P300-based Brain-Neuronal Computer Interaction for Spelling Applications

C.-C. Postelnicu and D. Talaba

Abstract—A brain-neuronal computer interaction (BNCI) system can provide a communication channel for severely disabled people or a supplementary control channel for able-bodied subjects. In this paper a physiological hybrid P300-based speller that uses a modified stimulus presentation paradigm—the half checkerboard paradigm (HCBP) is evaluated. The speller uses electrooculography (EOG) and electroencephalography (EEG) signals for selecting alphanumeric characters or commands arranged in an 8 x 9 matrix. In this study a group of subjects, who can voluntarily gaze at a target, used the checkerboard paradigm (CBP) and HCBP-based spellers in a counterbalanced fashion for comparing their performances under a series of online tests. A 16-character long text was spelled by each subject, while a 13-character long text was used for calibrating the system. By using the HCBP the time required for spelling one character is reduced, resulting in higher information transfer rates (ITRs). The results suggest that the HCBP has the potential to provide a more effective P300 paradigm with a major importance for people with neuromuscular diseases and also for healthy people as a supplementary communication channel.

Index Terms—Brain-neuronal computer interaction, Electroencephalography, Electrooculography, P300 speller, Hybrid BCI

I. INTRODUCTION

The brain-neuronal computer interaction (BNCI) defines a communication system that allows people to send commands to external devices, such as spelling devices, virtual environments, or robots by analyzing the user’s electrophysiological signals. The term was introduced by the European Commission (EC) and includes the Brain Computer Interfaces (BCIs) and devices based on electrophysiological signals, such as electrooculography (EOG) or electromyography (EMG) [2], often in combination. The BCI technology involves recording the brain electrical activity via electroencephalography (EEG) followed by a classification of the acquired signals in order to generate commands. Although some other methods for brain electrical activity recording have been proposed, such as functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), positron emission tomography (PET) or electrocorticography (ECoG), the EEG method is most frequently used because it requires relatively simple and inexpensive equipment [52]. Several EEG signals have been used for BCI control, for example: μ and β rhythms, synchronization and desynchronization evoked by motor imagery (ERS and ERD), slow cortical potentials, steady state visual evoked potentials (SSVEP) or the P300 event related potential (ERP). The P300 ERP represents a positive peak at about 300 ms in the EEG signals over parietal cortex that occurs after an auditory, visual or somatosensory stimulus that was presented to the user [17], [46]. The P300 ERP has been widely used in spelling applications [20], [26], [47], for environmental control [18] or Internet browser application [45].

Eye movements represent the voluntary or involuntary movements of the eyes, used for acquiring, fixing and tracking visual stimuli. Several methods such as magnetic coils, video processing or EOG were used for eye movement recognition [9], [14], [16]. The EOG is the measurement of the electrical signals around the eye. The principle is based on the fact that the human eye can be modeled as an electrical dipole with a positive pole represented by the cornea, and the negative pole by the retina. The electrical signals of the eye’s dipole can be measured by using pairs of electrodes placed above and below the eyes at reference positions [10]. The use of EOG signals was previously reported for several applications among which guiding a wheelchair for disabled people [8], [50], controlling a robotic arm by means of high-level commands [40], a movable robot [13], a multi-task gadget [24], or for navigation in a virtual environment [42]. Two EOG channels, vertical and horizontal, can be recorded by using the electrodes placed as in Figure 1.

Recently, experiments with combined systems of two BCIs, or one BCI and another system, namely hybrid BCIs (hBCIs) [5], [36], [39], suggested that higher accuracy rates and lower frustration ratings could be obtained [39]. For the research on hBCIs combinations of ERD and SSVEP [3], [4], [11] or P300 and SSVEP [19], [34] control signals have been evaluated. Furthermore, in the context of hBCIs combinations of EEG and EMG [32], [33] or eye gaze and BCIs [49], [53] have been proposed. Details over the hBCIs and the novel ways to extend BCIs can be found in [5].

This paper presents the results obtained by the authors in the case of a physiological hybrid paradigm based on the combined use of EOG signals and a BCI system. The
paradigm is designed and evaluated on a physiological hBCI P300-based speller application [5].

