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Individual EEG differences in affective valence processing in women with low and high neuroticism

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HIGHLIGHTS

- EEG channels showing generic and individual emotional patterns in women with high neuroticism are indicated.
- Individual specificity is studied in the affective valence processing of emotional visual stimuli.
- Support vector machine (SVM)-based classification is used for analyzing individual differences from EEG single trials.

ABSTRACT

Objective: In this study, individual differences in brain electrophysiology during positive and negative affective valence processing in women with different neuroticism scores are quantified.
Methods: Twenty-six women scoring high and low on neuroticism participated on this experiment. A support vector machine (SVM)-based classifier was applied on the EEG single trials elicited by high arousal pictures with negative and positive valence scores. Based on the accuracy values obtained from subject identification tasks, the most distinguishing EEG channels among participants were detected, pointing which scalp regions show more distinct patterns.
Results: Significant differences were obtained, in the EEG heterogeneity between positive and negative valence stimuli, yielding higher accuracy in subject identification using negative pictures. Regarding the topographical analysis, significantly higher accuracy values were reached in occipital areas and in the right hemisphere ($p < 0.001$).
Conclusions: Mainly, individual differences in EEG can be located in parietooccipital regions. These differences are likely to be due to the different reactivity and coping strategies to unpleasant stimuli in individuals with high neuroticism. In addition, the right hemisphere shows a greater individual specificity.
Significance: An SVM-based classifier asserts the individual specificity and its topographical differences in electrophysiological activity for women with high neuroticism compared to low neuroticism.

1. Introduction

Nowadays, individual differences analysis in human beings is a field which receives more and more attention from interdisciplinary approaches, from the more classical psychological approaches like the studies of Eysenck (1967), Dis et al. (1979) or Buss (1984) to the modern studies about genetic and neuroscience (Parasuraman and Jiang, 2012; Toga et al., 2006). Nonetheless, few works research on the individual differences within a determined personality factor.

The importance of quantifying the individual differences influence is well known in any clinical and psychophysiological context (Stemmler and Wacker, 2010). For instance, an accurate diagnosis of personality or emotional disorders or measuring correctly how deep a trauma impact is become important issues to guarantee

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later therapies effectiveness. However, the huge variability in the spectrum of the emotions in human beings, due to their genetic contribution and their experiences throughout their lives, makes difficult to get general patterns from the emotional processes. It is necessary to find out which characteristics are the most relevant depending on the application goal. Many research works on personality aim to find the relations between personality types and their specific behaviours (Amin et al., 2004), while other studies intend to discover the underlying anatomical structures or neurophysiological processes from diverse profiles (Britton et al., 2007; Ormel et al., 2013).

In this study, the individual differences reflected in the EEG during affective valence processing are analyzed in two populations of women with different tendency to neuroticism. Affective valence is one of the main axis from the dimensional model of emotions (Heller, 1993; Lang et al., 2008; Olofsson et al., 2008) and refers to the pleasure or displeasure elicited by a stimulus. On the other hand, neuroticism is defined as a personality trait characterised by a predisposition to experience negative emotions like anxiety, frustration, stress or anger and is evaluated on a continuum that varies between emotional stability and instability (Denissen and Penke, 2008). This personality trait is associated with a negative emotional bias which generally leads to rapid detection and reaction to negative stimulus (Wright et al., 2006; Norris et al., 2007).

Electroencephalography is a non invasive technique which can be explored to check individual specificity for better understanding the neurophysiological processes linked to neuroticism and emotions in general. Research works dealing with neuroimage and electrophysiology-based techniques have demonstrated that event related potentials (ERPs) are modulated by the personality type, specifically by neuroticism (Fjell et al., 2005; Georgiev et al., 2008; Jausovec and Jausovec, 2007). However, some of the results reported in the literature can be confusing due to the mentioned inter-individual heterogeneity since these peculiarities go accompanied by diverse affective reactions (Coan et al., 2006; Hagemann, 2004). Therefore, it is convenient to study neurophysiological individual differences merging these two concepts (emotion and neuroticism) with different emotional stimuli (Coan et al., 2006; Hamann and Canli, 2004).

Approaches which take into account the inherent individual influence in EEG signals taking them as whole entities have been hardly developed. Some components from the averaged ERPs have been widely investigated both in time domain (Aftanas et al., 2001; Carretie et al., 2001; Delplanque et al., 2004) and frequency domain (Güntekin and Basar, 2010; Herrmann, 2005; Wang, 2010) without considering any pattern from the original single trials. ERP computing is very useful in the field of the psychophysiology and for selecting the most relevant EEG channels (Duun-Henriksen et al., 2012), but the increasing research works on online applications, such as brain computer interface (BCI) for medical, therapeutic or recreational purposes, make a reliable single trial processing more and more needed (Bai et al., 2007). Single trials give valuable information that could be lost after averaging for computing the ERP, although their processing is harder and it is more difficult to reach so good results (Schuster et al., 2012). Thus, it is important to expound new manageable ideas to extract relevant information from single trials.

In this work, a classification technique is employed to study individual differences, instead of other traditional statistical methods. This approach allows tackling the digital EEG signals processing from a new point of view, taking each single trial as a complete set of features and representing them in a multidimensional space, where two classes can be split. This fact provides an advantageous and practical methodology and provides valuable information apart from other mathematical parameters like Pearson's correlation coefficient, standard deviation or similar measures of variance. The core of the method lies in making up two classes based on the experimental conditions (high neuroticism vs low neuroticism and negative valence vs positive valence) and quantifying, by means of the classifier accuracy (*acc*), how easy identifying a concrete subject is. The more accurate the classifier is, the more particular the EEG signal will be, so that the presence of an individual difference would be obvious.

