaluation, the behavioral regulation, and the analysis of the feedback derived from social interaction (Couto et al., 2013; Petroni et al., 2011). Particularly, the neurophysiological organization of EP have been studied in healthy individuals as well as in clinical samples (Doose-Grünefeld et al., 2015; Luyster et al., 2017; Müller et al., 2018; Pera-Guardiola et al., 2016). Furthermore, previous studies in military-related posttraumatic stress disorder (PTSD) have informed resting state connectivity alterations in the salience network and the default mode network (Kennis et al., 2016), as well as phenotypic data related to hyporeactivity to angry faces (DiGangi et al., 2017); however, there is limited evidence that explore EP brain connectivity in subjects exposed to chronic violent events without a PTSD

[1] http://www.reintegracion.gov.co/en

diagnosis.

Additionally, aggressive behavior in patients with neurological disorders or those who have suffered traumatic brain injury have been associated with dysfunctions in an affective regulation network encompassing the amygdala and prefrontal cortex areas (Bufkin and Luttrell, 2005; Klasen et al., 2013). In ex-combatants, the characterization of such network remains an open issue. Research into this topic would provide the possibility of identifying phenotypic data to help improving the design of social cognitive and behavioral trainings.

Graph theoretical analysis (GTA) has been widely used in the research of functional connectivity network (FCN) (Bullmore and Sporns, 2009; Stam and Reijneveld, 2007) and it provides tools to characterize network topology. The power of GTA consists on the detection of the so-called small-world network architecture (Bassett and Bullmore, 2006, 2009; Sporns and Zwi, 2004; Uehara et al., 2014). Disruption of the small-world network and randomization of network topology have been consistently related to neuropsychiatric diseases such as Alzheimer's disease (Stam et al., 2009; Stam and Reijneveld, 2007), depression (Li et al., 2015), and schizophrenia (Jalili and Knyazeva, 2011). Small-world network analysis provides information on how EP alters functional connectivity (FC) between brain regions (Kinnison et al., 2012) and it is useful in characterizing brain organization as a FCN during emotion-related processing (Ma et al., 2012; Rutter et al., 2013).

A successful small-worldness analysis relies on computing the optimal threshold for community detection in brain connectivity networks. However, finding an objective criterion for selecting such a threshold is not trivial and often obligates researchers to repeat their analysis in a range of several increasing thresholds (De Vico Fallani et al., 2014). This pitfall can be tackled by performing GTA of FCN using minimum spanning tree (MST), a graph method that corrects for comparison bias (Stam et al., 2014). MST analysis is also preferable to conventional GTA as it provides a normalized comparison between conditions or groups (Tewarie et al., 2015). A small-world network efficiently combines local specialization and global integration (Tewarie et al., 2015), which can be addressed in MST analyses by an increased MST diameter and decreased leaf fraction (Boersma et al., 2013; Chen et al., 2018).

Further analyses over the FCN metrics extracted from the graph (or tree) can be grouped into three approaches: (a) Hypothesis testing focused on the group differences, (b) statistical modelling for determining relations among FCN and behavioural outcomes, and (c) machine learning approaches to separate groups of brain graphs (De Vico Fallani et al., 2014). From these approaches, machine learning ones are preferable as they can deal with correlated and non-Gaussian variables. Besides, machine learning can identify the existence of patterns within behaviorally homogeneous populations, which can be interpreted as a neurophysiological marker or phenotype that helps characterizing the majority of the population under evaluation (John et al., 1992; Johnstone et al., 2005).

Numerous reports suggest the presence of FCN phenotypes within behaviorally homogeneous populations. For instance, Jamal et al. (2014) presents a supervised learning approach for classification of autism spectrum disorder from normal control using GTA from the FCN measures extracted from synchrostates with high accuracy (94.7% with SVM and four network measures). This study does not account for threshold computing, performing the GTA over the full graph. In (Jie et al., 2014), a FCN-based classification framework to identify mild cognitive impairment patients from normal controls is proposed, which involves the use of a graph-kernel-based approach to measure directly the topological similarity between connectivity networks achieving a classification accuracy of 91.9%. The main limitation of this study is that the performance of the proposed method may be affected by the unbalanced data, leading to overoptimistic results. Plitt et al. (2015) compares the performance of a FCN-based classifier with one based on behavior metrics to discriminate between autism spectrum disorder and controls. The accuracy achieved using behavior metrics outperforms the accuracy achieved with FCN metrics, suggesting that a combined analysis could lead to better classifications.

From these works, two main gaps have been identified: (a) How to assess if there is a functional reorganization during EP functional connectivity in individuals chronically exposed to combat, and (b) how to use such information to identify phenotypic data related to EP in ex-combatants. In this thesis, we devise a methodology aimed to examine the association of aggression with the neural correlates of EP in ex-combatants. Specifically, we implement a neuroscience-based classification scheme that integrates two different levels of information. First, Electroencephalography (EEG) data acquired with an emotion recognition task to assess potential disruptions or specific reorganization of the FCN that could be associated with the exposition to war experiences. Second, social cognition and behavior (SCB) evaluations that included the reactive-proactive aggression questionnaire (RPQ) (Raine et al., 2006) and the Scale of Social Skills (SSS) of Gismero (2000).

1.1 Objectives

To develop a methodology for comparing and analyzing EEG data from emotional tasks by performing connectivity analysis, to improve the estimation of the emotional processing in ex-combatants.

To accomplish this objective, we defined the following three specific objectives.

O1. To critically review the literature of connectivity strategies used to estimate emotional processing, testing those that are feasible to combine with EEG brain imaging techniques.

O2. To establish a model to perform an efficient estimation of the emotional processing, in terms of separation of classes between ex-combatants and controls when tested with the available tasks.

O3. To determine and implement a methodology for validating the model and comparing its performance with other state of the art approaches.

1.2 Outline

The chapters of this thesis are organized as follows. Chapter 2 gives the background concepts to help understanding the problem and methods. It begins with a definition of emotional processing, followed by the theory related to electroencephalography. This chapter continues introducing the general framework to functional connectivity network analysis. Thereafter, the chapter presents the theory to support vector machine classification. Finally, the rationale into canonical correlation analysis as a feature fusion technique is presented.

Chapter 3 presents the experimental setup, beginning with a description of the participants and the protocol to assess the social cognition and behavior scores. This chapter finally presents the steps involved in the acquisition and preprocessing of EEG data.

In Chapter 4, we discuss a first approach to EP assessment based on ERP features and SCB scores. With this framework, we establish an analysis baseline to validate the hypothesis of atypical EP in ex-combatants, with the limitation that it does not provide enough information to infer possible disruptions in the underlying functional processes in the brain. This motivates the introduction of FCN analysis to help elucidating changes on the neural reorganization elicited by combat experience.

Once we establish that behavioral and brain function measures of EP may provide assessment of neural reorganization in ex-combatants, in Chapter 5 we propose a FCN-based approach to characterize the EP in such population. This methodology follows the recommendation of the National Institute of Mental Health (NIMH) Research Domain Criteria (RDoC) initiative[2] into integrating several levels of information.

The classification accuracy is improved using a recursive feature elimination strategy to select the most discriminant set of FCN features. On the other hand, we used canonical correlation analysis to fuse the FCN features with the SCB scores.

The comprehension of the functional reorganization of the face and word EP among ex-combatants will be crucial to design intervention strategies that complement DDR programs. Chapter 6 explores this phenomenon and its link to behavioral data from the emotion recognition task, namely reaction times and accuracies. For this aim, we perform classical statistical analysis to find significant differences between ex-combatants and civilians.

Finally, general conclusions, main contributions derived from this study, and future work are presented in Chapter 7.

1.3 Methodology

To accomplish the proposed objectives, we first reviewed the literature on connectivity methods applied to EEG data. This review yielded the selection of five potential connectivity indices: Correlation, Cross-correlation, Coherence, Imaginary part of Coherency and the Phase-Lag In-

[2] https://www.nimh.nih.gov/research-priorities/rdoc/index.shtml

dex. In (Rodríguez-Calvache et al., 2017), we performed a comparative analysis that resulted in the final selection of Imaginary part of Coherency as our coupling metric.

To perform the connectivity analysis, we opted for a machine learning approach over a classic statistical one. For this aim, we proposed an initial strategy presented in (Quintero-Zea et al., 2016). In this paper, we performed a graph-based analysis to extract regional connectivity information. We additionally implemented two machine learning techniques to discriminate ex-combatants from civilians. Classification accuracy was similar to other state-of-the-art strategies.

From (Quintero-Zea et al., 2016), we identified three challenges to focus on: (a) The definition of a region of interest may bias the analysis, (b) connectivity networks have to be thresholded, and (c) the classifier must have the ability to handle imbalanced data. To overcome these challenges, in (Quintero-Zea et al., 2018a), we proposed a whole brain analysis from minimum spanning trees to extract graph-based metrics. Such features were used as input to an SVM classifier, which can deal with imbalances in the dataset.

We identified the need of adding information from other domains. In (Quintero-Zea et al., 2017), we use psychological evaluations to increase classification accuracies. Results in detail are presented in Chapters 4 and 5.

Finally, we performed a canonical correlation analysis to assess how the functional connectivity is related with the behavioral performance of the subjects in the task. These results are presented in Chapter 6 and in (Quintero-Zea et al., 2019).

All the analysis were performed in the Fieldtrip toolbox for Matlab, this choice was based on the results presented in (Quintero-Zea et al., 2018b).

1.4 Publications

The main contributions of this thesis are to establish a characterization framework to assess EP in ex-combatants and to identify some FCN metrics that would serve as markers of EP.

Peer-reviewed journals

Quintero-Zea, A., López, J. D., Smith, K., Trujillo, N., Parra, M. A., and Escudero, J. (2018a). Phenotyping Ex-Combatants From EEG Scalp Connectivity. *IEEE Access*, 6:55090–55098

Quintero-Zea, A., Trujillo Orrego, N., López, J. D., Rodríguez Calvache, M., Trujillo Orrego, S., Escudero, J., and Parra, M. A. (2019). Neural Reorganization During Emotional Face Processing in Ex-combatants. (In preparation)

Rodríguez-Calvache, M. V., Quintero-Zea, A., Trujillo-Orrego, S. P., Trujillo-Orrego, N., and López-Hincapié, J. D. (2017). Detecting atypical functioning of emotional processing in Colombian Ex-combatants. *TecnoLógicas*, 20(40):83–96

Conference papers

Quintero-Zea, A., Rodriguez, M., Trujillo, S., Vargas-Bonilla, F., Trujillo, N., and López, J. (2016). EEG graph analysis for identification of ex-combatants: A machine learning approach. In *2016 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*, pages 1–6

Rodríguez-Calvache, M., Quintero-Zea, A., Trujillo, S., Trujillo, N., and López, J. D. (2016). Classifying artifacts and neural EEG components using SVM. In *2016 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*, pages 1–5

Quintero-Zea, A., Sepúlveda-Cano, L. M., Rodríguez Calvache, M., Trujillo Orrego, S., Trujillo Orrego, N., and López, J. D. (2017). Characterization Framework for Ex-combatants Based on EEG and Behavioral Features. In Torres, I., Bustamante, J., and Sierra, D. A., editors, *VII Latin American Congress on Biomedical Engineering CLAIB 2016, Bucaramanga, Santander, Colombia, October 26th-28th, 2016*, volume 60 of *IFMBE Proceedings*, pages 205–208. Springer Singapore, Singapore

Quintero-Zea, A., Rodríguez, M., Cano, M. I., Pava, K. M., Suaza, M., Trujillo, N., and López, J. D. (2018b). How Does the Toolbox Choice Affect ERP Analysis? In Figueroa-García, J. C., Villegas, J. G., Orozco-Arroyave, J. R., and Maya Duque, P. A., editors, *Applied Computer Sciences in Engineering*, pages 385–394, Cham. Springer International Publishing

Chapter 2

Background

THIS chapter presents some background for the research presented in this thesis. The chapter begins with the explanatory concepts of emotional processing in Section 2.1 and electroencephalography in Section 2.2. Thereafter, we discuss the theory concerning functional connectivity analysis in Section 2.3. The basis for support vector machines is presented in Section 2.4. Finally, Section 2.5 presents the theory of canonical correlation analysis.

