SUBOPTIMAL SENSOR SUBSET EVALUATION IN A P300 BRAIN-COMPUTER INTERFACE

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ABSTRACT

A Brain-Computer Interface (BCI) is a specific type of human-computer interface that enables the direct communication between human and computers by analyzing brain activity. Oddball paradigms are used in BCI to generate event-related potentials (ERPs), like the P300 wave, on targets selected by the user. This paper deals with the choice of a reduced set of sensors for the P300 speller. A low number of sensors allows decreasing the time for preparing the subject, the cost of a BCI and the P300 classifier performance. A new algorithm to select relevant sensors is proposed, it is based on the backward elimination with a cost function related to the signal to signal-plus-noise ratio. This cost function offers better performance and avoids further mining evaluations related to the P300 recognition rate or the character recognition rate of the speller. The proposed method is tested on data recorded on 20 subjects.

1. INTRODUCTION

A Brain-computer interface (BCI) is a direct communication pathway between a human brain and an external device. Such systems allow people to communicate through direct measurements of brain activity, without requiring muscular movement [3]. BCIs may be the only means of communication for people who are affected by severe motor disabilities like spinal cord injuries and amyotrophic lateral sclerosis (ALS) [4]. Pattern recognition and signal processing techniques are used for the classification and the detection of specific brain responses. Most of the effective solutions use machine learning models [10, 13]. Whereas neuroscience knowledge guides the detection of expected signals, machine learning techniques allow modeling the signal variability over time and over subjects. One current challenge in the BCI community is to find an optimal set of sensors for a specific subject and paradigm. The choice of a reduced set of sensors decreases the time for preparing the subject/patient, the cost of a BCI, but it can also improve the performance of the classifier by selecting a reduced and better set of input features. Several strategies exist for selecting a sensor subset. First, it is possible to select sensors based on prior knowledge from previous experiments. In such case, the choice of the sensors is fixed and may be an issue for some subjects as the sensor subset varies across subjects [8]. Indeed, it is better to personalize the sensor subset in relation to the user. For a set with N sensors, there exist 2^N candidate subsets. We distinguish three main ways for searching the best subset: complete, random and sequential. The complete search is usually intractable as the search space grows exponentially. The random search starts with a randomly selected subset and add randomness in the sequential approach or it generates new random subsets, like the Las Vegas algorithm [1]. The sequential search does not guarantee optimality. Several variations are described in the literature, like the greedy hill-climbing approach, the forward selection, backward elimination, and bi-directional selection.

In this paper, we will consider the backward elimination. The problem that we address in this paper is how to find an efficient criterion for removing the less relevant sensors, *i.e.* how to evaluate the relevance of a particular sensor subset. The consequences of the selected sensors should be then evaluated in the P300 speller. The paper is organized as follows. The P300 speller is presented in the second section. The sensor selection strategy is explained in the third section. The different criteria for the sensor evaluation are given in the fourth section. Section five is dedicated to the proposed methods. Data and the protocol experiment are detailed in the sixth section. Finally, the performance of the sensor selection is discussed in the last section.

2. P300 SPELLER

A P300 speller allows people to write characters (letters, digits, symbols) on a computer screen. Oddball paradigms are used in BCI to generate event-related potentials (ERPs), like the P300 wave, on targets selected by the user. A P300 speller is based on this principle [6]. A 6×6 matrix containing all the available characters is presented to the user on a computer screen. To spell a character, the user has to focus on the character s/he wants to spell. When the user focuses on a cell of the matrix, it is possible to detect a P300 (a positive deflection in voltage at a latency of about 300 ms in the EEG) after the cell has been intensified. To generate ERPs, the row and columns are intensified randomly. Row/column intensifications are block randomized in blocks of 12 (6 rows and 6 columns). The sets of 12 intensifications is repeated N_{epoch} times for each character. Therefore, $2N_{epoch}$ possible P300 responses should be detected for the recognition of one character.