A. The P300 speller

The first P300-based speller was introduced by Farwell and Donchin [20]. In their application, a 6 x 6 matrix of flashing symbols is displayed and the user is able to select them by brain waves. Items are organized in rows and columns (row-column paradigm, or RCP) being intensified in a random order, which constitutes an “odd-ball” paradigm. The subject focuses his attention to one of the 36 items and only the flashing groups that contain the desired item would elicit a P300 wave in the EEG signals.

In [25] a different presentation method was proposed - the single character paradigm, or SCP. The speller flashes one item at a time, the results suggesting that the SCP produces higher P300 peaks than the RCP [26] and higher accuracy rates [25]. The amplitude of the P300 potential is higher for the SCP because the target appears rarely compared to the RCP, but compared to the RCP-based speller the SCP has a major disadvantage represented by a longer time required for spelling a character [26]. Recently, in [47] the “checkerboard” paradigm, or CBP, was proposed. It is based on an 8 x 9 matrix filled with characters and commands, and groups of non-adjacent items are pseudo-randomly flashed, thus avoiding the “adjacency-distraction problem” and the “double flash” issues that appear in the RCP [21], [47]. The study conducted with able-bodied subjects revealed higher values for accuracy and information transfer rates (ITRs). Also, the same study conducted with people suffering from amyotrophic lateral sclerosis (ALS) revealed higher online accuracy rates for the CBP [47]. The CBP avoids overlapping successive target epochs by applying restrictions in the flow of flashing the items. A follow-up study improved the original CBP design by adding a predictive solution to it, resulting in an increased ITR [43]. Furthermore, the CBP was improved by applying a supplementary restriction for the groups of flashing items, which assumes that adjacent items, on rows, columns or diagonals cannot flash in the same group [23].

A novel speller, the lateral single-character (LSC), proposed in [38] was tested on individuals with neuromuscular disorders. As it was proved by the conducted
tests, by using the hemispheric asymmetries in the visual perception improved ITRs and accuracy rates are obtained by the LSC paradigm compared with the RCP one. Thus, the paradigm is directly based on the use of user’s gaze to achieve the obtained results [38].

Recently, a paradigm that does not depend on the user’s gaze was evaluated, but lower ITRs were achieved [35]. The gaze independent paradigm is addressed to patients in the late stage of amyotrophic lateral sclerosis (ALS) disease that may lose all normal motor capacities, including extraocular muscle control [37], [48]. The elements are displayed sequentially in a central disk, thus the user being not obliged to perform eye movements to gaze at a target [35].

Other research teams proposed paradigms based on ‘multiple flashes’, in which multiple rows or columns are flashed at the same time [6], or on binomial coefficients, in which flashing items are arranged in a non-row-column manner [27], [28], [29], [30]. A complete review on P300-based presentation paradigms and their corresponding BCI applications is presented in [22].

B. Research problem

Recent results show that, for normal subjects, the accuracy of the P300 speller applications considerably depends on gaze direction [12]. Higher classification accuracies were obtained when the users were allowed to gaze at the desired character instead of gazing only at the center of the matrix [12]. In a recent study, we proposed a paradigm that uses both EOG and SCP in the same application for selecting commands to control a smart house [41], obtaining encouraging results. Based on the CBP and EOG, the performances of a novel physiological hybrid paradigm, the half checkerboard paradigm - HCBP, are evaluated in this paper. Compared with the CBP, our paradigm additionally splits the matrix in two separate regions – “left” and “right” (see Figure 2). By using the EOG, the area where the user gazes at can be identified. In this manner only the symbols that belong to that area will flash (36 symbols out of a total of 72 during the selection of an item). Thus, the assumption is that higher ITRs should be achieved. The paradigm is addressed to people who can voluntarily gaze at a target and to disabled people who still retain some eye movements. Another issue that is investigated in this paper is related to the influence of the eye movement artifacts, blinks or winks, superimposed over the EEG signals. An offline analysis is performed in order to assess the influence of such artifacts in the classification of the P300 potentials.

Although the proposed approach appears very logical, and is based on existing knowledge, this principle has never been formulated before. Our research establishes that combining EOG and BCI for spelling applications, and not only, could lead to better results. The particular motivation in this case is to increase the quality of life of disabled patients by using a physiological computer interface system which integrates in a hybrid approach their available biopotentials.

