Approach on affective valence detection from EEG signals based on global field power measure and SVM-RFE algorithm

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Abstract. *EEG signals have attracted the interest of scientific community for understanding how brain processes emotions. In order to extract objective conclusions, automatized methods that are able to reinforce the subjective visual explorations of the signals are desirable. In this work, a feature extraction + wrapped classification scheme is proposed for analysing how brain reacts to visual high/low valence stimuli and how the linked brain processes change when a novel or familiar stimulus is presented. For such purpose, experiments were carried out using the international affective picture system (IAPS) images. Global field power (GFP) from the recorded EEG signals is computed, and a support vector machine-recursive feature elimination (SVM-RFE) method is applied to the input signals. The combination of these techniques yielded up to 100% peak accuracy in both classification tasks, outperforming traditional statistical methods for group comparisons such as t-test.*

Keywords: Affective computing; EEG; Global field power; Habituation; SVM; SVM-RFE

1 Introduction

The dimensional model of emotions asserts that emotions can be mainly defined by two dimensions: arousal and affective valence [1]. Some studies concentrated on one of the dimensions of the space like identifying the arousal intensity (high versus low) or the valence (low/negative versus high/positive), and eventually a third class neutral state. Normally, emotions are elicited by (i) presenting an external stimulus (picture, sound, word or video) related to different emotions at some predefined interval, or by (ii) simply asking subjects to imagine different kinds of emotions.

Affective valence is an interesting, essential dimension in studies about emotion processing, which is influenced by several variables beyond the subject's anatomy and psychophysiology. Habituation is one of these variables, and consists of a reduction in the response to a stimulus when it is repeatedly presented [2] and affects either emotional or attentional processes [3, 4]. The interaction between habituation and affective valence processing is affected in diverse psychological and psychiatric disorders, like phobias or schizophrenia. In this work, the influence of habituation on the affective valence processing evoked by pleasant and unpleasant visual stimuli is analyzed using EEG signals.

Extracting the most relevant features linked to a specific emotional process from EEG signals is still a challenge. Amplitude and latency from the significant peaks from event related potentials (ERPs) in time domain have been usually reported in the literature [5], also some spectral measures have been computed for this purpose [6]. However, the huge variability among subjects and the high number of trials and channels needed for the analysis often become an important drawback. In this work, we propose Global Field Power (GFP) [7] as representative signal of the electrical activity of the brain at a determined time instant. GFP has been suggested as an unbiased measure from a momentary map which has the maximal field strength [8].

Traditionally, in psychological paradigms, statistical methods have been used for comparing different populations or pairs of experimental conditions. In this study, support vector machine-recursive feature elimination (SVM-RFE) [9], which consists of a wrapped method of feature selection based on the powerful SVM classification technique [10, 11] is implemented. SVM-RFE has been used in very different contexts like biomedical applications [12, 13], or marketing [14]. In this work, it is proposed for selecting features from the GFP signals computed from the ERPs. SVM-RFE allows to take a set of features as a whole and to work with a large number of them without requiring any statistical correction. Moreover, this algorithm for feature selection takes into account the individual differences influence by discarding irrelevant or extreme data.

2 Materials and Methods

2.1 Data Acquisition and Pre-processing

A total of 26 female volunteers participated in the study (age 18-62 years; mean=24.19; SD=10.46). A number of 21 Ag/AgCl channels of EEG (Fp1, Fpz, Fp2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, O1, Oz, O2), positioned according to the 10-20 system, and 2 EOG channels (vertical and horizontal) were sampled at 1kHz and stored. The impedances of all electrodes were kept below $5k\Omega$.

The EEG signals were recorded while the volunteers were viewing pictures selected from the International Affective Picture System (IAPS) repository [1], which is freely available and widely used in psychological experiments. It is composed of pictures classified by a large number of participants in terms of arousal and valence. A total of 24 high-arousal images, corresponding to an arousal score $s>6$, 12 of them with positive valence $(v = 7.29 \pm 0.65)$ and 12 with negative valence $(v = 1.47 \pm 0.24)$, were selected. Each image was presented three times in a pseudo-random order and each trial lasted 3500 ms: during the first 750ms a fixation cross was presented in the center of the screen, then one of the images was shown during 500ms, and finally a black screen followed for a period of 2250ms.

