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Enhancement of Group Perception via a Collaborative Brain-Computer Interface

Davide Valeriani, Riccardo Poli, and Caterina Cinel

***Abstract*—*Objective.* We aimed at improving group performance in a challenging visual search task via a hybrid Collaborative Brain-Computer Interface (cBCI). *Methods.* Ten participants individually undertook a visual search task where a display was presented for 250 ms, and they had to decide whether a target was present or not. Local Temporal Correlation Common Spatial Pattern (LTCCSP) was used to extract neural features from response- and stimulus-locked EEG epochs. The resulting feature vectors were extended by including response times and features extracted from eye movements. A classifier was trained to estimate the confidence of each group member. cBCI-assisted group decisions were then obtained using a confidence-weighted majority vote. *Results.* Participants were combined in groups of different sizes to assess the performance of the cBCI. Results show that LTCCSP neural features and eye movements features significantly improve the accuracy of the cBCI over what we achieved with previous systems. For most group sizes, our hybrid cBCI yields group decisions that are significantly better than majority-based group decisions. *Conclusion.* The visual task considered here was much harder than a task we used in previous research. However, thanks to a range of technological enhancements, our cBCI has delivered a significant improvement over group decisions made by a standard majority vote. *Significance.* With previous cBCIs groups may perform better than *single* non-BCI users. Here, cBCI-assisted groups are more accurate than *identically-sized* non-BCI groups. This paves the way to a variety of real-world applications of cBCIs where reducing decision errors is vital.**

***Index Terms*—Brain-computer interfaces, decision making, electroencephalography.**

I. Introduction

A. Decision Making in Groups

Group decision-making has been studied for decades, as understanding its processes and dynamics has important implications in many fields, including psychology, economics and politics [1], [2], [3].

Groups have many advantages compared to individuals. For example, they have augmented action capabilities: thanks to the joint forces of its members a group can do things that are beyond the strength or endurance of a single individual. Similarly, one would expect groups to show increased cognition and intelligence. Indeed, extensive literature has shown that making decisions in groups can be powerful (see, for example, [4], [5], [6], [7]) and can be superior to making individual decisions in many different contexts, including settings where individuals are involved in visual tasks [8].

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However, it is not always obvious whether or not a group decision can outperform individual decisions, and it actually seems that in many cases group performance, though typically better than average individual performance, does not exceed the performance of the best member of the group [7], [9]. How well a group performs depends on a large number of factors, including group cohesiveness, norms within the group, leadership, perceived expertise, stress, timing, and the type of task or decision to be made. All of these, and much more, can affect a member's contribution in the group, which in turn can make a collective decision better or worse than individual independent decisions [7], [10], [11], [5], [8], [12].

How dramatic this effect can be is shown, for example, in studies adopting the well known Asch experimental paradigm [13] where individuals are involved in a very simple perceptual task (e.g., assessing whether two lines have the same length). Here, in case of discrepancies, the influence of a group can be so strong that individuals often end up giving the incorrect response to align with the group, even if they know it is incorrect.

Despite all the negative effects that a group can have on an individual's decision process, as discussed above, there are still many reasons why a group decision is desirable and advantageous: group decision making, for example, allows pooling of information (e.g., [14]).

In previous research [15] we have suggested that, in circumstances where groups decisions are hampered, a system would be desirable that could provide the advantages of groups (e.g., pooling of information) while avoiding their pitfalls, many of which are caused by the direct interaction of the group members. We have, therefore, proposed and tested the idea that group decisions can be improved by estimating the confidence and combining the independent decisions of *non-interacting members* of a group. As we will discuss in Section I-C, this was demonstrated through a collaborative brain-computer interface with individuals engaged in decisions associated with a simple visual matching task.

In this article, we will extend this system in a number of ways and we will apply it to a much harder and important visual search task.

B. Visual Search

Visual search is an important perceptual process involving visually scanning the environment in search for an item of interest. We perform visual search tasks on a daily basis, e.g., when looking for a particular item in a drawer containing many different objects or scanning our home for misplaced keys. Visual search, in the form of looking for a suspect or

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a potential terrorist within a crowd or in surveillance video, is also a key element of policing and counter intelligence. Despite there being clear evolutionary advantages in animals quickly identifying dangerous elements in the environment, humans invariably find visual search tasks slow, taxing and difficult to carry out (although performance varies across different people, contexts and details of the task performed, as well as with the experience and age of the observer [16]).

Given the important role of visual search, it is not surprising that experimental visual search paradigms have been extensively used in the study of perception and visual attention for more than 30 years [17]. In a typical experiment, observers are asked to look at a display containing a number of different items and establish whether a specific *target* item is or is not present in the scene among many different *distractor* items.

Visual search experiments usually follow two main approaches [18]: the *percent correct* method, where the display is presented to an observer for a limited amount of time following which a decision about the presence or absence of the target is made, and the *speed-based* method, where the display is presented to the observer until he/she reaches a decision. In the former, the accuracy of the decisions made is used to evaluate the performance, while in the latter performance is evaluated using Response Times (RTs).

C. Collaborative Brain-Computer Interfaces

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 [19], [20], [21], [22], [23]. In the last few years, however, BCIs have been developed also for the cognitive augmentation of able-bodied individuals, e.g., to improve human decision accuracy or speed [24], [25], [26].

More recently, collaborative BCIs (cBCIs), i.e., BCIs where data from multiple users are integrated to achieve a common purpose, have also been proposed for improving the perceptual or cognitive performance of groups of users. Studies and applications of cBCIs include systems for a movement planning task [27], visual discrimination between rapidly presented pictures of cars and faces [28], [29], detecting the onset of visual stimuli presented on a black background [30], joint 2–D cursor control [31], rapid discrimination of airplanes in aerial images of urban environments [32] and group decision-making for a simple visual-matching task [15].

