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Highlights

1. We conduct a feasibility study with 14 individuals with cerebral palsy (CP) to evaluate their control of two online Brain-computer interfaces.
2. Eight of the individuals with CP were able to control at least one of the BCIs at a statistically significant level of accuracy.
3. Analysis of the results reveals that BCIs may be controlled by some individuals with CP.

On the control of Brain-computer interfaces by users with Cerebral palsy

Ian Daly[a], Martin Billinger[a], José Laparra-Hernández[b], Fabio Aloise[c], Mariano Lloria García[d], Josef Faller[a], Reinhold Scherer*[a,e], Gernot Müller-Putz[a]

[a]*Institute for Knowledge Discovery, Laboratory of Brain-Computer Interfaces, Graz University of Technology, Inffeldgasse 13/IV, 8010 Graz, Austria.*
[b]*Insituto de Biomecánica de Valéncia, Universitat Politécnia de Valéncia, Edificio 9C, Camino de Vera s/n, 46022 Valencia, España*
[c]*Neuroelectrical Imaging and BCI Lab, IRCCS Fondazione Santa Lucia, Via Ardeatina, 306, I-00179 Rome, Italy*
[d]*Avapace, Asociación Valenciana de ayuda a la parálisis cerebral, Pza. Jose M[a] Orense, 6 bajo, 46022 Valéncia, España*
[e]*Rehabilitation center Judendorf-Straßengel, Grazer Straße 15, 8111, Judendorf-Straßengel, Austria*

Abstract

Objective

Brain-computer interfaces (BCIs) have been proposed as a potential assistive device for individuals with cerebral palsy (CP) to assist with their communication needs. However, it is unclear how well-suited BCIs are to individuals with CP. Therefore, this study aims to investigate to what extent these users are able to gain control of BCIs.

Methods

This study is conducted with 14 individuals with CP attempting to control two standard online BCIs (1) based upon sensorimotor rhythm modulations, and (2) based upon steady state visual evoked potentials.

Email address: `reinhold.scherer@tugraz.at` (Reinhold Scherer*)

Results

Of the 14 users, 8 are able to use one or other of the BCIs, online, with a statistically significant level of accuracy, without prior training. Classification results are driven by neurophysiological activity and not seen to correlate with occurrences of artifacts. However, many of these users' accuracies, while statistically significant, would require either more training or more advanced methods before practical BCI control would be possible.

Conclusions

The results indicate that BCIs may be controlled by individuals with CP but that many issues need to be overcome before practical application use may be achieved.

Significance

This is the first study to assess the ability of a large group of different individuals with CP to gain control of an online BCI system. The results indicate that six users could control a sensorimotor rhythm BCI and three a steady state visual evoked potential BCI at statistically significant levels of accuracy (SMR accuracies; mean $\pm$ STD, 0.821 ± 0.116, SSVEP accuracies; 0.422 ± 0.069).

Keywords: Cerebral palsy, Brain-computer interface, Steady-state visual evoked potential, Motor imagery, Mental task, Sensorimotor rhythm

1. Introduction

Cerebral palsy (CP) is a non-progressive condition caused by damage to the brain during the early developmental stages, i.e. from the early stages of pregnancy through to 3 years old, and resulting in motor, and other, impairments (Holm, 1982; Odding et al., 2006). CP is caused by a one-time event and classified as "non-progressive" meaning the condition does not get worse with time (Badawi et al., 2008). However, specific symptoms may change over time as the individual's body grows and develops (Panteliadis et al., 2004).

CP can result in a range of symptoms and may be considered to be an umbrella term for any disabilities of movement, coordination, balance, posture, muscle tone regulation etc. resulting from damage during the brain's early development (Fong, 2005; Badawi et al., 2008). Individuals with CP may have a range of difficulties related to motor control including executing intended movements, automatic movements, and controlling postures (Krigger, 2006). Additionally, the brain damage may also in some cases result in problems with speech, comprehension, or mental retardation (Miller, 2004). In some cases CP may render the individual completely paralysed, in others frequent muscle spasms may occur (Krigger, 2006).

Individuals with CP may encounter a range of difficulties in everyday life. Communication may be very difficult as speech may be severely impaired or impossible (Miller, 2004). Additionally, individuals with CP may have severe restrictions on their independence and may have to rely on care-givers for many of their activities of daily living (Panteliadis et al., 2004).

A potential tool proposed to help with the communication and independent living needs of individuals with CP is a Brain-computer interface (BCI) (Neuper et al., 2003; Mir, 2009).

BCIs are devices which allow control of a computer, or other device, via either the controlled modulation of neurological activity or the evocation of electro-potential changes. As such they can allow their users to control external devices for communication (Wolpaw et al., 2002), locomotion (Leeb et al., 2007), neuroprosthesis control (Müller-Putz et al., 2006; Neuper et al., 2006), environmental control (Aloise et al., 2011), entertainment (Nijholt et al., 2009), or rehabilitation (Prasad et al., 2009; Ang et al., 2010; Kaiser et al., 2012).

BCI control often uses the electroencephalogram (EEG) to measure brain activity and is most commonly based upon one of three paradigms; P300 event-related potentials (ERPs), steady state visual evoked potentials (SSVEPs), or sensorimotor rhythm (SMR) changes. P300 ERPs are changes in amplitude in on-going EEG in response to a particular stimulus or event and may be used to identify which option from a set of choices a BCI user is attending to (Farwell et al., 1988).

SMR BCIs base control upon the modulation of on-going oscillatory activity in response to a range of mental tasks (Pfurtscheller et al., 2001). For example, these can include motor imagery in which the user imagines movement in some part of their body (Pfurtscheller et al., 2001), mental arithmetic in which the user attempts some mentally engaging arithmetic task, and word association in which the user attempts to recall words that begin with a specified letter (Millan et al. (2002); Obermaier et al. (2001); Faller et al. (2012a); Friedrich et al. (2012)).

SSVEPs are a response to attention by the user to a regularly oscillating visual stimuli (Calhoun et al., 1995, 1997; Jones et al., 1998; Ming et al., 1999; Middendorf et al., 2000). When attending to such a stimuli oscillatory activity at the corresponding frequency in the EEG recorded from the users occipital cortex increases in magnitude. Thus, by inspecting the power spectra of the EEG recorded over this region it is possible to discern which of a range of target stimuli the user is attending to (Middendorf et al., 2000).

