A Real-time classification algorithm for EEG-based BCI driven by self-induced emotions

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ABSTRACT

Background and Objective: The aim of this paper is to provide an efficient, parametric, general, and completely automatic real time classification method of electroencephalography (EEG) signals obtained from self-induced emotions. The particular characteristics of the considered low-amplitude signals (a self-induced emotion produces a signal whose amplitude is about 15% of a really experienced emotion) require exploring and adapting strategies like the Wavelet Transform, the Principal Component Analysis (PCA) and the Support Vector Machine (SVM) for signal processing, analysis and classification. Moreover, the method is thought to be used in a multi-emotions based Brain Computer Interface (BCI) and, for this reason, an ad hoc shrewdness is assumed.

Method: The peculiarity of the brain activation requires ad-hoc signal processing by wavelet decomposition, and the definition of a set of features for signal characterization in order to discriminate different self-induced emotions. The proposed method is a two stages algorithm, completely parameterized, aiming at a multi-class classification and may be considered in the framework of machine learning. The first stage, the calibration, is off-line and is devoted at the signal processing, the determination of the features and at the training of a classifier. The second stage, the real-time one, is the test on new data. The PCA theory is applied to avoid redundancy in the set of features whereas the classification of the selected features, and therefore of the signals, is obtained by the SVM.

Results: Some experimental tests have been conducted on EEG signals proposing a binary BCI, based on the self-induced disgust produced by remembering an unpleasant odor. Since in literature it has been shown that this emotion mainly involves the right hemisphere and in particular the T8 channel, the classification procedure is tested by using just T8, though the average accuracy is calculated and reported also for the whole set of the measured channels.

Conclusions: The obtained classification results are encouraging with percentage of success that is, in the average for the whole set of the examined subjects, above 90%. An ongoing work is the application of the proposed procedure to map a large set of emotions with EEG and to establish the EEG headset with the minimal number of channels to allow the recognition of a significant range of emotions both in the field of affective computing and in the development of auxiliary communication tools for subjects affected by severe disabilities.

Keywords— affective computing, BCI, classification algorithm, EEG signals, principal components analysis, self-induced emotions, support vector machine.

1. Introduction

Brain Computer Interface (BCI) is a computer based communication system that analyses signals generated by voluntary neural activity of the central nervous system. The subject, thinking at an intention, generates voluntary brain signals to be translated into commands for an output device. In this way a new channel of output for the brain is available [1, 2].

The neural activity useful for BCI can be measured by electroencephalography (EEG) [3-5] either by external electrodes or through microelectrodes implanted inside the skull. EEG with externally placed electrodes is safe, not expensive, not invasive, and maintains high temporal resolution [6]. Though BCI is currently applied in different fields ranging from video games to military, it is mostly applied in the field of affective computing and as a support for disabled people. In particular, in the last ten years BCI has revealed its possibilities especially for severely disabled and locked-in individuals with very limited capacities to interact with the ambient and other subjects [7-9].

Generally, a BCI is based on event-related signals; for example, the subject thinks at a particular action and the subsequent brain signals may be interpreted [10-12]; motion imagery could allow the movement of a robot device by using adaptive user interface, [13].

The analysis of EEG signals is a well-established field of research and the different techniques proposed mainly depend on the kind of signal to be analyzed and the information to be retrieved [14-21]. To classify the EEG signals, useful characteristics (the features) are extracted on a suitable transformation of the data; generally, the wavelet transform is used, [22, 23]. In particular, in [22] a time-frequency representation of the EEG signal, regarding two mental states, was obtained by Discrete Wavelet Transform (DWT). The feature vectors to be used in the classification process were the coefficients of the DWT computed for each trial. The most common features extracted from the EEG signals decomposed into different frequency bands by the Discrete Wavelet Transform were recalled in [15]: the entropy, the energy and the standard deviation. The problem of features' selection was considered also in [24], where first and second order spatial and temporal features based on a bilinear model were proposed to evaluate human EEG. In [25] the statistical features such as the mean of the absolute values of the coefficients of the DWT, the average power, the standard deviation and the ratio of the absolute mean values of adjacent sub-bands, were assumed.

The problem of reducing data dimension and facilitate features extraction may be addressed by considering Principal Components Analysis (PCA), Independent Component Analysis (ICA) or Linear Discriminant Analysis (LDA). In particular PCA has been used in many different applications, from video surveillance [26], to glucose variability analysis [27], for example, aiming at selection or extraction of useful discriminating features.

Different types of classifiers may be implemented to face with multiclass EEG signal classification; in [18] multilayer perceptron neural network, probabilistic neural network and multiclass support vector machines were considered to study EEG signals from subjects affected by epilepsy.

Efficient methods for classification of EEG signals are the Support Vector Machines (SVM), [18, 20, 21, 25, 28]. Generally the SVM are applied for two-classes classifiers but they can be extended for multi-class classifiers [16].

In the last years great attention has been devoted in the classification of emotional states by EEG-based functional connectivity patterns, [22, 23, 29, 30,31, 32] In [30] it has been stressed that for emotional processing it was preferable to examine the emotion perception process by means of multi-methodological approach, acquiring EEG signals, systemic SCR and heart rate, whereas in [31] the recognition of the emotion responses during multimedia presentation, using the EEG, was faced. In [32] a probabilistic neural network classifiers was proposed and an optimal nonlinear decision boundary was implemented to detect six basic emotions.