2.1 Emotional processing

Emotional processing (EP) is a cognitive process based on the ability of understanding emotional information conveyed by stimuli or situations, including facial expressions and words with emotional content (Carretié et al., 1997). The process starts when the subject identifies changes in external or internal circumstances that involve differences in valence, operating as a trigger situation (Plutchik, 1980). EP is crucial for an adequate interpersonal functioning and it facilitates a rapid and appropriate response to the social context (Batty and Taylor, 2003; Plutchik, 2001).

Assessing how ex-combatants are processing emotional information is important to provide an adequate intervention training. EP can be estimated using task events synchronized with neural acquisition techniques such as electroencephalography (EEG) and magnetoencephalography (MEG). EEG and MEG are preferred over other functional imaging techniques because several studies have evidenced that emotional stimuli are recognized and differentiated within the first 200 to 250 ms after their presentation, and fMRI is known to have a poor temporal resolution (Knyazev et al., 2010).

2.2 Electroencephalography

EEG is an electrophysiological technique to represent the electrical activity of the brain as recorded from N_c electrodes placed on the scalp. Due to its high temporal resolution, the main utility of EEG is in the evaluation of the brain dynamics (Rodichok, 1995).

EEG can be acquired during resting state or task related procedures. The first paradigm is believed to reflect intrinsic activity of the brain (van Diessen et al., 2015) which may reveal information on the so-called default mode network (Scheeringa et al., 2008). However, power spectra of resting state EEG is highly noisy and becomes a non-reliable way for extracting personality traits (Korjus et al., 2015). In task related paradigm, the EEG is recorded while the subject performs a specific motor or cognitive task. In this thesis, we work with EEG acquired from a task designed to stimulate emotional processes in the brain.

The acquired EEG signals may be characterized by well-defined rhythms that have specific frequencies. Spectral analysis is used to identify brain-wave characteristics by frequency range. These ranges have traditionally been labeled as delta waves (less than 4 Hz), theta waves (4 to 7 Hz), alpha waves (8 to 13 Hz), beta waves (13 to 30 Hz), and gamma waves (above 30 Hz) (Afshari and Jalili, 2016).

Task related EEG waveforms may also be averaged, giving rise to evoked potentials and event-related potentials (ERPs), that represent neural activity of interest that is temporally related to a specific stimulus. ERPs are used in clinical practice and research for analysis of neural mechanisms underlying EP (Balconi and Pozzoli, 2003; Kissler et al., 2009; Rawls et al., 2018).

2.3 Functional connectivity networks

Traditional ERP analyses in the time domain do not allow elucidating how functional interactions among different brain regions take place. In our case, exploring potential disruptions or specific reorganization associated with combat experience may provide valuable information for designing interventions in mental health. To provide answers on this subject, a widely-used approach is the so-called functional connectivity (FC). FC refers to linear or nonlinear statistical interdependencies between time series of recorded signals from EEG sensors (Friston, 1994). FC is assumed to reflect functional interactions among the underlying brain regions (Stam et al., 2009).

A general framework for EEG FC analysis comprises five steps (see Figure 2.1):

1. Nodes definition. EEG FC is a sensor-based analysis. Nodes can be assigned directly to sensors, to reconstructed cortical sources, or to regions of interest (ROIs).

2. Links estimation. In functional neuroimaging, the links of a brain graph are given by evaluating the similarity between two brain signals, through FC measures.

3. Graph filtering. Spurious links must be discarded by maintaining only those links whose weight corresponds to significant FC such as correlation, coherence, or phase lag index.

4. Graph metrics extraction. Brain networks can be characterized using topological properties of their graphs. Depending on the nature of the neuroimaging experiment, the FC method and the filtering threshold, some graph indices can result in being more appropriate than other ones.

5. Classification. After extracting topological metrics from the graph, the final step is to classify them to obtain potential markers.

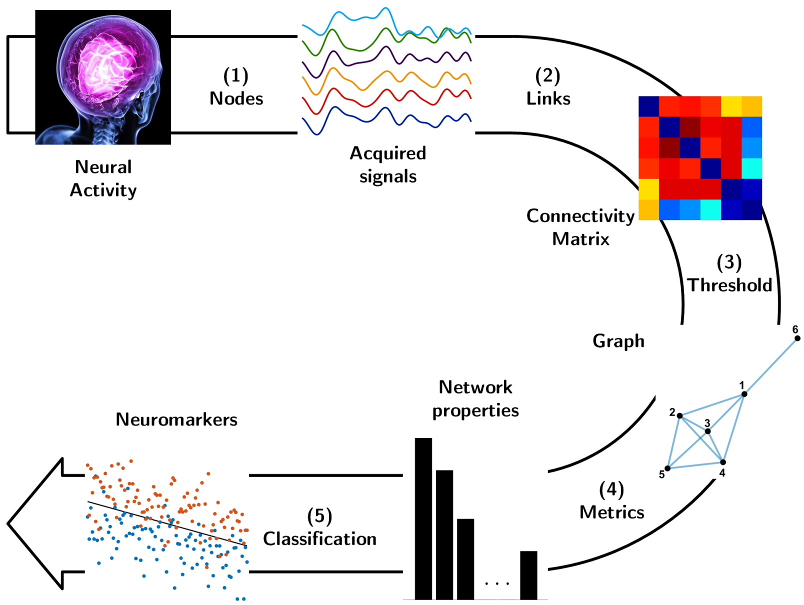


Figure 2.1: ***Pipeline for functional connectivity network modeling and analysis.*** *(1) Nodes correspond to EEG electrodes. (2) Links are estimated by measuring the FC between the time series of nodes; this information is held in a connectivity matrix. (3) Most relevant links are retained using a filtering procedure to constitute the brain graph. (4) The topology of the brain graph is quantified by different graph metrics. (5) These graph metrics are input to a classifier to look for potential neuromarkers. This figure was adapted from De Vico Fallani et al. (2014).*

2.3.1 Construction of networks

A functional connectivity network (FCN) is constructed through FC measures. EEG electrodes are likely to acquire activity of identical sources, resulting in strong correlations between recorded signals that reflect simple volume conduction rather than true FC (Nunez et al., 1997). To overcome this pitfall one may either study relations among time series of reconstructed sources or estimate links using techniques that extract relations among signals which are not due to volume conduction (Stam et al., 2009). The major pitfall of working with reconstructed sources time series is the absence of a unique solution and the lack of a reliable way to decide which model is the proper choice. Therefore, we limit this work to sensor level connectivity.

In Rodríguez-Calvache et al. (2017), we demonstrated that the imaginary part of the coherency between two signals proposed by Nolte et al. (2004) is a reliable way to estimate the functional connectome. Coherency is a measure of the linear relation between two EEG electrodes at a specific frequency (Nolte et al., 2004) that is less prone to effects of the volume conduction (Sekihara and Nagarajan, 2015). For two different time series of electrodes i and j, the coherency at each frequency (f) is defined as

$$\mathrm{COH}_{ij}(f) = \frac{S_{ij}(f)}{\sqrt{S_{ii}(f)\, S_{jj}(f)}}, \tag{2.1}$$

where $S_{ij}(f)$ is the cross spectrum of the signals acquired from electrodes i and j, while $S_{ii}(f)$ and $S_{jj}(f)$ are the respective autospectra for a given frequency f. From this formula, we only work with the imaginary part (iCOH) that captures true source interactions, which means that whenever it produces significant values some coordinated activity is taking place.

From a physiological point of view, EEG coherency reflects functional interactions among those brain areas under study (Babiloni et al., 2011). Therefore, higher values of coherency denote that two brain regions are working synchronized at a specific frequency.

The result of the FC estimation between all pairs of sensors leads to $N_c \times N_c$ relations that can be represented by a symmetric matrix $\boldsymbol{W} \in \mathbb{R}^{N_c \times N_c}$, containing all pairwise FC measures $w_{ij} = \mathrm{Im}\{\mathrm{COH}_{ij}\}$ corresponding to the weighted links of the brain graph. To avoid spurious relations, only the significant ones must be retained for further analysis. This process is known as graph filtering.

Graph filtering

FC measures can be affected by various non-neural phenomena, and possible difficulties related to the statistical uncertainty on the link weights can arise when interpreting the resulting extracted graph metrics (De Vico Fallani et al., 2014). To overcome this problem, it is good practice to filter the matrix $\boldsymbol{W}$ to retain only those links whose weight corresponds to significant FC.

A common approach for filtering is to fix an arbitrary threshold $T \in \mathbb{R}^+$ and remove the links whose weight w_{ij} is lower than it. This method may add bias and lead to misinterpretations of the topological metrics (De Vico Fallani et al., 2014; Stam et al., 2009; Stam and Reijneveld, 2007). A better way to filter $\boldsymbol{W}$ is to find the minimum spanning tree (MST) (Stam et al., 2014). The MST fully connects N_c nodes with $N_c - 1$ edges with low connection density and without forming loops. Analysis of the MST may be helpful as it avoids methodological biases when comparing networks (Tewarie et al., 2015). Two major algorithms have been described to construct the MST of a weighted graph (Kruskal, 1956; Prim, 1957). Here, we implement Kruskal's algorithm (see Algorithm 2.1). Prim's method produces the same MST if the weights of the original graph are unique.

2.3.2 Graph theoretical analysis

Graph theoretical analysis (GTA) provides a widely used framework to understand the topology of the brain FCN (Bullmore and Sporns, 2009; Stam and Reijneveld, 2007). Modern network science has developed a large number of measures to characterize the topology of complex net-

ALGORITHM 2.1: *Kruskal-MST*

Input: Graph $G = (V, E)$
Output: A minimum spanning tree of G

```
A ← ∅
foreach v ∈ V do
    MakeSet(v)
end
sort the edges of E in non-decreasing order
foreach e = {a, b} ∈ E, where e is taken in sorted order do
    V_a ← Find(a)
    V_b ← Find(b)
    if V_a ≠ V_b then
        A ← A ∪ {e}
        Merge(V_a, V_b)
    end
end
return A
```

works. These metrics are often linked to a particular filtering method. For instance, a tree does not reflect some properties, particularly those that depend upon cycles, such as clustering coefficient (Stam et al., 2014). In this work, we characterize the MSTs using three common metrics (Latora and Marchiori, 2001; Tewarie et al., 2015):

- Leaf fraction (LF): Fraction of leaf nodes in the MST network, where a leaf node is defined as a node with degree one. This measure is particularly useful to quantify the extent to which a tree is more pathlike (LF = $2/N_c$) or more starlike (LF = $1 - 1/N_c$). A high leaf fraction suggests that the communication of a network is largely dependent on hub nodes.

- Maximum degree (MD): Degree of the node with the highest number of links. A high value of MD denotes the existence of hubs within the tree. In a pathlike tree MD is two, while in a star MD is equal to the number of edges ($N_c - 1$).

- Diameter (D): The largest-shortest path length between any two nodes in the graph. The global efficiency in the communication of the tree can be defined to be inversely proportional to D. A pathlike tree has the worst efficiency with a diameter equal to ($N_c - 1$). In the case of a star, the diameter is two, leading to a high efficiency. Information may be efficiently processed between remote brain regions with low diameter.

2.4 Support vector machines

A support vector machine (SVM) is a discriminative classifier developed on statistical learning theory by Vapnik (1995) and modified by Cortes and Vapnik (1995). An SVM consists of supervised learning models that recognize patterns with classification purposes. An SVM aims to find a hyperplane that best divides a dataset into two classes.