The signals were pre-processed (filtered, eye-movement corrected, artifacts rejected, baseline compensated and segmented into epochs) using the NeuroScan software package. The single-trial signal length was 950ms, including 150ms previous to the stimulus onset.

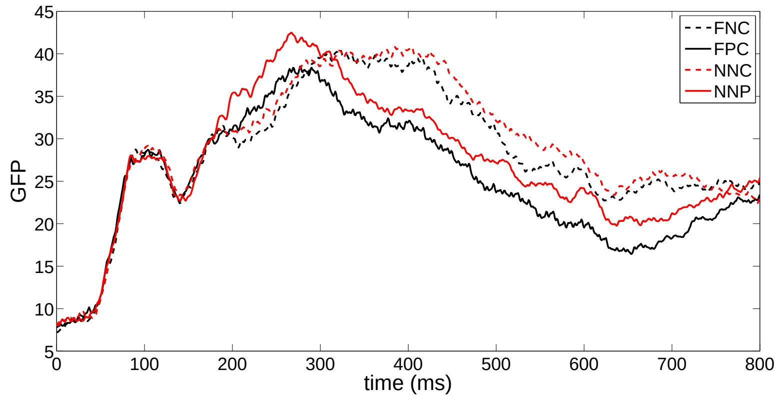

Fig. 1: Grand average of GFP signals used for classification. The baseline points were omitted. There are four conditions in the experiment: First time a negative/positive valence image appears (NNC/NPC, respectively) and third time a negative/positive image appears (FNC/FPC, respectively).

2.2 Feature Extraction

The high variability among subjects and even among epochs obtained from the same subject make difficult the interpretation of single-trials. Averaging trials obtained from the same condition has been widely proposed for reducing the variability and computing the ERPs. This procedure would yield one averaged trial for each recorded channel and experimental condition.

An alternative to gather the brain electrical signal occurring at a given time instant taken from the 21 EEG channels is the computation of the GFP. This measure quantifies the amount of activity at each time point in the field considering the data from all recording electrodes simultaneously, resulting in a reference-independent descriptor for the potential field. The GFP is defined as

$$GFP(t_k) = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}[u_i(t_k) - u_j(t_k)]^2}{2n}}, \tag{1}$$

where $u_i(t_k)$ and $u_j(t_k)$ are the EEG signals at each electrode at the time t_k, taken in all possible pairs, measured relative to a common reference, and n is the number of electrode positions used.

The GFP is computed from the ERPs for each subject. ERP are obtained by averaging the EEG epochs according to each condition (10-12 trials) for making up 4 groups to be used later in classification tasks:

- Novel negative condition (NNC): Average over the EEG signals induced by negative images appearing for the first time.
- Novel positive condition (NPC): Average over the EEG signals induced by positive images appearing for the first time.

- Familiar negative condition (FNC): Average over the EEG signals induced by negative images appearing for the third time.
- Familiar positive condition (FPC): Average over the EEG signals induced by positive images appearing for the third time.

These 4 groups will allow to define four classification tasks: distinguishing brain reaction to positive/negative valence image visualization when images contain a novelty component (first time they appear) or turn to be familiar to the subject (third time the same images appear). Figure 1 shows the grand average (averaged over all subjects) GFP signals for each condition.

2.3 Feature Selection

Modern techniques such as wrapped methods include classification techniques for determining the most discriminant features from two classes. SVMs separate a given set of binary labeled training data with a hyperplane that is maximally distant from the two classes (ω_1 and ω_2), known as the maximal margin hyperplane. The objective of SVM is to build a function $f : \mathbb{R}^M \longrightarrow \{\pm 1\}$ using training data, that is, *M*-dimensional patterns $\mathbf{x}_i$ and associated class labels y_i so that f will correctly classify new examples $(\mathbf{x}, y)$. Linear discriminant functions define such decision hyperplane in a multidimensional feature space, that is:

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

where $\mathbf{w}$ is known as the weight vector and b as the threshold. The weight vector $\mathbf{w}$ is orthogonal to the decision hyperplane and b determines the distance of the plane to the origin. In [9] it was suggested a feature selection technique (SVM-RFE) that eliminates recursively the features corresponding to the lowest values $|w_i|$. Then, the algorithm uses all the features the first time and rejects consecutively the τ features considered less relevant by sorting the absolute values of the entries of $\mathbf{w}$. This process is repeated as long as the classifier performance improves. After the elimination of the features the classifier is evaluated using the leave-one-out (LOO) cross-validation strategy. Note that after m iterations the vector $\mathbf{w}$ has $M \leftarrow M - m\tau$ elements as well as the feature vector $\mathbf{x}$.