Numerous algorithms and methods for validation, feature extraction and feature selection are described in the literature dealing with classifiers or machine learning (Guyon et al., 2002; Tan et al., 2006). In this article, a linear support vector machine (SVM)-based classifier is implemented (Burges, 1998). There are various reasons for this choice. In the first place, SVM has demonstrated to give excellent results in different neuroscience applications (Lopez et al., 2009; Lopez et al., 2013). Secondly, although the complete design could be quite complex due to the computing of some optimization factors, the main bases are easily understandable. Finally, the main idea of this technique, consisting of demarcating a hyperplane that separates both classes, is essential to obtain suitable conclusions about the existing individual differences in a specific experimental group (see Section 2.3.1).

There is evidence that women show different patterns of brain activation from men in response to emotional stimuli (Kemp et al., 2004). Women typically score higher in neuroticism scale than men and women with high neuroticism are more reactive to negative visual stimulation compared to those who score low in the same scale (Hamann and Canli, 2004; Lithari et al., 2010; Strien et al., 2009). Therefore only female participants were chosen in this experiment to guarantee higher homogeneity of the data and avoid gender differences.

2. Methods

2.1. Participants

Firstly, the initial sample was composed of 164 healthy female volunteers, who participated in the study responding to the neuroticism scale of the revised version of the NEO Personality Inventory (NEO PI-R) (Portuguese version) (Costa and McCrae, 2000). A general explanation and instructions were given to all the volunteers in a classroom.

Twenty-six participants were finally selected for completing the laboratory study (age 18–62 years; mean = 24.19; sd = 10.46), after sorting all the initial sample of 164 participants on the basis of their neuroticism score. Two groups, statistically different regarding their score ($p < 0.001$) were constituted:

- High neuroticism (HN group): The 13 women (belonging to the initial sample of 164 participants) with highest scores in neuroticism from the initial distribution (mean = 62.15; sd = 15.48) according to the NEO PI-R neuroticism scale.
- Low neuroticism (LN group): The 13 women (belonging to the initial sample of 164 participants) with lowest scores in neuroticism from the initial distribution (mean = 125.08; sd = 8.95) according to the NEO PI-R neuroticism scale.

All participants had normal or corrected to normal vision and none of them had a history of severe medical treatment, neither psychological nor neurological disorders. A signed informed consent was obtained from each participant before carrying out the experiment. This study was approved in accordance with the Declaration of Helsinki.

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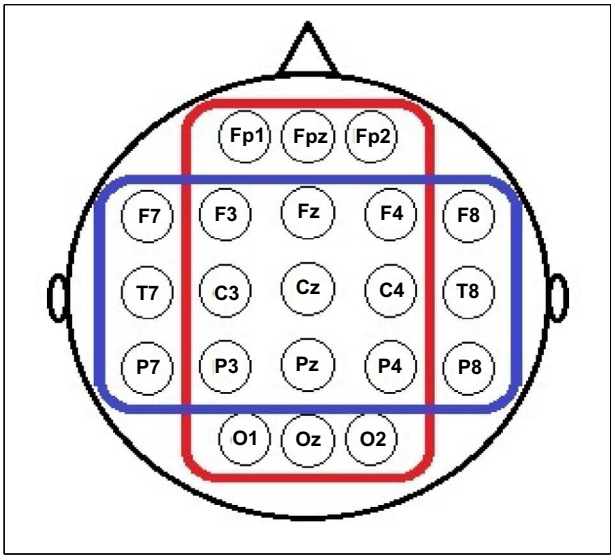

Fig. 1. Electrodes cap scheme. Channels inside red square were used in front-occipital location analysis. Channels inside blue square were used in laterality analysis.

2.2. Procedure

Each one of the selected participants was comfortably seated at 70 cm from a computer screen (17′), alone in an enclosed room. The volunteer was instructed to visualize some pictures, which appeared on the center of the screen, and to stay quiet. No responses were required.

2.2.1. Stimuli

The pictures were chosen from the International Affective Picture System (IAPS) (Lang et al., 2008), widely used in psychology research works (Aldhafeeri et al., 2012; Martini et al., 2012; Frantzidis et al., 2010). A total of 24 images with high arousal ratings (>6) were selected, 12 of them with positive affective valence (7.29 ± 0.65) and the other 12 with negative affective valence (1.47 ± 0.24).

In order to match as closely as possible the levels of arousal between positive and negative valence stimuli, only high arousal pictures were presented, avoiding neutral stimuli.

Three blocks with the same 24 images were presented consecutively. The picture order in each block was pseudo random to avoid expectancy phenomena. In each trial a fixation single cross was presented on the center of the screen during 750 ms, then, one image was presented during 500 ms and finally a black screen during 2250 ms (total duration = 3500 ms).

2.2.2. EEG recording

EEG activity on the scalp was recorded from 21 Ag/AgCl sintered electrodes (Fp1, Fpz, Fp2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, O1, Oz, O2) mounted on an electrode cap from EasyCap according to the international 10/20 system (see Fig. 1), internally referenced to an electrode on the tip of the nose. The impedances of all electrodes were kept below 5 kΩ. EEG signals were recorded, sampled at 1 kHz and pre-processed using software Scan 4.3 (Compumedics Neuroscan, Germany). Firstly, a notch filter centered in 50 Hz was applied to eliminate AC contribution. EEG signals were then filtered using a Butterworth passband filter from 0.1 Hz to 30 Hz.

