Walking Improves the Performance of a Brain-Computer Interface for Group Decision Making

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Abstract

In our previous work at University of Essex, collaborative Brain-Computer Interfaces (cBCIs) have been used to estimate the decision confidence of individuals from their brain signals and behavioural data, thereby, making it possible to improve group decision making. However, such studies used cBCIs in controlled lab conditions, where users were discouraged from performing movements to avoid contaminating the brain signals with muscular artefacts. In this chapter, we describe a cBCI developed for and tested in a dual-task situation where users perform decision-making tasks while walking on a treadmill at a leisurely pace. The participants in this study were presented with video sequences of a dynamic environment representing the viewpoint of a user walking at a constant pace along a corridor, where characters could briefly appear from side doorways. The participants had to decide whether each character was wearing a helmet or a cap and then to indicate their degree of confidence. Behavioural data (i.e., response time and degree of confidence) were collected and used by the BCI in addition to the electroencephalography data. Results showed that walking did not produce any negative effect on individual performance, instead improving cBCI/group performance in the task, likely due to increased level of alertness associated with walking. This suggests that cBCIs may work well on a wider range of operating environment than just a lab.

Keywords— Brain-computer interface, EEG, Decision-making, Mobile brain/body imaging, Dual task paradigm

1 Introduction

The advent of Brain-computer Interfaces (BCIs) created a direct communication channel that bypasses the biological neuro-muscular pathway to let people with severe disabilities act in the world (Vidal, 1973; Farwell & Donchin, 1988; J. Wolpaw et al., 2000). BCIs decode the intention of users from their neural activity, which is then used to generate commands to control external devices, like robots (Bell, Shenoy, Chalodhorn, & Rao, 2008), wheelchairs (Galán et al., 2008; Kaufmann, Herweg, & Kubler, 2014), prosthetic limbs (Lebedev & Nicolelis, 2006; Tariq, Trivailo, & Simic, 2018), computer cursors (Trejo, Rosipal, & Matthews, 2006; Citi, Poli, Cinel, & Sepulveda, 2008), or to assist with stroke rehabilitation (Cervera et al., 2018). Both invasive and non-invasive modalities exist to record the neural signals from the brain, but electroencephalography (EEG) remains the most widespread recording system within the BCI community because of cost and practicality (Cinel, Valeriani, & Poli, 2019; Kosmyna & Lecuyer, 2019).

Research on BCI has been traditionally focused on improving the quality of life of individuals with severe neuro-motor disabilities, such as amyotrophic lateral sclerosis, stroke, etc. (J. R. Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002; Birbaumer, 2006). However, advances over the last few decades – such as the development of hardware with better signal-to-noise ratio and innovative signal processing and machine learning techniques – have allowed the development of more reliable BCIs, broadening their areas of applications to include communication (Lazarou, Nikolopoulos, Petrantonakis, Kompatsiaris, & Tsolaki, 2018), text spelling (Rezeika et al., 2018), gaming (Zander & Kothe, 2011), military (Munyon, 2018) and passive monitoring of mental states of able-bodied users (Lin et al., 2008; Zhou, Xu, Cai, Wu, & Dong, 2017) and, more recently, applications to improve group decision-making (Poli, Valeriani, & Cinel, 2014; Valeriani, Poli, & Cinel, 2015, 2016; Valeriani, Cinel, & Poli, 2017; Bhattacharyya, Valeriani, Cinel, Citi, & Poli, 2019b, 2019a).

Years of research have shown that groups are generally better than individuals in making decisions (Bahrami et al., 2010; Kerr & Tindale, 2004), thanks to their augmented perception and cognition capabilities, achieved by integrating different views and percepts through the interaction of their members. However, groups may fail to perform as expected when there are difficulties in coordination and interaction between group members, or in cases of strong leadership, group judgement biases, etc. (Briskin & Erickson, 2009; Forsyth, 2018).

