Characterization Framework for Ex-combatants Based on EEG and Behavioral Features

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Abstract— **This paper presents a framework to characterize the emotional processing of Colombian ex-combatants from illegal groups. The classification process is performed using EEG-ERP data and behavioral features from psychological tests. The results show that ex-combatant and civilian populations can be automatically separated using supervised techniques. With this, we can provide a decision support system for psychologists to improve current interventions aimed to help ex-combatants to make a successful reintegration to civilian life.**

Keywords— **Emotional Processing, Emotional Recognition Task, ERP, Ex-combatants, Supervised Learning.**

I INTRODUCTION

Ex-combatants from illegal groups in Colombia manifest an increased expression of aggression. A previous work demonstrated that they present alterations on their emotional processing [1]. However, this study did not analyze early stages of physiological processing. Veterans mainly manifest differences on the processing of unpleasant or violent emotions [2]. On ex-combatants, we hypothesize an atypical functioning on similar mechanisms. In order to improve the current interventions, we need biological markers to characterize atypical functioning of emotional processing.

In this line, Electroencephalography (EEG) is widely used as an index of neurophysiological activity associated to electrical activations in the brain, measured with electrodes placed on the scalp [3]. Given that event-related potentials (ERP) capture neural activity related to both sensory and cognitive processes, it is the most used approach to characterize EEG changes [4].

Several studies have reported relations between ERP components and the behavior or personality of healthy subjects. Results in [4] show an overview of the different ERP waveforms and the major findings in various psychiatric conditions. Relations between impulsivity and P3 amplitude/latency were studied in [5] with subjects suffering of high anxiety. While [2] showed that combat veterans with PSTD exhibit greater ERPs.

This paper presents a framework based on ERP components and psychological tests for automatic characterization of ex-combatants, in order to design strategies that are useful for their reintegration into civilian life. For feature selection and extraction, Partial Least Squares (PLS) method is used as a supervised projection, aiming to preserve the components that are maximally related with the labels. Results show that we indeed can characterize ex-combatants from civilians. The proposed methodology can be used as a decision support system to develop efficient intervention protocols.

II MATERIALS

A Participants

The participants were 30 Colombian ex-combatants (two female) from *Agencia Colombiana para la Reintegración* (ACR) reintegration program, and 20 Colombian individuals (paired by sex, age and school level). All subjects participated voluntarily and signed an informed consent in agreement with the Helsinki declaration. Demographic information is provided in Table 1.

Table 1: Demographic information.

	Ex-combatants	Civilians	
	$n = 30$	$n = 20$	p
Gender	2:28	2:18	0.678
Age (years)	M = 37.50 SD = 8.22	M = 36.15 SD = 9.17	0.589
Educational level (years)	M = 10.33 SD = 3.10	M = 11.05 SD = 2.14	0.373

B Emotional Recognition Task Procedure

For this study, we implement a modification of the Dual Valence Association Task (DVAT) [6]. A two-alternative, forced-choice task, in which participants are asked to classify words or faces displayed on a computer screen according to their valence, into one of two categories (positive or negative) as quickly as possible [6]. Our modifications consisted in the inclusion of *Neutral* as a third valence level, and the removal of the simultaneous stimuli block described in [6].

Fig. 1 shows the pipeline of a single trial. Block trials are presented one-by-one with strict alternation between words and faces, and no more than two consecutive stimuli with the same valence.

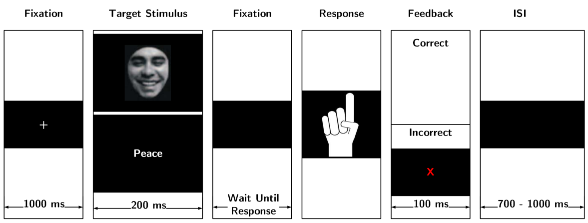

Fig. 1: **Experimental design.** Trials start with a fixation cross, followed by a target stimulus: single stimulus face or word. Feedback is provided only in error trials. Time between trial completion and onset of the subsequent trial (ISI) varies between 700 and 1000 ms.

C ERP Recordings

EEG signals were sampled at 1000 Hz from a 64-channel Neuroscan SynAmps2 amplifier. They were band-pass filtered between 0.1 and 30 Hz. We selected 60 electrodes for this study (HEO, VEO, CB1 and CB2 were excluded as they do not record neural activity). Acquired EEG signals were re-referenced off-line to average electrodes, and downsampled to 500 Hz. Continuous EEG data were segmented from 200 ms prior to the stimulus to 800 ms after. All segments contaminated with eye movement were removed from further analysis using Independent Component Analysis (ICA) and visual inspection. Artifact-free segments were averaged to obtain ERPs. The preprocessing stage was performed using EEGLAB Toolbox [7]. Unless DVT presents faces and words, only word stimuli were considered for this work.

