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User adaptive BCIs: SSVEP and P300 based interfaces

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ABSTRACT

Brain Computer Interfaces (BCI) represent a new communication option for those suffering from neuromuscular impairment that prevents them from using conventional augmented communication methods. This new approach has been developing quickly during the last few years, thanks to the increasing of computational power and the new algorithms for signal processing (Independent Component Analysis, Wavelets decomposition, Support Vector Machine etc.) that can be applied to the studies made on brain waves. Here follows two methodologies of approach based on making the computer adapt to the human brain activity and not vice-versa. The P300 and the SSVEP based BCIs, here presented, have the characteristics of not demanding specific training to the user.

Keywords: *Brain Computer Interfaces, signal processing, human computer interactions.*

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1. Introduction

A good hundred years after the first discoveries were made on the brain's electrical activity, Jacques Vidal published an innovative work explaining how to use the brain's electrical potentials for building a mental prosthesis [Vidal, 1973,1977]. This was the starting point for BCI research. Nowadays, about thirty research groups are following this approach for interfacing the computer [Kronegg, 2003].

In the first international meeting on BCI technology, which took place in 1999, at the Rensselarville Institute of Albany (New York), Jonathan R. Wolpaw formalized the definition of the BCI system :

"A brain-computer interface (BCI) is a communication or control system in which the user's messages or commands do not depend on the brain's normal output channels. That is, the message is not carried by nerves and muscles, and, furthermore,

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neuromuscular activity is not needed to produce the activity that does carry the message" [Wolpaw et al., 2000a].

Through this definition, BCI systems appear as a possible and sometimes unique mode of communication for people with severe neuromuscular disorders like spinal cord injury or cerebral palsy. As a matter of fact, such neural diseases can break the slim and fragile line between thoughts and actions. In these cases, neither medicine nor surgery can be of any use to give back to the person the control of his/her body. However, utilizing the residuals functions of the brain, it seems possible to give back a hope of communication to these people.

The human brain has an intensive chemical and electrical activity, partially characterized by particular electrical patterns, which occur at specific times and at well-localized brain sites. All of that is observable with a certain level of repeatability under well-defined environmental conditions. These simple physiological issues can lead to the development of new systems to communicate.

Here follows a list of the most utilized electrical activities of the brain for BCI:

- β and μ Rhythms

  These electrical activities are observable inside a frequency range from 8 Hz to 12 Hz (Mu) and 12 Hz to 30 Hz (Beta). These signals are associated with those cortical areas most directly connected to the brain's motor output and can be willingly modulated with an imaginary mental movement for example. The increases/decreases of this rhythm have been used several times as a support for a BCI. [Pfurtscheller, 1989], Pfurtscheller and Lopes Da Silva, 1999], [Mc Farland et al., 2000].

- P300 Evoked Potential

  This wave is a late appearing component of an Event Related Potential (ERP) which can be auditory, visual or somatosensory. It has a latency of about 300 ms and is elicited by rare or significant stimuli, when these are interspersed with frequent or routine stimuli. Its amplitude is strongly related to the unpredictability of the stimulus, the more unforeseeable the stimulus is, the higher is the amplitude. This particular wave has been used to make the subject chose between different stimuli [Farwell and Donchin , 1988] , [Donchin et al., 2000].

- Visual Evoked Potential

  They are ERPs with short latency that represent the exogenous response of the brain to a rapid visual stimulus. They are characterized by a negative peak around 100ms (N1) by a following positive peak around 200ms (P2).Since Vidal’s innovative works in the early 70’s, these potentials are being used as clues indicating the direction of the user’s gaze [Vidal, 1973, 1977], [Sutter, 1992].

- Steady-State Visual Evoked Potentials (SSVEP)

  These signals are natural responses for visual stimulations at specific frequencies. When the retina is excited by a visual stimulus ranging from 3.5 Hz to 75 Hz, the brain generates an electrical activity at the same (or multiples of the) frequency of the visual stimulus. They are used for understanding which stimulus the subject is looking at in case of stimuli with different flashing frequency. [Morgan et al., 1996b],[Muller et al., 1997]

- Slow cortical potentials (SCP)

  These electrical activities are slow potential variations generated in the cortex after 0.5 – 10.0s. Negative SCPs are generally produced by movement, instead positive SCPs are associated with reduced cortical activation. Bimbaumer and his colleagues [Bimbaumer et al., 1990] demonstrated that people, adequately trained, can control these potentials and use them to control the movement of a cursor on the screen.

BCIs have been investigated from different perspectives. For the sake of simplicity we will split them into two methods, direct (invasive) and indirect (non-invasive).

In the first approach, recording devices are required inside the brain. This makes it possible to capture the electrical patterns near their sources. This solution requires challenging technological, scientific and psychological competences. For example, highly complex implanted micro-sensors, biologically compatible, are pioneering researches. Algorithms which process huge amounts of data generated by neurons at high rates (>20 kHz), and which filter and classify in real-time the brain's electrical activity, are another critical point for the BCI direct approach. Furthermore, from a psychological point of view, it is not yet sure that anyone in the future will approve to receive an implanted device in the brain.

