Single tap identification for fast BCI control

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Abstract One of the major aims of BCI research is devoted to achieving faster and more efficient control of external devices. The identification of individual tap events in a motor imagery BCI is therefore a desirable goal. EEG is recorded from subjects performing and imagining finger taps with their left and right hands. A Differential Evolution based feature selection wrapper is used in order to identify optimal features in the spatial and frequency domains for tap identification. Channel-frequency band combinations are found which allow differentiation of tap vs. no-tap control conditions for executed and imagined taps. Left vs. right hand taps may also be differentiated with features found in this manner. A sliding time window is then used to accurately identify individual taps in the executed tap and imagined tap conditions. Highly statistically significant classification accuracies are achieved with time windows of 0.5 s and more allowing taps to be identified on a single trial basis.

Keywords BCI · DE · Feature selection · Finger tapping · Single trial

Introduction

Brain Computer Interfaces (BCIs) provide a means for controlling a computer that bypasses the peripheral nervous system by extracting signals directly from the brain (Wolpaw 2007). Control is therefore achieved via thought alone making BCIs well suited for use by disabled individuals who may otherwise be unable to use a computer,

communicate or exert control over their environment (Vaughan 2006).

BCIs may be used to control spelling and communication programs; allowing users to chat, send email etc. They may also be used to control a range of devices such as wheelchairs and prosthetic limbs, allowing their users to achieve a level of communication and control that may not otherwise be possible (Birbaumer 2000).

The Electroencephalogram (EEG) arises from the currents recorded via electrodes placed across the surface of the scalp which are generated by the summed field potentials of the simultaneous firings of large numbers of cortical neurons. It is a commonly used method for attaining the brain signals used for BCI control (Wolpaw 2007). This is because EEG is non-invasive, simple to setup and use and relatively portable. It is hence considered to be highly suitable for use by individuals in their own homes (Vaughan 2006).

A common paradigm for the control of a BCI is motor imagery. The BCI user imagines movement in some part of their body and in response the frequency content of the EEG recorded from electrodes located over, and close to, the motor cortex exhibits increases and/or decreases in power, referred to as Event Related Synchronization/Desynchronization (ERS/D); respectively (Pfurtscheller and Neuper 2001).

Many different types of motor imagery paradigm are used in BCI control, including the use of imagined hand and foot movement to achieve various types of control. A particular type of motor imagery paradigm is based on finger tapping (Ang 2008). The user imagines they are tapping their fingers and the task of the BCI is to identify when the subject is tapping for use as a control signal. For example imagined tapping may be used to turn on or off a switch, select from a series of options, move a cursor etc.

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Current finger tapping based BCIs make use of the self-paced tapping condition for control. The subject simply imagines they are repeatedly tapping their fingers at their own pace and the detection of this action is used as a basis for the BCI control (Congedo et al. 2006).

In Ang (2008) finger tapping over a period of 2 s is identified at accuracies ranging from 53.0 to 96.0% with mean accuracies of $73.3 \pm 2.8\%$ achieved by healthy subjects they recorded. An improvement in accuracy is achieved in (Blankertz et al. 2006) with a mean classification accuracy of 89.5% achieved when identifying continuous finger tapping within trials of length 2 s.

This work takes a different approach and attempts to investigate whether a more precise and accurate level of BCI control could be achieved via the identification of individual taps—as opposed to continuous tapping—and at what time resolution this may be achieved. First by using Differential Evolution to identify distinguishing features and then identifying individual taps in a manner analogous to online BCI operation. Hence this work comprises a step towards more intuitive, accurate and faster BCI operation.

Individual finger taps are potentially a very intuitive control paradigm, being analogous to key pressing, a computer control paradigm a great many people are familiar with. Hence identification of taps on a single trial basis could allow for much faster and more intuitive BCI control then is currently possible.

It is well known that executed finger movement and imagined finger movement produce very similar responses in the EEG (Ang 2008; Jeannerod 1995). Therefore EEG is recorded both during executed finger taps and imagined finger taps at different rates and with either the left or right hands.

The problem is approached as one of feature selection. It is necessary to identify first which channels and frequency bands give the most information about the tap events. To find the appropriate features—the channels and frequency bands of interest—Differential Evolution (DE) is used to search the parameter space of possible channel-frequency band combinations; all the channels in the International 10/20 system of electrode placement and all frequencies from 0.1 to 45 Hz are considered.

After identification of appropriate channels and frequency bands online BCI operation is simulated. A sliding window threshold function is trained and applied to classify the power of the selected frequency bands on the selected channels into tap vs. no-tap conditions. The shorter the time window at which taps can be accurately identified the faster and more accurate the BCI control that can potentially be achieved.