Artifacts rejection was performed based on amplitude values, following a visual inspection of all signals and rejecting epochs that presented clear artifacts. Regarding the ocular correction a semi-automatic method is applied by following the procedure described in software package Scan 4.3 (Compumedics Neuroscan, Germany). The method employs a regression analysis in combination with artifact averaging to produce a reliable model of the VEOG signal to be subtracted from the EEG channels (Gratton et al., 1993).

Finally, the signals are segmented into time locked epochs using the stimulus onset (picture presentation) as reference and baseline corrected. The length of the time windows was 950 ms: from 150 ms before picture onset to 800 ms after it (baseline = 150 ms). Fig. 2 shows examples of EEG single trials.

2.3. Data analysis

2.3.1. SVM classification

A SVM-based classifier separates a given set of binary labeled training data with a hyperplane, known as the maximal margin hyperplane, which is maximally distant from the two classes (ω_1

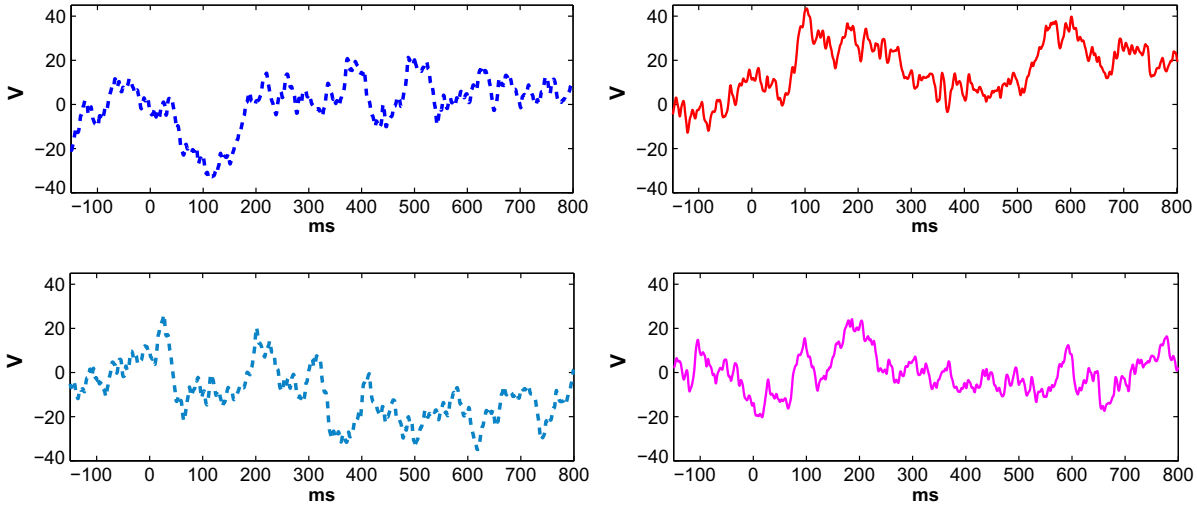

Fig. 2. Examples of single trials recorded in Oz channel from two different participants from the two experimental conditions. Low neuroticism scores and negative valence (upper left), high neuroticism scores and negative valence (upper right), low neuroticism scores and positive valence (down left) and high neuroticism scores and positive valence (down right).

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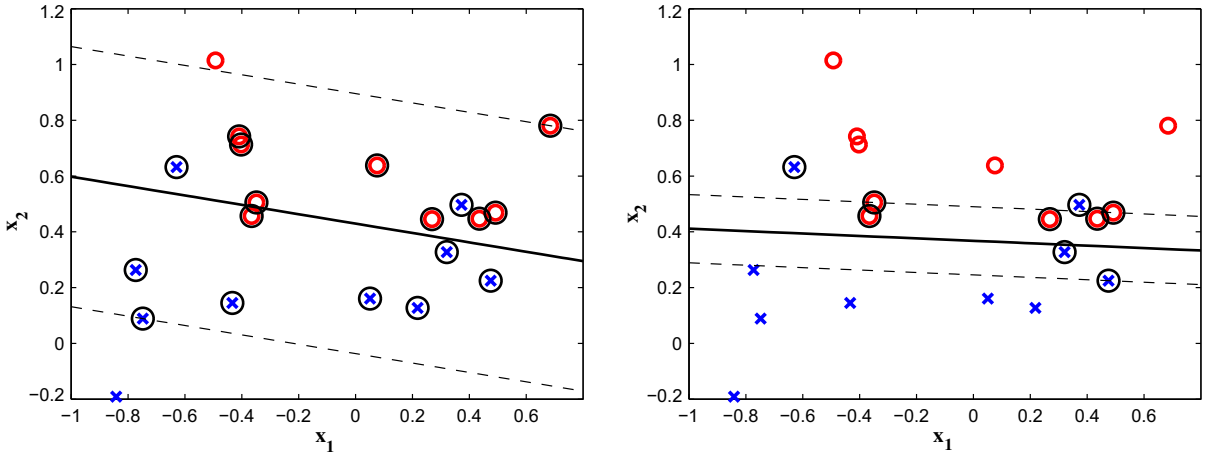

(a) $C = 1$ (b) $C = 100$

Fig. 3. SVM schemes using different C values.

and ω_2). The objective is to build a function $f : \mathbb{R}^M \longrightarrow \{\pm 1\}$ using training data, that is, M-dimensional patterns $\mathbf{x}_i$ and class labels y_i:

$$(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_S, y_S) \in \mathbb{R}^M \times \{\pm 1\}, \quad (1)$$

so that f will correctly classify new examples $(\mathbf{x}, y)$. S is the number of samples in the database.

