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Analysis of sensorimotor rhythms for the implementation of a brain switch for healthy subjects

Teodoro Solis-Escalante *, Gernot Müller-Putz, Clemens Brunner, Vera Kaiser, Gert Pfurtscheller

Laboratory of Brain-Computer Interfaces, Institute for Knowledge Discovery, Graz University of Technology, Krenngasse 37, 8010 Graz, Austria

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ABSTRACT

This paper presents an asynchronous brain switch using one Laplacian electroencephalographic (EEG) derivation. The brain switch is operated through foot motor imagery (MI) and is based on the classification of event-related desynchronization (ERD) during a motor task or event-related synchronization (ERS) after the termination of the task (also known as the beta rebound). The methods described in this work are suitable for operating a brain–computer interface (BCI) as an attractive control alternative for healthy users. A general description of ERD/ERS is obtained with several band power features and a rigid paradigm timing. Two support vector machines (SVMs) are trained in a novel fashion by using the patterns from motor execution (ME) and a priori information about the significance of ERD/ERS patterns. A maximum true positive rate (TPR) of 0.92 and a minimum of 0.43 was achieved (in 8 out of 9 subjects) during training of the classifiers; with a mean false positive rate (FPR) of 0.09 $\pm$0.05.

A simulation of an asynchronous BCI using MI data and the classifiers trained with ME data achieved a maximum TPR of 0.88, a minimum of 0.50 (in 6 out of 9 subjects) and an average FPR of 0.09 $\pm$0.04. This work presents a step forward towards an easy-to-set-up and easy-to-use asynchronous BCI system for healthy users.

1. Introduction

Non-invasive brain–computer interfaces (BCIs) based on electroencephalographic (EEG) signals are gaining attention as an alternative control technologies for disabled and able-bodied people [1,2]. However, several issues have yet to be addressed to bring a BCI system "out of the lab". Important issues are: (i) an easy montage of electrodes with a minimum number of EEG channels, (ii) a simple strategy to set up a classifier, ideally without expert help, (iii) the use of reproducible EEG patterns for classification and (iv) an asynchronous mode of operation. The latter means that the BCI must be continuously available to the user for self-paced control [3]. In such an asynchronous BCI, the number of false control commands should be minimized in order to make the system useful.

In recent publications the use of a BCI to switch an application on or off has been presented as an appealing control strategy. A BCI that detects only one predefined brain state or brain pattern from the ongoing EEG is referred to as a brain switch. In other words, a brain switch differentiates between the predefined brain state and any other activity [4]. Such a system is suitable for controlling several applications such as neuroprostheses, gaming and spelling devices [5–7].

A commonly used mental strategy for BCIs is motor imagery (MI). Both execution and imagination of the same limb movement activate similar neural structures [8,9] and result not only in a desynchronization (event-related desynchronization, ERD) of sensorimotor rhythms, but also in a beta rebound (beta event-related synchronization, beta ERS) after termination of the motor task [10]. The ERD and ERS phenomena were first described after active brisk finger movement [11] but are also present during passive movement, somatosensory stimulation, and both observation and imagination of a movement [12–14]. The most important features of the beta rebound are the somatotopic organization, its specificity [15,16] and the subject-specific stability. These features make the ERD/ERS phenomena suitable for realizing a brain switch [17].

An interesting issue is the minimum number of electrodes needed to detect and classify brain states reliably. One standard method for processing multichannel EEG data and discriminating between two brain states is the common spatial patterns (CSP) algorithm [18]. In two recent studies, it was shown that with 30 and 55 EEG channels, respectively, a classification accuracy between 80 and 90% can be achieved [7,19]. After selection of

Q1 * Corresponding author. Tel.: +43 316 873 5317; fax: +43 316 873 5349.
E-mail address: teodoro.solisescalante@tugraz.at (T. Solis-Escalante).

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one subject-specific Laplacian channel or one bipolar derivation, the classification accuracy dropped only by about 10%. Nevertheless, one EEG derivation (Laplacian or bipolar) can still be suitable to realize a BCI for specific applications. In this context, it is interesting to note that foot movement execution was successfully detected using only one Laplacian EEG derivation at the vertex with an adequate performance [20].

In this study, we report on the simulation of an asynchronous brain switch based on one Laplacian EEG derivation using brisk foot MI and the classification of the peri-imagery ERD and post-imagery ERS. The classifiers were trained in a novel fashion with data from brisk foot motor execution (ME) and were then applied directly to the brisk foot MI data. Our asynchronous brain switch addresses the four important issues mentioned above such that (i) there is only one derivation (i.e., a standard set of five electrodes), (ii) it uses ME to train the classifiers, (iii) it utilizes the stable phenomena of ERD/ERS, and (iv) it works in an asynchronous mode.

