A Collaborative Brain-Computer Interface for Improving Group Detection of Visual Targets in Complex Natural Environments

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***Abstract*— Detecting a target in a complex environment can be a difficult task, both for a single individual and a group, especially if the scene is very rich of structure and there are strict time constraints. In recent research, we have demonstrated that collaborative Brain-Computer Interfaces (cBCIs) can use *neural signals* and *response times* to estimate the decision confidence of participants and use this to improve group decisions. We successfully tested this approach with visual-matching and visual-search tasks with *artificial stimuli* (e.g., squares, rectangles, etc.).**

This paper extends that work in two ways. Firstly, we use a much harder target detection task where observers are presented with *complex natural scenes* where targets are very difficult to identify. Secondly, we complement the neural and behavioural information used in our previous cBCIs with physiological features representing *eye movements and eye blinks* of participants in the period preceding their decisions. Results obtained with 10 participants indicate that the proposed cBCI improves decision errors by up to 3.4% (depending on group size) over group decisions made by a majority vote. Furthermore, results show that providing the system with information about eye movements and blinks further significantly improves performance over our best previously reported method. This suggests that cBCIs may soon be ready for deployment in real-world decision tasks.

I. INTRODUCTION AND BACKGROUND

The human visual system is far superior to any computer system in the interpretation of visual scenes in ordinary conditions. However, in the presence of complex scenes, in the absence of sufficient time to complete the visual parsing, or when attention is divided, the human visual system is far from perfect [1], [2], [3], [4]. In these conditions, observers can only typically attend a subset of the features of the scene, thus affecting their ability to accurately assess situations, which may result in suboptimal decisions.

These perceptual and cognitive limitations can partly be overcome if multiple individuals are involved in the assessment and decision process. This is no surprise, of course, as much research on decision making has shown that group decisions can be superior to individual decisions [5], [6], [7], [8], [9]. However, it is also well known that the effectiveness of group decisions is hindered by difficulties in coordination and interaction between group members, reduced member effort within a group, strong leadership, group judgement biases, and so on [6], [9], [8]. In fact, in certain circumstances groups could be worse than individuals [10], [11], e.g., when there are strong time constraints on a decision.

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The situation is similar for the hugely researched area of computer-assisted decision-support systems [12], which can either help or hinder decision-making and situation awareness [13], [14], [15], [16].

In this paper we will propose a hybrid approach where group decisions are aided by a particular form of decision-support system based on a hybrid Brain-Computer Interface (BCI) which attempts to establish the confidence of the decision makers and exploit this to improve group decisions.

Usually BCIs provide an alternative communication channel for *individual* users with severe motor disabilities. However, in recent years *collaborative BCIs* (cBCIs) have started to be applied with good success to perform group action, group perception and also group decision-making for able bodied individuals [17], [18], [19], [20], [21], [22], [23], [24], [25]. In cBCIs, either the EEG signals or individual classifier outputs are integrated to determine the system's output.

For instance, for a movement-planning task, the cBCI proposed in [17] could make motor decisions much faster than a non-BCI user, but with a much lower level of accuracy. In [18] a cBCI could discriminate between pictures of cars and faces much faster than a non-BCI user, but a group using the cBCI could not compete with a group of non-BCI users in terms of decision accuracy. Similarly, in a task involving the detection of aeroplanes in aerial images of urban environments, the cBCI in [23] was much faster than non-BCI users, but could not reach equivalent accuracy.

Particularly relevant for this paper is some recent research [24] where we developed a cBCI for improving group decisions in a visual-matching task. We used neural features extracted from EEG and response times to predict the confidence of each participant in a decision. Then, we weighed the decisions of group members according to their confidence before combining them to produce a group decision. With our cBCI, for the first time, *cBCI-assisted groups were more accurate than identically-sized groups performing the same task*. However, the visual matching task performed by the users was based on *artificial stimuli* (triangle, squares, etc.).

In [26] we tested this cBCI on a traditional visual-search task (finding a red vertical bar among a large number of green vertical and horizontal bars and red horizontal bars). Also, we further improved its performance by using a spatio-temporal Common Spatial Pattern (CSP) filter [27] to extract neural features from EEG instead of the Principal Component Analysis (PCA) used in [24]. While results were even more encouraging, that work also used *artificial stimuli*.