Recently, a new interesting stimulus generated by the disgust produced by remembering an unpleasant odor has been presented [3] to be used as an alternative task to drive an EEG-based communication BCI for severely unpaired people, for which classical stimuli are ineffective. The paradigm proposed in [3] allowed the construction of a binary BCI in the class of affective BCI, based on the measurement of the emotions. In [3] a specific classification method, based on the short time Fourier Transform, was presented. The method was very simple and effective in classifying binary data (activation, through “disgust” and not activation, through “relax”) but it was too specific because it used the following constraints:

1) the disgust, being a negative emotion, was generated and located in the right hemisphere of the brain;
2) the emotions were normally measured in the range of gamma frequencies;
3) the signals to be classified had just binary outcomes (YES or NO).

For these reasons, the described classification strategy used just signals from the right hemisphere of the brain (signals from the left hemisphere were ignored), analyzed mainly the gamma frequencies (the alpha band was used just to confirm the classification results), and was specifically designed for binary outputs.

For a general and efficient BCI based on emotions classification, the cardinality of the alphabet has to be increased in order to reduce the time necessary for communication. This is possible by increasing the number of emotions to be recognized (for example, by considering, besides “disgust”, also “happiness”, “fear”, “hunger”, and so on). The increment of the number of emotions implies that also signals coming from the left side of the brain have to be considered, that the whole frequency spectrum has to be analyzed, and that other “features” have to be considered to help in discriminating between very similar, but different, emotions. This approach could contribute to avoid confusion between different emotions and to reduce the number of misclassifications.

In this paper the general EEG signal classification problem for multi-emotions based BCI was faced; more precisely, the aim was to provide an efficient, parametric, general, and completely automatic real time classification method of EEG signals from self-induced emotions. These signals were weaker than those induced by external stimuli and the subject could lose concentration during the task, thus requiring an ad hoc shrewdness; the particular aspects of signal pre-processing, analysis and classification were pointed out by exploring and adapting strategies like the wavelet transform, the PCA and the SVM. In the proposed strategy, the wavelet analysis was used just to pre-process the signals by filtering out noise. Then, a 2-steps classification procedure was applied. First, during a phase used for calibration of the system to the specific subject, the signal was suitably processed, a set of features was extracted and the more informative ones were selected by a PCA; an ad hoc classifier was tuned by applying the SVM theory. The second on-line step was the application of the obtained classifier to new data of the same subject. The proposed classification strategy was tested on data collected by a binary BCI based on the disgust produced by remembering an unpleasant odor, that is on self-induced signals [3]. For this reason, the considered EEG signals had low amplitude and this was also a challenge.

The reason of the application of the proposed strategy on these data was to ensure that our general purposes classification strategy gave as good accuracy results as those obtained by the more specific strategy used in [3]**.** The proposed classification method had also the possibility of further improving the classification accuracy by allowing the combination of the information coming from more than a single channel. In this way, different activation patterns for different activation stimuli could also be explored and found.

The paper is organized as follows. In Section 2 some useful mathematical tools are recalled and the proposed method is described in detail. The experimental set up and the numerical results on a case study are presented in Section 3; conclusions and future work are outlined in Section 4.

2. Materials and Methods

A fast and automatic method was provided for EEG signal classification, without a previous knowledge of the specific induced emotions. Neither simplifications nor constraints were used: different cerebral stages and different frequency bands, corresponding to unknown emotions, were considered.

The data needed to be processed by a transform to enhance the useful information content; by using wavelet transform with a suitable level of approximations and details, useful content of the signal was preserved and noise was filtered out. After that, features were calculated from the filtered signal. The most representative features were then selected by the PCA. On the reduced set of features the Support Vector Machines technique was applied to classify the signal. Figure 1 shows a raw block diagram of the overall procedure.

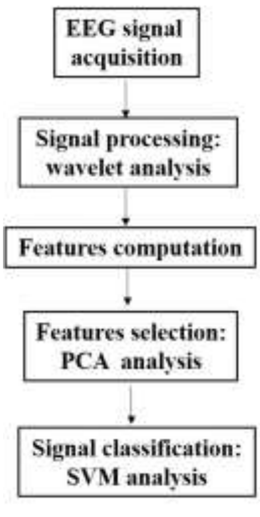

Fig.1. Block diagram of the used classification procedure.

In what follows, a brief review of the principal techniques used and adapted to the purposes of this paper is presented before the method is described in details.

1.1 Background

The wavelet transform enables to use adaptive windows for the signal analysis, with variable size in time-frequency domains [33, 34]. The wavelet transform of a signal is the sum of signal portions multiplied by shifted and scaled versions of the chosen wavelet function.

Let's denote by ϕ a generic wavelet function with scaling and shifting factors a and b, respectively.

By assuming a unitary sampling time, the DWT is:

$$C(k2^{-j}, 2^{-j}) = 2^{j/2} \sum_{n} s(n)\phi\left(2^{j}k - n\right) \tag{1}$$

The coefficient C represents the similarity between the analyzed signal and the chosen wavelet function. The DWT in dyadic scale hierarchically decomposes the signal in low frequency components CA_i (approximation coefficients), and in high frequency components CD_i (detail coefficients), yielding a downsampling of the data, where n is the number of the original samples. The approximations are smoothing versions of the signal, each proportional to the approximation level itself.

