Self-induced emotions as alternative paradigm for driving Brain-Computer Interfaces

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Abstract

A Brain Computer Interface (BCI) uses measurements of the voluntary brain activity for driving a communication system; it requires the activation of mental tasks. In the last few years, a new paradigm of activation has been used, consisting in the autonomous brain activation through self-induced emotions, remembered on autobiographical basis. In the present paper, such paradigm is implemented and the resulting BCI system is described, from the classification strategy to the graphic user interface necessary for synchronizing mental tasks and collecting EEG signals derived by emotions. Moreover, the proposed BCI is used for collecting and classifying signals, from 10 healthy subjects, of two different emotional states: the disgust produced by remembering a bad odour and the good sensation produced by remembering the odour of a good fragrance, with respect to relax. The classifications are performed in a binary mode, by recognizing disgust from relax and good sensation from relax, yielding an accuracy greater than 85%.

Keywords: brain computer interface; signals classification; self-induced emotions

1. Introduction

Human computer interface (HCI) yields the possibility of interaction between a subject and a computer to provide a new channel of communication; it has become more and more important in the last years, mainly due to the technology developments and to the new possibilities in supporting disabled people. Near-infrared spectroscopy (NIRS), magnetic resonance imaging (MRI), magnetoencephalography (MEG), pupil size oscillations, dry active electrode arrays, prosthesis and environment control, electrocardiogram (ECG) are possible interactions already proposed (Iacoviello and Lucchetti 2005; De Santis and Iacoviello 2006, 2009; Placidi et al. 2014; Ferrari et al. 2014; Basso Moro et al. 2014, 2016; Carrieri et al. 2016). The applications of HCI ranges from medical to non–medical framework, for hand free applications, for monitoring attention in long distance drivers and for military use.

Among all the signals generally used in HCI, a BCI provides a communication and control tool towards the external environment and is based on the direct monitoring of the brain activity (Wolpaw and al. 2002). Measurements of the brain activity are performed through electrocorticography (ECoG), magnetic resonance imaging (MRI), magnetoencephalography (MEG), near-infrared spectroscopy (NIRS), electroencephalography (EEG), and, also, hybrid systems (Weiskopf et al. 2004; Sitaram et al. 2007; Mellinger et al. 2007; Schalk and Leuthardt 2011; Sudre et al. 2011; Moghimi et al. 2013; Naseer and Hong 2015; Banville et al. 2017). Among these, EEG (Moghimi et al. 2013) is the most used due to its low invasiveness, good temporal resolution and low cost (Allison and Krusienski 2015) and we refer to EEG-BCIs when calling BCIs. BCIs are mostly based on event-related signals induced by external stimulations (Farwell et al. 1988) and synchronized with them (some examples are the visual, auditory, and tactile stimulations) or based on signals produced by sensory motor rhythms (Wolpaw et al. 1991). The canonical BCI framework, also known as “BCI cycle" (Van Gerven et al. 2009) pointed out in Figure 1, is based on the association between a set of specific brain tasks and a set of commands (executable by a computer or by actuators connected to it). After a preliminary training phase, the user is asked to follow the activation protocol by focusing on the task corresponding to the desired command, while an acquisition system records its cerebral activity.

Depending on its usage, BCI is considered invasive, semi-invasive and not-invasive. The invasiveness is often referred both to the technique used for measuring brain signals (for example, electrodes placed inside the brain are invasive), and to the paradigm used for eliciting a brain response. An externally elicited response could be considered invasive, at least semi-invasive, for its interference with the user’s will; generally, a BCI user is in front of a computer screen and must dress an EEG helmet (with electrodes placed on the skull), while responding to external stimulation (semi-invasive) or performing an autonomous mental task (not-invasive).

Several causes could compromise the possibility of using a BCI, often due to the brain activation tasks (Schreuder et al. 2010; Zhu et al. 2010; Muller-Putz et al. 2012). Different strategies have been followed for overcoming the impossibility of using a BCI, e.g. modifying the activation paradigm, improving the classification performance, and finding new alternative activation protocols (Muller-Putz et al. 2012; Vidaurre and Blankertz 2010; Millan and Mourino 2003). The use of emotions for driving a BCI represents a new direction toward innovative activation protocols.

