A Collaborative Brain-Computer Interface to Improve Human Performance in a Visual Search Task

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Abstract— **In this paper we use a collaborative brain-computer interface to integrate the decision confidence of multiple non-communicating observers as a mechanism to improve group decisions. In recent research we tested the idea with the decisions associated with a simple visual matching task and found that a collaborative BCI can significantly outperform group decisions made by a majority vote. Here we considerably extend these initial findings by: (a) looking at a more traditional (and more difficult) visual search task involving deciding whether a red vertical bar is present in a random set of 40 red and green, horizontal and vertical bars shown for a very short time, (b) using spatio-temporal CSP filters instead of the spatio-temporal PCA we previously used to extract features from the neural signals, while also reducing the number of features and free parameters used in the system. Results obtained with 10 participants indicate that for almost all group sizes our new CSP-based collaborative BCI yields group decisions that are statistically significantly better than both traditional (majority-based) group decisions and group decisions made by a PCA-based collaborative BCI.**

I. INTRODUCTION

A Brain-Computer Interface (BCI) is a communication and/or control system that allows the user to interact with the world through the recording and analysis of the user's brain activity. This technology has been tested in a large variety of applications, most typically to allow people with severe motor disabilities to communicate and operate actuators of different kinds [1], [2], [3], [4], [5]. However, in recent years, another avenue has started to emerge: using *collaborative BCIs* (cBCIs) for human augmentation, e.g., for improving the perceptual or cognitive performance of groups of users. In this paper we will introduce a cBCI that can improve group decision-making in a difficult visual search task. We will start by reviewing the areas of cBCI and decision making in the next section, and we will look at the contributions of this paper in Section I-B.

A. *Decision Making and cBCIs*

Decision-making has been studied for decades as understanding its processes and dynamics has important implications in many fields, including psychology and politics.

Extensive literature has shown that making decision is groups can be powerful (see for example [13], [14], [15], [16]) and can be superior to making individual decisions in many different contexts, including settings where individuals are involved in visual tasks [17]. However, there are circumstances in which the benefits of group decisions can be disadvantageous [18], [19]. For example, this happens when decisions have to be taken within a time window that is incompatible with communication within the group, when group decisions are affected by individual indecisions or when decisions are hijacked by a particularly influential member [14], [16], [17].

There is today also a reasonably consistent body of knowledge regarding the areas of the brain involved in making decisions and the event-related potentials (ERPs) associated with them (e.g., see [6], [7], [8], [9]). These have even been exploited for human augmentation in single-user BCIs that improve human decision accuracy or speed [10], [11], [12].

Several studies and applications of cBCIs have been proposed in the last few years. These include cBCIs for a movement planning task [20], the visual discrimination between rapidly presented pictures of cars and faces [21], [22], detecting the onset of visual stimuli presented on a black background [23], joint 2–D cursor control [24], rapid discrimination of aeroplanes in aerial images of urban environments [25], [26] and group decision-making for a simple visual-matching task [27], [28].

Most of these cBCIs have been shown to improve either speed or accuracy over single non-BCI users. However, for the first time, in [28] cBCI-assisted groups were provably more accurate than identically-sized groups performing the same tasks by traditional means. As the present work is an extension of [28], we will briefly summarise that work below.

In [28] we developed an EEG-based cBCI for improving group decisions in a task where participants had to decide whether or not two sets of shapes were identical. These were presented for a very short time, thus making individual (non-BCI) decisions difficult and often erroneous. Our approach was unusual in relation to previous cBCI studies in that we exploited not only neural data but also behavioural measures of confidence. That is, in addition to ERPs we also recorded the response times (RTs), as these are influenced by, and thus can reveal, the confidence in a decision [29]. Candidate neural features were extracted from ERPs via spatio-temporal PCA. We then optimally selected, combined and used neural and behavioural features extracted during a decision to estimate the objective level of confidence of each observer making that decision. To perform feature selection and parameter identification we used information of whether the response of our observers in each decision was correct or incorrect, on the assumption that participants were on average less confident in erroneous decisions than in correct ones. Group decisions were then determined by a modified weighted-

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majority algorithm which dynamically weighed individual decisions based on each observer's estimated confidence. Results showed that cBCI-assisted group decisions obtained in this manner were almost always statistically better than those obtained by equally-sized (non-BCI) groups adopting the majority rule.

