Emotional BCI

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***Abstract*—A Brain Computer Interface (BCI) is a system that takes a biosignal, measured from the brain of a person, and predicts (in real-time) certain aspects of the person's cognitive state [1] [2] or motor behavior bypassing the motor system.. The future of BCI for communication in case of completely (CLIS) or looked-in patients is the combination of different input signals. In this work we studied the implementation of BCI for binary recognition (binary question with yes-no answer) using information regarding emotional feedback (positive or negative emotion). This kind of approach could be used jointly with other solutions such as Electrodermal Activity (EDA), Electrocardiography (ECG), etc. In particular, we have combined EEG and ECG information. The main purpose is to increase the predictive power of the BCI using the emotional response, that is also connected to our unconscious and involuntary nervous system.**

The purpose of this study is to test a new means of communication for completely and locked-in patients based on emotions and to present future possible implementations.

***Index Terms*—BCI, Emotional response, Emotional BCI, binary classification**

I. Introduction

The discovery of EEG signal in 1929 by the German psychiatrist Hans Berger changed the way we understand the structure and functioning of the brain. In the figure 1 you can see how in these last years the interest for the BCI is at its maximum level.

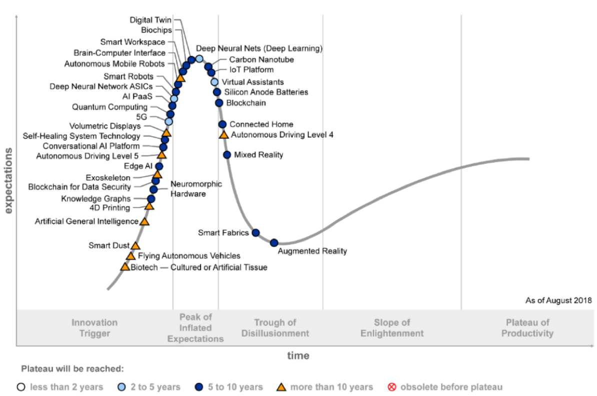

Fig. 1: 2018 Emerging Technologies Hype Cycle Garners Insights From More Than 2,000 Technologies [3].

Nowadays, the Brain Computer Interface (BCI) starts to be a well known technologies that allows to create a connection between the human and a computer. For the first time the term BCI is coined by Jacques J. Vidal in 1976; and in the last 40 years, direct brain-computer interaction went from simple communication programs to sophisticated BCI-controlled applications [4].

Fig. 2: First ever person in the locked-in state who communicated with a BCI. He wrote a letter to Professor Birbaumer asking for a visit from him and his team [5].

BCI is a particularly relevant resource for patients with locked-in syndrome (LIS). In these cases, BCI were installed at their home and long-term usage was established, resulting in increased quality of life (QOL).

In this work we introduce the study of the implementation of an emotional BCI, i.e. BCI based on the emotional response of our brain, in the scenario of locked-in patients answering with binary options (e.g. yes/no).

A. BCI

Generally speaking, a BCI is divided into 5 steps [6]:

- *Acquisition*: a biosignal is acquired;
- *Signal Processing*: the signals are filtered or processed to removed artifacts an useless information;
- *Features extraction*: relevant characteristics of the signal are extracted in order to be used in the classification step;
- *Classification*: identification of the membership class of the recorded signal and translation into a command;
- *Application and feedback*: execution of the task corresponding to command and feedback return to the patient.

B. Types of signals

Of particular relevance for BCIs are electrical potential and hemodynamic measurements. *Electrical potential* measurements include action and field potentials which can be recorded through *invasive* (e.g. electrocorticography) and *non-invasive* techniques (e.g. electroencephalogram and magnetoencephalogram). *Hemodynamic measurements* include functional magnetic resonance imaging (fMRI), positron emission

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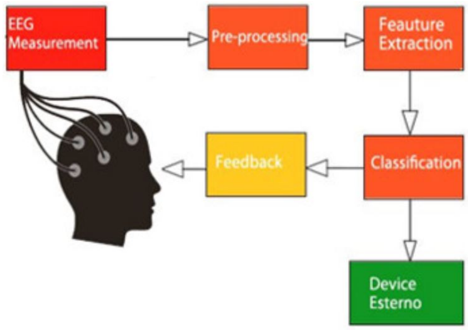

Fig. 3: BCI scheme

tomography (PET), and functional Near Infrared Spectroscopy brain monitoring (fNIRS) [7].

