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# A SCORE BASED METHOD FOR P300 COLLABORATIVE BCI

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ABSTRACT: Group decision-making is the process where two or more people are engaged in generating a solution for a given problem. In the last decade, researchers started exploiting collaborative Brain-Computer Interfaces to enhance group performance. Various methods have been proposed to integrate EEG data of multiple users showing the improvement in group decision-making over single-user BCIs and non-BCI systems. In this study, we investigate four EEG integration strategies: EEG averaging across participants, the standard majority voting rule and two weighted voting system. For each approach, we evaluate three different scenarios varying the number of iterations necessary to perform a single selection. In all cases, it is possible to exceed 90% of accuracy with at least one collaborative BCI.

## INTRODUCTION

Group (or Collective, or Collaborative) decision-making is the process where two or more people are engaged in generating a solution for a given problem [1]. Combination of sensing and cognition capabilities allow a group to make better decisions than single individuals [2]. Nevertheless, group decisions can be negatively affected by several factors, such as lacking of time, sharing of information, group and leadership style and communication biases [2, 3]. In the last decade, researchers started to use Brain-Computer Interfaces (BCIs) to enhance group decision-making. BCIs allow people to interact with the environment without requiring any peripheral muscle activity to complete the interaction [4]. Brain signals are acquired and processed by a computer to identify a particular type of neural process called event-related potential (ERP), which is the brain response resulting after specific sensory or cognitive events. ERP-based BCIs use an oddball paradigm to elicit the ERP components: the user has to focus on 'target' (rare) stimuli which are inserted in a stream of 'non-target' (frequent) stimuli. As target and non-target stimuli elicit different responses, they can be distinguished and exploited by the BCI. Single-user BCIs are widely exploited for clinical purposes, most of them aiming at restoring communication capabilities to severely disable people [5]. Instead, a collaborative Brain-Computer Interface (cBCI) is a system designed for integrating brain signals from a group of users for improving a decision-making process.

In the last decade, various approaches to integrate EEG signals have been proposed. For example, single-trial ERPs can be averaged across group members and then processed as a single-user BCI. Alternatively, neural features can be inferred from the EEG data of each user and concatenated afterwards to build a feature vector for the group, which is then passed to a single classifier. Finally, the output of several single-user BCI can be combined by means of a voting system to compute the group decision [6]. In [7], these approaches have been applied to the EEG data collected from 20 subjects in a movement-planning experiment. In the voting method, a SVM classifier was trained for each subject. The classification output was then weighted according to each user's training accuracy. All the three cBCIs outperformed the single-user BCIs. Moreover, the voting strategy turned out to be the optimal method for collaborative EEG-based classification. In [8] and [9] the same strategy has been applied to a visual target detection task and a visual Go/NoGo task, respectively. The output of the single-user SVMs has been used as the input for a second-layer SVM. In [10], the authors integrated the EEG of 20 individuals engaged in the discrimination among pictures of cars and faces, using various voting decision rules for combining information across user. The advantages of a cBCI has been evaluated also in [11], where data recorded using a P300 speller paradigm have been analyzed showing that combining data from users led to an improved accuracy with respect to fusing data from the same participant over time. In [3], a completely different weighted majority rule has been introduced. The authors developed a hybrid cBCI that does not predict the user decision but combines neural signals and response times to determine the decision confidence of each user and then weights their behavioral responses accordingly to produce the group decision. This hybrid cBCI was evaluated on several tasks, such as visual matching [3], visual search with simple shapes [12], visual search with realistic stimuli [2].

In literature, cBCIs have been tested on several visual tasks showing their reliability. Moreover, various studies suggest that voting methods are often optimal for collaborative EEG-based classification, especially when the scores of the single classifier (instead of the predicted class) are used for the integration [6]. In this work we propose a voting method for a cBCI that exploits several information behind a standard ERPs stimulation

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paradigm to achieve a global group decision.

## MATERIALS AND METHODS

*Datasets:* In this study, we test our voting strategy on a healthy-subject dataset recorded using a P300-Speller paradigm. The dataset can be downloaded from the BNCI Horizon 2020 database data09 (Dataset 9: Covert and overt ERP-based BCI (009-2014)). In a standard P300-Speller paradigm [13], cues are organized in a $6 \times 6$ matrix. Given a character (also referred as a trial) to select, each row and column of the matrix flash every 250ms in a pseudo-random order. A single flash is called stimulus. A block of twelve different stimuli, six rows and six columns, constitutes a stimulation sequence (or an iteration). Due to the low signal-to-noise ratio (SNR) of EEG signals, several iterations have to be carried out and then averaged in order to perform a single selection step. We analyzed data recorded from 10 participants that had to select a total of eighteen characters. Each selection consists of eight iterations. In summary, for each participant, we analyzed a total of 1728 stimuli (18 trials $\times$ 8 iterations $\times$ (6 columns + 6 rows)). The characters to select as well as the used pseudo-random stimulation sequences and timings are the same for all participants. Therefore it is possible to test offline the benefits of combining this EEG data to perform a group decision.