The wavelet signal decomposition consists of the collection of the last approximation level and all the details; for example, if a decomposition at level ℓ is chosen, the decomposition set is given by: $(CA_\ell \quad CD_1 \quad \cdots \quad CD_\ell)$. The choice of the decomposition level depends on the frequency of interest; more precisely, by assuming a sampling frequency of 500 Hz (the sampling frequency of the EEG system used in our experiments), and therefore the presence of frequencies in the signal up to 250 Hz, at the ℓ-level of a dyadic decomposition the approximation CA_ℓ contains information in the interval $\left[0, \frac{250}{2^\ell}\right]$ Hz, whereas the detail CD_ℓ yields information in the interval $\left(\frac{250}{2^\ell}, \frac{250}{2^{\ell-1}}\right]$ Hz. The dyadic wavelet decomposition was used in the proposed procedure to select and retain just specific frequency bands of the original signal before to skip to the following steps of the classification method. It is well known, [35], that the most relevant information in EEG signal is between 0 and 46 Hz; if some kind of information is available about the specific stimulus the band of interest may be selected ad hoc. This was not the case in our framework, therefore all the meaningful band interval [0, 46] Hz needed to be analyzed.

Generally, after frequency band selection, a set of features, i.e. characteristics describing the signal, is extracted and helps in the classification of the signal itself

The Principal Component Analysis is used to extract relevant information from the data set since the original ones may be noisy or redundant. PCA may be used for features selection or for features extraction. The latter consists, briefly speaking, in defining new features summarizing, in a weighted form, the information of interest. In this paper the features selection was considered, aiming at determining, among the proposed features, the ones that better characterized the acquired EEG signals; in particular the procedure proposed in [36] was adopted. The considered data were projected on a new Cartesian reference system, obtained by operating an orthogonal rotation of the original Cartesian reference system. In this way, a new reference system was obtained; its axes, the Principal Components, were characterized by the highest variability of the projection of the data. More precisely, the covariance matrix of the standardized data (i.e. data with zero mean and unit variance) was computed and its eigenvectors were sorted according to decreasing eigenvalues. The largest k eigenvalues, and subsequently the corresponding eigenvectors, were chosen. In Fig.2 an example of the graphical representation of the principal directions is proposed; it presents the components of the eigenvalues vectors.

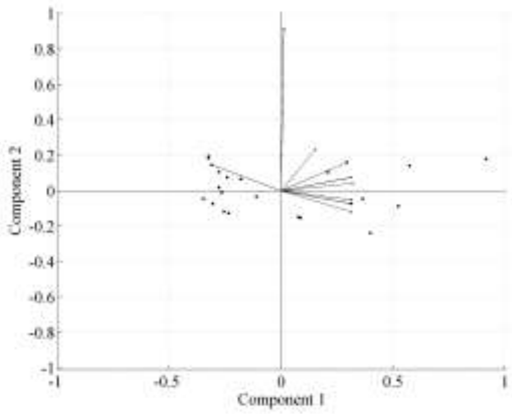

Fig.2 Example of a biplot representation

The chosen features are classified by Support Vector Machines. In general, the SVM separates data into two groups, aiming at determining the optimal hyperplane as a tradeoff between the requirement of maximizing the Euclidean distance between the closest points and the requirement of minimizing the error on misclassified points [37, 38]. The optimal separating hyperplane is obtained by solving the following Quadratic Programming Problem:

$$\min_{w,b,\xi} \frac{1}{2} w^T w + H \sum_{i=1}^{n} \xi_i \qquad (2)$$

with the constraint:

$$y_i \left(w^T x_i + \beta \right) \geq 1 - \xi_i, \quad \xi_i \geq 0\,, \qquad (3)$$

where w is the vector of the points perpendicular to the separating hyperplane and H>0 is a penalty parameter on the error term.

In Fig.3 the graphical representation of the classification problem at hand is shown.

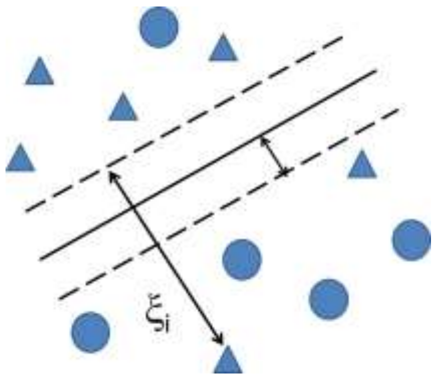

Fig.3 Graphical representation of the analyzed classification problem.

To make the elements x_i of the two classes linearly separable the idea is to map the data into a richer space, and determine the separating hyperplane in that space. As mapping function ϕ the radial basis function can be chosen and for the kernel function the following choice may be adopted:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j) = \frac{\left\| x_i - x_j \right\|_2^2}{2\alpha^2} \qquad (4)$$

where $\| \;\|_2$ represents the L_2 -norm. The two parameters to be evaluated, H and α, may be determined by using the 10-fold cross validation, [39]. The SVM algorithm LIBSVM 3.18 is generally adopted for the classification [22]. The parameters yielding the largest accuracy are used to train the SVM over training set; finally, this classifier is tested over the test set.

