Chapter 14

Brain-Computer Interface (BCI): Types, Processing Perspectives and Applications

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1 Introduction

A Brain-Computer Interface (BCI) is a system that aims to create a direct communication channel between the brain and a computer, with the purpose of transmitting messages and commands. Such systems utilize well defined underlying correlations between certain mental activities and electrophysiological signals associated with the brain. Depending on the positioning of the sensors used to record the aforementioned signals, BCI systems can be categorized as noninvasive when sensors are placed on the scalp, measuring either the electrical potentials produced by the brain which is called electroencephalography (EEG) or the magnetic fields with a technique called Magnetoencephalography (MEG); semi-invasive when electrodes are placed on the exposed surface of the brain in a practice called electrocorticography (ECoG); and invasive, when micro-electrode arrays are placed directly into the cortex.

Noninvasive systems, which currently lie in the research focus, mainly utilize EEG recordings because they are easily acquired by a plethora of commercial off-the-shelf devices at a relative low price. Every technique that has been based on EEG recordings has to address challenges that are inherent to EEG, specifically its poor spatial resolution, which results in interference from unwanted signals, and its low signal to noise ratio. MEG recordings have been utilized to drive BCI systems, taking advantage of MEG higher spatiotemporal resolution, but they place a need for sensitive sensors and magnetically shielded rooms and usually have limited their research potential.

Semi-invasive systems using ECoG provide better spatial resolution and signal-to-noise ratios than EEG at the cost of an invasive procedure called craniotomy. The biophysical characteristics of EEG and ECoG recordings are similar in many respects and systems based on ECoG exploit the same underlying neurophysiologic mechanisms as EEG based systems, which lead to a common approach from a signal processing point of view.

Invasive systems use implantable micro-electrodes placed into the cortex in a highly invasive procedure which has led research to focus on animals, mainly monkeys and rats, even though such systems have been demonstrated in humans. While recordings acquired from such electrodes have very high spatial resolution and signal-to-noise

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ratio, which results in significantly improved system performance, degradation of the signal quality over time due to brain tissue response to the electrodes presents an important challenge. Micro-electrode recordings exhibit large differences from EEG/ECoG recordings and require different signal processing approaches.

2 Principles of Noninvasive BCI operation

For noninvasive BCI systems the most common electrophysiological signal is the EEG which in order to be used as a basis for a BCI system, must be correlated with a mental process, that is either conscious or can be affected consciously so that it can be used to represent intention. Furthermore, it must be able to be well characterized for an individual, so that it can be reliably tracked and detected. There are several signals and corresponding mental processes that fulfill the aforementioned requirements that create corresponding strategies for the creation of BCI systems. These are described in the subsequent sections.

2.1 Event Related Potentials

For EEG recordings, some sensory stimuli and cognitive processes trigger stereotyped brain responses that are called Event Related Potentials (ERPs) [1]. ERPs which are recorded following an external stimulus are called Evoked Potentials (EPs) [2], [3], whereas when sensory organs are stimulated, they are called Sensory Evoked Potentials (SEPs) with the most important SEPs being the Visual Evoked Potentials (VEPs) and the Auditory Evoked Potentials (AEPs). The ERP waveforms are usually described by their amplitude and latency, thus ERPs are categorized as positive or negative (represented by the letters P or N respectively) and identified by the number of milliseconds after the trigger event that they occur. For example, a well studied ERP is the P300 [4], which is a positive deflection in voltage which can be witnessed roughly around $300\ ms$ after the triggering event. An example of an ERP recorded from channel C4, according to international 10/20 standard, which contains several components along with a dominant P300, is shown in Fig. 1.

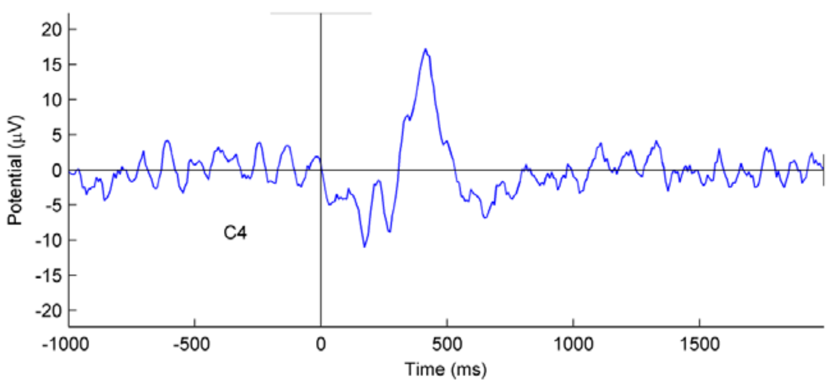

Fig. 1. An ERP containing a P300 component recorded by an electrode at the C4 position according to the international 10/20 standard. The actual component is the positive deflection that starts at about 300ms and ends at about 550ms. The time is zero at the presentation of the stimulus.

The P300 is a composite wave [5] which is recorded after stimuli that requires information processing, and one of its components occurs when the subject detects an occasional "anticipated" stimulus from a set of regular stimuli, a framework which is usually referred to as the "oddball paradigm". It has been documented [6] that the amplitude of this component is increased when the stimulus is less anticipated, but still remains relatively small and usually requires averaging of multiple recordings. The P300 waves of VEPs were used for the first time in a BCI in 1988 by Farwell and Donchin [6] in an application that displayed a 6 by 6 matrix of characters to the user where various rows or columns were highlighted. When a row or column that contained the character the user has selected was highlighted, a P300 response was elicited, since this was the target character, i.e., the "oddball paradigm". The matrix used in this first P300 BCI system is shown in Fig. 2. A talk command was contained because the system was connected with a speech synthesizer that had the ability to sound the word that had been selected.

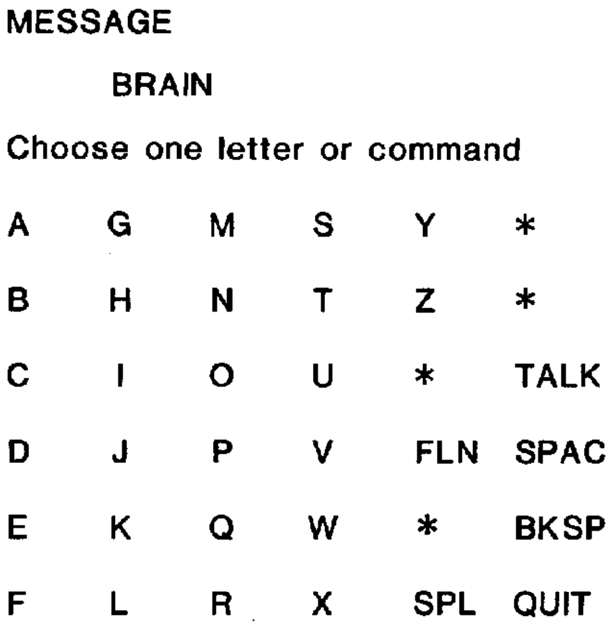

Fig. 2. The matrix that was used for the first BCI application using visually evoked P300 ERP [6].

