

Collaborative Brain-Computer Interfaces for Target Localisation in Rapid Serial Visual Presentation

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Abstract—The N2pc event-related potential appears on the opposite side of the scalp with respect to the visual hemisphere where an object of interest is located. In this paper, we propose a 2-user collaborative brain-computer interface that exploits this component for the automatic localisation of specific lateral targets in real aerial images displayed by means of the rapid serial visual presentation technique at speeds of 5–15 Hz. By combining the evidence from pairs of users using two different methods and with participant selection, we obtain absolute median improvements in the area under the receiver operating characteristic curve of up to 7.7% with respect to single-user BCIs.

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) convert electroencephalographic (EEG) signals from the brain into commands that allow users to control devices without the help of the usual peripheral pathways. Traditionally, BCIs have been developed with the aim of helping people with limitations in their motor control or their ability to communicate [1]–[3]. However, some forms of BCIs have recently started focusing on the augmentation of human abilities (e.g., speed) of able-bodied users, both individually and in groups by means of collaborative or cooperative BCIs (cBCIs) [4]–[8]. The latter work by merging EEG signals (or the corresponding control commands) from multiple users with the aim of controlling a single device.

Some of these forms of BCI focus on augmenting visual perception capabilities to speed up the process of finding pictures of interest in large collections of images [6], [9], [10]. These systems would find applications, for instance, in counter intelligence and policing, where large amounts of images need to be viewed and classified daily by analysts looking for possible threats or, more generally, targets [10]. Apart from detecting such targets accurately and at high speeds, it stands to reason that current triage systems would benefit from techniques, such as the one we will present in this paper, that could establish the position of targets within the images.

It has been shown that the combination of the Rapid Serial Visual Presentation (RSVP) protocol (which sequentially displays images in the same spatial location at high presentation rates [11]) with BCIs can effectively reduce triage time without a detriment in target detection accuracy. This is usually achieved by means of the P300 Event-Related Potential (ERP, a large positive wave typically peaking 300–600 ms after

stimulus onset) [7], [12]. This ERP is one of the most widely used ERPs for controlling BCIs (both in traditional and the newer paradigms), but it is just one of the many components that have been identified in EEG signals.

Another ERP that can be exploited in BCIs [13] and of particular interest for this work is the N2pc (a small negative asymmetric component preceding the P300) which, in the literature, has predominantly been related to processes associated with selective attention [14]–[16]. The N2pc ERP is elicited when participants are given a search template or object to look for and the search display shows at least one distractor (i.e., non-target) item apart from the target.

The usual approach to increase the signal-to-noise ratio in BCIs, which are highly contaminated by noise and artifacts, is to average signals from different trials to isolate the ERP of interest [17]. For example, in their N2pc-driven BCI, Awni *et al* performed averages across 3 repetitions of the stimuli (trials). They reported large variations in classification accuracy across participants when discriminating between left and right targets (different-colored numbers in a circle) [13].

However, it is not always possible to average across multiple trials (e.g., a person cannot make the same decision several times), or it might not be practical (e.g., when designing BCIs for healthy users, where speed is a key factor). In this type of situations, aggregating signals from a number of users has proven to be useful, thus creating a “multi-brain” or cBCI (e.g., [4], [18]).

The field of collaborative BCIs is relatively new, and there is a lack of consensus on the best way to form groups. Most of the work on this area is based on studies about group decision making. The general opinion is that bigger groups lead to better or more accurate decisions [19]. However, Kao and Couzin [20] showed that in many contexts where this “crowd wisdom” effect is not present, small groups can maximize decision accuracy, depending on correlations between the behavior of the members. In visual perception experiments, Bahrami *et al* found that observers performed better in pairs, provided that they had similar visual sensitivities and were able to communicate freely [21].

With respect to collaborative BCIs, it has been shown that groups are able to accelerate responses with respect to non-

BCI decisions (e.g., key presses), and bigger groups lead to higher accuracies [4], [8], [18], [22]. However, when compared to non-BCI users, non-BCI decisions might prove to be more accurate than those reached by means of cBCIs [18], [23].