Probably the work of neurologist Philip Kennedy and his colleagues [Kennedy et al., 2000] is the most impressive example for the direct approach. Johnny Ray, a patient of Kennedy, lived and talked to the world using cortical implanted electrodes. Other researchers, like Chapin from the Medical College of Pennsylvania and Nicolelis at the Duke University [Chapin et al., 1999], have used implanted electrodes inside monkeys' brains to control a robot-arm from distance.

The non-invasive way for BCI is less technologically and psychologically demanding. It requires sensors (electrodes) placed on the scalp to record electrical patterns. The necessary experimental set-up (i.e., electrodes, amplifiers, medical competence...) to carry out the indirect approach is more available to laboratories today than the require set-up for the invasive one. The disadvantage of listening to the brain activity from the outside of the scalp lies in the very low quality of the signals, due to the damping of the electrical activity signals on their way to the electrodes.

This non-invasive and easy to set-up approach has been used to study several sets of electrical patterns. These sets can be grouped into two main classes: the electrical patterns evoked by external stimuli (i.e., a blinking arrow) and the electrical patterns generated by means of wilful execution of particular cognitive tasks (i.e., imaging a spinning cube). It is the research goal or the physical boundaries imposed by the patients that decide the use of one or the other kind of electrical pattern.

The usage of this approach has given good results, even if there are no real and useful applications yet. To cite the most published works inspired by it, it's worthwhile to highlight the pioneering researches of Prof. Birbaumer. He was one of the first to use brain waves, influenced by the human will, to drive a speller [Birbaumer et al., 2003]. Another well-known researcher is Prof. Wolpaw. He developed a BCI based on μ and β EEG rhythms [Wolpaw et al., 1991]. The patient, after specific training, is able to move a cursor up and down just modifying those rhythms. A different strategy was proposed by the psychologist Donchin [Farwell and Donchin, 1988] using the P300 wave to control a speller. Whereas the previously cited works (Birbaumer and

Wolpaw) are based on the user's ability to control brain behavior, in Donchin's method a quasi-uncontrollable brain signal, the P300, is used.

The general idea of Donchin's solution is that the patient is able to generate this signal without any training. This is due to the fact that the P300 is the brain's response to an unexpected or surprising event and is generated naturally. Donchin has developed a BCI system able to detect an elicited P300 by signal averaging techniques (to reduce the noise) and used a specific method to speed up the overall performance.

The SSVEP (Steady State Visual Evoked Potential) activity is another successfully investigated brain signal. As presented previously, SSVEP [Morgan et al., 1996b], [Muller M.M. et al., 1997] is the natural brain response when the retina is excited by flickering visual stimuli. The SSVEP signals are strongly modulated by a selective spatial attention process: these signals are well defined within the extent, delimited by the user's visual attention. Outside this area, flickering visual stimuli don't generate the same meaningful activity.

Starting from the P300 and SSVEP works and trying to overcome their boundaries, two BCI systems have been developed in our laboratory.

2. Materials and methods

A fundamental aspect for a human machine interaction system, such as BCI, is the need for a proper development environment that allows a real time interaction between the subject and the machine. (This necessity is directed by the fact that the users need a short response time to keep up their attention level). For this purpose we created a flexible modular environment useful to develop and to experiment various BCIs

There are essentially two parts that every BCI system needs:

1. A dedicated hardware system that manages the stimulation, the EEG acquisition (electrodes and amplifier samplers etc) and the feedback (visual, acoustic, haptic ...)
2. A system that deals with advanced signal processing and interpretation.

We chose to use for the first part a commercial system for EEG analysis and for the signal analysis tool we opted for Matlab, which gives a great flexibility and easiness to the developing of the algorithms. In this system we studied two kinds of BCI: a first one based on an ERP (P300), and a second one based on SSVEP.

Both the BCIs studied share the video interface and the acquisition in the first elaboration part.

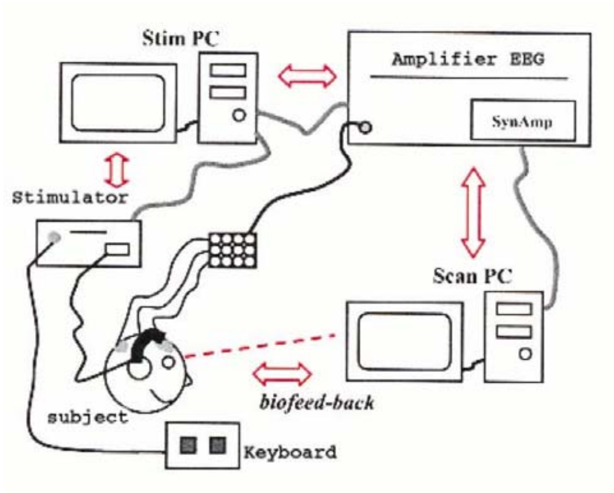

Figure 1: System for BCI development

2.1 The system: Hardware

The core of the first part is the NeuroScan System. This is a commercial system composed of :

- Neurostim: PC that manages the visual and acoustic stimulation for the subjects.
- SynAmps: which amplifies and filters high frequency components of the EEG signals.
- ScanPc: PC that manages the functioning of the whole system for acquisition, processing and visualization as well as the exchange of EEG data with external programs (ex.; Matlab). The possibility to exchange data with other programs is one of the main reasons to use Neuroscan for a research and development project.
- A set of electrodes (that can be fixed on a "quick cap") to be fitted on the subject's scalp.
- A 4-button keyboard whose stimulations are recorded synchronously with EEG by the SynAmp.