In this study, CBP and HCBP-based spellers are compared by analyzing the results obtained by a group of able-bodied subjects under a series of online spelling sessions. The accuracy, symbols per minute and ITR indicators are computed to assess the performances of the proposed paradigm.

II. MATERIALS AND METHODS

A. System architecture

The proposed system uses the subject’s biopotentials, EEG and EOG, for selecting items arranged in a matrix. It uses the EOG signals for the identification of an area where the user gazes at, the “EOG area search” block, and the EEG signals for the final selection. A calibration is first required in order to associate the user’s gaze with the location on the monitor, the “EOG calibration” block (see Figure 3). A modified expert system proposed in [42] was used to identify the eye movements. Several improvements were performed in order to track the user’s gaze for the entire spelling process. The selection of an item assumes a flashing process of the symbols contained by the matrix (see Figure 2) and the classification of the recorded EEG signals resulting for the flashed symbols. An EOG recalibration is required after each group of two spelled characters. This method was chosen in order to correctly identify a defined area for the entire spelling process, but the obtained value may vary according to the user’s EOG signals parameters.

![Fig. 3. System architecture](image)

B. Paradigm design

The CBP-based speller is based on flashing multiple symbols at the same time, with the restriction that adjacent symbols cannot be included in the same group. Items are considered to be adjacent if they are on the same row or column [47]. The CBP flashes groups of 6 symbols and it avoids overlapping target epochs (800 ms for the original design) used for the classification [23], [47].

Our paradigm assumes that the matrix is divided into two areas: “left” and “right” (see Figure 2). An area is identified by classifying the eye movements extracted from the user’s EOG signals. It results that only half of the total of 72 symbols are flashed, with a reduced time required for an item selection. In order to identify which item was chosen by the user an average has to be computed based on a number of
flashes corresponding to each item. Thus, each item must be flashed multiple times for a good classification of the signals.

We chose a total of 10 sequences during which items from an area are flashed in a random order, a sequence comprising all the items in that area. By flashing only 36 symbols it is not possible to flash groups of 6 symbols at a time without avoiding the temporary overlap of epochs corresponding to the items. Thus, in order to respect this restriction we superimposed the symbols from an area on two virtual matrices similar with the CBP, but we flashed groups of 4 or 5 items at a time, as presented in Figure 2. Randomly, for each sequence four groups are allocated with an extra item, thus, a sequence is defined by eight groups, four with 4 items and four with 5 items (see Figure 2). Each set of items flashed for 62.5 ms followed by a pause of 62.5 ms, resulting that one set flashed every 125 ms. One sequence was completed in 1 s, while the total time required for selecting an item was of 10 s (8 groups x 10 sequences x 125 ms). Each item of the identified area flashed 10 times, facilitating the classification of the P300 potentials.

Additionally, for the HCBP-based speller an EOG recalibration is required. Its duration is of 2 s and its purpose is the recalibration of the EOG algorithm that identifies the area where the user gazes at. For this phase, the user was instructed to gaze at the green rectangle situated in the center of the matrix. At this time the algorithm determines that the user is gazing at the origin of our system.

C. Influences of the EOG signals in the P300 classification: offline analysis

Initial tests were performed in order to validate the implemented application. Four users were asked to follow a simple task of spelling two groups of words “TRAINING_SET” (12 characters) and “TESTING_WORD” (12 characters). Two users reported that they were not able to count all the 10 flashes for a target item, reporting a number between 8 to 10 flashes. After an offline analysis, the fact that the users were blinking during a few flashes was revealed, being thus unable to see the flashing items. In Figure 4 two blinks are visible in the EOG-v (EOG vertical) channel, while in the sequences (Seq) channel several flashes appear during the blink action. The flashes that appear during the blink cannot be viewed by the user. A blink has an estimated duration of 0.1 – 0.4 s [44]; thus, the question that arises is whether the classification is influenced by this parameter.

A blink represents the rapid closing and opening of the eyelid, being performed every few seconds to keep the eyes from drying out and to protect them from irritants. In order to determine the influence of blinks in the classification process, an offline analysis based on two tests was performed as follows:

- the first test assumed a normal classification process for which a total of 10 flashes were averaged for each item contained by the matrix;
- the second test assumed exclusion of buffers corresponding to the items during which a blink was identified from the computed average. A few flashes were not seen by the user since the length of a blink is of around 100 - 400 ms, while a group of items is flashed for 62.5 ms.