1.2 The proposed method

The proposed method was completely parametrized and the data of all the channels could be analyzed separately to localize the specific task. Moreover, the peculiarity of the procedure relied in the lack of knowledge of the task and therefore of the frequencies band interval involved in the task.

An off-line stage allowed the identification of the most predominant features referring to the different conditions to be classified by considering that the stage of a given signal was unknown in advance. The on-line stage was the classification of a signal of which the allowance to each task was unknown in advance and had to be discovered by classification. The problem at hand may be faced in the framework of machine learning problems.

A number N of trials (a trial consisted of a series of parallel signals, one for each channel, obtained with a single self-stimulation occurrence) was considered for all the subjects. Being the proposed analysis completely parallel with respect to the channels, from now on we will refer to a generic channel. The N signals were randomly divided into three groups of size N_1, N_2, N_3: the first dataset (of size N_1) was used for the training, the second one (of size N_2) for the test step. The dataset of size N_3 was used to simulate the set of unlabeled trials to evaluate the goodness of the obtained classifier. This partition of the data was done to use the same number of trials of the different classes within the three groups; this shrewdness was motivated by the aim of not polarizing the training to one sense or the opposite. Figure 4 showed the flow-chart of the proposed method related to one channel and to a specific unknown task.

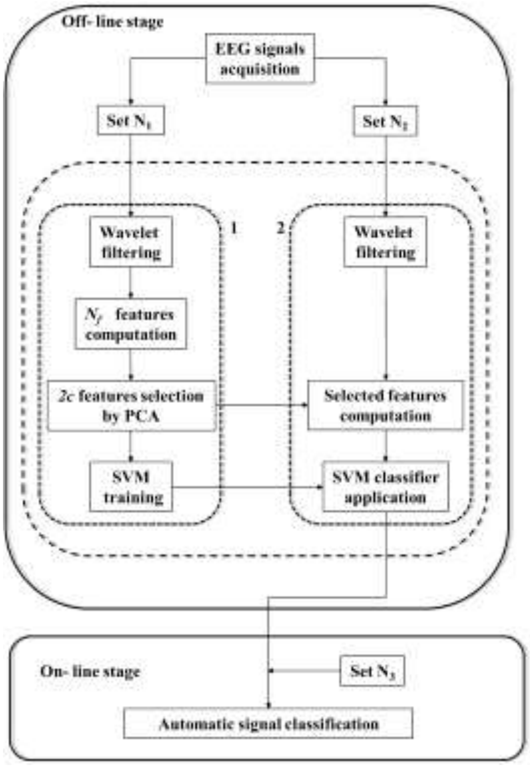

Fig. 4. Flow-chart of proposed method

Let s_i, $i = 1,..., N_1$, be the *i-th* trial of the generic subject referring to one of the considered channels. The mean value of the trial was subtracted to each element of the trial itself, thus obtaining zero mean signals. For each trial, being unknown the specific self-induced emotion, the entire meaningful frequency interval [0, 46] Hz had to be considered and this was done through wavelet decomposition. For EEG data orthogonal wavelet transforms are particularly useful for their capability in separating different frequency bands, [40], and for their significant de-noising effects, [41]. For these reasons, in the present application the Meyer wavelet was preferred to others; it is an orthogonal symmetric wavelet, infinitely differentiable, with infinite support.

The choice of the wavelet decomposition level depended on the frequencies of interest. The level 3 corresponding to the whole interval [0, 46] Hz was considered, and each trial was filtered. The information that was not available from a preliminary knowledge of the stimulus could be obtained by features calculation and analysis. Each filtered trial s_i consisted of a number ν of samples corresponding to a record of N_s seconds and it was divided into q sub-trials $s_{ih}, h = 1,..., q$ of N_q seconds, corresponding to ν_q samples, with an overlapping factor of *p* elements of the single trial, Fig.5:

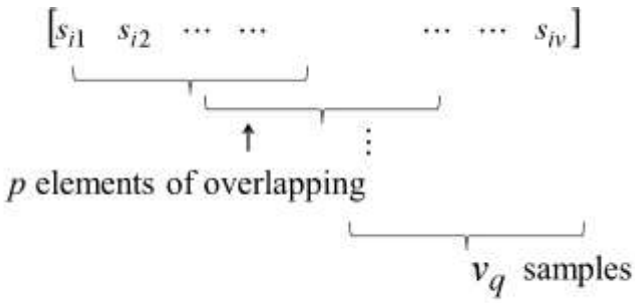

Fig.5 Trial division in q sub-trials with p overlapping points between consecutive sub-trials

The aim was to classify each trial as referring to one task among the *n* possible ones. Therefore, useful discriminating characteristics of each signal had to be evaluated. For the chosen decomposition level, a set of N_f features f_j was computed. Fixed a subject, a trial and a channel, let's denote with F the matrix of features whose element $f_{u\upsilon}$, $u = 1,...,q$, $\upsilon = 1,...,N_f$ was the feature f_υ of the $u-th$ sub-trial. The matrix of features for each trial had dimension $q \times N_f$.