This paper extends our previous work in two ways. Firstly, in an attempt to start moving our cBCIs towards real-world application domains involving more useful target-detection tasks, e.g., in policing or defence, we used a much harder search task where observers are presented with *complex natural scenes* and targets are very difficult to identify. Secondly, we complemented the neural and behavioural information used in our previous cBCIs to assess individual decision confidence, with physiological features representing the eye movements and eye blinks of participants during stimulus presentation and in the proximity of their decisions.

We introduced this second element as in our previous experiments we noticed that some participants tended to blink after the stimulus associated with a decision task had disappeared (as is reasonable), but somehow in synchrony with their decision. Also, we expected eye movements to be triggered by the presentation of stimuli as the analysis of a stimulus was initiated (but could not be completed, due to the rapidity of stimulus presentation). In the present study, we wanted to test whether eye movements and blinks would carry information about decision confidence.

The paper is organised as follows. Section II describes the participants, the stimuli presented, the data acquisition and manipulation and how group decisions are obtained in our cBCI. Results of experiments are presented and analysed in Section III. Finally, Section IV ends the paper with some conclusions and suggestions for further research.

II. METHODS

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. The research is funded by the UK's MoD through DSTL. The project received MoD and University of Essex ethical approval in July 2014.

B. Stimuli and Tasks

Participants were presented with 8 blocks of 40 trials, for a total of 320 trials. As shown in Figure 1, each trial started with the presentation of a fixation cross in the middle of the screen for 1000ms. This time allowed participants to get ready for the presentation of the stimuli and got EEG signals back to baseline after the response from previous trials. Then an image of an arctic environment, containing a variable number of penguins (non-targets) and possibly a polar bear (target), was presented. Each image was displayed in full screen mode and subtended approximately 30.29 degrees horizontally and 19.22 degrees vertically. Images containing a target were randomly built using five different environments (backgrounds), two different bear pictures and four possible positions of the target in the picture. This gave us 40 different target displays and 5 non-target displays. The stimulus was presented for 250ms and was immediately followed by a mask for 250ms so as to increase task difficulty. The mask was a black and white 24×14 checkerboard. After the mask, participants had to decide, as quickly as possible, whether or not a target was present in the image, by clicking (with the right hand) the left or the right mouse buttons, respectively. Response times (RTs) were recorded.

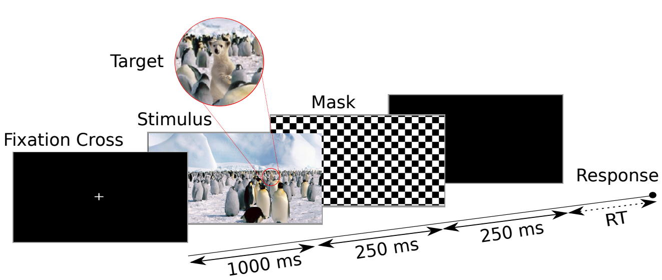

Fig. 1: Sequence of stimuli presented in a trial.

The sequence of displays used in the experiment was randomly generated, stored, and reused with all participants. This allowed simulating (offline) concurrent group decision-making. Target images were used in 25% of the trials.

Participants were briefed and prepared for the experiment. Then they were familiarised with the task by doing 2 training sessions of 10 trials each. Preparation and practice took approximately 45 minutes. During the experiment participants were comfortably seated at about 80 cm from a LCD screen.

C. Data Acquisition and Feature Extraction

1) Neural features: We recorded neural signals 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, band-pass filtered between 0.15 and 40 Hz and then low-pass filtered with a filter designed with the Remez exchange algorithm [28] with a pass band of 0–6Hz and a stop band of 8–1024 Hz. Artifacts caused by eye-blinks and other ocular movements were removed by using a standard subtraction algorithm based on correlations. 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. Stimulus-locked epochs lasted 1500ms and started in synchrony with the presentation of the stimulus. Each ERP was thus represented by 48 samples from each of the 64 available channels, i.e., a total of 3,072 values.