A classifier based on linear discriminant analysis (LDA) was trained using the EEG signals corresponding to the training words spelled “TRAINING_SET”, and subsequently, the accuracy of the classifier was verified by using the signals recorded for the second group of words “TESTING_WORD”. The entire classification procedure is described below, in Section II.G.

![Fig. 4](image-url) EOG artifacts are highlighted in the EEG and EOG signals. The example is given for the two proposed EOG rejection algorithms (Classifier 1, C1, and Classifier 2, C2), with rejected flashes highlighted.
Four electrodes, placed at Cz, Pz, PO7 and PO8 locations according to the 10/20 extended International (see Figure 1). Vertical movements were recorded by the A-B using four electrodes disposed in two bipolar configurations signals of the present study. The EOG signals were recorded Engineering GmbH, Austria), for electrophysiological signals were detected thus, we concluded that an evaluation has to be performed for each user in order to better calibrate the system.

Furthermore, for Subject 2 EOG artifacts were visible in the EEG signals (see Figure 4). Thus, a second test was performed in order to better assess the influence of the EOG signals in the process of the P300 potentials classification. The test assumed the exclusion of all flashing items during an epoch of 750 - 950 ms. The length of an epoch was variable, being computed by considering the length of the blink and its possible influence over the flashing items (see Figure 4, channel C2), while its reference value was of 750 ms (the length of the classification epoch). The results obtained for the experiment are listed in the last column of Table I, where it can be seen that higher accuracy rates were obtained for two subjects by considering the two rejection methods.

We concluded that the EOG artifacts do influence the classification accuracy rates. Thus, for the final evaluation we considered the inclusion of a test for each user in order to assess the influence of the EOG signals in the process of classifying the P300 potentials. The offline analysis was performed for each user after the calibration data were recorded and the most suitable classifier was chosen.

D. Participants

Ten healthy subjects (S1-S10, 7 male, 3 female, aged 24-30) participated in the experiments and all of them gave their written informed consent. All participants had normal or corrected-to-normal vision by their own report. Four of them (S1-S4) had previous experiences with EOG-based systems. Subjects tested for the offline analysis were not included in the online sessions.

E. Data acquisition and signal processing

A multimodal amplifier, g.USBaMg (g.tec Medical Engineering GmbH, Austria), for electrophysiological signals such as EEG, EOG or EMG, was used for recording the signals of the present study. The EOG signals were recorded using four electrodes disposed in two bipolar configurations (see Figure 1). Vertical movements were recorded by the A-B pair (EOG-v), and horizontal movements by the C-D pair (EOG-h). Four electrodes, placed at Cz, Pz, PO7 and PO8 locations according to the 10/20 extended International System [1], were used for recording the EEG signals, since most of the P300 energy in BCI applications is captured at these locations [23], [31], [43], [47]. All channels were grounded to the user’s forehead, electrode E, referenced to the right earlobe, electrode F, and all impedances were kept below 10 kΩ.

All signals were acquired at a sampling rate of 256 Hz and filtered by a 50 Hz notch filter. The EEG signals were band-pass filtered between 0.5 – 30 Hz, while the EOG signals were low-pass filtered at a cut-off frequency of 30 Hz. The filters were enabled from the acquisition device. The EOG signals were further high-pass filtered by a finite impulse response (FIR) filter with a Bartlett-Hanning window at a cut-off frequency of 0.05 Hz [42].

F. The expert system and EOG calibration

To build our hybrid system, EOG based eye movements (saccades, blinks and winks) identification algorithms have been implemented. Details about the expert system used for eye movement identification process are presented in [42]. Based on a set of fuzzy logic rules and a deterministic finite automaton the peak values in the EOG signals are associated with eye gaze angles. Compared to the original work, for the present study the user is not constrained to perform each eye saccade by gazing at the center of the screen. The user can freely gaze at a desired item and the algorithm identifies each eye saccade and computes in which area the user gazes at. During the “EOG symbol search” phase blinks and winks are searched within the vertical EOG acquired signal in order to reject them. Eye saccades are correlated with degrees of visual angle, and the algorithm can estimate the area where the user gazes at. For an eye saccade a corresponding peak appears in the horizontal EOG signal. In the present study we considered only the horizontal position of the user’s gaze since the vertical position is not relevant because of the vertical virtual separation line defined. Thus, saccades are searched only within the horizontal EOG signal, while blinks and winks are rejected by analyzing both EOG channels.