2.2 The system: Software

Thanks to NeuroScan's characteristics, which allow data exchange between different processes, we developed the artificial intelligence algorithms needed by our BCIs in Matlab and C++ code. This choice was determined by the notable flexibility of the software written in Matlab whose characteristics permit easy trials of new algorithms. The proposed system (Hardware and Software) carries out some fundamental operations in order to test the detection of the electrical potentials in real time. We use for this reason, the same system for both the BCIs we are studying.

2.3 P300 based BCI

For a P300-based BCI, we need to elicit an ERP. Therefore, to start with, the subject must be stimulated with an appropriate interface. Then the generated electrical potentials should be recorded and eventually processed in real time. Here follows the list of the main characteristics necessary to achieve these three steps (stimulation, recording and processing):

- The definition of an elicitation paradigm to evoke this ERP, using different kind of stimulations (acoustic or visuals modality according to the user's capabilities).
- Neuroscan that performs on-line acquisition of EEG data, synchronized with the stimuli (collected as ERPs epochs).
- A processing procedure that allows to reduce noise and enforce P300-related information.
- A pattern recognition algorithm that permits to check the absence or the presence of the P300 wave in the recorded ERP epochs.
- The procedures that carries out a epoch labelling, according to the previous stimulus type (target or non-target), in order to use them during off-line operations.
- A feedback mechanism to the subject, which sends him/her a visible signal on the monitor correlated to the recorded epoch.
- A pattern recognition algorithms that, using the labelled epochs previously collected, adapts its rules according to the user characteristics.

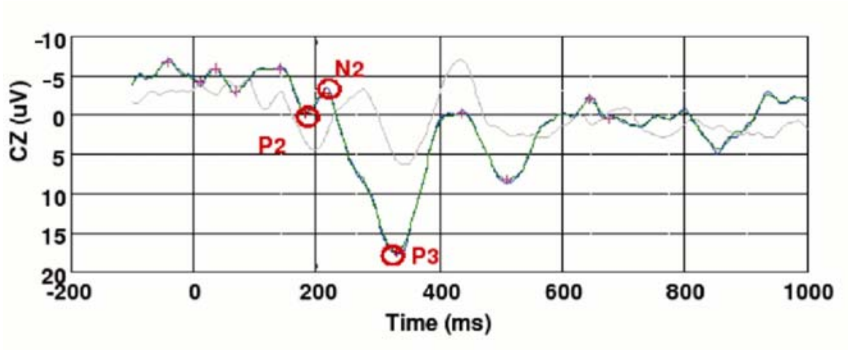

Figure 2: P300 wave

2.3.1 Algorithms for P300 studies: ICA and Support Vector Machine

Classification Algorithm

In order to understand whether a P300 pattern has been generated by the visual stimulus, a Support Vector Machine [Vapnik, 1995] was developed. Generally speaking, the Support Vector Machine implements the following idea: it maps the input vector ***x*** into a high-dimensional feature space ***Z*** through some non-linear mapping ***K***, chosen a priori. In this space, a hyper plane is constructed.
This hyper plane, in our case, separates the P300 patterns from the non-P300 patterns.

The core of a SVM classifier is the kernel function

$$K(x) \Rightarrow Z \qquad (1)$$

One of the most used kernel functions, as in our experimental sessions, is the radial basis kernel

$$K(x) = e^{-\gamma x^2} \qquad (2)$$

Using the SVM classifier, the following issues have been observed:

- A fast learning rate: typically a few seconds are sufficient to learn the training set.
- Quite coherent results between the off-line training, the testing phase and the real-time phase.
- Good numerical stability.

ICA algorithm

The raw signal, acquired by NeuroScan, follows four processing steps: first, all the signals recorded by scalp electrodes are processed in order to obtain a set of independent components. Since the locations of the brain that generate ERP cannot be determined easily by the scalp recordings (resolution problem), many algorithms have been studied in order to separate each signal in a set of independent sources (i.e., originating from different areas). One of the most promising algorithms is the so-called Independent Component Analysis (ICA) [Comon, 1994]. ICA determines what spatially fixed and temporally independent component activations compose an observed time-varying response, without attempting to directly specify where in the brain these activations arise. Practically the problem that ICA solves, is to recover sources from their instantaneous mixture without any previous knowledge of the sources and the mixing channel. Differently from Principal Component Analysis PCA that finds components that are uncorrelated, ICA is a much stronger criterion because it is based on statistical moments of a higher order, so ICA requires more than the uncorrelatedness of the components. The most general case can be so characterized: we consider **n** unknown sources signals $\mathbf{s_i(t), i=1,\ldots n}$, which are mutually independent, and we model the sensor's output as

$$s(t) = Ax(t) \qquad (3)$$

where **A** is an unknown non-singular mixing matrix, $\mathbf{x(t)= [x_1(t), \ldots x_n(t)]^T}$, $\mathbf{s(t)= [s_1(t), \ldots s_n(t)]^T}$. With no knowledge of the source signals and the mixing matrix, we want to recover the original signals from the observed signals **x(t)** by the following linear transformation:

$$y(t) = Wx(t) \qquad (4)$$

where $\mathbf{y(t)= [y_1(t), \ldots y_n(t)]^T}$ and **W** is the un-mixing matrix. Of course it is impossible to find the original sources without ambiguity, because they are not identifiable in a strictly statistical sense. However, up to some permutation, it is possible to obtain $\mathbf{c_i s_i(t)}$ where $\mathbf{c_i}$ are unknown non-zero scalar factors. In order to separate the components, ICA works on a learning algorithm that minimizes the dependency between the output components: such a dependency is measured by the Kullback-Leibler divergence (5) between the joint and the product of the marginal distributions of the output:

$$D(W) = \int p(y) \log \frac{p(y)}{\prod_{a=1}^{n} p_a(y_a)} dy \qquad (5)$$

Where $p_a(y_a)$ is the marginal probability density function (pdf). To perform this, some hypotheses are implicit and a training algorithm is needed to find the right un-mixing matrix **W**. The hypotheses are the following:

1. The signals recorded from the electrodes are an instantaneous mix of **n** statistically independent sources. This implies that the coefficients of the mixing matrix **A** are linear and time-independent. From a physiological point of view this is equivalent to saying that the sum of the electrical potentials coming from different areas of the brain on the scalp electrodes, is linear. To be more precise, it is not the result of non-linear distortion or temporal convolution of the sources.
2. The number of sources **n** does not exceed the number of electrodes. In physiology this means that the areas involved are stable and in a defined number.
3. The sources and the mixing process are stationary, they don't change their statistical properties in time.

The first hypothesis is well confirmed in literature [Makeig et al., 1997], [Jung et al., 2001]. The second hypothesis doesn't represent a problem because we can take as many sources as we want (in theory at least), in order to have the number of sources smaller than the number of electrodes. The third one is generally not verified but we can overcome this problem if we choose a time interval, small enough to consider with a good approximation, the signal stationary. According to these considerations we can apply the independent component analysis computation.

2.3.2 P300 based BCI: protocol and interface

The protocol used to test the proposed BCI device, consists of a P300 wave elicitation paradigm. It can be divided into two main phases, called learning and testing. Through this protocol we want to reach the following objectives:

1. Solving the "ad personam" system adaptation;
2. Quantifying the system performance;
3. Giving a visual bio-feedback to the subject.

To elicit the ERP (P300 wave) we submit the subject to a random sequence of visual stimuli on a computer screen, using a complex odd-ball paradigm. Inside our graphic interface, each stimulus has the shape of an arrow to give a directional meaning: up, right, down and left, for the total amount of four different stimuli (see Fig. 3). A stimulus consists of the single flash of an arrow lasting 150ms. The inter-stimulus interval is of 2.5 s, and the upper bound of a sequence of stimuli is of 90. Since the subject's task is to reach the goal (the red cross) with the movements of an object (the blue ball) he/she has to decide which direction (i.e.: the blinking arrow) is interested in and keep his/her attention on it. The stimulus desired by the user is called *target* (that is the one that would allow the object's movement in the direction chosen by the user), otherwise it is called *non-target*.

The main hypothesis, that we will use later, is that every target stimulus elicits the P300 wave.

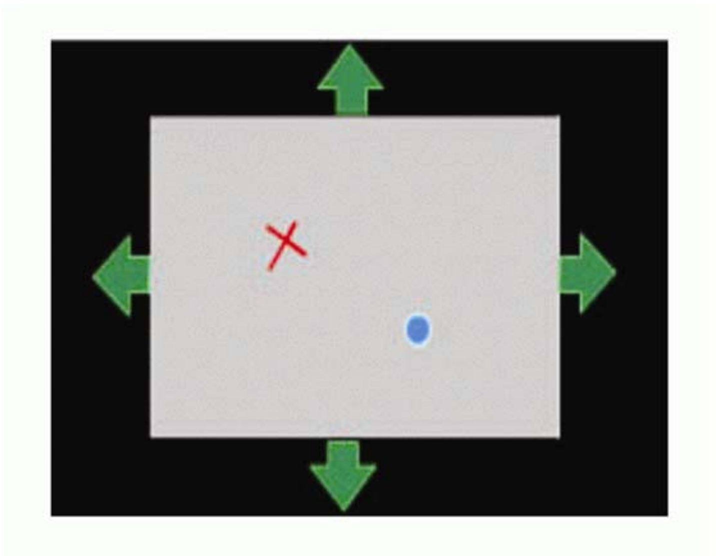

Figure 3: P300 interface: testing phase

2.3.2.1 Learning phase

During the learning phase, the subject learns to reach the red cross using the arrows.

For this phase two strategies can be followed, depending on the capacity of the subject to use the keyboard or not. For those who can't, a predefined path appears on the screen that they are taught to follow looking at the correct arrows. The object's movements are controlled by the software, thus every time that the subject receives a target stimulus (the next direction along the predefined path) the object makes a single step toward the cross, otherwise it does not make any step.

If the subject is able to move (one hand at least), we can apply another strategy for the learning phase: the person informs the system when he receives a target stimulus by pressing a key, so that every time he presses the key, the object on the screen makes a single step according to received stimulus.