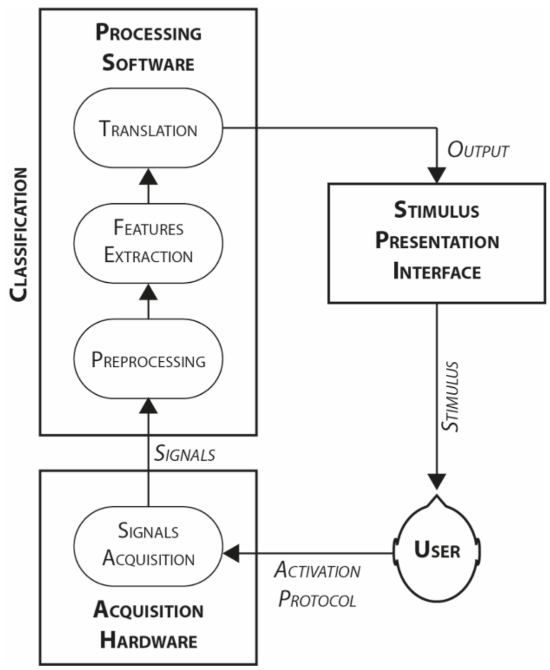

Figure 1- The BCI cycle. The user modulates activates a mental task; the signal is recorded, processed and translated into commands.

Although a huge effort was put in emotions classification, the exploitation of emotional states as voluntary input for a BCI is still moving its first steps. Emotions involve different aspects such as facial expressions, galvanic response, speech, ECG, muscle tension, and so on; these parameters may be not sufficient to detect an emotion and could be deceived. To identify an emotion, it is important to refer to a standardized classification; generally, the valence-arousal Russell graph is used (Russell 1980), with the arousal ranging from inactive (i.e. bored) to active (i.e. tense), and valence from unpleasant (i.e. sad) to pleasant (i.e. happy).

Driving a BCI requires that the computer presents a choice between two or more mental tasks (or states), associated with commands and the user chooses which one he wants to activate for executing the corresponding command. This reactive method makes the used easily tired and bored because he is driven by the BCI more than he drives the BCI itself.

The best approach would be the use of an active BCI, that is to use the direct and autonomous brain activity, corresponding to intentional actions, as electrophysiological source of control. In the emotional context, this modality could represent a more natural way for controlling a BCI, by using self-induced emotions. In the active paradigm, the user independence is preserved. In this paper, that is the extended version of the results proposed in (Di Giamberardino et al. 2018), the details of the entire paradigm of a BCI driven by emotions are described, from the activation stimuli and signal measurement to the classification algorithm, along with the proposed graphic user interface (GUI). The functional scheme of the proposed BCI is shown in **Errore. L'origine riferimento non è stata trovata.**.

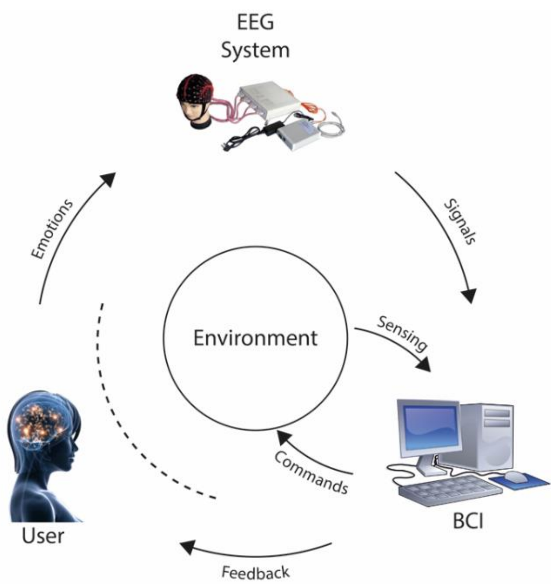

Figure 2- Schematic representation of a BCI driven by emotions as a mediator between the user and the external environment.

In the next section, all these aspects are deeply described, and, whenever possible, compared with similar approaches; it is worth to be noted the modularity of the overall BCI procedure, thus suggesting the substitution of one or more tools with a more efficient one, preserving the efficiency.

2. Materials and methods

The idea discussed in this Section is to design an active BCI by measuring the human brain reaction to self-induced emotions, those reproduced autonomously by recalling in mind situations that generated real emotions, and by using them as commands for a BCI.

The main reasons for choosing self-induced emotions are:

(1) emotional processing has been shown to be preserved in a significant portion of people with severe neurological disorders (Laureys et al. 2004; Heine et al. 2015);

(2) emotions could be an alternative paradigm where other stimuli have failed or were useless (Pistoia et al. 2015);

(3) the transmission of emotions towards the external world, for a living being, is the basis for establishing an affective relationship;

(4) being recalled in mind as desired by user, they represent an activation protocol which is not externally elicited, i.e. the user is completely free of using it autonomously without external stress;

(5) the resulting EEG signals are not affected by other stimuli (visual, auditory, etc.).

In order to use self-induced emotions as activation task, it is necessary to measure the brain activity they originate. The BCI system discussed therein is non-invasive because it uses an 8 channels wireless EEG (Enobio^{NE}, sampling frequency of 500Hz, dynamic range of 24 bits) with externally placed electrodes positioned as in Figure 3 and, more important, autonomously induced mental tasks, without external elicitation. In the positioning of electrodes, frontal and occipital locations are excluded to avoid signals (biases) related with the mnemonic task (the proposed activation strategy also includes an imagination task, involving the usage of the working memory area) and with the processing of visual information, respectively.