Moreover, there is the possibility to add information coming from systems different from the pure neural one. For example: *Electrocardiography (ECG)*, that represents the changes in electrical potential difference (voltage) during depolarization and repolarisation of the myocardial fibers; *Electromyography (EMG)*: used for the investigation of physiologic properties of muscles activity at rest and during contraction; *Electrodermal Activity (EDA)*, that describes changes in the electrical properties of the skin resulting from sweat activated by the autonomic nervous system. The variation are caused by the activity of sweating glands.

When we compute a mental task, our brain produces distinctive patterns in the EEG. Depending of the purpose of the BCI, it is necessary to extract the corresponding pattern to allow the classification step. The main sources and patterns in the EEG are listed below [7]:

- *Sensorimotor activity*: mu and beta rhythms (8-12 Hz and 13-30 Hz, respectively). A voluntary movement produces a power decrease in the mu and alpha bands, which is termed event related desynchronisation (ERD). The imagination of motor movements, in particular limb movements are used in several BCIs which identify the type of motor imagery (right/left hand/foot movement) using a classification algorithm that takes as features the power in the mu and beta bands [7].
- *P300*: a infrequent stimulus (auditory, visual or somatosensory), interspersed with the frequent or routine stimuli, typically evokes in the EEG a positive peak at about 300 ms after the stimulus presentation. P300-based BCIs operate by presenting the user with a set of choices (usually in a matrix form) and randomly highlighting all of them. A P300 appears in the user's EEG when her/his selected choice is highlighted.
- *Steady-state visual potentials*: signals that are natural responses to alternating visual stimulation at specific frequencies.
- *Slow cortical potetials (SCP)*: they are small changes in voltage that last from one to several seconds and are associated with changes in the level of cortical activity.

C. *Emotions*

Emotions are psycho-physiological phenomena associated with a wide variety of expressed subjective feelings, observable behaviours and changes in autonomic body state [7]. Several measures have been created for emotion classification but there is no classification universally accepted to categorise emotions yet. They are mainly divided into *Discrete* and *Dimensional* perspectives. In the first case, the emotion is identified in very specific manner (e.g. fear, calm, neutral). Whereas in case of Dimensional perspective human emotion are classified on a scale by the level of valence and arousal that is based on SAM Model. The most common assumed dimension for valence and arousal model is bipolar model of emotional classification [8]. In this model the Valence refers to the degree of 'pleasantness' that is associated with an emotion, i.e. the change of feeling in a person from negative to positive; whereas arousal refers to the strength of the experienced emotion, the level of excitement.

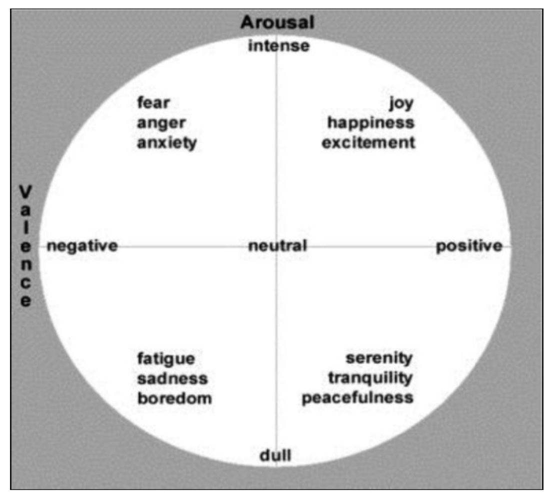

Fig. 4: Valence/ Arousal model [9]

II. State of Art

A. *Emotional BCI*

The emotional BCI is implemented with the main purpose of recognition of the feelings and the emotional states of the patient. The emotional recognition can pass through voice, body language and brain signals. In the last case, the selection of signals and its features are essential because only certain types of emotions can be recognized using EEG [8].