In particular, in [15] participants had to decide whether or not two sets of 2–D 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 behavioral measures of confidence. That is, in addition to EEG we recorded the RTs, as these are influenced by, and thus can reveal, the confidence in a decision [33]. Being based on both neural and behavioral features our system was, thus, a *hybrid* cBCI. Candidate neural features were extracted from EEG via spatio-temporal Principal Component Analysis (PCA). We then optimally selected, combined and used neural and behavioral 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 on 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.[1] The reasoning behind this assumption is that a rational observer is more likely to give an incorrect response when the perceptual processes leading to the decision do not provide all the necessary information to take the correct decision, hence making the user *uncertain*. On the other hand, it is reasonable to assume that the confidence with which an observer takes a decision would be higher for most of the "correct" trials.[2]

Finally, group decisions were determined by a weighted-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 identically-sized (non-BCI) groups adopting the majority rule. That is, while all previous cBCIs had been able to improve either speed or accuracy over single non-BCI users, for the first time, the system developed in [15] provably allowed cBCI-assisted groups to make more accurate decisions than groups performing the same tasks by traditional means.

D. Contributions

Previous research on cBCIs suggests that in the future these systems could be applied in various real-world situations to enhance individual or group performance, particularly in cases where critical decisions have to be made very rapidly (e.g., in defense) or with high level of confidence (e.g., in air traffic control). Many such systems would work equally well for people with impaired communication and motor control capabilities as for able-bodied operators. The present study represents another step towards moving cBCIs out of the lab.

More specifically, we propose a cBCI for improving group decisions based on visual perception. Like the cBCI in [15], this is a hybrid system in that it uses both the responses of the users and EEG and physiological measurements in order to produce better group decisions.

This paper extends the framework proposed in [15] along four main directions.

Firstly, we investigate whether a cBCI approach can be applied to a visual search task that is perceptually and cognitively different from the visual matching task previously tested. The high perceptual load (due to the large number of non-targets presented in each display), the difficulty of

[1]This was unlike previous cBCI and BCI research (see previous section) where systems are trained to classify EEG data to infer the intended response of an observer (e.g., target or not-target).

[2]In preliminary work [34] we actually put this interpretation to the test by verifying whether the opposite interpretation would yield significantly different results. Results of joint decisions were exceptionally bad when we adopted this alternative criterion, confirming our original line of reasoning.

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 very hard in this task. The choice of a different and more challenging task is important because, while in [15] we identified a reasonable way of obtaining and exploiting correlates of the individual degrees of confidence in decisions, it remained unclear whether the approach would generalize to other perceptual tasks and what performance level a cBCI could deliver in such cases. To the best of our knowledge every cBCI study reported in the literature used only one task (or a group of very similar tasks). Thus, exploring these issues is an important research goal for cBCI and the fact that here, too, cBCI-assisted groups are more accurate than *identically-sized* non-BCI groups represents a major stepping stone towards that goal.

Secondly, we improve our confidence estimators by replacing the spatio-temporal PCA we used previously to extract the neural features from the EEG data with a Local Temporal Correlation Common Spatial Pattern (LTCCSP) filter [35]. The original form of Common Spatial Pattern (CSP) filtering has been adopted in several BCI applications for its marked ability to capture important aspects of the data [36], [37], [38] but it does not include temporal information, which is quite important in studies based on Event-Related Potentials (ERPs). This is why researchers (e.g., [39], [40], [41], [42]) have recently developed forms of CSP that consider temporal variability, LTCCSP being one of them. LTCCSP allowed us to both increase the accuracy (thanks to the inclusion of temporal information) and reduce the number of neural features required by the system (from the 24 PCA components used originally), thereby promoting generalization and speed (see below).

Thirdly, the adoption of LTCCSP has allowed us to extend the information provided in input to the system. In [15] we could only use features extracted from response-locked epochs as we found in preliminary explorations that an increase of the feature vector size would cause the classifier to overfit the training data. However, thanks to the significant reduction of number of features allowed by LTCCSP, here it has been possible to provide the system with both stimulus-locked and response-locked representations of the ERPs. Stimulus-locked epochs allow to better capture the exogenous and endogenous components triggered by the stimulus [43]. These include the perception of task difficulty [44] and the processes of evaluation and categorization of the stimulus and context updating typically associated with the P300 [45]. Both are part of the decision making process and are expected to correlate with the decision confidence. This could, thus, complement the information extracted from the response-locked ERP representation (that captures well late endogenous components [43] and that we already used in [15]) and further improve our confidence estimates [43].

Fourthly, as LTCCSP is more than one order of magnitude faster than PCA, the speed of the system has much increased compared to our previous cBCI. The ability to produce outputs within a reasonable time window is a prerequisite for online systems to be applied in everyday life where responsiveness is needed [46]. So, while the speed up is not so important in our offline validation of the system, this is an added bonus as it makes the cBCI ready for future online experimentation.

This article is an invited extended version of a paper presented at the 7^{th} IEEE EMBS Neural Engineering Conference [47].

II. Methods

A. Participants

We collected data from 10 healthy volunteers (6 male, average age = 28.5, SD = 6.0) with normal or corrected-to-normal vision who gave written informed consent to take part in the experiment. The research received UK's MoD and University of Essex ethical approval in July 2014.

B. Stimuli and Tasks

In this study we adopted a combination of the *percent correct* and the *speed-based* visual search methods described in Section I-B. In particular, each display in the visual search task was shown for a short time (as in the *percent correct* approach). Then, we asked the observers to make their decisions as rapidly as possible (as in the *speed-based* approach). Therefore, both accuracy and speed were measured. We used this approach as it is a more realistic representation for the type of applications we are interested in.

Participants, comfortably seated at about 80 cm from an LCD screen, were asked to undertake an experiment consisting of 8 blocks of 40 trials, for a total of 320 trials. Each trial (Figure 1) started with the presentation of a fixation cross in the middle of the screen for 1 s (which allowed EEG signals to return to baseline after the response from previous trials). This was followed by 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, for 250 ms. Then, a mask (black and white 24×14 checkerboard) was presented for 250 ms. The participants task was 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*. They clicked the left mouse button with the index finger to signal the presence of the target, and the right mouse button with the middle finger to signal its absence. RTs were recorded. The mouse was always controlled with the right hand (RT differences between using the non-preferred hand over the preferred one are typically very small [48]).

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 instance of each type was present in the display. Targets (red vertical bars) 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.