A P300 speller is composed of two steps, each one being a classification problem. The first classification step is to detect the presence of a P300 in the electroen-

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cephalogram (EEG). The second one corresponds to the combination of a minimum of two P300 responses for determining the right character to spell (one row and one column). These two steps are sequential. The detection of P300 responses corresponds to a binary classification: one class represents signals that correspond to a P300 wave, the second class is the opposite. The timing of the flashing lights provide the triggers for the P300, which depends on the user. Although a P300 response can be expected at one particular latency, it is possible that the user does not produce a P300 response at the right moment as many artifacts can occur. In the character recognition step, the outputs of the P300 classification are combined to classify the main classes of the application (characters). In the oddball paradigm, a character is defined by a couple (row,column). The flashing lights are on each row and column and not on each character. The character is supposed to correspond to the intersection of the accumulation of several P300 waves. The best accumulation of P300 waves for the horizontal (resp. vertical) flashing lights determines the row (resp. the column) of the desired character.

We note $V \in \mathbb{R}^{12\times N_{epoch}}$ the matrix containing the cumulated probabilities of the P300 detection for each of the 12 flashes and for each epoch.

$$V(i,j) = \sum_{k=1}^{j} E_{P300}(P(i,k)) \qquad (1)$$

where $P(i,j) \in \mathbb{R}^{N_f \times N_e}$ is the pattern at the epoch j corresponding to the subject response for the flash i, $(i,j) \in \{1,\ldots,12\}\times\{1,\ldots,N_{epoch}\}$. N_f and N_e are the number of sensors and the number of sampling points representing the signal, respectively. E_{P300} is a classifier that returns a confidence value $v \in [1;0]$: 1 (resp. 0) denotes a perfect confidence that P300 response is detected (resp. not detected).

At each epoch j, it is possible to evaluate the coordinate (x_j, y_j) of the selected character by:

$$x_j = \operatorname*{argmax}_{1\le i\le 6} V(i,j) \qquad (2)$$

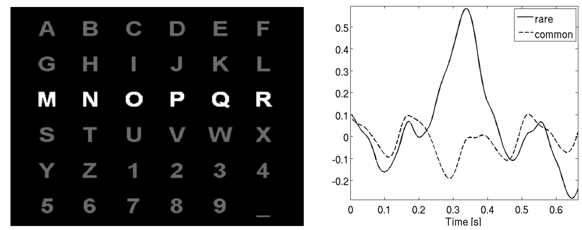
$$y_j = \operatorname*{argmax}_{7\le i\le 12} V(i,j). \qquad (3)$$

We denote by $E_{Speller}(\{P(1,N_{epoch}),\ldots,P(12,N_{epoch})\}) = (row, column)$, the selected character.

3. SENSOR SELECTION

3.1 Backward elimination

The chosen method for adaptively selecting relevant sensors is based on the backward elimination. It involves starting with all candidate variables and testing them one by one for their significance, deleting those that are not significant. At each iteration of the algorithm, each of the N_s remaining sensors is removed one by one, the subset of N_s-1 remaining sensors are tested and N_s performance scores are given. By choosing the subset with the highest score, the less relevant sensor is eliminated. A subset with a high score means that the removed sensor has a low impact on the performance score. In this



(a) Graphical User Interface (b) P300 evoked potentials

Figure 1: P300-BCI Speller. Fig. 1(a): Screen display, Fig. 1(b): Average P300 response on Cz

work, we eliminate the two worst sensors at each step of the algorithm, *i.e.* the sensors corresponding to the two subsets with the highest score. This iteration procedure is continued until two sensors only are left. The method leads us to rank the relevance of each sensor: a relevant sensor is never eliminated whereas a useless sensor is eliminated during the first steps of the algorithm. The rank of a sensor is defined by $N_s/2 - i$ where i is the iteration where the sensor was removed.