Section 2.1 first describes how the data is recorded for this investigation. Section 2.2 then introduces DE as a feature selection method and Sect. 2.3 describes how DE is

used to select channels and frequency bands for tap identification. Section 2.4 details the classification method used in this work and Sect. 3 presents the results of first finding appropriate channel-frequency band combinations and then identifying taps in the executed and imagined conditions. Finally Sect. 4 discusses the results and their applications to BCI.

Methods

Data recording

Subjects

Twenty four volunteer subjects participated in this study; 12 male and 12 female. Ages ranged from 22 to 31 years with a median age of 25. Ethical approval was obtained following the School of Systems Engineering, University of Reading procedures for experiments involving human subjects. Informed consent was obtained from all participants. Five of the subjects (2 male and 3 female) were eliminated due to left handedness/ambidextrousness and very high levels of artifact contamination. Therefore nineteen subjects are included in this study.

Recording

EEG is recorded via a Deymed Truscan32 amplifier system at a sampling rate of 256 Hz from 19 channels placed according to the international 10/20 system. Stimuli to cue when the subjects should tap is presented via custom written software. Stimuli presentation and EEG recording are time locked via a system developed in (Portelli and Nasuto 2008).

Subjects are seated in front of a 19 in. display monitor with a keyboard placed in front of their hands. The monitor is positioned 100 cm in front of the subject. Stimuli are presented in the center of the screen (visual angle $\approx 5.72^\circ$) to minimize eye movement. Video is recorded of the subjects hands and checked for unexpected movement.

Subjects are cued to—at specific times—perform one of the following actions.

1. Tap once with the right hand index finger.
2. Tap once with the left hand index finger.
3. Imagine they are performing one tap with the right hand index finger.
4. Imagine they are performing one tap with the left hand index finger.

The experiment includes four sessions; two of which record the executed movement condition and two of which record the imagined movement condition. For each session

cues are displayed on screen to indicate with which hand the subject should tap. For the executed movement condition when the subject taps they depress a key and the cue disappears.

Cued taps have variable inter-stimulus intervals ranging from between 0.5 and 2.0 s. The order of sessions; imagined or executed taps, inter-stimulus intervals for the tap cues and the duration of the rest periods are varied randomly with the taps coming in blocks of between 4 and 6 to avoid subject pattern learning. For example the subject may be cued to perform 4 taps with their right hand each 2 s apart, then 5 taps with their left hand each 1 s apart then given a rest period of random duration.

Preprocessing

For each subject EEG is filtered between 0.1 and 45 Hz on every channel and visually inspected for artifacts; portions of EEG containing artifacts are discounted from analysis. Prior to the application of DE the data is segmented into trials.

Inspection of delay times between cue presentation and subjects response (as measured by key presses in the execution condition) reveals a mean subject reaction time of 0.71 (± 0.07 s). Assuming that the electrophysiological correlates of movement intention and control occur before and during tap execution a natural choice of trial time is to define trials as portions of EEG from tap cues to 1.0 s after for trials expected to contain tap events. Trials not expected to contain taps are taken from 1 s portions of EEG recorded during times when the subject is in a cued rest period.

Trials are split into three sets; training, testing and verification. Each set contains either, a third of the tap trials and a third of the non-tap trials for tap vs. no-tap differentiation, or a third of the left tap trials and a third of the right tap trials for left vs. right tap differentiation. After artifact removal the training, testing and verification sets each contain approximately 80 trials in each condition.

All trials are randomly shuffled; presented in random order to prevent serial regularities. A frequency decomposition of each channel in each trial is performed by applying a fourier transform to calculate the power spectra within each of the trials.

Trials are therefore constructed from frequency bands of 0.1–45 Hz (of width 1 Hz). Mean power of the frequency content within each frequency band is calculated for each trial on each of the 19 EEG channels recorded.

Differential evolution

Differential evolution (DE) is an evolutionary search technique which may be used as a wrapper based evolutionary meta-heuristic search technique, similar in operation to a Genetic Algorithm. It has been shown to be highly

successful in identifying near optimal solutions when applied to a wide range of different search spaces (Storn and Price 1995).

A population of candidate solutions is first generated. From this initial population a new generation of candidates is produced by combining selected individuals from the first generation via a mutation—crossover scheme. These new population members replace their parents if they have a higher fitness; if they result in a better solution.

The DE algorithm operates as follows.

