A Poll Oriented Classifier for Affective Brain Computer Interfaces

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Abstract: Affective Computing and Brain Computer Interface (BCI) are two innovative and rapidly growing fields of research. Affective Computing aims at equipping machines with the human capabilities of observe, understand and express affecting features; BCI aims at discovering novel communication channels and protocols, through the monitoring of the brain activity. Emotion recognition plays a central role in both these research fields. In this work we present an EEG poll based classification algorithm for self-induced emotional states used for BCI. We tested the approach using three emotions: the disgust produced by remembering an unpleasant odor (a stink), the pleasantness induced by the memory of a fragrance and a relaxing state. Preliminary experimental results are also reported.

1 INTRODUCTION

Recent years have been characterized by an exponential evolution of the interaction and communication protocols between humans and computer. Until a short time ago a keyboard represented the only input channel to the computer: nowadays, digital devices can understand body gestures, speech, facial expressions, etc. An emerging branch of the Human Computer Interaction (HCI) is the Affective Computing (Picard, 2000).

Since emotions play a lead role in the daily life, machines equipped with empathic capabilities represent, at the same time, a necessary step and a fascinating challenge. Emotions can be recognized from different sources: tone of voice, facial expressions, gestures and physiological responses such as the heart rate and/or the cerebral activity. The latter, especially monitored by means of electroencephalography (EEG), has been widely investigated in order to classify emotional states (Choppin, 2000; Chanel et al., 2006; Bos, 2006; Zhang and Lee, 2009; Wang et al., 2014). In these studies, typically emotions were elicited by external stimuli such as video or images.

The analysis of the brain activity due to the emotions can be applied also to the design of a BCI. A BCI offers the user an alternative communication toward the external environment, based on analyzing the brain activity (Wolpaw and Wolpaw, 2012), and can be an essential tool for people who have lost the standard modalities for communication due to severe disabilities.

Besides the classical types of stimulation, in particular sensory-motor (Bin He, 2014), visual (Xiaorong et al., 2003), or auditory (Furdea et al., 2009), a BCI can be also implemented by using emotions as stimulation tasks. Though to use emotions could appear strange, for some patients this stimulation is the only usable, due to the fact that other modalities have proven to be ineffective or are not recommended (for example, rapidly-varying visual stimulation could produce seizures).

Understanding the effect on the brain activity generated by an emotional state can be used both to adapt the system response to the emotional variations, e.g. to detecting and/or to removing the emotional bias, and to allow the user to drive the BCI through emotion modulation (Molina et al., 2009).

The latter situation can be obtained in two ways:

1) by eliciting the emotions through an external input (Bos, 2006);
2) by using a self-inducing strategy.

Obviously, the second strategy is preferable since it does not require any additional equipment, leaving the user free to choose how and when activate a

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given emotional state. On the other side, this strategy often produces low-amplitude (noisy) signals that could lead to blurry interclass boundaries.

For this reason, efficient classification strategies have to be explored (Liu et al., 2010; Placidi et al., 2015a; Placidi et al., 2015b, Iacoviello et al., 2015). Placidi et al., (2015a) described an algorithm tailored to detect the disgust produced by remembering unpleasant odors (self-induced disgust). In the present work, an extension of that classification method, by introducing a poll-based, was proposed.

We tested the proposed approach in two ways: by trying to detect, separately, two different emotions (the disgust caused by remembering an unpleasant odor and the pleasantness due to the memory of a fragrance, with respect to a relaxing situation); by classifying EEG signals searching the three emotional states at the same time (including relax).

The paper is structured as follows: Section 2 details the acquisition set up and proposes the new poll system approach; Section 3 describes the data analysis and reports the classification results; Section 4 concludes the paper and indicates future developments.

2 MATERIALS AND METHODS

The acquisition set up along with the experimental protocol used to acquire the EEG signals is presented herein. After a brief summary of the emotion detection algorithm presented by Placidi et al., (2015a), the proposed poll system approach is outlined.

