# BRAIN COMPUTER INTERFACE APPROACHES TO CONTROL MOBILE ROBOTIC DEVICES

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This paper presents and compares two approaches for brain computer interface to steer a wheelchair, namely a new visual based P300 paradigm consisting of 8 arrows randomly intensified used for direction selection and a motor imagery paradigm for discrimination of three commands. Classification follows Bayesian and Fisher Linear Discriminant approaches both based on prior statistical knowledge.

Results in P300 paradigm reached false positive and false negative classification accuracies above 90%. Motor imagery experiments presented about 70% accuracy for left vs. right imagery and imagery vs. non-imagery.

*Keywords*: BCI, P300, Motor Imagery.

## 1. INTRODUCTION

For people suffering from severe motor disabilities such as amyotrophic lateral sclerosis and locked-in syndrome, Brain Computer Interfaces (BCI) emerge as a feasible type of human interface that can allow these patients to interact with the world. Standard interfaces such as language processing, eye tracking and head or teeth switches are not suitable for people with lack of total movement control.

Current non-invasive BCI systems based on electroencephalographic (EEG) data are divided in four main classes according to the type of neuromechanisms: slow cortical potentials (SCP),[1] event related synchronization and desynchronization (ERD/ERS) of $\mu$ and $\beta$ rhythms usually associated with motor imagery,[2,3] visual evoked potentials (VEP) and steady-state VEP (SSVEP),[4] and finally, P300.[5,6] The first two approaches require that the subjects learn to control their brain rhythms. This is often a long and difficult task and it can happen that users are unable to learn how to control them. Control of $\mu$ and $\beta$ rhythms is usually reached through mental tasks such as motor imagery, for instance, imagining that a left hand task is being performed. After some training period with visual feedback, users usually can create their own mental mechanisms. Knowing the map of the motor cortex (motor homunculus) it is possible to select different motor tasks with known spatial distribution so that different motor cortex areas be activated. Motor imagery requires a high degree of concentration and some mental effort. The number of discriminative patterns is usually limited due to the low spatial resolution of EEG. The number of classes proposed in current research works almost never goes beyond four classes. See for example the work presented in Ref. 7 where the imagination of left hand, right hand, foot and tongue tasks was used to discriminate four different patterns. A clear advantage of motor imagination is that this neuromechanism only depends on imagination, i.e. it does not depend on visual focus or gaze like some stimulus-based BCIs (e.g. SSVEP). For this reason this approach is called a true BCI. Another important advantage comes from the unnecessary use of synchronism cues. The user starts, stops and selects mental imagination when he wants, nevertheless the training process is usually performed with synchronized cues. The stimuli based approaches are much more human passive in the sense that they use natural brain responses to external events and therefore do not require learning. Users only have to focus attention on the stimuli that are displayed in the field of view. However, in SSVEP the user has to fix stimuli positioned in some part of the screen which implies the movement of the eyes. Consequently it can not be called a true BCI. The P300 neuromechanism is related with attentional focus and therefore there is no need to gaze the specific stimulus. One major disadvantage of P300 arrives from the fact that the user has to wait the occurrence of the desired stimulus which randomly appears. It is not the user who decides when to provide an intention but rather the emergence of the stimulus.This synchronism permits that several user intentions be represented by a unique brain pattern. This reflects a high volume of information, but not necessarily a high transfer rate because this one depends of the number of stimuli.

Two systems based on motor imagery and P300 are being developed and compared at the Institute for systems and robotics (ISR). The main goal is to evaluate the applicability of a BCI in patients unable to steer a wheelchair with common standard devices.[8] The same goal is being pursued by Millan's research group with interesting results. In their work,[9] a ERD/ERS BCI based is used to discriminate 3 different commands to steer a wheelchair with navigation assistance in indoor environment.