2.2 Steady State Visual Evoked Potentials

A distinct case of VEPs stems from visual stimulus that is modulated to a specific frequency ranging from 3.5 to75 Hz, with most often used the 13 Hz. The brain response, which is called Steady State Visual Evoked Potential (SSVEP), has the same fundamental frequency as the stimulating frequency and usually includes harmonics. An example of the spectral content of an EEG recording during the presentation of a visual stimuli modulating at 7Hz is depicted at Fig. 3.

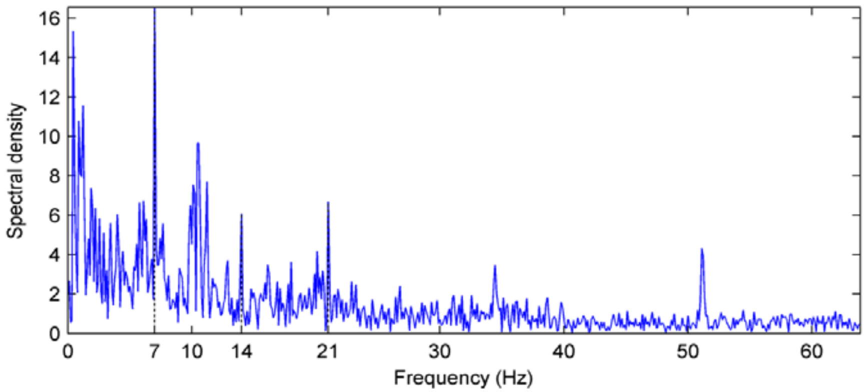

Fig. 3. The spectral content of an EEG recording during the presentation of a visual stimuli modulating at 7Hz. The fundamental frequency of 7 Hz is visible so are the first and second harmonics at 14 and 21Hz, respectively.

When two or more frequencies are simultaneously modulating the visual stimuli the frequency that has the focus of the user's gaze is prevalent and thus SSVEPs can be used as a basis for a BCI design, as successfully was demonstrated in 2000 by Middendorf *et al.* [7]. This BCI application had two virtual buttons on a computer screen, flashing at different frequencies and used SSVEPs to allow users to select the button they desired by looking at it.

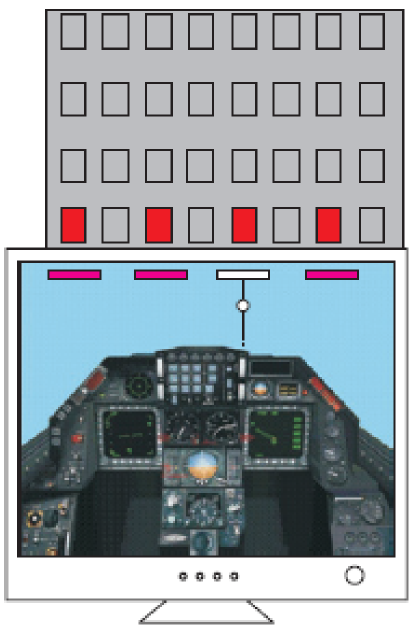

Fig. 4. An SSVEP BCI used to control a computer game [8]. The flashing LED array was positioned above the computer screen.

One limitation of the BCI systems based on SSVEPs is that users must have good voluntary control of their eye movements but overall it has been suggested that such systems are more feasible than others [8]. An example of a visual stimulus interface which has 32 buttons, four of which are used to control a computer game which involves flying an airplane, is depicted at Fig. 4.

2.3 Event-Related De/Synchronization

Internally or externally paced events are linked not only with ERPs but also with an ongoing change in the EEG. It has been shown that certain events or mental processes can reduce or desynchronize ongoing alpha wave brain activity [9]. These event-related phenomena result in specific changes in the ongoing EEG activity and consist, in general terms, of power increases or decreases in certain frequency bands [10]. A decrease in the spectral power is called event-related desynchronization (ERD), while an increase is called event related synchronization (ERS). These phenomena are considered to be due to a decrease or an increase in the synchronization of the underlying neuronal populations, respectively. ERD and ERS events for a frequency band of interest are measured as a function of the power of that frequency band in the period after the event (denoted as A) and the power of the same frequency band in a reference period (denoted as R), by the following formula as defined in [10]:

$$ERD/ERS(\%) = \frac{A-R}{R} * 100 \tag{1}$$

An ERD of the upper alpha and lower beta frequency bands $(8-12\ Hz)$ and of the beta band $(20-24Hz)$, localized close to the corresponding sensorimotor cortex areas[1] has been linked with ongoing voluntary movements [10], [11]. The same ERD has been witnessed in imaginary movements [12], [13] a phenomenon which has been utilized for the creation of the Graz brain-computer interface II, the first BCI application that uses imaginary hand and foot movements to distinguish between three different EEG patterns: planning or preparation of movement of the left index finger, right index finger and right foot.

A common setup for a simple two-class BCI is the recording of three channels (C3, Cz and C4 according to the international 10/20 standard, depicted in Fig. 5. Channel C3 is located above the left sensorimotor cortex; channel C4 above the right sensorimotor cortex and CZ lies between the two.

The ERD from an imaginary left hand movement is depicted in Figs. 6 and 7. There, the spectrograms of channels C3 and C4 are depicted, respectively, recorded during an experiment where the subject was instructed at $t = 3\ s$ to imagine a left hand movement. Since the left hand is controlled by the right sensorimotor cortex, channel C4 demonstrates ERD (suppression of the mu frequencies $(9-12)\ Hz$), while channel C3 remains unaffected. Similarly, Figs. 8 and 9 illustrates the spectrograms of channels C3 and C4 during the same experiment but when the subject was instructed to imagine a right hand movement. Channel C3 exhibits ERD while channel C4 remains unaffected.

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[1] Movement of the left side of the body is controlled by the sensorimotor cortex located in the right side of the head and vice-versa.

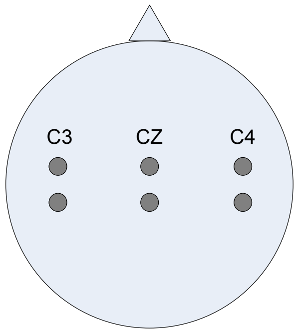

Fig. 5. A common electrode positioning scheme for the implementation of a simple two class BCI based on imaginary left and right hand movements. The locations of the channels are identified (left to right) as C3, CZ and C4 according to the international 10/20 standard.

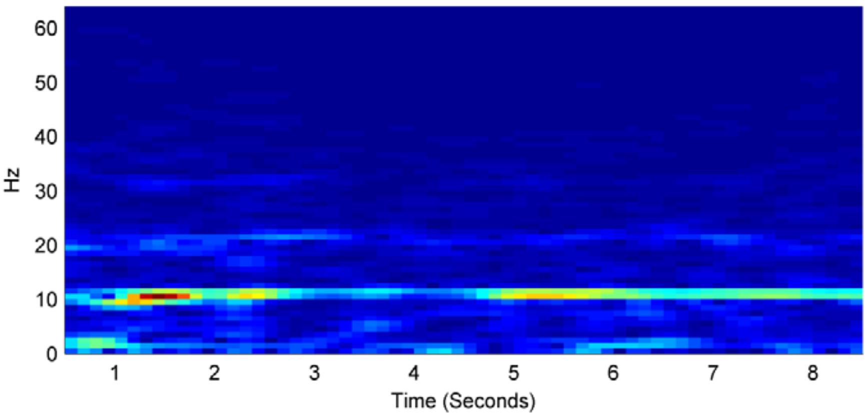

Fig. 6. The spectrogram from channel C3 during an imagined left hand movement that starts at about $\boldsymbol{t = 3\ s}$; as expected, the mu rhythm remains unaffected.