1. First generate a population of N D-dimensional parameter vectors where each parameter vector contains a randomly selected potential solution (a random location in the search space). Formally $X_{i,G}$ where $i = 1, 2, \dots, N$ and G denotes the current generation.
2. Mutation; For a given ‘target’ vector $X_{i,G}$ in the population X at generation G three vectors in the population are picked at random— $X_{r_1,G}$, $X_{r_2,G}$ and $X_{r_3,G}$ —such that the indices i , r_1 , r_2 and r_3 are distinct. The difference between two of these population vectors is then calculated and this difference is multiplied by some weighting factor, F and added to the third selected population member. The resultant new vector is referred to as the ‘donor’ vector $V_{i,G+1}$ in the generation $G + 1$. Formally

$$V_{i,G+1} = X_{r_1,G} + F(X_{r_2,G} - X_{r_3,G}) \quad (1)$$

where the weighting factor F is a constant in the range $[0,2]$.

3. Crossover; A crossover scheme is applied to the ‘target’ vector $X_{i,G}$ and the ‘donor’ vector $V_{i,G+1}$ using the scheme detailed in (Storn and Price 1995) to produce the ‘trial’ vector, $U_{i,G+1}$. The crossover probability used in this step is determined by the crossover constant (CR), which aims to bring diversity into the population by selecting which elements of each of the ‘target’ and ‘donor’ vectors to combine to form the ‘trial’ vector. Formally the ‘trial’ vector is constructed via

$$U_{j,i,G+1} = \begin{cases} V_{j,i,G+1} & \text{if } \text{rand}_{j,i} \leq \text{CR or } j = I_{\text{rand}} \\ X_{j,i,G} & \text{if } \text{rand}_{j,i} > \text{CR and } j \neq I_{\text{rand}} \end{cases} \quad (2)$$

where $i = 1, 2, \dots, N$, $j = 1, 2, \dots, D$, $\text{rand}_{j,i} \sim U[0, 1]$ and I_{rand} denotes a random integer drawn from the range $[1, 2, \dots, D]$ which ensures that $V_{i,G+1} \neq X_{i,G}$.

4. Selection; the ‘target’ vector of the generation $G + 1$, $X_{i,G+1}$, is replaced by the ‘trial’ vector $U_{i,G+1}$ if the ‘trial’ vector has a better fitness than the ‘target’ vector, otherwise place the ‘target’ vector from generation G into the new generation. Formally

$$X_{i,G+1} = \begin{cases} U_{i,G+1} & \text{if } f(U_{i,G+1}) \leq f(X_{i,G}) \\ X_{i,G} & \text{otherwise} \end{cases} \quad (3)$$

where $i = 1, 2, \dots, N$ and $f(\cdot)$ evaluates the fitness of a particular candidate vector for meeting the requirements of the desired solution.

The four steps in the DE algorithm are iterated until some stopping criterion is met. This can, for example in the case of a classification problem, be met by the classification accuracy reaching 100% (or close to, within a certain threshold). It can also be met by the number of iterations for which the search has run exceeding some maximum limit.

DE has been shown to outperform a range of other common meta-heuristic search techniques, including Genetic Algorithms (GAs), on a range of established search space tests (Storn and Price 1995). It is therefore considered a suitable choice of search technique for use in this study to identify the optimal channels and frequency bands for tap identification.

Feature selection

DE is applied to select the most informative channels and frequency bands for identifying tap events in the left hand/right hand and movement/motor imagery conditions. The objective function used is a Naive Bayes (NB) classifier trained on the selected features from the training set. Thus the task of DE is to identify a feature set—a selection of channels-frequency bands—which maximizes the rate of identification the trained classifiers can achieve on the testing set.

The set of features identified by DE therefore indicates which channels and frequency bands are most suitable for the identification of tap events. The choice of channels-frequency bands is then verified by applying the selected channels and frequency bands to classify trials in the verification sets.

Thus the use of DE to select good channels-frequency bands for identification of taps can be summarized as follows.

1. The training and testing datasets are both made available to the DE algorithm.
2. The DE algorithm makes some choice of which features to use for the identification of taps.
3. The selected features are extracted from both the training and testing sets.
4. The objective function—the NB classifier—is trained on the features extracted from the training set and applied to classify trials of features extracted from the testing set.

5. The accuracy of the tap vs. no tap differentiation in the verification set is evaluated via the Area Under the ROC Curve (AUC) metric. The higher the AUC the better the differentiation of taps and the higher the value DE's fitness evaluation function will return. The ROC curve is calculated by applying a threshold—varied from 0 to 1—to the posterior class probabilities returned by the NB classifier.
6. Finally when the DE stopping criterion is reached the choice of channels and frequency bands are verified by using the best identified set of channels-frequency bands and the associated trained classifier to classify tap events in the verification set.