A correlation between degrees of visual angle and the user’s gaze point is automatically performed during the “EOG calibration” phase (see Figure 2) when the application starts. The user is instructed to look at a series of fixed green squares that are successively shown on the monitor of the computer. The squares are drawn at fixed distances: 0 cm (origin - see Figure 2), 1.75 cm, 3.5 cm, 5.25 cm, 4.4 cm, 8.85 cm and 13.4 cm being correlated with the degrees of the visual angle: 2°,
are allocated for each step in the eye gaze sequence). The time required for the EOG calibration is of around 90 s (2 s range 10-15°, respectively for the negative interval. The total identified, then that value is computed using the ratio for the peak amplitude value higher than the specified range is assumed linearity by intervals was used. If an eye saccade with linearly for the entire interval 2-15°; thus, a model that amplitude values corresponding to eye saccades do not vary filtered horizontal EOG signal and user’s gaze point. The correlation between the peak amplitude values from the followings values an average of a total of three left/right saccades: ±2°, ±5°, ±10°, and ±15° is computed (see Figure 5). Three intervals are defined for each left or right saccades as follows: 2-5°, 5-10°, 10-15°, and the corresponding negative ones. The intervals were defined in order to achieve a high correlation between the peak amplitude values from the filtered horizontal EOG signal and user’s gaze point. The amplitude values corresponding to eye saccades do not vary linearly for the entire interval 2-15°; thus, a model that assumes linearity by intervals was used. If an eye saccade with peak amplitude value higher than the specified range is identified, then that value is computed using the ratio for the range 10-15°, respectively for the negative interval. The total time required for the EOG calibration is of around 90 s (2 s are allocated for each step in the eye gaze sequence).

G. Classification

Initially, calibration data must be collected for each user. Each user was asked to attend to words HEALTH and SPELLER, one letter at a time, without feedback. This procedure lasted approximately 3 min. The calibration data were processed using LDA to derive the weighting coefficients, since this method was previously used with success to classify the P300 potentials in spelling applications [25]. Thus, epochs of 750 ms of the EEG signals, starting at the onset of flashed items, were averaged over the 10 sequences displayed for the selection of an item. Further, all averaged epochs x location features are entered into the LDA. The LDA weights each input and indicates the class (target or non-target) the item belongs to. This process is performed using two conditions as it was described in Section II.C. The EEG signals were downsampled at a rate of 4:1 in order to reduce the amount of data entered in the LDA.

The first classifier (C1) assumes the rejection of the flashing groups the user was not able to see them (the user blinked during the flashes, having his eyes closed) – automatically identified by the algorithm that searches for blinks or winks in the EOG signals during the spelling process. A number between 1 and 3 groups is rejected according to the length of the blink/wink. The second classification (C2) method assumes the rejection of all flashing groups that may be contaminated by EOG artifacts as it was explained in Section II.C. Around 6 to 8 buffers may contain EEG signals contaminated with EOG artifacts, and the algorithm will reject them from the average computed for each item of the matrix.

Both analyses are based on training a classifier with the signals recorded for the HEALTH word. Subsequently, the classifier is tested by using the SPELLER word. Two accuracy rates are obtained for each user according to the classification methods. For each user, the classifier that offers the highest accuracy is chosen (see Table II). After the method is selected, the classifier is trained by using the EEG signals recorded for both the HEALTH and SPELLER words, then it is used for the online classification session. The same analysis is performed for both CBP and HCBP-based spellers used in the present study.

H. Experimental procedure

In the present study, two paradigms have been used to implement the P300 speller: the CBP and the proposed HCBP. Both spellers show 72 items on the computer screen (see Figure 2). The differences perceived by the users between the two spellers appear at the level of EOG calibration and recalibration stages. A group of items is flashed for 62.5 ms and the interval between two successive flashes is of 62.5 ms. It results an inter stimuli interval (ISI) of 125 ms. The subject’s task is to attend to the indicated item and to mentally count the number of times it is highlighted, counting being used to help the subject remain focused on the task [25].