Linear discriminant functions define the decision hyperplanes, which separates both classes, in a multidimensional feature space:

$$g(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + b = 0, \quad (2)$$

where $\mathbf{w}$ is known as the weight vector and b as the threshold. The optimization task to design the classifier consists of finding the unknown parameters ($w_i, i = 1, \ldots, M$, and b), which separate the two classes optimally. Given a new element $\mathbf{x}$, the predicted label is then:

$$g(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + b \Rightarrow \begin{cases} g(\mathbf{x}) > 0 & \mathbf{x} \in \omega_1 \Longleftrightarrow label \equiv 1 \\ g(\mathbf{x}) < 0 & \mathbf{x} \in \omega_2 \Longleftrightarrow label \equiv -1 \end{cases}$$

Fig. 3 illustrates a 2D toy-example of a binary classification problem, where the points $\mathbf{x} = [x_1 x_2]$ marked as $\circ$ belong to class ω_1 and the ones marked as $\times$ belong to class ω_2. The problem is not linearly separable because it is not possible to find a hyperplane (line, in 2D case) that separates all training instances of the two classes. However, if a small number of misclassifications is tolerated, the problem remains linearly separable. The figure shows the result of two training sessions with the same data but different margins. The decision hyperplane, in all examples, is represented by the thicker line which is in the middle of two other hyperplanes whose distance characterize the margin of the classifier. The position of the decision hyperplane is determined by vector $\mathbf{w}$ and b: the vector is orthogonal to the decision plane and b determines its distance to the origin. The vector $\mathbf{w} = \sum_i^{N_s} y_i \lambda_i \mathbf{x}_i$ is a weighted sum of the *support vectors* which are the N_s elements of training set chosen during the training phase inside the margin or misclassified. In the Fig. 3 these *support vectors* are marked with circles around the training data points. And $0 < \lambda_i < C$ are the corresponding Lagrangian parameters which are also optimized during training. Finally, the value of the threshold b is estimated by solving the equations related to the hyperplanes that define the margin. In (Ben-Hur et al., 2008) an extensive algebraic explanation of SVM, applied to biological sciences, is reported.

The value of C needs to be assigned to run the training optimization algorithm. It is a parameter that indirectly controls the width of the margin of the classifier (see Fig. 3). However, during the optimization process C represents the weight of the penalty term of the optimization function that is related with the misclassification error in the training set. Therefore, the optimization determines the trade-off between the width of the margin and the number of accepted misclassifications. There is no optimal procedure to assign this parameter but it has to be expected that:

- If C is large, the misclassification errors are relevant during optimization. A narrow margin has to be expected.
- If C is small, the misclassification errors are not relevant during the optimization. A large margin has to be expected.

2.3.2. Cross validation

The SVM classifier was evaluated using the leave-one-out (LOO) cross validation strategy that consists of using all the samples in the dataset for training the system except one, which is used as test. This procedure is repeated S times, being S the number of samples in the dataset, after which a global value of accuracy is computed.

2.3.3. Implementation

All the routines needed to apply the completed method were implemented in the software MATLAB (version R2011a, Mathworks, USA). In particular, tools from SVM-package were required. The internal parameter C was kept by default on $C = 1$. No special optimization process was required, since the aim of this study is to compare the accuracy values of the subject identification tasks, rather than designing any complex classifier. The LOO strategy was also implemented in MATLAB in order to get automatically the global accuracy.

2.3.4. Individual differences

The classification technique was applied on binary subject identification tasks. The classification tasks consisted of taking all possible pairs of two different subjects belonging to the same group (HN group or LN group) in similar condition (negative or positive valence) and carrying out binary classifications for discriminating the identity of the subject from one test trial. Therefore, the two classes ω_1 and ω_2 were constituted by single trials of each subject, respectively, both of the same valence condition.

The maximal number of possible couples combinations by condition is equal to 78 (i.e. $N(N-1)/2$ pairs, where N is the number of participants in each group ($N = 13$)). Therefore 78 binary classifiers (pair-wise distinctions) are trained. In the complete set of test there are always 12 evolving decisions related to a particular

participant, resulting from the comparison with the other 12 participants of the same group. The average of accuracies of the 12 classifiers related to a person gives an indication of how the person is distinct from the others.

As it was mentioned before, the capability to discriminate was measured by means of a linear SVM classifier (see Section 2.3.1) and assessed by LOO strategy (Section 2.3.2). Single trials are directly used as input for the classifier, taking the time instants from 0 ms to 800 ms post-stimulus (i.e. a total of $M = 800$ samples by trial). In each single classification task, a total of 30 artifact free single trials were selected per condition for each participant, so that $S = 60$ in each of these classification tasks.

The higher the accuracy rates, the more distinguishable the subjects are between them. Therefore, higher accuracy values imply greater contribution to individual differences. In contrast, accuracy values close to 50% imply that the two classes are hardly distinguishable and may not be properly separated using a hyperplane due to an overlap in the M-dimensional space. This overlap can be interpreted as a high stability in the evoked potentials among participants or as a result of an extreme variability intra-subject. Then, high accuracy results represent peculiar patterns in EEG signals, whereas low accuracy values are related to a more general pattern.