2. Methods

2.1. Data recording

Nine healthy subjects participated in this study. Each subject performed three runs of ME and three runs of MI with the same paradigm. Each run was comprised of 30 trials and all runs were recorded on the same day with several minutes of breaks in between. The subjects were sitting in front of a monitor and were asked to perform/imagine a brisk movement of both feet (dorsiflexion) right after the presentation of the cue. At the beginning of the trial ($t = 0$ s), a fixation cross was presented on the screen. At $t = 2$ s, a beep and an arrow pointing downwards served as a cue for the motor task. After 1.25 s, the arrow disappeared from the screen and at $t = 6$ s the cross disappeared, indicating the end of the trial. In between the trials, a short pause (during which the screen was blank) with a random duration between 1.5 and 3 s was included.

One single Laplacian derivation at electrode position Cz was computed by subtracting the average of the four orthogonal neighboring electrodes [21]. Ag/AgCl electrodes were used to record the EEG signals with a sampling rate of 250 Hz. Reference and ground electrodes were located at the left and right mastoid, respectively. A bandpass filter between 0.5 and 30 Hz was used in combination with a notch filter at 50 Hz. The sensibility of the channels was set to 100 μV. Fig. 1 illustrates the timing of the paradigm as well as the positions of the electrodes.

Six out of the nine participants were experienced with BCIs but unfamiliar with this particular paradigm. The remaining three were naive subjects. All subjects gave written informed consent prior to their participation. No feedback was presented to the subjects at any time during the recording sessions.

The analysis of the data was divided into two parts. First, two classifiers were trained with the data from ME and applied to one MI run; second, a simulation of an asynchronous BCI was performed with the remaining two MI runs. In this section, the steps for training the classifiers are described. Fig. 2 illustrates the methods.

2.2. Synchronous processing

2.2.1. Definition of time windows for ERD/ERS classification

Quantification of ERD/ERS was achieved by the computation of a time–frequency map from the ME task. To this end, sinusoidal wavelets were used to assess changes in the frequency domain by computing the spectrum within a sliding window, squaring and subsequent averaging over the trials [22]. The statistical significance of the ERD/ERS values was determined by applying a t-percentile bootstrap algorithm [23] with a significance level of $p = 0.05$. This analysis was carried out for frequencies between 6 and 40 Hz and time points from 0 to 7 s. The resulting type of data representation is termed an ERD/ERS map.

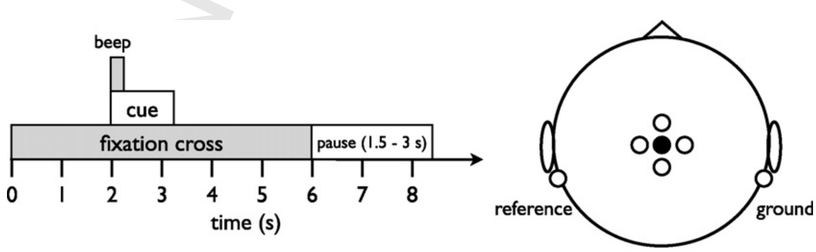
Such an ERD/ERS map was computed for every subject; the time windows with the largest ERD or ERS significance were identified by visual inspection by selecting those time points with the highest ERD/ERS significance. Additionally, three constraints were taken into account for the selection of these intervals: (i) patterns occurring before the cue or at most 0.5 s after its presentation were not considered, (ii) an ERD pattern should be present before the ERS and (iii) the length of the trial (and thus the possible existence of a pattern) was restricted to 6 s and the duration of the ERD was set to 1 s (due to the ME duration in the paradigm). The length of the ERS was not restricted. These two windows (one for ERD and one for ERS) were regarded as the intentional control (IC) period and used for feature labeling and training of the classifiers [3].

2.2.2. Feature extraction

Twenty-nine logarithmic band power (logBP) features were used to describe the power of the EEG signals. These features were computed with a set of filters (FIR order 20) between 6 and 36 Hz (2 Hz bandwidth with 1 Hz overlap). Every trial was filtered, squared, smoothed with a moving average filter (250 samples) and transformed with the logarithm. Then, 11 overlapping segments (50% overlap) of 1 s were extracted as features. The features lying within the IC window were labeled as class 1; all other features were labeled as class 0. The labeling procedure was done twice, once for ERD vs. the rest classification and a second time for ERS vs. the rest. Note that with this approach, ERD and ERS are treated as independent phenomena.