For the CBP-based speller the same conditions were implemented as described in the original work [47]. A CBP

<table>
<thead>
<tr>
<th>Subject</th>
<th>Classification method</th>
<th>CBP accuracy [%]</th>
<th>HCBP accuracy [%]</th>
<th>CBP bit rate [bits/min]</th>
<th>HCBP bit rate [bits/min]</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>C1</td>
<td>81.25</td>
<td>81.25</td>
<td>14.01</td>
<td>18.03</td>
</tr>
<tr>
<td>S2</td>
<td>C1</td>
<td>93.75</td>
<td>100</td>
<td>17.67</td>
<td>25.75</td>
</tr>
<tr>
<td>S3</td>
<td>C2</td>
<td>100</td>
<td>93.75</td>
<td>20.01</td>
<td>22.74</td>
</tr>
<tr>
<td>S4</td>
<td>C2</td>
<td>93.75</td>
<td>87.5</td>
<td>17.67</td>
<td>20.28</td>
</tr>
<tr>
<td>S5</td>
<td>C1</td>
<td>75</td>
<td>87.5</td>
<td>12.39</td>
<td>15.28</td>
</tr>
<tr>
<td>S6</td>
<td>C2</td>
<td>87.5</td>
<td>81.25</td>
<td>15.75</td>
<td>18.03</td>
</tr>
<tr>
<td>S7</td>
<td>C1</td>
<td>93.75</td>
<td>100</td>
<td>17.67</td>
<td>25.75</td>
</tr>
<tr>
<td>S8</td>
<td>C1</td>
<td>87.5</td>
<td>81.25</td>
<td>15.75</td>
<td>18.03</td>
</tr>
<tr>
<td>S9</td>
<td>C2</td>
<td>100</td>
<td>100</td>
<td>20.01</td>
<td>25.75</td>
</tr>
<tr>
<td>S10</td>
<td>C2</td>
<td>100</td>
<td>93.75</td>
<td>20.01</td>
<td>22.74</td>
</tr>
</tbody>
</table>

Mean 91.25 90.625 17.1 21.74 21.08 31.25
selection took 15 s (125 ms x 24 flashes x 5 sequences = 15 s). For the HCBP-based speller each item from an area is highlighted 10 times, being included in the 8 groups flashed during a sequence. A selection time of 10 s (125 ms x 8 groups x 10 sequences = 10 s) results. A 3.5 s pause was inserted between the selections of two items in order to allow the user to visually acquire the next target item. The inserted pause includes the time required (classification epoch of 750 ms) for filling the last buffers that contain the EEG signals corresponding to the last group highlighted.

Each participant was asked to complete two experimental sessions, one for each paradigm-based speller. The online sessions were performed in a counter-balanced manner, so that half of the participants began with the CBP-based speller and the other half with the HCBP-based. A pause of 5 min was inserted between the two sessions. For each speller the users were asked to spell a 16-character long text “VERY_SIMPLE_TEST”.

### III. RESULTS

#### A. Online accuracy and bit rate

For each participant and speller implementation the online accuracies were measured. Table II shows the online accuracies, the method used for classification, online bit rate including the pauses between symbols, and online bit rate excluding the pauses for each participant.

For the CBP-based speller the total time required for spelling the given text was of 296 s (16 characters x (15 s + 3.5 s) = 296 s), that lead to 3.24 selections/min. The HCBP-based speller required a spelling time of 230 s (16 characters x (10 s + 3.5 s) + 7 EOG recalibrations x 2 s = 230 s). Each character selection lasted 10 s and a pause of 3.5 s was inserted when the application started as well as between each two consecutive selections. After each two spelled characters an EOG recalibration of 2 s was inserted. The HCBP-based speller achieved 4.17 selections/min.

In order to assess the BCI performance the ITR metric is computed according to the formula from [51]:

$$ITR = M \left[ \log_2(N) + P \log_2 P + (1-P) \log_2 \left( \frac{1-P}{N-1} \right) \right]$$

(1)

where: $N$ is the number of possible selections, $P$ the probability that the desired item will be selected (accuracy), and $M$ is the number of possible decisions per minute.