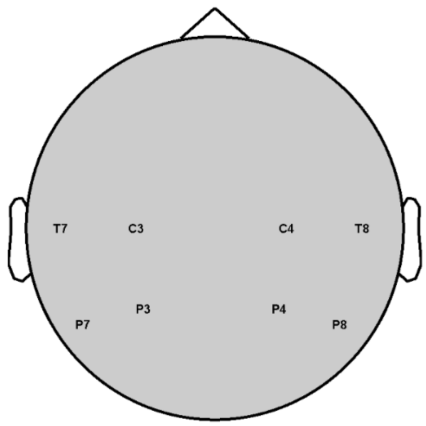

Figure 3- Electrodes montage scheme

Activation tasks and experimental protocol

An emotion is a complex psychological state that involves a subjective experience, a physiological response, and a behavioural or expressive response (Mauss and Robinson 2009). A relative right hemispheric activation is associated with withdrawal stimuli or negative emotions, such as fear or disgust, and a relatively greater left hemispheric activation is associated with approach stimuli or positive emotions, such as joy or happiness (Henkin and Levy 2001). This lateralization can be exploited for the BCI development.

Recently, a prototype of a binary active BCI driven by emotions, based on remembering just a single emotion (the disgust produced by remembering unpleasant odours) and on a relaxing state, has been designed and implemented (Placidi et al. 2015b), tested on healthy people (Iacoviello et al. 2016) and on a subject affected by a severe neurological disorder (Pistoia et al. 2015). Disgust is a primordial, strong emotion, localized in the right brain hemisphere. The signal of a self-induced, remembered, emotion presents a lower amplitude with respect to that generated by really felt emotion, but it is more localized both in space, because it is less affected by other environmental stimulations (such as audio-visual) since the mnemonic task requires concentration, and in frequency, because the remembered emotional task affects mainly the gamma band. Moreover, the disgust is an uncommon and unnatural feeling, and it would unlikely happen during the BCI use; therefore, it is a good candidate as a BCI command because it is well recognized with respect to other emotions. However, besides disgust, also other basic emotions could be effectively used for driving a BCI. For example, by following the imaginary olfactory sensations, it could be feasible to consider the good sensation produced by remembering the odour of a good fragrance. This is what is described therein.

Classification Strategy

For classifying EEG signals from emotions, an efficient classification method based on Short-Time Fourier transform is here adopted (Placidi et al. 2015b).

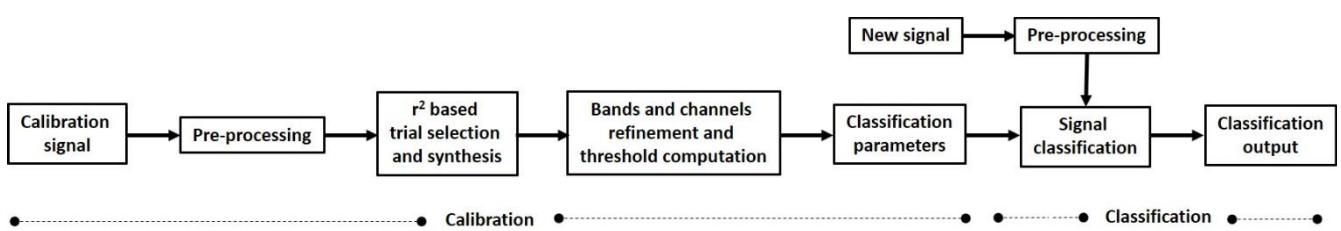

Figure 4- Flow-chart of the used classification strategy

The strategy used for classification is divided into two phases, Calibration and Classification (Figure 4). The Calibration is applied on a set of trials belonging to known classes.

Considering a set *C* of channels, the Short-Time Fourier Transform is applied on each of them separately, by partitioning the signal, also called trial, into *q* sub-trials, with an overlap of *p* samples between consecutive segments. After that, sub-trials are filtered with band-pass filters for retaining just the frequencies 8-12 Hz (demonstrating cerebral activity due to concentration in the α band) and 30-42

Hz (demonstrating emotions activity in the γ band) (Coan and Allen 2004). Then, the mutual similarity between sub-trials is evaluated by means of the r^2 computation (Draper and Smith 1998), defined as follows:

$$\boldsymbol{r_c^2(f)} = \left(\frac{\sqrt{L_1 L_2}}{L_1+L_2}\frac{\mu(X_{1c})-\mu(X_{2c})}{\sigma(X_{1c}\cup X_{2c})}\right)^2 \quad (1)$$

where X_{1c} and X_{2c} are the compared pieces of power spectra of the sub-trials corresponding to the channel c and defined into a neighbourhood $2\Delta f$ of f ($2\Delta f$ has to be not too wide to avoid loss of resolution, usually it is 3 or 5 Hz), L_1 and L_2 are the numbers of samples (in our case $L_1 = L_2$), μ the mean value, and σ the standard deviation. Large r^2 denotes low similarity (or, equivalently, high dissimilarity) between the q sub-trials. The computation of r^2 allows to pick the differences between input signals and has been also successfully used in other EEG classification strategies (Jin et al. 2015, Jin et al. 2017).