3.2 Subset evaluation

Two types of criterion can be used for evaluating a subset. First, independent criteria aim at evaluating the goodness of a feature or a set of features by considering the underlying characteristics without involving any classification algorithm. For instance, independent criteria can be based on information measures, distance measures, dependency measures, and consistency measures [2]. Second, a dependency criterion requires a predetermined mining algorithm in feature selection. It uses the performance of the mining algorithm applied on the selected subset to determine which features are selected. In a classification problem, the accuracy is often used as a dependent criterion for feature selection. As features are selected by the classifier that will use these same selected features for classifying unseen signals, this strategy usually provides better performance as it finds features that are better suited to the task. However, such method tends to be more computationally expensive as they require training and testing models (with a K-fold cross validation to overcome overfitting). In a P300 speller, three main criteria can be used for the subset evaluation: the evaluation of the EEG signal, the recognition of the P300 responses (E_{P300}) and the evaluation of the speller, *i.e.* the application ($E_{Speller}$). Besides, the classification of the P300 can include a preprocessing steps for creating spatial filters (SF).

The criteria that are used during the backward elimination as a function for selecting the best subsets are resumed in Table 1. These criteria can be viewed as three basic criteria applied without ($C1$, $C2$, $C3$) or with ($C4$, $C5$, $C6$) spatial filtering as preprocessing. $C1$ and $C4$ correspond to the signal to signal-plus-noise ratio (SSNR), which can be directly compared from signal properties. The other criteria needs classification results. It requires the classification of the P300 responses with E_{P300} ($C2$ and $C5$) or the complete character recognition steps with E_{P300} and $E_{Speller}$ ($C3$ and

$C1$:			$SSNR$		
$C2$:			E_{P300}		
$C3$:			E_{P300}	+	$E_{Speller}$
$C4$:	SF	+	$SSNR$		
$C5$:	SF	+	E_{P300}		
$C6$:	SF	+	E_{P300}	+	$E_{Speller}$

Table 1: The criteria for evaluating sensor subsets.

$C6$). For $C2$ and $C5$, the criterion represents the recognition rate of the P300 speller that is defined as the average recognition rate over every epoch. For $C3$ and $C6$, it represents the recognition rate of character for the P300 speller. It is worth mentioning that $E_{Speller}$ requires E_{P300}. The more steps are added, the more the method gets computationally expensive. The goal here is to identify the best criterion, to analyze the impact of spatial filtering and if the performance is related to the number of processing steps.

4. METHODS

This section is dedicated to the methods that were used for creating the spatial filters, evaluating the SSNR and classifying the P300 responses.

4.1 Spatial filters

For the evaluation of the EEG signal we consider the xDAWN algorithm that is fully described in [15, 14]. This method is based on two main hypotheses. First, there exists a typical response synchronized with the target stimuli superimposed with an evoked response by all the stimuli (target and non-target). Second, the evoked responses to target stimuli could be enhanced by spatial filtering. We consider an analytical model of the recorded signals X that is composed of three parts: the P300 responses (D_1A_1), a response related to every superimposed evoked potentials (D_2A_2) and the residual noise (N)

$$X = D_1A_1 + D_2A_2 + N. \tag{4}$$

where $X \in \mathbb{R}^{N_t \times N_s}$, N_t and N_s are the number of sampling points over time and the number of sensors, respectively. D_1 and D_2 are two real Toeplitz matrices of size $N_t \times N_1$ and $N_t \times N_2$ respectively. D_1 has its first column elements set to zero except for those that correspond to a target. For D_2, its first column elements set to zero except for those that correspond to stimuli onsets. N_1 and N_2 are the number of sampling points representing the target (the P300 response) and superimposed evoked potentials, respectively. N is a real matrix of size $N_t \times N_s$.

By applying spatial filters $U_1 \in \mathbb{R}^{N_s \times N_f}$, the goal is to enhance the signal to signal-plus-noise ratio (SSNR) of the enhanced P300 responses ($D_1A_1U_1$), where N_f is the number of spatial filters

$$XU_1 = D_1A_1U_1 + D_2A_2U_1 + NU_1. \tag{5}$$

We define the SSNR in relation to the spatial filters by:

$$SSNR(U_1) = \frac{Tr(U_1^T \hat{A}_1^T D_1^T D_1 \hat{A}_1 U_1)}{Tr(U_1^T X^T X U_1)} \tag{6}$$

where $\hat{A}$ corresponds to the least mean square estimation of A_1.