B. *Stimuli*

To be able to record an emotion, it is fundamental to use the right elicitation techniques to evoke the emotional response. Al-Nafjan et al. [8] made a great classification work studying, reviewing and classifying 285 articles regarding emotional recognition based on EEG BCI. "Different emotion elicitation techniques have been developed and reported. Critical examples of emotion elicitation techniques include standardized emotional stimuli (e.g., pictures, films, and audio), imagination techniques (e.g., guided imagery and autobiographic recall), present social interactions (e.g., games), and directed facial action tasks" [8].

Technique	Number of Articles	Domain (*Medical, Non-Medical*)
Visual-based elicitation using images	88	26% , 73.9%
Prepared task	43	25.6%, 47.4%
Audio-visual elicitation using short film video clips	38	18.4%, 81.6%
Audio-based elicitation using music	29	17.2%, 82.8%
Multiple techniques	19	26.3%, 73.9%
Other	17	11.7%, 88.2%
Imagination techniques/memory recall	10	20%, 80%
Social interactions	4	25%, 75%

Fig. 5: Emotion elicitation techniques [8]

In addition to external stimuli, in some cases the patient is required to memorize through imagination techniques. They consist in methods like autobiographic recall and guided imagination in order to evoke a certain emotion [7]. Subjects have the task to remember a particular situation from their past that elicits emotional response [10]. For instance, they could recall the memory of a real life episode, a video they have watched or a songs; in some cases also an olfactory stimulus can evoke a strong emotional response [11].

C. EEG Signals and Features correlated with emotions

In Al-Nafjan et al. [8] it is reported that the most used neuro-physiological phenomena associated to the emotional response and used in the emotional BCI are:

- Event-related potentials (ERP);
- Frontal EEG asymmetry;
- Event-related desynchronization/synchronization (ERD/ERS);
- Steady-state visual evoked potentials (SSVEP).

Moreover, the main computational methods to extract and classify emotional features from EEG are [8]:

- Frequency domain (using Fourier Transform): power spectral density, band power;
- Time domain: Activity, mobility and complexity (using Hjorth Parameters), Fractal dimension (using Higuchi Method);
- Wavelet domain (using Wavelet Transform): Entropy, Energy;
- Statistical features: Median, Standard deviation, Kurtosis symmetry, etc.

Although it is not clear yet which are the most emotional-relevant EEG features, power features from different frequency bands are still the most popular in the context of emotion recognition [8]. In particular, it has been shown [11] [12] [13] that power spectral density (PSD) extracted from EEG signals performs good results in the classification of effective states.

D. Algorithms

As reported in [8] we can identify two groups of classification algorithms.

1) Classical Approach: The first group use hand made features obtain from EEG (like the ones explained in section II-C) in combination with traditional machine learning algorithm, like the Support Vector Machine (SVM) K-Nearest Neighbors (K-NN), Linear Discriminant Analysis (LDA) or Random Forest to classify EEG trials.

A well establish method that use this paradigm is the FBCSP (Filter Bank Common Spatial Pattern) algorithm developed by Zhang et al in [14]. This algorithm performed a frequency filtering to divide the EEG signal in 9 different band (4-8Hz, 8-12Hz etc), followed by a spatial filtering with the CSP algorithm. The most important features obtained with this procedure are then classified with a SVM classifier or a K-NN classifier. Some paper also present the use of a Bayesian classifier. An example of the use of FBCSP in emotion recognition can be find in the work of Kothe et al. [15] where they used a modify FBCSP to create a binary classifier of positive/negative emotion with a 71.3% precision.

Despite the wide use of these methods some problems remain; the principal one is the choice of the features to use to classify the EEG that must be done by the creators of the BCI. Since the EEG signal has a very low signal-to-noise ratio and that some feature could change between patient an automatic feature extraction method would be preferred.

2) Deep Learning Approach: Neural networks are a type of algorithm that are vaguely based on the structure of human brain and process the data in layers of neurons. The first layer receive the raw data in input and subsequent ones always receive the output of the previous layer. This allows neural network to learn an abstract representation of the data and find patterns of the data without external aid. Thanks to the development of GPUs in the last decade the field of neural networks has experienced significant growth, especially with the introduction of Deep Learning. This paradigm involves the use of several layers inside a neural network to allow the network to find very complex features and patterns inside the data in an automatic way. In the field of BCI, and especially Emotional BCI, this can be very useful since it allows to build a model that can automatically adapt to the patient and extract the relevant features without fine-tuning of human experts. Example of this kind of work can be find in the work of Zhang et al in [16] where a Deep Belief Network (DBN, a particular type of neural network) is used to automatically extract features from raw EEG data and the classify them. The outcome of the study showed that feeding the raw EEG data into the DBN in order to learn effective features is as effective as manually selecting features for learning.