There is only a small amount of previous work attempting to investigate the potential use of BCIs by individuals with CP. One previous study, (Neuper et al., 2003), investigated the long term use of a BCI by a single individual with CP and found that BCI control was possible for this individual. A motor imagery based BCI was provided and, over a period of several months, the individual was trained to use it, achieving an average level of accuracy of above 70 %. However, there are no studies exploring the potential use of BCIs by populations of individuals with CP between whom particular motor function impairments, neurological damage, and other, individual specific conditions such as degrees of spasticity may vary greatly. Additionally, the nature of the brain damage in individuals with CP and related symptoms makes it unclear whether such individuals will be able to (1) generate the necessary modulations in their neurological activity to control a BCI, and (2) produce EEG with a small enough amount of artifacts for use in BCI.

Therefore, to begin to answer these questions a feasibility study is conducted. Fourteen adults with CP are engaged in experimentation with two different online BCI systems in order to investigate if they are able to achieve online control and to assess the quality of their EEG. Two commonly used

BCIs are chosen, the sensorimotor rhythm (SMR) based BCI and the steady state visual evoked potential (SSVEP) based BCI. Note, P300 BCIs were not investigated at this stage as prior pilot studies with a small group of 6 individuals with CP showed more users were able to produce a significant SSVEP response than P300. Additionally, users indicated a preference for either SSVEP or SMR BCIs over P300 based BCIs.

The two BCIs used in this study represent very different control paradigms involving different cognitive processes and different cortical regions. SMR-based BCIs involve attempting mental tasks, with cortical activation primarily located in the motor cortex regions. In contrast, SSVEP BCIs involve attending to oscillatory stimuli with neurophysiological responses located primarily in the occipital cortex. Therefore, these two BCIs allow individuals with CP to attempt two diverse control paradigms.

We set out to investigate whether individuals with CP are able to gain control over either an SSVEP or a SMR-based BCI.

2. Methods

2.1. Subjects

Fourteen individuals with CP voluntarily participated in this study (seven male, age range 20 to 58 with a median age of 36, SD = 10.97). Institutional review board (IRB) ethical approval was obtained for all measurements. Details of the participants are summarised in table 1.

User	Gender	Age	GMFCS	Orthopaedic disorders	CP type	Sensory disturbances	Dominant hand
01	M	53	V	MMII, MMSS	Dystonic	-	L
02	M	36	V	MMII, MMSS	Dystonic-spastic	-	L
03	F	52	IV	MMII	Spastic diplegia	Myopia	R
04	M	22	IV	MMSS, MMII	Acquired cerebral damage	-	R
05	M	32	V	MMII	Acquired cerebral damage	Blindness, left eye. Deafness, left ear.	B
06	F	20	-	MMII, MMSS	Dystonic	-	-
07	M	34	IV	MMSS, MMII	Athetosic	-	L
08	F	58	IV	MMII	Spastic diplegia	Myopia	R
09	F	32	IV	MMII	Spastic	-	L
10	F	36	V	MMII, MMSS	Spastic	-	L
11	M	38	V	MMII, MMSS	Dystonic-spastic	-	L
12	F	36	V	MMII, MMSS	Dystonic	Myopia	L
13	M	37	IV	MMII, MMSS	Spastic	-	-
14	F	31	IV	MMII, MMSS	Spastic	-	-

Table 1: Subject details. GMFCS denotes the Gross motor function classification system score, Orthopaedic disorders are denoted by codes which indicate lower limb disorders (MMII) or upper limb disorders (MMSS). The subjects dominant hand is either left (L), right (R), bilateral (B), or unknown (-).

2.2. Recording

EEG was recorded from 16 electrode channels via the g.tec GAMMAsys system with g.LADYbird active electrodes (g.tec, Austria). Channels were arranged primarily over the motor and parietal cortical areas according to the international 10/20 system.

We used channels AFz, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, PO3, POz, PO4, O1, Oz, and O2. The reference electrode was placed on either the right or left ear according to the particular condition of each subject and the ground electrode was placed either behind the left ear at either TP7, TP9 or at FPz (again according to particular subject conditions).

Accelerometer sensors were used to record the subjects head movements in the x, y and z dimensions by placing a PLUX accelerometer at position Fz (xyzPLUX triaxial accelerometer). Additionally, for some subjects, a PLUX blood pressure sensor was placed on one finger of either the left or right hand (bvpPLUX). The hand and finger used varied from subject to subject according to comfort and the particular condition of each individual with CP.

Synchronisation of signal timing between the EEG and the accelerometer was achieved via the TOBI signal server (Müller-Putz et al., 2011; Breitweiser et al., 2011). EEG data was sampled at a frequency of 512 Hz and saved to file during both training and feedback runs while the accelerometer and blood pressure were both sampled at a rate of 128 Hz. Only the EEG signals were used in this study with the other physiological signals retained for future analyses.

2.3. BCI systems

Two online BCI systems were implemented to test the ability of individuals with CP to control either an SSVEP or an SMR based BCI. Users were shown demonstrations of each BCI prior to beginning the measurements. This was to familiarise them with the tasks and make sure they understood what was required.

Individuals with CP who participated in our pilot study reported that they felt more comfortable and secure when given some measure of control over the experimental setting. Thus, users were free to choose which system they would like to try. After each run they were again asked if they would like to (1) continue with the current system, (2) try the other system, or (3) stop. Users reported that giving them these choices helped them stay motivated and allowed them to feel more secure and comfortable in the novel setting of the EEG measurement environment.

When given free choice of which paradigm to choose, it was hypothesised that users may exhibit strong preferences for one paradigm. This preference may bias the results. For example, if the SSVEP paradigm was chosen first by all users then lower results at the SMR BCI may be explained, in part, by subject fatigue from first attempting the SSVEP BCI.