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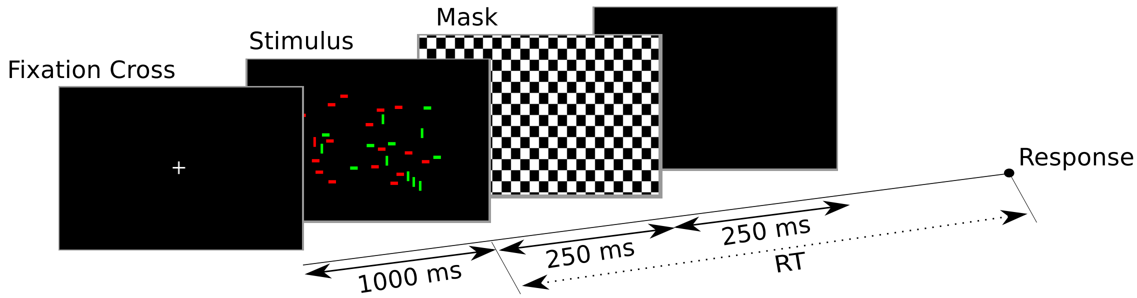

Figure 1: Sequence of stimuli presented in the trials of our experiment.

Briefing, preparation of participants and task practice (2 blocks of 10 trials each) took approximately 45 minutes, while the actual experiment lasted approximately 25 minutes.

C. Data Acquisition and Preprocessing

RTs were measured by time-stamping the clicks of an ordinary USB mouse. As indicated in [15], this produces a *maximum* jitter of 14 ms which is negligible when compared with even the shortest RTs.

Eye movements were recorded by using a Jazz eye tracker which provided data at a sampling rate of 2 kHz. The eye tracker was safely placed on the forehead of the participant to record horizontal and vertical eye movements.

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 [49] with a pass band of 0–6 Hz and a stop band of 8–1024 Hz. Consistently with our previous study [15], the data were finally down-sampled to a sampling rate of 16 Hz, since this still allows detecting meaningful variations (e.g., P300s) in the EEG data.[3]

The EEG data were segmented into two types of epoch — response-locked and stimulus-locked — and de-trended. Response-locked epochs lasted 1500 ms and started 1000 ms before the user's response. Stimulus-locked epochs also lasted 1500 ms but started in synchrony with the presentation of the stimulus.[4] Each epoch was thus represented by 48 samples from each of the 64 available channels, i.e., a total of 3,072 values. It should be noted that the average RT across participants is just above 900 ms. So, in most trials the response- and stimulus-locked epochs do overlap (albeit to different degrees). However, the stimulus-locked epochs are still very different from the response-locked ones and, so, together they carry more information than each type on its own.

D. Relabelling

In order to estimate the decision confidence via machine learning algorithms, 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.

Therefore, we adopted the same approach used in [15] that associates confidence to correctness. Specifically, we have relabelled all the trials in the training set where the decision made by a participant was correct (independently from the presence or absence of the target) as "confident" (-1 label) and the trials where the decision was incorrect as "non-confident" ($+1$ label). As indicated in Section I-C and verified in [34], [15], this is a reasonable approximation.

That is, our cBCI predicts whether a user gave a confident (correct) or a non-confident (incorrect) response, and *not* whether the response of the user was target or not-target.

E. Feature Extraction

We used neural, behavioral and physiological features to identify the confidence of the user in the decision made in each trial of our experiment.

1) Neural features: CSP filtering projects the multi-channel EEG data into a low-dimensional spatial subspace in such a way to maximize the variance of the different classes of the signals. While the standard CSP algorithm uses only the global spatial covariances to build the transformation matrix, LTCCSP also considers temporally local information in the variance modeling. In particular, it introduces a weight matrix to impose larger coefficients on patterns that are similar within a local temporal range τ (that we empirically set to 10 samples). For a detailed explanation of the LTCCSP method, the reader can refer to [35].

In this work we have used LTCCSP to extract features from a standard two-classes task where we wanted to discriminate between correct and incorrect decisions. Therefore, the LTCCSP filter maximized the variance between the neural signals associated with these two classes.

[3] As suggested by one reviewer, we have verified that it is possible to slightly improve the performance of the cBCI (0.06% of average relative improvement on group sizes 1-10) by increasing the sampling rate to 32 Hz. However, this has the significant disadvantage of increasing feature extraction time from 17 s to 49 s.

[4] For efficiency, the final low-pass filtering and down-sampling mentioned above were carried out on the epochs themselves. These were extended by 400 ms, filtered and then trimmed back to 1500 ms to avoid transient effects.

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For each subject, we have applied LTCCSP to the response- and stimulus-locked epochs of the training set to obtain two projection matrices (W_{Rlckd} and W_{Slckd}, respectively). Then, we have transformed the original EEG data to the new feature space where the columns of the resulting matrices are organized in such a way that the first and the last columns of each have the maximum and the minimum difference in terms of variance, respectively.

To obtain maximum efficiency and generalization, 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 columns of each matrix and we used their variances as neural features to represent decision confidence. As this worked well, we did not have to revisit this decision. Therefore, we have used 4 LTCCSPs in total as neural features.

2) Response times: We used RT as a behavioral feature that can indicate the confidence of the user in each decision. As suggested in [33] and empirically verified in [15], shorter RTs tend to be more frequently associated to correct decisions (i.e., where the user is more confident) than to incorrect ones.

3) Eye movements: We used the vertical component of the eye-movement recorded by our eye tracker to extract physiological features as this also includes information about the occurrence of eye blinks. Four different features were extracted:

1) the total distance covered by the eyes along the vertical axis during the stimulus presentation (250 ms time window);
2) the standard deviation of the vertical eye movements during the stimulus and the mask presentation (500 ms);
3) the mean of the numerical derivative of the vertical eye movements during the stimulus and the mask presentation (500 ms);
4) the mean of the derivative signal in a 500 ms time window centered on the response.

We chose these features as they seem to be the most effective as confidence indicators based on preliminary results [50].

F. Making Group Decisions

In collaborative decision-making, different approaches can be followed to combine the answers of multiple participants to obtain a group's decision. Voting systems seem to be the most appropriate for distributed cBCI, i.e., where each user has his own BCI sub-system.