In this work, the initial data vector $\mathbf{x}$ corresponds to the GFP signals without considering the baseline time points, that is, the initial dimension of each $\mathbf{x}_i$ is 800, $i = 1, ..., 52$ (26 for each class). Therefore, each feature refers to a single time instant from the GFP signal.

3 Results and Discussion

Classification results obtained after applying SVM-RFE to the GFP signals are shown in Fig. 2. Each curve represents the accuracy values obtained in each iteration (m=160, τ=5) of the SVM-RFE algorithm for each classification task. The first two curves show the ability of the designed system to distinguish between novel and familiar images

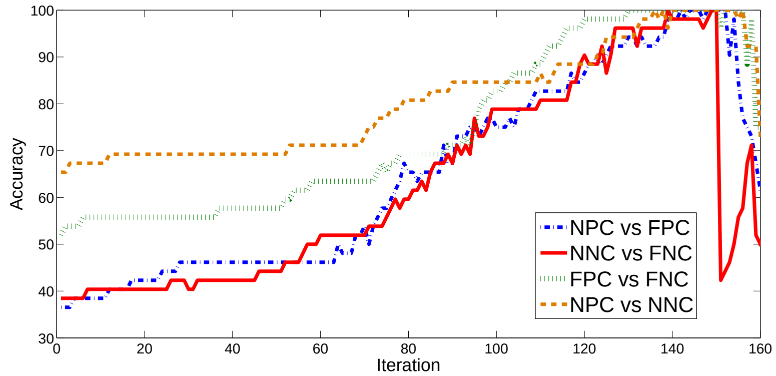

Fig. 2: Accuracy (%) curves obtained for each classification task. The SVM-RFE selection method performs 160 iterations. When about 50-150 features out of 800 are used, the system reaches up to 100% peak accuracy values.

(habituation evaluation), for each valence sign, positive and negative, respectively. The third and fourth curves represent the separability of the GFP patterns according to the sign of the valence (affective valence evaluation), for familiar and novel pictures, respectively. In general, slightly higher values of accuracy are obtained for valence separation tasks than for habituation detection, even from the first iteration of the algorithm, when all features were included.

In order to compare the capability of the system with other traditional methods, we also applied a t-test to the same sets of GFP signals as a feature selection strategy. Only those points statistically significant ($p \leq 0.05$) where chosen for classification. Furthermore, a feature elimination loop was also included so that classification was tested on a decreasing number of features, this time ranked by their associated p value. The selected features were then used to train a linear SVM classifier. In general, the classification results, based on statistically significant features, were less satisfactory in terms of accuracy values. Best results obtained using this approach are summarized in Table 1.

Table 1: Peak accuracy values obtained by selecting feature with t-test statistical method.

Task	NPC vs FPC	NNC vs FNC	FPC vs FNC	NPC vs NNC
Accuracy	67.31%	59.61%	73.07%	75%

For each classification task, Fig. 3 shows the location of the features selected by means of SVM-RFE method for which the system reaches 100% accuracy peak values. Figure 4 shows the location of the significant features obtained by paired t-test. Note

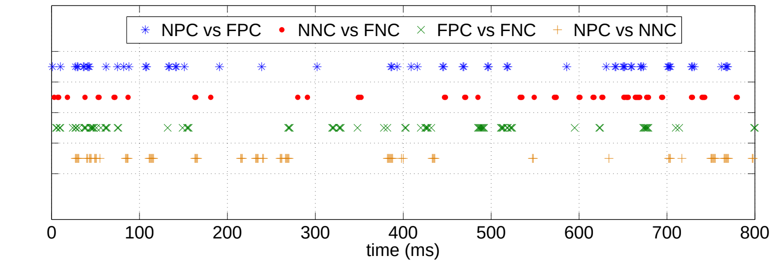

Fig. 3: Time instants selected from GFP signals by SVM-RFE algorithm for reaching 100% accuracy in the four different classification tasks.