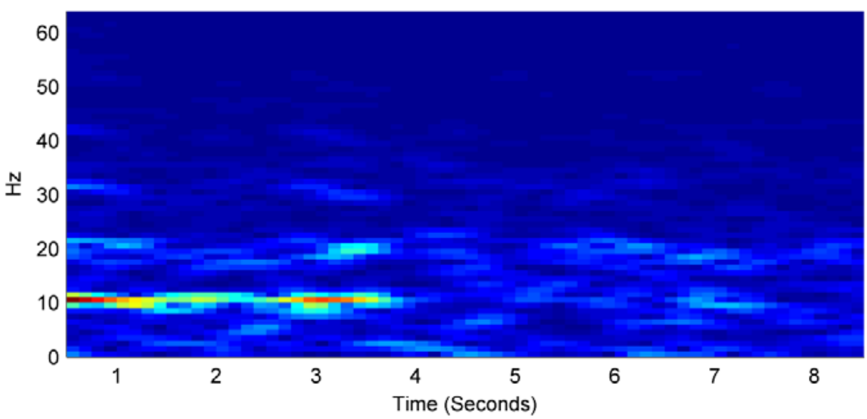

Fig. 7. The spectrogram from channel C4 during an imagined left hand movement that starts at about $\boldsymbol{t = 3\ s}$; as expected, the mu rhythm is suppressed while the imaginary movement lasts.

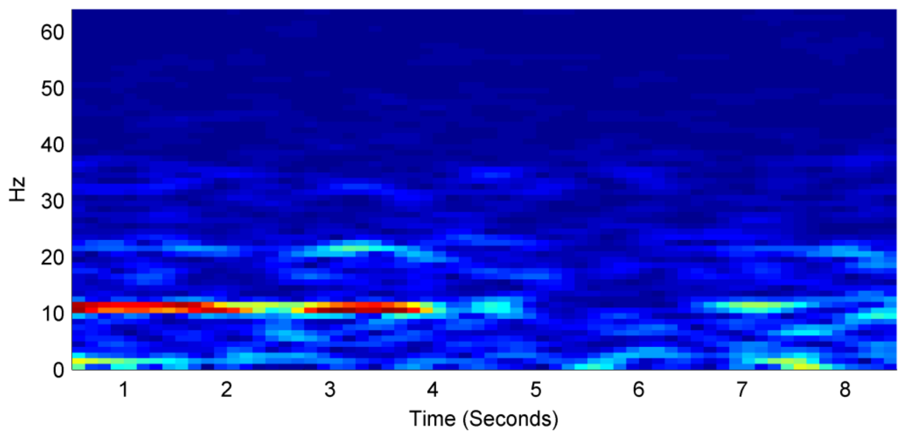

Fig. 8. The spectrogram from channel C3 during an imagined right hand movement that starts at about $\boldsymbol{t} = \mathbf{3}\ \boldsymbol{s}$; as expected, the mu rhythm is suppressed while the imaginary movement lasts.

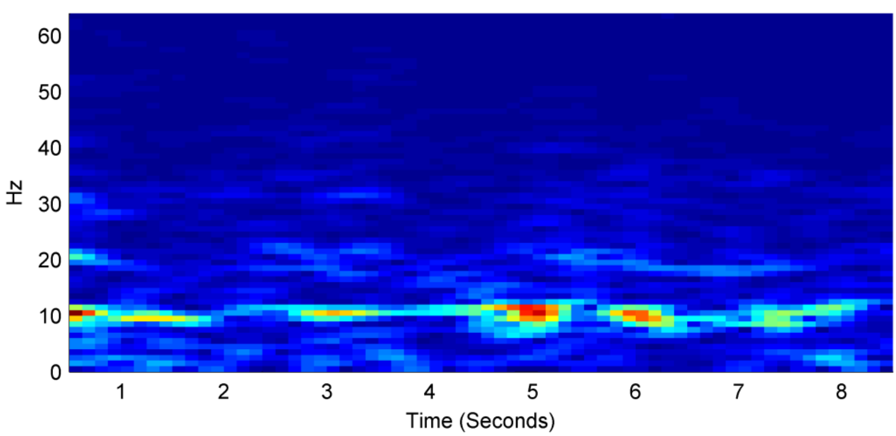

Fig. 9. The spectrogram from channel C4 during an imagined right hand movement that starts at about $\boldsymbol{t} = \mathbf{3}\ \boldsymbol{s}$; as expected, the mu rhythm remains unaffected

2.4 Slow Cortical Potentials

Slow Cortical Potentials (SCP), which are also known as DC potentials, are surface recorded waves with frequencies less than $2\ Hz$ that are linked with various cognitive events, for example anticipation, cognitive preparation and motivational states of apprehension and fear; thus, individuals can be trained to modify SCPs by using feedback. They manifest as positive or negative shifts and physiologically are presumed to reflect the extent to which apical dendrites of the cortical pyramidal cells are depolarized. In an effort to identify the cortical sources of the SCP phenomena fMRI imaging was used [14] to locate the areas of the brain that are activated during self-regulation of SCPs. Generation of negativity was accompanied by a widespread activation in central, pre-frontal, and parietal brain regions, as well as the basal ganglia, while generation of positivity was accompanied by widespread deactivation in several cortical sites, as well as activation primarily in frontal and parietal structures, as well as insula and putamen. This means that negative shifts are associated with increased cortical activation and positive shifts are associated with decreased cortical activation. The activation and deactivation of cortical areas during negativity and positivity is depicted at Fig. 10, where areas painted red are indicative of significant activation and areas painted green are indicative of deactivation when compared to a baseline.