In [27], a Support-Vector Machine (SVM) classifier was used to predict the answer of each participant. The SVM predictions were then weighted according to each user's training accuracy to build group decisions. A similar approach has been used in [29], [30] where, instead of using a weighted majority, a second-layer SVM has been used to transform the outputs of the individual SVMs into group decisions. In [28] individual ensembles of linear classifiers were trained for the participants. Their outputs were then combined using a weighted sum where the weights were optimally determined based on the performance of the users on the training set. [28] also tested a form of performance-adjusted majority vote where different thresholds were applied to the outputs of individual classifiers to convert them into votes, the thresholds, again, having been chosen based on training-set performance.

Our cBCI uses a similar approach (a weighted majority rule) to build the group's decision although, unlike [27], [29], [30], [28], it does not predict the user decision (in our system this is already known from the user's behavioral responses) but the user confidence in that decision. Also, unlike [27], [29], [30] and the optimal linear classifier in [28], in determining group decisions our system does not weight different users differently based on their training accuracy.[5] Finally, while we, too, use a linear combination to integrate evidence across multiple users, as discussed later in our system the weights are adjusted independently for every decision.

More specifically, the weights associated to each user in the group are computed from an estimation of his or her confidence in a particular decision given by a linear regressor. These weights are then multiplied by the individual decisions gathered from each participants of a group to build the final decision as follows:

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

where $\mathtt{sign}$ is the sign operator, n is the group's size, $d_i = \{-1, 1\}$ is the decision of participant $i = 1, \ldots, n$ and $w_i \in \mathbb{R}^+$ is the weight associated with the confidence of participant i in the current decision. The cBCI is responsible for computing the w_i's. In case of ties (i.e., $d_{group} = 0$), a random decision is made.

The w_i's have been computed using the Least Angle Regression (LARS) [51] method. In our cBCI, LARS has to predict the confidence in a decision, which is given by

$$f = \sum_j a_j \cdot x_j + \epsilon \qquad (2)$$

where a_j for $j = 1, 2, ...$ and ϵ are constant coefficients (to be identified via a training set) and x_j are the features representing an epoch (two LTCCSP neural features extracted from the response-locked epoch, two LTCCSP neural features extracted from the stimulus-locked epoch, the response time and four features extracted from the eye movements). Note that in [15] 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 was not necessary. Hence, here neural, behavioral and physiological 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*:

$$w_i = \exp(-2.5 - f_i). \qquad (3)$$

This function was chosen based on prior experience [15] and was motivated by the desire to allow confident users to count substantially more than uncertain users in the group's decision.

[5]We think that a system that gives identical chances to individuals having the same confidence is more likely to be seen as acceptable, and thus be adopted, by future end users.

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In order to ensure that results were not affected by overfitting, we made use of *10-fold cross-validation* so that the estimation of the system's performance and the feature-extraction/machine-learning elements of the cBCI (namely, LTCCSP filtering and LARS) were always performed on independent data sets. Hence, in each fold we used 90% of the trials for training and the remaining 10% for testing. The same non-overlapping sets were built for each participant.

G. Group Simulation

We applied our method to the $\binom{10}{n}$ groups of size n that could be assembled with our 10 participants, for $n = 2, 3, \ldots, 10$. For each group, we computed the errors made by the group when the decision was made according to both the majority rule (i.e., w_i of Equation 1 are the same for all the group's members) and our confidence-based method in Equations (1)–(3). For comparison, for the latter we considered not only our current cBCI (based on LTCCSP features, RT and eye movements features) but also a version based on 24 PCA components selected as in [15] and RT, a version based on LTCCSP features and RT (to establish the impact on the performance of the features extracted from the eye movements), and two versions that used only the RT or the RT and the eye movements features to estimate the confidence. Then, for each group size we averaged the errors made by the different groups.

To test if the observed differences in error rates using different methods were statistically significant, we compared the error *distributions* within each group size by using the one-tailed Wilcoxon signed-rank test with the Bonferroni correction. We have chosen this paired-data test since all methods (i.e., Majority and the four confidence-based cBCIs) were applied to the same groups.

III. Results

A. Individual Performance

Since the main aim of this study was to improve human performance, we start 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 (the solid line in the figure) was 21.0% with a standard deviation of 9.2%.

For comparison, in [15] the average error rate for a visual matching task was 12.5%, corroborating the hypothesis that the visual search task used here would be significantly harder.

B. Group Performance

Figure 3 shows the mean decision-error rate for different group sizes using the majority rule as well as our confidence-based methods. Table I provides a numerical representation of the same information.

As we found in [15], also for a visual search task a reason why confidence-based rules perform better than the simple majority rule is that they remove ties (which are otherwise resolved with a random decision) in even-sized groups. Indeed,

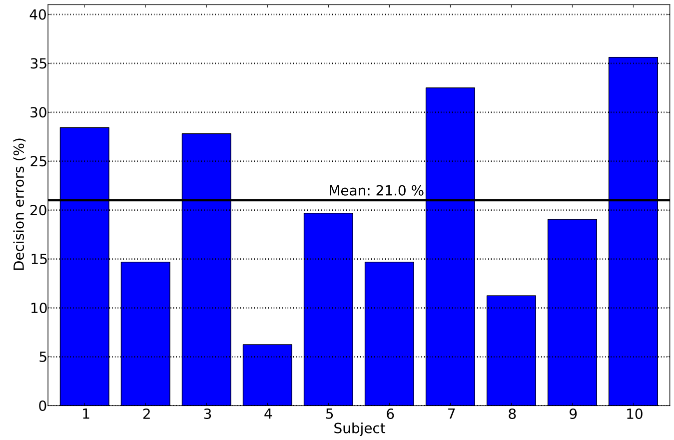

Figure 2: Participant mean errors averaged over 320 trials. The solid line represents the average errors across participants.