2.3.5. Statistical comparisons

Analysis of variance (ANOVA) and t-tests were used for computing statistical significance for the pertinent intra-group and inter-group comparisons. Mauchy's sphericity test was performed on the analysis and the Greenhouse–Geisser correction was applied on the degrees of freedom when sphericity could not be assumed. Bonferroni correction has been conveniently applied in post hoc analyses when multiple comparisons have been carried out.

ANOVAs were taking the 78 accuracy values obtained as output of the classifiers from the binary classifications in both groups (factor 1: neuroticism; two levels: HN and LN) in the two experimental conditions (factor 2: affective valence; two levels: negative (−) and positive (+)). Additional factors were defined for topographical analysis (front-occipital location and left–right location) with five levels each one.

3. Results

3.1. Neuroticism and valence analysis

Figs. 4 and 5 show the averaged accuracies for each experimental condition. Significant differences were not found between groups ($F(1,154) = 1.484; p = 0.225; \eta^2 = 0.01; acc_{HN} = 74.15\%; acc_{LN} = 75.07\%$). However, significant differences ($p < 0.05$) were obtained by comparing both affective valence conditions within participants ($F(1,154) = 16.161; p < 0.001; \eta^2 = 0.095; acc_{-} = 75.45\%; acc_{+} = 73.77\%$). Also, a significant valence*neuroticism interaction was found ($F(1,154) = 9.363; p = 0.003;$

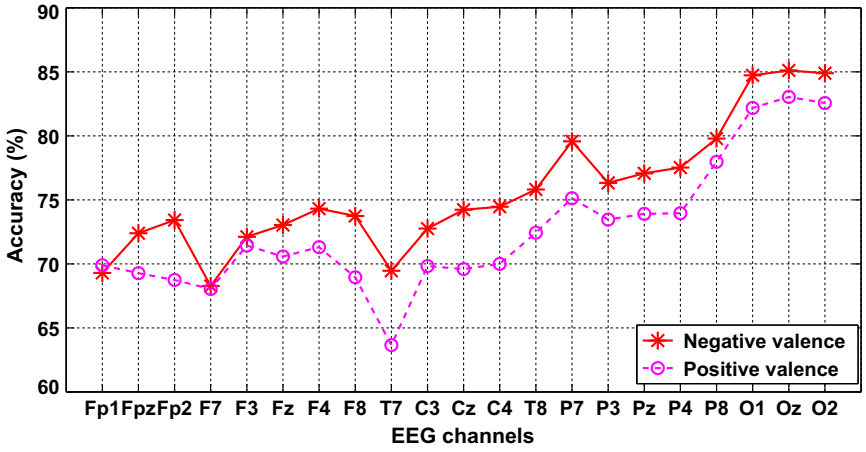

Fig. 4. Mean accuracy values for every EEG channel in high neuroticism (HN group) per condition.

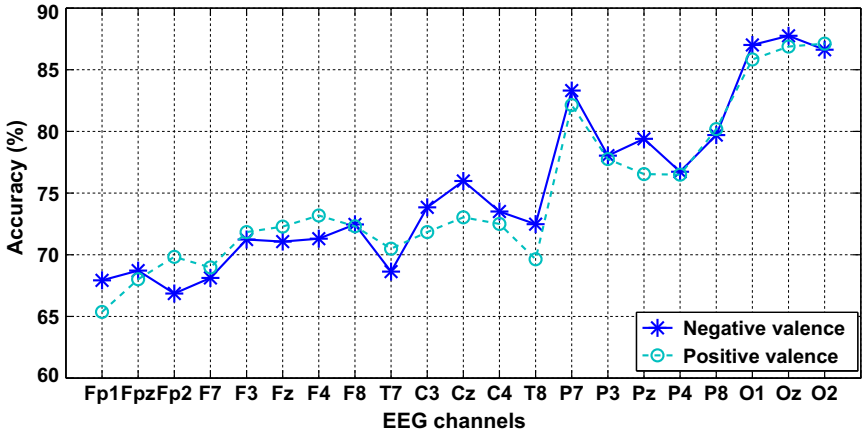

Fig. 5. Mean accuracy values for every EEG channel in low neuroticism (LN group) per condition.

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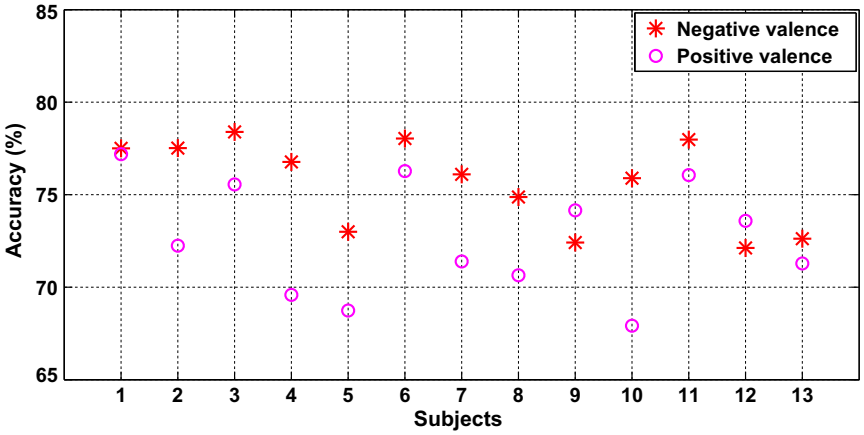

Fig. 6. Global accuracy values, averaging all EEG channel results, for every participant from high neuroticism (HN group) per condition.