E. Research course

- **Liu et al. [17]**: in this work three EEG channels are acquired (FC6, F4 and F3) to perform a classification of brain electrical signals in human emotions. The channel FC6 is used to classify emotions regarding the level of excitement; whereas, the channels F3 and F4 are used in the quantify the level of the valence. According to the authors, in the forebrain of an individual can be

identified greater activation in one hemisphere during the feeling of positive emotion and greater activation in the left hemisphere during feeling a negative emotion. But what hemisphere has a higher activation during a specific emotion depends on each individual.
- **Sari et al. [18] and Savran et al. [19]**: it is highlighted that it is impossible to recognize emotional states using the EEG signal and facial expressions at the same time. In fact, the contractions of the muscles of the face produce artifacts and a high level of noise that make it impossible to achieve the recognition task.
- **Bos [20]**: a recognition of human emotions is performed recording three channels, F3, F4 and FPZ, according to the international 10-20 system. Later, the author used a band pass filter to extract only the features in the frequency range 8-30 Hz. The original signal is divided into frequency bands using the frequency Fourier analysis and the principal components analysis is performed to reduced the number of features. Finally, Bos used a binary Fisher linear classifier obtaining a rate of 82.1% accuracy in classification of emotions in brain signals.
- **Murugappan et al. [21]**: the authors test two classification methods, the k nearest neighbors and linear discriminant. After the acquisition of 64 EEG channels, a Laplace filter was applied in pre-processing and the wavelets transform algorithm analysis decomposed the signal into five frequency bands (delta, theta,alpha, beta and gamma). The authors calculated the statistical data of alpha band (entropy, energy, standard deviation and variance) and applied this information as input for the classifiers. They obtained a maximum accuracy of 78,04 % for k nearest neighbors and 77,83 % for the linear discriminant.
- **Quesada-Tabares et al. [22]**: they focus on the usage of a Single EEG Channel, showing that is possible to obtain results comparable to a multi-channel sensor.
- **Zheng et al. [23]**: they created a EEG-based emotion recognition models for three emotions (positive, neutral and negative). In this case, they used a deep belief network (DBN) feeding with differential entropy features extracted from multi-channel EEG data. They obtained a value of 86.65% as best accuracy result.
- **Soleymani et al. [24]**: They performed a classification using Long-short-term-memory recurrent neural networks (LSTM-RNN). They arrived at the same conclusion of Sari et al. [18] and Savran et al. [19], that is most of the emotionally valuable content in EEG features are as a result of this contamination of facial muscle activities.

III. Our approach

A. Targets and Dataset

As said before, only certain types of emotions can be recognized using EEG. In general, most of the articles regarding the emotional BCI tries to detect unpleasant, pleasant, and neutral emotions; or positive, negative, and neutral emotions that are based on the valence-arousal dimensional emotion. We decide to focus on the study on the classification of the dimension *positive-negative* emotions. Since the subjects used in this study were completely or semi locked-in patients, the common and most used databases already available (i.e. DEAP [25], MAHNOB [26], etc.) were not entirely representative. For this reason we created our specific dataset based entirely on completely or semi locked-in patients.