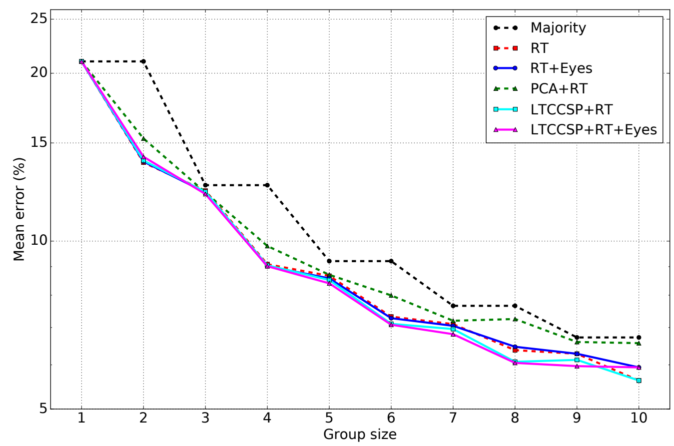

Figure 3: Average percentage of errors vs group size for group decisions made by: (1) the majority rule, (2) a RT-based decision system, (3) a RT- and eye-based decision system, (4) a cBCI using PCA neural features and RTs, (5) a cBCI using LTCCSP neural features and RTs, and (6) a cBCI using LTCCSP neural features, RTs and eye movements features. The y axis uses a logarithmic scale.

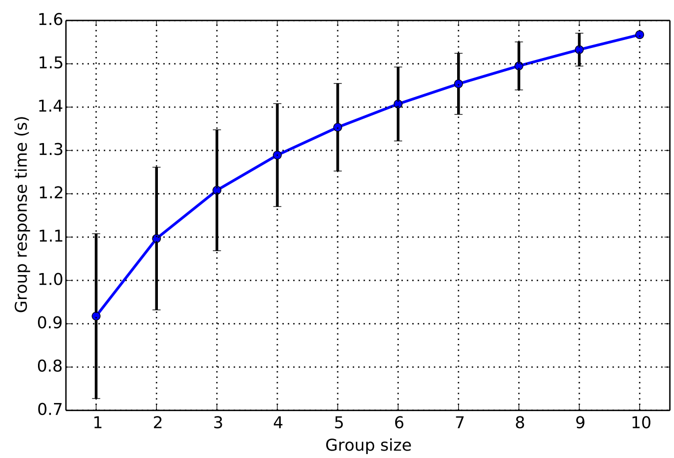

Figure 4: Average time needed for groups of different size to reach a decision. This is equal to the average RT of the slowest participant in each group. The plot also shows the standard deviation of each group size.

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Table I: Numerical representation of the plots in Figure 3. The best results for each group size are showed in boldface while the worst are shown in italics.

Group Size	Majority	RT	RT +Eyes	PCA +RT	LTCCSP +RT	LTCCSP +RT+Eyes
1	**21.00**	**21.00**	**21.00**	**21.00**	**21.00**	**21.00**
2	*21.00*	**13.83**	13.88	15.28	13.94	14.17
3	*12.60*	12.31	12.23	12.22	12.26	**12.15**
4	*12.60*	9.09	**9.01**	9.80	9.05	**9.01**
5	*9.21*	8.66	8.58	8.70	8.52	**8.40**
6	*9.21*	7.32	7.28	7.99	7.11	**7.07**
7	*7.66*	7.10	7.05	7.20	6.96	**6.81**
8	*7.66*	6.38	6.47	7.25	6.08	**6.05**
9	*6.72*	6.28	6.28	6.59	6.13	**5.97**
10	*6.72*	**5.62**	5.94	6.56	**5.62**	5.94

as we can see both in Table I and Figure 3, the difference in performance for such groups is usually much greater than for odd-sized groups. However, all our confidence-based systems, but particularly the cBCI based on LTCCSP, RTs and eye movements features, manage to augment human decision-making performance also with odd-sized groups (with statistically significant differences, as we discuss later in this section).

We have also verified one of our previous findings [15]: the performance of the cBCI system using only behavioral (RT) features was worse than when using a combination of neural and behavioral features for most group sizes.

The p-values of the Wilcoxon tests performed to compare the error distributions across different methods are reported in Table II. Sample sizes (the number of groups of each size) are indicated in the last row of the table. It is clear that for all group sizes our new LTCCSP-based cBCI yields group decisions that are significantly better than traditional (majority-based) group decisions. Also, for many group sizes such decisions are significantly better than those made using a PCA-based cBCI. The PCA-based cBCI is also significantly better than majority, as we found in [15], but it is never better than the LTCCSP-based cBCI.

Finally, let us analyze the decision times. Figure 4 shows the average time required by groups of different sizes to make a decision, i.e., the time needed by the slowest member of the group to respond. The plot clearly shows that groups increase decision times by up to 70%. However, as we did in [15], group RTs can be shortened by allowing only the fastest respondents to contribute in the group's decision. With this technique, there are many choices that allow cBCI-assisted groups to be both faster and more accurate than single individuals. For instance, by allowing only the fastest 2 respondents in groups of 5 to decide in our LTCCSP-based cBCI, error rates are halved while RTs are approximately 200 ms shorter than for an average individual.

C. Performance Across Tasks

To gather some preliminary evidence on the degree of performance improvement (or otherwise) that our cBCI can deliver across tasks, in Figure 5 we compare the results obtained in [15] with the less challenging visual matching task described in Section I-C and the results of the present work with a more difficult visual search task. For a fairer

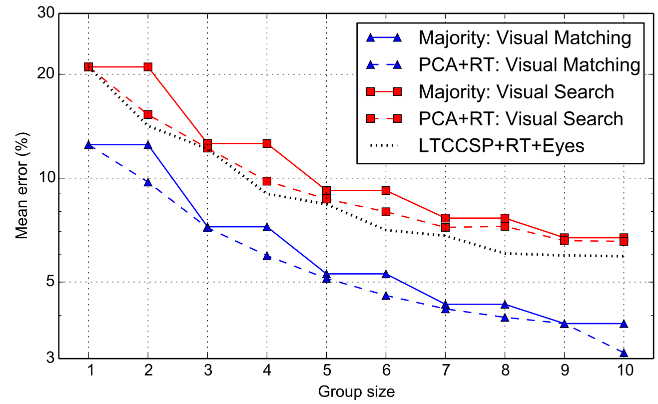

Figure 5: Comparison of the results obtained in [15] with a visual matching task (blue lines) and the results of the present work with a visual search task (red lines) obtained with Majority (solid lines) and PCA-based cBCIs (dashed lines). The black dotted line represents the results of the LTCCSP-based cBCI that also exploits eye movements in the visual search task. The ordinate axis uses a logarithmic scale.

comparison, in either case we report the results obtained with Majority (solid lines) and PCA-based cBCIs (dashed lines) using the same number of principal components. We have plotted these data using a semi-logarithmic scale as this makes it possible to compare the *relative* improvements across systems (equal distances along the ordinates correspond to equal improvement percentages). For reference we also report the results of our best method: the LTCCSP-based cBCI that also exploits eye movements (black dotted line).