2.1 Acquisition Set Up and Experimental Protocol

In the experimental step, we aimed at classifying three different emotional states: the disgust associated to remembering an unpleasant odor, the pleasant sensation evoked by remembering a good fragrance and a relaxing state (the absence of previous states). In terms of Valence-Arousal model (Russell, 1979), the two olfactory emotions have different level of arousal (the disgust is stronger) and opposite valence.

The emotional tasks that we aimed to detect had to be suitable to drive a BCI and self-inducible.

Preliminary experiments consisted in the collection of EEG data from two healthy, male and right-handed subjects (29 and 32 years old, respectively).

The experiments took place in a quiet, lighted room and the examined subjects were sat on a comfortable armchair. The experiments consisted in showing a sequence of symbols on a pc monitor, each presented for 3.66 seconds. Three symbols were used: a cross, indicating that the subject had to relax; a down arrow, meaning that the subject had to concentrate himself on the memory of a stink; an up arrow, meaning that the subject had to remember a fragrance.

Three acquisition sessions were performed for each subject. In the first session, S_1, a sequence of 108 symbols, composed by 54 crosses (relax) and 54 down arrows (disgust), was presented in a random order. In the second session, S_2, 54 crosses (relax) and 54 up arrows (pleasure due to remembering a fragrance) composed the sequence. The last session, S_3, consisted in the display of a sequence made of 25 occurrences for each of the three symbols, for a total of 75 symbols.

We used the Enobio^{NE} system (Neuroelectrics, 2015), an 8-channels wireless EEG equipment, to record the subjects' brain activity. This hardware collects signals at 500 Hz, 24 bit in amplitude resolution (corresponding to 0.05 uV). The electrodes were placed in the positions T8, C4, F4, F8 and their symmetrical T7, C3, F4, F8 of the 10-20 international positioning system (Figure 1).

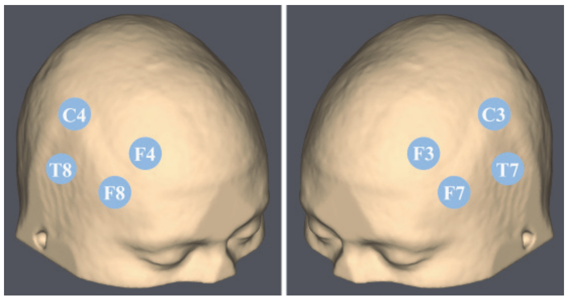

Figure 1: Electrodes montage locations respect to the 10-20 international system.

Sequences visualization and data collection were performed by using the BCI2000 framework (Schalklab, 2015); data analysis was performed by using Matlab® (Mathworks, 2015) scripts implementing the proposed classification technique described below.

2.2 Brief Review of the Adopted Binary Classification Algorithm

In the original binary classification algorithm, the signals were filtered with a band-pass filter to maintain just the bands of frequencies 8-12 Hz and 30-42 Hz. These two bands mainly contain the cerebral activity due to concentration, the former, and that due to emotions, the latter (Li and Lu, 2009). Moreover, being the algorithm designed for a negative emotion classification, the set of channels considered for the classification were P4, C4, T8 and P8 (Niemic and Warren 2002; Henkin and Levy 2001).

The method consisted of two phases, Calibration and Classification (Figure 2). The Calibration started from a set of trials (signals) belonging to two known classes (i.e. activation, by imagining a disgusting odor, and non-activation, or relaxing), used to train the system. The Classification guessed the class of an incoming unknown signal.