The power spectra of the q sub-trials are compared: the s most similar are averaged together while the others are discarded. The aim of the process is to exclude signal segments highly affected by noise. The spectra of the C channels are stored and classified separately.

After the pre-processing step, an r^2 based selection and synthesis is performed again between each trial belonging to the same class, so that the information of a synthetized trial is obtained for both classes. At this point, the r^2 function is used to identify the frequencies where the differences, in r^2, between “activation” and “non-activation” trials are maxima. The maximum values of r^2 occurring inside each of the considered bands, and the absolute minimum of r^2, are also used to define the classification thresholds, t_α and t_γ (see Placidi et al. 2015b for more details). In the classification phase a signal of an unknown class is analysed: first, the pre-processing phase used for Calibration is applied; then, the resulting spectra are compared, by using r^2, with those synthetized in the Calibration phase for “activation” and “non-activation” stages. The obtained values for parameters are compared with the thresholds for obtaining the Classification output for the current signal. In this work, the binary classification method is adopted to recognize, separately, the disgust produced by the memory of an unpleasant odour, and the pleasantness evoked by remembering a fragrance, both referred to a relaxing state.

It has been already noted the modularity of the overall procedure; in particular it is possible to substitute the classification procedure herein recalled with another one that, could be more efficient from some point of view.

More precisely, for better dealing with weak signals, like those deriving from remembered emotions, it has been also used a machine learning approach and its generalization for multiple emotions classifications (Iacoviello et al. 2015b; Iacoviello et al. 2016; Placidi et al. 2016b), despite the procedure becomes slower than with the previously described method and uses a higher number of parameters (it would be preferable to use these techniques once general information on emotions are collected, such as regarding most active channels and specific frequencies, for facilitating their classification). GIUSEPPE: NON è MOLTO CHIARA QUESTA FRASE, PERO' L'IDEA MI PIACE; POTRESTI SCRIVERE UNA O DUE FRASI IN CUI CONFRONTI QUESTO TUO APPROCCIO CON IL NOSTRO? SENZA PARLARE MALE DI QUESTO (ALTRIMENTI CI CHIEDONO DI PRIVILEGIARE L'ALTRO) MA SENZA PARLARE MALE DELL'ALTRO CHE è SUCCESSIVO

Graphic-User Interface

Once the robust recognition of at least one emotion is achieved, it is integrated in an interactive control framework (Avola et al. 2013). In (Placidi et al. 2016a) a modular graphic user interface (GUI), implementing a tabular GUI, is described. The proposed framework is intended to allow the implementation of a BCI by constructing a matrix of graphic symbols to be represented on a computer screen and a software that, cyclically, passes through the rows/columns of the matrix and remains on each symbol for a fixed time interval (usually between 2 and 4 s). When the system enlightens the row containing the desired symbol, the user concentrates on a pre-determined mental task (in this case on a specific emotion) in order to select that row. The same procedure is repeated for the symbols associated with the chosen row.

The GUI is hosted on a computer, which collects the EEG signals from the user and performs a real-time signal analysis and classification; based on the classification outcome, the BCI performs the corresponding action in order to allow the GUI to present the communication message composed or to activate the specific command associated to the chosen symbol.

The GUI also contains a specific module used for the calibration procedure. This function is necessary for selecting the classification parameters necessary for characterizing the class corresponding to each task. This operation is performed by showing on the computer screen, cyclically and randomly, sequences of symbols (usually crosses and arrows, as shown below) whom specific mental tasks are assigned to. When the calibration process is activated, the GUI provides the sequence of symbols and memorizes both the order of symbols presentation and the corresponding EEG signals. The type of symbols to be shown, their number, the showing duration per symbol, and the interval between consecutive symbols (duration of an obscured screen) can be freely set. For the experiments performed and illustrated hereinafter, the described GUI is used in the Calibration configuration only.

3. Results and discussions

By using the previously presented BCI, the classification of three different emotional states is performed: the disgust, produced by remembering an unpleasant odour (task #1); the pleasant sensation, evoked by remembering the odour of a good fragrance (task #2); a relaxing state (task #3). Once recognized, the emotional tasks can be used for driving a BCI.