The SSNR is maximized by:

$$\hat{U} = \underset{U_1}{\operatorname{argmax}}\, SSNR(U_1). \tag{7}$$

In the definition of the SSNR, we replace $\hat{A}_1$ by $B_1^T X$ where B_1^T is a part of the least mean square estimation. Then, we apply a QR decomposition on $D_1 = Q_1R_1$ and $X = Q_xR_x$. Finally, one can express Eq. (6) as:

$$SSNR(V_1) = \frac{Tr(V_1^T (Q_x^T B_1 R_1^T R_1 B_1^T Q_x) V_1)}{Tr(V_1^T V_1)}, \tag{8}$$

where $V_1 = R_xU_1$. V_1 is therefore obtained from the Rayleigh quotient, whose solution is the concatenation of N_f eigenvectors associated with the N_f largest eigenvalues of $Q_x^T B_1 R_1^T R_1 B_1^T Q_x$ [7]. These vectors are estimated thanks to a singular value decomposition (SVD) of $R_1 B_1^T Q_x = \Phi\Lambda\Psi^T$, Φ and Ψ being two unitary matrices and Λ is a diagonal matrix with nonnegative diagonal elements in decreasing order.

The solution of Eq. (7) provides the spatial filters, which are ordered in decreasing order by relevance impact.

$$\hat{U}_1 = R_x^{-1}\Psi \tag{9}$$

4.2 SSNR

The evaluation of the SSNR depends on the application of the spatial filters. If the spatial filters are used, it is possible to directly obtain the SSNR thanks to Eq. (7). Indeed we have after simplification:

$$SSNR(V_1) = \frac{Tr(V_1^T (\Psi\Lambda^2\Psi^T) V_1)}{Tr(V_1^T V_1)}. \tag{10}$$

By considering again the Rayleigh quotient for V_1, the associated solution corresponds to the N_f largest eigenvalues of $\Psi\Lambda^2\Psi^T$, which are Λ^2. In addition, the denominator can be easily simplified to the trace of the identity of size $N_f \times N_f$, as Ψ and Q_x are unitary matrices. Therefore, the SSNR of the enhanced signal, *i.e.* after spatial filtering, can be defined by:

$$SSNR = Tr(\Lambda^2)/N_f. \tag{11}$$

When spatial filters are not used for the evaluation of the SSNR, the SSNR shall be calculated directly by replacing U_1 by the identity I:

$$SSNR = \frac{Tr(\hat{A}_1^T D_1^T D_1 \hat{A}_1)}{Tr(X^T X)} \tag{12}$$

4.3 Classifier

For the binary classification of P300 and no P300 responses, we consider the Bayesian linear discriminant analysis (BLDA) [12]. This classifier has been proved efficient, it is fast to train and does not require hyperparameters to adjust [8]. It finds a discriminant vector w such that the distance between the associated vector of a class c and $w^T p$ is minimized when the input vector p belongs to the class c. The vector p is obtained by the concatenation of the different time-course signals. For the classification, only the four first components of the enhanced signal are considered ($N_f = 4$ if $N_s \geq 4$, $N_f = N_s$ otherwise). This classifier is used for E_{P300}.

5. DATA AND PROTOCOL EXPERIMENT

5.1 Data acquisition

The EEG signal was recorded on 20 healthy subjects (average age=26 ,standard deviation=5.7) [11]. For testing the different subset evaluations methods, we consider two sessions: one for training the classifier, the other for testing. For the training and test sessions, the subject had to write 50 and 60 characters respectively. Each row and column in the spelling matrix was randomly intensified for 100ms. The delay between two consecutive intensifications was 70ms for the training (resp. 130ms for the test), leading to an interstimulus interval (ISI) of 170ms for the training session (resp. 230ms for the test). For each symbol, the number of epochs was 10 ($N_{epoch} = 10$).