B. Contribution

The present study improves and extends the cBCI described in [28] and summarised in the previous section, along two directions.

Firstly, we investigated whether a collaborative BCI approach can be applied to a visual search task that is perceptually and cognitively different from (and harder than) the visual matching task previously tested. In the visual search task, observers were asked to search for a specific target amongst a large number of non-targets. The high perceptual load (due to the large number of non-targets presented in each display), the difficulty of discriminating between targets and non-targets (due to the shared features between the target and the non-targets) and the fast presentation of each display render decisions quite hard to make in this task.

Secondly, we replaced the spatio-temporal PCA we used previously to extract the neural features from ERPs with a spatio-temporal Common Spatial Pattern (CSP) filter. CSP filtering was adopted for its marked ability to capture important aspects of the data (as already demonstrated in several BCI applications [30], [31], [32], [33]) allowing us to significantly reduce the number of neural features required by the system (from the 24 PCA components used originally), thereby promoting generalisation. Also, as CSP is two orders of magnitude faster than PCA, this allowed us to extend the analysis to both a response-locked ERP representation (as was done in [28]) and a stimulus-locked representation. As the latter may contain early indications of perceived task difficulty (as suggested in [9]), we hoped this would also correlate with decision confidence further increasing cBCI-assisted group-decision accuracy.

II. METHODOLOGY

A. Participants

We gathered data from 10 participants (aged 28.5 ± 6.0, 4 females) with normal or corrected-to-normal vision who gave written informed consent to take part in the experiment. The research is part of a project funded by the UK's MoD through DSTL which received MoD and University of Essex ethical approval in July 2014.

B. Stimuli and Tasks

Participants were asked to undertake an experiment consisting of 8 blocks of 40 trials, for a total of 320 trials. Each trial started with the presentation of a fixation cross in the middle of the screen for 1 second (Figure 1). This time allowed participants to get ready for the presentation of the stimuli and allowed EEG signals to get back to baseline after the response from previous trials. Then participants were presented with a display containing a set of 40 bars, either green (RGB (0,1,0)) or red (RGB (1,0,0)), vertical or horizontal, on a black background. This lasted for 250ms and was immediately followed by a mask for 250ms. The mask was a black and white 24×14 checkerboard. Following the presentation of the mask, participants had to decide, as quickly as possible, whether or not there was a vertical red bar, *the target*, among the vertical green, horizontal green and horizontal red bars, *the distractors*. Their choice was indicated by pressing the left mouse button to signal the presence of the target and the right mouse button to signal its absence. RTs were recorded. The mouse was controlled with the right hand.

The position of the bars was randomly selected (without allowing overlaps between bars) within a rectangular screen region subtending approximately 17.7 degrees horizontally and 11.9 degrees vertically. Bars subtended approximately 1.09 degrees in their longer dimensions and 0.36 degrees in their shorter dimension. The number of distractors of each type was also randomly selected, but ensuring that at least one distractor of every type was present in a display. Targets (red vertical rectangles) were presented in 25% of trials.

The random displays used in the experiment were precomputed and stored so that identical sequences of stimuli were used for all participants. This was done in order to make it possible to test offline the benefits of combining the decisions of different participants to form group decisions.

Briefing, preparation of participants (including checking and correcting the impedances of the electrodes used for EEG recordings) and task familiarisation (2 blocks of 10 trials each) took approximately 45 minutes. Participants were comfortably seated at about 80 cm from an LCD screen.