Parameter $M$ is computed from:

$$M = 60 \left( N_{rep} \times N_{groups} \times ISI + N_{groups} \times SP \right)$$

(2)

where: $N_{rep}$ is the number of repetitions for each item, $N_{groups}$ represents the number of groups, $ISI$ is the time interval between two consecutive highlights and $SP$ is the spelling pause between two consecutive items. Additionally, for the HCBP-based speller, EOG recalibration pauses must be considered for each two spelled characters.

The paired t-test performed on the online accuracy showed no significant differences between the two spellers $t(9) = 0.287$, $p = 0.780$. A selection lasted less time for the HCBP and the selections/min performance indicator was higher for the proposed paradigm (3.24 selections/min for the CBP and 4.17 selections/min for the HCBP). The online bit rate was significantly different between the two paradigms $t(9) = 5.766$, $p < 0.001$ (17.1 bits/min for the CBP, respectively 21.74 bits/min for the HCBP). Also, by excluding the pauses between selections in calculating the bit rate significant differences were identified between the two spellers $t(9) = 8.945$, $p < 0.001$ (21.08 bits/min for the CBP and 31.25 bits/min for the HCBP).

#### B. Practical bit rate

A more valid metric of performance is considered to be the practical bit rate [28], [29], [47]. In case of an error the user...
would normally attempt to correct it. For every error made a minimum of two additional selections are required, first a backspace, then a correction selection. According to the formula from [47] we computed the practical bit rate when the user would attempt to correct the errors. The estimated practical bit rate for each user is shown in Table III. The HCBP practical bit rate, 18.28 bits/min, was significantly higher than the CBP practical bit rate, 14.53 bits/min, \( t(9) = 2.567, p = 0.030 \). The decrease in performance is similar for both paradigms 0.6 selections/min for the CBP and 0.69 selections/min for the HCBP. A similar decrease is also noticed for the practical bit rate parameter, 2.45 bits/min for the CBP and 3.46 bits/min for the HCBP.

C. Offline bit rate

In order to compare the performances of the current work with those obtained in the original study of the CBP, an offline analysis was conducted. We performed an analysis to determine the minimum number of flashing sequences required for the spelling process by maintaining the same accuracy rate. A predefined number of 10 sequences were used in the present study in order to achieve high accuracy rates, but a lower number of sequences might achieve the same classification accuracy. The analysis assumed the use of the recorded signals and the EOG rejection method chosen for each user for the online session. The restrictions were to maintain the same accuracy rate and to include at least one visible flash for each item. The evaluation was performed for both paradigms and the obtained results are listed in Table IV.

For the CBP-based speller similar results (22.78 bits/min) were obtained for the present study compared with the work (23.17 bits/min) from [47]. As for the HCBP, a significant higher ITR was obtained compared to the CBP, \( t(9) = 3.102, p = 0.013 \). Similar values are obtained also for the selections/min performance indicator, 4.21 sel/min in the present study and 4.68 sel/min in [47], while the HCBP achieved a higher number of 5.23 sel/min (\( t(9) = 6.568, p < 0.001 \)).

D. The influence of EOG in the present paradigm

By considering the EOG signals for the area identification phase, the classification accuracy achieved a maximum rate for the entire spelling process. The recalibration required after each two selected items provided the correct identification of an area for the entire spelling process, avoiding the undesired effect of flashing the items from the other area.

For the artifact removal process two classifiers were used for each participant. In order to better assess the usefulness of EOG artifact removal methods we performed an offline analysis. Thus, for each participant a supplementary offline evaluation was performed to identify the classification accuracies for no artifact removal (NAR) case. Similar with the classification phase an LDA classifier was trained based on the dataset recorded for the training phase, and further the evaluation was based on the analysis of the dataset recorded during the testing phase. For both training and testing phases, the NAR classifier was used. Values obtained for this offline analysis area listed in Table V. In the case of NAR classifier no differences were found in the accuracy rates for one subject (S8), while two subjects (S4 and S6) presented increases for both paradigms. For two subjects (S3 and S9) the NAR classifier presented a high decrease in the accuracy rates of 19.75%. High amplitude EOG artifacts were found for these subjects at Cz and Pz locations. The average decrease in accuracy was of 6.875% for the CBP, and 5.625% for the HCBP.