As we mentioned above, BCIs have been used for the automatic detection of targets in images by means of the EEG with reasonably good results [10], [24]. In [5], we reported on preliminary work on the collaborative classification of aerial images by means of the RSVP paradigm at different presentation rates (5–15 Hz) and varying the number of targets that participants were asked to look for. By grouping pairs of observers (from a pool of five), we were able to speed up the process of revising the images and obtained noteworthy higher accuracies than with single observers.

This work was extended in [6], where we obtained EEG signals from 10 participants and used them to form groups of 2 and 3 observers. We found statistically significant differences between groups and single-user BCIs.

Several forms of combining evidence from multiple individuals have been considered [25], [26]. Whether one form or another performs best may depend on the field of application. In [5], [6], we found that the best way of integrating information from multiple participants for our P300-based cBCI is to average the outputs of individual support-vector machines (SVMs), each specialised to classify the data of one participant. Tests with directly averaging the ERPs from each participant suggested that this is a suboptimal strategy. However, the N2pc has a relatively low latency jitter (which depends more on stimulation regime rather than on the user, as opposed to other ERPs). So averaging signals across participants might work well in left vs right classification.

The work presented in this paper uses the stimulation protocol proposed in [5], [6]. Also, a subset of the participants used for this study were originally tested in such prior work. However, as we indicated above, in this paper we have applied the concept of collaborative BCIs to the location of targets within images via N2pc ERPs. In addition, we will explore the effects of selecting the participants which form the groups in collaborative BCIs. This will be done on the basis of performance similarity.

II. METHODS

A. Participants and setup

Due to the nature of RSVP, participants were screened for any personal or family history of epilepsy. We gathered data from 9 volunteers with normal or corrected-to-normal vision (age 24.7 ± 3.9 , three females). They all read, understood and signed an informed consent form approved by the Ethics Committee of the University of Essex.

Participants were comfortably seated at approximately 80 cm from an LCD screen where the stimuli were presented. EEG data were acquired with a BioSemi ActiveTwo system with 64 electrodes mounted in a standard electrode cap following the international 10-20 system plus one electrode on each earlobe (all impedances < 20 k Ω). The EEG was referenced to the mean of the electrodes placed on the earlobes. The

initial sampling rate was 2048 Hz. Signals were band-pass filtered with cutoff frequencies of 0.15 and 25 Hz before downsampling to 64 Hz. A form of correction for eye-blinks and other ocular movements was performed by applying the standard subtraction algorithm based on correlations [27] to the average of the differences between channels Fp1 and F1 and channels Fp2 and F2.

B. Experimental design

The images for our experiments consisted of 2,400 aerial pictures of London. Images were converted to grayscale and their histograms were equalised. Picture size was 640×640 pixels. Pictures were shown to participants in sequences (or bursts) of 100 images with no gaps between two consecutive stimuli (Inter-Stimulus Interval, ISI=0 ms). Out of these, 10 were “target” images, and they differed from the non-targets in that a randomly rotated and positioned plane had been (photo realistically) superimposed as exemplified in figure 1(left). Non-target pictures did not contain planes, as illustrated in figure 1(right).

Approximately 60% (144 out of 240) of our target images contained a lateral target (i.e., a target that appeared on the left or right side of the picture). More specifically, we had 59 Left Visual Field (LVF) target pictures and 85 Right Visual Field (RVF) target pictures, which, as will be shown later, we expected to cause an N2pc ERP that would allow the system to localise the plane within a target-containing picture. Targets that do not appear on either side of an image are central targets.

We created 5 different “levels of difficulty” which differed in the presentation rate. Each level consisted of 24 bursts which were presented in order of increasing presentation rate at 5, 6, 10, 12 and 15 Hz, whilst keeping the ISI = 0 ms. Hence, sequences of images lasted between 20 (for the slowest presentation rate) and 6.67 seconds (for the fastest).

Participants were instructed to try to minimise eye blinks and general movements during a burst in order to obtain EEG signals with as few artifacts as possible. They were assigned the task of mentally counting the planes they saw within each burst and were instructed to report the total at the end of a burst (to encourage them to stay focused on the task). Participants could rest after bursts and were free to decide when to start the next sequence. Bursts started upon the participant clicking on a mouse button. Experiments lasted no more than 90 minutes.