The most apparent feature in the figure is that the lines representing the visual matching task (blue) and those representing the visual search task (red) run almost parallel, indicating that both Majority and the PCA-based cBCI provide the same relative benefits as the group size varies. Of course the cBCI lines are below the Majority lines (as we have already discussed). However, the distances between the solid and the dashed lines of each color follow a very similar profile. This indicates that the relative benefits obtained by the cBCI over Majority at each group size are comparable across the two tasks. Indeed, the average (across group sizes) increase in performance brought by the PCA-based cBCI is 8.6% for visual matching and 8.7% for visual search.

These results corroborate the hypothesis (testing which was one of our aims) that our approach to obtaining and exploiting correlates of decision confidence with a cBCI does indeed generalize to tasks of different nature and difficulty.

D. Speed of the System

We also measured the processing time needed to extract neural features and to train the classifier using the LTCCSP-based cBCI and the PCA-based cBCI. Tests were executed on an Intel i7-4930K workstation with 32GB RAM running Ubuntu 14.04. Only one CPU core of the 6 available was used.

As shown in Figure 6 (left), when using LTCCSP the cBCI is more than one order of magnitude faster than with PCA

Table II: Statistical comparison of methods for group decisions for different group sizes. The table reports the p-values 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 using PCA neural features and RTs, confidence-based using LTCCSP neural features, RTs and eyes features, confidence-based using LTCCSP neural features and RTs, confidence-based using RTs and eyes features, and confidence-based using only RTs). 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 Bonferroni-corrected statistical significance level $0.05/7 = 0.0071$ are in bold face.

	Group size							
Comparison	2	3	4	5	6	7	8	9
Is RT better than Majority?	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0063**
Is PCA+RT better than Majority?	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	0.2284
Is LTCCSP+RT+Eyes better than Majority?	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0026**
Is LTCCSP+RT+Eyes better than RT?	0.9773	**0.0000**	0.0266	**0.0000**	**0.0000**	**0.0000**	**0.0000**	0.0264
Is LTCCSP+RT+Eyes better than RT+Eyes?	0.9811	**0.0001**	0.4176	**0.0000**	**0.0000**	**0.0000**	**0.0000**	0.0116
Is LTCCSP+RT+Eyes better than LTCCSP+RT?	0.9548	**0.0001**	0.2921	**0.0000**	0.1362	**0.0000**	0.2810	0.0599
Is LTCCSP+RT+Eyes better than PCA+RT?	**0.0000**	0.0724	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	0.0107
Sample size	45	120	210	252	210	120	45	10

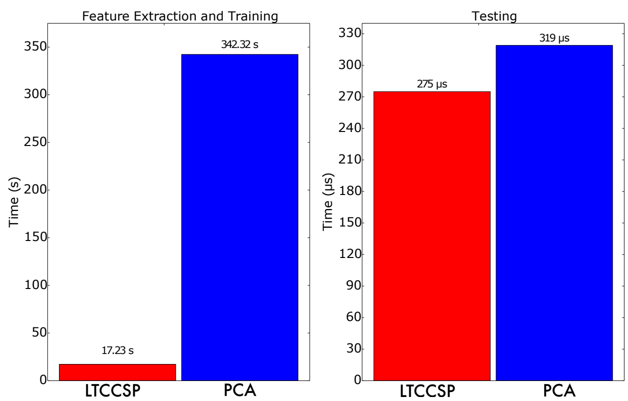

Figure 6: Average processing time required to train a classifier (left, times in s) and to classify a trial (right, times in μs) for the two feature-extraction methods considered in the paper.

at extracting features and training the classifier for confidence prediction. With LTCCSP this takes less than 18 *seconds* as opposed to the 5+ *minutes* required when using PCA. This makes the system ready to be used almost immediately after the acquisition of a training set.

We should note that, as shown in Figure 6 (right), the time needed by a *trained* classifier (whether LTCCSP-based or PCA-based) to predict the decision confidence on an unseen trial is truly negligible for both feature sets.

E. ERP Analysis

We complemented these results with an ERP analysis. Since we use neural signals to estimate the confidence in a decision, we focused our analysis on the differences in the statistical distributions of ERPs for correct and incorrect responses. Also, since our cBCI uses both stimulus-locked and response-locked epochs, we show results in both representations. The only difference between the data used by the cBCI and the data used in this analysis is that in the latter we down-sampled the data to 64 Hz (instead of 16 Hz) for better visualization.

Figure 7 shows the stimulus-locked and response-locked grand averages of a representative subset of the 64 electrode sites used for EEG recording (i.e., Fz, Cz, Pz, Oz, C3, C4, P3 and P4). The p-values from a two-tailed Wilcoxon signed-rank test for paired samples which compared the mean individual ERPs for the two classes obtained are also shown.

The first three rows of Figure 8 report scalp maps representing the grand averages for the correct and incorrect trials and their differences at 600 ms after stimulus presentation and 250 ms before the response. The last row shows scalp maps of the p-value of the Wilcoxon test used to compare the ERPs in the two classes. It is clear that statistically significant differences are present at many electrode sites in both stimulus-locked and response-locked representations.

IV. Discussion

Our cBCI combines neural, behavioral and physiological features to estimate the decision confidence of multiple users for the purpose of achieving better group decisions in a visual search task. The task was very difficult, involving detecting a target in a set of 40 random distractors, where targets could only be recognized by a conjunction of two features (color and orientation), and so there was no pop-out effect.