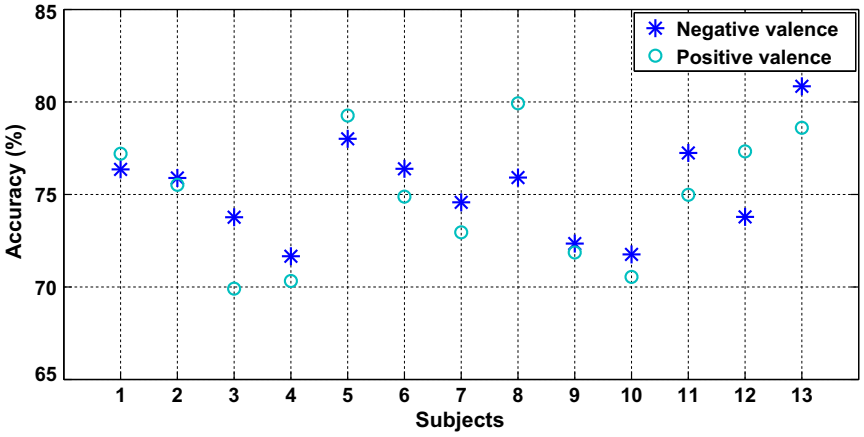

Fig. 7. Global accuracy values, averaging all EEG channel results, for every participant from low neuroticism (LN group) per condition.

$\eta_p^2 = 0.057$; $acc_{HN-} = 75.63\%$; $acc_{HN+} = 72.66\%$; $acc_{LN-} = 75.27\%$; $acc_{LN+} = 74.87\%$).

Figs. 6 and 7 show the global accuracies per condition for each participant, averaging the accuracy values from the 12 binary classifications task related to one person (Section 2.3.4) and from all the EEG channels. Note that in HN group only two participants obtained a slightly higher accuracy value with positive than with negative valence.

3.2. Topographical analysis

In order to complete a more detailed topographical study on the individual differences, two different ANOVAs were performed on two different subsets from the complete database. The selected EEG channels for each analysis are delimited in Fig. 1.

3.2.1. Front-Occipital location

In order to study the relevance of the EEG channels depending on the front-occipital axis position, besides the previous defined factors (see Section 2.3.5) a third factor was added to the ANOVA (factor $3_{front-occipital}$: front-occipital location; five levels: prefrontal, frontal, central, parietal and occipital). As Fig. 1 shows, each level is composed of three EEG channels centered in the middle of the scalp region. A clear and statistically significant influence of this factor was confirmed ($F(2.729, 152.3) = 197.5; p < 0.001; \eta^2 = 0.562$). Parietal and occipital areas showed higher accuracy values than more frontal regions (see Figs. 4 and 5).

Some interactions were significant, as location*neuroticism ($F(2.729, 152.3) = 6.72; p < 0.001; \eta_p^2 = 0.042$), being more evident the influence of the EEG channels position in the LN group ($acc_{HN_{prefront}} = 70.5\%; acc_{HN_{occip}} = 83.75\%; acc_{LN_{prefront}} = 67.79\%; acc_{LN_{occip}} = 86.87\%$), and location*valence interaction ($F(3.305, 151.7) = 3.16; p = 0.021; \eta_p^2 = 0.02$) ($acc_{prefront+} = 68.52\%$; $acc_{prefront-} = 69.77\%; acc_{occip+} = 84.6\%; acc_{occip-} = 86.02\%$). On the other hand, interaction location*neuroticism*valence was not proved ($F(3.305, 151.7) = 0.278; p = 0.859; \eta_p^2 = 0.002$).

3.2.2. Laterality

In addiction, the laterality influence was studied. In this case, the third factor was defined according to the left–right location (factor $3_{left-right}$: left–right location) and a total of five levels were defined from left to right sides, where the middle level corresponds to the central position. Each level groups three EEG channels (see Fig. 1). A significant effect from this factor was evidenced ($F(2.752, 152.2) = 10.73; p < 0.001; \eta^2 = 0.065$).

Generally, right hemisphere region showed higher accuracy values than left hemisphere, specially in HN group ($acc_{HN_{left}} = 70.69\%$; $acc_{HN_{right}} = 74.78\%; acc_{LN_{left}} = 73.61\%; acc_{LN_{right}} = 74.46\%$) which was statistically proved with the laterality*neuroticism interaction ($F(2.752, 152.2) = 5.062; p = 0.003; \eta_p^2 = 0.032$). The laterality*valence interaction ($F(3.136, 151.9) = 0.945; p = 0.422; \eta_p^2 = 0.06$) and laterality*neuroticism*valence interaction ($F(3.136, 151.9) = 1.448; p = 0.227; \eta_p^2 = 0.09$) were not significant.