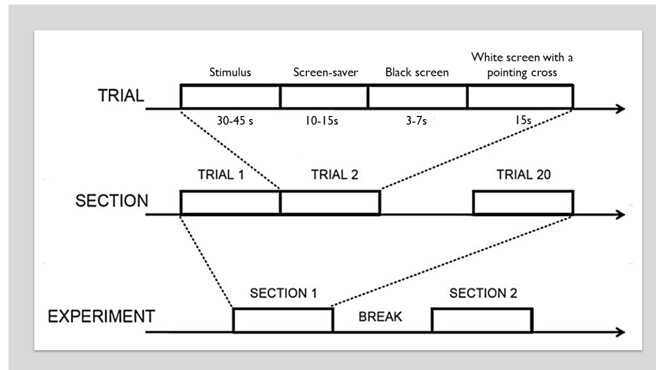

Fig. 6: Database scheme

A scheme of the procedure used to record the database can be found in the Figure 6. The database is composed by different sections, each composed by 20 consecutive trials without break in the middle. Two consecutive sections are taken with a time distance that goes from some days to some weeks, in order to collect the most representative possible signal. A trial consists in 4 moments:

- presentation of the stimulus that could be a picture, a video or a auditory stimulus, representing positive or negative feelings. The emotional stimuli (image, audio, and video) are usually taken from reputable sources, such as the International Affective Picture System (IAPS) database and the International Affective Digitized Sounds (IADS). Other sources from the Internet can be also used as Youtube, Facebook, etc.). The stimulus is presented for a duration between 30-45 seconds;
- a screensaver is presented with relaxing neural shapes and colours (Figure 7). The duration is 10-15 seconds;
- a black screen lasts for 3-7 seconds;
- a white screen with a central pointing cross is presented for 15 seconds. In this period the subject should evoke the positive/negative feeling depending on the presented stimulus. In this sense, the initial stimulus has two purposes: presentation and elicitation of the emotion to be evoked later and to give an example that can be used by the subject to evoke the right emotion.

The variability of the moment duration was specially added to avoid automatic responses that can occurs with monotonous routine.

B. Setting

As recording instrumentation, we used the Quik-cap, NuAmps (Compumedics NeuroScan Inc., El Paso, TX, USA)

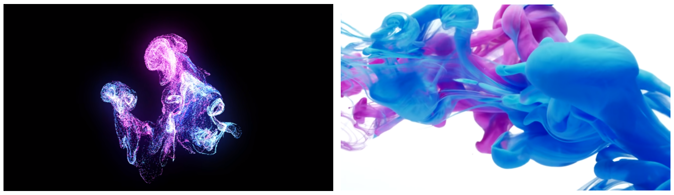

Fig. 7: Screensaver examples

[27] that allows to record up to 32 electrodes placed according to the International 10-20 electrode placement standard (as shown in Figure 8). For the purpose of this work, we have subsequently selected and use the information from the electrode F3 (left hemisphere) and F4 (right hemisphere), with a choice similar to [20].

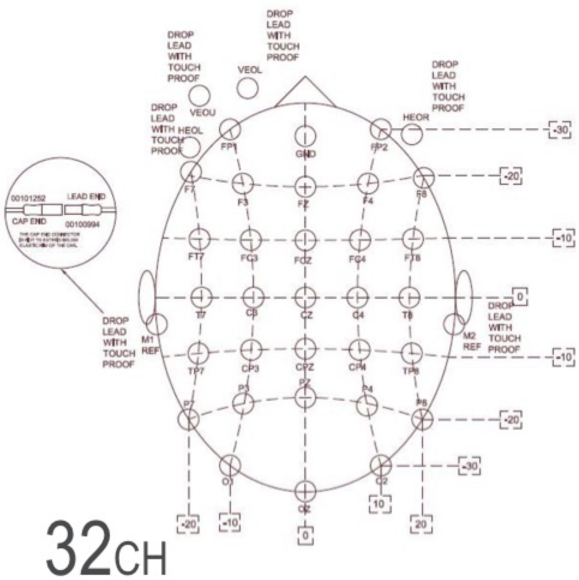

Fig. 8: Scheme of the placement of the 32 electrodes recorded by the Quick-cap [27].

C. *Signal processing and features extraction*

For each electrode, we have selected only the central 10-seconds segment of the evoking moments described in Section III-A. We proceed with a Wavelets transform algorithm analysis to decompose the signal into five frequency bands (delta, theta, alpha, beta and gamma). We have kept only theta and alpha rhythms since human emotions are related with them [28]. For each electrode, we have computed a Time-frequency analysis of EEG data using the Matlab function *spectrogram*. It is based on the computation of the signal power corresponding of a specific time and frequency using a sliding window and the short-time Fourier transform [29]. In the end, you can get a image similar to Figure 9 where in the upper part you can find the data regarding the electrode F3, while at the bottom there are the data regarding the electrode F4. The intensity on the color corresponds to the power level. This representation is quite useful since it contains both time and frequency information in a single data. Also we can treat the data as images and consequently use Convolutional Neural Networks to analyze them.