To determine if there was such a bias in choice, either in terms of a preference for one or the other of the BCI paradigm types or in the order paradigms were selected, two tests were applied. First, the number of times each paradigm type was chosen was assessed against the null hypothesis of equal probability of each paradigm being chosen. Second, the fraction of times each paradigm was chosen within each of the first three runs (subsequent runs were not completed by enough users for valid statistical testing) was assessed against the same null hypothesis. Rejection of the null hypothesis in the first test would indicate a significant preference for one or other of the paradigms by the subjects. Rejection of the null hypothesis in one or more of the runs in the second task would indicate that there is some preference for the order of the runs exhibited by the subjects.

2.3.1. SSVEP

The SSVEP paradigm consisted of four square targets in the form of four red boxes arranged on a computer screen in a quadrangle. Stimuli were rapidly changed between red and black colours at frequencies of (clockwise from top left) 6.66 Hz, 8.57 Hz, 12 Hz, and 15 Hz. These frequencies were chosen based upon pilot experiments with three healthy subjects. Users were periodically cued to attend to one of the targets via an arrow placed in the centre of the screen and remaining in place for 6 s. Additionally, a fifth null condition was cued by a cross appearing for 6 s in the centre of the screen. Feedback about successful accomplishment of the task was provided immediately by highlighting a selection frame around the target. Inter-trial intervals were uniformly distributed between $3-5$ s.

Each condition was randomly chosen from a uniform distribution for each trial. Trials were grouped into runs and one SSVEP run consisted of 20 trials with equal numbers of trials for each class.

Classification was performed via the canonical correlation analysis (CCA) method described in (Seber, 1984) and applied in (Horki et al., 2010). Correlations were found between two sets of data (1) the EEG recorded on multiple channels arranged over the occipital cortex and (2) the SSVEP stimulation frequencies. The largest correlation coefficient was used to identify the stimuli the user was attending to. Thresholding was used to test for the null condition that the user was not attending to a stimuli. Thresholds were initially set to 0.2 for each of the four SSVEP stimulation frequencies based upon a prior pilot study with 3 healthy subjects.

CCA was applied in a sliding window to segments of the EEG of length 2 s with a step size of 0.0625 s. Feedback was presented to the user if the output of the CCA method exceeded the threshold for 0.5 s consecutively.

In addition to the classification accuracy it is interesting to ask in what percentage of trials the users manage to achieve correct feedback. Thus, the "hit rate" (HR) was measured as the percentage of trials for which a user managed to produce a sufficiently large SSVEP response to achieve correct feedback.

2.3.2. Sensorimotor rhythms

The sensorimotor rhythm paradigm - based upon work in (Faller et al., 2012b) - consisted of an initial calibration phase followed by an online feedback phase.

During the calibration phase the user was asked to perform four different mental tasks in response to a cue. The tasks were:

1. Kinaesthetically imagined movement of either hand
2. Kinaesthetically imagined movement of the feet
3. Mental arithmetic
4. Mental word-letter association

No feedback was provided during this initial phase. Instead the system used the data recorded to select the two of the four tasks which were best suited for individual control.

The timing of individual trials was as follows.

Second 0: a fixation cross appeared in the centre of the screen and remained there for the duration of the trial.

Second 1.5: a cue appeared on screen indicating which task to perform. This cue remained until second 3.5.

Remaining time: the time from the appearance of the cue to the end of the trial at second 8 was designated as the imagery period and the user was instructed to perform the cued task during this time and halt when the cross disappeared.

One of the four different conditions was randomly chosen from a uniform distribution for presentation to the user during each trial.

After sufficient trials were recorded in the calibration phase for accurate estimation of the class boundaries the BCI automatically proceeded to the feedback phase. The two most discriminative classes were selected for use and randomly presented to the user, following the same timing as used in the calibration phase, during each trial.

During the imagery period in the feedback phase a bar was displayed on screen indicating the LDA classifier distance estimated from attempting to classify features from the users SMR strength. Increased LDA classifier distance causes the bar to fill from left to right. Additional feedback in the form of a smiley face was presented to the user in the case of the classifier prediction matching the true class label for more than 50 % of the duration of the imagery period in the trial.

An individual run in both the training and feedback phases contained 32 trials. The number of trials per class was balanced per run, thus, in the training run there were 8 trials per class and in the feedback run there were 16 trials per class.

The exception to this arose when sufficient trials for classification were gathered from the calibration phase in the middle of a run. In this case the run changed from the calibration to the feedback phase immediately and the run may therefore be said to have contained both calibration and feedback trials.

During the feedback phase the distribution of the EEG components related to the tasks continued to be estimated to attempt to further improve the accuracy with which the system responded to the user.

During both the calibration phase and feedback phase artifacts in the EEG were automatically identified and labelled. This allowed comparisons to be made between the classifier outputs and any patterns or repetitions found in the generation of artifacts. Artifacts were automatically identified via the thresholding of a number of key metrics from the EEG as described in (Faller et al., 2012b).

There were four stages to the classifier setup outlier rejection, feature selection, segment selection, and classifier training. Outlier rejection was based upon thresholding kurtosis, probability, and statistical properties of the features. Logarithmic band power features were then extracted from the EEG in the bands 9-14, 13-17, 16-24, and 23-29 Hz. During the calibration phase the feature that showed the highest between-class discriminability (as measured by Fischer's score) and the time period (within the activity period) that scored the highest median accuracy after leave-one-out cross-validation, was used for training the LDA classifier applied during the online feedback phase.

The LDA classifier was applied in a sliding window approach during online classification. A window of width 1 s was used with a step size of 1 sample. This is further detailed in (Faller et al., 2012b).

2.4. Performance

Online classification performance is reported for both the SSVEP and SMR BCI systems. The statistical significance of the performance was calculated at each time point against the null hypothesis of equal probability of each class being selected by the classifier. The subsequent significance level ($p < 0.05$) is illustrated against the plots of performance accuracy over time.

Additionally, it may be argued that there was a multiple comparisons issue related to the calculation of the significance on a sample by sample basis. However, this was a non-trivial problem as there was a large amount of dependency between subsequent EEG sample points. Thus, a Bonferroni multiple comparisons correction was not appropriate. To this end the mean area under the accuracy curves for each BCI system was also calculated. The area was calculated during the imagery period for the SMR BCI and during the SSVEP stimulation period for the SSVEP BCI. The significance of this area under the accuracy curve was then estimated via a bootstrapping approach.