Note that the DE parameters N and D are set to 15 and 10, respectively for this study. The weighting factor F is set to 0.8 and the cross-over probability CR is also set to 0.8. Parameters are chosen based upon direct experimentation looking for parameter values which produce a good balance between fast convergence and accurate/robust results.

Classification

After selection of the most informative channels and frequency bands a thresholding function is applied within a sliding window to identify taps in an approach analogous to the operation of an online BCI. Within the window the features selected by DE—the best channels-frequency bands—are extracted and classified. The dataset is evenly split into training and verification sets with the first half of the data in the training set and the second half in the verification set. This is reflective of online BCI operation where—by necessity of design—training data will be recorded prior to BCI operation.

Classifiers are trained on the features extracted from the sliding window applied across the training set. They are then applied to the verification dataset. The classification algorithm used is the NB classifier.

A range of time windows are used from 100 to 1,000 ms. The shorter the time window in which taps can be accurately identified the greater the theoretical BCI bit rate as the subject may achieve accurate control at a faster rate of tapping.

Time windows that are identified as containing taps are compared against the cue times to determine whether the subject was cued to tap within that time window. A classification accuracy is hence calculated to judge the methods accuracy at identifying single tap events. The Area Under the ROC Curve (AUC) metric is used to evaluate the success at differentiating tap vs. no tap events via the use of a sliding window.

Statistical significance of the AUC's returned on each dataset are evaluated against the null hypothesis that the selected features may not enable discrimination/partitioning of data according to the class labels. Surrogate datasets are created within which the trial orders are shuffled. Trials are then classified and their AUC's calculated against the un-shuffled class labels. A distribution of AUC's under the null hypothesis is hence built and the probability of the identified AUC being drawn from this distribution may be calculated to identify a P -value of the AUC and hence its statistical significance.

Results

The results may be split into a number of distinct sections based upon the conditions; tapping vs. not tapping and left tapping vs. right tapping in both the imagined and real (executed) tap conditions that the subjects perform. Information about the hand with which the tap is to be performed (or imagined) may also be discounted such that DE attempts to identify features for differentiating tap vs. no tap conditions across all the trials regardless of the tapping hand used.

Firstly the results achieved by using the DE feature selection algorithm to find features for differentiating between tap and no tap conditions on each of the datasets for the different subjects and for both imaginary and executed taps are listed. The selected channels and frequency bands to be used in the subsequent sliding window based task are also presented.

Secondly the results achieved by moving the sliding window along the length of the EEG recorded from the subjects under each of the conditions—imagined or executed taps—are listed. This approach is analogous to the operation of an online BCI and provides an indication of the ability to differentiate control conditions, based upon individual taps for use as a BCI control signal.

Figure 1 provides an example of typical EEG recorded during imagined finger taps made by a representative subject with their right hand and recorded on electrode C4. Note the period of relaxation followed by a block of cued taps each one second apart.

Figure 2 illustrates on which channels and at which frequency bands taps may be identified in the executed tap condition. The channels and frequency bands found to best differentiate taps and none taps for each subject are amalgamated into the figure providing an illustration of the range of different frequencies and channels which may be used to differentiate tap and none tap conditions. Figure 3 illustrates which channels and frequency bands may be used to differentiate imagined taps from imagined none tap events.

Fig. 1 Typical raw EEG recorded during imagined finger taps made by the right hand of a representative subject and recorded on electrode C4. Dashed lines indicate tap cue onset

Fig. 2 Channels and frequency bands identified by DE for the differentiation of tap and non tap events across all subjects in the executed tap condition

Fig. 3 Channels and frequency bands identified by DE for the differentiation of tap and no tap events across all subjects in the imagined tap condition

Table 1 AUC's achieved by the NB classifier on features identified DE for differentiation of taps recorded in the executed tap condition when the tapping hand is discounted

Subject	Training set AUC	Verification set AUC
A	0.832	0.770*
B	0.923	0.900*
C	0.841	0.759*
D	0.738	0.714*
E	0.877	0.795*
F	0.855	0.752*
G	0.760	0.684*
H	0.726	0.649*
I	0.922	0.921*
J	0.803	0.666*
K	0.838	0.725*
L	0.760	0.671*
M	0.706	0.628*
N	0.930	0.920*
O	0.885	0.827*
P	0.817	0.556
Q	0.740	0.577
R	0.903	0.864*
S	0.846	0.714*

* Significant AUC's ($P < 0.05$)

As can be seen from Figs. 2 and 3 both the executed and imagined tap events may be differentiated using a wide range of channels and frequencies. There is a great deal of inter-subject and inter-condition variability in the channels and frequency bands which may be used to best identify taps. It is difficult to identify a general pattern to the channels and frequency bands that are best for tap identification. Channels over the Motor cortex such as Cz and channels over the Parietal cortex such as Pz are frequently selected although many of the other channels are also selected occasionally. Frequencies in the range 10–30 Hz are most often used to differentiate tap and none tap conditions, although frequencies outside this range are also used.