Previous research has investigated the possibility of using a collaborative BCI (cBCI) (Wang & Jung, 2011) to improve single-user BCI performance through groups. This idea has been tested, for example, in a simple discrimination task where groups of 8 cBCI-assisted observers were more accurate and faster than single non-BCI users (Eckstein, Das, Pham, Peterson, & Abbey, 2012). However, the performance of the cBCIs presented in that study was still worse than that achieved by non-BCI groups. Other studies have shown similar limitations (Cecotti & Rivet, 2014).

A marked improvement of cBCI performance in decision making has been obtained by adopting a hybrid approach where not only neural signals but also behavioural data are exploited. In (Poli et al., 2014), for example, EEG signals and response times (RTs) were used to estimate the probability of the decision of each group member being correct (objective confidence). Then these confidence values were used to weigh the corresponding member responses when pooling the individual decisions together to get a final group decision. The cBCI described in this chapter uses a similar approach.

This cBCI system has been previously tested on variety of tasks of increasing realism, including visual matching tasks (Poli et al., 2014), visual search with simple shapes (Valeriani et al., 2015, 2016), visual search with realistic stimuli (Valeriani et al., 2017), face recognition (Valeriani & Poli, 2019) and target detection from video feeds of poor quality (Bhattacharyya et al., 2019b) and added time pressure (Bhattacharyya et al., 2019a). In all tasks, decisions assisted by the cBCI systemwere found to be statistically significantly superior to non-BCI counterparts (standard majority). In general, the approach is particularly suited for circumstances where decisions need to be fast, but where the nature of the task is such that individual decision makers are unsure as to which decision to make.

One of the limitations of the aforementioned cBCI research is that data are collected in strictly controlled lab conditions, i.e., in a quiet environment, with low electromagnetic noise, and where users (which are typically able-bodied) are asked to limit muscular activity in an unnatural manner. In such conditions it is difficult to assess whether or not cBCIs are usable in real-life scenarios, where users often perform multiple concurrent tasks, such as speaking or walking, while making decisions. It has been reported that humans tend to alter their strategy while engaged in dual tasking (Yogev-Seligmann, Hausdorff, & Giladi, 2008) that involves motor and cognitive tasks, which leads to adaptation of neural processing strategies for performance optimisation (Bradford, Lukos, Passaro, Ries, & Ferris, 2019). Several studies have demonstrated that increased physical activities during motor tasks require additional cortical resources, which are taken away from cognitive tasks (Doppelmayr, Sauseng, & Doppelmayr, 2007; Bullock, Cecotti, & Giesbrecht, 2015; Enders et al., 2016). Previous research has studied the neural dynamics during dual task experiments where participants performed cognitive tasks while walking at different speeds (Kline, Poggensee, & Ferris, 2014) or while running (Gwin, Gramann, Makeig, & Ferris, 2010). Results have indicated changes in the neural dynamics associated with inhibitory control of the cognitive task while walking/running when compared to a controlled, seated, single-task condition that suggests recalibration of the cortical resources for optimal dual task perfromance (De Sanctis, Butler, Malcolm, & Foxe, 2014).

In this chapter, we have adopted a dual-task paradigm where participants are asked to do a decision-making task while walking on a treadmill, with the main aim of assessing the effects of walking on cBCI assissted decisions. This experiment is more realistic to our previous experiments where the participants were seated in a comfortable chair while doing the decision-making experiment. More specifically, the goals of this study included: (i) compare the changes in the decision-making behaviour (which includes responses, RTs and confidence in decisions) while walking and sitting, and (ii) testing to what degree our cBCIs for assisting group decision-making would work in a realistic dual-task paradigm.

In this study, group decisions were simulated by combining the individual responses and comparing (a) standard majority, (b) weighted majority based on confidence reported by the participants after each decision (confidence majority) and (c) weighted majority based on confidence estimated by a cBCI using neural signals, RTs and reported confidence.

2 Methods

2.1 Participants

Data were collected from ten healthy participants (five females, one left-handed, mean age = 28.3 years, standard deviation = 5.9 years) performing the experiment in isolation. All volunteers signed an informed consent form and received a monetary compensation of £16 for their time. This research received ethical approval from the United Kingdom's Ministry of Defence Ethics Committee (MODREC; protocol 814/MoDREC/17) in July 2017 and the experiment was performed in accordance with relevant guidelines and regulations. All participants taking part in the study were over the age of 18.