Multiple bootstrap replications of the performance curves were generated via first shuffling the class labels prior to calculating classification accuracy. Mean areas under the accuracy curves were then calculated from each bootstrap replication and used the estimate the distribution of mean areas under accuracy curves under the null hypothesis of random classification. From this the significance of the observed accuracy curve was estimated.

2.5. Relationships between subject details and performance

It is interesting to ask if there is a relationship between any of the subject details, such as age, CP type etc., and their performance with each of the BCIs. For example, if some sub-group of subjects (e.g. some age group) perform better at one type of BCI then this could inform and guide the design of future BCI systems for sub-groups of individuals with CP. To this end stepwise multi-linear regression was performed with subject details as predictor variables and the resulting accuracies at controlling each of the BCIs online as the criterion variables. Two separate regression analyses were performed (1) for the criterion variable SSVEP performance accuracies and (2) for the criterion variable SMR performance accuracies. The predictor variables used were subject gender, age, Gross motor function classification system (GMFCS) score, orthopaedic disorders, CP type, sensory disturbances, and dominant hand.

3. Results

3.1. Run order

Table 2 lists the orders of runs selected by each user.

User	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8
01	SSVEP	SSVEP	SMR_t	SMR(18/14)	SMR_f			
02	SMR_t	SSVEP	SMR(9/23)					
03	SMR_t	SSVEP	SMR_t	SSVEP	SMR(23/9)	SSVEP		
04	SSVEP	SSVEP	SMR_t					
05	SSVEP	SSVEP	SMR_t	SMR(10/22)	SSVEP			
06	SMR_t	SSVEP	SSVEP					
07	SMR_t	SSVEP	SMR_t					
08	SSVEP	SMR_t	SMR(8/24)	SSVEP	SMR_f	SSVEP		
09	SMR_t	SSVEP	SMR(13/19)					
10	SSVEP	SMR_t						
11	SSVEP	SMR_t	SMR(2/30)					
12	SMR_t	SSVEP	SSVEP	SSVEP	SMR_t	SSVEP	SMR_t	SMR_f
13	SSVEP	SSVEP	SMR_t	SMR(9/23)				
14	SSVEP	SMR_t	SSVEP	SMR(11/21)				
p	0.183	0.061	0.035	-	-	-	-	-

Table 2: Order and number of BCI runs chosen by each user. SSVEP denotes the choice to try the SSVEP BCI for a particular run. SMR denotes the choice to try the SMR BCI for a particular run. The subscripted SMR choices (SMR_t and SMR_f) denote runs for which the user had to go through 4 class trials to train the classifier (SMR_t) and trials for which feedback was provided (SMR_f). Feedback was provided as soon as enough trials had been gathered by the classifier for adequate classification results to be obtained. Therefore, for runs during which feedback was provided from a point part way through the run the number of training / feedback trials in the run are indicated in parenthesis and the subscripts are dispensed with. The final row indicates the probabilities of bias in the selection of BCI paradigms by users during each run assessed against the null hypothesis of equal probability of each paradigm being selected.

It is worth noting that all users tried both tasks with no observable preferences. This is confirmed by the tests for bias in paradigm selection performed. Over all runs and subjects null hypothesis (that there is equal probability of each paradigm being chosen) is not rejected ($p = 0.104$). Table 2 lists the p values of probabilities of rejecting the null hypothesis that each paradigm is equally likely to be chosen during each run. Note, for run three the null hypothesis is rejected ($p = 0.035$). However, is may be argued that it is necessary to apply multiple comparisons correction to correct for the three runs. When Bonferroni correction is applied the null hypothesis is no longer rejected as $p = 0.035$ is greater than the adjusted significance level of $p = 0167$.

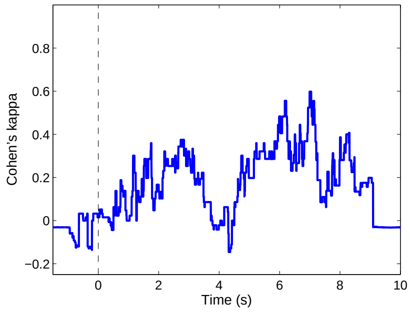
Users commented on the first day of measurements that false positive selections of SSVEP stimuli were distracting. Therefore, from the second day of measurements onwards (users 4 to 14) the thresholds, used by the CCA method to identify the SSVEP stimulation frequency the users were attending to, were adjusted from 0.2 to 0.3 for each stimulation frequency. This had the effect of reducing the number of false postive identifications as desired. However, it also reduced the number of true positive identifications, making it harder for the users to produce any feedback.

3.2. SSVEP

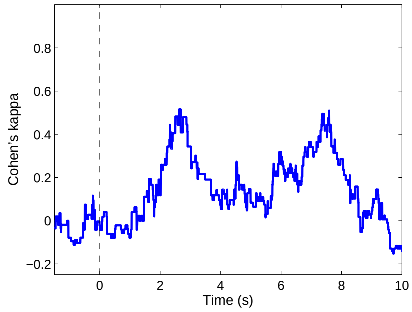
During attempted online control of a BCI via SSVEP, 5 users were able to achieve control at a statistically significant level ($p < 0.05$). Figure 1 illustrates online classification accuracies achieved by the best performing user for each stimuli who was able to control the SSVEP BCI at statistically significant accuracies ($p < 0.05$). Table 3 then lists the peak and mean online accuracies over all stimuli achieved by each user when attempting to control the 5-class SSVEP BCI online along with the HR, the percentage of trials for which users were able to achieve correct feedback.

However, it's important to note that a multiple comparisons correction may be necessary to adjust for the multiple subjects in the study. Bonferroni correction may be used to do this. The alpha significance level is adjusted by $1/N$ were N indicates the number of comparisons and in this case equals 13. After applying Bonferroni correction we observe that three users exhibit significant ($p < 0.05$) peak and mean classification accuracies.