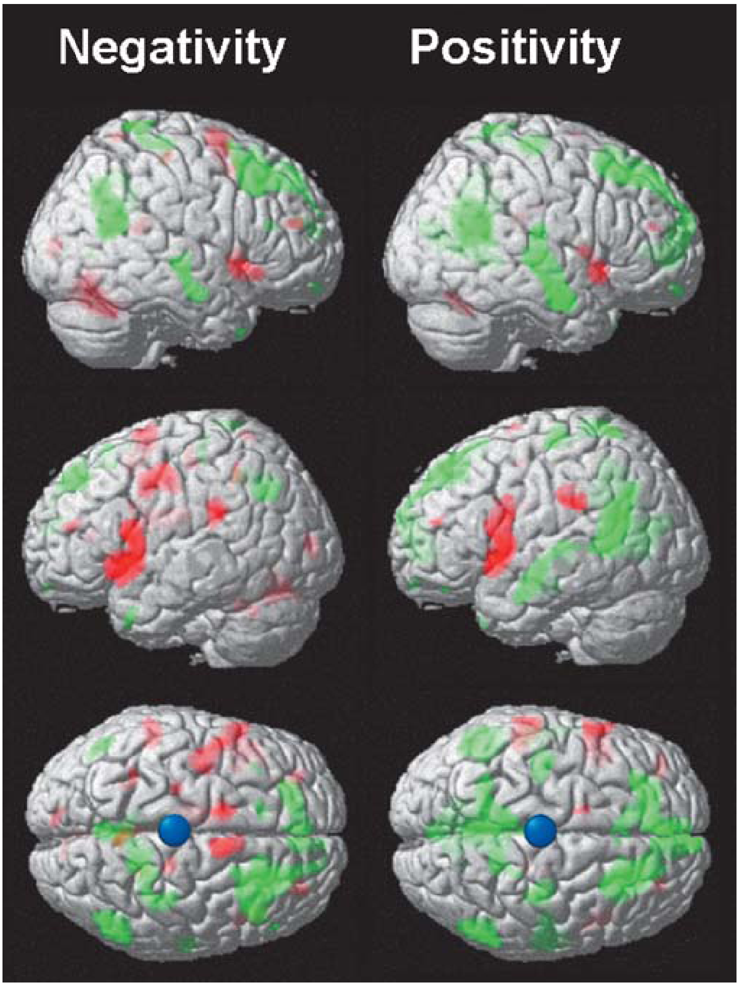

Fig. 10. Activation and deactivation of cortical areas during negativity and positivity. Areas painted red are indicative of significant activation and areas painted green are indicative of deactivation when compared to a baseline. The positivity task shows deactivations in frontal and temporo-parietal areas. The blue dot in the bottom pictures marks the active central electrode position used for feedback. Image was adapted from [14].

An example of EEG recordings during self regulation of SCPs is shown in Fig. 11. The recordings were acquired from electrode location C4 according to international 10/20 standard where the increased activation and deactivation are evident.

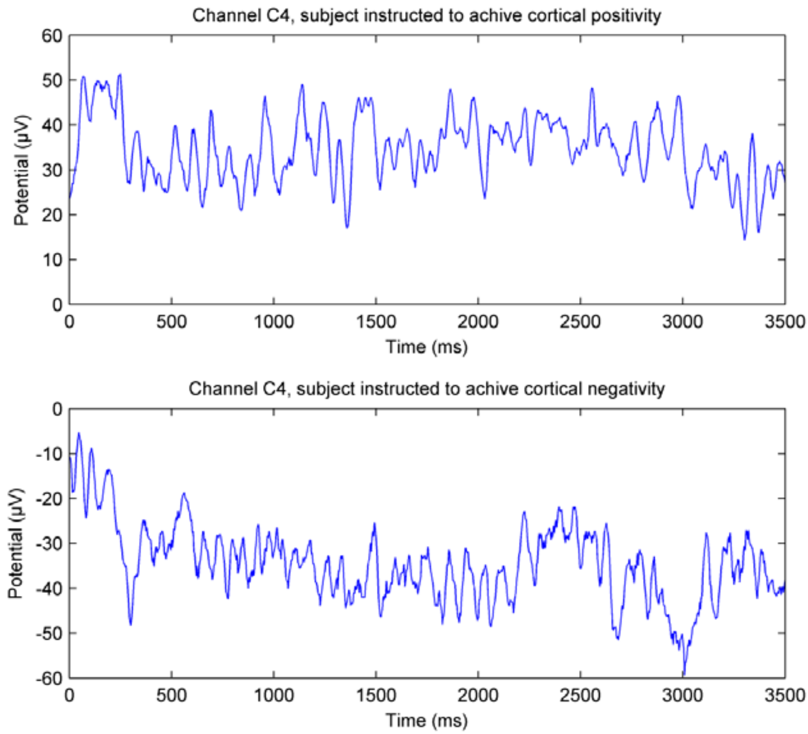

Fig. 11. Example of EEG recordings during self regulation of SCPs. The recordings were from electrode location C4 according to international 10/20 standard where the increased activation and deactivation are evident.

3 State-of-the-Art in EEG-Based BCI Signal Processing

All EEG-based BCI classes have to face the problem of separating the control signal from interfering noise signals which have two sources: non-EEG artifacts, such as recording noise, power line interference, eye movement, eye blinking, EMG and ECG; and EEG signals that are not used as control signals. The two noise classes differ from the control signal either in their frequency distribution, their topographical location of their source in the brain or both. For example, eye movement signals have maximal frequency content in low frequencies ($< 5\ Hz$) and are located over anterior head regions. Similarly, the visual alpha rhythm lies inside the frequency range of most BCI control signals and it is more evident in the parieto-occipital cortex [15]. While the elimination of noise sources whose frequency distributions lie outside the frequency range of the control signal can be easily implemented by filtering, the elimination of the other noise sources poses a far more difficult problem and necessitates the use of advanced signal processing methodologies. After the control signal is separated from unwanted noise, it is fed to a classifier to convert it to a command signal, which can be used for control and to a user's feedback visualization component, which helps the user refine the control signal. A block-diagram of a typical EEG-based BCI application is illustrated in Fig. 12. A description of the most commonly used methods for signal separation and classification follows.

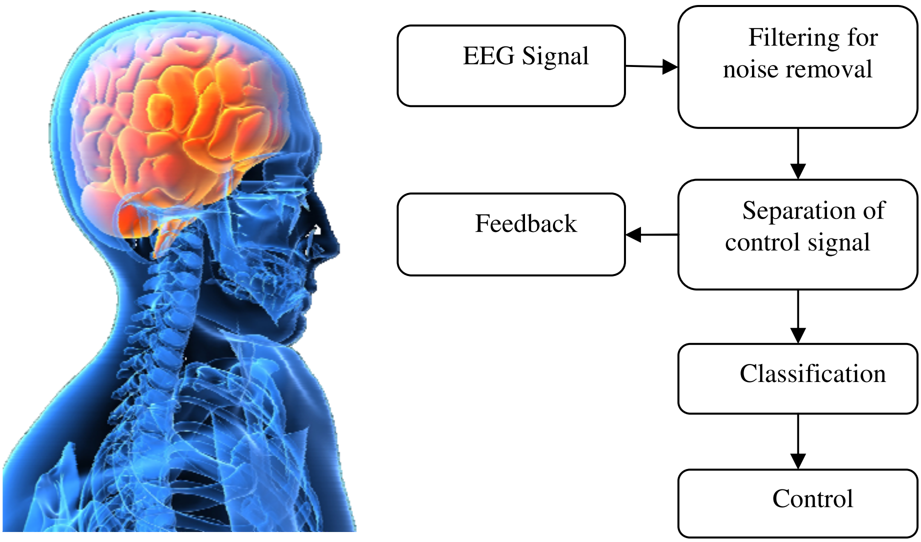

Fig. 12. A block-diagram of a typical EEG-based BCI application. After the EEG signal is acquired, it is filtered for basic noise removal. The control signal is then separated from artifacts and contamination by EEG signals unrelated to the target mental process, and a feedback based on the raw control signal is presented to the user. The control signal is also entered to a classifier that generates the control commands which are also presented.