The experiments, like those performed in (Iacoviello et al. 2015a, 2015b, 2016; Placidi et al. 2015a, 2016b), consists in the collection of EEG data from 10 (5 male and 5 female) healthy, right-handed, subjects with average age of 31.

For data collection, each subject sits in a comfortable armchair in a quiet and lit room. A random sequence of symbols "↓", "↑" or "+" is proposed to the subject; each symbol is presented for 3.6 seconds on a computer screen with no interruptions between them (time interval equals to 0). The subject is prepared informing him that when the symbol "↓" appears on the computer screen, he has to concentrate on the unpleasant odour, with the symbol "↑" he has to concentrate on the good fragrance odour while a relaxed status has to follow to the symbol "+". The mental status must be active for each symbol until it changes. During this time, the EEG signal, composing the current trial, is recorded. The order of presentation is random, but the number of symbols is equally distributed between the three tasks: for each subject, a single experiment consists of 300 trials, 100 for each task, grouped into a single session of about 20 minutes. After the acquisition, the order of the collected trials is modified. Anonymous symbols, like arrows and crosses, are used just for synchronizing tasks while soliciting the corresponding mental states, but not for eliciting the mental state themselves (it is not like using an image from the IAPS (Lang et al. 2008)).

Data analysis and classification procedures are implemented in Matlab®. The signal corresponding to each trial, whose duration is 3.66 s (1830 samples), is divided into four segments of 0.96 s (480 samples), with an overlap of 0.06 s (30 samples). After the r^2 calculation, the best two segments are maintained and averaged together. The binary classification algorithm is applied separately between tasks #1 and #3 and between tasks #2 and #3, each time by using 200 trials (for task #3 the 100 trials are both used for recognizing class #1 and class #2). For each binary classification, given the 200 trials per subject, 40 are used for the calibration (20 for each class), 40 for the validation (20 for each class), and the remaining 120 (60 for each class) for the test. The choice of the trials used for calibration, validation and test is performed after order randomization. For each subject, all the collected trials are used for the experiments. The results of the obtained classification are represented in terms of accuracy as the ratio between the number of correctly classified trials with respect to the total ones expressed in percentage. The classification results are summarized in Table 1.

Table 1- Optimal values for classification parameters of disgust with respect to relax (C1) and of pleasant sensation with respect to relax (C2) for 10 healthy subjects (S1-S10). The classification accuracy and the most active brain hemisphere and channel were also reported

C1	**Best γ freq.**	**Best α freq.**	**Best Hemisphere**	**Best channel**	**Accuracy**
S1	32	9	R	T8	89,3
S2	32	10	R	T8	92,5
S3	36	12	R	T8	93,6
S4	32	8	R	C4	90,5
S5	34	10	R	T8	89,2
S6	32	10	R	P4	95,6
S7	36	8	R	C4	93,7
S8	32	12	R	C4	88,2
S9	30	10	R	T8	90,4
S10	34	10	R	P4	93,0
C2	**Best γ freq.**	**Best α freq.**	**Best Hemisphere**	**Best channel**	**Accuracy**
S1	36	8	L	C3	85,3
S2	36	12	R	C4	83,6
S3	34	12	L	C3	90,4
S4	34	8	L	T7	87,2
S5	36	10	R	T8	83,5
S6	32	12	R	T8	90,2
S7	36	10	L	C3	91,6
S8	34	8	L	T7	89,7
S9	34	12	R	C4	83,6
S10	36	12	L	C3	89,1

The r results show that the classification of the disgust with respect to relax (C1) is characterized by a greater accuracy once compared to the classification of pleasant fragrance with respect to relax (C2). A possible reason, confirmed also by interviews of the subjects after the sessions, is the fact that the sensation felt when remembering disgust is stronger than the one experienced with the memory of good fragrance. Another relevant aspect is that disgust effects are strongly polarized in the right brain hemisphere, while good sensation mainly affects the left hemisphere: this is in line with the premises that negative emotions mainly affect the right brain hemisphere and positive emotions privilege the left hemisphere. In terms of brain activation, roughly considering it as directly proportional to the accuracy level, it can be deduced that subjects greatly involved by negative emotions are also highly sensitive to positive emotions (S3, S6, S7, S10), with some exceptions (S2 and S8).

As an example, the accuracy map, averaged in frequency but separately evaluated in different channels, is reported in Figure 5 for subject S7, both for negative and positive emotions classification with respect to relax.

