Classification of Emotional Signals from the DEAP Dataset

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Abstract: A Brain Computer Interface (BCI) is a useful instrument to support human communication, frequently implemented by using electroencephalography (EEG). Regarding the used communication paradigm, a very large number of strategies exist and, recently, self-induced emotions have been introduced. However, in general the actual emotion-based BCIs are just binary, since they are capable of recognizing just a single emotion. A crucial node is the introduction of more than a single emotional state for improving the efficiency of a BCI. In order to be used in BCIs, signals from different emotional states have to be collected, recognized and classified. In the present paper, a method for mapping several emotional states was described and tested on EEG signals collected from a publicly available dataset for emotion analysis using physiological signals (DEAP). The proposed method, its experimental protocol, and preliminary numerical results on three different emotional states were presented and discussed. The method, based on multiple binary classification, was capable of optimizing the most discriminative channels and the features combination for each emotional state and of recognizing between several emotional states through a polling system.

1 INTRODUCTION

BCIs provide new channels of output for the brain, (Shih, 2012), yielding an enormous help to disabled people (Shih, 2012; Kubler et al., 2005; Hochberg et al., 2006). The neural activity is often recorded by EEG (Fisch, 1999) and is based on event-related signals (Babiloni et al., 2000). Recently, in (Placidi et al., 2015a) an EEG-based BCI that used the stimulus generated by the disgust produced by remembering an unpleasant odor has been proposed and it has been demonstrated to be particularly useful for severely disabled people (Pistoia et al., 2015).

Being the signals resulting by a self-induced emotion weak, a series of competitive classification strategies have been proposed (Placidi et al., 2015b; Iacoviello et al., 2015a; Iacoviello et al., 2015b; Iacoviello et al., 2015c). However, the BCI obtained by using just "disgust" versus "relax" was only binary, (Placidi et al., 2015c). In order to improve
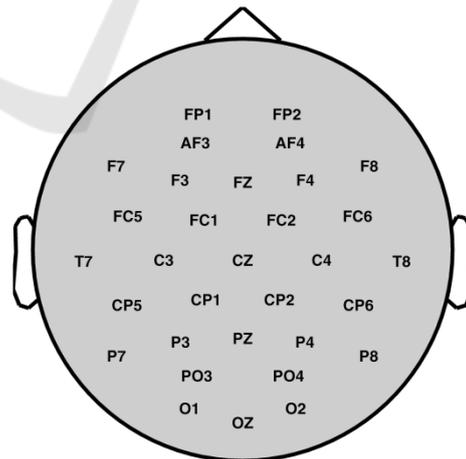

Figure 1: Electrodes used in the 10-20 international brain positioning system.

the efficiency of an emotional BCI (i.e. to increase the cardinality of the "alphabet" and to reduce the time necessary for communication), a series of

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different emotions should be recognized and used (Guler and Ubeyli, 2007). Before using different emotions on a BCI, their characteristic expressions (activation sites and specific features) have to be discovered and compared. In the present paper, the classification strategy proposed in (Iacoviello et al., 2015c) is used on EEG signals collected in the DEAP dataset (Koelstra et al., 2012), a database containing a collection of physiological EEG signals of emotions from different subjects both for negative and positive emotions. In particular the participants watched music videos and rated each video in terms of arousal, valence, like/dislike, dominance, and familiarity. As the subjects watched the videos, their EEG and physiological signals were recorded. The stimuli used in the experiment were selected in different steps: first, 120 initial stimuli were selected; then, a one-minute highlight part was determined for each stimulus; finally, through a web-based subjective assessment experiment, 40 final stimuli were selected. Being DEAP a reference database for tagged EEG emotional signals freely usable, we selected some of the stored experiments in order to study the brain activations due both to negative and positive emotions and to recognize the most significant. In particular, goals of this paper are: a) to verify that, for a subset of subjects from the DEAP dataset, the activated brain region for a negative emotion (negative valence and high arousal) is located in the right brain hemisphere; b) to classify positive emotions (high valence and high arousal) from the selected subjects; c) to verify the separation, in terms of activated channels and selected features, between negative and positive patterns; d) to propose a method for classifying several emotional states to be used in future multi-emotional BCI. The paper is organized as follows. In Section II, the DEAP dataset and the experimental protocol adopted are described along with the considered classification method. In Section III the obtained results are proposed and discussed, whereas in Section IV the conclusions and future works are outlined.