## 2. Methods

### 2.1. *Subjects and recorded data*

Two healthy subjects, one male and one female participated at the experiments. The two different experimental paradigms were performed in different days. The subjects were seated in front of a computer screen at about 60 cm. In P300 experiments, EEG activity was recorded from 12 Ag/Cl electrodes at positions Fz, Cz, C3, C4, CPz, Pz, P3, P4, PO7, PO8, POz and Oz, and in motor imagery experiments EEG was recorded at C3, C4, CP3, CP4, P3, P4 according to the internacional 10-20 standard system (see Fig. 2). The electrodes were referenced to the right mastoid and the ground was placed at AFz. The EEG channels were amplified with a gUSBamp (g.tec, Inc.) amplifier, bandpass filtered at 0.1-30 Hz and notch filtered at 50 Hz and sampled at 256 Hz. All electrodes were kept with impedances under 5 $K\Omega$.

### 2.2. *P300 Paradigm*

The present P300 visual paradigm simulates a virtual joystick as shown in Fig. 1. This differs from the majority of other P300 paradigms which are used as spelling devices.[5] It represents an arrow joystick composed by 8 arrows and a square gray colored in a black background. Each arrow and square is randomly intensified during 100 ms with a green color. The time interval between each intensification was 100 ms. Each arrow indicates one of 8 possible directions to steer the wheelchair. The central square is used as a stop command. The subject has to be attentive to the desired target arrow/square. The occurrence probability of a target stimulus and a non-target stimulus is respectively $\approx 1/9$ and $8/9$.

P300 is an event related potential (ERP) elicited by an oddball paradigm. In this paradigm there are two events, one infrequent and the other common. It is asked to the subject to mentally count the infrequent events. In response, a positive peak (P300) will appear around 300 ms after the stimulus (see Fig. 2). The ERP P300 component has a large variance and its magnitude is in the order of the ongoing EEG activity. This variance is highly dependent of subject's focus and of the presence of artifacts such as noise and muscular activity. The P300 pattern component become apparent averaging a large number of epochs. Fig. 2 shows the P300 average and standard deviation for $\approx 70$ target epochs (0-1 second after the intensification) and the average and standard deviation of $\approx 500$ nontarget epochs.

### 2.3. *Motor imagery paradigm*

The motor imagery experiment is similar to the one presented in Ref. 7, but with a different visual cue. It consists on a sequential repetition of cue-based trials.

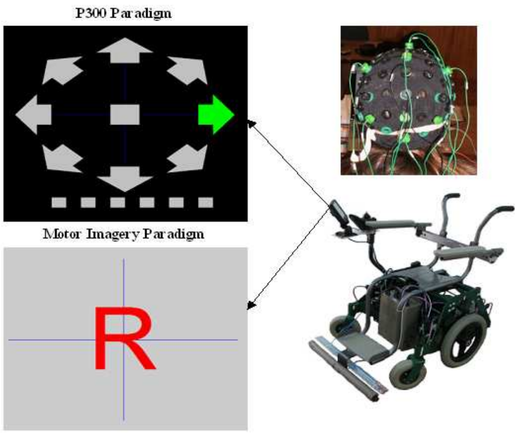


Fig. 1. Left: P300 and motor imagery paradigms; Right: Robchair[8] prototype and subject with electrodes cap.

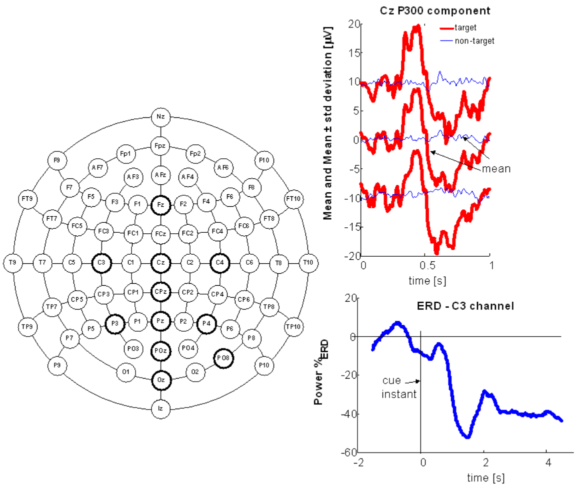


Fig. 2. Left: EEG electrodes used for data acquisition according to 10-20 international standard system; Right: mean and mean $\pm$ standard deviation of Cz P300 component for target and non-target stimuli and C3 $\mu$ rhythm ERD power average.