C. Feature selection and classification

Following the onset of each lateral-target picture on the screen, we extracted 200 ms epochs of EEG signal from approximately 200 ms to 400 ms after stimulus onset (the temporal window where the N2pc most often occurs according to the literature). Including samples at the epoch’s limits (200 and 400 ms, respectively), this resulted in 14 samples per channel at the 64 Hz sampling rate used. The data were referenced to the mean value of the 200 ms interval before stimulus onset.

Consistently with previous literature on the N2pc (e.g., [16]) and due to the small size of the set of lateral-target images



Fig. 1. Examples of target (left) and non-target (right) images used in our experiments. The target plane in the image on the left has been highlighted for presentation purposes.

(with the associated potential overfitting risks), we decided to use only four differences between pairs of electrode (PO7–PO8, P7–P8, PO3–PO4 and O1–O2) for left vs right discrimination. Concatenating these electrode differences yields the feature-vector representation of each epoch used for classification. This includes only $14 \times 4 = 56$ elements.

1) *Individual classification*: We started our analysis by focusing on whether we could detect the N2pc component in single trials in the conditions of our RSVP experiment.

With our input representation, we trained a linear SVM classifier for each participant to distinguish between LVF and RVF targets. We divided the epochs in our set of 144 LVF and RVF pictures into two: 65% of the epochs (corresponding to 55 RVF and 38 LVF images) were used as a training set — which itself was used for 10-fold cross-validation to find the optimal C value when training the SVMs — and the remaining 35% were used as an independent test set for N2pc detection.

2) *Collaborative classification*: We used two methods to merge signals from multiple participants in our cBCIs. First, we averaged the feature vectors across pairs of participants and trained a new SVM classifier for each group (Single Classifier cBCI, SC-cBCI). For our second method, we averaged the outputs of the individually tailored classifiers from each member of the group, thus creating a Multiple Classifier cBCI (MC-cBCI).

In order to assess the performance and behaviour of the classifiers, we recorded the analogue output scores of the SVMs, with which we then computed the Receiver Operating Characteristic (ROC) curve for each participant we then condensed the information contained in each ROC curve into a single performance figure: the Area Under the Curve (AUC) [28], [29].

3) *Group-member selection*: In relation to the selection of group members, we used a method where pairs are formed according to the similarity in performance of individual participants, using different levels of similarity. More specifically we allowed pairs of participants to work as a group if the absolute difference of their AUC values, a value that we term *dissimilarity index*, was below a threshold δ . More formally, participants i and j formed a pair if

$$|AUC_i^f - AUC_j^f| \times 100\% \leq \delta,$$

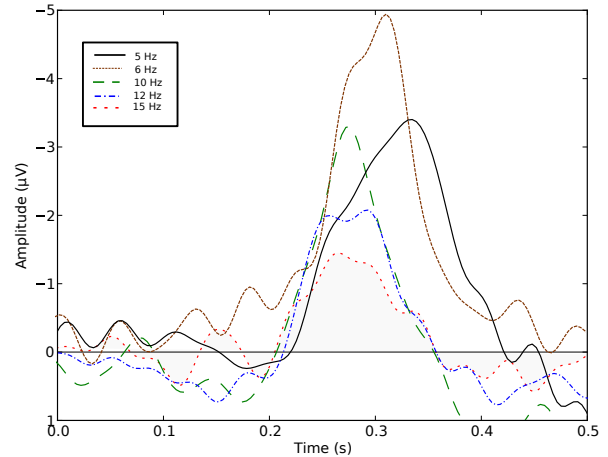


Fig. 2. Difference plot of the contralateral minus the ipsilateral grand-averages at channels PO7 and PO8 across all lateral targets from the training set. Amplitudes are measured in μV .

where AUC_x^f represents the AUC value for participant x (with $x = 1, \dots, 9$) at a presentation rate of f Hz, (with $f = 5, 6, 10, 12, 15$). We created groups by setting the threshold δ at 5, 10, 15 and 20% and considered only the cBCIs from pairs of subjects for which the dissimilarity index is below the threshold.

Of course, this selection process reduces the number of groups that can be included in the analysis (from the 36 possible groups of two participants). However, given that cBCIs are conceived with the aim of augmenting human capabilities, it is reasonable to select participants based on their individual performance when forming groups. For comparison, we have included the results when no group selection is performed and all pairs are considered ($\delta = 100\%$).