D Psychological Tests

Both ex-combatants and civilians completed a neuropsychological evaluation. It included two psychological tests: the Social Ability Scale of Gismero (EHS) [8], and the Reactive-Proactive Aggression Questionnaire (RPQ) [9].

The EHS measures the assertion of individual's everyday social interaction. It consists of 33 items, 28 redacted in negative sense (absence or lack of abilities), and 5 in positive sense. It explores 6 dimensions of the social skills. This scale allows obtaining a global score and punctuations for each of the six dimensions [8].

The theoretical foundation of the RPQ suggests that the exploration of reactive and proactive aggression has to include the motives associated with behavior, context and type of reaction; such as physical and verbal aggression [9]. It has 23 items divided in two dimensions rated as *never*, *sometimes* and *often* for frequency of occurrence [9].

III METHODS

A Features Extraction

The main ERP components and their properties are summarized in [10]. In accordance with the nature of the DVAT, two peaks are identified as dominants: (*i*) N170, a a member of the N2 family with latency between 156 and 189 ms, which reflects expert object recognition; and (*ii*) P300 (or P3), which occurs in response to an unexpected stimulus type approximately 300 ms after the stimulus onset.

In this work, we use the following procedure to identify the lag and amplitude of the N170 and P300 ERP components: *i*) a multilevel 1-D non-decimated Haar wavelet decomposition is calculated for the ERP signal, *ii*) the minimum (N170) and maximum (P300) values of the first approximation coefficient are found between 150 and 350 ms, *iii*) the occurrence time of both peaks is brought to the original ERP signal, and *iv)* the peak amplitudes are calculated. Fig. 2 shows a random ERP signal, its first approximation coefficient, and the detected peaks.

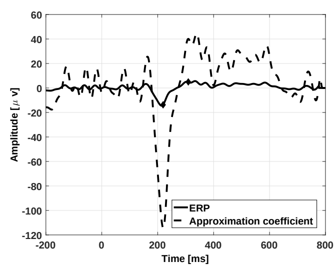

Fig. 2: **ERP component detection.** The peaks N170 and P300 are detected from the first approximation coefficient of the non-decimated Haar wavelet decomposition of the ERP. The peaks amplitudes are then obtained from the original ERP signal.

Finally, we complete the feature vector with the psychological scores. Specifically, for each participant we take the global score from the EHS, the punctuations in each dimension (reactive and proactive) of the RPQ, and the total RPQ punctuation.

B Partial Least Square Regression

The main idea of PLS regression is to find a linear model to describe some predicted variables $\mathbf{X}$ in terms of other observable variables $\mathbf{Y}$. For a L classification problem as in [11], with $(\mathbf{x}_i, y_i) \in \mathbf{X} \times \{C_1, \ldots, C_L\}$, $\mathbf{x} \in \mathbb{R}^p$, with Q the number of features and n the number of observations. The sample vectors $\mathbf{X}$ and response $\mathbf{Y}$ matrices are given by:

$$\mathbf{X} = \begin{bmatrix} x_{11} & \ldots & x_{1Q} \\ \vdots & \ddots & \vdots \\ x_{n1} & \ldots & x_{nQ} \end{bmatrix} \qquad \mathbf{Y} = \begin{bmatrix} 1 & 0 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 1 \end{bmatrix} \tag{1}$$

where each row of $\mathbf{Y}$ contains ones in positions denoting class labels. PLS regression searches for a set of components (called latent vectors) that perform a simultaneous decomposition of $\mathbf{X}$ and $\mathbf{Y}$ as in Eq. (2). These components explain as much as possible of the covariance between $\mathbf{T}$ and $\mathbf{U}$ [12].

$$\begin{cases} \mathbf{X} & = \mathbf{T}\mathbf{P}^\top + \mathbf{E} \\ \mathbf{Y} & = \mathbf{U}\mathbf{Q}^\top + \mathbf{F} \end{cases} \tag{2}$$

Here, matrices $\mathbf{E}$ and $\mathbf{F}$ are the error terms, assumed to be i.i.d. normal, $\mathbf{P}$ and $\mathbf{Q}$ are orthogonal loading matrices, and $\mathbf{T}$ and $\mathbf{U}$ are the projections of $\mathbf{X}$ and $\mathbf{Y}$. The algorithm used in this work for PLS implementation is the well–know Non-Linear Iterative Partial Least Squares Algorithm (NIPALS).

C k-Nearest Neighbors Classifier

The k-Nearest Neighbors (kNN) algorithm starts from a training set $\mathbf{X}_e = \mathbf{x}_1, \ldots, \mathbf{x}_m \subset \mathbf{X}$, $m < n$, labeled with a class label $y_j \in \mathbf{Y}$. Its objective is to classify an unknown sample χ. According to [13], for each $\mathbf{x}_i \in \mathbf{X}_e$ the distance between χ and $\mathbf{x}_i$ could be calculated as follows:

$$d\{\chi, \mathbf{x}_i\} = \sum_{q \in Q} w_q \delta(\chi_q, x_{iq}), \tag{3}$$

where δ is any distance metric, i.e., Mahalanobis, Euclidean, Minkowski, Hamming, among others; and w_q is the distance weighting function. The k nearest neighbors are selected based on this distance metric. The class of χ could be assigned to the majority class among the nearest neighbors; nevertheless, there are several ways to select the χ label, according to the weighting factor.