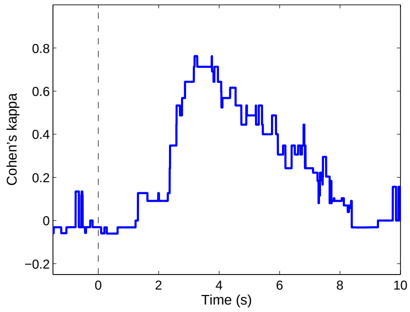
Accuracies may be listed on a per stimulation frequency (class) basis using a one-vs-rest classification scheme. The balanced accuracy and Cohen's kappa are reported to adjust for the bias in the number of trials. Mean



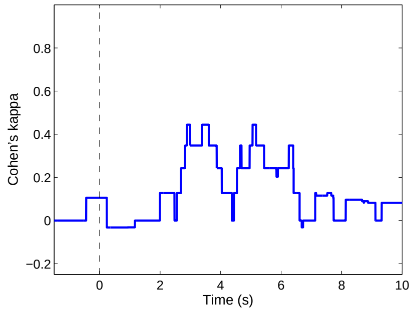
(a) Top left, 6.66 Hz



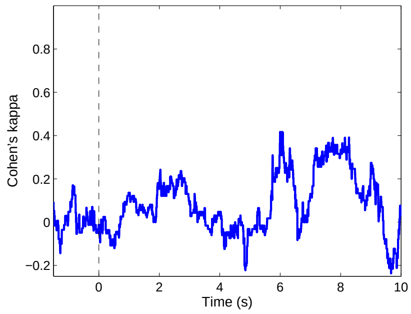
(b) Top right, 8.57 Hz



(c) Bottom left, 12 Hz



(d) Bottom right, 15 Hz



(e) Null condition, the cross in the centre of the screen

Figure 1: Online classification results achieved by the best performing user (user 5) when attempting online control of the SSVEP based BCI. Each plot illustrates the Cohen's kappa coefficient for each of the four SSVEP stimulation frequencies positioned in each corner of the screen and the null condition. Cohen's kappa is used due to the imbalance in class numbers entailed in reporting results for one class against the rest. The abscissa shows the time course over the trial starting from the onset of the visual cue (vertical, dashed line).

User	Peak accuracy	p		Mean acc.	Trials	HR
01	0.400	0.002	*	0.234	40	56.2
02	0.350	0.067		0.168	20	56.2
03	0.366	0.002	*	0.219	60	62.5
04	0.325	0.035		0.208	40	50.0
05	0.500	0.000	*	0.296	60	60.4
06	0.350	0.067		0.219	20	50.0
07	0.400	0.023		0.235	20	50.0
08	0.200	0.525		0.194	60	00.0
09	0.250	0.327		0.201	20	00.0
10	0.200	0.545		0.191	20	00.0
11	0.200	0.545		0.187	20	00.0
12	0.200	0.522		0.189	80	00.0
13	-	-		-	-	-
14	0.200	0.532		0.191	40	00.0

Table 3: Columns two and three list peak online classification accuracies for control of the SSVEP based BCI by each user and the corresponding p-value against the null hypothesis of equal chance of each of the 5 classes (4 stimuli and the no-target condition) been classified. Asterisks (*) indicate users who achieved statistically significant ($p < 0.05$ adjusted via Bonferroni to $p < 0.0038$) accuracies as measured via the bootstrapping significance test. Columns four and five list mean accuracies during the stimulation period and the number of trials attempted by each user. Additionally, the HR (the percentage of trials for which the user was able to attain the correct feedback) is listed. Note, user 13 attempted SSVEP control but because of the position of their head rest was pressing on the occipital electrodes no usable signals could be recorded for this paradigm.

and standard deviations of balanced accuracy values for each stimulation frequency and the null condition (when the user does not look at any stimuli) are listed in table 4. A 2x2 Anova with the factor stimulation frequency revealed no significant effect of frequency on performance $F_{(4,69)} = 0.57, p = 0.683$.

Note, users $1-3$ had CCA thresholds set to 0.2 while the remaining users had thresholds set to 0.3. Significant classification accuracy is achieved by some users with each threshold value.

Condition	Accuracy (mean ± std)	Kappa (mean ± std)
6.66 Hz stimuli	0.606 ± 0.112	0.191 ± 0.204
8.57 Hz stimuli	0.639 ± 0.165	0.209 ± 0.259
12 Hz stimuli	0.603 ± 0.135	0.176 ± 0.195
15 Hz stimuli	0.586 ± 0.116	0.202 ± 0.266
No stimuli	0.571 ± 0.090	0.176 ± 0.215

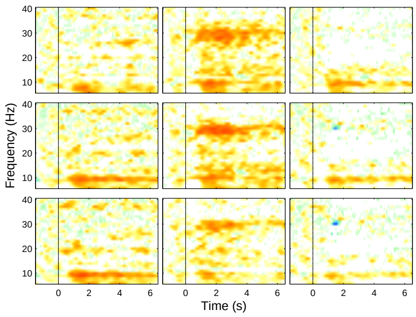
Table 4: Mean and standard deviation of balanced accuracies and Cohen's kappa related to attending to each SSVEP stimulation frequency and the null condition (attending to no stimuli).

3.3. Sensorimotor rhythms

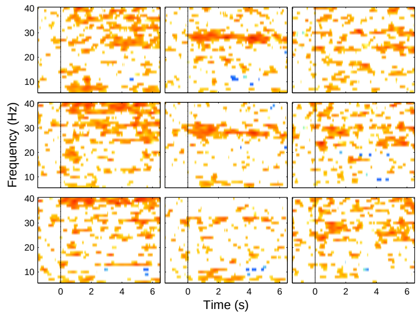
During attempted online BCI control clear sensorimotor rhythms are visible in 12 users with artifacts contaminating the spectra in the remainder. Examples of good, artifact free, spectra generated by a user are illustrated in figure 2. ERD/S spectra are illustrated on common average referenced (CAR) channels FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, and CP4 for each of the 4 mental tasks employed.

The online classifier identifies enough trials to be trained with 10 users and online classification is statistically significant ($p < 0.05$) in 8 of those users. Of those users, two exhibit significant correlations between the classifier output and the automatically identified artifacts present in the signal. Thus, of the 14 users who attempted online BCI control via SMR modulation 6 were successful.