C. Data Acquisition and Preprocessing

RTs were measured by time-stamping the clicks of an ordinary USB mouse. As indicated in [28], this produces a *maximum* jitter of 14ms which is negligible when compared with even the shortest RTs.

The neural data were recorded from 64 electrode sites using a BioSemi ActiveTwo EEG system. Each channel was referenced to the mean of the electrodes placed on each earlobe. The recorded data were sampled at 2048 Hz and then band-pass filtered between 0.15 and 40 Hz with a 14677-tap FIR filter obtained by convolving a windowed low-pass filter with a windowed high-pass filter. Artifacts caused by eye-blinks and other ocular movements were removed by using a standard subtraction algorithm based on correlations. The data were then low-pass filtered with an optimal 820-tap FIR filter designed with the Remez exchange algorithm [34] with a pass band of 0–6Hz and a stop band of 8–1024 Hz. The data were finally down-sampled to a sampling rate of 16 Hz.

The EEG data were segmented into epochs using both a response-locked and a stimulus-locked approach. Response-locked epochs lasted 1500ms and started 500ms before the user's response, while stimulus-locked epochs also lasted 1500ms but started in synchrony with the presentation of the stimulus. Each ERP was thus represented by 48 samples

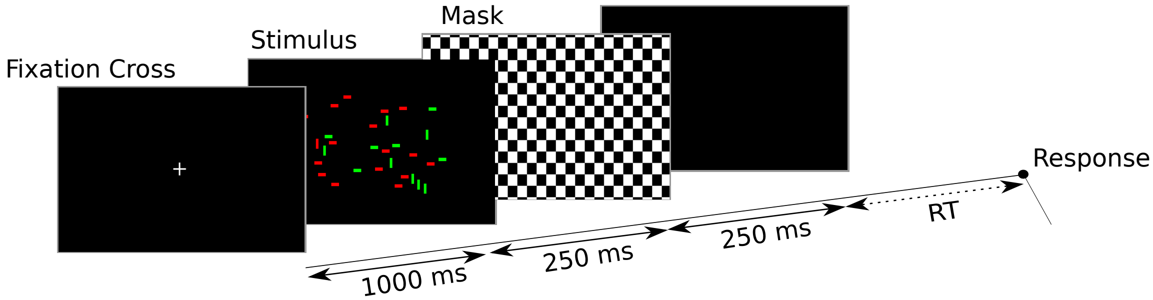

Fig. 1: Sequence of stimuli presented in each trial.

from each of the 64 available channels, i.e., a total of 3,072 values.

D. Feature Extraction

We used neural and behavioural features to identify the confidence of the user in the decision made in each trial of our experiment. These are described below.

1) Neural features: CSP filtering projects the multi-channel EEG data into a low-dimensional spatial subspace. The projection matrix is constructed in such a way to maximise the variance of the different classes of the signals. In this work, the task that we wanted to carry out, discriminating between correct and incorrect decisions (more on this later), was a standard two-classes task and, so, the CSP filter maximised the variance between the neural signals associated with these two classes.

After applying CSP to the training set for each subject, we obtained a $3,072 \times 3,072$ projection matrix, the columns of which were the spatial patterns. These are organised in such a way that the first and the last columns of the matrix are the most significant patterns, i.e., those that have the maximum difference in terms of variance.

To obtain maximum efficiency and generalisation, we took the decision to start from the smallest number of features and increase this number if required. So, we chose only the first and the last spatial patterns as neural features to represent decision confidence. As this worked well, we didn't have to revisit this decision.

2) Response times: We used RT as a behavioural feature that can indicate the confidence of the user in each decision, as shorter RTs tend to be more frequently associated to correct (more confident) decisions than incorrect (less confident) ones (as suggested in [29] and empirically verified in [28]).