The system relies on an approach for obtaining and exploiting correlates of the individual degrees of confidence in decisions that we had previously trialled in a cBCI with a much simpler and cognitively different visual matching task [15], with very encouraging results. Based on that experience, here we have redesigned our system to further improve its performance in terms of both accuracy and speed.

A. Main Findings

Results indicate that the approach proposed in [15] does generalize across tasks. More specifically, for almost all group sizes our new cBCI yields group decisions that are statistically significantly better than both traditional (majority-based) group decisions and group decisions made by a PCA-based cBCI. Also, LTCCSP filtering provided not only an improvement in decision accuracy but also a significant reduction of the training time with respect to the PCA-based system we used in [15]. While speed is not so important in an offline

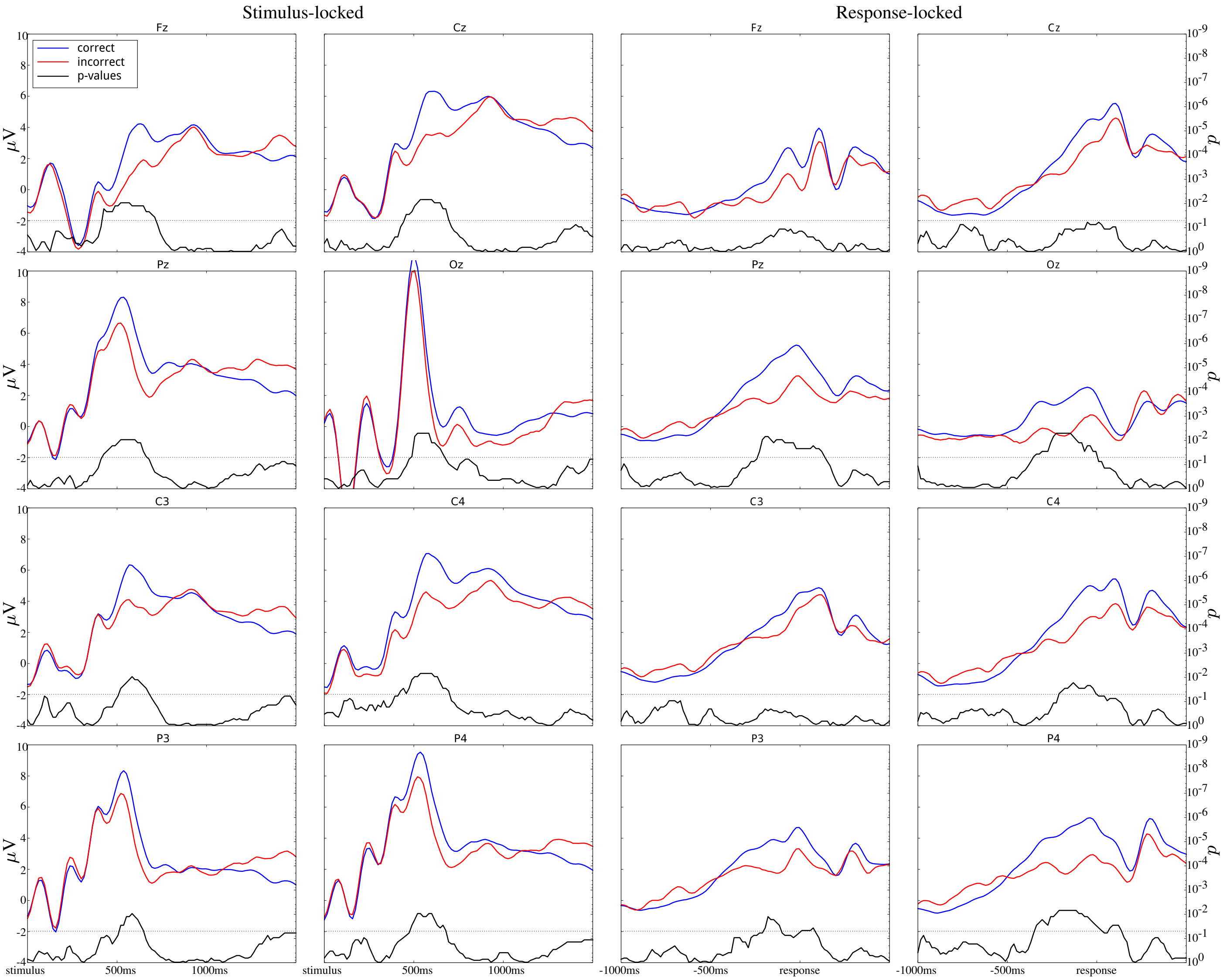

Figure 7: Stimulus-locked (left) and response-locked (right) grand averages for channels Fz, Cz, Pz, Oz, C3, C4, P3, P4 and corresponding temporal profile of the *p*-values of the two-tailed Wilcoxon signed-rank test (black) comparing participant-by-participant averages for all recordings in each error class: correct (blue) and incorrect (red).

validation, its fast training and execution time make our cBCI "online-ready", which is an added advantage of our design.

Further increases in accuracy were provided by the exploitation of eye movements in estimating decision confidence and by the fact that, for the first time, we were able to provide the cBCI with both a stimulus-locked and a response-locked ERP representation, without overfitting.

The stimulus-locked ERP representation (Figure 7(left)) allows the cBCI to see in full resolution [43] and, thus, exploit differences in exogenous and endogenous ERPs associated with the processing and evaluation of the stimulus. In this representation, major differences between correct and incorrect trials occur at approximately 600 ms after stimulus onset, where a slow positive wave (a P300 in the centro-parietal channels) has a statistically significantly greater amplitude for the correct than the incorrect decisions. This is likely to be due to the fact that when a trial is particularly hard and, hence, users being unsure of their decision, the amplitude of the P300 is reduced [45], reflecting a more elaborate decision process.