To disregard the sub-trials acquired in loss of concentration that could induce misclassification, in each trial the sum of the absolute value of the differences among one feature and the others, of the same type, was computed as follows:

$$d_{h\upsilon} = \sum_{j=1}^{q} \left| \bar{f}_{h\upsilon} - \bar{f}_{j\upsilon} \right|, \quad h = 1,...q \tag{5}$$

For each $\upsilon = 1,....,N_f$, the features with the r smaller values $d_{h\upsilon}$ were kept, thus preserving only the informative segments of the signal; finally the mean value of these r features was evaluated, for each $\upsilon = 1,....,N_f$, thus obtaining a unique value for each of the N_f features. Therefore, for each trial s_i, a vector of the N_f features $(\bar{f}_{i1}\ \bar{f}_{i2} \cdots \bar{f}_{iN_f})$ was available. The vector of features for each trial had dimension $1 \times N_f$.

To obtain comparable data, within each trial, the elements of the features vector were normalized: for each $j = 1,....,N_f$ the new elements of the vector of features of the *i-th* trial were:

$$f_{ij}^{norm} = \frac{\bar{f}_{ij} - \min\limits_{1 \le j \le N_1}(\bar{f}_{ij})}{\max\limits_{1 \le j \le N_1}(\bar{f}_{ij}) - \min\limits_{1 \le j \le N_1}(\bar{f}_{ij})} \tag{6}$$

Therefore, for each kind of feature, the data considered were the N_f normalized features, one for each trial. The matrix $\overline{F}$ of the data (the normalized features) had dimension $N_1 \times N_f$.

To reduce the number N_f of features and consider the most significant ones, the PCA features' selection methodology recalled in the previous section and inspired by [36] was used. The correlation matrix of $\overline{F}$ was evaluated with its eigenvalues; let's denote by λ_i the *i-th* eigenvalue associated to the i *-th* Principal Component (PC). By considering just the first c principal components, the percentage of variance preserved, and therefore the retrieved information, was given by:

$$P_c = \frac{\sum_{i=1}^{c} \lambda_i}{\sum_{i=1}^{N_f} \lambda_i} \cdot 100 \, . \qquad (7)$$

For each of the considered principal components the two most significant features were considered, i.e. the features with higher weights, thus providing additional and robust information. Obviously a rationale in the choice of c must be $c < N_f / 2$.

Once the set of $2c$ features, for each of the N_1 trials, has been selected, they were evaluated also on the sets N_2 and N_3, by the same procedure adopted for the signals of the training set N_1.

The signals were then classified by the SVM's procedure.

More precisely, once trained the classifier over the training set N_1 and determined the best parameters (H^*, α^*) by using the 10-fold cross validation, the classification accuracy was evaluated on the test set N_2. The evaluation of the classification accuracy closed the off-line procedure and the classifier obtained with the parameter (H^*, α^*) was assumed for all the incoming signals of the subject.

The percentage of success of the classification was evaluated on the third dataset (of which we knew the true labels), by comparing the estimated labels $\tilde{y}_i,\ i = 1,2,\ldots,N_3$ with the corresponding true ones $y_i^{true},\ i = 1,2,\ldots,N_3$. The number of errors, N_E, normalized by the number of trials in the dataset, N_3, provided the error percentage, E:

$$E=100\ N_E/N_3 \tag{8}$$

The percentage of success in classification was defined as:

$$PS = 100 - E\,. \tag{9}$$

3. Experimental results

As case study, the proposed procedure was applied to a binary BCI based on the disgust produced by remembering an unpleasant odor. The EEG data of ten males of age between 25 and 40 years old, in the following indicated by M_i $i=1,2,\dots,10$, were considered.

In order to collect data, each examined subject was sat in a comfortable armchair in a quiet and lit room. The experiment consisted in showing a sequence of symbols "↓" or "+", each presented for 3.6 seconds on a computer screen. The subject was previously informed that when the symbol "↓" was shown on the computer screen, he had to concentrate on the disgust; whereas when the symbol "+" appeared, he had to relax (the experimental protocol consisted of two tasks). Each of the self-induced stimuli had to be maintained until the symbol changed. The subjects received instructions through the projection of a brief video, on the modality and duration of the experiments. During this time, the EEG signals, composing the current trial, were recorded. The order of presentation of the symbols was random but the number of symbols "↓" was equal to the number of symbols "+" and their sum was always the same. At the end of the record session the subject was required to fill a form providing a feedback about his difficulties in concentrating.

Two sequences containing 100 trials (50 trials for each class, where a class was associate to "↓" and another to "+") were recorded for each subject. In each sequence, the trials of the two classes were mixed in a random order, executed without interruptions for 6 minutes. The order of execution of the two sequences was alternated (the first sequence from the first subject; first sequence from the second subject and so on; second sequence from the first subject; second sequence from the second subject and so on) with 14 minutes of interruptions between consecutive subjects (for preparation of the following subject), and another break of 0.5 hour between the two acquisitions. In this way, each subject experienced a relaxing period of about 4 hours between the first and the second experiment.

The system used to record the EEG was EnobioNE®, [42], an 8 channels (two more channels are used one as reference and another for ground) precise and robust wireless EEG equipment, [43]. The main characteristics of the measured signals based on the disgust produced by remembering an unpleasant odor were: amplitude resolution of 24 bits (0.05 uV); sampling rate of 500 Hz; band-pass filtering between 1 Hz and 46 Hz. The signals were captured directly through the BCI2000 [44].