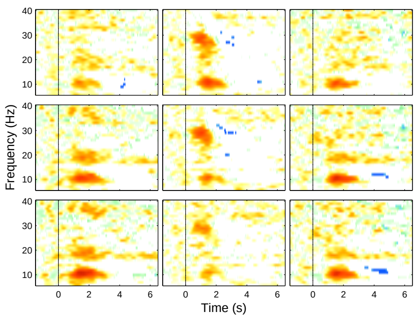
Online classification accuracies achieved by the 6 users able to control the SMR based BCI at statistically significant accuracies, without significant correlations found with the automatically identified artifacts, are illustrated in figure 3. The peak online classification accuracy for each user during the SMR based BCI control in the period 2 - 6 s relative to the cue, the corresponding p-values, and the correlation R-values and p-values between the classifier output and the automatically identified artifacts are listed in table 5. Additionally, the hit rate (HR), the percentage of trials for which each user is able to achieve a smiley feedback, is listed.



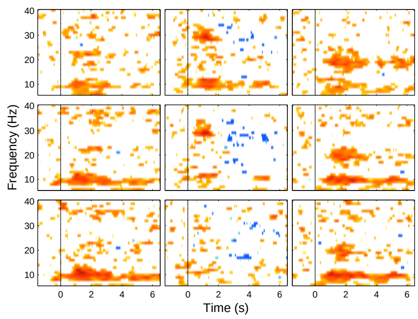
(a) Hand imagery



(b) Feet imagery

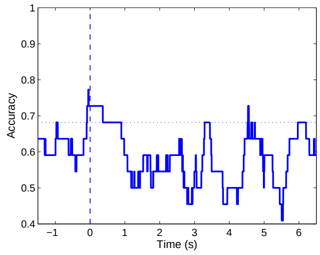


(c) Mental arithmetic

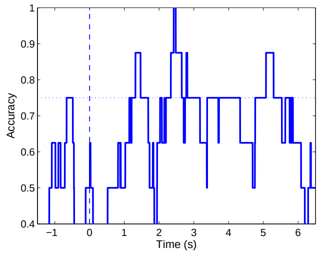


(d) Word association

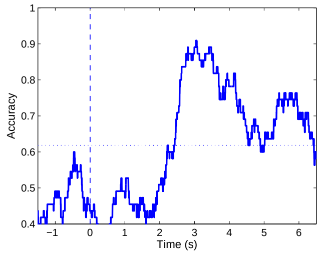
Figure 2: Examples of SMRs, from a user with relatively clean EEG, relating to each condition, (hands / feet imagery, mental arithmetic, and word association). Each plot is split into 9 subplots illustrating the common average referenced channels FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, and CP4. Red colours indicate significant periods of ERD and blue significant periods of ERS. Significance is determined via the bootstrapping approach described in (Graimann et al., 2002). The vertical line at 0 s denotes the cue presentation time.



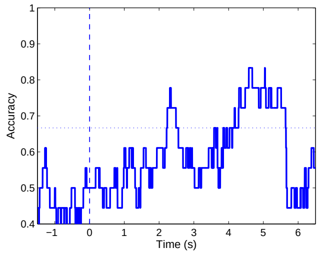
(a) User 02



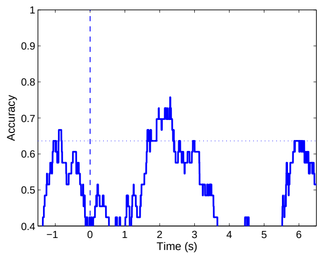
(b) User 03



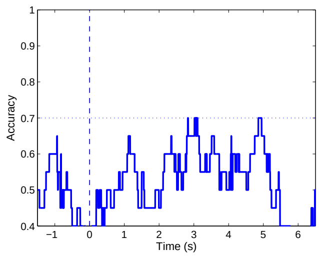
(c) User 08



(d) User 09



(e) User 11



(f) User 14

Figure 3: Online classification accuracies achieved by users who were able to achieve statistically significant ($p < 0.05$) classifier accuracies when attempting online control of an SMR based BCI and for whom there is not a significant correlation betwen classifier results and artifacts. Times are listed relative to the cue presentation time (denoted by the veritical dashed line) and the horizontal dotted line illustrates the significance level at ($p < 0.05$). Note, the position of this line varies dependent upon how many trials each user completed in the feedback phase.

	Classification				Correlation					
User	Peak acc.	p		Mean acc.	$p < 0.01$	R	p	HR	Trials	Selected classes
01	0.667	0.008	*	0.541	*	-0.144	0.000	48.9	46	F / M
02	0.727	0.008	*	0.568	*	0.004	0.168	63.6	23	F / W
03	1.000	0.000	*	0.695	*	0.004	0.319	87.5	9	F / W
04	-	-	-	-	-	-		-	-	-
05	0.571	0.192		0.464		0.002	0.405	38.1	22	F / W
06	-	-	-	-	-		-	-	-	-
07	-	-	-	-	-		-	-	-	-
08	0.909	0.000	*	0.699	*	0.002	0.152	100.0	56	H / M
09	0.833	0.001	*	0.627		0.003	0.238	27.8	19	F / M
10	-	-	-	-	-		-	-	-	
11	0.757	0.001	*	0.498		0.002	0.284	48.5	34	F / M
12	0.806	0.000	*	0.621	*	-0.022	0.000	100.0	32	H / W
13	0.682	0.067		0.489	*	0.000	0.902	45.5	23	F / H
14	0.700	0.021	*	0.520	*	0.002	0.547	65.0	21	F / W

Table 5: Online peak classification accuracies (Peak acc.), in the period 2 - 6 s relative to the cue, for control of the SMR based BCI by each user and corresponding p-values against the null hypothesis of equal chance of each of the 2 classes selected for online control been classified. Statistically significant peak accuracies are indicated via asterisks (*). Note, after application of Bonferroni correction the statistical significance threshold is adjusted from $p < 0.05$ to $p < 0.005$. Mean accuracies and their significance, as evaluated via the bootstrapping method, are also listed. The Pearson's correlation coefficient, and corresponding significance level, between the classifier output and automatically identified artifacts are also listed. HR denotes the hit rate; the percentage of trials for which the user achieved the goal of displaying a smiley face on screen. The trials column lists the numbers of trials performed by each user in the feedback condition. The final column lists which classes were selected for use in the online feedback phase, feet (F), hands (H), word association (W), or mental arithmetic (M). Note, rows left empty indicate users who elected to halt BCI training before sufficient artifact free trials had been gathered to train the classifier.