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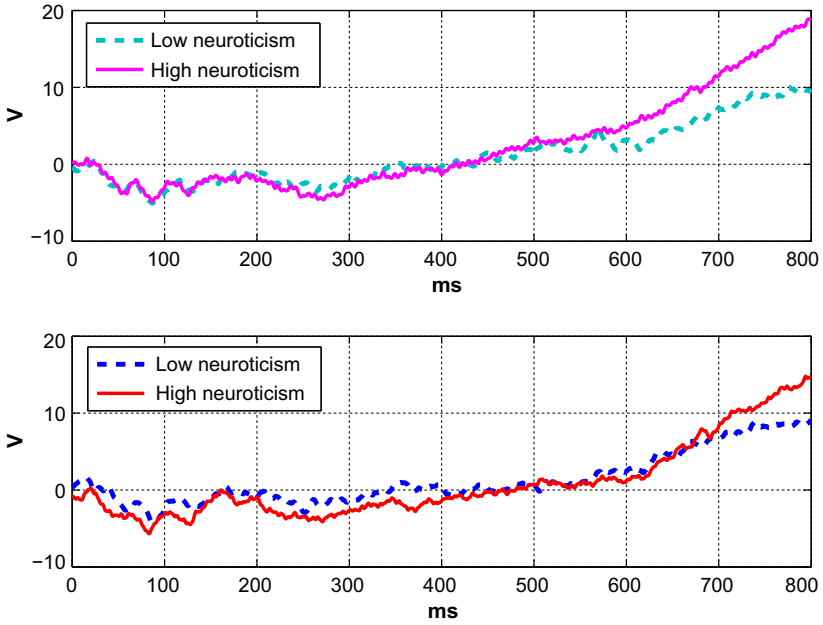

Fig. 8. Grand average from event related potentials (ERPs) from Fp1 channel. Positive valence (upper), negative valence (down).

3.2.3. Most relevant EEG channels

Finally, it is interesting to point out the EEG channels which reach the maximal and minimal accuracy peaks, since they will be important to determine global neurophysiological patterns or more particular electrophysiological features dependent on the specific application goal. Thus, the EEG channel that yields the highest accuracy values is Oz in 46% of the participants (see examples from single trials recorded from this electrode in Fig. 2), whereas the EEG channels that give the lowest accuracy values are located in the left front-temporal region (i.e. Fp1, F7 and T7).

Fig. 8 shows the grand average of the ERP from Fp1. The signals recorded with Fp1 channel are the most similar among participants in affective valence processing, according to the obtained accuracy values in both groups and both valences.

4. Discussion

The first question that has to be answered is if the women with high neuroticism scores differ among them, more, less or similarly compared to the group composed of women with low neuroticism scores. According to the obtained results (see Section 3.1) the individual differences contribution is equivalent in both populations. Nonetheless, it is necessary to analyze some interaction effects that can show more specific differences in the pattern from any delimited scalp region. It is important to stress that these results do not mean that participants that score high in neuroticism show identical patterns to stable participants while they are visualizing pictures, but within both groups the general level of their own patterns is the same, showing high within-group homogeneity. As far as we are aware, there are not similar previous research works which study the individual differences with this aim.

In regard to the affective valence, the results suggest that a more generic pattern exists when positive visual stimuli are processed. The emotional processing of a picture with negative valence elicits more varied brain responses among different people. This might be due to the interaction of particular traumas or bad experiences and personality characteristics, which can have a remarkable influence on the reactions to negative stimuli for a better environmental adaptation. One possible explanation to these individual differences can be related to different individual forms of reappraisal that subjects might use when confronted with aversive stimuli (Ochsner et al., 2004). Another possibility can be related to individual differences in state negative affect associated with an increase of the left insular activity, which has been suggested to be implicated in interoceptive processes that contribute to subjective emotional experience (Mériau et al., 2009). Overall, the evidence seems to indicate that the neural activity elicited by viewing negative pictures depends both on biological factors and on the individual's personal characteristics and histories, which is compatible with our findings of higher inter-individual variability in response to negative valence stimuli.

The neuroticism*valence interaction suggests different strategies for negative stimuli processing in women with high neuroticism. This result strongly confirms the conclusion explained in the previous paragraph specially for participants that score high in neuroticism. The greater reactivity of people with high neuroticism (Wright et al., 2006; Norris et al., 2007) makes them more prone to vary their cognitive skills, behaviours and underlying neurophysiology, becoming more pronounced their individual differences in negative contexts. Compatible with this idea, a recent study has shown that neural activity at the early phases of affective processing can be modulated by personal traits, such as neuroticism or mindfulness, being related to more difficulties in emotion regulation or more healthy emotional functioning, respectively (Brown et al., 2013).

One of the most interesting conclusions extracted from this study is the topographical distribution of the individual differences (Section 3.2 and Figs. 4 and 5). In general, for every participant from both groups (LN group and HN group) and for any valence, the most remarkable inter-individual differences exist in occipital and parietal regions. These regions are mainly linked to perceptive processes in visual cortex, although some findings claim the implication of posterior areas in affective processing, specifically with high neuroticism (Heller, 1993; Schmidtke and Heller, 2004).

On the other hand, the unequal individual heterogeneity, across the scalp, likely could be influenced by the myelination development. The interaction between the location in the rostrocaudal brain axis and the neuroticism hints that the individual differences are wider spread all over the scalp in LN group than in HN group.

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As it is known, myelination progression covers the rostrocaudal axis from posterior to anterior brain areas and lasts several years (Gibson, 1991). Therefore, whereas frontal regions depend notably on the personal experiences, parietal and occipital regions might preserve a more evident and distinguisable genetic brain signature. Thus, the higher susceptibility to personal experiences attributed to frontal regions could lead to higher intra-individual variability, since it is more likely that individuals will respond differently to different stimuli, based on their individual experiences with that stimulus, situation, etc. This higher intra-individual variability would lead to a lower classification accuracy (see Section 2.3.4), since the various trials of a particular individual would be less homogeneous, and thus it would be more difficult to distinguish between individuals. As a consequence, a lower classification accuracy would be expected in frontal areas, compared to posterior areas, which is what was found in the present study.