*Pre-Processing and Classification:* For each participant, we analyze six pairs of training and test sets. Pairs differ in terms of the number of training trials. More in detail, the number of training characters ranges from one to six. As a result, the number of test trials varies from seventeen to twelve. We use a linear Support Vector Machine (SVM) [14] to classify the response of each stimulus. This classifier discriminate brain responses by means of a separating hyperplane, that is built on the basis of the training data, and it is defined as:

$$f(x) = w^T x + b \tag{1}$$

where $w$ is the vector containing classification weights and $b$ is the bias term. In (1) the right-hand side is called decision value. Its absolute value represents a measure of the distance of the sample point $x$ from the separating hyperplane. In a typical P300-Speller [13], based on the assumption that the P300 is elicited by one of the six rows/columns stimuli, the target class is assigned to the stimulus matching the maximum decision value for the respective rows, as well as for the columns. The predicted character is identified as the intersection of the predicted row and column in the matrix [15]. In this work we use the *Decision Weighted Function (DWF),* introduced in [16] to classify the brain responses. Consider, without loss of generality, the rows stimuli. The computed decision values are normalized by dividing for the norm of vector $w$ and sorted in decreasing order. We assign a score to each stimulus based on both the sign of their decision values and their position with respect to the separating hyperplane. We set a distance-threshold ($t$) equal to the median of the normalized decision values. This threshold represents an overall measure of the stimuli's distribution with respect to the separating hyperplane. We assign a score to each stimulus based on both the sign of their decision values and their position with respect to $t$. The score $s_i^j$ is defined for redstimulus $i$ at the iteration $j$ as:

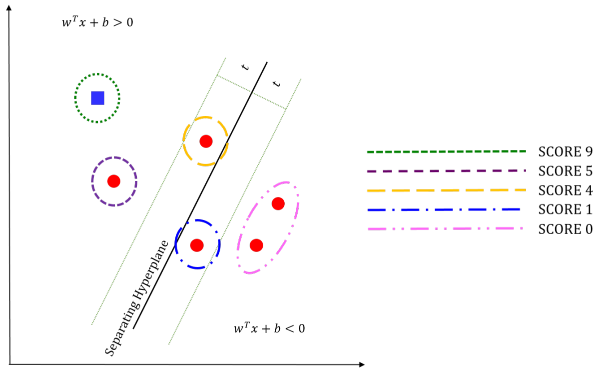


Figure 1: Score assignment procedure. Consider rows stimuli. The stimulus having the maximum decision value (the blue square) gets the maximum score, that is equal to 9 (obtained as round$(1.5 \times 6)$. The stimuli that fulfill the second condition in (2) get a score equal to 5 (obtained as round$(0.85 \times 6)$). A score equal to 4 (obtained as round$(0.6 \times 6)$) is assigned to stimuli fulfilling the third condition. Stimuli with negative decision values and that fulfill condition number four get a score equal to 1 (obtained as round$(0.1 \times 6)$), otherwise they get a score equal to 0.

$$s_i^j = \begin{cases} 1.5 \times n, & \text{if } d_i^j = \max_i(d_i^j) \\ 0.85 \times n, & \text{if } d_i^j \geq 0 \wedge |d_i^j| \geq t \\ 0.65 \times n, & \text{if } d_i^j \geq 0 \wedge |d_i^j| < t \\ 0.1 \times n, & \text{if } d_i^j < 0 \wedge |d_i^j| < t \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

For each stimulus, the assigned scores are summed up iteration by iteration. We assign the target class to the stimulus having the highest total score at the last iteration. Whenever the maximum score at the last iteration corresponds to more than one stimulus, a suitable rule for breaking the ties is applied looking to the scores at the previous iterations. The same procedure is applied over columns stimuli. The predicted character is identified as the intersection of the predicted row and column in the matrix. Figure 1 shows an example of score assignment procedure given the distribution of the decision values assigned to six stimuli (think as an example to six rows of P300 Speller matrix).

*Collaborative BCI:* Four different collaborative decision making approaches are evaluated.

**EEG Grand-Averaging (Avg_EEG)**: For each stimulus, the EEG responses are averaged across participants. The obtained responses are then classified using the DWF.