Both protocols make the subject believe that every time he/she wants to move the ball, the machine is able to *read* the subject's will and moving consequently the object. This is done to recreate the closest situation to the testing phase. At the end of the learning phase, the system has recorded a set of signals (ERP epochs) that should be similar to the ones it will deal with during the testing session. In such a way the adaptive algorithm can learn the specific P300 wave of each subject. It can then discriminate the ERPs data epochs between target stimuli (the one which elicits P300s) and non-target stimuli. To do this, some off-line operations must be performed:

- trace filtering (low-pass filtering);
- ICA decomposition, to extract the un-mixing matrix **W**;
- feature extraction and normalization;
- Support Vector Machine training.

Once the system completes the training, the testing phase can start. The above processing and training procedure can be performed after every testing session, in order to improve the system performance.

2.3.2.2 Test phase

During the testing phase, the subject actually performs the task, like in the learning session, but with a substantial difference: the object's movements are controlled by the output of the adaptive algorithm, trained on the subject's previous tracks. So, in this phase, the user can see directly on the screen the result of the classification algorithm (the movement of the ball).

The recognition algorithm assesses the presence of the P300 wave into the single-sweep tracks related to every stimulus. If a P300 is detected, then the system moves the object on the graphical interface according to the stimulus just received by the subject, otherwise the object stays still. If the subject is interested in a particular direction, left for example, he normally will elicit a P300 wave only when he sees the left arrow flashing. If the classification algorithm works correctly, the subject should see the ball moving one step left. Otherwise, he/she will see the ball moving in a direction he/she is not interested in or no movement at all. The subject will consider as a reward the movement of the ball in the desired direction (positive biofeedback). Otherwise, a non-desired movement (negative biofeedback) will push the subject to concentrate more on the stimulus, trying to control it better. As in the learning session, the subject informs the system about target stimulus by pressing a key if he/she can. This allows track labelling and, successively, re-training the system using information retrieved during the testing session.

2.4 SSVEP-based BCI: protocol and interface

The second BCI we are studying is based on the steady-state visual evoked potential (SSVEP).The SSVEP is a continuous and periodic signal, elicited by visual stimulus flickering in the frequency range between 3.5 Hz-75 Hz. SSVEP is described as a near sinusoidal signal oscillating at the same, or multiple, stimulus frequency and it's particularly detectable in the occipital-parietal region of the skull. These signals are readily quantifiable in the frequency domain and can be easily extracted from background electroencephalogram noise.

2.4.1 Assessment studies

The first step of our research consisted in assessing the feasibility of creating a screen based visual interface able to elicit SSVEP signals. The visual stimulus is given by some items of the graphic interface that flicker at different frequencies. An important part of the work concerned with the definition of the item features, such as light intensity, colour, shape, dimension and flickering frequency. We performed a set of experiments in order to understand how to increase the amplitude of the recorded brain responses to the flickering stimuli.

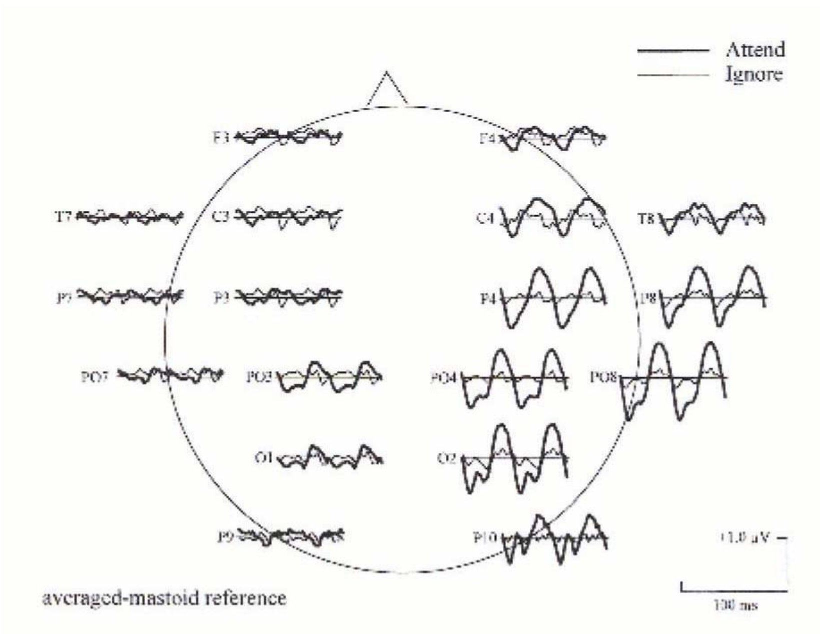

Figure 4: SSVEP distribution over the scalp

We reached these conclusion:

- Confirming what is said in literature [Regan, 1989], the occipital electrodes, specially *PO8* (figure 4), are the one where the response to the stimuli is higher. This was verified through a set of experiments, made on 5 subjects (figure 5). From the figure, It can be seen also that the second harmonic is the one which has the greatest amplitude [Ventura, 2002].
- We confirm the fact that the increase of the SSVEP amplitude is directly correlated with the spatial attention processes [Muller and Hillyard, 1997], [Morgan et al., 1996], [Silberstein, 1990]. To test this hypothesis we associated to the action of concentrating on the stimulus, a cognitive task like counting a blue spot that appears randomly on the regions where the stimuli are flashing. This task increases the amplitude on the SSVEP recorded.
- It has been shown [Blanchard and Epstein, 2000] that it is possible through the feedback to make some subjects increment some brain wave activities. For such a purpose we put a bar next to every flashing symbol, showing in real time the brain activity correlated to that flashing frequency.