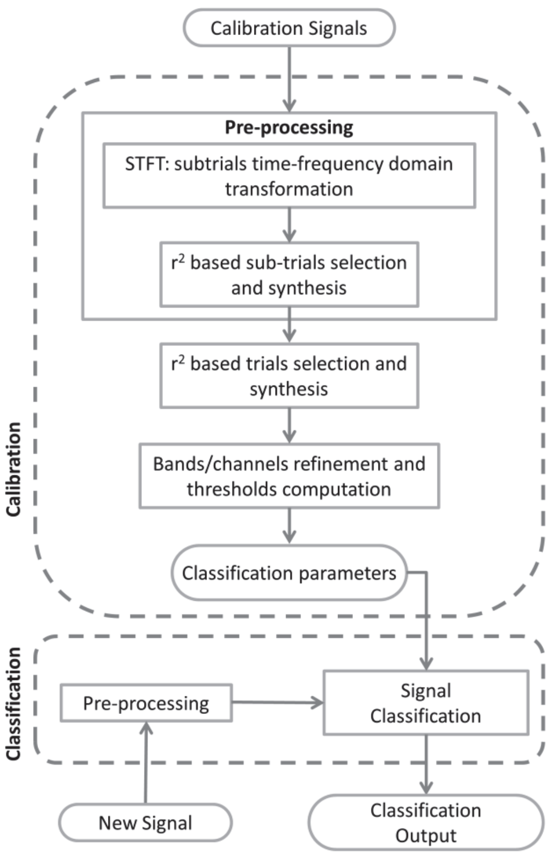

Figure 2: Flow-chart of the binary classification algorithm. The output of the Calibration Phase characterizes the Classifier.

In both phases the trials followed a preprocessing step in which the Short-Time Fourier Transform was applied to split each signal into a set of partially overlapping segments (or sub-trials) and to obtain their frequency coefficients. Then, the mutual similarity between sub-trials was evaluated by means of the r^2 computation (Draper and Smith 1998). From a comparison of the power spectrum of each sub-trial, the more similar were averaged together, the others were discarded.

After the pre-processing step, an r^2 based selection and synthesis was performed again between each trial belonging to the same class. In this way, the information of a synthetized trial was obtained for both classes. The r^2 evaluation was used to identify the frequencies where the differences between activation and non-activation trials were larger.

The Classification phase analyzed a signal of an unknown class. First, the pre-processing phase used also for the Calibration, was applied. Then, the resulting spectrum was compared, in terms of r^2, with those synthetized in the Calibration phase for the activation and the non-activation stages. The values assumed in the chosen frequencies were compared with the defined thresholds to obtain the Classification output for the current signal. The present method had the advantage of giving a very good accuracy level (more than 90%), despite the quality of the signals, and made robust the classification process.

However it had the following drawbacks: the considered channels were predetermined as well as the considered frequencies bands and, more important, the contributions of the channels were averaged together, thus reducing the spatial resolution.

2.3 Emotion Detector Generalization

To generalize the binary classification algorithm it has been observed that since the power spectra of all analyzed channels were averaged together, only channels exhibiting synchronous activation were suitable for this approach. Conversely, if two or more channels had different behavior (synchronization at different frequencies or bands), this approach could weaken their contributions.

For this reason, we designed our approach by managing both these situations. The main idea was that, by testing different combinations of frequency bands and subsets of channels with the original algorithm, it could be possible to find the more distinctive with respect to the target emotions and to perform a classification that could take advantage from all contributes.

To this aim, we modified the hypothesis of the original algorithm as follows:

1) the considered bands of frequencies remained

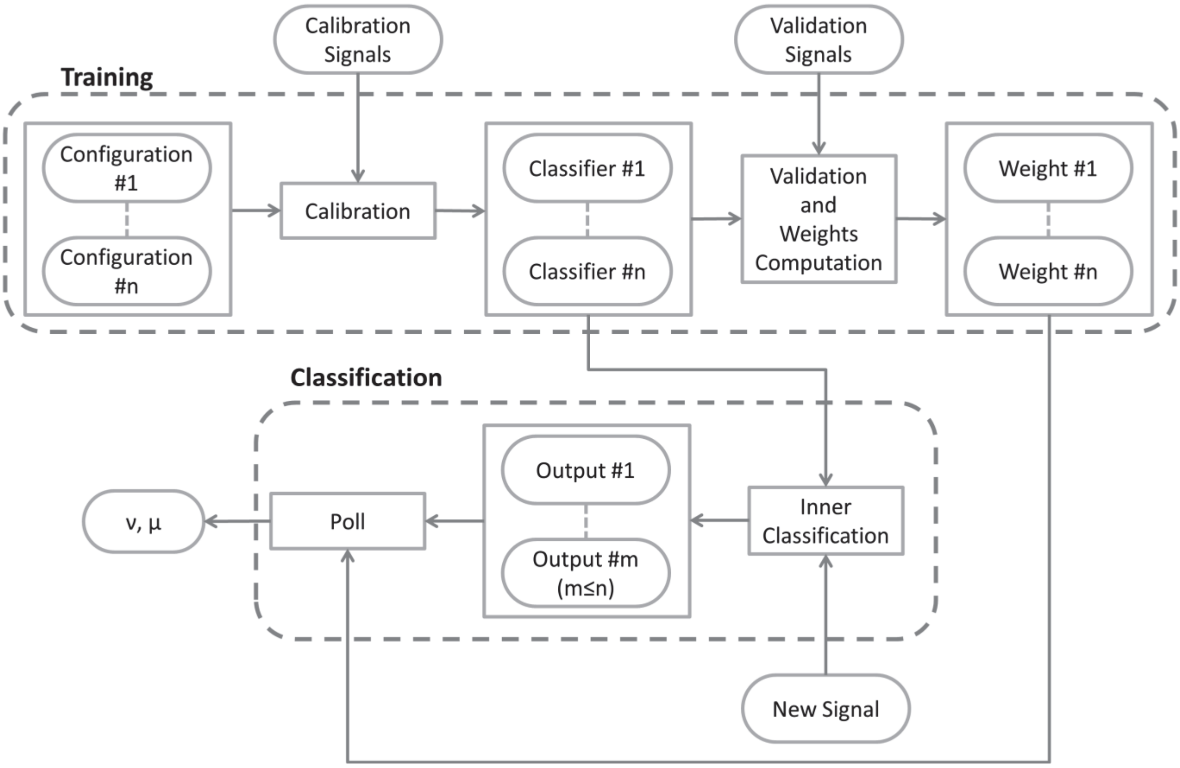

Figure 3: Flow-chart of the poll based algorithm.

two, but the couple of frequencies could be chosen into a larger intervals (frequency resolution was 1 Hz);

1) the measured channels were analyzed separately in order to ensure that only the most significant were considered.

The proposed poll-based algorithm consisted of two phases, Training and Classification, (Figure 3).

The Training phase took as input a set of known, labelled, trials (Calibration Signals) and a group of n Configurations ($c_1,\ldots,c_n$), each specifying the frequency bands and the set of channels that had to be analyzed. The first step consisted in the application of the Calibration phase of the original algorithm *n* times (one for each Configuration), resulting in *n* Classifiers (each characterized by the Classification Parameters reported in Figure 2).

Then, another set of labelled trials was used (Validation Signals) as input for the Classifiers. In this way, it was possible to compute the resulting poll weight of the k-th Classifier, as follows:

$$\omega_k = \begin{cases} 0 & if\ \alpha_k < \tau \\ \dfrac{(\alpha_k - \tau)}{1-\tau} & if\ \alpha_k \geq \tau \end{cases} \tag{1}$$

where $\alpha_k \in [0,1]$ was the accuracy of the k-th Classifier, evaluated on the validation set (Fig.3) and $\tau \in [0,1]$ was a minimum accuracy threshold whose value depended on the cardinality of the dataset used for the classifier validation.