The subjects are seated in a chair with armrests and are asked to perform a motor imagination indicated by a visual cue. The cue is a letter 'L' or 'R' indicating respectively a left and right motor imagination (Fig. 1). Each trial starts with an empty screen. At time t=2 s a cross appears. Then at t=3 s the letter appears for 1.25 s. The subject has to imagine a left or right movement until the cross disappears (t=7 s). It is aimed to discriminate three different patterns: left imagery, right imagery and non-imagery (rest). The non-imagery should correspond to a stop command.

The $\mu$ rhythm (8-13 Hz) appears in the central cortex usually associated with motor movement.[10] When a motor task is performed, the $\mu$ rhythm suffers a desynchronization which results on a decrease of its amplitude. During relaxation (motor inactivity) there is a synchronization and therefore an amplitude increase. These phenomena are respectively called event related desynchronization and synchronization (ERD/ERS) and are induced from internal events rather than from external events as it happens with evoked potentials such as VEP and SSVEP. The ERD becomes visible also during motor imagery which allows the application of this neuromechanism for BCI. Fig. 2 shows the occurrence of an ERD in $\mu$ rhythm. The plot represents the power decrease in percentage relative to a baseline period (before imagination) for an average of 100 filtered trials according to:

$$\bar{P}(j) = \frac{1}{N}\sum_{i=1}^{N} x_f(i,j)^2 \tag{1}$$

where N is the number of trials and $x_f(i,j)$ is the sample $j$ of $ith$ trial $8-13$ Hz bandpass filtered.

### 2.4. *Classification*

The EEG time sequences were segmented and normalized. In the case of P300, after each stimulus event, a time window typically between 200 and 650 ms is recorded. This time window is called an epoch. In the case of motor imagery, the period after the visual cue is segmented in time windows of 1 s. Each time window is normalized to zero mean and unitary standard deviation. The P300 classification follows a Bayesian approach and motor imagery classification uses a Fisher linear discriminant (FLD). These two classifiers are now briefly described.

#### 2.4.1. *P300 - Bayesian Approach*

The prior knowledge of the average and standard deviation of target and non-target events form the two models for Bayesian classification. For a full description see Ref. 11. Consider $x^i(t)$ the EEG amplitude of the $i_{th}$ $(i = 1\cdots 12)$ channel at instant $t$. The training set averages and standard deviations for target and non-target events are respectively defined for each time instant $t$ as $\mu_k^i(t)$, $\sigma_k^i(t)$ where $k = 1$ stands for target and $k = 2$ for non-target. Under a gaussian distribution assumption, the probability of observing $x^i(t)$ given the model $w_1^i$ (target class) or $w_2^i$ (non-target class) is given by:

$$p(x^i(t)|w_k(t)) = \frac{1}{\sqrt{2\pi}\sigma_k(t)} \exp\left(-\frac{(x^i(t)-\mu_k(t))^2}{2\sigma_k(t)^2}\right) \tag{2}$$

This conditional probability is called the likelihood function of $w_k$.[12] If the $\mathbf{x}^i$ time sequence is a vector with $n$ observations, then $\mu_k^i$ is a vector $[n \times 1]$ and the full covariance $\Sigma$ is a $[n \times n]$ matrix. The joint probability of all time sample is:

$$p(\mathbf{x}^i|(\mu_k^i, \Sigma_k^i)) = \frac{1}{(2\pi)^{n/2}|\Sigma_k^i|^{1/2}} \exp\left(-\frac{(\mathbf{x}^i-\mu_k^i)^T(\mathbf{x}^i-\mu_k^i)}{2\Sigma_k^i}\right) \tag{3}$$

To reach the posterior probability $p(w_k|\mathbf{x})$ the Bayes rule is applied:

$$p(w_k|\mathbf{x}) = \frac{p(\mathbf{x}|w_k)P(w_k)}{p(\mathbf{x})} \tag{4}$$

where $p(\mathbf{x})$ is the unconditional density of $\mathbf{x}$ called the evidence and $P(w_k)$ is the prior unconditional probability of each of the classes: $P(w_1) = 1/9$ and $P(w_2) = 8/9$. The estimated class follows the maximum likelihood principle.