E. Making group decisions

In our system, after gathering the decisions of all the members of a group, these were weighed proportionally to the confidence of each user. The group's decision was computed as follows:

$$d_{group} = sign(w_1 \cdot d_1 + w_2 \cdot d_2 + \cdots + w_n \cdot d_n) \tag{1}$$

where n is the group's size, $d_i = \{-1, 1\}$ is the decision of participant $i = 1, \cdots, n$ and $w_i \in \mathbb{R}^+$ is the weight associated with the confidence of participant i in the current decision. The cBCI was responsible for computing the w_i's.

As usual in BCI, also the w_i's are computed through a process that relies on machine learning to optimise performance on a participant-by-participant basis. The problem is that in order to estimate decision confidence, we would need to have ground-truth information on the actual confidence with which the decisions in an appropriate training set were made. However, this information is not directly available. We could ask a participant to rate his or her degree of confidence in a decision, but this measure would likely be biased and not objective. In [28] we found that we could form an objective (but approximate) decision-confidence training set by relabelling the trials where the decision made by a participant was correct as "confident" (-1 label) and the trials where the decision was incorrect as "non-confident" ($+1$ label). Thus, the BCI system needs to predict if a user gave a confident (correct) response or a non-confident (incorrect) one.

For this, we used the Least Angle Regression (LARS) [35] method. In our LARS the predicted confidence in a decision is given by

$$f = a_0 + \sum_i a_i \cdot x_i \tag{2}$$

where a_i are constant coefficients (to be identified via a training set) and x_i are the two CSP neural features and the RT representing an epoch. Note that in [28] 24 PCA-based neural features and the RTs were used to train two different classifiers the outputs of which were then combined to obtain a confidence estimator. However, in this work we found that this added complexity wasn't necessary. So, here neural and behavioural features have been combined in a single linear model, which further reduced the free parameters in our cBCI.

Once a confidence estimate, f_i, is available for a particular decision of participant i, we compute the weights used in Equation (1) for that decision using the following *negative exponential weighting function*:

$$w_i = \exp\big(-(2.5 + f_i)\big). \tag{3}$$

The choice of this function was based on prior experience [28] and was motivated by the desire to allow confident users to count substantially more than uncertain users in the group's decision.

In order to ensure that results were not affected by overfitting, we made use of *10-fold cross-validation* so that the

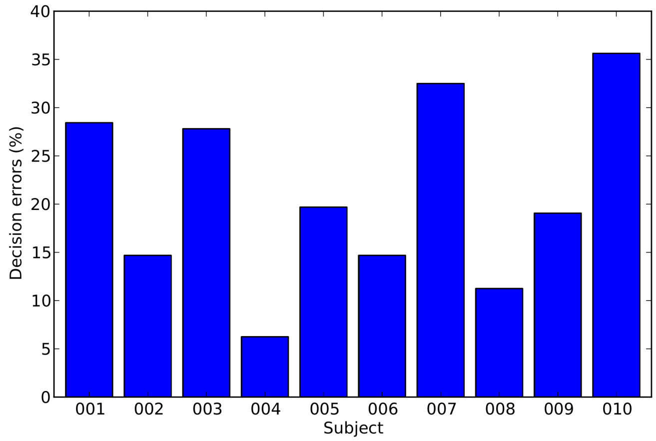

Fig. 2: Participant mean errors averaged over 320 trials.

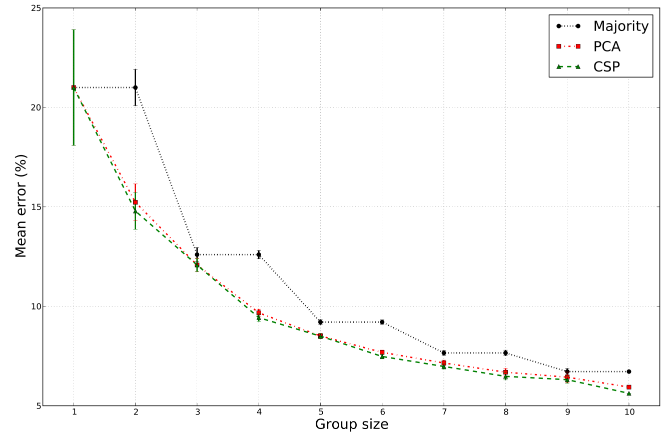

Fig. 3: Average percentage of errors vs group size for group decisions made by a CSP-based cBCI, a PCA-based cBCI and the majority rule.

estimation of the system's performance and the feature-extraction/machine-learning elements of the cBCI (namely, CSP filtering and LARS) were always performed on independent data sets. Results are reported in the next section.

