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Visual P300-based BCI to steer a Wheelchair: a Bayesian Approach

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Abstract— **This paper presents a new P300 paradigm for brain computer interface. Visual stimuli consisting of 8 arrows randomly intensified are used for direction target selection for wheelchair steering. The classification is based on a Bayesian approach that uses prior statistical knowledge of target and non-target components. Recorded brain activity from several channels is combined with a Bayesian sensor fusion and then events are grouped to improve event detection.**

The system has an adaptive performance that adapts to user and P300 pattern quality. The classification algorithms were obtained offline from training and then validated offline and online. The system achieved a transfer rate of 7 commands/min with 95% false positive classification accuracy.

I. INTRODUCTION

Brain computer interface (BCI) is a new type of human interface that can contribute to the augmentation of human capabilities, namely for people affected by severe motor disabilities. Typical diseases include neurological diseases such as amyotrophic lateral sclerosis and locked-in syndrome but also certain types of cerebral palsy where there is no control of voluntary movements. In such cases, standard interfaces such as language processing, eye tracking and head or teeth switches are not suitable.

Current BCI systems use mainly four different neuromechanisms, namely slow cortical potentials (SCP) [1], event related synchronization and desynchronization (ERD/ERS) of μ and β rhythms usually through motor imagery [2] [3], visual evoked potentials (VEP) and steady VEP [4], and finally, P300 [5] [6]. The first two approaches require that the subjects learn to control their brain rhythms. This usually takes a long term training and some subjects are unable to learn how to control their brain rhythms. The two other approaches use neuromechanisms that do not require learning since they are natural brain responses to external events. Users only have to focus attention on the stimuli. However, the user intention depends on the emergence of the desired event/stimulus which can slow down the transfer rate.

We are developing at the institute for systems and robotics (ISR) a visual P300-based BCI system to be used for wheelchair steering [8]. The system intends to be used for people suffering from general motor disabilities. Specific application cases are being studied in collaboration with motor neurological diseases associations. The goal is to evaluate the applicability of a BCI in patients unable to steer a wheelchair with standard devices such as head switches synchronized with a scanning display.

Some works have already been proposed to steer a wheelchair using BCI and reached relative success. In [7], a BCI based on ERD/ERS is used to discriminate 3 different commands which allow to steer a wheelchair (with navigation assistance) in indoor environment. This is a new research area to ISR, notwithstanding other human machine interfaces (HMI) have already been developed, for instance a voice HMI to steer a wheelchair [8]

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 (visual or auditory).

The majority of P300 paradigms are used as spelling devices. The present study follows a different approach as it intends to detect a desired direction to follow, nevertheless the applied oddball concept is similar to the other approaches.

II. METHODS

Two healthy subjects, one male and one female participated at the experiments. The subjects were seated in front of a computer screen at about 60 cm.

The EEG activity was recorded from 12 Ag/Cl electrodes at positions Fz, Cz, C3, C4, CPz, Pz, P3, P4, PO7, PO8, POz and Oz according to the internacional 10-10 standard system (see Fig. 1). 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 $K\Omega$.

A. P300 Paradigm

The P300 visual stimuli paradigm is showed in Fig. 2. It is composed by 8 arrows and a square, gray colored, in a black background. Each arrow and square is uniform randomly intensified during 100 ms with a green color. The time interval between each intensification was 100 ms settled. Each arrow indicates one of 8 possible directions to steer the wheelchair. The central square is used as a stop command.

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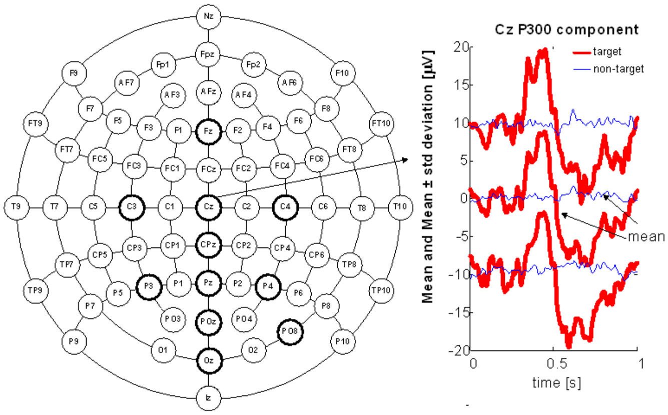

Fig. 1. Electrodes of the 10-10 international standard system. The EEG electrodes used for data acquisition are marked with a solid circle. The right side of the figure shows the average and standard deviation of Cz P300 component for target stimulus and the average of non-target stimulus. The data segment epochs are raw data, i.e. without any pre-processing.