Thanks to this feedback we noticed (with a high statistical significance) an increase of the wave amplitude of 10-20% (Table 3) [Ventura, 2002].

- We found also that the couple of frequencies easier to discriminate was the couple 6 Hz and 10 Hz. This couple was the one in which each frequency interferes less with the other (as can be see on the figure 6).

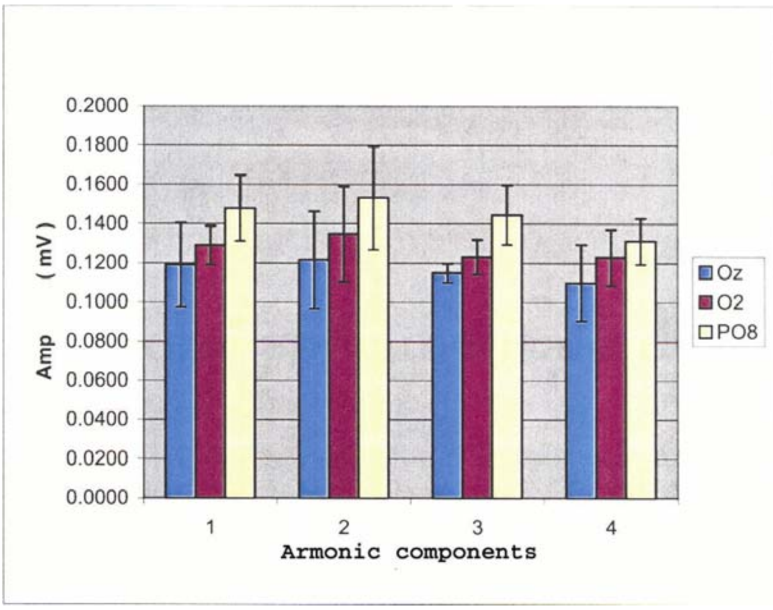

Figure 5: Harmonic Components of 6 Hz (left) and 10 Hz (right) stimulation for the different electrodes: as it can be see the PO8 is the one with higher amplitudes

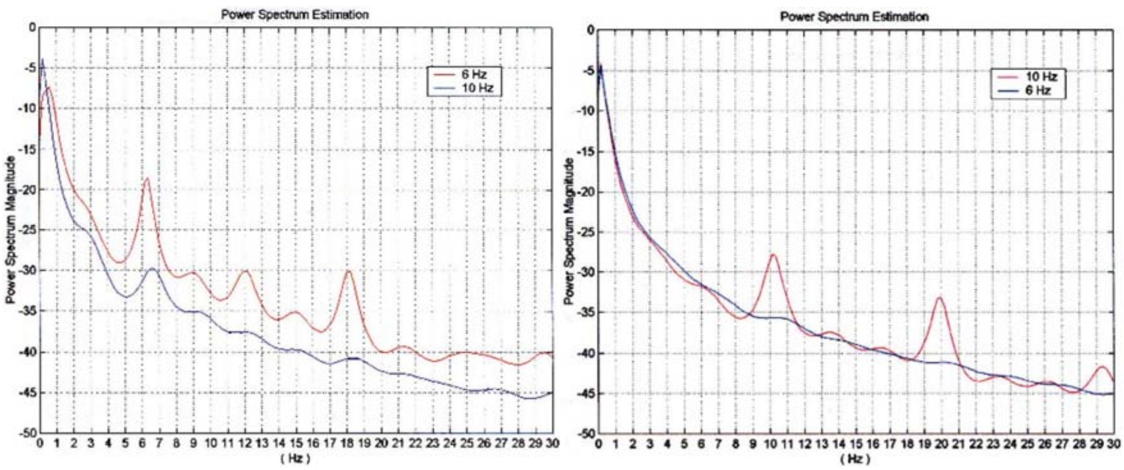

Figure 6: Power spectrum of SSVEP for the couple 6-10 Hz when the subject is looking at the flashing stimulus at 6 Hz on (figure on the left) and at 10 Hz (figure on the right)

2.4.2 Algorithms for SSVEP studies: MA, ALE, Subspace Averaging

The EEG signal is processed with a method named *Subspace Averaging* [Davila and Srebro,2000],[Davila et al.,1998].

This technique is a combined application of two signal elaboration methods called *Signal Averaging* and *Signal Space Projection*.

The latter one was introduced in 1987 by Ilmoniemi and is used to separate the EEG signal from a generic noise signal (cardiac or oculographic artifacts). See [Ilmoniemi and Williamson, 1987], [Ilmoniemi et al., 1987] and [Ilmoniemi and Uusitalo, 1997]. This technique has been widely applied in the telecommunication field and, recently, has been applied in the analysis of physiological signals such as EEG or MEG. The computational simplicity and the short processing time, make this method preferable to others and allow an easy and efficient implementation, especially for on-line application.

The classification has been implemented by a linear threshold algorithm, that recognizes the SSVEP signal if its amplitude exceeds the threshold value for, at least, 2 seconds.