3.1 Laplacian Spatial Filtering

The Laplacian method emphasizes electrical activity which originates by radial sources immediately below the electrode by calculating the second derivative of the instantaneous spatial voltage distribution. High spatial resolutions can be achieved with this method by using many electrodes. To calculate the Laplacian derivations, a finite difference method is used which approximates the second derivative by subtracting the mean activity from surrounding electrodes of the electrode of interest using the following formula defined in [15]:

$$V_i^{LAP} = V_i^{ER} - \sum_{j \in S_i} g_{ij} V_j^{ER}, \tag{2}$$

where

$$g_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_{j \in S_i} \frac{1}{d_{ij}}}, \tag{3}$$

S_i is the set of electrodes which surround the i^{th} electrode and d_{ij} is the distance between electrodes i and j.

The effects of the Laplacian filtering vary with the distance between the electrodes thus a uniform Laplacian filter may not be appropriate in all BCI cases. Even though the method was one of the first that was used, recent studies [16] have shown that it performs comparably to more recent methods as Independent Component Analysis (see §3.3).

3.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a linear transformation that expands the data into a set of orthogonal components ordered by their variance. The fact that the transform kernels are orthogonal achieves maximum decorrelation and can separate the signal and noise components more efficiently than transforms which use kernels that are independent of the data. In case of a dataset $\boldsymbol{X}$ which is a $m \times n$ matrix, where m is the number of measurements and n is the number of samples for each measurement, the analysis of $\boldsymbol{X}$ of into its principal components $\boldsymbol{P}$ is done using the formula:

$$\boldsymbol{Y} = \boldsymbol{P} \cdot \boldsymbol{X} \tag{4}$$

In order to calculate $\boldsymbol{P}$ matrix, the constraint that the covariance matrix of $\boldsymbol{Y}$, $\boldsymbol{C_Y}$ defined as $\boldsymbol{C_Y} = \boldsymbol{Y} \cdot \boldsymbol{Y^T}$**,** is diagonal is applied. It is deduced that the principal components can be calculated by the eigenvectors of $\boldsymbol{C_X}$ which is the covariance matrix of the measurement data matrix $\boldsymbol{X}$**.** PCA decomposition has been used together with wavelet analysis and has been suggested that it can be used to extract meaningful components for analysis with some limitations [17].

3.3 Independent Component Analysis (ICA)

The concept of Independent Component Analysis (ICA) lies into decomposing a multivariate signal into additive source signals with the assumption that they are statistically independent. Considering a multichannel signal as $\boldsymbol{x}(n)$, and the signal components as $x_i(n)$, the $x_i(n)$ signals are independent if:

$$p_X\big(\boldsymbol{x}(n)\big) = \prod_{i=1}^{m} p_x(x_i(n)), \forall n \tag{5}$$

where $p_{\boldsymbol{X}}$ is the joint probability distribution, $p_x(x_i(n))$ are the marginal distributions and m is the number of the signal components.

The ICA is used to solve the general problem of blind source separation (BSS) which is to estimate and recover the source signals using only the information of their observed mixtures; a problem which takes the name of its acoustic analog thus referred to as the "cocktail party problem". The separation is made by using a separating matrix $n \times m$ where n is the number of recordings, hence in EEG-based BCI problems the number of the electrodes, and m is the number of independent sources, with $n \geq m$.

Two main strategies have been used to quantify the statistical independence between the acquired EEG signals. The first is by using Mutual Information (MI) of $\boldsymbol{x}$ which is zero if and only if the components of $\boldsymbol{x}$ are mutually independent and is strictly positive otherwise [18]. Two ICA algorithms (widely used in BCI applications), which use this strategy are FastICA [19] and INFOMAX [20]. The second is through the use of higher-order cumulants, since it is known that if at least two components of $\boldsymbol{x}$ are statistically independent then all cumulants involving these components are zero.

The use of ICA for the removal of a wide variety of artifacts from EEG recording in non-BCI applications was demonstrated first [21] followed by a widespread use in all BCI classes. In P300 based BCIs, ICA was used both to remove unwanted artifacts [22] and to separate target and non-target ERPs [23] by the selection of meaningful independent components using *a priori* physiological knowledge. In addition, ICA was used for SSVEP-based BCIs, where the more conventional methodology of Fourier analysis is mainly used to aid the selection of the signal and reference channels, as proposed by Wang *et al.* in [24]. Applications based on imaginary movements and the detection of ERD are the best candidates for the application of ICA, since the two sensorimotor cortices lie on different sides of the head and are thought to be statistically independent. ICA has been used as a spatio-temporal filter [25] in a BCI paradigm which uses 59 electrodes, and as a means to separate the two sources in a much simpler BCI case with only three channels.

3.4 Common Spatial Patterns (CSP)

The common spatial patterns method is primary used in BCI systems based on ERD/ERS phenomena and since it is parallel by nature it is well fitted for on-line data processing. The method was introduced in the field of EEG analysis by Koles *et al.* in 1990 [26] and was used with respect to EEG-based BCI applications by Muller-Gerking *et al.* in 1999 [27]. The method works by constructing very few new time-series whose variances contain the most discriminative information, that are subsequently used to feed a classifier.

Let $\boldsymbol{V}_a^i$ denote the raw data of trial i, under the condition a which is represented as a $N \times T$ matrix where N is the number of channels and T is the number of samples. Let R_a^i represent the normalized covariance matrix of $\boldsymbol{V}_a^i$ calculated by

$$R_a^i = \frac{V_a^i \cdot \overline{V_a^i}}{trace\left(V_a^i \cdot \overline{V_a^i}\right)}, \tag{6}$$

and let R_b^i represent the normalized covariance matrix of $\boldsymbol{V}_b^i$. The normalization is done to eliminate inter-trial variations in the absolute values of the standard deviation. Next, the normalized covariances are averaged over trials thus creating matrices R_a and R_b, respectively. Afterwards, the composite covariance matrix is created $R_c = R_a + R_b$ and its eigenvectors matrix B_c and eigenvalues matrix λ are computed. The whitening transformation matrix

$$W = \lambda^{-\frac{1}{2}}\overline{B_c} \tag{7}$$

transforms R_a and R_b to

$$S_a = WR_a\overline{W} \tag{8}$$

and

$$S_b = WR_b\overline{W}. \tag{9}$$

Since S_a and S_b share the same eigenvectors, the eigendecomposition of S_a or S_b gives the orthonormal matrix U. The projection of whitened EEG epochs on U gives feature vectors that are optimal in the least squares sense for discriminating between the two populations and can be seen as time-invariant EEG source distribution vectors.

The method has been used in [28] with high classification results, and in a comparison with the most prominent algorithms for spatial filtering [16] it yielded better results compared to all other algorithms. Furthermore, the utilization of CSP in [29] demonstrates the application of the method when more than two classes (conditions) exist.

3.5 Linear Discriminant Analysis Classifier

One of the oldest but widely used classification processes is the Linear Discriminant Analysis (LDA) [30]. LDA classifiers are commonly used in SSVEP-based BCI paradigms [31], but due to their simplicity and high performance are used in all BCI classes [32].