2.4.1 Hyperplane classifiers

To describe SVMs, it is important to understand what a hyperplane classifier is. To this aim, consider the empirical data

$$(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_{N_p}, y_{N_p}) \in \mathcal{H} \times \{\pm 1\}, \tag{2.2}$$

where $\mathcal{H}$ denotes some inner product space from which the patterns $\boldsymbol{x}_i$ are taken; and the y_i are called labels. Furthermore, consider the hyperplanes

$$\langle \boldsymbol{w}, \boldsymbol{x} \rangle + b = 0, \tag{2.3}$$

where $\boldsymbol{x}, \boldsymbol{w} \in \mathcal{H}$ and $b \in \mathbb{R}$, which corresponds to the decision function

$$f(\boldsymbol{x}) = \operatorname{sgn}\left(\langle \boldsymbol{w}, \boldsymbol{x} \rangle + b\right). \tag{2.4}$$

Among all hyperplanes separating data, there is a unique optimal one, given by the maximum margin of separation between any training point and the hyperplane (see Figure 2.2 for a graphical representation of the geometrical problem). The optimal hyperplane can be found by solving the constrained optimization problem

$$\begin{aligned} \underset{\boldsymbol{w} \in \mathcal{H},\, b \in \mathbb{R}}{\text{minimize}} \quad & J(\boldsymbol{w}) = \frac{1}{2} \|\boldsymbol{w}\|^2 \\ \text{subject to} \quad & y_i(\langle \boldsymbol{w}, \boldsymbol{x}_i \rangle + b) \geq 1, \quad i = 1, \ldots, N_p. \end{aligned} \tag{2.5}$$

Problems of this kind are dealt with by the introduction of Lagrange multipliers $\alpha_i \geq 0$ and a Lagrangian

$$L(\boldsymbol{w}, b, \boldsymbol{\alpha}) = \frac{1}{2} \|\boldsymbol{w}\|^2 - \sum_{i=1}^{N_p} \alpha_i (y_i(\langle \boldsymbol{w}, \boldsymbol{x}_i \rangle + b) - 1). \tag{2.6}$$

The Lagrangian L is minimized with respect to the primal variables $\boldsymbol{w}$ and b, and maximized with respect to the dual variables α_i.

Taking the derivatives of L with respect to the primal variables and setting them equal to zero leads to

$$\sum_{i=1}^{N_p} \alpha_i y_i = 0 \tag{2.7}$$

and

$$\boldsymbol{w} = \sum_{i=1}^{N_p} \alpha_i y_i \boldsymbol{x}_i. \tag{2.8}$$

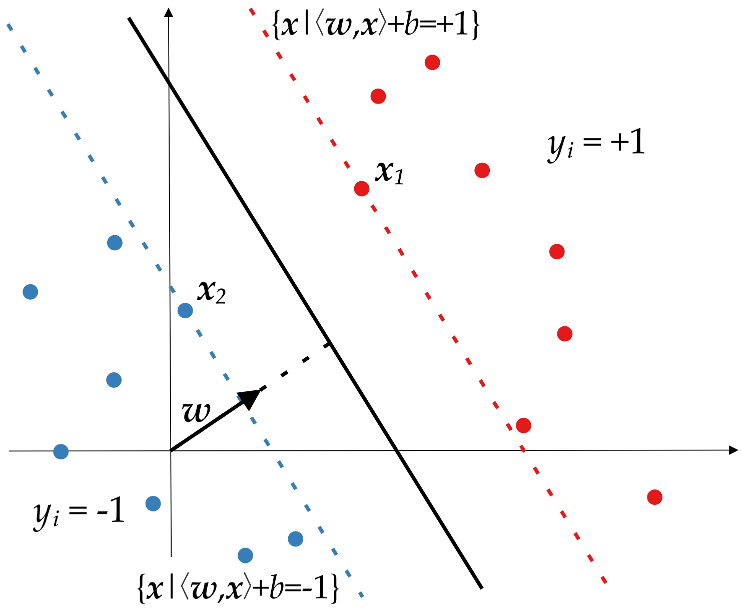


Figure 2.2: ***Binary classification toy example.*** *The optimal hyperplane is shown as a solid black line. The support vectors lie on the dashed line margins.*

By substituting (2.7) and (2.8) into (2.6), the so-called dual optimization problem is obtained

$$\begin{aligned} \underset{\alpha \in \mathbb{R}^{N_p}}{\text{maximize}} \quad & \sum_{i=1}^{N_p} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N_p} \alpha_i \alpha_j y_i y_j \langle \boldsymbol{x}_i, \boldsymbol{x}_j \rangle \\ \text{subject to} \quad & \alpha_i \geq 0, \qquad i = 1, \ldots, N_p, \\ & \sum_{i=1}^{N_p} \alpha_i y_i = 0. \end{aligned} \tag{2.9}$$

And the decision function becomes

$$f(\boldsymbol{x}) = \operatorname{sgn}\left(\sum_{i=1}^{N_p} \alpha_i \, y_i \, \langle \boldsymbol{x}, \boldsymbol{x}_i \rangle + b \right). \tag{2.10}$$

2.4.2 SVM classification

The hyperplane classifier requires the patterns $\boldsymbol{x}_i$ to belong to an inner product space and to be linearly separable. The SVM formulation can deal with the first restriction by expressing the inner product $\langle \boldsymbol{x}, \boldsymbol{x}' \rangle$ in terms of a mapping function $k(\boldsymbol{x}, \boldsymbol{x}')$ known as a kernel. By applying this transformation, the dual optimization problem becomes

$$
\begin{aligned}
\underset{\alpha \in \mathbb{R}^{N_p}}{\text{maximize}} \quad & \sum_{i=1}^{N_p} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N_p} \alpha_i \alpha_j y_i y_j k(\boldsymbol{x}_i, \boldsymbol{x}_j) \\
\text{subject to} \quad & \alpha_i \geq 0, \qquad i = 1, \dots, N_p, \\
& \sum_{i=1}^{N_p} \alpha_i y_i = 0.
\end{aligned} \tag{2.11}
$$

with decision function

$$
f(\boldsymbol{x}) = \operatorname{sgn}\left(\sum_{i}^{N_p} \alpha_i \, y_i \, k(\boldsymbol{x}, \boldsymbol{x}_i) + b \right). \tag{2.12}
$$

The kernel function may be any function that satisfies Mercer's conditions (Mercer, 1909). In this work, we use the widely-used Gaussian radial basis function (G-RBF) kernel defined as

$$
k(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp(-\gamma \left\| \boldsymbol{x}_i - \boldsymbol{x}_j \right\|^2), \tag{2.13}
$$

where γ is the bandwidth of the kernel.

One way to deal with the linearly separable problem is to introduce slack variables ξ_i to reformulate (2.5) as

$$
\begin{aligned}
\underset{\boldsymbol{w} \in \mathcal{H},\, b \in \mathbb{R}}{\text{minimize}} \quad & \frac{1}{2} \left\| \boldsymbol{w} \right\|^2 + C \sum_{i=1}^{N_p} \xi_i \\
\text{subject to} \quad & y_i(\langle \boldsymbol{w}, \boldsymbol{x}_i \rangle + b) \geq 1 - \xi_i, \quad i = 1, \dots, N_p, \\
& \xi_i \geq 0.
\end{aligned} \tag{2.14}
$$

where $C > 0$ is a constant that determines the trade-off between margin maximization and training error minimization. This model is known as a soft margin classifier. In this case, the dual optimization problem is the same as (2.11), but subject to the constraints

$$
0 \leq \alpha_i \leq C, \quad i = 1, \dots, N_p, \quad \text{and} \quad \sum_{i=1}^{N_p} \alpha_i y_i = 0 \tag{2.15}
$$

2.4.3 SVM recursive feature elimination

The goal of recursive feature elimination (RFE) is to find the subset of features that maximizes the performance of the predictor using a SVM classifier. The importance of a particular feature is determined by the influence it has on the margin of a trained SVM (Guyon et al., 2002). The SVM-RFE iterative algorithm proposed by Guyon et al. (2002) is presented in Algorithm 2.2.

Rakotomamonjy (2003) presented an extension of the SVM-RFE algorithm when it is implemented with non-linear kernel functions. In this case, the ranking criterion for feature ℓ is given

ALGORITHM 2.2: *SVM-RFE*

Input: Initial feature set, F
Output: Rank list, R

$R \leftarrow \emptyset$
repeat
  Train SVM using F
  Compute and sort the ranking criteria
  Update the ranking list R
  Remove the feature with smallest rank from F
until F is empty
return R

by:

$$J(\ell) = \frac{1}{2}\sum_{i,j=1}^{N_p} y_i\, y_j\, \alpha_i\, \alpha_j\, k(\boldsymbol{x}_i, \boldsymbol{x}_j) - \frac{1}{2}\sum_{i,j=1}^{N_p} y_i\, y_j\, \alpha_i\, \alpha_j\, k\left(\boldsymbol{x}_i^{(-\ell)}, \boldsymbol{x}_j^{(-\ell)}\right), \tag{2.16}$$

where $\boldsymbol{x}_i^{(-\ell)}$ stands for pattern $\boldsymbol{x}_i$ after removing the ℓ-th feature.

2.5 Canonical correlation analysis

Canonical correlation analysis (CCA) is used to identify and measure associations among two sets of variables. In this thesis, we have features coming from electrophysiological data as well as psychological tests. For this reason, we use a feature fusion technique based on CCA (Sun et al., 2005) to obtain a single set of features, which is more discriminant than any of the other feature sets.

There are several ways to define the canonical correlations of a pair of matrices. In this work, we use the linear algebraic formulation of Golub and Zha (1994) based on the singular value decomposition (SVD) (Avron et al., 2014; Björck et al., 1973) of matrices $\boldsymbol{A} \in \mathbb{R}^{N_p \times N_a}$ and $\boldsymbol{B} \in \mathbb{R}^{N_p \times N_b}$. The aim of this approach is to find the linear transformations $\boldsymbol{X} = \boldsymbol{A}\boldsymbol{W}_A$ and $\boldsymbol{Y} = \boldsymbol{B}\boldsymbol{W}_B$, where $\boldsymbol{W}_A$ and $\boldsymbol{W}_B$ are canonical projection matrices whose columns are canonical weights for $\boldsymbol{A}$ and $\boldsymbol{B}$, respectively. Algorithm 2.3 shows the procedure for finding $\boldsymbol{W}_A$ and $\boldsymbol{W}_B$.

As defined in Sun et al. (2005), feature-level fusion is performed either by concatenation or summation of the transformed feature spaces:

$$\mathbf{Z}_1 = \begin{pmatrix} \boldsymbol{X} & \boldsymbol{Y} \end{pmatrix} = \begin{pmatrix} \boldsymbol{A} & \boldsymbol{B} \end{pmatrix} \begin{pmatrix} \boldsymbol{W}_A & \mathbf{0} \\ \mathbf{0} & \boldsymbol{W}_B \end{pmatrix}, \tag{2.17a}$$

$$\mathbf{Z}_2 = \boldsymbol{X} + \boldsymbol{Y} = \boldsymbol{A}\boldsymbol{W}_A + \boldsymbol{B}\boldsymbol{W}_B, \tag{2.17b}$$

where $\mathbf{Z}_1 \in \mathbb{R}^{N_p \times 2r}$ and $\mathbf{Z}_2 \in \mathbb{R}^{N_p \times r}$, with $r = \min(\text{rank}(\boldsymbol{A}), \text{rank}(\boldsymbol{B}))$, are called the canonical correlation discriminant features (CCDF). $\mathbf{Z}_1$ and $\mathbf{Z}_2$ are further used as the sets of features for

ALGORITHM 2.3: *CCA*

Input: Original matrices, $\boldsymbol{A}$ and $\boldsymbol{B}$
Output: Canonical projective matrices, $\boldsymbol{W}_A$ and $\boldsymbol{W}_B$

Compute the SVD of $\boldsymbol{A} = \boldsymbol{U}_A \boldsymbol{\Sigma}_A \boldsymbol{V}_A^\top$
Compute the SVD of $\boldsymbol{B} = \boldsymbol{U}_B \boldsymbol{\Sigma}_B \boldsymbol{V}_B^\top$
Compute the SVD of $\boldsymbol{U}_A^\top \boldsymbol{U}_B = \boldsymbol{U} \boldsymbol{\Sigma} \boldsymbol{V}^\top$
Compute $\boldsymbol{W}_A = \boldsymbol{V}_A \boldsymbol{\Sigma}_A^{-1} \boldsymbol{U}$
Compute $\boldsymbol{W}_B = \boldsymbol{V}_B \boldsymbol{\Sigma}_B^{-1} \boldsymbol{V}$
return $\boldsymbol{W}_A$ and $\boldsymbol{W}_B$

---

classification.

2.6 Hypothesis testing

In this thesis we used *t*-tests and ANOVA analyses to find statistical differences among groups, stimuli, or conditions. In hypothesis testing, the goal is usually to reject the null hypothesis. The null hypothesis is the null condition: no difference between means or no relationship between variables. A t-test is a type of hypothesis testing used to determine if there is significant difference between the means of two groups, which may be related in certain features. On the other hand, ANOVA is used to determine whether the means of more than two groups are equal.