By analyzing the accuracy rates of both paradigms and rejection algorithms (C1 and C2 vs. NAR) we found significant differences for the CBP vs. CBP-NAR pair (\( t(9) = 2.283, p = 0.048 \)) and no significant differences for the HCBP vs. HCBP-NAR pair (\( t(9) = 2.077, p = 0.068 \)). The values of 5.625% and 6.875% may seem low, but in the P300-based speller applications it is very important to achieve high accuracy classification rates. Thus, although only one paradigm presented significant differences we conclude that the proposed artifact removal methods are useful for the classification of P300 potentials, and the NAR condition must be considered for further tests since it presented higher accuracy rates for two subjects.

E. Discussion

This study intended to develop a physiological hBCI, or BNCI, based on EOG and EEG electrophysiological signals. The interface aims to offer a feasible communication channel for disabled people, and also a supplementary control channel for able-bodied persons. To accomplish this, the EOG signals were used to detect an area were the user gazes at, and the P300 potentials were used for the selection of an item from a matrix. An expert system was used for the classification of the user’s eye movements, and also for computing the user’s gaze point on the monitor. A calibration is required in order to detect where the user’s gaze is on the monitor, and a classifier based on the LDA was used to identify the item chosen by the user. Two methods that assume the rejection of the EOG artifacts were evaluated, and for each user the method that revealed the highest classification accuracy was used.

Two paradigms have been considered for the P300 speller...
development: the CBP and the HCBB. A group of ten users were asked to follow a test with each paradigm. The mean accuracies were similar for both interfaces, while the online and the practical bit rates performance indicators were significantly higher for the HCBB-based speller.

In order to detect the user’s eye movements, the EOG signals were chosen because they are a non-invasive and cost effective solution. Other systems used for eye movements tracking, such as eye trackers, sclera search coil method or dual Purkinje image eye tracker represent bulky or high cost solutions [7], [14], [15]. The EOG method implies only the use of four supplementary electrodes. Therefore, minimal requirements must be done in order to achieve this. Furthermore, EEG signals are usually contaminated with EOG artifacts. As we had the EOG signals recorded, an offline analysis was performed in order to assess the influence of the EOG artifacts in the classification process. It was determined that the EOG signals do influence the classification of the P300 potentials and two methods were proposed and successfully used for rejecting the influence of the artifacts. The number of EOG recalibrations may be reduced according to each user’s parameters, by reference of amplitude, contact impedance or signal-to-noise ratio. For example, one recalibration may be required for each 4 or 5 spelled characters, leading to shorter time required for the recalibration process.

The proposed BNCI system represents a simple and less expensive solution compared with eye tracking alternatives, and it also may require less precise eye movements. This is an important factor to increase the comfort of patients who are thus not required anymore to concentrate for precise gazing. In addition, low precision eye movements may be the only possible movements for some end users. The results obtained in the present study are encouraging, and their validation for such applications assumes a complete series of dedicated tests with target users which will be performed in a future research.

IV. CONCLUSIONS AND FUTURE WORK

In this paper a novel BNCI system based on EOG and EEG signals was proposed and evaluated. The users are able to select items organized in a matrix in order to ‘type’ a text by using their biopotentials. The system identifies the user’s eye movement through the EOG method, and combined with the EEG P300 potentials, it accurately detects which item was selected by the user. High accuracy rates were obtained for the proposed paradigm, and compared with the CBP, higher ITRs were achieved. The novel part of the present paradigm is the combined use of EOG and EEG signals in the classification process to improve the speller’s performances, and the experiments confirmed a higher ITR for the proposed paradigm. Based on existing knowledge, the goal of our approach was to point out the possibility to use the combined BCI-EOG approach to reduce the amount of information that needs to be presented to the user. The validation of this principle opens the way for multiple hBCI applications.

Additionally, the principle presented in this paper suggests that the speller application can be further improved by adding a third area which may contain a predictive system (see [43] for example). Nevertheless, this has to be investigated and designed according to each user EOG signals particularities by reference to target people (e.g. disabled persons suffering from ALS, locked-in syndrome, etc.), and will be addressed by the authors in a separate research.

ACKNOWLEDGMENTS

This paper is supported by the Sectoral Operational Programme Human Resources Development (SOP HRD), financed from the European Social Fund and by the Romanian Government under the contract number POSDRU/88/1.5/S/59321. The authors would like to thank also the reviewers for the very useful comments and suggestions that contributed to the final content of the paper.

REFERENCES

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.