Table 1 lists the AUC's achieved in the classification of features identified by DE on both the training and verification sets recorded in the executed tap conditions across all subjects. The hand used to make the tap is discounted for these results. Subjects with statistically significant AUC's ($P < 0.05$) are indicated with an asterisk.

By way of comparison Table 2 lists the accuracies achieved in both the training and verification sets when classifying the data into tap vs. none tap conditions via features selected by DE when the tapping hand is discounted. Again statistically significant accuracies ($P < 0.05$) are indicated with an asterisk.

Table 2 AUC's achieved by the NB classifier on features identified DE for differentiation of taps recorded in the imagined tap condition when the tapping hand is discounted

Subject	Training set AUC	Verification set AUC
A	0.834	0.903*
B	0.753	0.739*
C	0.720	0.623*
D	0.816	0.726*
E	0.800	0.604*
F	0.874	0.665*
G	0.871	0.722*
H	0.773	0.585
I	0.991	0.990*
J	0.759	0.659*
K	0.830	0.696*
L	0.871	0.722*
M	0.712	0.589
N	0.797	0.782*
O	0.791	0.701*
P	0.758	0.539
Q	0.734	0.604*
R	0.851	0.758*
S	0.853	0.690*

* Significant AUC's ($P < 0.05$)

As is seen from the table very high AUCs can be achieved with the majority of subjects in both the executed and imagined tap conditions. In the majority of cases AUCs are statistically significant ($P < 0.05$) as assessed against the null hypothesis detailed in Sect. 2.4. Only subject P did not achieve statistically significant AUCs in both the executed and imagined tap conditions. Two other subjects (subject H and subject M) also did not achieve statistically significant AUCs in the imagined tap condition and statistically significant AUCs were also not achieved for subject Q in the executed tap condition.

As the results demonstrate the tap vs. no-tap conditions may be differentiated with a high AUC for both conditions. The AUCs achieved are, in general, lower for the imagined condition than for the executed condition for the majority of subjects. However for some of the subjects the AUCs achieved from the imagined tap condition are marginally higher; although these differences in AUCs between imagined and executed taps are generally not statistically significant ($P \geq 0.05$).

The hand—which performs the tap or in which the tap is imagined—is now considered as a control condition. EEG trials are split into left vs. right taps in both the imagined and executed conditions and DE is applied to identify appropriate channel-frequency band combinations to differentiate the conditions. Table 3 lists the channel-frequency band

Table 3 AUC's achieved by the NB classifier at differentiating left vs. right executed taps

Subject	Executed taps		Imagined taps	
	Training	Verification	Training	Verification
A	0.713	0.587	0.705	0.508
B	0.796	0.786*	0.722	0.706*
C	0.650	0.535	0.734	0.596*
D	0.759	0.589*	0.757	0.657*
E	0.783	0.759*	0.702	0.569
F	0.754	0.552	0.748	0.551
G	0.782	0.545	0.822	0.782*
H	0.729	0.558	0.778	0.620*
I	0.674	0.666*	0.783	0.782*
J	0.800	0.530	0.783	0.607*
K	0.783	0.598*	0.716	0.481
L	0.708	0.586	0.732	0.425
M	0.776	0.648*	0.756	0.674*
N	0.582	0.547	0.606	0.602*
O	0.876	0.768*	0.870	0.903*
P	0.778	0.535	0.755	0.554
Q	0.733	0.560	0.722	0.570
R	0.825	0.689*	0.788	0.690*
S	0.804	0.742*	0.714	0.526

* Significant accuracies ($P < 0.05$)

combinations DE identifies for differentiating left vs. right taps in the EEG recorded during both the executed and imagined tap conditions. The accuracies achieved by the classifier on the test set using the selected channels and frequency bands are also listed.

As evidenced from the table it is possible to differentiate left vs. right taps in the executed condition at a statistically significant rate ($P < 0.05$) for approximately half of the subjects, specifically subjects; B, D, E, I, K, M, O, R and S. This may be contrasted with the AUCs for differentiating the tapping hand in the imagined tap condition. The tapping hand may be identified at a statistically significant rate for the following subjects in the imagined tap condition; B, C, D, I, G, H, I, J, M, N, O and R. This demonstrates that it is possible to use the tapping hand as a control variable for single tap BCI control in approximately half of the investigated cases.