D Support Vector Machine Classifier

Support vector machines (SVM) are linear classifiers developed on statistical learning theory (SLT) by Vapnik [14]. SVM are supervised learning models that aim to find an optimal hyperplane to separate the points of two classes. C-SVM is a widely used type of SVM (see [15] for implementation details).

For linearly separable data, the maximum margin hyperplane is determined by the constrained optimization problem

$$\begin{aligned} \underset{\alpha}{\text{minimize}} \quad & \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} y_i y_j \alpha_i \alpha_j \kappa(\mathbf{x}_i, \mathbf{x}_j) - \sum_{j}^{m} \alpha_j \\ \text{subject to} \quad & \sum_{i=1}^{m} \alpha_i y_i = 0, \\ & 0 \le \alpha_i \le C, i = 1, \ldots, m, \end{aligned} \tag{4}$$

where $\kappa(\mathbf{x}_i, \mathbf{x}_j)$ represents a kernel function, and C is the penalty factor that controls the complexity of the SVM. The decision function is

$$f(\mathbf{x}) = \operatorname{sgn}\left(\sum_{i}^{m} \alpha_i y_i \kappa(\mathbf{x}_i, \mathbf{x}) + b \right) \tag{5}$$

For the C-SVM model specification, the Gaussian (or radial basis) kernel is defined as

$$\kappa(\mathbf{x}, \mathbf{y}) = \exp\left(\frac{-\|\mathbf{x} - \mathbf{y}\|^2}{2\sigma^2} \right) \tag{6}$$

The penalty factor C and the parameter σ of the kernel must be tuned by minimizing the estimated generalization error.

IV Results and Discussion

We used the classification accuracy to tune the parameters of both the number of PLS components, and the number of neighbors for the kNN classifier. The highest results were obtained with two components and three neighbors. The C-SVM model selection was made by grid search. The best performance was reached with $C = 1.6$ and $\sigma = 1.0$.

Results show that although both classifiers achieved over 75% of accuracy (see Table 2), the SVM-based classifier presented better performance, achieving 80.00% of accuracy with a confidence interval of (63.87 - 90.88)%. Despite that evidence points out the existence of alterations in the emotional processing 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.

The sample size of our study was modest because neuropsychological assessment combined with ERPs in illegal ex-combatants is difficult and uncommon.

Table 2: Accuracy, sensitivity and specificity reached with the proposed methodology.

Method	Accuracy (%) (Conf. Interval)	Sensitivity (%) (Conf. Interval)	Specificity (%) (Conf. Interval)
KNN	77.50 (61.14 - 89.03)	85.00 (69.48 - 94.39)	70.00 (53.29 - 83.21)
SVM	80.00 (63.87 - 90.88)	85.00 (69.48 - 94.39)	75.00 (58.48 - 87.14)

Regarding to the population grouping, Fig. 3 shows that ex-combatants conform a well defined group, while civilians tend to share some features with the other group, *i.e.* some civilian samples mix with the ex-combatants group of samples. This complicates their identification as a group.

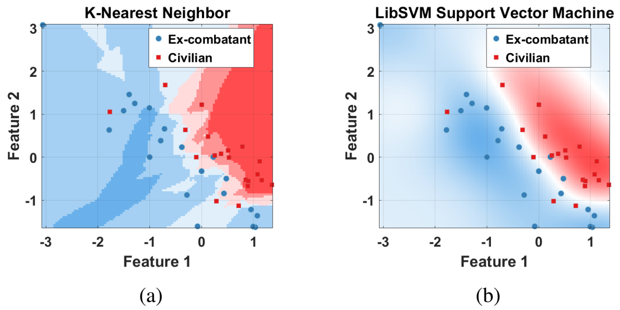

Fig. 3: **Classification results for (a) *k*NN and (b) SVM.** Note that civilians are spread, while ex-combatants are more compact. This drive to lower specificity values.

V Conclusion

This paper introduced a framework to characterize ex-combatants from civilian people, as a first step to design interventions to treat their rage issues. This study showed that supervised techniques with EEG and behavioral features may differentiate emotional processing from ex-combatants with high accuracy and sensitivity.

Acknowledgements

The authors appreciate the assistance of *Agencia Colombiana para la Reintegración*. This work was partially supported by Colciencias Grants [122266140116 and 111556933399], CODI-UDEA INV518-16, doctoral fellowship call 647 (year 2014), and research project 762 (*Universidad de Medellín* and *Neurocentro de Pereira*).

Conflict of Interest

The authors declare that they have no conflict of interest.

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