III. RESULTS

Since the main aim of this study was to improve human performance, let us start our analysis by looking at the errors of each participant in the visual search task used in our experiment. As shown in Figure 2, participants had very different individual levels of performance, with error rates ranging from 6.25% to 35.63%. The average error rate was 21.0% with a standard deviation of 9.2%. For comparison in [28] the average error rate was 12.5%, thus corroborating our hypothesis that the visual search task we chose is significantly harder than our previous task.

We then applied our method to the $\binom{10}{n}$ groups of size n that could be assembled with our 10 participants, for $n = 2, 3, \cdots, 10$. For each group, we computed the errors made by the group when the decision was made according to both the majority rule and our confidence-based rule in Equations (1)–(3). Then, we averaged the errors over different group sizes. Figure 3 shows the mean decision-error rate for different group sizes using the majority rule as well as our confidence-based rule. For comparison, for the latter we considered both our current cBCI (based on two CSP features and RT) as well as a version based on 24 PCA components selected as in [28].

To test if the observed differences in error rates of Figure 3 were statistically significant, we compared the error *distributions* within each group size by using the one-tailed Wilcoxon signed-rank test. We have chosen this test since all methods (i.e., majority and the two confidence-based cBCIs) were applied to the same groups. The corresponding p-values and *W* statistics (in brackets) are reported in Table I. Sample sizes (the number of groups of each size) are indicated in the last row of the table. As indicated by the "Wins" column, which reports the number of group sizes where p-values were below the 0.05 statistical significance level, for almost all group sizes our new CSP-based collaborative BCI yields group decisions that are statistically significantly better than both traditional (majority-based) group decisions and group decisions made by a PCA-based collaborative BCI. The PCA-based BCI is also statistically significantly better than majority as we found in [28]. Note also that the PCA-based cBCI is never better than the CSP-based cBCI.

Table II shows the mean errors (in %) associated with different group sizes obtained using the majority rule as well as the confidence-based rules in Equations (1)–(3) based on either using 24 PCA components or using two CSPs.

As we found in [28], also for a visual search task a reasons why a confidence-based rules perform better than the simple majority rule is because they remove ties in even-sized groups. Indeed, as we can see both in Table II and Figure 3, the difference in performance for such groups is usually much greater than for odd-sized groups. However, both our cBCIs, but particularly the CSP-based one, manage to statistically significantly augment human decision-making also with odd-sized groups.

IV. CONCLUSIONS

In this paper we have presented a collaborative brain-computer interface that estimates and integrates the decision confidence of multiple non-communicating observers to achieve better group decisions. In previous research [28] we had tested this approach with a simple visual matching task and found that cBCIs can significantly outperform group decisions made by a traditional majority vote. Here, based on this experience, we have redesigned our system to further improve its performance and have put it to the test by applying it to a more difficult visual search task involving detecting a target in a set of 40 random distractors where targets could only be recognised by a conjunction of two features (colour and orientation), and so there was no pop-out effect.

A key improvement in the system was the adoption of spatio-temporal CSP filters which replaced the spatio-temporal PCA we previously used to extract features from

TABLE I: Statistical comparison of methods for group decisions for different group sizes. The table reports the p-values and corresponding W statistics (in brackets) returned by the one-tailed Wilcoxon signed-rank test when comparing the performance of groups of different sizes adopting different decision methods (i.e., Majority, confidence-based with PCA and confidence-based with CSP). The number of groups of each size that could be assembled with our 10 participants is indicated in the last row of the table. p-values below the statistical significance level 0.01 are in bold face, while p-values below 0.05 are in italics. The "Wins" column reports the number of group sizes where p-values are below 0.05.