2.7 Summary

In this chapter, we presented the theoretical and conceptual framework used in this thesis to analyze EP of Colombian ex-combatants using functional connectivity analysis from EEG data. As mentioned in Section 2.2, EP can be assessed in a reliable way with task-related EEG recordings. In Chapter 3, we will present the experimental setup carried out in this research to acquire such a data.

Chapter 3

Experimental setup

THIS chapter describes the experimental setup adopted for the current research work. The first section describes the source and number of participants and provides their demographic information. The second section presents the instruments used to assess the social cognition and behavior profile of the subjects. The third and last section details the experimental setup of the EEG acquisition, detailing the system configuration and the experimental procedure. Moreover, it describes the preprocessing steps employed to prepare the acquired signal for further processing stages.

3.1 Participants

The sample consisted of $N_p = 50$ participants. Of these, 30 were ex-combatants from illegal groups of the Colombian armed conflict who, by the time of the study, were enrolled in the DDR program offered by the ARN; and 20 Colombian citizens without combat experience. Volunteers that reported psychiatric or neurological disorders were excluded from the study. Individuals that were not able to perform the task were also excluded. The decision about excluding participants was made by the lead psychologist group before the EEG session. Both groups were matched according to age, gender, and years of education (see Table 3.1).

Table 3.1: *Demographic information of ex-combatant and civilian participants.*

	Ex-combatants $n = 30$	Civilians $n = 20$		
	M (*SD*)	*M* (*SD*)	*t/Chi2* (*p*)	Bayes Factor
Age (Years)	37.50 (8.22)	36.15 (9.17)	0.543 (0.589)	4.083
Education (Years)	10.23 (3.02)	11.05 (2.14)	-1.118 (0.269)	2.871
Gender (Female:Male)	2:28	2:18	0.181 (0.670)	3.232

Ex-combatants were mainly men (28 men, all right-handed), their ages ranged from 27 to 57, with an average education of 10.23 years (standard deviation, SD = 3.03). The control group consisted of 20 volunteers (18 men, 19 right-handed) with ages ranging between 24 and 55 years and a mean education of 11.05 years (SD = 2.14).

All participants read and signed an informed consent before starting the study. The study procedures and informed consent were approved by Ethics Committee of the Faculty of Medicine, *Universidad de Antioquia*, Medellín, Colombia. Participants were informed about the aim of the study, the confidentiality of the collected information, and about procedures of psychological tests and electroencephalographic recordings.

3.2 Assessment of social cognition and behavior

Both ex-combatants and civilians completed a neuropsychological evaluation to assess SCB. It included two psychological tests: the Scale of Social Skills (SSS) (Gismero, 2000), and the Reactive-Proactive Aggression Questionnaire (RPQ) (Raine et al., 2006).

3.2.1 Scale of social skills

Assertive and socially skilled behavior was assessed by means of the scale of social skills (SSS) (Gismero, 2000). SSS is a self-report instrument that inquires about individuals ability to interact with others in different situations. The SSS scale consists of 33 items grouped in six dimensions: (1) self-expression in social situations, (2) defense of own rights as a consumer, (3) expression of anger or displeasure, (4) stopping interactions and saying no, (5) making requests, and (6) starting positive interactions with the opposite gender. Individuals responded to the questions using a 4-item Likert scale (I do not identify at all / Does not apply to me, although sometimes happens / This describes me, although I do not always act or feel this way / Strongly agree and would feel or act as such in most cases). In this study, we focused on the Global SSS score. Larger values of this score suggest reduced social assertion.

3.2.2 The reactive–proactive aggression questionnaire

To assess aggressive behavior, we administered the RPQ (Raine et al., 2006). The RPQ is a self-report instrument aimed to distinguish between reactive (i.e. impulsive) and proactive (i.e. instrumental) aggression. The RPQ consists of 23 items of which 11 items assess reactive aggression and 12 items assess proactive aggression. Each item is rated using a 3-point Likert-type scale (Never / Sometimes / Often). Summed scores provide a measure of reactive or proactive aggression, as well as total aggression. In this study, we focused on the individual ratings. Higher scores indicate higher levels of aggression.

3.3 EEG data collection and preprocessing

To evaluate the neural correlates of EP, we implemented an emotion recognition task synchronized with EEG recordings.

3.3.1 Emotion Recognition Task

Participants performed an emotion recognition task (ERT) aimed to identify facial expressions and words with emotional content. The stimuli consisted of 90 pictures of female and male faces (30 happy, 30 neutral, and 30 angry) from the MMI Facial Expression Database (Pantic et al., 2005). Additionally, 90 words (30 pleasant, 30 neutral, and 30 unpleasant) were selected from the linguistic corpus generated by the communications department at *Universidad de Antioquia* (Preseea, 2005). Both faces and words were adapted following the Ibáñez et al. (2011) methodology. The task sequence is shown in Figure 3.1.

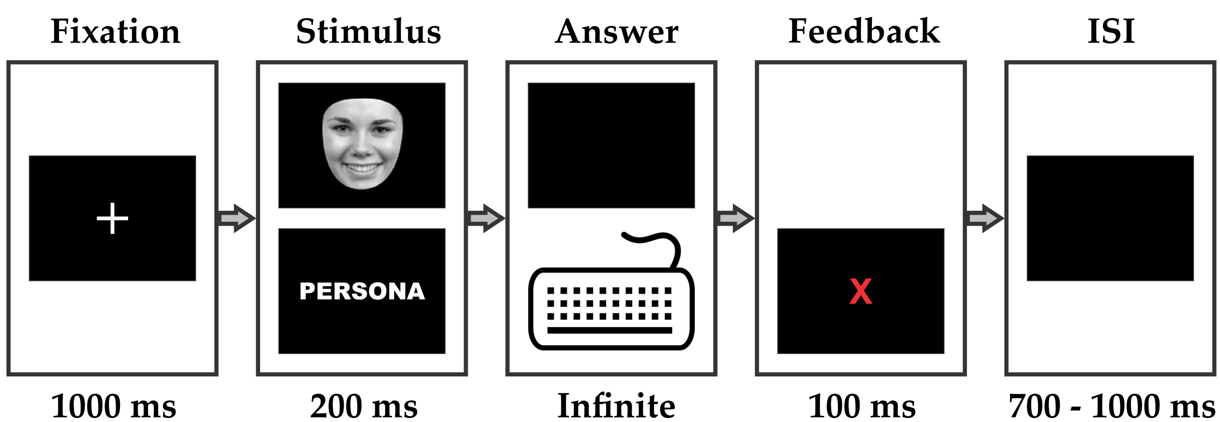
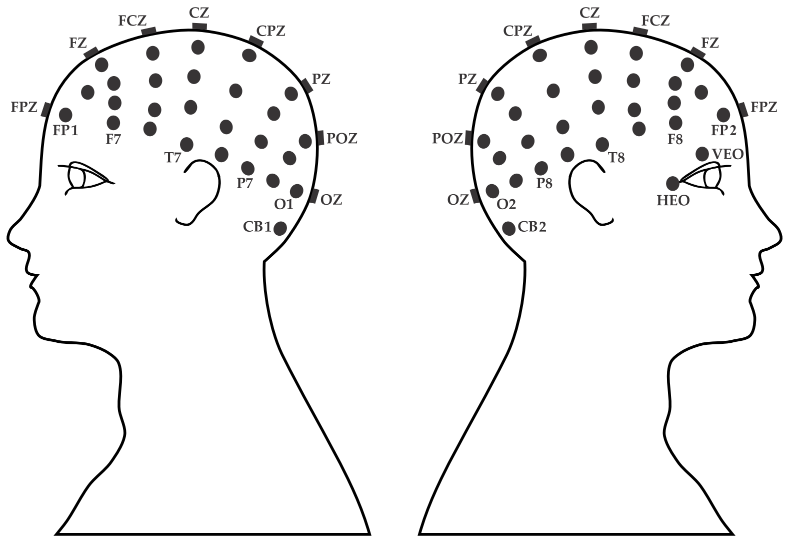


Figure 3.1: ***Example trial of the Emotion Recognition Task.*** *The schema shows a single trial sequence. Face and word trials are independently presented for a short time. Stimuli of positive, negative, and neutral valence are presented in a randomized sequence. The participant is required to classify each stimulus. A negative feedback is given when an error is made.*

Each trial began with a fixation cross presented for 1000 ms, followed by the stimulus (i.e., face or word) presentation for 200 ms. Following face or word presentation, participants had to categorize the valence of the stimulus displayed on the computer screen into one of three response categories (positive, negative, or neutral). Participants entered their responses by pressing one of three keys previously allocated on a standard PC keyboard. Correct responses were followed by an interstimulus interval (ISI) black screen, which appeared for a random duration between 700 and 1000 ms. The incorrect response was indicated by a red letter "X" that appeared in the center of the screen for 100 ms. The negative feedback was introduced to ensure that the subject paid attention throughout the task. The feedback screen was followed by the ISI described above.

3.3.2 EEG Recordings

The ERT was synchronized with EEG recordings. EEG data were acquired by the research group of mental health (GISAME) at *Universidad de Antioquia*. EEG registers were acquired with a 64-electrode NeuroScan EEG SynAmps2 amplifier at a sample rate of 1000 Hz. The electrodes were placed according to the international 10-20 system (Klem et al., 1999). Electrode placement is depicted in Figure 3.2.



(a) (b)

Figure 3.2: ***Schematic of electrode placement based on the international 10-20 system***. *Left (a) and right (b) lateral views of the placement of 60 electrodes for brain activity registration, two cerebellar electrodes (CB1 and CB2) and two EOG electrodes (HEO and VEO).*

During the registration, participants performed the ERT previously described. They were seated in a comfortable chair in front of a 17-inch PC screen at a distance of 60 cm, located in a Faraday cage with dimmed lights to guarantee electric isolation. Participants were asked to try not to blink, move, nor speak while performing the task. Impedances between electrodes and scalp were maintained below 10 kΩ to ensure a good conductivity between scalp and electrodes.

3.3.3 Signal preprocessing

EEG recordings were preprocessed using the FieldTrip Toolbox (Oostenveld et al., 2011) for MATLAB. The original signals were band-pass filtered between 0.1 and 30 Hz with a zero-phase shift FIR filter. Continuous EEG data was epoched from 200 ms prior to the stimulus to 800 ms after it. Epochs were baseline corrected using the −200 ms to 0 ms window, downsampled to 500 Hz, and offline re-referenced to average. All trials were visually inspected for EMG or other artifacts not related to blinks removal, so that any trial containing electrical activity below −50 µV or above 50 µV was rejected. No more than 5% of the trials were marked as bad. An Independent Component Analysis (ICA) was performed to remove electrooculography (EOG) artifacts. A maximum of two artifactual components were removed. Thereafter, epochs were separated according to experimental tasks (Words or Faces).

3.4 Summary

This chapter presented the experimental setup used to acquire the SCB scores and the EEG data from the participants. Furthermore, the chapter also presented how EEG data was preprocessed to obtain clean time series to be used in the further analyses presented in Chapters 4 and 5.

Chapter 4

Analysis of emotional processing of ex-combatants

This chapter is partially based on our work "Characterization framework for Ex-combatants based on EEG and behavioral features" published in **IFMBE Proceedings, vol 60.**

https://doi.org/10.1007/978-981-10-4086-3_52

Ex-combatants from illegal groups in Colombia present alterations on their EP (Tobón et al., 2015). The reviewed literature revealed that EP can be estimated from EEG recordings using ERP or FCN analyses. As a first approach to assess EP in ex-combatants, we start with an ERP analysis along with the SCB scores. For this aim, we propose a characterization framework to automatically discriminate between ex-combatant and civilian populations (described in Section 3.1) using a SVM classifier. The proposed methodology is presented in Section 4.1, followed by the results in Section 4.2. Finally, Section 4.3 summarizes some of the key findings.