2 MATERIALS AND METHODS

The DEAP database consists of the EEG physiological signals of 32 participants (16 men and 16 women, aged between 19 and 37, average: 26.9) recorded while watching 40 one-minute long music videos on different arguments. Before starting the viewing, a two-minutes long EEG signal was collected by each subject while relaxing watching a

fixation cross on the screen. The EEG signals, sampled at 512 Hz, were recorded from the following 32 positions (according to the international 10-20 positioning system, see Figure 1): Fp1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1, Oz, Pz, Fp2, AF4, Fz, F4, F8, FC6, FC2, Cz, C4, T8, CP6, CP2, P4, P8, PO4, and O2. The proposed music videos were demonstrated to induce emotions to different users (Koelstra et al., 2012) represented in the valence-arousal scale (Russell, 1980). The participants had to rate each video in terms of arousal, valence, like/dislike, dominance and familiarity (the degree of valence and arousal was ranged by using the self-assessment manikins questionnaire). The same videos had an on-line evaluation that could be used for comparison. The videos were the same for all the participants but the sequence of visualization for each subject was random. As a first step, in the present study just the dimensions valence and arousal were considered. Data were provided both as they were acquired (raw data) and in the preprocessed form. In this study, the raw data were used and, before their usage, they were filtered between 1 Hz and 46 Hz.

2.1 The Experimental Protocol

The main goal of this study was to use DEAP to map the emotions through the EEG signals from different subjects, by considering the results on the classification of a strong negative emotion, the disgust (Placidi et al., 2015b). To this aim, we started by selecting subjects that experienced the "strongest" and reciprocally "farthest" couple of emotions, one corresponding to minimum negative valence and maximum arousal (in the following indicated with NVHA) and the other corresponding to the maximum valence and maximum arousal (in the following indicated with HVHA). Between the selected subjects, we further selected those whose self-assessment of NVHA and HVHA corresponded to videos having the same on-line evaluation: this was done in order to eliminate careless subjects (possible cases of wrong evaluations). From the selected subjects, besides the EEG signals corresponding to these two emotional states, we extracted the EEG signals corresponding to the relaxing phase. In fact, after the selection of the subjects and of the signals of the chosen emotions, we aimed at classifying these two emotional states both with the corresponding relaxing signals and reciprocally. The one-minute signals corresponding to the emotional state elicited by a music video was broken into non-overlapping trials, 3.52 seconds long, and separately

used for classification. In the same way, also the relaxing signals was divided in contiguous trials of 3.52 seconds.

2.2 The Classification Method

The method introduced in (Iacoviello et al., 2015a; Iacoviello et al., 2015c) aimed at the classification of EEG signals induced by remembering the disgust produced by unpleasant odor: it was a self-induction, without any external stimulation. One of the conclusions of that research was that the most involved channels were the T8 and P4 ones, both belonging to the right brain hemisphere. In the present study, the same method was used to classify trials from two classes at once corresponding, respectively, to NVHA (E1) versus Relax (R), HVHA (E2) versus Relax (R) and E1 versus E2, thus implicitly allowing a multiclass classification (through the construction of a polling system). The signals herein considered were not self-induced and corresponded to the disgust elicited while watching music videos. Data from the DEAP dataset were produced by an external stimulation and, since the stimulation involved different aspects (videos, music, secondary emotions, and so on) they guaranteed low specificity, from the localization point of view.

Each acquired signal g (trial) was first processed by diadic Wavelet decomposition to extract just the useful information content (Daubechies, 1992; Mamun et al., 2013). To this aim the Meyer wavelet was used to provide the wavelet φ transform:

$$C_d(k2^{-j}, 2^{-j}) = 2^{j/2} \sum_n g(n)\varphi(2^j k - n) \qquad (1)$$

thus decomposing the signal in the approximation and in the detail coefficients. The level l=3 allowed to retain the gamma and alpha bands of the original signal yielding the CD_3 details representation in the band $(250/2^3, 250/2^2]$ Hz. After bands selection, the trial was divided into q sub-trials having an overlapping zone of p points (points in common between consecutive sub-trials) to maintain continuity between pieces. The overlapping region has been introduced to avoid the exclusion of useful information that could be present on the tails of consecutive sub-trials. The classification used the division in sub-trials in order to discard the noisy pieces of each signal while retaining and averaging the useful information (Petrantonakis and Hadjileontiadis, 2011). In this set of sub-trials, a group of N_f characteristics describing the signal,