In the Classification Phase, a new unclassified trial was processed by the Inner-classification step, (i.e. the Classification phase of the original algorithm), for each of the *m* Classifiers that had weights (Eq.1) greater than 0. Considering the Inner-classification binary output μ_k (0 corresponded to the absence of the target emotion, 1 to its presence), it was possible to compute the whole Classification confidence value ν:

$$\nu = \frac{\sum_{k=1}^{m} \mu_k \omega_k}{\sum_{k=1}^{m} \omega_k} \tag{2}$$

and the corresponding Classification output:

$$\mu = \begin{cases} 0 & if\ \nu < 0.5 \\ 1 & if \nu \geq 0.5 \end{cases} \tag{3}$$

2.4 Three Classes Poll System Approach

In order to classify two emotions (with three possible classes: (E_A) first emotion, (E_B) second emotion or (E_C) absence of both the previous emotions), it was possible to build a Classifier that

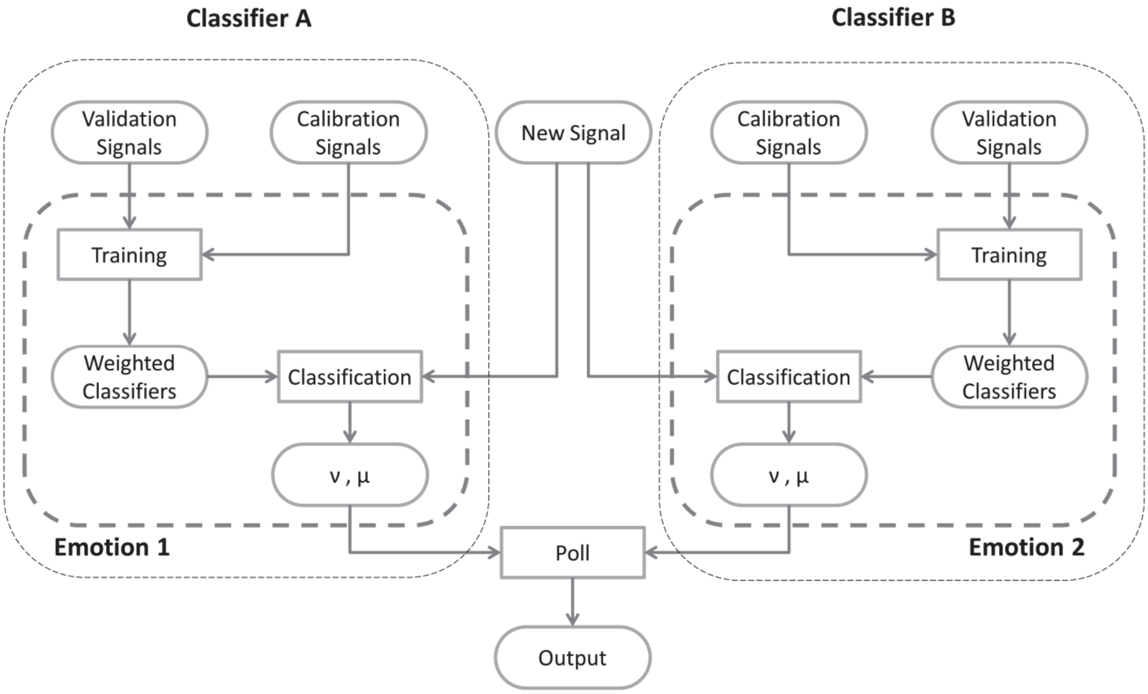

Figure 4: Flow-chart of the poll based algorithm extended to the three classes case.

was the composition of two emotions' detectors. The underlying process, based on a higher order polling system, is reported in Figure 4.

First, two distinct poll based classifiers were trained and validated as described for the single emotion case (subsection 2.2), in order to obtain a set of Weighted Classifiers for both the emotions. When an unknown trial had to be classified, it was analyzed by both. Let A and B be the classifiers for two emotions; four possible cases could occur:

- neither A nor B detected their target emotions (μ_A=0, μ_B=0): this case had output E_c
- A detected its emotion but B did not (μ_A=1, μ_B=0): this case had output E_A (first emotion)
- B detected its emotion but A did not (μ_A=0, μ_B=1): this case had output E_B (second emotion)

both A and B detected their emotions (μ_A=1, μ_B=1): in this case the confidence values ν_A and ν_B were compared. The chosen emotion was the one having greater confidence value. If both classifiers gave the same confidence value, the classifier was unable to choose (very improbable).