	Group size								
Comparison	2	3	4	5	6	7	8	9	*Wins*
Majority wins over PCA	1.000000 (1035.00)	1.000000 (3267.00)	1.000000 (21690.00)	1.000000 (21513.00)	1.000000 (21390.00)	1.000000 (4458.00)	1.000000 (1000.00)	0.943359 (34.50)	0
Majority wins over CSP	1.000000 (990.00)	1.000000 (2425.50)	1.000000 (22155.00)	1.000000 (21802.00)	1.000000 (22150.00)	1.000000 (5022.00)	1.000000 (990.00)	0.994141 (49.00)	0
PCA wins over Majority	**0.000000 (0.00)**	**0.000000 (649.00)**	**0.000000 (46.00)**	**0.000000 (1492.00)**	**0.000000 (138.00)**	**0.000000 (693.00)**	**0.000000 (35.00)**	0.103516 (10.50)	7
PCA wins over CSP	0.993952 (648.50)	0.498915 (2184.50)	0.999792 (10582.00)	0.501097 (10152.50)	0.999830 (10500.00)	0.999114 (3412.00)	0.973101 (501.50)	0.906250 (25.50)	0
CSP wins over Majority	**0.000000 (0.00)**	**0.000000 (130.50)**	**0.000000 (0.00)**	**0.000000 (776.00)**	**0.000000 (5.00)**	**0.000000 (231.00)**	**0.000000 (0.00)**	*0.015625 (6.00)*	8
CSP wins over PCA	**0.006164 (254.50)**	0.501823 (2186.50)	**0.000208 (5708.00)**	0.499143 (10148.50)	**0.000170 (5610.00)**	**0.000892 (1638.00)**	*0.027318 (239.50)*	0.171875 (10.50)	5
Sample size	45	120	210	252	210	120	45	10	

the neural signals. This had important consequences. Firstly, we were able to obtain more accurate results with only two CSPs (as opposed to the 24 PCAs used previously) thereby significantly reducing the number of features and free parameters used in the system. Indeed, results obtained with 10 participants indicated that for almost all group sizes our CSP-based collaborative BCI yields group decisions that are statistically significantly better than both traditional (majority-based) group decisions and group decisions made by a PCA-based collaborative BCI. Secondly, CSP filtering is much faster than PCA and this allowed us to extend our ERP representation to include stimulus-locked potentials, in addition to the response-locked representation used before, thereby further marginally improving performance, while at the same time shortening the training process to a fraction of the original (a few seconds as opposed to a few minutes).

In this work we used the original CSP filter. However, in recent years several extensions of CSP have been proposed which further improve its performance (i.e., [36], [37]). In future research we will test some of these extensions in our cBCIs to evaluate their advantages and drawbacks.

Furthermore, we will also investigate whether other physiological measures such as heart rate, breathing frequency, skin conductance and eye movements can complement our current feature-set and lead to even more accurate confidence estimators.

We also plan to verify our offline findings with an online experiment, where 2–3 participants will simultaneously make decisions on identical or closely related tasks.

TABLE II: Mean errors (in %) for different group sizes using the majority rule, the method in Equations (1)–(3) using 24 PCAs and RT (as in our previous work) and the same method using two CSPs and RT (as in our new cBCI). The best value of each row is reported in bold face, while the worst is reported in italics.

Group size	Majority	PCA	CSP
1	**21.000**	**21.000**	**21.000**
2	*21.000*	15.229	**14.792**
3	*12.599*	12.081	**12.076**
4	*12.599*	9.674	**9.432**
5	*9.208*	8.512	**8.498**
6	*9.208*	7.686	**7.478**
7	*7.656*	7.151	**6.977**
8	*7.656*	6.687	**6.479**
9	*6.719*	6.438	**6.312**
10	*6.719*	5.938	**5.625**

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