Online BCI operation is simulated by the use of a sliding window. The features (mean power at the channels and frequency bands selected by DE) are extracted from within the sliding window and classified to attempt to identify tap events in the ongoing stream of EEG data. The data is split into training and testing data sets to first train and then evaluate the classification algorithm.

The length of the sliding window is varied from 0.1 to 1.0 s. For each window length the window is slid over the

EEG and classification accuracies (as measured via the AUC) are calculated. The shorter the window length the less EEG is required before classification is performed. Shorter window lengths mean more taps may be performed by the subject within a given time period and the BCI may hence be operated faster providing a greater level of responsiveness to the subject.

Figure 4 provides an illustration of how varying the windows size effects the classification accuracy for a representative subject with EEG recorded in the imagined condition. As illustrated the longer the window length the greater the classification accuracy achieved as a more accurate estimate of the motor intention of the subject is reflected in the frequency content of the EEG. It is important to note also that statistically significant accuracies ($P < 0.05$) are achieved with window lengths of 0.3 s or greater, highly significant accuracies ($P < 0.01$) are achieved with window lengths of 0.5 s or greater.

Bits per minute (bits/min) is an important measure of BCI performance (Dennis et al. 2003). Figure 5 shows how the theoretical (bits/min) achievable with an online BCI using the AUCs achieved with the sliding window based classification technique varies with the size of the windows.

Table 4 lists the AUCs achieved on the verification sets for each subject in both the executed and imagined tap conditions when the optimal window size and threshold, found from the training set, are applied. Note that statistically significant AUCs are achieved on both conditions for the majority of the subjects, although as highlighted in Fig. 4 these accuracies fall to insignificance when the sliding window length is shortened towards 0.2 s or less.

As shown in the table the accuracies achievable for differentiating tap vs. none tap conditions are statistically

Fig. 4 Accuracies for different window sizes as determined from applying thresholding within a sliding window to a representative subject on EEG recorded during the imagined tap condition. Dashed line level of statistical significance ($P < 0.05$) and dotted line; level of high significance ($P < 0.01$)

Fig. 5 Theoretical bits per minute achievable by an online BCI using the sliding window approach as a function of window size

Table 4 Accuracies, as measured by AUC, for single tap identifications via the sliding window approach from EEG recorded during the executed and imagined tap conditions

Subject	Executed taps AUC	Imagined taps AUC
A	0.595*	0.583
B	0.742*	0.810*
C	0.655*	0.679*
D	0.667*	0.578
E	0.681*	0.714*
F	0.641*	0.701*
G	0.600*	0.501
H	0.697*	0.611*
I	0.736*	0.804*
J	0.561	0.698*
K	0.676*	0.611*
L	0.750*	0.676*
M	0.684*	0.689*
N	0.770*	0.808*
O	0.669*	0.662*
P	0.661*	0.651*
Q	0.659*	0.726*
R	0.580	0.640*
S	0.682*	0.650*

* Statistically significant AUCs ($P < 0.05$)

significant in both the imaginary and real conditions for a number of subjects. Coupled with typical window lengths of 0.5 s this demonstrates that it is possible to identify single tap events in the EEG using a sliding window approach with the appropriate channels and frequency bands.

Additionally cross-condition training is applied to test the ability of classifiers trained on EEG recorded in the executed tap condition to classify imagined taps. The

electrophysiological correlates of real and imagined taps are known to be similar (Jeannerod 1995) and therefore using real taps as the training set to inform about imagined taps in the verification set is feasible. It's also worth noting that in the executed tap condition it's possible to know the exact time of executed taps from the subjects pressing of a button. Thus more accurate estimates of the times of executed taps can be used to inform the training of a threshold to differentiate imagined taps, where the exact tap time is unknown.

When applying cross-condition training a mean AUC of 0.815 ± 0.017 may be achieved in the verification sets across all subjects. This demonstrates that statistically significant differentiation of tap vs. no-tap conditions in EEG recorded in the imagination condition is possible when the threshold value has been trained in the execution condition. Thus it may be inferred that the mean magnitude of the frequency content of the EEG on the DE-selected channels and frequency bands is similar between the imagination and execution conditions.

Discussion

Finger tapping is a popular paradigm for motor imagery BCI control in which the user imagines making repeated movements with their fingers in order to control a switch or device. Most current implementations of the finger tapping paradigm require the user to make many repeated taps before the act of tapping is recognized as a control signal (Pfurtscheller and Neuper 2001; Congedo et al. 2006; Balakrishnan and Puthusserypady 2005; Stavrinou et al. 2006). This work investigates if it is possible to identify the tapping condition with fewer taps and whether individual taps are a feasible control condition for BCI. This may be thought of as an analogous study to much of the work going on in single trial Event Related Potential (ERP) analysis [for example (Williams et al. 2009)], which aims to detect ERPs on a single trial basis and thus allow for faster and more intuitive BCI control via the ERP based paradigm.