2.4.3 Protocol

The experimental protocol has been divided in two phases: training and testing. The training phase has the purpose of establishing the parameters of the typical SSVEP activity of every subject (maximal amplitude) in order to fix the threshold for the classification part. The subject sits at 70 cm distance from the screen and the electrodes (Oz,O2,PO8) are applied. In this first phase, during which the feedback signal is not given to the subject, the subject has to focus his/her attention for 20 s on the left flashing symbol, after 2s at the centre of the screen and finally for 20 s at the left flashing symbol. To check the exact moment in which the subject changes direction, he/she has to press one of the three buttons according to which flashing light the subject is looking at.

In this second phase, the subject has been told to focus his/her attention on the flashing arrows, following the sequence of the directions to look at on top screen (D for Right, S for Left as it can see on the figure 7). The current letter (corresponding to a direction) will change colour if the subject manages to keep the amplitude (according to the magnitude bar) of the brain wave corresponding to the frequency of the stimulus he is looking at, for at least 2 seconds. We measure, for each trial, the correct selections, the errors, the null events (defined as the event when both the amplitude bars reach the top for two seconds) and the time to complete the trial. After each trial the subject's amplitude thresholds are recalculated adaptively in order to track the changes on the individual behaviour. This simple game is an easy trick to keep the subject always engaged.

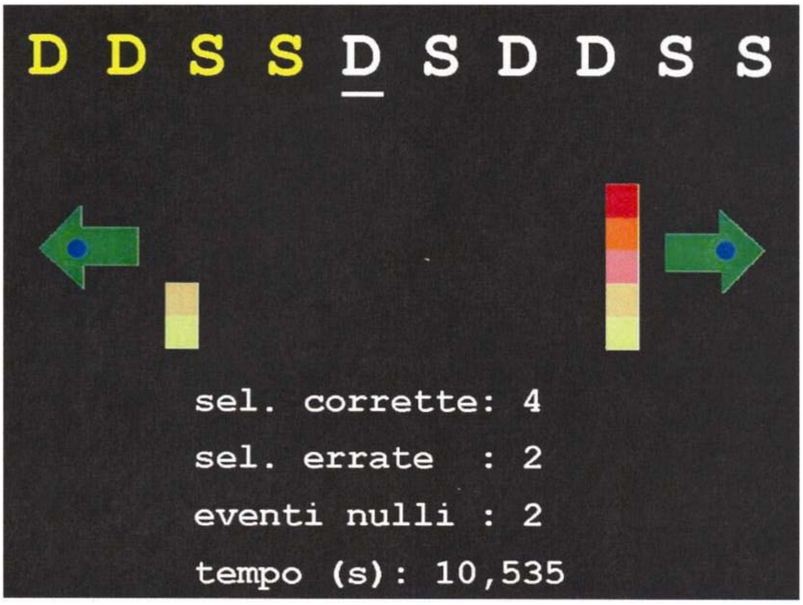

Figure 7: SSVEP visual interface during the testing phase

3. Results

3.1 P300

P300 based BCI has now achieved a good developing level, in terms of both the system architectural choices and the early results. Since the beginning of our project, 3 years ago, the whole system has changed many times. We started with an acoustic protocol, but we had to drop this approach because of the difficulty to handle a stimulus with a high semantic component (P300 had latency and shape that depended too much on the particular stimulus). The evolution of the system passed through hundreds of tests on healthy and pathological subjects and through many modifications of the classification algorithm (we started from a simple Bayesan classificator, we shifted to neural networks and finally we chose a Support Vector Machine).

The following tables sum up briefly the results we had. The first one, related to the neural network approach, (Table 2) is divided into healthy and pathological subject, and the second one represents the new promising SVM approach (Table 3). In the tables we define:

- *Performance*: the percentage of the exact classification;
- *Instr./min.*: the number of correct instructions per minute;
- *Err P300*: error in classification of P300 waves;
- *Err. Not P300*: error in classification of non-P300 waves;
- *Err. tot*: total error.

	Healthy		Pathological	
Subject N	7		5	
Performance	66.8		56.7	
Instr./min.	3.39		3.59	
Age: Mean- Var	33	22-43	40	30-53
Err.P300: Mean –StD	0.4966	0.16	0.5864	0.1544
Err. Not P300: Mean –StD	0.2707	0.0794	0.3665	0.106
Err. tot.: Mean –StD	0.3318	0.0777	0.4327	0.986

Table 2: P300 results: NN approach healthy Vs Pathological

Subject N	5	
Performance	71.1	
Instr./min.	5.34	
Age: Mean -Var	32	23-45
Err. P300: Mean -StD	0.59	0.109
Err. Not P300: Mean -StD	0.123	0.0291
Err. tot.: Mean -StD	0.2888	0.0397

Table 3: P300 results: SVM approach.

It is necessary to keep in mind the way our interface works in order to interpret these data tables. A random stimuli sequence is presented to the user, who has to concentrate only on the one is interested in. It appears evident that the most critical error is due to the misinterpretation of the not-P300 wave. This causes a wrong action on the interface while a P300 wrong classification doesn't create any output. That is the reason why we tend to minimize the error on not-P300 classification without caring of the corresponding error on P300. Using such a strategy, the user will only experience a great difficulty to move the object in the desired direction and this sensation will push him/her to concentrate more.