In the LDA process, a classification criterion (Bayes' rule) is used to minimize the total error of classification (TEC) tending to make the proportion of object that it misclassifies as small as possible. In other words, TEC should be thought of as the probability that the rule under consideration will misclassify an object. If there are g groups, the Bayes' rule is to assign the object to group i where $P(i|\mathbf{x}) > P(j|\mathbf{x}), \forall j \neq i.$, where $\mathbf{x}$ denotes a set of features from measurements (feature vector). With the help of Bayes' theorem and if we assume that each group has multivariate normal distribution and all groups have the same covariance matrix ($\boldsymbol{C}$), we get what is called as LDA formula,

$$f_i = \boldsymbol{\mu}_\mathbf{i}\mathbf{C}^{-1}\mathbf{x}_\mathbf{k}^\mathbf{T} - \frac{1}{2}\boldsymbol{\mu}_\mathbf{i}\mathbf{C}^{-1}\boldsymbol{\mu}_\mathbf{i}^\mathbf{T} + \ln(p_i), \tag{10}$$

where $\mathbf{x_k}$ represents the features of object k; p_i is the prior probability about the group i known without making any measurement (if we do not know the prior probability, we just assume it is equal to the total samples of each group divided by the total samples); $\boldsymbol{\mu_i}$ is the mean of features in group i, which is average of $\mathbf{x_i}$. Using (10), LDA assigns object k to group i that has maximum f_i.

3.6 Support Vector Machines

Support Vector Machines (SVM) is a category of classification methods which use supervised learning to separate two different classes of data. The idea behind SVM is to construct a hyperplane, described by a weight vector $\boldsymbol{w}$ and a bias value b, which will separate the two different classes of data, using a training set of l samples with data vectors $\boldsymbol{x}_i$ and corresponding class labels y_i, where $\boldsymbol{x}_{i\in}R^N$ and $y_i \in \{-1,1\}$ [33]. In the test phase, the class of a new data vector $\boldsymbol{y}$ can be predicted by projecting $\boldsymbol{y}$ on the weight vector $\boldsymbol{w}$ as follows:

$$f(\boldsymbol{y}) = \boldsymbol{w} \cdot \boldsymbol{x} + b \tag{11}$$

The sign of this projection will identify the predicted class label. Because there are several possibilities for the selection of hyperplanes separating the data into two subsets, a suitable criterion for the selection of a weight vector is the maximization of the separation margin γ between the two classes. To describe this optimal hyperplane, the vectors which lie on the margin (called support vectors) are only necessary.

4 Invasive BCI Systems

As it was documented through experiments initially on monkeys and subsequently on humans, electrical activity generated by individual cortical or subcortical neurons that are associated with movements can be used as a basis for the creation of an invasive BCI system. Such neurons have been located both in the primary motor cortex and in the posterior parietal cortex. Since invasive BCIs tap directly into the brain's motor commands processing functions, they do not require extensive training to control the output, even though performance increases are witnessed. Different approaches have been suggested to record this neuronal activity. Some approaches use local field potentials, which are recordings of the summation of electrical activities of neurons which reside inside a particular volume of tissue, while others use recordings from small or large samples of individual neurons from single or multiple units.

Even though some studies have claimed that recordings from small numbers of highly tuned neuronal groups have been sufficient for good BCI performance, the fact that the surgical procedure of implanting a microelectrode results in a partially random selection of neurons, means that the existence of highly tuned neurons in a typical recording is rare. Therefore, the recordings of large samples of neurons are preferable either to increase the probability of detecting highly tuned neurons or to increase the accuracy and reliability of such systems by reducing individual neuron firing variability.

The acquisition of recordings either from individual neurons or from local field potentials presents major technological challenges which are a result of the broad issue of biological compatibility. Current microelectrode designs typically enable recordings for a duration of months but quality often deteriorates possibly due to electrode encapsulation by fibrous tissue and death of the cells that are being recorded. Higher recording durations have been reported for certain examples and certain species, but high quality, long term recordings still remain elusive. Apart from biocompatibility issues, research into microelectrode designs focuses on the creation of electrode matrices capable of simultaneously recoding hundreds of neuronal signals, to satisfy the need for large sample recordings, like the Utah electrode array probe [34], which is depicted in Fig. 13.

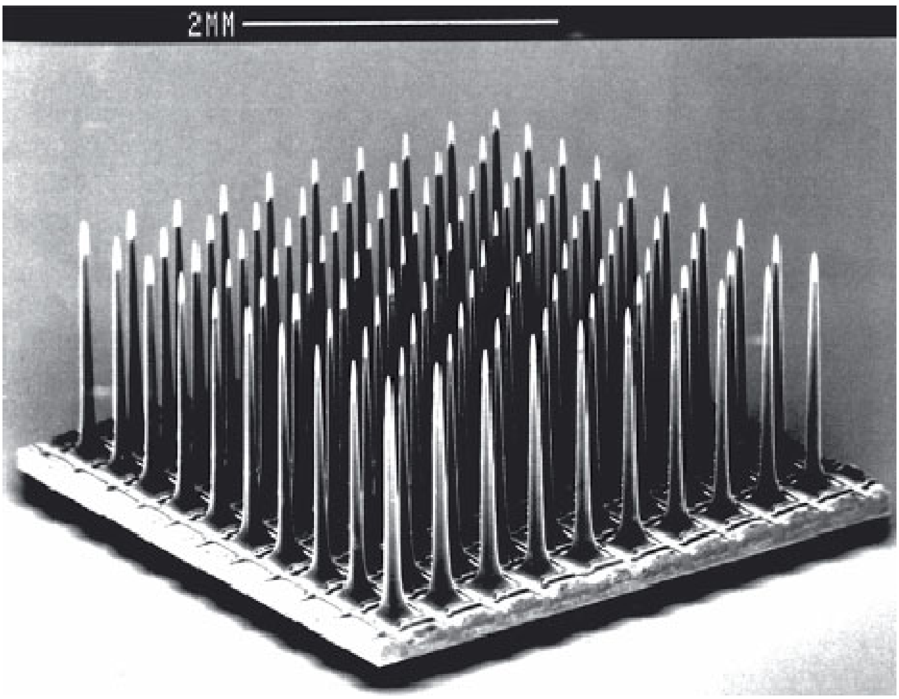

Fig. 13. The Utah electrode array consisting of 100 electrodes that extend 15mm from the $10 \times 10\ mm$ substrate. With permission from *Encyclopedia of Sensors* [34].