We used a spatio-temporal CSP filter to extract neural features from ERPs, as this was found to have better performance than PCA in [26]. We applied CSP on a participant-by-participant basis to transform the training set data into spatial patterns that maximise the variance between classes (correct/incorrect). We then used the first and the last spatial patterns as neural features.

2) Response times: We used RTs input features in our cBCI as they tend to vary in an inversely proportional matter with the degree of confidence [29]. We recorded RTs by computing the time difference between the end of the mask and the click of an ordinary USB mouse. As indicated in [24], this adds negligible jitter to the RTs.

3) Eye movements and blinks: Eye movements were recorded by using a Jazz eye tracker which provided data at a sampling rate of 2 kHz. The following features were extracted from the recordings of the *vertical* component of the eye movements:[1] (1) total distance covered by the eyes along the vertical axis during stimulus presentation (250ms), (2) standard deviation of the vertical eye movements during stimulus and mask presentation (500ms), (3) mean of the numerical derivative of the vertical eye movements in the same time window, and (4) mean of the derivative signal in a 500ms time window centred on the response.

D. Making group decisions

Our cBCI uses the features listed above to estimate the confidence of participants in their decisions and uses this to weigh such decisions when making a group decision.

In order to train a classifier to predict the confidence of a decision, ground-truth information on the confidence is needed. However, this information is not available. In our previous research [24] we made the assumption that a correct response given by a participant in a trial is most likely the result of a confident decision, while an incorrect response is likely to be an indication of an uncertain decision. Since the results we obtained based on this assumption were good, in the current study we followed the same approach. As in previous work, we used Least Angle Regression (LARS) [30] to predict the confidence in a decision of each participant.

Once a confidence estimate c_i for each of n participants is available, group decisions were made as follows:

$$d_{group} = \mathtt{sign}(w_1 \cdot d_1 + \cdots + w_n \cdot d_n) \qquad (1)$$

where d_i is the decision of member i of the group and $w_i = \exp(-2.5 - c_i)$ is the corresponding weight.

The data available were processed using *10-fold cross-validation*. This used 10 training sets to compute the optimal coefficients for LARS and the corresponding independent test sets to evaluate the performance of the system.

III. RESULTS

Performance across individual participants was quite varied. Error rates ranged from 8.75% to 42.5%, the average error rate being 18.47% with a standard deviation of 9.36%, confirming the difficulty of the task for a single individual.

We considered all groups of size n that could be assembled with our 10 participants, for $n = 2, \ldots, 10$. For each group, we computed the errors made by the group using the following methods: (1) the ordinary majority rule, (2) a cBCI exploiting only neural and behavioural features (EEG+RT) as in our previous research [24], [26], (3) a cBCI based on neural and eye blink/movement features (EEG+Eye), and (4) a cBCI using neural, behavioural and physiological eye blink/movement features (EEG+RT+Eye).

Table I shows the mean error rate (%) for groups of increasing size when making decisions with the aforementioned methods (the best result of each row is shown in bold face, the worst in italics). This suggests that even with a realistic search task and natural images our cBCIs always perform better than the majority rule. Moreover, it suggests that the integration of neural, behavioural and physiological (eye blinks/movements) features can further improve the performance of the system.

TABLE I: Mean errors (in %) for different group sizes using traditional and cBCI group decision-making systems.

Group size	Majority	EEG+Eye cBCI	EEG+RT cBCI	EEG+RT+Eye cBCI
1	**18.47**	**18.47**	**18.47**	**18.47**
2	*18.47*	15.23	15.24	**15.04**
3	12.04	*12.11*	12.02	**11.99**
4	*12.04*	10.56	10.53	**10.44**
5	*9.98*	9.90	9.82	**9.75**
6	*9.98*	8.95	8.91	**8.79**
7	*8.91*	8.69	8.74	**8.64**
8	*8.91*	8.11	8.16	**8.01**
9	*8.12*	**7.69**	8.03	7.78
10	*8.12*	**7.19**	7.50	**7.19**

These findings are confirmed by the statistical analysis shown in Table II where we used the one-tailed Wilcoxon signed-rank test to compare the error distributions within each group size for different group-decision systems. The table reports the p-values and W statistics (in brackets) for each comparison. The last row gives the number of groups of each size that one can build with 10 participants. The "Wins" column reports the number of group sizes where p-values were below the 0.05 statistical significance level. p-values below 0.05 are in italics, those below 0.01 are in bold face.