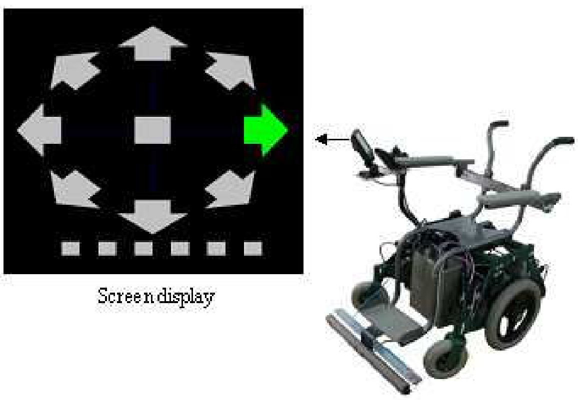

Fig. 2. Robchair prototype[8] and P300 Paradigm at computer screen.

The subject has to fixate attention to the target arrow/square that he wants to follow. The occurrence probability of a target stimulus and a non-target stimulus is respectively $\approx 1/9$ and $8/9$. These probabilities ensure the effectiveness of an oddball paradigm, however it is possible to include extra stimulus (small squares in Fig. 2) to decrease the probability of the infrequent event.

The on-line identification of the target stimulus follows two approaches: 1) the identification is only taken after 9 intensifications which include the 9 possible targets (1 trial). The most probable target is chosen. The number of trials to make the decision can be adjusted to the desired classification accuracy; and 2) the identification is performed after each intensification or after the average of several intensifications. These approaches allow an adaptive system performance in accordance to P300 data quality. In the best scenarios, a target would be detected each 3 seconds in the first approach, and in the second approach a target would be identified one second after its appearance, which are non-realistic scenarios as described in the next section.

B. Signal Processing and Classification

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. 1 shows the P300 average and standard deviation for ≈ 70 target epochs (0-1 second after the intensification). Fig. 1 presents also the average and standard deviation of ≈ 500 nontarget epochs. The large variance shows the difficulty to perform classification based on a single epoch of a single channel.

1) Pre-processing: Before classification, EEG data are pre-processed as follows:

1) **Filtering -** data are low-pass filtered by a 4th order Butterworth filter with 7 Hz cut frequency. This filter is used to remove unwanted ongoing EEG activity and noise;
2) **Downsampling -** depending on the classification algorithm data may have to be downsampled to improve the computational effort;
3) **Windowing -** after each stimulus, a data segment is collected (epoch). Typical epochs correspond to the data samples between 200 and 650 ms after the intensification. However, this window is adjusted to each channel and depends of the algorithm;
4) **Normalization -** each epoch is normalized to zero mean and unitary standard deviation, according to:

$$x_N = \frac{x - \mu_x}{\sigma_x} \tag{1}$$

The normalization allows to adjust trial to trial and session to session variances. Also, sensor fusion is more robust.

2) Bayesian Approach: Taking the average and standard deviation information of target and non-target stimuli for each individual channel, it is possible to build target and non-target models suitable for a two-class Bayesian classifier.

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 [9]. If the $\mathbf{x}^i$ time sequence is a vector with n observations, then μ_k^i is a vector $[n \times 1]$ and the full covariance Σ is a $[n \times n]$ matrix. The joint probability of all time sample is given by:

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

In order to have a tractable computation, eq. (3) requires that $\mathbf{x}$ has a small number of observations. This can be obtained either through choosing a small epoch window or by downsampling the time sequence. Another approach is to use only the diagonal matrix under the assumption of observations independence. The joint probability is given by the product of the density probability of each observation (2):

$$p(\mathbf{x}^i|w_k) = \prod_{t=1}^{n} p(x^i(t)|w_k) \quad (4)$$

The probability that has to be derived is the posterior probability $p(w_k|\mathbf{x})$, i.e. the probability of a data pattern belong to class w_k knowing an observation vector $\mathbf{x}$. This probability is obtained through the Bayes rule:

$$p(w_k|\mathbf{x}) = \frac{p(\mathbf{x}|w_k)P(w_k)}{p(\mathbf{x})} \quad (5)$$

where $p(\mathbf{x})$ is the unconditional density of $\mathbf{x}$ called the evidence and that will be treated here as a normalization factor, and $P(w_k)$ is the prior probability of each of the classes. As already referred above, the unconditional prior probability of a target intensification $P(w_1)$ is $1/9$ and the probability of a non-target intensification $P(w_2)$ is $8/9$. The estimated class $\hat{w}_j$ follows the conditional risk principle [9] which associates a cost function $C(\hat{w}_j|w_k)$ with correct or incorrect classification:

$$R(\hat{w}_j|\mathbf{x}) = \sum_{k=1}^{2} C(\hat{w}_j|w_k)P(w_k|\mathbf{x}) \quad (6)$$

The cost function is slightly different of the uniform cost function used in MAP classifier:

$$\begin{array}{ll} C(\hat{w}_j|w_k) = 0 & \text{if } j = k \\ C(\hat{w}_1|w_2) = \Delta_1 & \\ C(\hat{w}_2|w_1) = \Delta_2 & \end{array} \quad (7)$$

This modification allows to adjust the rate of false positive vs. false negative in the classification process. The Bayes decision function is written as:

$$\hat{w}(\mathbf{x}) = argmax\{\{\Delta_2 p(\mathbf{x}|w_1)P(w_1)\},\{\Delta_1 p(\mathbf{x}|w_2)P(w_2)\}\} \quad (8)$$

The arguments of the decision rule returns the probabilities for a single EEG channel.

A sensor fusion is required to combine the probabilities of all channel recorded data. Under the assumption of channel independence, the joint conditional probability can be written as the product of the individual channels conditional probabilities:

$$p(\mathbf{X}|w_k) = p(\mathbf{x^1} \wedge \mathbf{x^2} \wedge \cdots \mathbf{x^{12}}|w_k) = \prod_{i=1}^{12} p(\mathbf{x}^i|w_k^i) \quad (9)$$

The new decision rule is obtained replacing $p(\mathbf{x}|w_k)$ by $p(\mathbf{X}|w_k)$ in (8).

3) Assemble of Events: Let define a trial as the assembly of 9 different events (which comprises one target and 8 non-targets, all unknown) and consider the classification probability of the event j given by $v_j(\mathbf{X})$ and obtained from (8) using (9). Let $W_{Target}(\mathbf{X}) = \{\cdots, v_i^T(\mathbf{X}), \cdots\}$ and $W_{nonTarget}(\mathbf{X}) = \{\cdots, v_k^{NT}(\mathbf{X}), \cdots\}$ $i,k \in 1\cdots 9$ $i \neq k$ be respectively the set of probabilities of events detected as targets and non-targets, then:

$$\hat{w}(\mathbf{X}) = \begin{cases} argmax(W_{Target}(\mathbf{X})) & \text{if } W_{Target} \neq \emptyset \\ \\ argmin(W_{nonTarget}(\mathbf{X})) & \text{if } W_{Target} = \emptyset \end{cases} \quad (10)$$

If more then one event (arrow or square) is detected as target, it is chosen the one with larger associated probability. If none of the events is detected as target then it is chosen the event with minimum probability within $W_{nonTarget}(\mathbf{X})$.

III. RESULTS

Several data sets were collected in several sessions for classification training. Each session consisted of 70 target events, 560 non-target events and 350 events that are neither target nor non-target. These events were created to increase the temporal interval between target events and therefore to reduce the target inter symbol interference (ISI). Each session lasted about 5 min. Classification models were obtained off-line and then tested on-line.

The performance of each channel was evaluated individually. The classifier used the decision rule (8). Classification was performed for different number of averaged-epochs for the 12 channels as shown in Fig. 3. The performance measure was the rate of false positive (FP) and false negative (FN). These measures are much more relevant than the simple error rate because the probabilities of the two events are substantially different. If a FP occurs, a wrong arrow direction will be detected which substantially degrades the performance of the overall system. If a FN occurs it simply reduces the transfer rate. Therefore, it is preferable to have a higher error rate of FN than FP. To control these rates, the Δ parameters in (7) were adjusted during training. Fig. 3 shows that for some channels after an average of 7 epochs the FP rate is zero or almost residual and the FN rate is zero for almost all channels. Consequently, after 7 averaged epochs we have almost a perfectly reliable system (see Fig.3). 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 (9). Fig. 4 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 (see Table I). After 5 epochs average, the FP rate is about 1%.