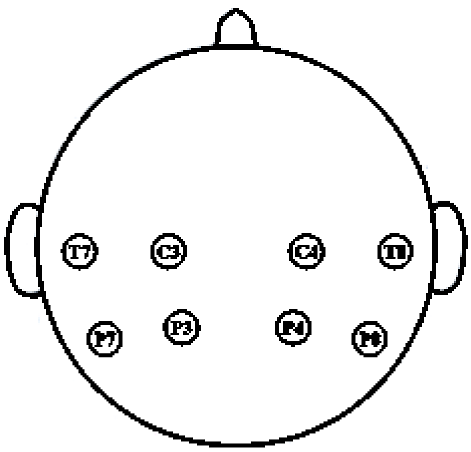

Fig.6. Position of the recorder channels in the international 10-20 positioning system.

For each analyzed subject, data allowing to different tests were grouped in a single group of N=200 trials. Each trial was composed by $\nu = 1800$ elements, corresponding to a record of $N_S = 3.6\,\text{sec}$; each trial was divided into $q = 7$ sub-trials corresponding to $\nu_q = 300$ elements, Fig.5. This number was chosen to capture, if present, significant features in the different segments of the signal. To avoid the exclusion of useful information eventually present on the tails of the sub-trials, an overlapping region of $p = 50$ samples, corresponding to 0.1sec. was assumed between consecutive sub-trials. The data were split in three sets of size $N_1 = 80$, $N_2 = 40$ and $N_3 = 80$. A decomposition with Meyer wavelet at level $\ell = 3$ was assumed and the detail CD_3 was considered in order to contain all the useful frequencies bands of an EEG signal (up to 46 Hz) and to avoid spurious noise oscillations located at 50Hz or above. From the filtered signal a set of feature was chosen, see Table 1.

Feature	Meaning
f_1	The mean value
f_2	The median value
f_3	The mode
f_4	The largest element
f_5	The minimum element
f_6	The range of the values
f_7	The standard deviation
f_8	The mean value of the absolute value of the difference between the vector and its mean value
f_9	The median value of the absolute value of the difference between the vector and its mean value
f_{10}	The sum of all the elements
f_{11}	The norm
f_{12}	The maximum value

Table 1. Features considered for the trial classification

The features considered were the most common in the relevant literature [16, 45, 46].

By applying (5), a number $r = 4$ of sub-trials (the most similar) was retrieved, therefore about 1.5 sec. of the signal was disregarded; this conservative choice was assumed since the subject could have difficulties in maintaining concentration for the whole duration of the trial (about 3.6 seconds).

The set of features was reduced by means of PCA, assuming the choice of $c = 2$ that guaranteed a percentage P_c (7) greater than 80% for the experiments on the 10 subjects considered.

For the classification, the kernel function adopted, allowing the mapping in the feature space and representing the similarity measure between points, was the previously recalled Radial Basis Function (RBF) because it is more general and versatile than linear kernel. As already said the two parameters H

and α, along with β, were determined by using the 10-fold cross validation [43] and the classification was performed by the cited SVM algorithm LIBSVM 3.18, a simple and efficient open source software for SVM classification and regression [28].

Different random choices for the specific division of the data into the three sets N_1, N_2, N_3 were assumed with the only constraint of using the same number of trials in each class (stimulus/relax). The three data sets were composed by the normalized features x_j (evaluated by (6)) and the corresponding label $y_j \in \{1,-1\}$ that expressed the class, stimulus situation (task #1) or a relax one (task #2), to which x_j belonged. The percentage of errors in classification was calculated as in (8).

It has been stressed [3] that the right hemisphere of the brain, and in particular the channel T8, is more sensible, as could be observed by averaging inter-subjects data and maintaining distinct information for the channels. Therefore from now on we will show the results on channel T8, being anyway available the elaboration for all the channels.

To evaluate the goodness of the obtained classifiers, the average classification accuracy (in %) for each subject and by using the single channel T8, calculated among twenty different random choices of the training sets, was evaluated, along with the standard deviations, and reported in Table 2. In the same Table, also the mean value and the standard deviation the parameters H and a, over the whole set of random choices, have been reported. These last calculations aimed at showing the variability of H and a for different random choices, because they did not correspond to any really assumed value. For this reason, the median values of H^* and α^* were also reported in Table 2, along with the corresponding classification accuracy, in order to show the classification accuracy variation when using the central value for H and a.

Subject	Average H	Average a	Median values of H^*	Median values of α^*	Classification accuracy for H^* and α^*	Average Classification accuracy
M_1	5.88±0.41	2.22±0.23	6.08	2.41	99.2%	99.4±0.6
M_2	4.72±0.80	-6.20±0.51	4.80	-6.54	97.7%	96.1±3.7
M_3	3.76±0.43	-1.83±0.82	4.13	-2.25	96.3%	97.1±2.5
M_4	1.51±0.64	-2.21±0.30	2.04	-2.51	66.1%	65.1±7.3
M_5	4.21±0.52	-3.78±0.66	4.60	-4.21	92.4%	90.7±3.4
M_6	17.2±1.96	-19.50±0.91	18.23	-20.58	84.2%	84.1±5.3
M_7	1.85±0.45	-4.21±0.83	2.56	-4.65	86.1%	85.3±6.4
M_8	2.1±0.32	-2.10±0.34	2.34	-2.38	91.8%	92.7±3.8
M_9	1.98±0.32	-3.98±0.54	2.21	-4.46	96.1%	95.8±3.5
M_{10}	11.98±0.92	-7.72±0.76	12.74	-8.35	94.2%	95.7±3.3

Table 2. Classification accuracy obtained for each subject by using the single channel T8. First two columns: average values for H and a, respectively, with the corresponding standard deviation, calculated over the whole random choices. The following three columns reported the median values of H and α , and the classification accuracy calculated by using the median couple of values.. Last column: the average classification accuracy, with standard deviation, calculated over the whole random choices.