2.2 Experiment

Participants were presented with video sequences (frame rate = 4 Hz) of a dynamic environment representing the viewpoint of a user walking at a constant pace along a corridor (Bhattacharyya et al., 2019b), where individuals could appear from side doorways for one frame (see Figure 1). Each participant had to decide, as quickly as possible and within 2.5 s, whether the character walking across the corridor was wearing a helmet (by clicking the left mouse button) or a cap (by clicking the right mouse button). After reporting their decision, the participant was asked to indicate, within 2 s and using the mouse wheel, their degree of confidence in that decision using an 11-point scale, ranging from 0 (not confident) to 100 (very confident) in steps of 10. The experiment was composed of 12 blocks of 42 trials (i.e., doorways encountered). In each block, 14 trials had empty doors (no decisions required), 14 trials contained a person wearing a helmet, and 14 trials contained a person wearing a cap. The sequence of trials was randomised, and the same sequence was used with all participants, which allowed simulating group decisions offline. RTs were recorded in addition to accuracy and confidence.

Participants performed the task for six blocks of trials while walking (Figure 2) and six blocks while sitting in a comfortable chair, in a counterbalanced order. In either case they were at a distance of about 80 cm from a display. In walking blocks participants walked on a treadmill at a leisurely pace of 2 km/hour while performing the tasks. Prior to the start of the experimental session, each participant underwent a brief training session of 28 trials (approximately 2 minutes) to familiarise them with the task. The total duration of the experiment was between 50 and 70 minutes depending on the speed of response of the participants. Our experimental protocol required participants to only respond in the presence of specific stimuli (i.e., characters wearing a helmet or a cap), a feature associated to go/no-go tasks. However, to achieve realism, we used ecologically-valid stimuli and asked participants to press different mouse buttons depending on whether the character is wearing a cap or a helmet, which makes it more similar to a recognition/classification task, rather than a go/no-go task.

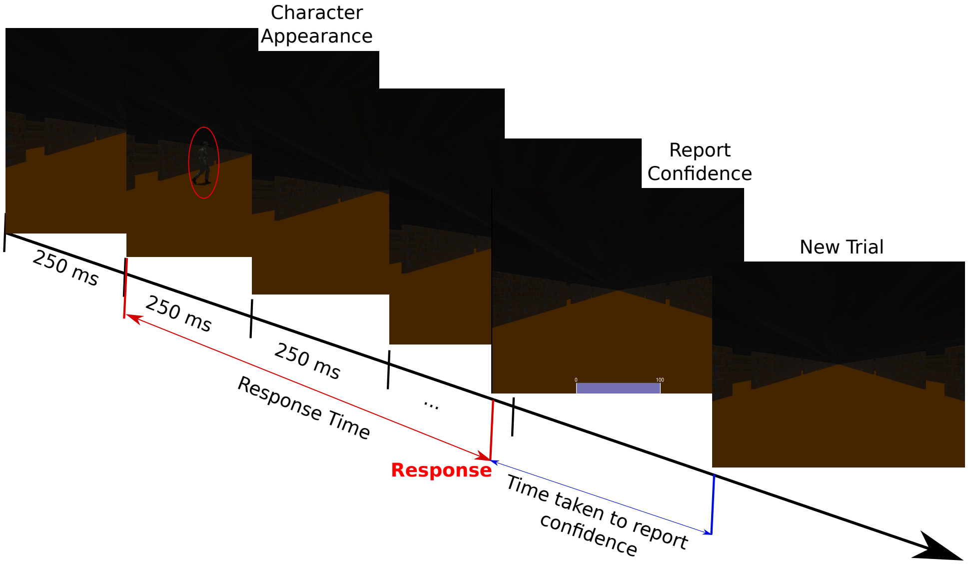


Figure 1: Examples of video sequences in a single trial of the Corridor Experiment. The character appears in the second frame, after which participants had to indicate their response (marked in red) and confidence (shown as 100 in this example).

Figure 2: A participant getting ready to perform the corridor experiment while walking on a treadmill.