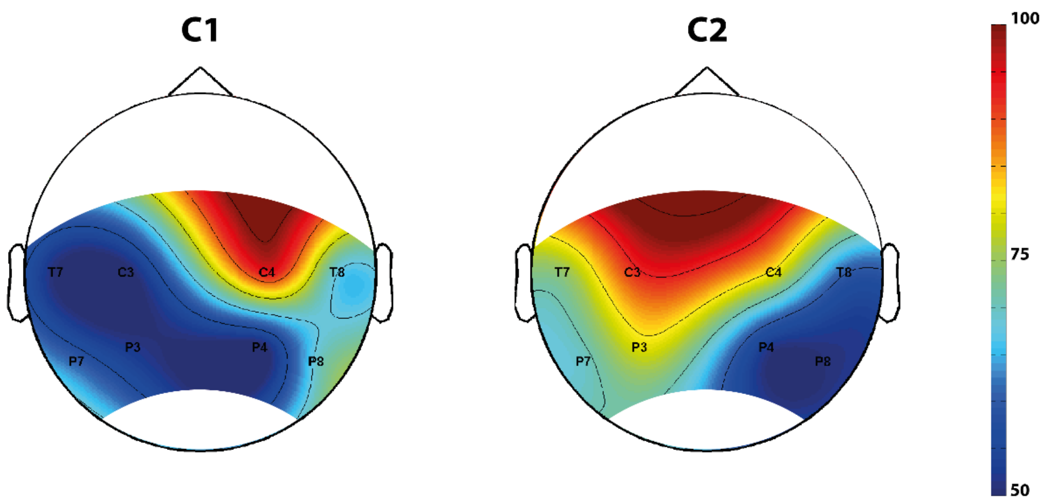

Figure 5- Accuracy maps for subject S7. Classification results related to the disgust with respect to relax (C1, left) and to the pleasant fragrance with respect to relax (C2, right). Frontal and occipital regions are withe because signals from these regions have not been collected.

By summarizing the previous results, it can be observed that all the subjects involved in the experiments can use the proposed activation paradigm, as demonstrated by classification accuracy level well beyond the chance value; both emotions are classified with an accuracy of about 90% for disgust and 85% for positive fragrance imagination, though the second with a lower spatial polarization than the first one. These considerations are encouraging for extending the binary emotion-based BCI to a ternary one, by including also a positive self-induced emotion, though some further work is required for allowing joint classification between negative and positive emotions.

An attempt for the generalization of emotion recognition by EEG signals and to verify the modularity of the overall BCI procedure is proposed in (Placidi et al. 2016b) where all the described algorithm has been applied to signals from the public database DEAP (Database for Emotion Analysis using Physiological Data) containing EEG signals collected while subjects were watching videos involving different emotional aspects (negative and positive) and various stimuli (visual and auditory). The results evidenced are characterized by a low specificity from the localization point of view; nevertheless, three emotions (two strong emotions and a relax status) are considered and successfully classified by using the discussed binary classifier in a sequential procedure, thus preserving the possibility of increasing the alphabet of emotions, with a low computational cost. Another consequence of an efficient and reliable self-induced emotion recognition is therefore to provide specific signatures of emotions to allow a discrimination of each emotion from the other, yielding an alphabet. The first results regarding two strong emotions induced by visual stimuli (one emotion involving low valence and high arousal, and the other related to high valence and high arousal) showed that they have well recognizable features-channels-emotions shapes that allow us to assign to a given unknown EEG signal one of the signatures of the alphabet. The success of the overall procedure, even if applied on signals different from the ones for which it has been designed, ensures its robustness, also in view of its applications to a reduced number of channels.

4. Conclusions

A complete BCI paradigm has been described step by step and tested. In particular, binary classification results, obtained by measurements collected by 10 healthy subjects while imagining the disgust produced by remembering a bad odour, the good sensation produced by remembering the odour of a good fragrance, and a relaxing situation, have been presented and discussed. Though the classifications are performed in a binary mode, by recognizing disgust from relax and good sensation from relax, the accuracy is greater than 85%. This would suggest that an improvement of the binary BCI, by including also a positive emotion, is possible, though an effort must be done regarding the study of an efficient n-ary classification strategy (where n>2 is the number of emotions). In the same time, it has been demonstrated that the described binary BCI could be efficiently used for recovering emotion signature, both in space and in frequency.

The research in this field is intriguing because it can be useful in different disciplines, ranging from neurology, for evaluating the consciousness state in Minimal Consciousness State subjects and allowing them to communicate with the external word, to affective computing, biometrics and security, and, of course, engineering, anthropology, sociology and artificial intelligence.

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References

Allison BZ, Krusienski DJ. 2015. Noninvasive brain-computer interfaces. In Encyclopedia of Computational Neuroscience. Springer New York.

Avola D, Spezialetti M, Placidi G. 2013. Design of an efficient framework for fast prototyping of customized human–computer interfaces and virtual environments for rehabilitation. Computer Methods and Programs in Biomedicine. 110(3):490-502.

Banville H, Gupta R, Falk TH. 2017. Mental Task Evaluation for Hybrid NIRS-EEG Brain-Computer Interfaces. Computational Intelligence and Neuroscience. 2017:3524208.