the features, was calculated; the most common features used in literature (Subasi, 2007; Cvetkovic, 2008) and considered herein were: the mean and the median values, f_1 and f_2 respectively, the mode f_3 (i.e. the most frequent value in a sub trial), the largest and the smallest elements, f_4 and f_5 respectively, the range f_6 of the values and their standard deviation f_7, the mean value f_8 and the median f_9 of the absolute value of the difference between the vector and its mean value, the sum f_{10} of all the elements, the norm f_{11} and the maximum value f_{12}. Since the set of the original features could be redundant, their number was reduced to s by applying the Principal Component Analysis (PCA) in the modified form proposed in (Song et al., 2010). In particular, the covariance matrix of the standardized data was computed and its largest eigenvalues, and its corresponding eigenvectors, were selected. The selected features were the ones with the higher weights in the covariance matrix. Hence the classification of the signal was performed through Support Vector Machine (SVM) by using the remaining features.
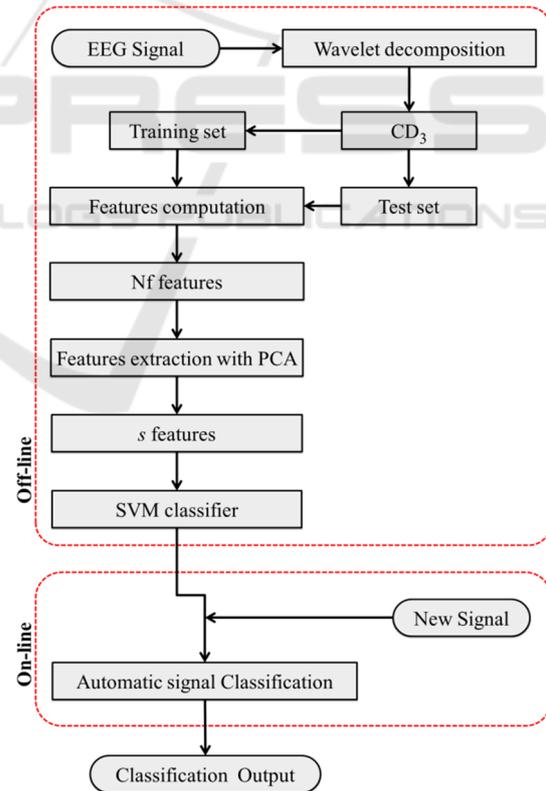

Figure 2: Block diagram of the classification procedure.

The SVM determined the optimal hyperplane to separate data in two classes, Class 1 and Class 2, and

it was obtained as a trade-off between the requirement of maximizing the Euclidean distance between the closest points and the requirement of minimizing the error on misclassified points. The classification method is summarized in the block scheme of Figure 2.

The off-line step was the calibration: the most predominant features referring to the two different conditions, namely, to an activation stage (class #1) or to another (class #2), were selected by considering that the class of the given signal was known in advance; then the SVM classifier was trained. The on-line step was the classification of a signal of which the placement to the class #1 or #2 was unknown in advance. More details can be found in (Iacoviello et al., 2015c).

3 RESULT AND DISCUSSION

As specified above, the proposed classification procedure was applied to a set of 32 trials for the E1 (NVHA) emotion, 32 for the E2 (HVHA) emotion and 32 trials for the relaxing state R for each subject (in the DEAP database, they corresponded to the subjects #1, 2, 22, 24, 25, and 9 indicated by $S_1 - S_6$, respectively, in this study) in a single test. The extracted signals were analyzed in order to verify the absence of abnormal spikes. In particular, the subject #9 (S_6) was discarded since his EEG signals contained very high spikes of difficult explanation and reduction; a more sophisticated method to discard a subject was proposed in (Petrantonakis and Hadjileontiadis, 2011). For each of the selected subjects, the same emotion was associated to at least two videos. The corresponding signals were inserted in the same set of trials (in the same class). Of the whole set of trials, 16 were leaved for calibration of the methods (in particular, 8 trials were used for training and 8 for validation) and 48 were used to simulate real-time classification.

Parameters for the classification method: Each trial was divided into q=7 sub-trials, each corresponding to 300 elements, by considering p=50 overlapping points. The number of retained sub-trials was 5.

The SVM was applied on a subset of features extracted by PCA on the basis of the averaged values of the features calculated on the selected 5 sub-trials. The considered emotions were clearly recognizable (classification accuracy close to 100%) from the relaxing condition, for most of the considered subjects, both from the left and from the right hemisphere of the brain. This occurred also

when considering the classification of the two emotions reciprocally. However, by considering just the channels whose accuracy was exactly 100%, it may be noted that the right hemisphere was prevalent. Moreover, the channel PO4 recurred in all the subjects and was useful both to classify the two emotions from "relax" and the two emotions reciprocally. This was particularly evident for the subject S_3 that represented the worst case, among the considered subjects, in terms of accuracy distribution between channels (Figure 3).