4.1 Proposed methodology

4.1.1 Signal processing

Clean EEG signals obtained from the preprocessing stage of Section 3.3.3 were averaged over trials for each task (face or word) to obtain the ERP waveforms per subject. We did not take into account ERPs for different stimulus valences since previous studies have supported the idea that these differences are not relevant to this population (Trujillo et al., 2017a,b). In accordance with the nature of the ERT described in Section 3.3, two peaks were identified as dominant (Fonarayova Key et al., 2005; Trujillo et al., 2017b):

- N170, a member of the N2 family with latency between 150 and 200 ms, which reflects expert object recognition.
- P300, which occurs in response to an unexpected stimulus type approximately 300 ms after the stimulus onset.

Hereafter, we used the following procedure to identify the latency and amplitude of the N170 and P300 ERP components:

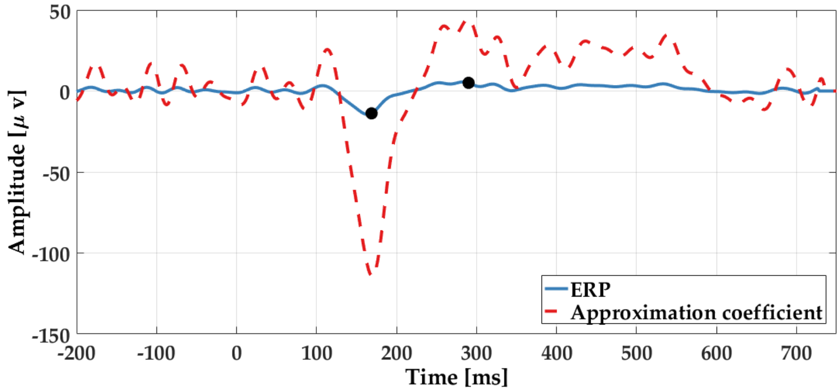


Figure 4.1: ***ERP component detection.*** *The peaks N170 and P300 (depicted as black dots) are detected from the first approximation coefficient of the non-decimated Haar wavelet decomposition of the ERP (n this case from PO5), shown as red dashed line. The peak amplitudes are then obtained from the original ERP signal, depicted in blue.*

1. The ERP signal was decomposed using a multilevel 1-D non-decimated Haar wavelet (Alexandridi et al., 2003).

2. The minimum (N170) and maximum (P300) values of the first approximation coefficient were found between 150 and 350 ms.

3. The occurrence times of both peaks are reported as the latency of the component and mapped to the original ERP signal to calculate the peak amplitudes.

This procedure was applied to ERPs from PO5 and PO6 electrodes. These electrodes were selected as representatives based on the prior research, where regions of interest were selected (see Trujillo et al., 2017b). Figure 4.1 shows a selected ERP signal from electrode PO5, its first approximation coefficient, and the detected peaks.

4.1.2 Classification

For the classification stage, we selected an SVM with a G-RBF kernel function. Due to our limited number of samples, a stratified 10-fold cross-validation strategy was employed to evaluate the performance of the classifier. In k-fold, we first divide the training set into k subsets of equal size. Sequentially, one subset is tested using the classifier trained on the remaining $k-1$ subsets. The hyper parameters of the SVM, namely C and γ, were tuned for each fold separately using a nested cross-validated 3-stage grid-search. Accuracy, sensitivity, and specificity were used to quantify the performance of the classifier based on the results of the cross-validation stage. These parameters are defined as:

$$\begin{aligned} \text{Accuracy} &= \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}} \times 100\% \\ \text{Sensitivity} &= \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \\ \text{Specificity} &= \frac{\text{TN}}{\text{FP} + \text{TN}} \times 100\% \end{aligned} \tag{4.1}$$

where TP is the number of ex-combatants correctly classified; TN is the number of civilians correctly classified; FP is the number of civilians classified as ex-combatants; and FN is the number of ex-combatants classified as civilians.

4.1.3 Statistical analyses

SCB and ERP data were analyzed using the Statistical Package for Social Sciences (IBM SPSS version 23.0 for Windows). Independent samples *t*-tests were performed to assess differences between-groups of these scores. For all statistical analyses, a *p*-value of less than 0.05 was considered to be statistically significant.

4.2 Results

4.2.1 Social cognition and behavior

We found significant between-group differences in both the global social skills score (GSSS) from EHS, and proactive and reactive aggression scores from RPQ. Table 4.1 shows the mean, standard deviation from both groups, and *t*-tests results of SCB scores.

As SCB scores were statistically significant for the two groups, we used a SVM classifier to estimate the prediction accuracy using only these three features with these results: accuracy 70.00%, 0.95 CI [55.22% - 81.93%], sensitivity 93.33%, 0.95 CI [81.59% - 98.89%], and specificity 35.00%, 0.95 CI [22.44% - 49.70%].

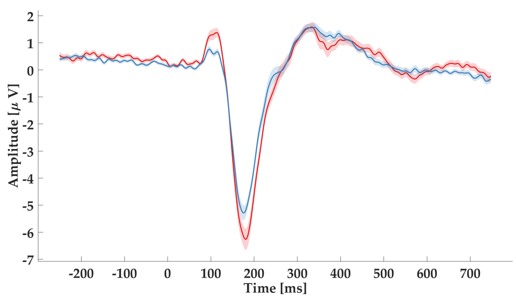
Table 4.1: *Group results of the SCB scores and t (and p) values for between group comparisons based on Student's t-test.*

	Ex-combatants	Civilians	
	$M \pm SD$	$M \pm SD$	t (p)
GSSS	68.10±15.86	80.40±25.56	-2.10 (**0.041**)
Proactive	3.63±3.40	1.50±1.91	2.83 (**0.007**)
Reactive	7.33±3.17	5.50±2.91	2.07 (**0.044**)

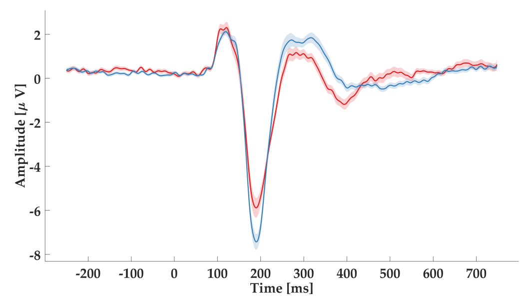
Note. Bold values indicate significant *p*-values.

4.2.2 ERP components

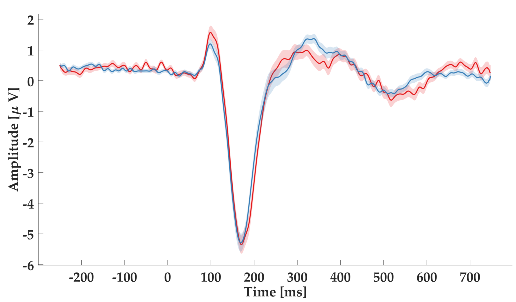
The grand average ERPs to each stimuli at PO5 and PO6 electrodes in both ex-combatants and civilians are shown in Figure 4.2. The two components on which the analyses focused, N170 and P300, can be identified in these recordings. N170 was identified within the interval between 166.2 and 226.2 ms, and P300 within the interval between 277.4 and 369.0 ms.



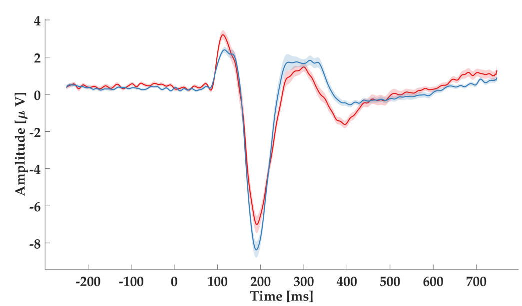
(a) PO5, word stimuli



(b) PO5, face stimuli



(c) PO6, word stimuli



(d) PO6, face stimuli

Figure 4.2: ***Grand average ERPs.*** *Waveforms are collapsed over stimulus (face or word) for analyzed electrodes for civilians (in red) and ex-combatants (in blue). Shaded areas represent the standard error of the mean.*

Descriptive statistics for amplitude and latency are summarized in Table 4.2. Despite ex-combatants consistently exhibit higher amplitudes for the face stimuli in comparison to civilians, between-group differences were not observed for either N170 or P300 components elicited by words and faces, Table 4.3 summarizes *t*-tests results. These results are in line with previous studies (Tobón et al., 2015; Trujillo et al., 2017b) and might indicate a neural reorganization of their cognitive architecture supporting EP to develop emotional undifferentiated mechanisms, which tend to prioritize faces over word stimuli.

Table 4.2: *Group results of N170 and P300 peak amplitudes and latencies.*

		Ex-combatants		Civilians	
Component	Task	Amplitude (μV)	Latency (ms)	Amplitude (μV)	Latency (ms)
PO5					
N170	Words	5.338 ± 2.304	189.669 ± 9.348	6.064 ± 3.197	189.115 ± 5.940
	Faces	8.206 ± 3.258	195.818 ± 10.332	6.732 ± 3.795	195.278 ± 10.487
P300	Words	1.964 ± 1.231	328.818 ± 21.318	2.290 ± 1.318	327.030 ± 19.109
	Faces	2.771 ± 1.633	317.133 ± 21.658	2.108 ± 1.068	323.229 ± 22.720
PO6					
N170	Words	5.034 ± 2.440	188.868 ± 12.288	5.191 ± 2.232	183.753 ± 8.656
	Faces	9.439 ± 4.210	198.259 ± 10.583	8.338 ± 4.431	197.899 ± 10.805
P300	Words	2.135 ± 1.045	321.962 ± 24.330	1.981 ± 1.154	317.346 ± 22.605
	Faces	2.988 ± 2.183	312.291 ± 19.992	2.593 ± 1.819	323.369 ± 20.607

Note. Values are given as M±SD.

Table 4.3: *t-tests results of N170 and P300 peak amplitudes and latencies.*

		Amplitude		Latency	
Component	Task	$t(48)$	p	$t(48)$	p
PO5					
N170	Words	0.933	0.355	-0.234	0.815
	Faces	-1.465	0.149	-0.180	0.857
P300	Words	0.892	0.376	-0.302	0.763
	Faces	-1.597	0.116	0.956	0.343
PO6					
N170	Words	0.230	0.818	-1.611	0.113
	Faces	-0.887	0.379	-0.116	0.907
P300	Words	-0.488	0.627	-0.675	0.502
	Faces	-0.668	0.506	1.896	0.064

4.2.3 Classification results

Classification results are summarized in Table 4.4. We trained the SVM with two different sets of features. The first conformed to the ERP features (Table 4.2) and the second integrating ERP and SCB features (Tables 4.1 and 4.2). The SVM-based classifier presented better performance with the later set of features, achieving 72.00% accuracy with high sensitivity. Despite this evidence pointing to the existence of alterations in EP of ex-combatants, the confidence intervals are wide due to the limited size of the sample, and because some of the features found also reflect non-emotional cognitive processes that may be common to both populations.

Table 4.4: *Accuracy, sensitivity and specificity reached with the proposed methodology.*

Feature Set	# Features	Accuracy (%) [0.95 CI]	Sensitivity (%) [0.95 CI]	Specificity (%) [0.95 CI]
ERP features	16	60.00% [45.20% - 73.37%]	76.67% [62.23% - 87.30%]	35.00% [22.44% - 49.70%]
ERP + SCB features	19	72.00% [57.29% - 83.57%]	76.67% [62.23% - 87.30%]	65.00% [50.14% - 77.72%]

4.3 Summary

In this chapter, we proposed an SVM-based framework to automatically discriminate between ex-combatant and civilian populations using a set of features composed by ERP measures. We achieved a higher classification rate when the ERP features were complemented with SCB scores. This suggests that EP can be more accurately assessed with a multidimensional featuring scheme. With this framework, we provide a decision support system for psychologists to improve current interventions in mental health aimed to help ex-combatants to make a successful reintegration to civilian life.

In conclusion, the methodology presented in this chapter further supports the notion of combat-experience-related alterations in the cognitive architecture supporting EP to prioritize the recognition of faces over word stimuli, regardless their valence. Behavioral and brain function measures of EP may provide valuable additional tools for clinical assessment of neural reorganization in ex-combatants.