Basso Moro S, Bisconti S, Muthalib M, Spezialetti M, Cutini S, Ferrari M, Placidi G, Quaresima V. 2014. A semi-immersive virtual reality incremental swing balance task activates prefrontal cortex: a functional near-infrared spectroscopy study. Neuroimage., 85:451-460.

Basso Moro S, Carrieri M, Avola D, Brigadoi S, Lancia S, Petracca A, Spezialetti M, Ferrari M, Placidi G, Quaresima V. 2016. A novel semi-immersive virtual reality visuo-motor task activates ventrolateral prefrontal cortex: A functional near-infrared spectroscopy study. J. Neur Engineering. 13(3):1-14.

Carrieri M, Petracca A, Lancia S, Basso Moro S, Brigadoi S, Spezialetti M, Ferrari M, Placidi G, Quaresima V. 2016. Prefrontal cortex activation upon a demanding virtual hand-controlled task: A new frontier for neuroergonomics. Frontiers in Human Neuroscience. 10:1-13.

Coan J, Allen J. 2004. Frontal EEG asymmetry as a moderator and mediator of emotion. Biological Psychology. 67(1-2):7-50.

De Santis A, Iacoviello D. 2006. Optimal segmentation of pupillometric images for estimating pupil shape parameters. Computer Methods and Programs in Biomedicine., 84:174-187.

De Santis A, Iacoviello D. 2009. Robust real time eye tracking for computer interface for disables people. Computer Methods and Programs in Biomedicine. 96:1-11.

Di Giamberardino, P, Iacoviello, D, Placidi, G, Polsinelli, M, Spezialetti, M. 2018. A brain computer interface by EEG signals from self induced emotions. Lecture Notes in Computational Vision and Biomechanics, 27: 713-721

Draper N, Smith H.1998. Applied regression analysis. Wiley. New York.

Farwell L, Lawrence A, Donchin E. 1988. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalography and clinical Neurophysiology. 70(6):510-523.

Ferrari M, Bisconti S, Spezialetti M, Basso Moro S, Di Palo C, Placidi G, Quaresima V. 2014. Prefrontal Cortex Activated Bilaterally by a Tilt Board Balance Task: A Functional Near-Infrared Spectroscopy Study in a Semi-Immersive Virtual Reality Environment, Brain Topography, 27(3):353-365.

Heine L, Castro M, Martial C, Tillmann B, Laureys S, Perrin F. 2015. Exploration of Functional Connectivity During Preferred Music Stimulation in Patients with Disorders of Consciousness. Frontiers in psychology. 6:1704.

Henkin R, Levy L. 2001. Lateralization of Brain Activation to Imagination and Smell of Odors Using Functional Magnetic Resonance Imaging (fMRI): Left Hemispheric Localization of Pleasant and Right Hemispheric Localization of Unpleasant Odors. Journal of Computer Assisted Tomography. 25(4): 493-514.

Iacoviello D, Lucchetti M. 2005. Parametric characterization of the form of the human pupil from blurred noisy images. Computer Methods and Programs in Biomedicine. 77:39-48.

Iacoviello D, Petracca A, Spezialetti M, Placidi G. 2015a. A Real-time classification algorithm for EEG-based BCI driven by self-induced emotions. Computer Methods and Programs in Biomedicine. 122: 293-303.

Iacoviello D, Pagnani N, Petracca D, Spezialetti M, Placidi G. 2015b. A poll oriented classifier for affective brain computer interfaces. In proc. 3rd International Congress on Neurotechnology, Electronics and Informatics, NEUROTECHNIX. 978-989. Lisbon (Portugal).

Iacoviello D, Petracca A, Spezialetti M, Placidi G. 2016. A classification algorithm for electroencephalography signals by self-induced emotional stimuli. IEEE Trans. on Cybernetics. 46(12): 3171-3180.

Jin J, Sellers EW, Zhou S, Zhang Y, Wang X, Cichocki A. 2015. A P300 brain–computer interface based on a modification of the mismatch negativity paradigm. International journal of neural systems, 25(03): 1550011.

Jin J, Zhang H, Daly I, Wang X, Cichocki A. 2017. An improved P300 pattern in BCI to catch user's attention. Journal of neural engineering, 14(3): 036001.

Lang PJ, Bradley M, Culthbert BN. 2008. International affective picture system (iaps): Affective ratings of pictures and instruction manual. Technical report A-8.

Laureys S, Perrin F, Faymonville ME, Schnakers C, Boly M, Bartsch V, Majerus S, Moonen G, Maquet P. 2004. Cerebral processing in the minimally conscious state. Neurology. 63:916-918.

Mauss IB, Robinson MD. 2009. Measures of emotion: A review. Cognition & Emotion. 209–237.