2.3 Data Recording and Pre-processing

A Biosemi ActiveTwo EEG system was used to record the neural signals from 64 electrode sites following the 10-20 international system. The EEG data were sampled at 2048 Hz, referenced to the mean of the electrodes placed on the earlobes, and band-pass filtered between 0.15 to 40 Hz to reduce electrical noise. Artefacts caused by eye-blinks and other ocular movements were removed using a standard subtraction algorithm based on correlations with the averages of the differences between channels

Fp1-F1 and Fp2-F2. Then, for each trial, the data were segmented into response-locked epochs starting 1 s before the response and lasting for 1.5 s. The epochs were then detrended and baseline corrected using the average voltage recorded in a time window of 200 milliseconds before the stimulus. Epochs were then low-pass filtered at a pass band of 0-14 Hz and stop band of 16-1024 Hz with an optimal Finite Impulse Response filter designed with the Remez exchange algorithm. Finally, the data were down-sampled to 32 Hz. Each epoch was then labelled as *correct* or *incorrect*, depending on whether the participant had made a correct or incorrect decision in that trial, respectively. In addition to EEG recording, we have also recorded the heart rate variability, galvanic skin response and respiration rate from the participants but we have not used these data in this study.

2.4 Neural-Based Confidence Estimation

We used Common Spatial Pattern (CSP) (Ramoser, Muller-Gerking, & Pfurtscheller, 2000) to extract characteristic neural features from each epoch that can distinguish between the correct and incorrect trials (Valeriani et al., 2016). CSP projects the multi-channel EEG data onto a low-dimensional spatial subspace with a projection matrix, capable of maximising the variance ratio of the two class signal matrices. The logarithm of the variances of the first and the last spatial subspaces have been used as neural features in our cBCI.

Along with the CSP, the RTs and reported confidence of the participants were employed as additional behavioural features. The RTs were measured by timestamping the click of an ordinary USB mouse. Therefore, the feature vector of each trial for estimating the cBCI confidence was composed of two neural CSP features, and two behavioural features, i.e., RTs and reported confidence.

A logistic regression model was designed for each participant p to predict the confidence weight of trial i, $w_{p,i}$, from the four features. The model was fitted using L2 normalisation and a regularisation strength C=1000. We used 8-fold cross-validation for both CSP feature extraction and confidence weight classification to ensure the results were not affected by over-fitting. To evaluate the group performance, each fold randomly selected 21 trials for testing and the remaining 147 trials for training (the empty doorways were not considered).

2.5 Group Decisions

Group decisions were computed offline as follows:

$$d_{pair,i} = \mathtt{sign}\left(\sum_{p=1}^{m} w_{p,i} \cdot d_{p,i}\right),$$

where $d_{p,i}$ is the decision of participant p in trial i, and $w_{p,i}$ is the corresponding confidence weight.

Groups of size $m = 2, \ldots, 10$ were formed offline by considering the $\binom{10}{m}$ combinations of the 10 participants. The performance of groups assisted by cBCI (based on CSPs, RT and reported confidence) were then compared with the performance obtained by traditional groups using standard majority (i.e., $w_{p,i}$=1, $\forall p, i$) and confidence majority (where $w_{p,i}$ is the confidence reported by the participant in each trial). Finally, accuracies were used to assess group performance.

3 Results

In this section we examine whether decision-making performance, in terms of accuracy, reported confidence and RTs, of individuals as well as group performance is affected by whether participants are walking or sitting.

3.1 Individual Behavioural Performance while Walking and Sitting

Figure 3a shows the individual accuracies of the ten participants while walking (in red) and sitting (in blue). It is apparent that these were very similar for sitting and walking, as also shown by the average decision accuracy (dashed lines in the figure) which was similar for the two conditions. Slow-pace walking did not have any (statistically-significant) negative impact on the decision-making capabilities of individuals.