Chapter 5

On a phenotyping scheme for emotional processing in ex-combatants

This chapter is based on our work "Phenotyping Ex-Combatants From EEG Scalp Connectivity" published in **IEEE ACCESSS, vol. 6**
http://doi.org/10.1109/ACCESS.2018.2872765

In Chapter 4, we found that ex-combatants tend to prioritize the recognition of faces over word stimuli, regardless their valence. This may suggest abnormal recruitment of neural resources to process emotional stimuli in such a population. These FCN alterations can be assessed with GTA, which makes it possible to fully characterize FCNs (Bullmore and Sporns, 2009, 2012).

In this chapter, we propose a methodology to identify potential neurophysiological phenotypes related to EP of faces and words in ex-combatants. First, we use graph theory to characterize the ex-combatants' FCN, in comparison with the non-combat-experienced control group. Second, we use CCA to assess the relation between the network analysis and the SCB scores. Finally, a SVM is used to obtain class representative patterns. Such patterns are used to empirically identify potential phenotypes.

5.1 Proposed methodology

5.1.1 Signal processing

The signal analysis was based on estimating the iCOH (Eq. (2.1)) of all pairs of sensors during each trial for each of the 50 subjects. We performed the described analysis for each of the following frequency bands: delta (less than 4 Hz), theta (4 to 7 Hz), alpha (8 to 13 Hz), and beta (13 to 30 Hz). We calculated the cross spectrum and autospectra of each data channel using the multitaper method based on discrete prolate spheroidal sequences as tapers to estimate spectra (Babadi and Brown, 2014). Both spectral and iCOH calculations were performed using the FieldTrip toolbox (Oostenveld et al., 2011).

Afterward, we computed the MST from every connectivity matrix by Kruskal's algorithm. Thereafter, we performed a GTA over these MST graphs to estimate their leaf fraction (LF), maximum degree (MD), and diameter (D) (see Section 2.3.2 for explanation). As already reported (Boersma et al., 2013; Tewarie et al., 2015), these measures allow describing and characterizing the topology of the related MST graphs.

5.1.2 Feature selection

The GTA yielded a total of 24 features (three features per band per task). We performed SVM-RFE to select the most discriminant subset of features. Subsequently, we performed CCA over the reduced feature set given by the top features selected by the SVM-RFE for the FCN metrics and the SCB scores. The SVM was implemented in the same way described in Section 4.1.2.

5.1.3 Classification

After selecting the discrimination features, the final task was to inquire about the existence of cognitive phenotypes. The classifier adopted here was the SVM (Cortes and Vapnik, 1995), as it is one of the most robust and accurate classifiers. The SVM was implemented in the same way described in Section 4.1.2.

5.1.4 Statistical analyses

All FCN data were analyzed using the Statistical Package for Social Sciences (IBM SPSS version 23.0 for Windows). Independent samples t-tests were performed to assess differences between-groups of these scores. p-values were corrected for multiple comparisons using the two-stage FDR method (Benjamini et al., 2006). For all statistical analyses, a p (or q) value of less than 0.05 was considered to be statistically significant.

5.2 Results

5.2.1 Functional connectivity network

We used the procedure originally introduced in Nolte et al. (2004) to depict the connections between all pairs of electrodes. In this procedure, the scalp is depicted as a large circle. Small circles are placed at the location of each electrode also representing the scalp and containing the absolute value of iCOH for the respective electrode (marked as a black dot) with all other electrodes. From the qualitative comparison of maps shown in Figure 5.1, the iCOH for ex-combatants shows a spatial pattern similar to that for civilians.

Between-group differences were not observed for the whole brain-averaged level of iCOH. Both groups were therefore indistinguishable, meaning that the overall level of connectivity did

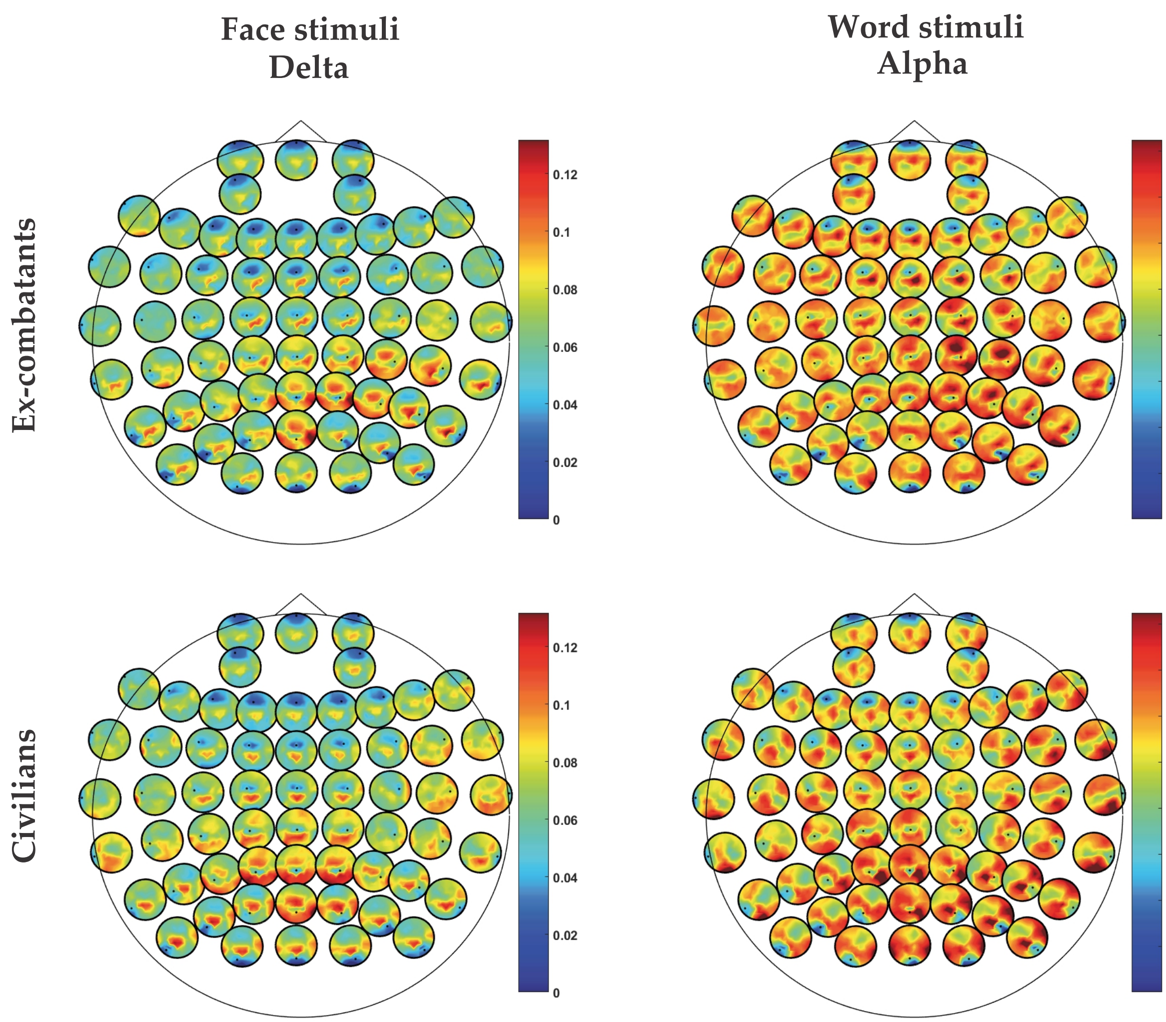


Figure 5.1: ***Absolute value of the imaginary part of coherency.*** *These maps correspond to the face stimuli in the delta band, and to the word stimuli in the alpha band, as they were further validated to be the top-ranked discriminative features.*

not define a phenotype. Table 5.1 summarizes the mean value, the standard deviation, and the test results per task per band.

Table 5.1: *Group comparisons based on Wilcoxon rank-sum test. Results for iCOH, Z-scores, and p-values.*

		Ex-combatants	Civilians	
Band	Task	$M \pm SD$	$M \pm SD$	Z (p)
Delta	Words	0.061±0.020	0.061±0.019	-0.139 (0.890)
	Faces	0.067±0.016	0.071±0.022	-0.297 (0.766)
Theta	Words	0.077±0.022	0.077±0.037	-0.891 (0.373)
	Faces	0.094±0.028	0.097±0.025	-0.535 (0.593)
Alpha	Words	0.056±0.014	0.055±0.016	-0.574 (0.566)
	Faces	0.065±0.020	0.066±0.017	-0.673 (0.501)
Beta	Words	0.035±0.011	0.035±0.006	-0.693 (0.488)
	Faces	0.038±0.012	0.037±0.008	-0.257 (0.797)

For the word task, significant differences between groups were obtained for leaf fraction (LF) and maximum degree (MD) for the delta band; and LF, MD and diameter (D) for the alpha band. For the face task, we found significant differences in LF for the delta band; LF, MD and D for the theta band; MD for the alpha band; and LF for the beta band. Table 5.2 shows the mean, standard deviation, and test results for the network metrics per task per band.

Table 5.2: *Group results of the network metrics, Z-scores, and corrected p-values for their group comparisons based on Wilcoxon rank-sum test.*

		Leaf fraction			Max. degree			Diameter		
		Ex-combatants	Civilians		Ex-combatants	Civilians		Ex-combatants	Civilians	
Band	Task	$M \pm SD$	$M \pm SD$	Z (q)	$M \pm SD$	$M \pm SD$	Z (q)	$M \pm SD$	$M \pm SD$	Z (q)
Delta	Words	0.749±0.060	0.711±0.063	-3.389 (**0.004**)	18.578±6.253	16.400±6.416	-2.363 (**0.036**)	9.622±2.009	10.217±2.084	1.500 (0.164)
	Faces	0.761±0.053	0.733±0.055	-2.864 (**0.017**)	19.733±8.067	17.317±5.803	-1.650 (0.136)	9.167±1.874	10.100±2.097	2.675 (**0.021**)
Theta	Words	0.753±0.060	0.736±0.060	-1.409 (0.184)	18.956±6.413	17.667±6.027	-1.306 (0.211)	9.500±1.973	9.767±2.174	0.629 (0.467)
	Faces	0.810±0.049	0.779±0.052	-3.728 (**0.002**)	25.789±8.288	21.783±7.461	-2.832 (**0.017**)	7.978±1.635	8.683±1.818	2.366 (**0.036**)
Alpha	Words	0.740±0.057	0.709±0.048	-3.789 (**0.002**)	17.111±6.306	14.300±4.666	-2.529 (**0.028**)	9.789±1.963	11.117±2.415	3.521 (**0.003**)
	Faces	0.760±0.051	0.740±0.056	-1.826 (0.115)	19.189±5.904	17.817±7.808	-2.183 (0.053)	9.244±2.063	9.617±2.132	0.634 (0.467)
Beta	Words	0.717±0.069	0.699±0.057	-1.759 (0.116)	15.700±6.942	14.850±5.963	-0.525 (0.508)	10.644±2.745	10.917±2.472	0.884 (0.378)
	Faces	0.722±0.064	0.695±0.061	-2.719 (**0.021**)	15.011±5.049	14.150±5.665	-1.758 (0.116)	10.667±2.308	10.750±2.297	0.285 (0.570)

Note. Bold values indicate significant q-values.

5.2.2 Feature selection

We defined a 24-dimensional neurophysiological set comprised of the FCN network metrics (see Table 5.3). We performed SVM-RFE to determine which of them were most predictive of ex-combatant or civilian classification. Classification accuracies for this step are reported in Figure 5.2. We found that the subset comprised of leaf fraction and diameter for the face stimuli in delta band, and leaf fraction and diameter for the word stimuli in alpha band showed the highest discriminability.

Furthermore, the CCA was performed using the top four FCN ($N_a = 4$) and the 3-dimensional

Table 5.3: *List of features extracted from FCN analysis.*

Band	Stimulus type	Feature name	Rank in SVM-RFE
Delta	Words	Leaf fraction	15
		Maximum degree	10
		Diameter	6
	Faces	**Leaf fraction**	**1**
		Maximum degree	11
		Diameter	**4**
Theta	Words	Leaf fraction	13
		Maximum degree	24
		Diameter	14
	Faces	Leaf fraction	12
		Maximum degree	5
		Diameter	8
Alpha	Words	**Leaf fraction**	**3**
		Maximum degree	22
		Diameter	**2**
	Faces	Leaf fraction	19
		Maximum degree	21
		Diameter	7
Beta	Words	Leaf fraction	17
		Maximum degree	20
		Diameter	16
	Faces	Leaf fraction	18
		Maximum degree	23
		Diameter	9

Note. Top-ranked features are shown in boldface.

set comprised of the SCB scores ($N_b = 3$). With this final step, we identified six different sets of features, presented in column one of Table 5.4.