In the online experiments, the algorithms with best performance and best ranked channels were used. In the first experimental approach, the decision was made after averaging several epochs. The number of epochs was selected to 6 using the average of selected channels, achieving a 3.5 commands/min transfer rate. The fusion algorithm with 5 averaged epochs returned 4 commands/min. In the second

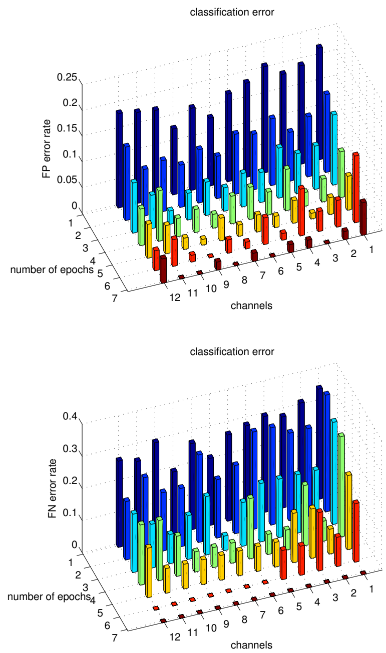

Fig. 3. FP (top) and FN (bottom) error rate for different number of epochs per trial. The electrodes channels are ordered as: Fz, Cz, C3, C4, CPz, Pz, P3, P4, PO7, PO8, POz and Oz.

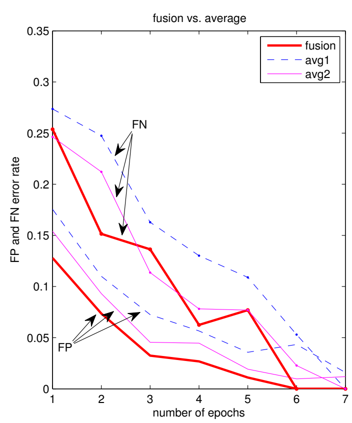

Fig. 4. FP and FN error rates for different number of epochs per trial. The curves represents: 1) fusion of selected channels (fusion); 2) average of selected channels (avg2); and 3) average of all channels (avg1).

experimental approach the decision was made only after two trials, each trial composed by one target epoch and 8 non-target epochs. The decision rule follows (10). The event with larger probability is chosen. For one trial, the FP, FN and error rate were respectively (0.0205, 0, 0.1642) and for two consecutive trials a residual error rate was achieved. This approach allowed a significant improvement achieving a 7 commands/min transfer rate. The results are summarized in Table II. All presented transfer rates were obtained with a FP accuracy above 95%.

IV. CONCLUSIONS AND FUTURE WORKS

A P300-based visual paradigm is proposed for wheelchair steering. The experimental off-line and on-line validation

TABLE I

OFFLINE RESULTS FOR AVERAGE AND FUSION OF SELECTED CHANNELS

Average of selected channels			
number of epochs	FP rate	FN rate	error rate
1	0.1541%	0.2463%	0.1878%
2	0.0931%	0.2121%	0.1272%
5	0.0192%	0.0769%	0.0449%
6	0.0097%	0.0227%	0.0445%
Fusion of selected channels			
1	0.1437 %	0.1279 %	0.2537%
2	0.0833 %	0.0736 %	0.1515%
5	0.0192 %	0.0110 %	0.0769%
6	0 %	0%	0%

TABLE II

ONLINE RESULTS: TRANSFER RATES

method	command/min
channel average (6 epoch)	3.5
channel fusion (5 epoch)	4
2 trials (1 target ep & 8 non-target ep)	7

showed that this system can be used as an effective BCI. Using a Bayesian classifier with sensor fusion, transfer rates of 7 commands/min were achieved. Notwithstanding the good results when compared with other reported works, the experimental validation was performed with only 2 healthy subjects, so more experimental results are needed to attest the system robustness. ISI compensation and artifact elimination are two relevant issues that have to be studied in future work. The first one was overcame extending the number of events. The artifact problem was minimized during experimental sessions.

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