Figure 3b shows the distributions of the confidence reported by the participants for correct and incorrect responses while sitting (in blue) and walking (in orange). As expected, the participants were more confident when they responded correctly than when they were wrong (Kruskal-Wallis test $p = 0.005$). This is aligned with previous research, which consistently showed that confidence levels are higher when responses are correct than when they are incorrect (Valeriani et al., 2017; Bhattacharyya et al., 2019a).The distribution of reported confidence in correct trials (first and last box-plots) did not differ between conditions ($p = 0.25$). In other words, when responding correctly, participants had similar levels of confidence when sitting and walking. However, when looking at the incorrect responses (middle box-plots), it is clear (and highly statistically significant) that participants reported much lower confidence values while walking than when sitting. This suggests that walking at a slow pace gives participants a better metacognitive accuracy than sitting.

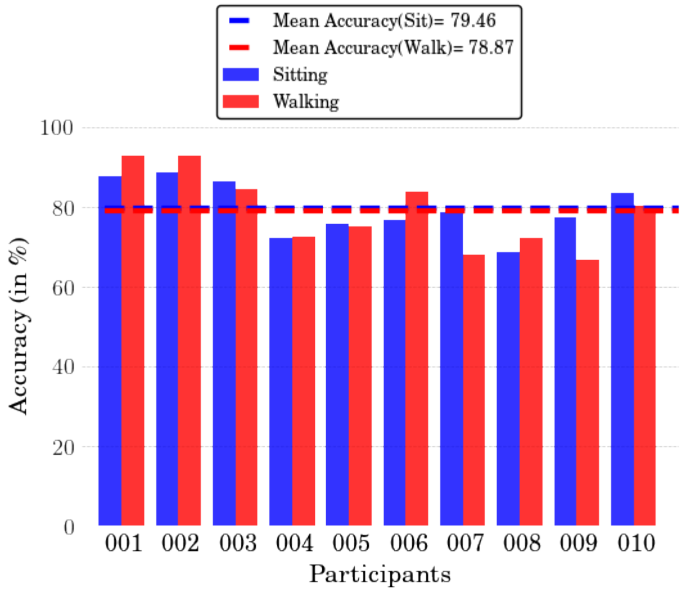
Figure 3c reports a box-plot of the response times for correct and incorrect responses while sitting (in blue) and walking (in orange). As expected, participants took longer to respond when making incorrect decisions (first and last box-plot) than correct ones (middle box-plots) for both sitting and walking ($p = 0.005$). However, they were faster at responding while walking than sitting, albeit the difference in distribution is not significant for the incorrect responses.

Overall, despite accuracy being very similar in the two conditions, participants were better at estimating their confidence and faster to respond while walking. For this reason, one might expect group performance while walking to be better than group performance while sitting (more on this in the next section).

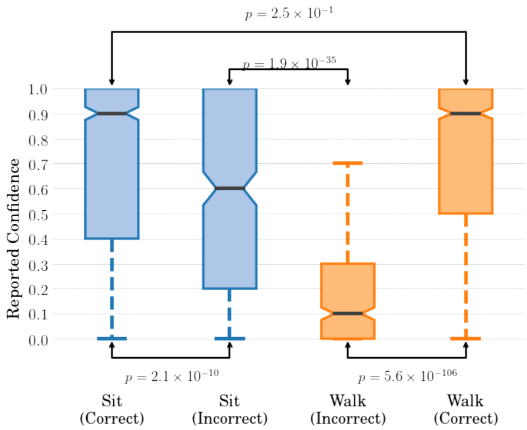
3.2 Group Performance

As mentioned earlier (Section 2.3), the cBCI confidence estimates for group decisions are determined by using a combination of neural features, reported confidence, and RTs. The participants performed the walking and sitting experiments in a counter-balanced manner, meaning that the participants were divided in two subsets: the five that performed the experiment first sitting and then walking, and the five that first walked and then sat. Hence, the maximum group size for this experiment is five.