Significant differences between the ERPs elicited in correct and incorrect trials are also present in the response-locked analysis (Figure 7(right)). Here the traditional stimulus-locked ERPs associated with early visual processing (such as the P1, N1, P2, and N2) are almost completely absent due to the blurring effect associated with wide RT distributions (see [43] for details) and the preprocessing taking place in the system (in particular the de-trending of the epochs). However, it is apparent that the final phases of the decision-making process (i.e., a few hundred milliseconds before the response) are associated with different amplitudes for correct and incorrect trials, particularly for posterior and occipital channels.

These findings are also confirmed by the scalp maps in Figure 8, which also indicate that there is complementarity between the stimulus-locked and the response-locked representations: the former shows statistically significant differences in the anterior, central and parietal areas, and the latter

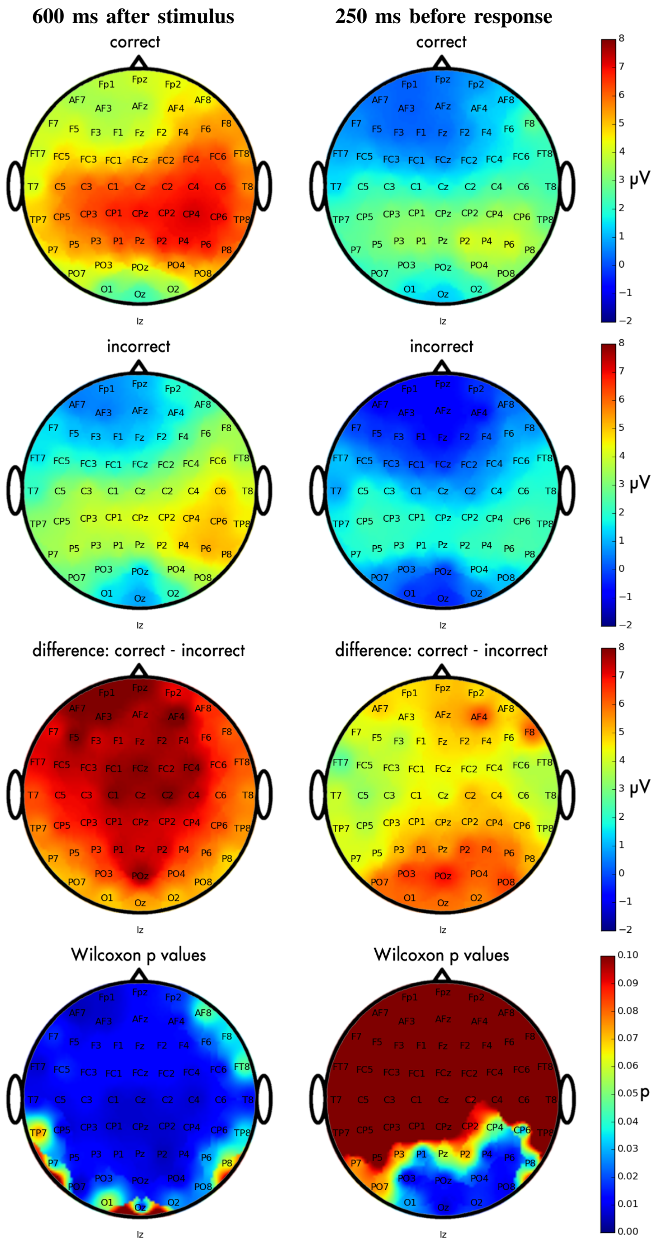

Figure 8: Scalp maps of the grand averages of the EEG activity recorded 600 ms after stimulus onset (first column) and 250 ms before the response (second column). Rows represent the activity for correct and incorrect trials (first two rows), the difference between them (third row) and the p-values obtained by using the Wilcoxon test over the two sets (last row).

carries statistically significant evidence in the parietal and occipital channels. This corroborates our assumption that both representations are useful to estimate decision confidence.

Lastly, the comparison between the error rates achieved by both Majority and a PCA-based cBCI in the visual matching task of [15] and the error rates yielded by corresponding systems in the visual search task used here indicated that the benefits of cBCI are similar across tasks and group sizes.

B. Limitations

In this study, we recorded data from participants performing the experiment individually and then simulated group decisions. A drawback of this approach is that it does not consider the impact that collaboration and, in general, being in a group can have on an individual's behavior and cognitive processing, and, ultimately, on neural activity. The interaction in a real environment would most likely change the neural signals thereby affecting the performance of a cBCI.

While this is certainly true, due to the well-known inefficiencies of groups induced by communication (discussed in Section I-A), we feel that a cBCI such as our, where users are not allowed to interact, could potentially be superior to one where interactions are allowed.

Taking this into consideration, we have recently carried out an online experiment with pairs of interacting users. Preliminary results have shown that allowing people to interact significantly reduces their individual performance as well as group performance in the decision task. However, statistically significant improvements are still obtained when using our cBCI. These early results suggest that, despite the changes in the neural signals due to the interaction, the cBCI is still able to extract and exploit confidence correlates.

C. Future Work

There are multiple promising future research directions. For instance, additional features could be extracted from biological signals and used to further improve the quality of our confidence estimates. Physiological measures such as heart rate, breathing frequency and skin conductance can complement our current feature set and lead to even more accurate results. Also, real-world stimuli could be used to test the performance of the cBCI out of the lab.[6] Furthermore, in future research we plan to corroborate our offline findings with an online experiment, where 2–3 participants will simultaneously make decisions on identical or closely related tasks with real-world stimuli.

V. Conclusions

We developed a collaborative brain-computer interface that estimates the decision confidence of multiple users from a combination of neural, behavioral and physiological features. The cBCI achieves significantly better group decision compared to equally-sized non-BCI-assisted groups and our previous PCA-based cBCI. This implies that our approach to making decisions based on a measure of confidence generalizes to different settings. We have also significantly reduced the training time of the system, making another step towards its practical applicability.

This research paves the way to a variety of real-world applications of cBCIs where reducing decision errors is vital. For instance, in defense or medical diagnosis applications the improvements in decision accuracy yielded by a cBCI could mean saving human lives. Similarly, in financial decision-making or trading applications cBCIs could save millions.

[6] In recent research [50] we have explored the use of natural stimuli (participants were asked to search for a polar bear in an Arctic environment with hundreds of penguins) obtaining very encouraging results, but further corroboration is required.

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