The results show that with the realistic search task used in this study, our new EEG+RT+Eye cBCI is statistically significantly better than equally sized groups using straight majority for most group sizes. Also, it is statistically superior to our previously proposed best cBCI [24], [26] for group of sizes 4–8. Furthermore, it is never statistically inferior to any of the methods under test.

IV. CONCLUSIONS

We have proposed a hybrid cBCI for improving group decisions in an extremely difficult, realistic visual-search task where participants were given a 250ms glimpse of an arctic landscape crowded with hundreds of penguins and had to decide whether a polar bear was hiding among them.

Results show that in the conditions of extreme perceptual load of our experiment, tapping in to the unconscious mind of individuals with our neural, behavioural and physiologic features to evaluate their decision confidence brings considerable benefits. Not only is the proposed cBCI much more accurate than a single non-BCI user (unsurprisingly), but it also reduces decision errors by up to 3.4% (depending on group size) over decisions made by equally-sized groups of non BCI-users. Also, results show that providing the system with information on eye movements and eye blinks further improves performance over our best previous cBCIs for group decision-making [24], [26]. This is noteworthy as in those cBCIs we used easier tasks and artificial stimuli.

This suggests that cBCIs may soon be ready for deployment in real-world visual search tasks, e.g., for suspect/threat detection in policing or defence.

[1] We used the vertical eye-movement component as this is also influenced by eye blinks and also because in preliminary tests we found that the horizontal component did not seem to contribute any additional information.

TABLE II: Statistical comparison of methods for group decisions for different group sizes.

	Group size								
Comparison	2	3	4	5	6	7	8	9	*Wins*
EEG+Eye cBCI vs Majority	**0.000002 (114.00)**	0.988531 (1131.50)	**0.000000 (749.50)**	**0.001012 (4639.00)**	**0.000000 (511.00)**	**0.000000 (776.50)**	**0.000000 (5.50)**	*0.015625 (0.00)*	7
EEG+RT cBCI vs EEG+Eye cBCI	0.552544 (440.50)	*0.015148 (705.50)*	0.252085 (7010.00)	**0.006180 (4560.50)**	0.050969 (4495.50)	0.961593 (1295.00)	0.848450 (246.00)	1.000000 (21.00)	2
EEG+RT cBCI vs Majority	**0.000001 (130.00)**	0.476353 (630.50)	**0.000000 (821.50)**	**0.000000 (3049.50)**	**0.000000 (459.00)**	**0.000197 (992.50)**	**0.000000 (15.00)**	0.265625 (6.00)	6
EEG+RT+Eye cBCI vs EEG+Eye cBCI	0.147186 (298.00)	**0.000030 (213.00)**	**0.002006 (4928.00)**	**0.000000 (2709.50)**	**0.000000 (2157.50)**	0.053534 (783.00)	*0.013289 (94.50)*	0.781250 (18.50)	5
EEG+RT+Eye cBCI vs Majority	**0.000000 (102.50)**	0.146402 (575.50)	**0.000000 (360.00)**	**0.000000 (2478.00)**	**0.000000 (264.50)**	**0.000000 (769.00)**	**0.000000 (10.00)**	*0.031250 (2.00)*	7
EEG+RT+Eye cBCI vs EEG+RT cBCI	0.083047 (341.00)	0.200529 (405.00)	**0.005421 (4534.00)**	**0.001286 (3220.00)**	**0.000006 (2887.00)**	**0.000256 (470.50)**	**0.003562 (110.00)**	0.062500 (0.00)	5
Sample size	45	120	210	252	210	120	45	10	

In the future we will test our cBCI online, where group members perform a task simultaneously, and we will evaluate whether providing the system with other physiological measurements, such as heart rate, breathing frequency or skin conductance, can further improve performance.

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