**Majority (Maj)**: For each participant a single classification task is performed. According to a standard majority voting system, the target class is assigned to the character chosen by the majority of the participants. Ties are ran-

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domly broken by a flip of coin.
**Accuracy-weighted voting rule (AW)**: For each participant a single classification task is performed. Let $y_i$ be the character chosen by the participant $i$ among the $j$ available characters. The accuracy-weighted voting rule is defined as follows:

$$y^* = max_j \sum_i w_i y_i \quad (3)$$

where $w_i$ is the weight of the i-*th* participant. The weight $w_i$ is given by the training accuracy of the $i$-th participant. In case of parity, a random selection is performed among the contenders.
**Confidence-weighted voting rule (CW)**: A classification task is performed for each participant. The confidence-weighted voting rule is defined as in (3), but the weight $w_i$ is defined as follows: let $t$ be the target trial, and let $s_t^i$ be the total score assigned to it by DWF, the confidence of the $i$-th subject is computed as

$$w_i = \frac{\sum_{t=1}^{n} s_t^i}{nS}$$

where $n$ is the number of training trials and $S$ is the maximum achievable score. Note that $w_i \in [0,1]$.
In case of ties, a random decision is made.
We also investigate whether a cBCI approach can be applied in order to reduce the number of iterations necessary to select a single character and, therefore to speed up the selection rate. Indeed, in BCI systems, to perform a single selection step, several iterations are carried out and averaged in order to improve the EEG signal-to-noise ratio. Typically, a larger number of iterations implies higher accuracy but lower selection rate. We then evaluate three different scenarios: in the first scenario, we consider each iteration as a single selection step. As a result, let $n$ be the number of characters to copy-spell and let $t$ the number of iteration we perform $n \times t$ selection steps. In the second scenario we consider two iterations as a single selection step, therefore we perform $n \times t/2$ selection steps. In the third scenario we evaluate four iterations at a time, thus performing $n \times t/4$ selection steps.

## RESULTS

Table 1 shows the accuracy (i.e., the percentage of correctly classified characters) over the test set for both single-user and collaborative BCIs using all the available iterations (i.e., considering a block of eight iteration as a single selection step). The single-user classification accuracy varies according to the number of characters used to train the model. It is not possible to identify a common trend across the participants. Six training characters allow participants 01, 02, 05, 07 and 10 reaching the 100% of accuracy. For users 02, 05 and 10 the same result can be obtained also with a number of training characters ranging from three to six. Three or at most four training characters are necessary to achieve the 100% of accuracy for subjects 04 and 09. Subjects 03, 06 and 08 reach their best result using five and four training characters, respectively. Note that for the single-user BCIs in some cases increasing the number of training characters can lead to a decay of the performance due to overfitting. Except for the accuracy-weighted voting rule with two training characters, all the evaluated cBCIs allow to get the 100% of accuracy with any number of training characters.

| Models | Number of training trials | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| *01* | 29.41 | 81.25 | 86.67 | 78.57 | 84.61 | 100 |
| *02* | 47.06 | 62.5 | 93.33 | 92.86 | 100 | 100 |
| *03* | 23.53 | 43.75 | 60.0 | 50.0 | 61.54 | 58.33 |
| *04* | 64.71 | 68.75 | 100 | 100 | 92.31 | 91.67 |
| *05* | 94.12 | 87.5 | 100 | 100 | 100 | 100 |
| *06* | 52.94 | 50.0 | 80.0 | 85.71 | 84.61 | 83.33 |
| *07* | 23.53 | 43.75 | 86.67 | 57.14 | 76.92 | 100 |
| *08* | 47.06 | 37.5 | 73.33 | 85.71 | 76.92 | 75.0 |
| *09* | 82.35 | 93.75 | 93.33 | 100 | 92.31 | 91.67 |
| *10* | 94.12 | 93.75 | 100 | 100 | 100 | 100 |
| *Avg_EEG* | 100 | 100 | 100 | 100 | 100 | 100 |
| *AW* | 100 | 93.75 | 100 | 100 | 100 | 100 |
| *Maj* | 100 | 100 | 100 | 100 | 100 | 100 |
| *CW* | 100 | 100 | 100 | 100 | 100 | 100 |

Table 1: Single-user and collaborative BCIs test accuracy using all the available iteration with training characters ranging from 1 to 6

Figure 2 shows the cBCI accuracy over the test set considering each iteration as a single selection step varying the number of training characters. None of the cBCIs allow to reach the 100% of accuracy. All the cBCIs reach a high accuracy (> 85%) using only three training characters. This implies that these systems can be efficiently used to communicate.