Also in this worst case, the two emotions activated mostly the right hemisphere, and the channel PO4 was the most important (100% of accuracy) both to recognize the considered emotions from "relax" and to recognize the emotions each other, though with different feature sets. In this case, also the channel AF4 (80% in accuracy) was useful to recognize both the emotions with respect to relax, though it was not specific to recognize one emotion with respect to the other. These results confirmed what was previously found in (Placidi et al., 2015a) and (Placidi et al., 2015b) with respect to the activation of the right hemisphere for a negative emotion but, differently from other works (Song et al., 2010; Davidson et al., 1979), the brain lateralization between the two types of emotions was not clearly evident.
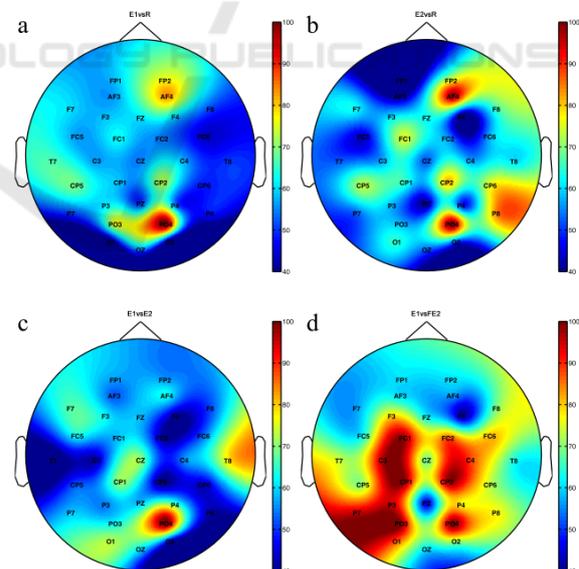

Figure 3: Accuracy values for each channel for the subject S3 (our worst case). The reported maps are referred to binary classifications between: negative emotion vs relax (a), positive emotion vs relax (b), negative vs positive (c), and negative vs flipped positive (left-right brain hemispheres) (d), respectively.

For better clarifying this aspect, we also tried to classify the signals of the first emotion with those of the second one having flipped the two brain hemispheres of the second emotion. In this case, we observed that most of the channels were recognizable to one another (accuracy close to 100%), thus demonstrating that a correlation between channels of opposite hemispheres were absent. In particular, Figure 3d shows the good symmetry of the accuracy distribution for the subject S_3, confirming the absence of a relationship between channels of opposite hemispheres. The activation of a considerable number of channels could be due to the elicitation protocol: being an external stimulation, it would activate multiple mental processes corresponding to the activation of different brain regions. Conversely, in the case of self-induced emotions (Placidi et al., 2015), the activation, being generated by a concentration task that reduces the possibility of distraction, was concentrated in a specific brain location.

It is useful to evaluate the importance of the features after the PCA selection. Table I shows the channels in which the accuracy was above 80% and the corresponding 4 most important features used for classification, reported in order of descending importance.

The most activated channels were those with higher accuracy, expressed as the ratio between the number of right answers with respect to the total number of trials in percentage. It is important to note that, due to the protocol used to collect the data of the DEAP database (audio-videos were used to elicit emotions), both temporal (influenced by listening audios) and occipital (influenced by viewing videos) channels were left out. Moreover, just accuracy above 80% was considered.

From the analysis of Table I it can be further observed that, even between the 4 most influent features used for classification in different channels there was a sort of recurrence: features 5, 7, 9 and 10 occurred very often, though with different order.

The previous results demonstrated that the proposed method could be effectively used for finding the proper, optimized and minimal combination of channels/features for effective classification of the 3 considered emotional states. The choice of leaving separated the EEG channels in the classification process was finalized at the evaluation of the contribution of each channel to the whole classification process. The obtained results demonstrated also that the method could be applied for effective classification of the 3 considered emotional states by using a polling system after the application of 3 mutual binary classification methods.

Table 1: Best channels (accuracy above 80%) and the corresponding 4 best features used for classification. Temporal and occipital channels were not considered.