5.2.3 Classification results

The SVM classifier was implemented using the libsvm library (Chang and Lin, 2011). To tune the hyper parameters of SVM, we performed a 3-level grid search using growing sequences in the range $[2^{-5}, 2^{17}]$ for C, and $[2^{-17}, 2^{3}]$ for γ. Additionally, to account for imbalances in the dataset, we set the parameter `wi` to be 1.5 for the positive class (ex-combatants) and 1.0 for the negative one (civilians). Classification performances of the SVM classifier with each set of features are summarized in Table 5.4.

The use of SVM-RFE to identify the top-ranked FCN features allowed improving the classification rates from 60.00 % to 75.29 %. With the inclusion of CCA to fuse FCN and SCB features,

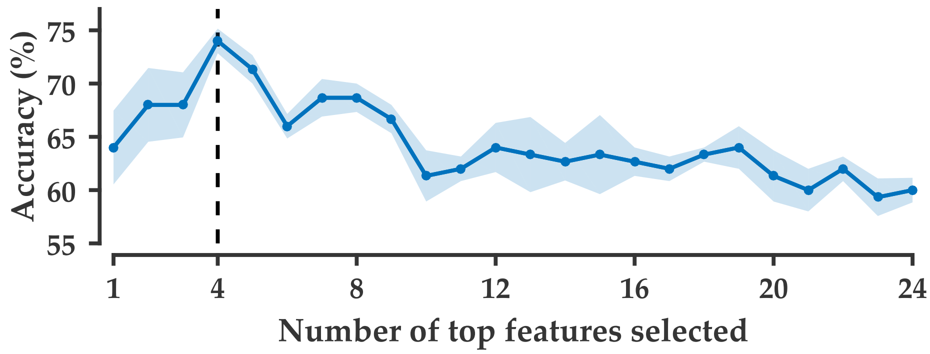


Figure 5.2: ***SVM-RFE results on FCN features.*** *Average classification accuracy with respect to the number of features selected. The shaded area represents the variability of cross-validation, one standard deviation above and below the mean accuracy score drawn by the curve.*

Table 5.4: *Accuracy, sensitivity and specificity reached with the proposed methodology.*

Feature Selection Algorithm	# Features	Accuracy (%)	Sensitivity (%)	Specificity (%)
FCN features	24	60.00 ± 2.53	67.22 ± 1.85	50.07 ± 3.06
FCN + SCB features	27	61.33 ± 3.50	67.69 ± 3.44	51.66 ± 4.39
SVM-RFE	4	75.29 ± 1.01	80.60 ± 1.73	68.58 ± 2.94
SVM-RFE + SCB features	7	78.67 ± 2.42	82.34 ± 3.27	73.30 ± 2.18
SVM-RFE + CCA concatenation	6	81.00 ± 4.15	83.21 ± 2.64	77.66 ± 6.64
SVM-RFE + CCA summation	**3**	**84.33 ± 1.97**	**85.61 ± 2.24**	**82.32 ± 2.34**

Note. Bold values indicate best results. Values are given as M ± SD.

the classification accuracy reached values of up to 84.33 % for the summation fusion. This value outperformed the results obtained in previous works (in Quintero-Zea et al. (2017) we achieved 80.00 %, and in Rodríguez-Calvache et al. (2017) a mean accuracy of 58.4 %).

Furthermore, SVM-RFE allowed identifying a potential phenotype given by the pair Leaf fraction–Diameter in the delta band elicited by face stimuli, and in the alpha band elicited by word stimuli. Specifically, controls have higher diameter values that reflect the presence of networks with reduced global efficiency (Tewarie et al., 2015). Conversely, higher values of leaf fraction in ex-combatants show the presence of clustered nodes that dominate the network topology, and it is thought confer high integration of information within the network for specialized processing (Bullmore and Sporns, 2009; Chen et al., 2018; Su et al., 2017; Vourkas et al., 2014).

Results from MST analysis showing increased leaf fractions and decreased diameters indicate that a more integrated topology of the global FCN is seen in ex-combatants. This suggests that FCNs became more centralized (star-like topology) and with increased global efficiency in the theta band for face stimuli and in the alpha band for word stimuli in ex-combatants compared with civilians.

In war scenarios, the ability to react fastly to adverse stimuli is crucial for survival. Therefore, FCN reorganization in ex-combatants could be elicited by a cortical adaptation to efficiently react to potentially threatening stimuli.

5.3 Summary

In this chapter, we proposed a methodology to identify potential cognitive phenotypes linked to alterations in the cognitive architecture supporting EP, using SCB features and graph metrics from EEG FCN. Results show the existence of a cognitive phenotype related to increased values of the leaf fraction and reduced values of the diameter of the FCN in ex-combatants, in comparison with controls. This suggests that combat experience forces a reorganization of the EP-related FCN in ex-combatants.

This methodology provides new empirical knowledge on the reorganization of EEG-FCN of ex-combatants. It remains to be seen if the potential phenotype given by the pair Leaf fraction–Diameter may prove to be an effective biomarker for impairments in EP. In addition to the promise as a diagnostic marker, these features merit further investigation as functional markers of response to psychological interventions conducted to reduce the prevalence of aggressive attitudes in ex-combatants.

Chapter 6

Accounting for neural reorganization extent

RESULTS from previous chapters suggested atypical reorganization of neural resources to process emotional stimuli in ex-combatants. In Chapter 4, we proposed a methodology that enabled us to find atypical responses in ERP data within the ex-combatants population. Subsequently, in Chapter 5, we used MST metrics to find potential phenotypic data related to the increase of global efficiency of the FCN in ex-combatants. In both methodologies, we integrated SCB scores to the analyses, to accomplish the recommendation of the NIMH RDoC initiative into integrating several levels of information.

In this chapter, we assess the extent of such neural reorganization over two widely used behavioral variables related to the ERT. For this aim, we carry out CCA to study relationships between MST metrics as the predictor set, and behavioral data from the ERT as the criterion set.

6.1 Proposed methodology

6.1.1 Behavioral data from ERT

We calculated reaction time and accuracy for each of the six stimuli of the ERT: (1) Happy faces, (2) neutral faces, (3) angry faces, (4) pleasant words, (5) neutral words, and (6) unpleasant words; to account for the behavioral response of the EP. Reaction time was used to infer how long it takes for a subject to process emotional stimuli and accuracy to infer whether the task was completed correctly.

Moreover, we calculated the inverse efficiency (IE) score, which combines speed and accuracy to allow comparisons among conditions uncontaminated by possible speed-accuracy tradeoffs (Spence et al., 2001). IE is computed as the median RT divided by the proportion of correct trials for a given condition (Kitagawa and Spence, 2005). A higher IE value indicates worse performance.

6.1.2 Functional connectivity analysis

We followed the procedure described in Section 5.1.1 to obtain the leaf fraction and diameter of the MSTs for the face stimuli (happy, neutral, and angry) in the delta band, and for the word stimuli (pleasant, neutral, and unpleasant) in the alpha band. This selection is consistent with them being the most discriminating set of features in the SVM-RFE presented in Section 5.2.2.

6.1.3 Statistical analysis

To analyze each of the behavioral features, i.e. reaction time, accuracy, and IE; we used a three-way mixed ANOVA model. The stimulus type (Faces vs. Words) and the condition (Happy vs Neutral vs Angry / Pleasant vs Neutral vs Unpleasant) were entered as the within-subjects factors, and the group was the between-subjects factor with two levels (Ex-combatant vs Control). The FCN metrics were analyzed with a two-way mixed ANOVA model for both faces and words with the condition as the within factor and the groups as the between one. To further explore significant interactions, we used Bonferroni corrected post-hoc tests adjusting the Alfa level according to the number of contrasts. For the interactions we calculated effect size (η_p^2) and power (β).

Furthermore, we conducted CCA using the six MST metrics as predictors of the nine behavioral conditions to evaluate the multivariate shared relationship between the two variable sets. This analysis was performed for both faces and word stimuli.

All data were analyzed using the Statistical Package for Social Sciences (IBM SPSS version 23.0 for Windows). All effects are reported as significant at $p < 0.05$.

6.2 Results

6.2.1 ERT behavioral data

Descriptive statistics are presented in Table 6.1, and the ANOVA results are presented in Table 6.2. For reaction time, we found significant main effects of the three factors. Post-hoc analysis indicated that ex-combatants (M = 1022 ms, SEM = 63) tended to answer in shorter times than controls (M = 1283 ms, SEM = 77). Furthermore, face stimuli (M = 1110 ms, SEM = 54) are recognized faster than words (M = 1195 ms, SEM = 52). Finally, stimuli with positive valence (M = 1093 ms, SEM = 54) are identified faster than stimuli with negative (M = 1169 ms, SEM = 51) or neutral (M = 1195 ms, SEM = 53) valence.

There were also significant main effects of the condition on accuracy. Contrasts revealed that positive valences (M = 80.2 %, SEM = 2.3 were better classified than negative (M = 70.0 %, SEM = 2.7) and neutral (M = 61.6 %, SEM = 2.8) valences.

Regarding to IE, there were significant main effects of the condition. Post-hoc analysis revealed that tasks associated with positive valence stimuli present the best performance (M = 1513 ms, SEM = 112), followed by the negative valence ones (M = 1984 ms, SEM = 186). The worst performance was achieved by neutral valence tasks (M = 2377 ms, SEM = 212). An interaction effect between stimulus and group was significant for IE. The contrast Face vs. Word stimuli yielded a statistically significant difference for ex-combatants ($t(29)$ = -3.169, p = 0.004), with a better performance for the face task (M = 1693 %, SEM = 157) than the word task (M = 2068 %, SEM = 171). For civilians, we did not find significant differences ($t(19) = 0.729$, $p = 0.475$). Furthermore, between groups differences were not found for face ($t(48) = -1.242$, $p = 0.058$), nor word ($t(29) = 0.448$, $p = 0.752$) stimuli.

Table 6.1: *Descriptive statistics for behavioral data*

	Ex-combatants $M \pm SD$	**Civilians** $M \pm SD$
Faces		
Reaction time (ms)		
Happy	909 ± 317	1191 ± 600
Neutral	981 ± 269	1357 ± 580
Angry	984 ± 268	1242 ± 560
Accuracy (%)		
Happy	82.8 ± 19.1	87.0 ± 18.7
Neutral	61.5 ± 24.1	64.3 ± 22.5
Angry	62.9 ± 21.8	73.7 ± 18.9
Inverse efficiency (ms)		
Happy	1333 ± 1006	1634 ± 1501
Neutral	2209 ± 1892	2587 ± 2002
Angry	1942 ± 1143	2133 ± 2284
Words		
Reaction time (ms)		
Pleasant	1033 ± 302	1243 ± 488
Neutral	1112 ± 417	1330 ± 449
Unpleasant	1116 ± 351	1338 ± 456
Accuracy (%)		
Pleasant	69.0 ± 20.2	81.9 ± 13.5
Neutral	56.1 ± 21.8	64.6 ± 19.3
Unpleasant	65.2 ± 25.2	78.4 ± 17.9
Inverse efficiency (ms)		
Pleasant	1697 ± 714	1592 ± 751
Neutral	2550 ± 1763	2319 ± 1176
Unpleasant	2096 ± 1201	1920 ± 1291

Table 6.2: *ANOVA results for behavioral data*

	df1, df2	**F, p, η_p^2, β**
Reaction time (ms)		
Stimulus	1, 48	**4.527, 0.039, 0.086, 0.550**
Condition	2, 96	**5.351, 0.006, 0.100, 0.830**
Group	1, 48	**6.977, 0.011, 0.127, 0.735**
Stimulus × Group	1, 48	1.263, 0.267, 0.026, 0.196
Condition × Group	2, 96	0.469, 0.616, 0.01, 0.122
Stimulus × Condition	2, 96	0.641, 0.529, 0.013, 0.155
Stimulus × Condition × Group	2, 96	0.656, 0.521, 0.013, 0.157
Accuracy (%)		
Stimulus	1, 48	3.070, 0.086, 0.060, 0.404
Condition	2, 96	**33.658, <0.001, .0412, 1.000**
Group	1, 48	3.633, 0.063, 0.070, 0.463
Stimulus × Group	1, 48	3.007, 0.089, 0.059, 0.397
Condition × Group	2, 96	0.994, 0.374, 0.020, 0.219
Stimulus × Condition	2, 96	**6.546, 0.002, 0.120, 0.901**
Stimulus × Condition × Group	2, 96	0.371, 0.691, 0.743, 0.108
Inverse efficiency (ms)		
Stimulus	1, 48	0.625, 0.423, 0.013, 0.124
Condition	2, 96	**12.000, <0.001, 0.200, 24.000, 0.994**
Group	1, 48	0.296, 0.589, 0.006, 0.083
Stimulus × Group	1, 48	**5.074, 0.029, 0.096, 0.598**
Condition × Group	2, 96	0.054, 0.947, 0.001, 0.058
Stimulus × Condition	2, 96	0.317, 0.729, 0.007, 0.099
Stimulus × Condition × Group	2, 96	0.054, 0.947, 0.001, 0.058

Note. Bold values indicate significant differences.