The DE algorithm is first used to select informative EEG channels and frequency bands at which the mean power may be used for classification of tap events into different conditions; imagined taps and executed taps made with either the left hand or the right hand or with the tapping hand discounted. A large variety of different frequency bands on different channels are selected by the DE algorithm for these classifications. These channel-frequency band selections may be used to achieve statistically significant levels of tap identification, as assessed via the method described in Sect. 2.4.

The variety of frequencies and channels selected reflects the well known inter-trial and inter-subject variability in

the EEG (Thulasidas et al. 2006). Task relevant components of the EEG are known to change in temporal, spatial and spectral location and morphology from trial to trial and from subject to subject. This variability is a known issue in BCI research and can lead to a lack of robustness and reliability in BCI systems.

In this work the DE algorithm selects—for every subject and every condition—a number of different channels and frequency bands to use in the classification of tap events. In doing so the classifier is able to use a number of spectral and spatial locations which could, potentially, lead to more robust classification results. Further to this, because the selection of the channels and frequency locations is made individually for each subject and each condition inter-trial and inter-subject variabilities may be better accommodated for.

AUCs achieved in differentiating tap vs. none tap events using mean frequency powers identified by DE exceed 0.90 for some of the subjects in the executed condition and one subject in the imagined condition. In general the AUCs are in the range of 0.6–0.9 which compares well with analogous 1-dimensional motor imagery BCI paradigms such as (Fabiani et al. 2004) which achieves accuracies of between 71.8 and 74.3% or (Ang 2008) which achieves a mean accuracy of $73.3 \pm 2.8\%$.

Differentiating left vs. right hand taps in the executed and imagined tap conditions produces statistically significant discriminations in a number of cases in the executed tap condition. AUCs produced are around 0.70 with a maximum of 0.79 this compares reasonably to (Pfurtscheller and Neuper 2001) which reports an average accuracy of left vs. right hand movement imagery differentiation of 75.0%. Although it should be noted that left-right taps could only be differentiated at a statistically significant rate in approximately half of the subjects.

A sliding window approach is applied to attempt to identify individual tap events in the EEG. The electrode channels chosen by DE are used as the basis for control. The mean band powers of the EEG at the selected frequencies are calculated on these channels. A classification function is then applied within the sliding window to identify tap events. Thus DE is used to first select which channels and frequency bands to concentrate on. Classification is then applied in a manner analogous to online BCI operation.

The subjects are cued to tap at different rates from once every 0.5 s to once every 2 s, interspersed with occasional blocks of rest periods. The length of the sliding window is varied from 0.1 to 1.0 s in steps of 0.1 s. The sliding window is therefore likely to contain just one tap event and, when it's length is 0.5 s or less, it's guaranteed to contain just one tap event.

Classification applied within time windows of 1 s and less produces highly statistically significant identification

of taps, both imagined and executed. Shorter time windows also allow classification of taps at a statistically significant rate although the AUC decreases as an inverse function of the window length. The minimum window length at which highly statistically significant ($P < 0.01$) rates of tap identification can be achieved is 0.5 s, therefore single taps can be identified via a sliding time window in an analogous manner to online BCI operation.

Importantly using channel and frequency band combinations identified by the DE feature selection algorithm allows identification of the correct channels and frequency bands for tap identification to be performed. Within these channel-frequency band combinations classification may be used to identify executed and imagined movements and hence allow highly statistically significant identification of executed and imagined taps.

The hand in which the subject performs, or imagines performing, a tap may also be used as a control condition. Statistically significant identification is achieved in identifying the tapping hand for approximately half of the subjects, suggesting a possibility for the use of the tapping hand as an additional control condition in a number of cases

Additionally EEG recorded during imagined taps is informative for the differentiation of tap vs. none tap events in the imagined tap condition. This indicates that the channels and frequency bands used to differentiate taps from none taps in the executed condition may also be used to differentiate taps from none taps in the imagination condition. This further confirms the results reported in (Jeannerod 1995) that the neurophysiological correlates of motor imagery and motor execution are similar.