III. RESULTS

Figure 2 shows the grand averages (averages of participant-by-participant averages) of the differences between contralateral and the ipsilateral ERPs across all lateral-target epochs from the training set, for different presentation rates, measured at electrode sites PO7 and PO8. We plotted these using an *inverted ordinate axis*, so higher means more negative. When the presentation rate is increased (up to 10 Hz), the latency of the N2pc (as measured by the time when it reaches its peak) is shortened. We can also see from this figure how peak amplitudes decrease as presentation rates increase above 6 Hz.

The first row of table I shows the median AUC values obtained for left vs right classification for single-user BCIs for each level of difficulty. Consistently with the ERP plots from figure 2, performance decreases with increasing values of the presentation rate for frequencies higher than 10 Hz. This was expected, as the peak of the difference between contralateral and ipsilateral electrode sites decreases in amplitude as the stimulation frequency increases making it more difficult to detected by the BCI.

TABLE I

MEDIAN AUC VALUES FOR SINGLE-USER BCIs AND MEDIAN IMPROVEMENT OVER THE BEST PARTICIPANT IN THE GROUP WHEN USING COLLABORATIVE BCIs, AS A FUNCTION OF PRESENTATION RATE AND THE DISSIMILARITY-INDEX THRESHOLD δ .

Method	δ	5 Hz	6 Hz	10 Hz	12 Hz	15 Hz
sBCI	N/A	77.6%	76.8%	79.8%	66.5%	51.8%
SC-cBCI	5%	+7.7%	+3.8%	-1.1%	+1.2%	+0.9%
	10%	+7.6%	+0.2%	+1.1%	+0.2%	-1.6%
	15%	+5.2%	+0.2%	+1.0%	-0.3%	-2.1%
	20%	+5.2%	-1.6%	+1.0%	-1.1%	-2.1%
	100%	+2.2%	-4.0%	-1.6%	-1.6%	-3.6%
MC-cBCI	5%	+6.5%	+3.2%	+4.1%	+3%	0.0%
	10%	+6.5%	+2.2%	+3.6%	+1.6%	0.0%
	15%	+5.6%	+1.9%	+2.6%	+0.3%	0.0%
	20%	+5.6%	+1.0%	+2.6%	0.0%	0.0%
	100%	-0.5%	-6.8%	0.0%	0.0%	0.0%

TABLE II

PERCENTAGES OF GROUPS THAT ARE ACCEPTED BY OUR SELECTION MECHANISM FOR DIFFERENT VALUES OF THE STIMULATION FREQUENCY AND THE DISSIMILARITY-INDEX THRESHOLD, δ .

δ	5 Hz	6 Hz	10 Hz	12 Hz	15 Hz
5%	41.7%	19.4%	30.6%	22.2%	50.0%
10%	47.2%	41.7%	41.7%	44.4%	69.4%
15%	66.7%	50.0%	50.0%	63.9%	80.6%
20%	66.7%	63.9%	50.0%	80.6%	80.6%
100%	100.0%	100.0%	100.0%	100.0%	100.0%

The remaining rows of the table report the median gains in performance over the better participant of each pair for each stimulation frequency, separately for our two types of collaborative BCIs, SC-cBCIs and MC-cBCIs, for different values of the dissimilarity-index threshold δ .

With 9 participants, in principle we can form up to 36 distinct pairs. In table II we quantify the effects that different values for this threshold have on the fraction of pairs that can be accepted.

IV. DISCUSSION

A. Single-user BCI

One of the objectives of our experiment was to see in what ways the N2pc ERP changes when varying the presentation rate of our RSVP paradigm (whilst keeping the ISI = 0).

Our ERP analysis revealed that the N2pc components evoked using our paradigm change in both amplitude and latency as the presentation rate varied.

In relation to latency, we observed a decrease in latency when the presentation rate is increased. For a presentation frequency of 10 Hz, the shape and timing of our grand-average difference plot of the N2pc was consistent with those reported in the literature [14]–[16]. The decrease in amplitude for rates higher than this might be caused by either the uncertainty of the participant at such high presentation rates¹ or the temporal proximity of lateral targets within a burst for high speeds, which might cause subsequent targets to fall within a possible refractory period for this ERP.