6.2.2 ERT connectivity data

Table 6.3 summarizes the descriptive statistics for each of the MST metrics. Furthermore, results for the ANOVAs are shown in Table 6.4. Note that increased leaf fractions and decreased diameters in ex-combatants are preserved for each stimulus type. Despite these results, there were no significant main effects of the condition on either leaf fraction or diameter. This suggests that the neural reorganization in ex-combatants might be driven by the stimulus type regardless of their valence.

In concordance with the results obtained in Table 5.2, there were significant main effects of the group on all the MST metrics, indicating higher values of leaf fraction and lower MST diameters in ex-combatants. Furthermore, we did not find significant interaction effects between the condition and the group for either faces or words stimuli.

Table 6.3: *Descriptive statistics for MST metrics*

	Ex-combatants $M \pm SD$	**Civilians** $M \pm SD$
Faces		
Leaf fraction in delta band		
Happy	0.767 ± 0.051	0.736 ± 0.055
Neutral	0.762 ± 0.050	0.728 ± 0.057
Angry	0.753 ± 0.059	0.736 ± 0.054
Diameter in delta band		
Happy	9.000 ± 1.948	9.900 ± 1.944
Neutral	9.100 ± 2.006	10.250 ± 2.197
Angry	9.400 ± 1.694	10.150 ± 2.231
Words		
Leaf fraction in alpha band		
Pleasant	0.745 ± 0.052	0.720 ± 0.043
Neutral	0.734 ± 0.066	0.696 ± 0.052
Unpleasant	0.739 ± 0.053	0.712 ± 0.047
Diameter in alpha band		
Pleasant	9.567 ± 1.675	10.550 ± 2.564
Neutral	9.800 ± 1.990	11.650 ± 2.300
Unpleasant	10.000 ± 2.228	11.150 ± 2.368

Table 6.4: *ANOVA results for network metrics*

	df1, df2	**Faces** F, p, η_p^2, β	**Words** F, p, η_p^2, β
Leaf fraction			
Condition	2, 96	0.48, 0.617, 0.010, 0.13	1.89, 0.156, 0.038, 0.38
Group	1, 48	**4.85, 0.033, 0.092, 0.58**	**7.01, 0.011, 0.127, 0.74**
Condition × Group	2, 96	0.60, 0.550, 0.012, 0.15	0.32, 0.726, 0.007, 0.10
Diameter			
Condition	2, 96	0.38, 0.686, 0.008, 0.11	1.58, 0.212, 0.032, 0.33
Group	1, 48	**6.55, 0.014, 0.120, 0.71**	**9.69, 0.003, 0.168, 0.86**
Condition × Group	2, 96	0.14, 0.870, 0.003, 0.07	0.68, 0.509, 0.014, 0.16

Note. Bold values indicate significant differences.

6.2.3 Canonical correlation model

For the face stimuli, the analysis yielded six functions with squared canonical correlations (R_c^2) of 0.507, 0.428, 0.285, 0.138, 0.106, 0.015 for each successive function. The full model across all functions was statistically significant using the Wilks' $\lambda = 0.153$ criterion, $F(40,183.06) = 1.51$, $p = 0.024$. For the set of four canonical functions, the r^2 type effect size was $1 - \lambda = 0.847$, which indicates that the full model explained about 84.7 % of the variance shared among the variable sets.

Given the R_c^2 effects for each function, only the first three functions were considered noteworthy in the context of this study (50.7 %, 42.8 % and 28.5 % of shared variance, respectively).

The standardized canonical function coefficients and structure coefficients for functions 1 to 3 are summarized in Table 6.5. The squared structure coefficients are also given as well as the communalities (h^2) across the three functions for each variable.

Looking at the function 1 coefficients, only one criterion variable (accuracy for happy faces) had a relevant contribution to the synthetic criterion variable. Regarding the predictor variable set in function 1, diameter for neutral faces and leaf fraction for neutral and angry faces were the primary contributors to the predictor synthetic variable.

From all the criterion variables, reaction time and inverse efficiency for angry faces did not have any relevant contribution to the model, albeit the magnitude of its structure coefficient was just below 0.4. In the case of the predictor set, the only variable that did not contribute to the model was the leaf fraction for angry face stimuli.

Table 6.5: *Canonical solution for MST predicting task behavior for functions 1, 2, and 3.*

Variable	Function 1			Function 2			Function 3			
	Coef	r_s	r_s^2 (%)	Coef	r_s	r_s^2 (%)	Coef	r_s	r_s^2 (%)	h_s^2 (%)
Happy faces										
Accuracy	-0.219	**-0.481**	23.13	0.743	0.043	0.18	1.166	**-0.412**	16.94	**40.25**
Reaction time	-0.399	0.069	0.48	-0.846	**-0.521**	27.12	-0.970	0.285	8.10	35.70
Inverse efficiency	1.524	0.377	14.19	2.182	-0.311	9.66	2.202	**0.468**	21.92	**45.77**
Neutral faces										
Accuracy	0.065	-0.173	2.99	0.850	**0.433**	18.73	0.223	**-0.467**	21.84	**43.56**
Reaction time	-0.541	-0.020	0.04	-0.460	**-0.577**	33.24	0.932	**0.547**	29.88	**63.15**
Inverse efficiency	0.215	0.083	0.68	0.101	**-0.537**	28.83	0.315	**0.689**	47.41	**76.92**
Angry faces										
Accuracy	0.968	0.024	0.06	-1.260	-0.097	0.95	-1.331	**-0.560**	31.39	32.40
Reaction time	-1.062	-0.153	2.35	-0.173	-0.359	12.87	-0.633	0.252	6.36	21.58
Inverse efficiency	0.762	0.191	3.65	-1.429	-0.309	9.57	-1.236	0.391	15.27	28.49
R_c^2			50.7			42.8			28.5	
Happy faces										
Leaf fraction	-1.103	-0.317	10.07	-0.055	0.123	1.50	0.246	-0.172	2.97	14.54
Diameter	-0.484	-0.141	1.99	-0.004	0.028	0.08	1.055	**0.741**	54.88	**56.95**
Neutral faces										
Leaf fraction	0.132	**0.402**	16.16	0.907	**0.563**	31.69	-0.393	-0.105	1.10	**48.95**
Diameter	-0.502	**-0.489**	23.90	0.445	-0.146	2.13	-0.152	-0.080	0.63	26.67
Angry faces										
Leaf fraction	0.765	**0.431**	18.59	-0.925	0.195	3.81	0.720	0.289	8.35	30.75
Diameter	0.221	-0.212	4.49	-1.103	**-0.672**	45.16	0.001	-0.355	12.60	**62.24**

Note. Structure coefficients (r_s) greater than $|0.40|$ and communality coefficients (h^2) greater than 40 % are shown in boldface. Coef = standardized canonical function coefficient; r_s = structure coefficient; r_s^2 = squared structure coefficient; h^2 = communality coefficient.

For the word stimuli, we did not find a significant canonical correlation model. This suggests an atypical word valence processing in ex-combatants, perhaps related to the fact that in war contexts, words may be less relevant than visual stimuli.

6.3 Summary

In this chapter, we performed CCA using MST metrics as predictors and behavioral data from ERT as criteria. Behavioral data indicated that ex-combatants exhibit lower reaction time when processing face stimuli, and make more mistakes when analyzing word stimuli. Furthermore, positive valence stimuli are better processed in both groups, followed by negative valence stimuli. Stimuli with neutral valence are the worst processed in both populations.

The canonical correlation yielded associations between MST metrics and behavioral variables. For instance, reaction time, inverse efficiency, and leaf fraction for angry faces were the only variables that did not contribute to the model. Words proved to be less informative in ex-combatants than in controls. This conclusion was supported by two facts: (a) Ex-combatants made more mistakes when processing word stimuli. (b) This finding could not be due to lower literacy in ex-combatants as the ANOVA did not yield main effects of the group in the inverse efficiency, and both groups were matched according to their education.

Chapter 7

Concluding Remarks

THE analyses reported within this thesis explored the hypothesis that atypical modulation of emotional processing in ex-combatants is associated with a neural reorganization elicited by their combat experience. With this in mind, we proposed three analysis approaches to assess the extent of such a reorganization: (a) A classification framework using ERP features alongside SCB scores, (b) a phenotyping scheme based on MST metrics and SCB scores, and (c) a canonical correlation model to relate MST metrics and ERT behavioral data. Below some conclusions from these approaches are shown, as well as some recommendations for future works.

7.1 Conclusions

Design of a characterization framework for ex-combatants based on EEG and SCB features. The framework proposed in Chapter 4 sets up a first approach for assessing EP in ex-combatants. The classification process was performed using ERP data and behavioral features from psychological tests. Results show that ex-combatant and civilian populations can be automatically separated using supervised techniques. Furthermore, we demonstrate that inclusion of SCB scores entailed improvement of the classification rate. This result is especially remarkable, as it confirms that using data from different domains (psychological and electrophysiological) lead to better characterization of the EP in ex-combatants.

Development of a SVM-based system to estimate cognitive phenotypes related with emotional processing in ex-combatants. In Chapter 5, we proposed a framework to differentiate EP in ex-combatant using FCN metrics and SCB scores. To our knowledge, this is the first phenotyping scheme based on behavioral and brain FCN measures of emotional processing in this population. In our experiments, we reached the highest accuracy using a method of feature fusion based on CCA.

Results show the existence of potential phenotypic data in ex-combatant linked to disruptions of the small-world network, which was addressed by an increased MST diameter and decreased leaf fraction in ex-combatants. This demonstrates that combat experience modulates the EP in ex-combatants by forcing a reorganization of their FCN. Using CCA not only helped improve classification rate but it also suggested relationships among neural reorganization and aggression traits in ex-combatants.

If further validated, we would expect this approach to help in the monitoring of DDR programs in countries with internal conflicts, such as Colombia, and to provide a new research approach to characterize affective problems in populations that do not fall within the classical definitions of disease.

Identification of relationships among FCN and ERT performance. Finally, in Chapter 6, we implemented CCA to take into account the extent of small-world network disruption in performance during task development. For this aim, we exploited three widely used behavioral variables in cognitive psychology: (a) Accuracy, (b) reaction time, and (c) inverse efficiency.

Results showed that ex-combatants exhibit atypical modulation of word processing, as they made more mistakes when processing such stimuli in comparison to controls. This indicates that ex-combatants have developed specialized skills to process emotional content in facial expression over written information.

Moreover, while stimuli with neutral valence proved to be worst processed in both populations, positive valence stimuli were better processed. This suggests that EP is prone to the ambiguity of the multi-valence context of the ERT.

The resulting canonical correlation model yielded significant associations among disruptions in the small-world network and behavioral data related to emotional face processing. This could help elucidate how the neural reorganization in ex-combatants might modulate the perceptual and mental processes associated to face processing.

7.2 Future work

Following the research line described in this thesis, two main projects could be taken up:

1. Further efforts to include different domains related to EP in ex-combatants, such as attentional bias toward threat-related paradigms.

2. Development of model-driven connectivity methodologies to explore how combat experience in ex-combatants affects their neural reorganization.

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