To improve the emotion recognition we also used the ECG (Electrocardiography) as a secondary source of data. We choose ECG because heart rate is another signal that can be heavy influenced by emotional state and unlike others collectable data (like facial expression or sugar level) it is robust, easy to record and the subject has no control over it.

To adapt the ECG data to our classifier we perform a series of operations. First of all, we have found the R peaks of the ECG signal using a peak detector [12] (you can find some examples in Figure 10). Then we have considered a window of 500 ms centered in the detected peaks, we have segmented the signals and we have plot all the peaks of each trial in a single black and white image of shape [150, 200]. At the end, the ECG data consists of a three dimension array [number of trials, 150, 200] with values in range [0,1]. Figure 11 shows some examples of this data.

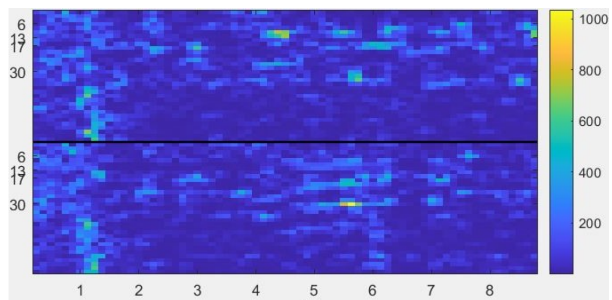

Fig. 9: Image resulting from the computation of the spectrogram of the electrodes F3 (above) and F4 (below). The x axis represents the time information (seconds); while the y axis represents the frequency information (Hz). The intensity on the color corresponds to the power level of the signal.

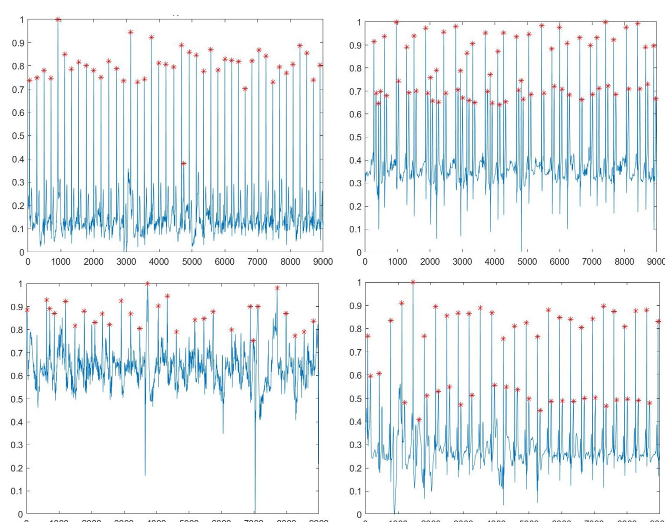

Fig. 10: Four examples of peaks detection of ECG records.

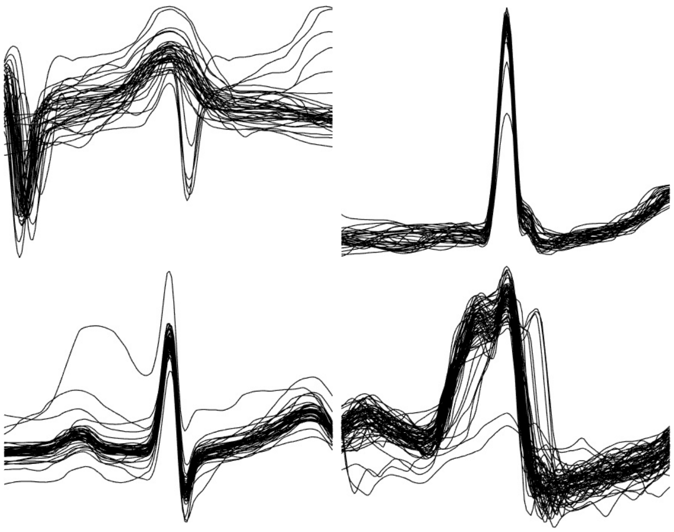

Fig. 11: Examples of the final result of the signal processing for ECG recordings.