The probabilities of the overall channels are combined assuming channel independence, i.e. the joint conditional probability is written as the product of the individual channels conditional probabilities.[11]

### 2.4.2. *Motor imagery - Fisher Linear Discriminant Approach*

Taking the $\mu$ band power as features for left imagery vs. right imagery and imagery vs. non-imagery two different classifiers were modeled following the well-known two-class FLD. The goal is to maximize the intercluster distance between the two classes and minimize the intracluster within a given class in the new dimension space.[13] Let the within scatter matrix be defined as:

$$S_W = S_1 + S_2 \tag{5}$$

where $S_1$ and $S_2$ are the scatter matrices:

$$S_i = \sum_{x \in H_i} (x - m_i)(x - m_i)^T \quad , i = 1, 2 \tag{6}$$

The between scatter-matrix is defined as:

$$S_B = \sum_{i=1}^{2} (m - m_i)(m - m_i)^T \tag{7}$$

where $\mathrm{x} = (x_1|x_2|\cdots|x_n)$ is the vector with all $x_i$ $d-$dimensional features (training vectors), $m_i$ is the mean of the samples in class $i$, and $m$ is the mean of all samples. For the new feature vector $\mathrm{y} = \mathrm{W}^T\mathrm{x}$, then $\hat{W}$ is given by:

$$\hat{W} = S_{\mathrm{W}}^{-1}(\mathrm{m}_1 - \mathrm{m}_2) \tag{8}$$

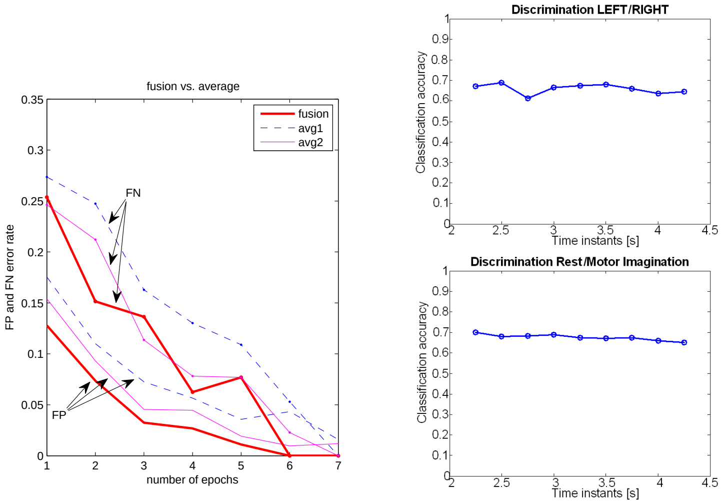


Fig. 3. Left: FP and FN error rates for different number of epochs per trial. The curves represents: 1) fusion of selected channels (fusion); 2) average of selected channels (avg2); and 3) average of all channels (avg1). Right: left vs. right discrimination and imagination vs. non-imagination classification.

## 3. RESULTS

### 3.1. *P300 experiments*

The performance of each channel was evaluated individually. Classification was performed for different number of averaged-epochs for the 12 channels. The system evaluation is made from performance measures false positive (FP) and false negative (FN). After an average of 7 epochs the FP rate was zero or almost residual and the FN rate was zero for almost all channels. These classification results were used to establish a channel ranking score. The 4 best channels (CPz, P3, PO7 and PO8) were used for Bayesian fusion. Fig. 3 compares the FP and FN rate using: 1) fusion of selected channels, 2) average of selected channels; and 3) average of all channels. Fusion improves both the FP and FN rates. After 5 epochs average, the FP rate is $\approx 1\%$.

### 3.2. *Motor imagery experiments*

Two non-experienced subjects tested the system online after a 50 min training (200 trials). A visual feedback bar with amplitude proporcional to the classification output was provided to the subject indicating his online performance. The achieved results for left vs. right discrimination and imagination vs. non-imagination (rest) discrimination are plotted in Fig. 3.

## 4. CONCLUSIONS AND FUTURE WORKS

Two approaches suitable for BCI were presented with some preliminary results. The experimental validation showed nice results with P300 paradigm but moderate results with motor imagery. This somehow demonstrates that the non-experienced subjects need to acquire the ability to learn to control their rhythms. P300 neuromechanism seems to be an effective approach to be used for mobile robotic devices. Notwithstanding the good results when compared with other reported works, the system was tested with only 2 healthy subjects, so more experimental validation is needed to attest the system robustness.

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