3 NUMERICAL RESULTS AND DATA ANALYSIS

By using the acquired data, three studies were carried out, one for each session. In the first two, the aim was to train and test the emotion detector for the memory related to disgust (E1) and to the pleasant sensation induced by fragrance imagination (E2), respectively, with respect to the relax (E3).

In the last, the three states were classified at the same time, using the approach of the composite poll system.

The configurations used in the training phases were the following: each trial, whose duration was 3.66 seconds (1830 samples), was divided in four segments of 0.96 seconds (480 samples), with an overlap of 0.06 seconds (30 samples). After the r^2 mutual computation, the best two segments were maintained. Eight configuration sets (c_1,…c_8), each composed by a single channel (respectively T8, C4, F4, F8, T7, C3, F3, F7), were used. All configurations considered the 30-42 Hz and the 8-12 Hz bands.

For the current number of trials composing a sequence, we set τ = 0.67 (a value which was significantly higher than the chance value of 0.5 for a binary choice).

3.1 Study 1 – Unpleasant Odor Recognition

From S_1, a set made of 8 trials (corresponding to 4 crosses and 4 down arrows) was used for

Calibration. The Validation phase was performed on a set of 50 trials equally distributed between the unpleasant odor (E1) and to relax (E2). As shown in Figure 5, the validation phase, in both subjects, found 4 channels whose accuracy was higher than τ. For the first subject, T8 (with accuracy value α = 0.68), F4 (α = 0.76), F8 (α = 0.68) and F3 (α = 0.72) were the best, while, for the second subject, T8 (α = 0.72), F4 (α = 0.82), C3 (α = 0.7) and F3 (α = 0.78) overcome τ.

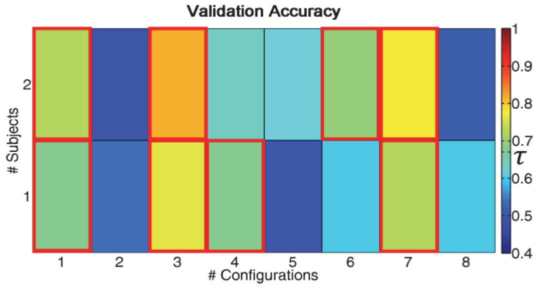

Figure 5: Validation accuracy for disgust/relax detection. Configurations with red borders had an accuracy value greater than the threshold and were chosen for the poll phase.

The Test phase, performed on the set composed by the remaining 50 trials from the first sequence, exhibited an accuracy value of 0.82 and 0.84 for the first and the second subject, respectively. Both significantly above the chance (0.5). The errors, reported in Table 1, were equally balanced between the two classes for the first subject and more concentrated in E2 for the second subject.

Table 1: Classification results for the disgust/relax detector.

Subject	E1 hits	E1 errors	E2 hits	E2 errors	E1 acc.	E2 acc.
1	20	5	21	4	0.8	0.84
2	23	2	19	6	0.92	0.76

The classification results confirmed that this approach had accuracy values similar to that obtained by Placidi et al., (2015a).

3.2 Study 2 – Pleasant Odor Recognition

In the second study we repeated the same process on the S_2 dataset, in order to train a detector for the pleasant sensation (trials E2) with respect to the relax (trials E3), The division between classes performed in Study 1 was assumed.

Data reported in Figure 6 show that E2 was more difficult to be detected than E1. Only two configurations for each subject presented accuracy above the threshold: C4 (α = 0.72) and C3 (α = 0.68) for the first subject, F4 (α = 0.7) and T7 (α = 0.68) for the second subject.