D. Classification algorithm

The neural network classifiers have been implemented through a multi-branches Convolutional Neural Network (CNN) built with Keras. The classifier structure can be seen in figure 12. The two branches of the network are identical convolution network. Their outputs are subsequently flattened, passed through a dense layer and merged together. Then the vector passes through 3 dense layers that return a vector with two elements. The first element indicates the probability that the trial belongs to the "positive emotion" class instead the second element indicates the probability that the trial belongs to the "negative emotion" class. There are in total 5 convolution layers, each one with a kernel size of 5. The number of the filters of each layer are respectively 8, 16, 32 and 64. The activation function is the ReLU. Between each convolution layer and the respective activation there is a batch normalization layer to speed up the training. The dense layer in each branch has a dimension of 500 neurons with ReLU activation function. The dimensions of the last 3 dense layer are respectively 200, 50 and 2 neurons. The activation function is ReLU for the first two layer and softmax for the last layer. Some dropout layers with probability 0.15 were also added to avoid overfitting.

We choose to use a Convolutional neural network because this kind of architecture allows the network to automatically extrapolate features from our representation of the data. In this way the model can be easily adapt to every subject.

E. Future Improvement

The improvement in our work can be done in two main area: network structure and network training.

1) Network structure: The branch structure has been chosen to allow our network to see different type of data. This allows the algorithm to extract features from different type of basic data (EEG spectrogram and ECG) and combine them together in a complex representation in the deeper layers of the network. The classification power of the algorithm can be improved adding different branch with different data representation or substitute one or both branches with different type of data. Example of new type of data to use can be:

- ECG spectrogram (Combined frequency and temporal representation of ECG).
- EEG raw data (full temporal representation regarding EEG).
- Fourier transform of EEG (full frequency representation of the EEG).
- Fourier transform of ECG (full frequency representation of the ECG).
- A combination of different information using some kind of feature extraction algorithms and approaches.

2) Network training: In the last year various studies use unsupervised learning to pre-train the network in a way that is more optimized for EEG analysis.

An example can be find in the work of Stober et al in [30] where an auto-encoder was fed with raw EEG data and was trained in reconstructing the input data. In this way the encoder part of the network learns to extrapolate the most important features from the data to reconstruct them. Subsequently the encoder was used as feature extractor in a standard Feed-Forward-Network. Another example is the work of Movahedi et al in [31] where they review the use of DBN in various studies as automatic feature extractor.

Future improvement in our network can exploit similar techniques to increase the accuracy of our network and its ability to find significant features in the data. The results in [16] and [31] are especially encouraging. So pre-train the branch of the network as convolutional-DBN appears as the next logical step. This strategy could also allow to save a lot of time since once we have the pre-trained model it can be used as a based for each subject. In this way we have only to fine-tuned the model for everyone instead that train the entire model for everyone.

IV. Possible uses

A. Why do we need to understand emotions for BCI?

As explained in the article by Garcia et al. [7], the emotion can deeply influence the use and developement of BCI. This influence can be expressed in two modes:

1) Passive use of emotion: Emotion can alter the brain activity in different way. It has been demonstrated that some emotion can emphasize some features inside the EEG. So we can developed a BCI that exploits features elicited by emotional state and use this enhanced feature to built a more robust classifier.

2) Active use of emotion: The other way to use emotion explained in [7] was to use emotions as input command. We can create a BCI that is able to recognize emotions and use these states as different commands for some devices. More examples of this can be found in the following section (section IV-B).

B. Possible Application

An example of the use of emotion inside the BCI is presented by Fattouh et al. in [32]. In this paper they used an emotional BCI to improve the control system of a wheelchair.

The original control system based on a simple BCI was based on four commands (*move forward*, *move backward*, *turn right*, *turn left*)After training the BCI, to select a command the user had to think and continue to concentrate on that mental state to continue the execution of the command. This requires a continuous concentration by the user and it can be stressful and burdensome in the long run.