In Figure 7 the results relative to the ten examined subjects, evaluated according to formula (7) for the T8 channel, were presented. The results were obtained as the average among the ones obtained by considering the twenty different random choices of the training sets; also the standard deviations were shown.

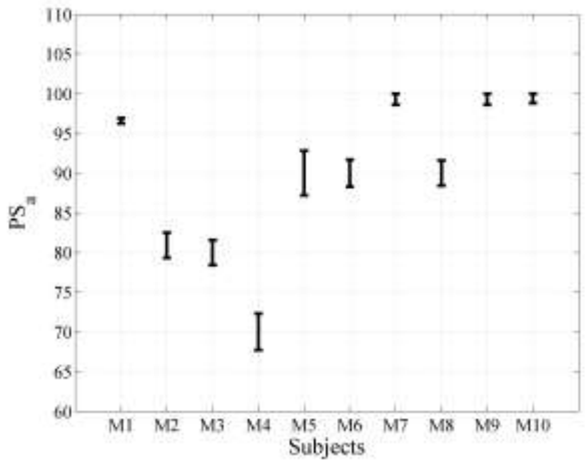

Fig. 7: Average and standard deviation percentage of success (PS_a) for channel T8 for all the examined subjects.

The subjects showed a different capability of self-inducing the stimulus; nevertheless, it may be observed that all the subjects, with the exception of subject M_4, obtained high percentage of success, above 90%in the average. Subject M_4 showed not satisfactory results also in the training phase, as could be observed from Table 2. In fact, he declared to have particular difficulties in self-inducing the stimulus and to maintain concentration during the task, as confirmed by the form filled after the experiment session.

Regarding the computational time the algorithm, implemented in Matlab® on a personal computer (Intel(R) Core(TM) i7-4790 CPU @3.60 GHz 3.60 GHz RAM: 16,0 GB), it took about 10 minutes for processing all the trials used for the calibration step, 15 minutes for the off-line stage (120 trials), 0.10 minutes for the on-line (80 trials) and $0.8 \cdot 10^{-4}$ sec. for a single trial processing.

Table 3 reported the features used to classify the signals of T8 for all the analyzed subjects.

Subject	Channel T8
M_1	$f_1; f_2; f_8; f_{10}$
M_2	$f_1; f_2; f_7; f_{11}$
M_3	$f_1; f_2; f_3; f_8$
M_4	$f_1; f_2; f_7; f_{11}$
M_5	$f_1; f_2; f_7; f_8$
M_6	$f_1; f_2; f_8; f_{10}$
M_7	$f_1; f_2; f_3; f_{11}$
M_8	$f_1; f_2; f_7; f_{11}$
M_9	$f_1; f_2; f_3; f_5$
M_{10}	$f_1; f_2; f_7; f_{11}$

Table 3: Features selected by the PCA for the channel T8 by considering the first two Principal Components.

At a first glance, the sets of features selected by the PCA appeared to be different between the subjects but the couple of features f_1 and f_2 was selected all the time.

The results using just T8 were encouraging and in line with those obtained in [3], where a more specific classification strategy was used. Moreover, the collected signals had low signal to noise ratio, being the results of the self-induction of a stimulus, and this reinforced the quality of the obtained classification accuracy. The methodology proposed herein yielded similar results with those obtained in [3], but some advantages may be outlined. It could allow a multi-class classifier by considering different self-induced emotions thus, by classifying also signals coming from the left side of the brain, identifying a sort of map of the emotions in the scalp. This was confirmed by data shown in Figure 8, where the average classification accuracy is reported for the whole set of measured channels for each of the examined subjects. The maps indicated the following issues: 1) the right hemisphere of the brain was the most active during the task (the classification accuracy was around 50% for “inactive” channels; 2) channel T8 was normally the most active, with the exception of subject M4; 3) it can be possible to create a map of activity/inactivity for the considered task by mixing the information coming both from the active channels and from the inactive ones. This last point is particularly important because it could allow to recognize very similar emotions (for example, an emotion that activated both the right and the left hemispheres of the brain could, in this case, be recognized as different from the disgust that, as demonstrated herein, seemed to activate the right brain hemisphere while taking inactive the left brain hemisphere) and/or to improve the classification accuracy when a single emotion is recognized (for the reported experiments it could allow to reach 100% of accuracy by combining information coming from different channels). The possibility of increasing the cardinality of the alphabet should reduce the time necessary for communication, identifying different activation patterns for different activation stimuli.