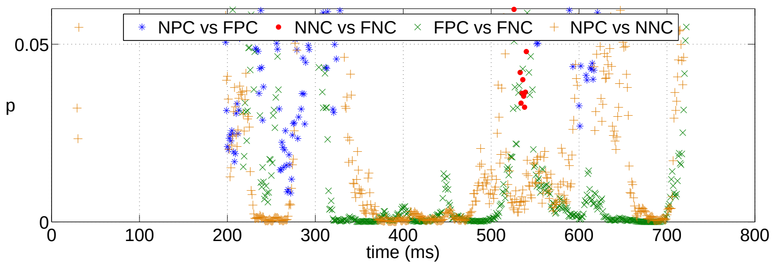

Fig. 4: Time instants selected from GFP signals by paired t-test strategy. Time instants linked to $p \leq 0.05$ were selected as initial set of features.

that the number of features in the initial input for this statistical feature selection is not equal for each classification task, being larger for valence classification than for habituation detection.

In the present experiment, the classification tasks that focused on affective valence detection have shown to be more precise than the habituation discrimination using both methods for feature selection. Whereas using t-test method the accuracy peak values in habituation detection have been lower than 70%, the maximum 100% of accuracy has been reached up using SVM-RFE algorithm. However, in the case of SVM-RFE, the range of possible number of selected features for making a 100% correct decision in habituation detection is tighter than for affective valence discrimination, where a wider window of possible features works properly (see Fig. 2).

By comparing the selected time instants shown in Fig. 3 and Fig. 4, it is obvious that they poorly match up due to the two methods use different approaches. Statistical methods like t-test or analysis of variance are useful in order to contrast hypoteses about the similarity of mean values in measures taken from different populations or different experimental conditions. Nevertheless, they do not always give so good results for feature selection in classification systems and might involve corrections, when multiple comparisons are maken, that could obscure the conclusions. In this study, t-test results are convenient to prove that negative stimuli are less prone to habituation phenomenom than positive. This conclusion can be deduced from the lower number of significant time instants (red vs blue points in Fig. 4). This fact is essential in terms of human beings survival.

Wrapped methods are convenient in the design of classification systems, since they come from similar approaches. These feature selection algorithms deal with the set of initial features as a whole without directly comparing with another opposite observation. In general, when a signal classifier is being tested, it takes only one observation without being able to compare with another antithetical signal. For this reason, wrapped methods need to take some features which might have identical mean values in different conditions (for instance, early time instants post-stimulus) because they give valuable information joined to the other features (see Figs. 1 and 3). The larger the training database is, the more reliable the results about features relevance will be.

The *curse of the dimensionality* is a well-known problem in pattern recognition and consists of having a great number of input features in comparison with the number of available samples in the database (small sample size problem). Considering this, the GFP computation is advantageous over taking the EEG channels separately, since it reduces the dimension of the input space and at the same time it brings together generic information from the scalp activity. In addition, this measure compensates possible topographical imprecisions caused by the displacement of the layout of the electrode cap with different subjects, which could have influence on the final results if EEG channels were taken individually. In other words, GFP can be considered like a sort of normalization rule.

In future research, the use of GFP can be convenient for discriminating among other psychological processes, personality profiles or even pathologies, either for medical applications or recreational purposes. Other global measures like dissimilarity, inter-hemisphere asymmetry or the use of combinations of these features may also be suitable for studying the interaction between emotion and habituation.

4 Conclusions

In this work, support vector machine-recursive feature elimination (SVM-RFE) is applied on global field power (GFP) signals for selecting features in order to understand how affective valence is processed by the brain and to study the linked habituation phenomenon. GFP is a measure that considers a general spatial activity, which is interesting for studying brain emotional processes from a holistic point of view. On the other hand, the use of GFP as input space mitigates the well-known small sample size problem in pattern recognition, reducing the dimension of the input space and making it more comparable to the sample size. Our approach outperformed t-test selection when a SVM classifier is used for identifying the most relevant features in the affective valence processing elicited by visual stimuli, yielding up to 100% peak accuracy for the designed classification tasks.

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