5 Resources for BCIs

Research and applications in BCIs and EEG signal processing has been greatly aided by the availability of two high quality tools, namely the EEGLab and BCI2000. EEGLab is an active open source project that is currently being developed by the Swartz Center for Computational Neuroscience (SCCN) of the Institute for Neural Computation at the University of California San Diego (UCSD) in collaboration with the

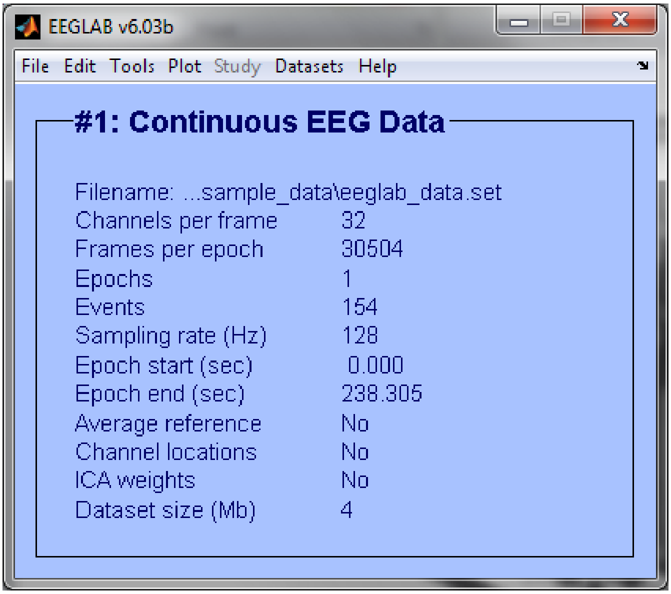

Fig. 14. The main interface of EEGLab

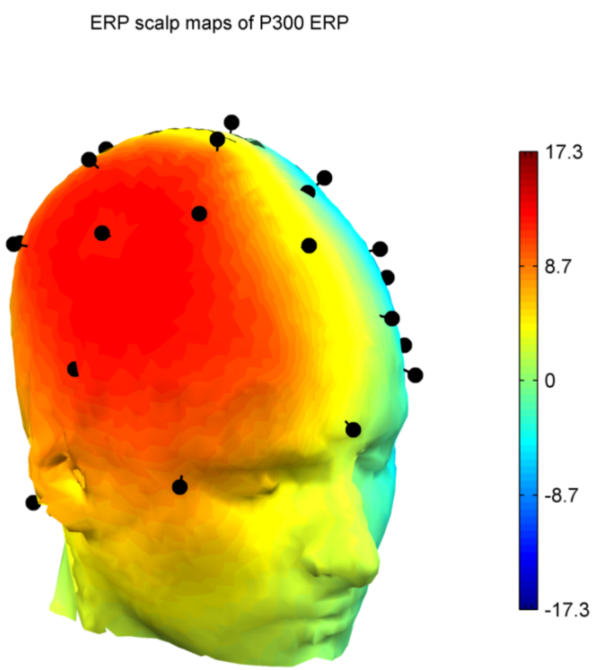

Fig. 15. A 3D scalp map of an ERP signal with a P300 component within the EEGLab

CNRS CERCO laboratory in France. It is mainly focused on processing continuous and event-related EEG, MEG and other electrophysiological data, thus it is very well suited for analysis of signals related to BCIs. Many of the signal processing tools commonly used for BCIs and some useful visualization schemes are implemented natively or by plug-ins for EEGLab. The main interface of EEGLab and a 3D scalp map of an ERP signal with a P300 component are depicted in Figs. 14 and 15.

BCI2000 is developed by the BCI R&D Program at the Wadsworth Center of the New York State Department of Health in Albany, New York, USA, in collaboration with the University of Tübingen in Germany. BCI2000 is a complete open source BCI research system that consists of several modules and can operate either as based on the P300 evoked potential or based on the ERD of the mu rhythm.

6 Applications of BCI Research

The main scope of BCI research lies with medical applications directed to individuals with inabilities that require an alternative communications or control channel. Patients with amyotrophic lateral sclerosis (ALS) or locked-in syndrome have been able to use BCI systems with success to control aspects of the environment or communicate. BCI applications have also been used to control robotic limbs by patients with amputations. Furthermore patients with spinal cord lesions have used BCIs in conjunction with functional electrical stimulation (FES) devices.

6.1 Invasive BCIs

Commercial applications oriented towards medical uses of BCIs have been created with non-invasive, as well as with invasive BCI systems. In the area of invasive BCI applications a company named BrainGate is currently engaged in clinical trials for an implantable system that decodes imagined limb movements to control prosthetic arms, wheelchairs or personal computers [35].

6.2 Noninvasive BCIs

Contrary to invasive systems, non-invasive BCI system are currently reliable enough to be used as an alternative means of communication for patients outside dedicated laboratories, at the ease of their homes [36]-[43]. Although this requires the training of caretakers in the application of electrodes and the recognition of recording problems, such advances are already a reality. The creation of systems which use reduced montages (eight channels or less) and the use of "dry electrodes" that do not require gel will helps address these concerns.

Commercial applications have already been created to demonstrate that BCI technology can reliably allow patients to affectively control movement and day-to-day functions in a smart home by using an evolved P300 speller. A virtual 3D representation of a virtual home along with control masks have been defined to allow realization of everyday tasks, such as moving around, opening doors, watching television and listening to music. The system was created by a company named g.Tec (www.gtec.at) and it is depicted in Figs. 16-18.

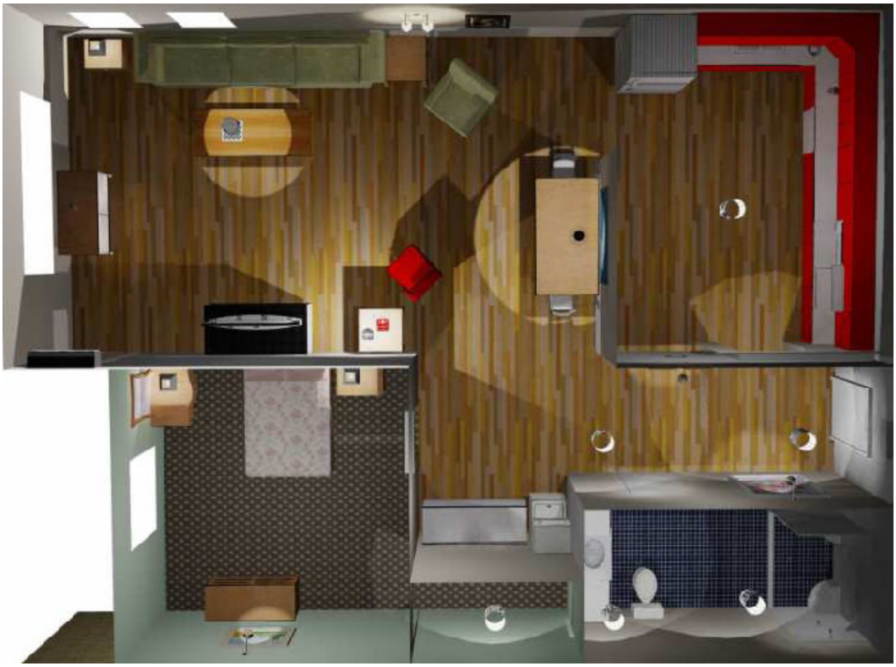

Fig. 16. The layout of the smart virtual home (with permission from g.Tec)