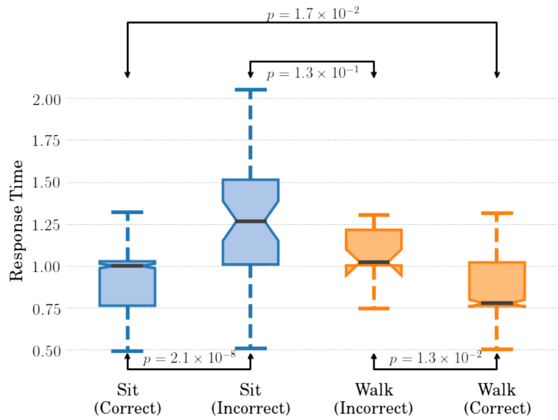
Figure 4 shows the mean accuracies for group sizes one to five, using standard majority (in black), confidence majority (in blue) and cBCI (in red) while walking



(a) Decision Accuracy



(b) Reported Confidence



(c) Response Time

Figure 3: The mean accuracy of ten participants over 336 trials in the experiment while walking (in red) and sitting (in blue). The dashed lines represent the average accuracy across participants for the two conditions. Distribution of (b) confidence values reported by the 10 participants and (c) their response times including their corresponding p-values while performing the corridor experiment while sitting (in blue) and walking (in orange).

(solid lines) and sitting (dashed lines). The cBCI and confidence majority are clearly better performers than standard majority for both the sitting and walking conditions, but the differences are statistically significant only for groups of sizes three and four ($p < 0.05$ for Wilcoxon signed-rank tests). The reason for such improvement is that confidence-based methods break ties more accurately than standard majority (which breaks ties by flipping a coin). The performance of cBCI tends to be slightly better than confidence majority, but these differences are only statistically significant for the seated condition and groups of sizes two and three.

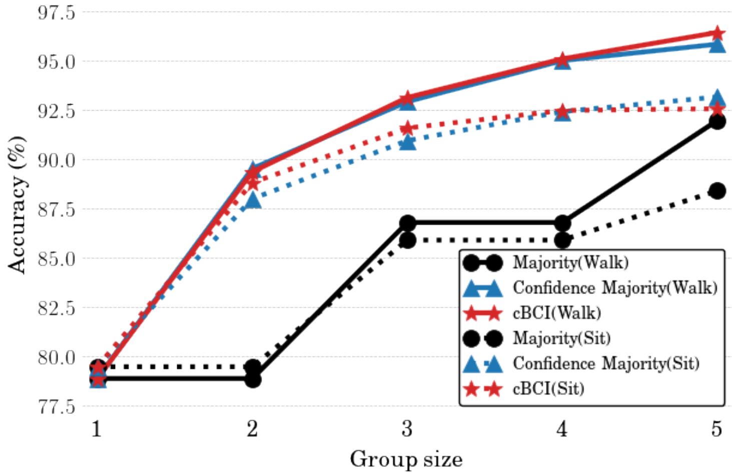


Figure 4: Average group accuracies for groups of size 1 to 5 using standard majority (in black), reported confidence (in blue), and cBCI (in red) while sitting (dashed lines) and walking (solid lines).

On comparing the sitting (dashed lines) to walking (solid lines) conditions, we see that walking improves the group performance for all decision-aggregation methods. The improvement is statistically significant for reported confidence and cBCI. This confirms the hypothesis formulated in Section 3.1, that is that the better distribution of reported confidence and RTs observed when walking would lead to better group performance.

4 Discussions and Conclusions

This study found that performing a decision-making task while walking had no negative impact on an individuals' decision-making performance. On the contrary, it improved the participants' reported confidence and RT without affecting accuracy. This then led to an improvement in the decision-making accuracy of group of walking decision makers with regard to sitting ones.

Results in the previous section showed that cBCI and reported confidence are very similar to each other in performance. However, it is not unlikely that by further tuning neural features and machine learning algorithms, the cBCI will eventually perform better than the reported confidence, which was the case in most of our previous cBCI work.

Irrespective of that, it is clear that confidence-assisted group decision-making benefits from gentle walking. It remains to be seen if more strenuous activity would lead to further improvements or, as previously reported in other conditions (Bradford et al., 2019), as the physical activity becomes more demanding, more cortical resources are allocated to it, leading to an attenuation of cognitive activity and reduction of performance in the decision making task.

Acknowledgements

This research was supported by the Defence Science and Technology Laboratory (Dstl) on behalf of the UK Ministry of Defence (MOD).

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