An important criterion for ranking BCIs is the bit rate—bits per minute (bits/min)—a measure of the speed of information transfer that the BCI may achieve. As shown in Fig. 5 the theoretical bit rate for a BCI based upon single finger tap identifications in the left and right hands varies as a function on the size of the sliding window. The shorter the window the better the bit rate the BCI can achieve but also the lower the accuracy, as the bit rate measure incorporates individual trial accuracies this suggests that the best choice for a practical BCI is to use a short window length which still achieves statistically significant levels of accuracy, e.g. 0.5 s.

Single tap identification is an important result for BCI because it paves the way for much faster, more accurate motor imagery based BCI's. This could potentially include BCIs operated by users imagining patterns or sequences of rapid taps to achieve different control conditions in a fast and intuitive manner. It could also lead to the use of patterns of taps as a control mechanism for BCI, something akin to a tap based morse code for BCI control. Future work will focus on building online BCI systems to

differentiate different tap conditions, including tap pattern recognition.

Conclusion

Motor imagery is a common BCI paradigm that can make use of finger tapping imagery. This work looks at identification of single taps as a control signal, as opposed to other finger tapping based BCIs which rely on the user making/imagining repeating many taps to achieve control of the BCI.

A DE algorithm is applied to identify appropriate channels and frequency bands for tap identification. A sliding window is then applied, in a manner analogous to online BCI operation, to attempt to identify taps from the mean band power on the selected channels and at the selected frequency bands.

Taps are identified over very short time windows in both the executed movement and imagined movement conditions. Left hand vs. right hand single taps may also be differentiated for approximately half the subjects. This presents the possibility for both faster BCI control and tap pattern based control.

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References

- Ang KK (2008) A clinical evaluation of non-invasive motor imagery-based brain-computer interface in stroke. *Proc A Int Conf IEEE Eng Med Biol Soc* 2008:4178–4181
- Balakrishnan D, Puthusserypady S (2005) Multilayer perceptrons for the classification of brain computer interface data. In: *Proceedings of the IEEE 31st annual Northeast bioengineering conference*, 2005. IEEE, pp 118–119
- Birbaumer N (2000) The Thought Translation Device (TTD) for completely paralyzed patients. *IEEE Trans Rehab Eng* 8(2): 190–193
- Blankertz B, Dornhege G, Krauledat M, Müller KR, Kunzmann V, Losch F, Curio G (2006) The Berlin Brain-computer interface: EEG-based communication without subject training. *IEEE Trans Neural Syst Rehab Eng Publ IEEE Eng Med Biol Soc* 14(2): 147–152
- Congedo M, Lotte F, Lecuyer A (2006) Classification of movement intention by spatially filtered electromagnetic inverse solutions. *Phys Med Biol* 51(8):1971–1989
- Dennis J, McFarland William A, Sarnacki JRW (2003) Brain-computer interface (BCI) operation: optimizing information transfer rates. *Biol Psychol* 63:237–251
- Fabiani GE, McFarland DJ, Wolpaw JR, Pfurtscheller G (2004) Conversion of EEG activity into cursor movement by a brain-computer interface (BCI). *IEEE Trans Neural Syst Rehab Eng Publ IEEE Eng Med Biol Soc* 12(3):331–338
- Jeannerod M (1995) Mental imagery in the motor cortex. *Neuropsychologia* 33:1143–1419
- Pfurtscheller G, Neuper C (2001) Motor imagery and direct brain-computer communication. *Proc IEEE* 89(7):1123–1134
- Portelli AJ, Nasuto SJ (2008) Toward construction of an inexpensive brain computer interface for goal oriented applications. In: *AISB, Aberdeen, AISB*, pp 2–7
- Stavrinou ML, Moraru L, Pelekouda P, Kokkinos V (2006) A wavelet tool to discriminate imagery versus actual finger movements towards a brain computer interface. In: *Biological and medical data analysis of 7th international symposium, Thessaloniki, Greece*, pp 323–333
- Storn R, Price K (1995) Differential evolution—a simple and efficient adaptive scheme for global optimization over continuous spaces
- Thulasidas M, Guan C, Wu J (2006) Robust classification of EEG signal for brain-computer interface. *IEEE Trans Neural Syst Rehab Eng Publ IEEE Eng Med Biol Soc* 14(1):24–29
- Vaughan TM (2006) The Wadsworth BCI research and development program: at home with BCI. *IEEE Trans Neural Syst Rehab Eng Publ IEEE Eng Med Biol Soc* 14(2):229–233
- Williams N, Daly I, Nasuto SJ, Saddy D, Warwick K (2009) ERP classification using empirical mode decomposition. In: *The 5th UK and RI postgraduate conference in biomedical engineering & medical physics*, Oxford, pp 5–6
- Wolpaw JR (2007) Brain-computer interfaces as new brain output pathways. *J Physiol* 579(Pt 3):613–619