Regarding the individual specificity in laterality considering which group a participant belongs to (HN or LN), it can be asserted that women with high neuroticism show a greater difference between hemispheres, showing a slight more generic pattern on the left scalp area, specially for frontal channels (see Fig. 4). This conclusion is extracted from the significant laterality*neuroticism interaction (Section 3.2.2). In many experiments dealing with emotional processes, an anterior EEG asymmetry has been widely analyzed, specially in alpha band (Coan et al., 2006; Hagemann, 2004). Although, this inter-hemisphere asymmetry has not been the target of this study, the statistical results mentioned previously from Section 3.2.2, partially suggest that the two brain hemispheres contribute differently to the affective valence processing specially in HN group.

In the case of low neuroticism, the inter-hemisphere difference is not so evident, although a general left-lateralized negative valence processing has been suggested in some research works (Beraha et al., 2012). No hemisphere could be considered as clearly dominant in the affective valence processing based on the results from this study. This fact can be related to the lower reactivity elicited by negative stimuli in stable people compared to people that score high in neuroticism (Amin et al., 2004; Britton et al., 2007). However, a significantly higher accuracy is obtained from the middle EEG channel (Cz) with respect to its sides.

Among all the employed EEG channels, it is worth pointing out two of them: Oz and T7. Oz is the channel which yields the highest accuracy values for identifying subjects. This result suggests that occipital area is one of the most suitable scalp region for determining particular contributions to the evoked potential's shape in affective valence processing. In contrast, T7 is the least relevant EEG channel for such purpose, specially for HN group, i.e. T7 is the channel that would show a more generic pattern, probably influenced by the noise generated by the blood stream from the temples. Furthermore, according to the results, frontal EEG channels generally are the least relevant to investigate the individual differences contribution in emotional processing. Therefore, frontal areas could provide valuable information for inter-groups comparisons in research on emotion (see Fig. 8), although they are not the most used for computing the psychological components from ERPs.

Comparing the similar shapes of the grand averages signals from Fig. 9 to the extremely different single trials taken as examples in Fig. 2, the usefulness of the classification technique for tackling single trial signals, where it is impossible to measure ERP components directly, is evident. In Fig. 9 the grand average of Pz channel is represented, where P3 component is often measured. While single trials do not allow a clear measurement of ERPs, grand averages do not allow drawing conclusions about individual differences, which is the strongest contribution of the method used in the present work.

Determining the most relevant EEG channels where a greater individual contribution exists is essential for extracting reliable features from a patient. Moreover, in BCI devices and other apparatus for diagnosis or therapies it is very important to take into account the scalp regions where signals are more stable, either for obtaining accurate results or optimizing electronic resources. The larger the database for training the classifier is, the more reliable the conclusions will be. In future works it would be interesting to provide vast databases of different populations. In addition, this methodology can provide valuable information to applications which deal with other types of neurophysiological signals apart from electroencephalography, such as magnetoencephalography among others, in order to determine the individual differences existing in diverse pathologies or to quantify gender differences.

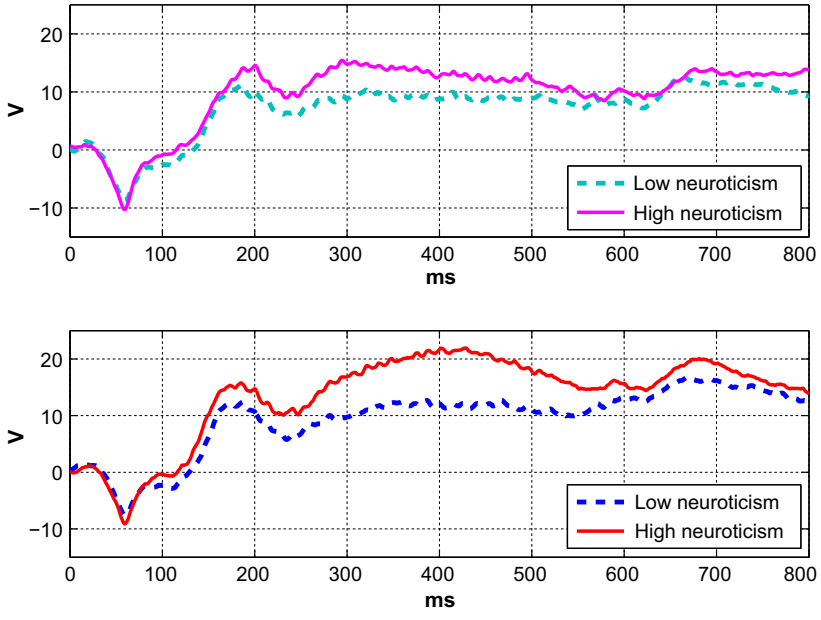

Fig. 9. Grand average from event related potentials (ERPs) from Pz channel. Positive valence (upper), negative valence (down).

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5. Conclusions

In the present study, individual EEG differences on scalp regions have been identified, mostly in right hemisphere and parietooccipital areas in women who score high in neuroticism. Moreover, a higher homogeneity between individuals is clear with positive stimuli in stable people, whereas it is not so evident in the high neuroticism group, particularly with negative stimuli. The use of different emotion-regulatory strategies, such as reappraisal, and differential insular activity reflecting differences in state negative affect could be linked to the higher heterogeneity of individuals scoring high in neuroticism. This study points out that there may be important individual differences even in samples commonly studied as homogeneous groups, such as individuals scoring high in neuroticism. This fact should be carefully taken into account both in experimental or clinical studies, since variation between individuals is not always considered.

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