3.4. Signal quality

During the online measurements considerable EMG and movement related artifacts were observed in 3 users with transient EMG observed in another 8 users. The remaining 3 users exhibited relatively clean EEG with only occasional blinks and EOG. In two users classification results were significantly correlated with artifacts (one of whom produced statistically significant online peak control accuracies). In the remainder (12 users) this was not the case. The following further general observations may be made on the EEG recorded from individuals with CP.

Considerable EMG and other artifacts are present on occipital channels in the majority of individuals. These arise from neck muscles and/or head supports exerting pressure on the occipital electrodes. While efforts were made to prevent head supports exerting pressure on occipital electrodes this was not always feasible for the complete duration of the measurement session. Periods of short-lived transient EMG may also be observed over the whole head in many users. However, these are often short lasting ($< 10\,\mathrm{s}$). Electrode pop artifacts also occur frequently due to involuntary head movements causing pulling at leads in some users.

The active electrode system used has a better signal to noise ratio (SNR) on the cable between the electrode and the amplifier, potentially leading to less noise in the signal. However, in 2 users (user 6, 2 runs, user 12, 1 run) problems with the ground channel disconnecting due to large head movements introduced large line noise artifacts in some runs and rendered the signals un-usable. These runs were removed from the dataset prior to analysis and are not incorporated into the classification results.

3.5. Relationships between subject details and performance

The small number of subjects involved in this study means the impact of the statistical analysis of the relationships between subject details and their performance is limited and should be interpreted with caution. The results of the multi-linear stepwise regression analysis reveal a statistically significant ($p < 0.05$) relationship between the predictor variable subject gender and the criterion variable, the subjects performance at the SMR BCI with feedback provided ($r^2 = 0.501$, $p = 0.0136$). Further analysis reveals the accuracies achieved by male users and female users are seen to be significantly different (female user accuracies, mean $\pm$ SD (number of subjects); 0.849 ± 0.112 (5), male user accuracies; 0.681 ± 0.071 (5)), with female users achieving significantly higher accuracies $p = 0.022$ when compared via a paired t-test.

4. Discussion

It has been shown that some users with CP are able to volitionally modulate their neurological activity in order to control a BCI at statistically significant levels of accuracy. Although the levels of accuracy are too low to demonstrate usability this result indicates that some individuals with CP can, with no prior training or experience, control a BCI and could potentially, in future, be able to use BCIs as assistive devices in selected circumstances.

The suitability of each BCI paradigm for each user depends on individual circumstances. Many users were observed to exhibit poor signal quality on occipital channels resulting from uncontrolled neck muscles and / or their head supports exerting pressure on the occipital electrodes. For this reason the suitability of SSVEP - and potentially also P300 - BCI control is limited and dependent upon either these users being able to control their neck muscles, and do without head support, or on suitable artifact removal methods being developed. By contrast SMR based BCIs could be controlled by 6 out of 14 users with task related SMRs observable in 12 users.

The SSVEP accuracies illustrated in figure 1 are observed to exhibit differences in granularity at different frequencies. Some explanation is needed for this. Inspecting the a-posteriori probabilities for each stimulation frequency reveals large differences for different stimulation frequencies. The mean a-posteriori probabilities are 0.49, 0.15, 0.29, 0.05 and 0.02 for the stimulus types null condition, 6 Hz, 8 Hz, 12 Hz, and 15 Hz respectively. Thus, the classifier is biased towards lower frequencies resulting in outputs at these frequencies being more frequently presented and finer grained plots resulting from greater numbers of switches at these stimulation frequencies.

The bias towards lower stimulation frequencies in the classifier may be physiological. Indeed in a pilot study performed on a small number of individuals with CP prior to the work reported here it was observed that the power spectrum of occipital EEG from individuals with CP exhibited larger spikes in response to lower stimulation frequencies then higher stimulation frequencies. Although it's important to note the well-known high inter-subject variability in EEG responses and the relatively small number of subjects in this study mean stronger conclusions cannot currently be drawn.

Peak accuracies, along with time courses of accuracy, are used to report performance at each of the BCI systems. This is common practice in BCI research and provides some measure of both the best performance and the performance over time (Treder et al., 2011; Fazli et al., 2012; Allison et al., 2010a). However, it may be argued that peak accuracy alone does not provide a complete measure of statistically significant performance. To this end mean accuracies are also reported and their significance checked via a bootstrapping method. This reveals that users who achieve significant peak accuracies with the SSVEP BCI also achieve significant mean accuracies. However, two users (09 and 11) who achieved significant peak accuracies with the SMR BCI did not exhibit significant mean accuracies. This may be due to the small number of trials with user 09 (19 trials) or an unstable performance with a large period of false classifier results (user 11). By way of contrast, users 01, 02, 13, and 14 exhibit significant mean accuracies despite not exhibiting significant peak accuracies.

The hit rate (HR) records the percentage of trials for which the user achieves correct feedback. While correct feedback alone is not enough to indicate feasible BCI control it does give some measure of how successful control appears to be to the user and it is encouraging to see that for 7 of the SSVEP BCI users HRs of 50.0 and above are achieved. Although this must be contrasted with the remaining users who were not able to produce any correct feedback.

When inspecting the time courses of the classification accuracies achieved by each of the 6 users successful in controlling the SMR BCI at statistically significant levels of accuracy users 8, 9, and 11 achieve sustained levels of significant control. However, users 2, 3, and 14 only achieve significant control for transient periods of time or, in the case of user 3, the user attempted so few trials (9) that the impact of the results is very low. Users 2 and 14 completed 23 and 21 trials respectively. It's conceivable that with more trials a more sustained period of significant classification could emerge. However, this is currently only speculative and sustained, significant BCI control can currently only be seen to be achieved by 3 users.