Mellinger J, Schalk G, Braun C, Preissl H, Rosenstiel W, Birbaumer N, Kubler A. 2007. An MEG-based brain-computer interface (BCI). Neuroimage. 36(3): 581-593.

Millan JR, Mourino J. 2003. Asynchronous bci and local neural classifiers: an overview of the adaptive brain interface project. IEEE Trans. on Neural Systems and Rehabilitation Engineering. 11(2): 159-161.

Moghimi S, Kushki A, Guerguerian AM, Chau T. 2013. A review of eeg-based brain-computer interfaces as access pathways for individuals with severe disabilities. Assistive Technology. 25(2): 99-110.

Muller-Putz GR, Klobassa DS, Pokorny C, Pichler G, Erlbeck H, Real GRL, Kubler A, Risett M, Mattia D. 2012. The auditory p300-based ssbci: a door to minimally conscious patients? In 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 4672-4675.

Naseer N, Hong KS. 2015. fNIRS-based brain-computer interfaces: a review. Frontiers in human neuroscience. 9:3.

Pistoia F, Carolei A, Iacoviello D, Petracca A, Sacco S, Sarà S, Spezialetti M, Placidi G. 2015. Eeg-detected olfactory imagery to reveal covert consciousness in minimally conscious state. Brain injury. 29(13-14): 1729-1735.

Placidi G, Avola D, Ferrari M, Iacoviello D, Petracca A, Quaresima V, Spezialetti M. 2014 A low-cost real time virtual system for postural stability assessment at home. Computer Methods and Programs in Biomedicine. 117 (2): 322-333.

Placidi G, Petracca A, Spezialetti M, Iacoviello D. 2015a. Classification strategies for a single-trial binary Brain Computer Interface based on remembering unpleasant odors. Engineering in Medicine and Biology Society (EMBC) 37th Annual International Conference of the IEEE. 7019-7022.

Placidi G, Avola D, Petracca A, Sgallari F, Spezialetti M. 2015b. Basis for the implementation of an eeg-based single-trial binary brain computer interface through the disgust produced by remembering unpleasant odors. Neurocomputing. 160:308-318.

Placidi G, Petracca A, Spezialetti M, Iacoviello D. 2016a. A Modular Framework for EEG Web Based Binary Brain Computer Interfaces to Recover Communication Abilities in Impaired People. Journal of Medical Systems. 40(34):1-14.

Placidi G, Di Giamberardino P, Petracca A, Spezialetti M, Iacoviello D. 2016b. Classification of Emotional Signals from the DEAP dataset. In proc. 4th International Congress on Neurotechnology, Electronics and Informatics, NEUROTECHNIX. 15-21. Porto (Portugal).

Schalk G, Leuthardt EC. 2011, Brain-computer interfaces using electrocorticographic signals. IEEE reviews in biomedical engineering. 4:140-154.

Schreuder M, Blankertz B, Tangermann M. 2010. A new auditory multiclass brain-computer interface paradigm: spatial hearing as an informative cue. PloS one. 5(4).

Sitaram R, Caria A, Veit R, Gaber T, Rota G, Kuebler A, Birbaumer N. 2007. fMRI Brain-Computer Interface: A Tool for Neuroscientific Research and Treatment. Computational Intelligence and Neuroscience. 2007:25487.

Sudre G, Parkkonen L, Bock E, Baillet S, Wang W, Weber DJ. 2011. rtMEG: a real-time software interface for magnetoencephalography. Computational intelligence and neuroscience. 2011:11.

Van Gerven M, Farquhar J, Schaefer R, Vlek R, Geuze J, Nijholt A, Ramsey N, Haselager P, Vuurpijl L, Gielen S, Desain P. 2009. The brain-computer interface cycle. Journal of neural engineering. 6(6): 041001.

Vidaurre C, Blankertz B. 2010. Towards a cure for bci illiteracy. Brain topography. 23(2):194-198.

Weiskopf N, Mathiak K, Bock SW, Scharnowski F, Veit R, Grodd W, Goebel R, Birbaumer N. 2004. Principles of a brain-computer interface (BCI) based on real-time functional magnetic resonance imaging (fMRI). IEEE Trans. on Biomedical Engineering. 51(6):966-970.

Wolpaw JR, McFarland DJ, Neat GW, Forneris CA. 1991. An EEG-based brain-computer interface for cursor control. Electroencephalography and Clinical Neurophysiology. 78(3):252–259.

Wolpaw JR, Birbaumer N, McFarlandand DJ, Pfurtscheller G, Vaughan TM. 2002. Brain–computer interfaces for communication and control. Clinical Neurophysiology. 113(6):767-791.

Zhu D, Bieger J, Molina GG, Aarts RM. 2010. A survey of stimulation methods used in SSVEP-based BCIs. Computational intelligence and neuroscience. 2010:1.