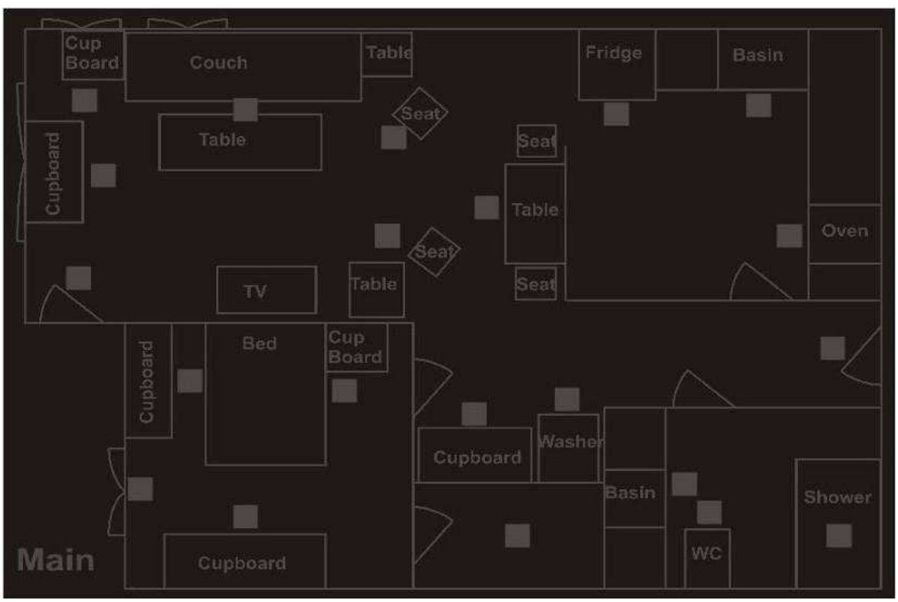

Fig. 17. The location selection matrix for the virtual home depicted in Fig. 16. The user of the BCI system can select the object to interact with by focusing on it; the system recognizes the selection using the principles behind the P300 BCIs (with permission from g.Tec).

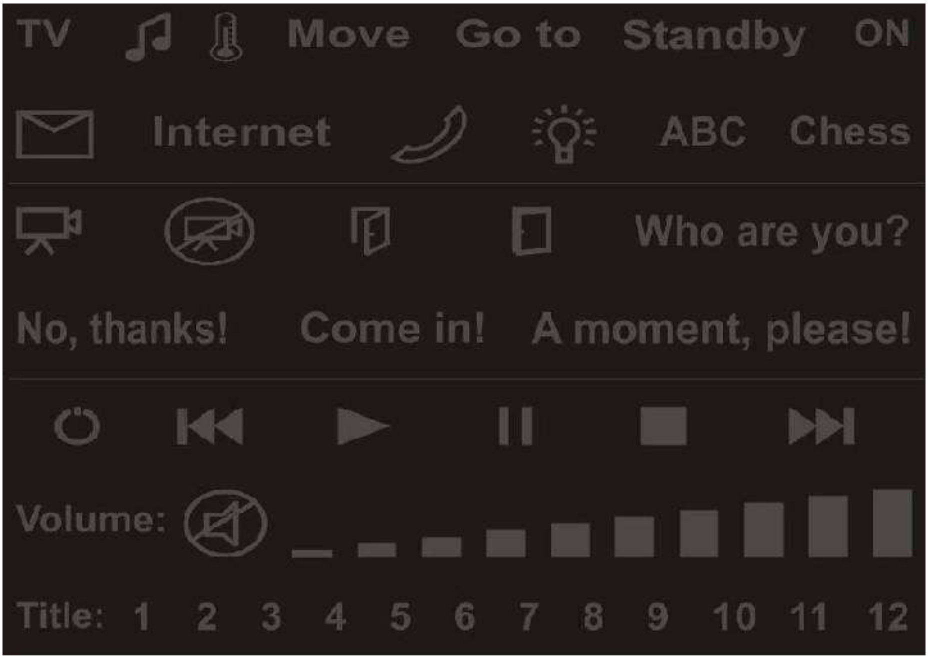

Fig. 18. The selection matrix for the television (with permission from g.Tec)

7 Concluding Implications

There is huge potential for the BCI applications in the form of products in so many different areas. The most beneficial application for the humans will be to help the disabled people. Paralyzed people will be able to move more easily, they will be able to perform most of the normal day activities with limited help/supervision from another individual. Another area where BCI can be very effectively used is in the field of surgery. Recently, there have been surgeries performed where the surgeon is one part of the world and the patient is in another part of the world and using robotic arms the procedure was performed. But in these kind of surgeries, the surgeon has to control the robotic arm using some controls at his end. If BCI technology can be effectively used at the surgeon's end that will be huge breakthrough in the field of surgery. The surgeon will use some kind of non-invasive BCI device and just looking at the patient's live images on computer screen and by the thoughts that go through his mind, he would be able to control the robotic arms to perform the procedure. BCI devices like the ones which have been developed by Emotiv (www.emotiv.com), the video gamers can play the games on computer using their thoughts and simple body movements, which will be step ahead from Wii. BCI technology has not been explored to much extent yet for law enforcement agencies but there is lot of applications which can be developed. MEG and MRI can construct the images of a person from human brain and display on the computer. So during interrogation the sketches from the arrested person's brain can be developed which can lead to further investigation about other people involved.

There are many technical challenges currently faced by this technology. One of the technical challenges is of calibration. The non-invasive device needs to be calibrated before every use and this calibration step can take some time. So developing a fast calibrating system is a challenge. Another challenge is use of use. Some BCI devices require some training before they can be used effectively especially in case of disabled people and there is large range of complexity and different brain state from one individual to another. So developing a BCI which can be used to a vast population of people without extensive training is a challenge. Another big challenge facing brain-computer interface researchers today is the basic mechanics of the interface itself. Non-invasive BCI blocks some of the signals from the brain and it has been a challenge for the developers. Another challenge is that these devices cannot capture all the signals from the brain. As brain uses electrochemical signals, these devices can only sense the electric signals and the chemical processes cannot be read by these devices, so the signal received might not be a complete one. In addition, selection of the dependent variable (i.e., external stimulus or predicted state) poses an interesting issue in modeling and classification processes within a BCI system. Finally, there are many legal and social challenges of BCI devices. What information can be shared and what information the BCI device extracts. There will be privacy issues associated with the BCI devices. Some of the challenges will be that what information that device collects, how it is used, how it is saved, where it is saved and who will have access to it.

Additional issues that acquire attention are [44]: the nonstationarity of the neurophysiological changes in time and space; how to cope with adaptability in the subject's and the BCI controller's site; BCI generalization to a variety of tasks; how to optimally bridge the time scale of spike events (msec) with the time scale of behaviors (sec); enhancement of BCI robust behavior through more sophisticated self-organizing adaptive principles.

In any case, BCI systems could serve as experimental platforms were brain theories could be tested, revealing all the ingredients of cognitive experimentation with high resolution, providing synchronous measurement access both at the input (e.g., spike trains) and at the behavior level. Collaboration amongst engineers, neuroscientists, physical scientists, and social and behavioral scientists, towards the integration and convergence of engineering tools and methods in the areas of sensors and signal processing, noninvasive and minimally invasive recording techniques from the brain and the peripheral nervous system, neural tissue engineering, neural imaging, nonlinear dynamics, chemical and biological transport, computational neuroscience and multiscale modeling, nano/micro technological neuroscience, control theory, systems integration, and robotics share the same endeavor; that is, to permit control of movement where normal neural pathways do not exist. Transformational solutions being pursued are leading to better understanding of the central and peripheral nervous systems and pushing forward the frontier of scientific discovery.

As a bottom line, the evolution of the BCI systems proves that they have already started to show potential and surely will have great societal impact, with growing interest on the part of industry to commercialize and market BCI systems for medical and non-medical applications both in the shortcoming and long term; the scientific challenge is clearly present.

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