A simply way to increase the bit-rate without changing the classificator, consists in reducing the interstimulus time. Presently, the interstimulus period is of 2.5 seconds whereas the computation time is of 400ms. This implies that we can reduce the interstimulus at most to 400 and this will bring up the bit-rate magnitude of 5 times. This solution will be investigated accurately because it hides many interrogatives about what the user reaction will be to such high frequency stimulation.

3.2 SSVEP

The experimental sessions were run at the San Camillo Hospital in Venice. 5 healthy subjects, aged between 24 and 32 years old were tested. The experimental sessions validated the feedback efficacy in improving the man-machine communication process. The importance of the feedback signal is particularly evident in its capability of adapting the SSVEP response of the subject to the classification algorithm request. This adaptation process has been observed in all the subjects. As it can be seen from the table 4 there is a significant increase of the amplitude of SSVEP when using the biofeedback bar. Another interesting result is that all the subjects show a decrease of the signal amplitude after 7-8 trails. When asked, the subjects replied that this interface is very tiring and that they find it hard to concentrate. The last observation, according to the results obtained in the testing phases, is the accuracy of this kind of interface (the average accuracy is of 95.71% with a standard deviation of 2.73%). This high accuracy was obtained because we kept the threshold for selecting the stimulus high in order to decrease the false negative classification that is very harmful in BCI systems; in other words, only 4.3% of the instructions are misinterpreted. Practically this results in increased difficulty for the subject that has to keep concentrated to reach the selection. In spite of this increment of difficulty, the subject achieved a satisfactory communication rate (10 instructions in 97.16 seconds).

Freq. Stim.	Subject	Percent. Incr.	P
10 Hz	1	10.93	0.085
	2	28.22	0.045
	3	10.01	0.013
	4	21.35	0.004
	5	10.09	0.034
6 Hz	1	9.08	0.025
	2	34.71	0.027
	3	14.51	0.046
	4	10.67	0.01
	5	19.58	0.029

Table 4: Tables comparing the percentual increase of amplitude for every subject and the statistical significativity *P.*

4. Discussion

Both BCI systems studied have the advantage that they do not need a particular training (Birbaumer, Wolpaw) because they exploit a natural brain behaviour. Thanks to the feedback, subjects can learn how to improve the communication rate. We see also that the performance can be greatly improved by increasing the engagement of the subject in the task. It turns out that the subject participation and willingness is as important as the classification tools of the system. It is evident that the more the subject is concentrated on the task, the higher will be the bit-rate of whole systems. Therefore the study of physical interfaces and of the stimulating strategies become critical.

Many ways can be explored to improve the whole system performance:

- virtual reality involvement;
- competition between subject in a video-game, one after the other or one against the other;
- reward/penalty distribution strategy improvement.

The drawback of such an attention-dependent system is that it is very tiring and consequently the performances decrease in time (as it can be seen on the figure 8 referring to one SSVEP session).

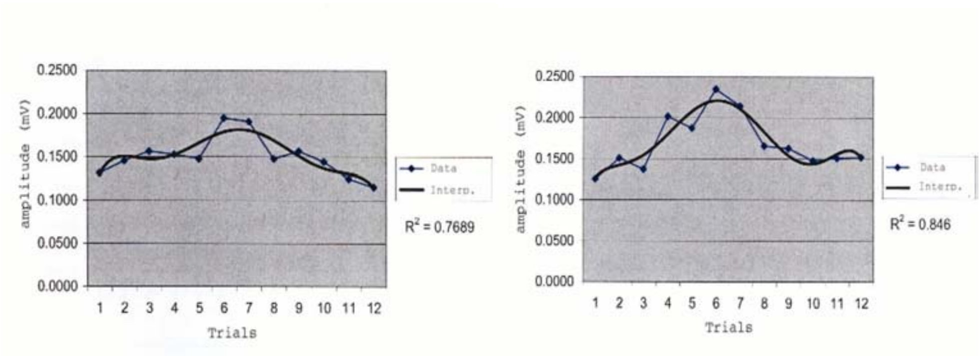

Figure 8: SSVEP amplitude (6 Hz, 10 Hz) decreasing during the testing session for 2 subjects

5. Towards the future

P300 interface and SSVEP interface are still at this stage an open research topic. The results we show are in their early stages but some interesting points can be observed.

In general, it's quite clear that the two interfaces require a good attention level by their users. So, a particular effort has been dedicated to all the aspects regarding the user's side of the interfaces. Two simple examples are, the colours used for P300 interface arrows and the feedback channel studied for the SSVEP interface.

The classifier performance or the ICA filtering is not as important as the user's feeling toward the interfaces. The more the user is aware of the task proposed by the BCI, the more the brain activity will be recognizable by the machine.

To improve the involvement of the subject, which has been seen as a critical point for the performance of both the interfaces, many solutions can be explored. A massive use of Virtual Reality is probably the first step toward a real and usable BCI, especially for all the aspects regarding the multiple sensorial stimulations provided by this technology. Another really important issue is the user's emotional involvement when he/she uses the interface.

A sort of game-competition, maybe mediated in a Virtual Reality environment, could amplify and focus the brain activity toward a specific target. As an example, the P300 wave is strongly related to the level of surprise: it's quite easy to imagine an engaging game, with colours and sounds, able to generate unexpected events.

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