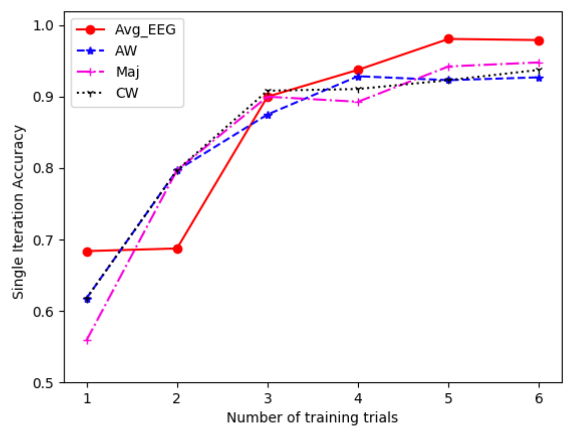


Figure 2: Comparison of the different cBCIs considering each iteration as a single selection step with training characters ranging from 1 to 6

Figure 3 depicts the cBCI accuracy over the test set considering each pair of iteration as a single selection step varying the number of training characters. Except for the Avg_EEG approach, all the cBCIs guarantee an accuracy

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$> 90\%$ using only two training characters. The grand-average of the EEG signals across the users allows reaching 100% of accuracy using only four training characters. Figure 4 shows the cBCI accuracy over the test set look-

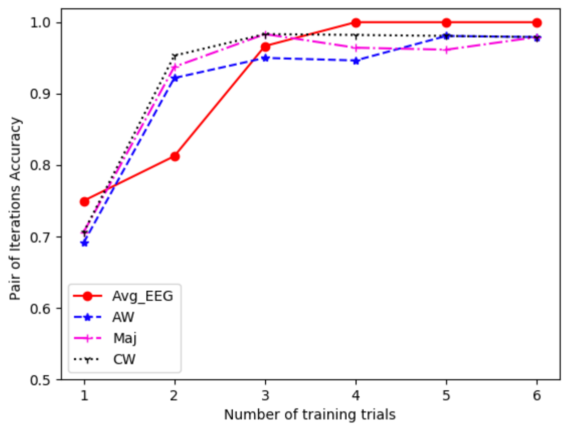


Figure 3: Comparison of the different cBCIs considering each pair of iteration as a single selection step with training characters ranging from 1 to 6

ing upon a block of four iterations as a single selection step and varying the number of training characters. All the cBCIs allow reaching an accuracy $> 90\%$ using only one training character. Moreover, three training trials are sufficient to get 100% of accuracy with any collaborative approach.

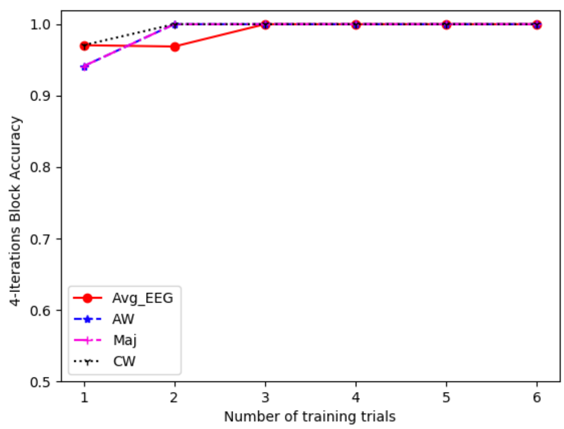


Figure 4: Comparison of the different cBCIs looking upon a block of four iterations as a single selection step with training characters ranging from 1 to 6

DISCUSSION AND CONCLUSION

In the last decade, researchers started exploiting collaborative BCIs to enhance group performance. Various methods have been proposed to integrate EEG data of multiple users showing the improvement in group decision-making over single-user BCIs and non-BCI systems. In this study, we investigated four EEG integration strategies: EEG averaging across participants, the standard majority voting rule and two weighted voting system. All the evaluated cBCIs outperform single-user BCIs confirming the trend found in the collaborative BCI literature. Moreover considering all the available iterations per selection step, it is possible to obtain 100% of accuracy with just one training character. The possibility to reduce the number of training characters preserving the test accuracy not only reduces the training computational effort but also corroborates the reliability of the evaluated cBCIs. A high number of iterations typically means higher accuracy but lower selection rate. In this work, we also investigated whether it was possible to reduce the number of iterations necessary to make a group decision preserving the 100% of accuracy. We thus evaluated three different scenarios choosing three different values for the number of iterations necessary to perform a single step selection: one iteration, pairs of iterations and blocks of four iterations. Note that this implies that we could speed up the test phase of a factor of 8, 4 or 2 depending on the chosen number of repetitions. In all the examined scenarios, it is possible to exceed 90% of accuracy with at least one collaborative BCI. Thus the systems can be efficiently used for communication. More in details, at least four iterations per selection step are necessary with one training character. With two or three training characters two iterations per selection step are enough. From four training characters on, a single iteration is enough. The minimum number of training characters and iterations that allow reaching 100% of accuracy is two and four respectively. Our results corroborate the cBCIs stability and indicate that it is possible to choose the best scenario depending on the application, in other terms based on the desired trade-off between accuracy and communication speed.

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