The choice of which two out of the four classes are chosen for the online feedback condition over all users shows a slight preference for the feet motor imagery condition (chosen 8 times). Other classes are chosen similar numbers of times to one another (hand imagery 3 times, mental arithmetic 4 times, and word-letter association 5 times). The reason for this observed preference could be that the feet motor imagery condition produces an SMR pattern in these users which is more distinct and, therefore, differentiable then the other classes. However, this will require further research to verify due to the relatively small number of subjects involved in this study.

The users involved in this study received no prior BCI training. It is, therefore, interesting that a number of them were none-the-less able to achieve significant levels of control with one or other of the BCIs they attempted. Furthermore, it is interesting to note that this was achieved with BCIs which were not optimised for individuals with CP. Training sessions with the users - either BCI training or training at meditation - could improve the performance of BCI control with a number of users and, potentially, allow more users to achieve significant levels of control (Tan et al., 2009; Mahmoudi et al., 2006).

However, it's important to note that statistically significant levels of accuracy do not mean usable BCI control may be achieved. Useable BCI control may be defined as a sufficient level of control to allow users to complete a reasonable number of desired tasks. For binary control this is defined as 70 % accuracy, based upon the results of two patients described in (Kübler et al., 2001). During attempted online control of the two-class SMR BCI 5 out of the 6 users who achieved significant control are seen to produce either brief or sustained control above the 70 % threshold. However, a larger number of trials would allow for further confirmation of this result.

Additionally, the use of more sophisticated signal processing methods, machine learning methods, and / or feature types may, potentially, also help to improve performance in a number of users with CP. It may be possible to allow some users who are not currently able to control a BCI at a statistically significant level of accuracy to do so. Investigations into improved methods are an on-going topic of research in BCI and have the potential to yield impressive results in future work.

The active electrodes used in this study have a considerably shorter setup time, when compared to the passive electrode systems more commonly used in BCI studies. However, this comes at the expense of potentially poorer signal quality due to the lack of an impedance measure in the particular amplifier system used. None-the-less, this was a successful decision as during online control no major problems with setup time were encountered and the proportion of usable signals is similar to that observed with passive electrode system used in other studies. In future work it may be possible to measure the signal quality during BCI operation via the use of alternative metrics which work in situations where impedance measures are not available, such as that proposed in (Daly et al., 2012).

Other issues encountered during measurements include EMG, head movement, electrode pops (short lasting sharp amplitude changes caused by movement of the electrode), EOG, and eye blink artifacts, which are frequently observed, although this varies considerably between users. Users with spasticity exhibited considerably more EMG artifacts in their EEG than users without. However, correlation analysis between classifier outputs and automatically detected artifacts revealed statistically significant classification accuracy was based upon artifacts in only 1 case.

No formal survey of user experiences was conducted in this study. This was due to two reasons (1) many of the users became tired quickly and an additional survey conducted before, during, or after the measurements would have been an additional source of fatigue and (2) the users exhibited widely differing abilities to communicate (from normal speech to eye gaze communication via letter boards) which were prohibitive to attempts to administer a formal survey.

Many users became fatigued during use of the BCIs. This could, in part, be resolved by a more engaging paradigm. In particular some users complained that the mental arithmetic task was particularly difficult and the SSVEP stimuli were "annoying". This may be contrasted with the motor imagery tasks which were described by some users as "enjoyable". A proposed solution is the use of context aware BCIs, as proposed in (Zander et al., 2012; Scherer et al., 2012), in which the BCI is augmented by additional information relating to the subject and/or environment (e.g. measures of subject engagement).

Analysis of the relationship between subject details and performance with the SSVEP and SMR BCIs reveals a significant relationship between subject gender and their performance with the online SMR BCI. However, it's worth noting that only 10 of the 14 subjects were able to attempt online control of the SMR BCI. Of these 10 users 5 were male and the females achieved higher classification accuracies. However, with only 10 subjects and differing numbers of trials over subjects (no significant difference was found in the number of trials between males and females, ($p = 0.852$), paired t-tests) it is not, at this stage, clear how generalisable this finding is to a wider population of individuals with CP. Future work will explore whether further statistical relationships emerge with more subjects.

The results reveal that not all approaches work for every user. Indeed, 6 of the 14 users can control the SMR BCI at above significant levels of accuracy and 3 can control the SSVEP BCI at above significant levels of accuracy, with one user overlap. This leaves 6 users who could not control either BCI at a statistically significant level.

This finding may be considered alongside a large meta-analysis performed by (Kübler et al., 2008) in which the efficacies of three different types of BCI for use as communication and control devices with a range of patient populations were assessed. The three BCIs assessed were SMR, slow cortical potential, and ERP based BCIs. Individuals with spinal cord injury, amyotrophic lateral sclerosis, brain stem stroke, multiple sclerosis, traumatic brain injury, and post-anoxic encephalography were considered. Subjects were ranked in terms of impairment and no statistical relationship was found between their performance and their degree of impairment when completely locked in subjects were excluded from the analysis.

Our results also show that for the individuals with CP involved in our study no statistical relationship was found between the degree of impairment and their ability to control a BCI. Thus, our findings add to and support those reported in (Kübler et al., 2008).

When considering the performance of the SSVEP paradigm the result is somewhat surprising. SSVEP accuracies are generally relatively high when compared to other BCI paradigms. For example, (Allison et al., 2010b) reports a mean accuracy of 91.85 % over 106 healthy subjects using an SSVEP BCI. However, when one considers the particular conditions of individuals with CP, in particular that a number of individuals exhibit spasticity and have problems controlling their neck muscles or require head rests, it is not so surprising that this particular user group exhibits considerably lower accuracies with the SSVEP task then might be expected from healthy subjects, or even other BCI target user groups.

Ultimately, the large degrees of differences in individual needs and results achieved indicate that BCIs need to be tailored to meet each user's needs and requirements. Doing so offers the possibility of producing BCIs which could be controlled by a number of individuals with CP. However, the results at this stage ultimately indicate that providing BCIs that are useful as assistive devices to this user group presents a significant challenge. Nevertheless, the fact that BCI control was achieved by some naïve untrained individuals with CP is an encouraging initial finding.

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