Also the total accuracy assessed during the test phase was lower than that related to the disgust: 0.72 for the first subject 1 and 0.7 for the second subject. However it was yet well above the chance level. In this study, misclassifications were equally divided between the two classes, as shown in Table 2.

This was a particular case of the algorithm application: for both subjects, only two channels had accuracy values above the threshold and one channel was significantly better than the other. This implied that the best channel acquired the “majority share” of the detector. On a binary detection problem, this channel drove the whole process. However, the output of the channel with smaller weight was not completely ignored: during the polling process of a composite classifier, it could affect the classification result.

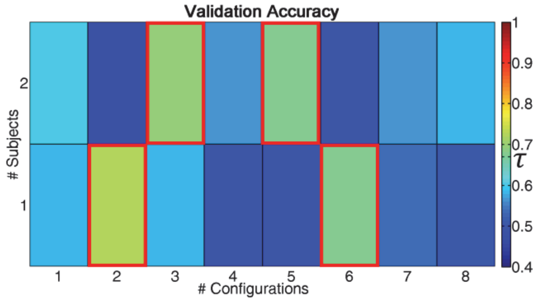

Figure 6: Validation accuracy for pleasantness/relax detection. Configurations with red borders had an accuracy value greater than the threshold and were chosen for the poll phase.

These results suggest a correspondence between the arousal of an emotion and its effect over the signals: the disgust, a strong emotion (also in terms of side effects, such as vomit or increasing sweating), seems to be associated with stronger signals compared to the pleasantness. Moreover, the disgust is a sensation farther than the pleasantness, with respect to the environment in which the experiments took place. In some sense, the room’s “odor” had more in common with a fragrance than with a stink.

Table 2: Classification results for the pleasantness/relax detector.

Subjects	E2 hits	E2 errors	E3 hits	E3 errors	E2 acc.	E3 acc.
1	18	7	18	7	0.72	0.72
2	17	8	18	7	0.68	0.72

3.3 Study 3 – Three Class Classification

The last study regarded the classification of the data allowing to S3 through the composite classifier described in Figure 3. The Calibration parameters were the same of the previous studies. Results showed accuracy values of 0.64 for the first subject and 0.63 for the second.

Also in this case, the first subject exhibited more balanced accuracy between the three classes than the second subject (Table 3).

It is important to note that, in case of a three classes classification problem, like this, the chance level was 0.33. Also in this case, therefore, the classifier accuracy was significantly greater than this value.

Table 3: Classification results for the composed classifier.

Sub.	E1 hit	E1 err	E2 hit	E2 err	E3 hit	E3 err	E1 acc.	E2 acc.	E3 acc.
1	16	9	15	10	17	8	0.64	0.6	0.68
2	15	10	14	11	18	7	0.6	0.56	0.72

4 CONCLUSIONS

A poll based emotion classification strategy was presented. This approach was based on a frequency similarity research through selectable frequency bands and channels sets. The strategy was suitable for two emotional states detection or, extending the underlying poll process, for multiple emotional states classification and channels selection. The more informative channels were selected through the proposed poll method.

The proposed approach was tested in different scenarios: detection of the disgust produced by the memory of a stink with respect to relax; detection of the pleasantness elicited by remembering a fragrance with respect to relax; classification of all the previously tested emotional states at the same time.

For the last classification problem, the obtained classification accuracy (about 63%) was acceptable by considering that all the emotional states were self-induced and not externally elicited and that the considered emotional states shared a significant brain region of activation (Rolls et al., 2003).

The stepping from two recognized emotional states to three emotional states could allow to obtain a faster BCI system (larger is the alphabet, smaller is the number of symbols necessary to compose the same message).

Future developments will be dedicated to:

1) test the proposed classification strategy in real time;

2) extend the proposed algorithm in a multi-states classification (more than three between those that can be self-induced);

3) implement an emotional BCI based on the proposed protocol.

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