The improved version used in addition to the standard setup an Emotional BCI to continuously monitor the emotional state of the subject, in particular if the subject is *frustrated* or *not frustrated*. In this version when a command is selected it is repeated until the user's emotional state is *not frustrated*. When the Emotional BCI detects the status *frustrated* it blocks the wheelchair and the user has to select a new command.

An experiment on the same path shows that, with the improve setup with emotional BCI the user concentration had a 67% reduction comparing with the traditional setup.

Despite these first results seem promising, in practice this approach is quite fragile and requires further study and improvements to be able to distinguish the various commands in a robust and reliable way.

The wheelchair used in the experiment was the Autonomous Vehicle for People with Motor Disabilities (VAHM-3) and it is visible in figure 13. The EEG was acquired through the Emotiv EPOC headset shown in figure 14.

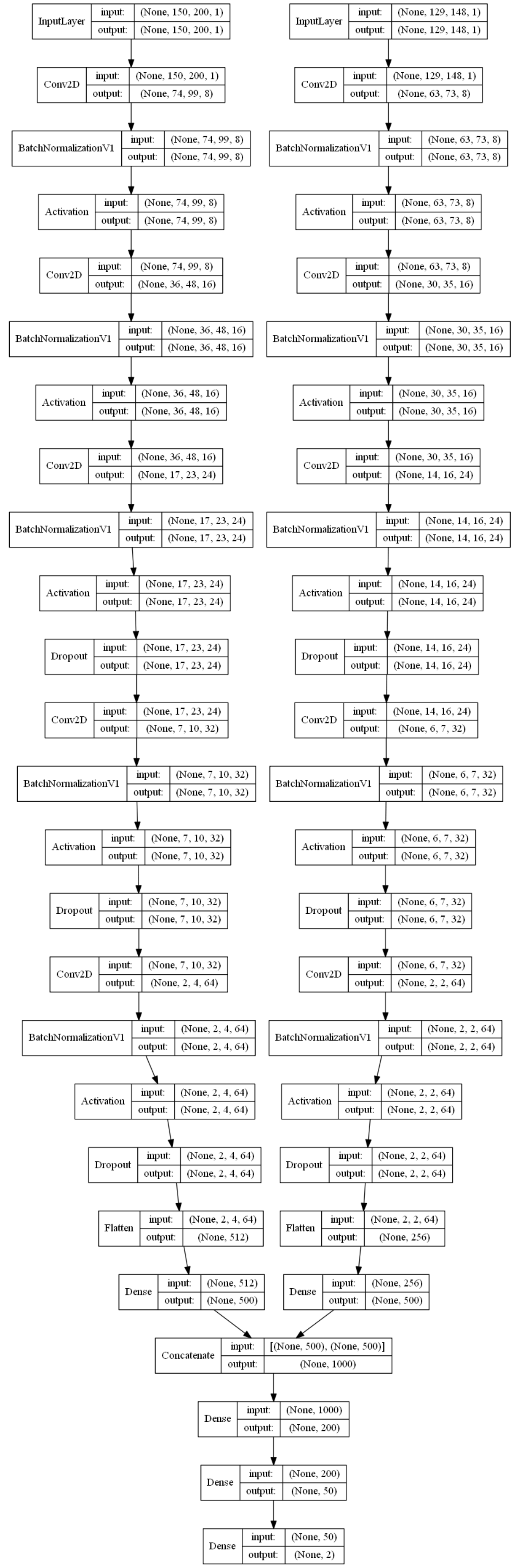

Fig. 12: Scheme of our neural network classifier

Fig. 13: Wheelchair used in [32]

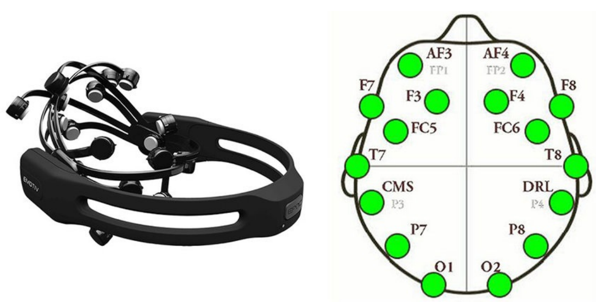

Fig. 14: BCI used in [32]

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