5.2 Pre-processing

The EEG signals are sampled at 100Hz. Before processing the data, they were first filtered by bandpass filter with cut-off frequencies at 1Hz and 20Hz. The signal was then down sampled to obtain 25 sampling points per second. For each sensor, the signals were then normalized as to have a zero mean and standard deviation equal to one.

Although the spatial filters and the classifier can be used independently as a cost function during the backward elimination, we always use spatial filters for enhancing the signals before training the classifier once the sensor subset are defined. Indeed, this method has been shown efficient in previous works [15, 14].

6. RESULTS

Figure 2 presents the accuracy on the test database for each subset evaluation method and for different sizes of subset. The selection methods that do not consider the spatial filters ($C1$, $C2$ and $C3$) provide the worst results (between 66.42% and 89.58% for a subset of eight sensors). With eight sensors, the average recognition rate of the speller is 94.92%, 94.00% and 93.00% for the selection with $C4$, $C5$ and $C6$ respectively. These results suggest that eight sensors suffice and provide good results. With 32 sensors, the recognition rate of the speller is 95.83%. From 8 to 32 sensors, the gain in peformance is less than 1%, showing the relevance of the method for sensor selection. For eight sensors, the impact of the spatial filters in the sensor subset evaluation is 5.34%, 11.25% and 26.58% for $C4$, $C5$ and $C6$ respectively, suggesting that the criterion based on the SSNR is less dependant to the spatial filters. It also proves that spatial filtering has a critical impact on the selection of suitable sensors. Finally, $C4$ is sufficient for creating suboptimal sets of sensors. This criterion based of SF+SSNR can be done in one step thanks to the xDAWN algorithm. It avoids considering further steps like the E_{P300} and/or $E_{Speller}$, which increase the complexity of the sensor selection procedure and provide less relevant sensors.

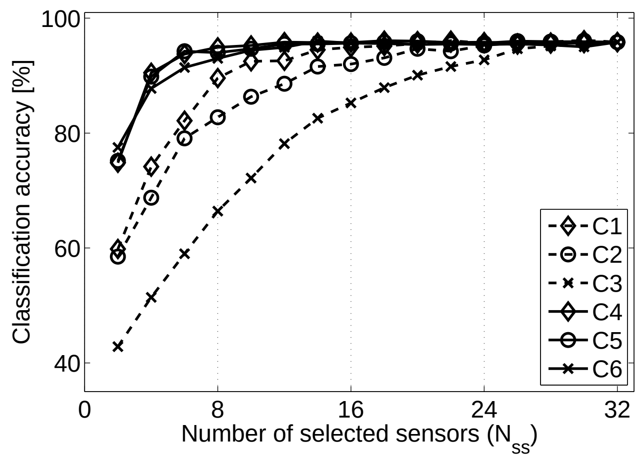


Figure 2: Accuracy of the P300 speller in relation to the number of selected sensors, after 10 epochs.

The accuracy of the P300 speller in relation to the number of epochs is presented in Fig. 3. While the performance naturally decreases in relation to the number of epochs, the accuracy remains acceptable till about five epochs. The best performance are always produced with $C4$ and $C5$.