	E1vsR		E2vsR		E1vsE2	
	Ch	Features	Ch	Features	Ch	Features
S1	AF3	5 9 10 7	AF3	9 5 10 7	CP1	8 6 3 1
	F3	5 9 10 2	F3	5 9 10 2	F4	9 5 1 3
	C3	5 9 7 10	C3	9 5 7 10	C4	5 9 3 1
	CP1	9 5 10 7	CP1	8 9 2 10	PO4	9 5 10 8
	F4	5 9 10 7	F4	4 5 10 3		
	C4	9 5 7 10	C4	9 5 7 10		
	PO4	5 9 7 10	PO4	5 9 7 10		
S2	CP1	5 9 7 1	FC1	5 9 10 7	FC1	9 5 3 1
	FC1	9 5 3 1	CP2	5 9 10 7	C3	5 9 10 1
	C3	9 5 10 7	F4	9 5 10 7	PO4	9 5 7 10
	F3	5 9 7 10	PO4	9 5 7 10		
	CP6	9 5 7 10				
	C4	5 9 7 3				
	PO4	9 5 7 10				
S3	AF4	9 5 7 3	FC1	9 5 7 2	PO4	3 1 2 10
	CP2	9 5 7 10	CP5	9 5 8 6		
	PO4	9 5 2 7	AF4	9 5 7 2		
			CP2	9 5 7 1		
			PO4	3 1 2 10		
S4	FC5	5 9 7 10	AF3	5 9 10 7	FC1	9 5 10 7
	FC1	9 5 7 10	FC1	9 5 7 10	CP1	5 9 10 7
	FC2	5 9 7 10	CP5	4 5 10 7	PO3	9 5 10 7
	P4	5 9 7 10	CP6	5 9 2 10	CZ	9 5 3 1
	PO4	5 9 7 4	PO4	9 5 7 4	FC6	6 8 10 7
					C4	5 9 1 3
					PO4	5 9 10 7
S5	AF3	9 5 10 7	AF3	9 5 10 7	F3	9 5 7 3
	F3	5 9 7 10	C3	9 5 7 10	FC5	9 5 7 10
	AF4	5 9 3 1	CP1	5 9 10 7	CP1	5 9 10 7
	C4	5 9 10 7	AF4	5 9 7 10	FC6	9 5 10 7
	PO4	5 9 10 7	F4	9 5 10 7	C4	5 9 7 10
			CP2	5 9 10 7	PO4	5 9 10 7
			PO4	5 9 10 7		

The choice of considering simple binary classifications instead of more articulated multi-class strategies (ternary in our case) was twofold: first, binary classification was really simple and its results could be more reliable than those of a multi-class strategy (in that phase, we were still trying to comprehend the neurophysiologic complex mechanisms and the brain/features mapping of different emotions and we would avoid biases from the classification strategy); second, the extension of the proposed method to the classification of more than 3 classes could be very simple (the addition of a class simply involves the addition of a series of binary classifiers). Finally, the results showed that the proposed method could be easily applied for

classification of emotions that have similar spatial activation pattern because they could be recognized through their specific features combination.

Regarding the computational time, the algorithm was implemented in Matlab® on a personal computer (Intel(R) Core(TM) i7-4790 CPU @3.60 GHz 3.60 GHz RAM: 16,0 GB): the classification method took 17.2 minutes for processing all the trials used for the calibration step, 36.4 minutes for the training, 35 sec for the validation and 2.2×10^{-3} sec for processing a single trial. Time could be strongly reduced by using just a single channel for classification (PO4).

4 CONCLUSION AND FUTURE DEVELOPMENTS

A comparison of EEG emotional signals from different subjects of the DEAP database was performed by using a competitive machine learning based classification method. The compared emotions were NVHA and HVHA both with the relaxing state and reciprocally.

The obtained results showed that, though defining different feature sets for different channels, most of the measured channels allowed high classification accuracy. This was true both by comparing each emotion with "relax" and by comparing the two emotions. In order to highlight if there was a lateralization between the brain hemispheres when subjected to opposite emotions, we also compared the data of the first emotion with those of the second after the flipping of the right hemisphere data with those of the left hemisphere of the second emotion. The results showed that, being the classification accuracy very high for most of the channels, the activation was not differently distributed between hemispheres for different emotions. The obtained results demonstrated that the proposed classification method could be efficiently applied both to discover the neurophysiological mechanisms of different emotional states and to efficiently recognize the minimal channels/features set for recognizing each of the considered emotions from the others and from the relaxing state. Moreover, the method could be efficiently used for classification of an incremental number of emotions through the further introduction of a set of binary classifiers and a proper polling scheme.

Future work will be spent in

1) refining the strategy of subjects selection (Petrantonakis and Hadjileontiadis, 2011),

2) mapping the channels/features pattern of new emotional states,
3) inserting the previous emotional states in the classification process,
4) classifying the considered emotional states in groups (more than two emotions at once)
5) exploring a deeper wavelet prefiltering, assuming the decomposition that better enhance the significant part of the elicited signal,
6) selecting the most informative subset of channels,
7) selecting a strategy of self-induction of a set of emotions in order to allow also the usage of the neglected channels,

applying the obtained channels-features maps to implement a classification strategy for multi-emotions based BCIs to be used for communication purposes or for affective computing applications.

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