¹Indeed, the reported number of planes for 12 and 15 Hz was lower than for slower rates, showing that many targets were missed by participants, and those that do not fall within the foveated area are more likely to be missed.

Turning to amplitudes, as the amplitude of the N2pc has been linked to subject engagement, we expected it to vary as a function of the presentation rate. The increase in amplitude observed when switching from 5 Hz to 6 Hz, considering that no other parameter has been changed in the experiment, might be linked to participants being more attentive for this second level of difficulty, as the task's demands increased.

Classification results for the single-trial sBCI for the left vs right classification of targets indicate that the N2pc can reliably be detected in the conditions of our experiments for presentation rates of up to 10 Hz (the median AUC value is almost 80%). In fact, performance seems to increase in the interval 5–10 Hz, and then starts decreasing for higher speeds. Still, even for the rates as high as 12 and 15 Hz, most participants are well above chance levels with the top quartile of our participants showing AUCs $\geq 72.2\%$ and $\geq 60\%$, respectively.

B. Collaborative BCI

In this paper, we also showed that collaborative BCIs can outperform “traditional” single-user BCIs when group selection is done in terms of a dissimilarity index, i.e., when similar performers are grouped together. Since our BCI systems are designed for able-bodied users, as opposed to traditional BCIs, participants could conceivably be selected based on performance and neural responses so as to best match the requirements of our BCIs. Thus, while performance variance across participants is a traditional worry for BCI, it is less so for our systems, both in the individual and in the collaborative forms.

Consistently with our findings in [6], by varying the dissimilarity index when pairing participants, we are able to increase further the performance of the group (with respect to that of the better participant individually) by combining evidence from users that are more similar to each other. This is reflected by the results from table I, where lower values of the dissimilarity index obtain higher improvements over the better of the two members than higher values of the dissimilarity index. Also, when $\delta = 100\%$ we see that cBCIs are almost always either worse or on par to corresponding sBCIs.

This seems reasonable, considering that when a participant with a high AUC is paired with a low scorer (thus showing a high dissimilarity index), the extra information of the latter with respect to the former is not enough to translate into an improvement in the performance of the better one.

If we now compare the absolute improvements across our two types of cBCIs, we can see that the reported improvements are consistent for the lower presentation rates for SC-cBCI and MC-cBCI. However, for presentation rates of 10 Hz or more, the MC-cBCI method performs better than the SC-cBCI option.

V. CONCLUSIONS

In this paper we looked at the possibility of exploiting the N2pc ERP in a collaborative BCI which approximately establishes the horizontal position of the target within pictures known to contain one.

The results of LVF vs RVF in single-trial classification based on the N2pc electrode-sites and time-window are very encouraging even for single-user BCIs, producing a median AUC which is comparable to current P300-based BCIs, despite the much smaller amplitude of this ERP.

In [6] we used collaborative BCIs for the detection of targets within aerial images by means of the P300. Future research should explore ways of combining our P300 and N2pc classifiers, which is an obvious next step once it has been shown that it is possible to detect both ERPs independently. With the lessons learnt from this work, we can now envision a cascade of the two classifiers: the first one would decide whether a given image contains or not a target (P300 detection); the second (LVF vs RVF classifier) would help limit the area of search within a given image when a target has been detected in the first step. Thus, it would be possible to improve current visual search RSVP systems by roughly locating targets after detection, which would in turn reduce the workload of an external observer that had to manually check the images classified as targets.

Furthermore, in future research we will need to extend the work to different targets and types of images, to see to what extent it is possible to build BCIs that can be used for target detection and localisation across a range of target types.

Lastly, in this paper we have studied a method of combining signals from different observers in terms of a dissimilarity index. If we assume that the AUCs from single-user BCIs are correlated to the sensitivity of the individual's visual system, our results are consistent with those of Bahrami *et al* [21] in their visual perception experiment. We achieved improvements in performance when users for the cBCI were paired using a low threshold δ (i.e., observers with similar visual sensitivities), despite the fact that in our experiment observers are not able to communicate. However, when the threshold δ was increased (corresponding to pairs being constituted by users with different visual sensitivities), the overall performance of the cBCI decreased. We did not study this effect in our target-detection cBCIs in [5], [6], so our results may still benefit from this approach. We will also study this in future research.

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