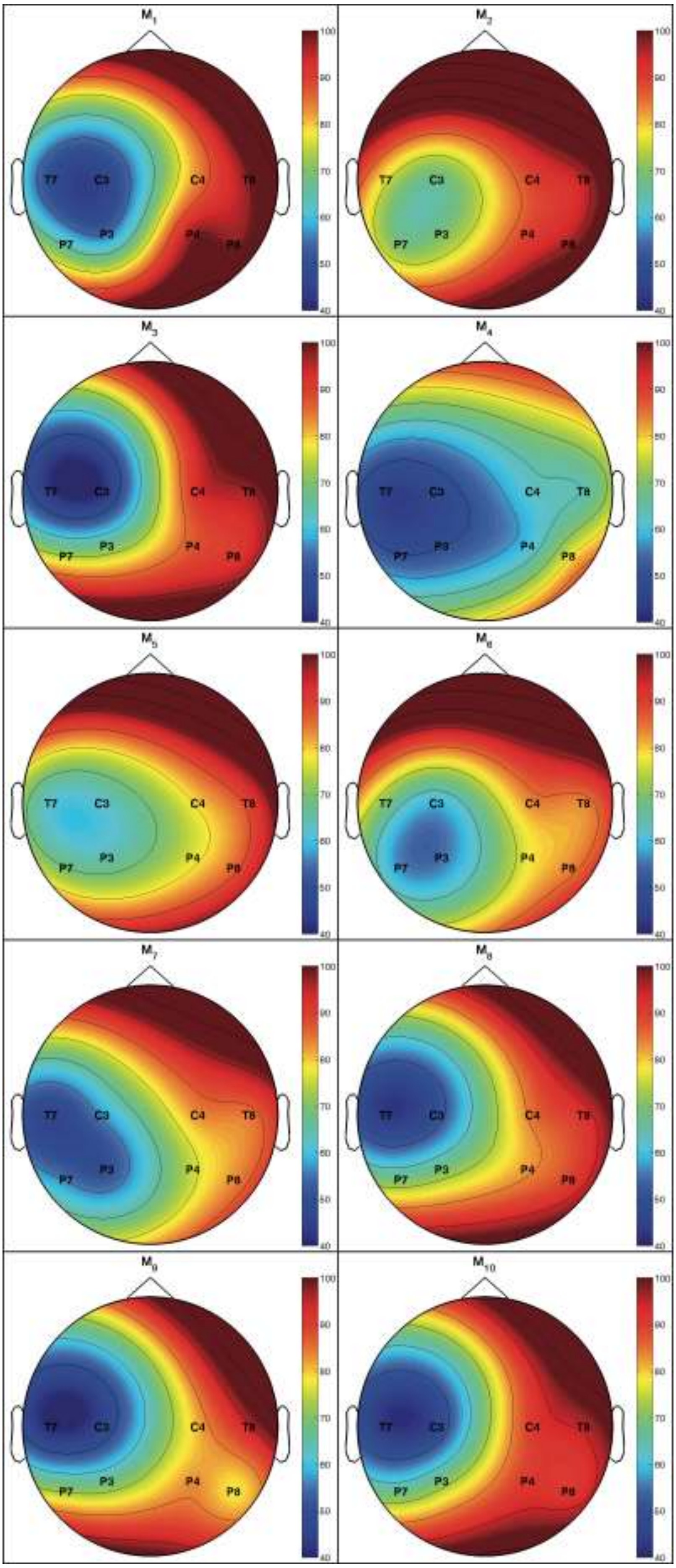

Figure 8: Average classification accuracy, in percentage, shown for all the examined subjects. The color scale was always the same.

4. Conclusions

In this paper a fully automatic and general real time algorithm for the classification of low amplitude EEG signals produced by different emotional states has been presented and applied on signals produced by the disgust self-induced by remembering an unpleasant odor and allowing to dataset collected from ten different subjects.

The signals were classified by a two stages algorithm: the first one was an off-line stage, aiming at the training of a suitable classifier whose input were the selected features; the second stage was the application of the classifier to new data. The specific considered signal required the use and the adaptation of mathematical tools like Wavelet Signal Decomposition theory, Principal Components Analysis and Support Vector Machine. The chosen decomposition level was general to include all the frequencies generated by emotions, also occurring at different times. However, the frequency band could be also restricted to the bound interested by a particular stimulus in the case of very specific stimuli. The procedure was applied to real data for a binary BCI based on the disgust produced by remembering an unpleasant odor yielding accuracy results generally over 90% (average accuracy greater than 90%), with a single exception below 70% mainly due to the impossibility for the subject to concentrate on the task. Furthermore, since it has been shown the predominance of the right hemisphere in revealing the stimulus and specifically the robustness of channel T8, encouraging results were obtained using just the information of the T8 channel. These results were completely in accordance with those obtained by the specific classification algorithm presented in [3], thus confirming that the proposed method performed very well on the given data, though it was more general and more complex (it used more parameters in order to be prepared to classify a larger number of tasks) than that reported in [3] for the specific classification of the disgust, as confirmed by the fact that all the measured channels could potentially enter in the classification process.

An ongoing work is the application of the proposed procedure to classify and label EEG signals generated by different emotions and to realize a general and efficient BCI driven by a well distinguishable set of emotions [47]. Besides that, our intention is to use the proposed classification strategy to map a significant set of emotions with EEG and to establish the minimal EEG headset (the

EEG headset with the minimal number of channels) to allow the recognition of the whole range of emotions considered with a really minimal EEG system to be used both in the affective computing field and as communication tool for subjects affected by severe disabilities.

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