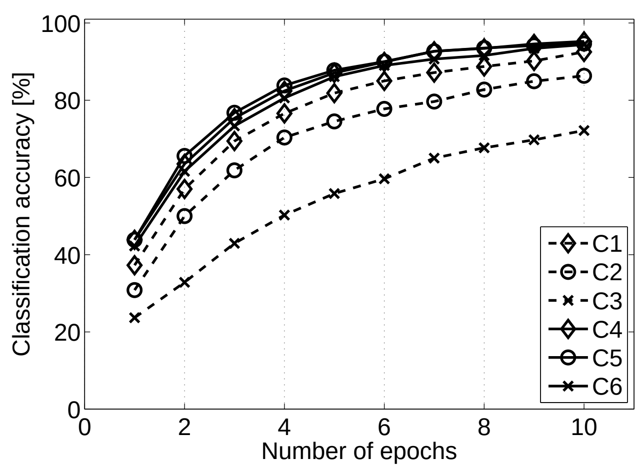
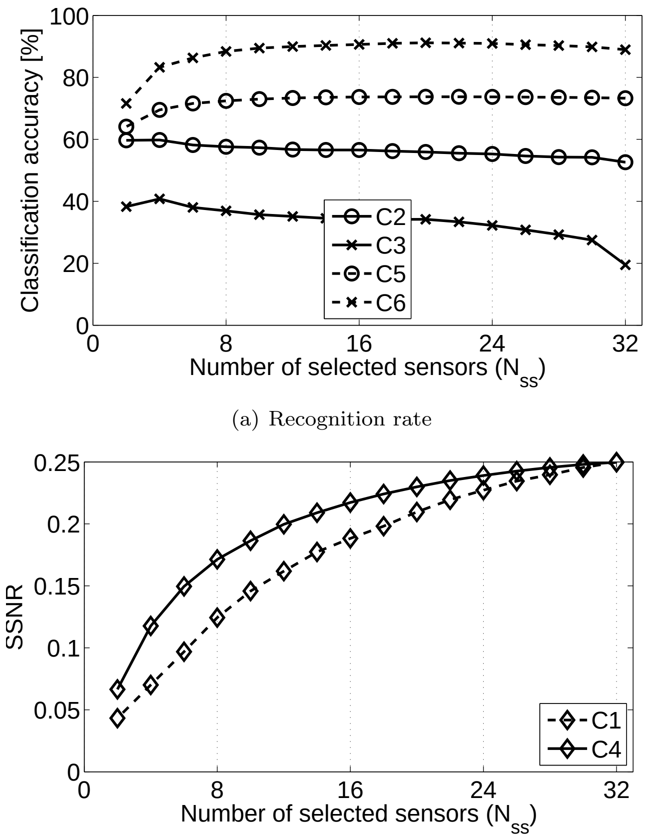


Figure 3: Accuracy of the P300 speller in relation to the number of epochs, for 8 selected sensors.

The evolution of the sensor selection criterion over the number of selected sensors is presented in Fig. 4. The selection criterion value decreases in relation to the number of remaining sensors in the backward elimination, as expected. However, we observe the inverse behavior when there is no spatial filters. This is probably due to the large size of the input data and the low number of training samples. With pre-processing, feature reduction improves the accuracy for the selected classifier. The evolution of the values for $C1$ and $C4$ also decreases in relation to the number of remaining sensors during the backward elimination. In addition, the use of spatial filters in $C4$ allows keeping the SSNR higher while decreasing the number of sensors. The impact of the spatial filters is higher when the number of remaining sensors is low as the gap between $C1$ and $C4$ is large.



(a) Recognition rate

(b) SSNR

Figure 4: Evolution of the different criteria in relation to the number of selected sensors.

7. CONCLUSION AND PROSPECTS

Several strategies for the sensors subset evaluation of a P300-BCI speller have been evaluated. The best strategies always consider spatial filters. In addition, the two best methods are based on the evaluation of the SSNR and the P300 recognition, showing that it is useless to take into account the speller stage. While the SSNR and the P300 recognition provide both equivalent results, both consider spatial filters based on the xDAWN algorithm. Hence, the SSNR is directly computed during the creation of the spatial filters whereas the P300 classification requires several training and testing. It shows that the evaluation of the SSNR with spatial filtering ($C4$), which can be done in one step, is sufficient for creating suboptimal sets of sensors, *i.e.* suboptimal sets of features for the classifier. This strategy allows avoiding further processing while keeping good performance.

Preliminary analysis of the ranks of each sensor obtained with $C4$ evaluation suggest that several sensors are common to every subject. For the different subsets of eight sensors, which are personalized to each subject, five sensors are common to half of the subjects. These sensors are mostly located on the occipital area, confirming previous works suggesting that occipital sites are relevant [5, 9]. Further works will treat the selection of universal sensor locations, a common subset that provides high accuracy for the majority of individuals.

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