2.2.3. Training the classifiers with ME

After labeling the segments from all trials from the ME data, one of the runs was chosen randomly to train a support vector machine



(a) Timing of the paradigm. (b) Electrode positions (the filled electrode Cz was used as a Laplacian derivation).

Fig. 1. Paradigm and electrode setup. (a) Timing of the paradigm. (b) Electrode positions (the filled electrode Cz was used as a Laplacian derivation).

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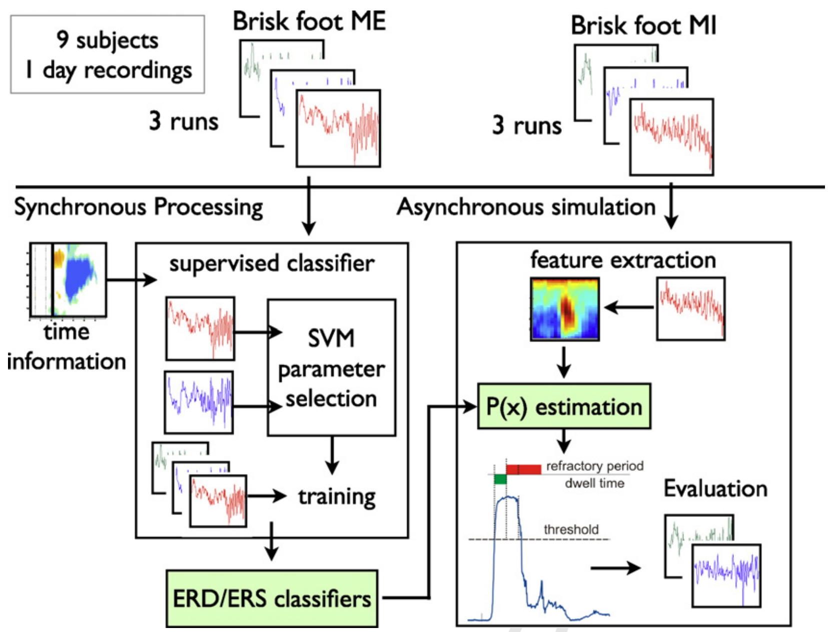

Fig. 2. Diagram of the methods used for the data analysis.

(SVM) [24] with a specific set of parameters for the Gaussian kernel (the performance of an SVM depends on the regularization parameter C and the width of the kernel σ). This classifier was tested with one of the remaining ME runs and the performance was measured with the true positive rate (TPR) and the false positive rate (FPR) on a segment-by-segment basis. This procedure was repeated in an iterative manner during an exhaustive search for parameters (C was varied from 2^{-10} to 2^{15} and σ was varied from 2^{-15} to 2^{12}, for every step the value of the current parameter was doubled).

A definitive set of parameters was selected from the performance measures. The selection was divided into two parts: (i) a first subset was created with the parameters that achieved the maximum value of TPR and (ii) the minimum value of FPR was then used as the criterion to further reduce the set of parameters. In the case of a tie between two or more sets of parameters, the set that included the smallest regularization parameter was chosen. The winning parameters were used to train a final SVM using all patterns from the three ME runs. The ERD- and the ERS-based classifiers were trained to predict the posterior class probability [25].

2.3. Asynchronous simulation

2.3.1. Post-processing parameters

The first recorded MI run was continuously classified by the ERD- and ERS-based classifiers trained with ME data. This run was described with the logarithmic band power features as described in the previous section. The features obtained were used as input to the classifiers and two output signals were obtained, namely the ERD and the ERS posterior probabilities. These outputs were used to optimize the post-processing parameters.

Since a switch-like behavior is intended, only one control event is needed for the whole IC interval. With this objective, a threshold, a dwell time (DT) and a refractory period (RP) were used for the post-processing of the classifier outputs [26]. At this stage, the optimal values were determined from a set of receiver operating characteristics (ROC) curve analyses, where the threshold was varied from 0 to 1 (in steps of 0.01) and the dwell time was chosen among the values 25, 50, 62, 75 and 100 samples. The refractory period was computed according to $\mathrm{DT} + \mathrm{RP} = 500$. This definition ensures that only one control event is detected in every trial. Larger values for the dwell time (up to 200 samples) were tested in a preliminary study but the results showed no improvement.

One control event was counted every time the classifier output exceeded the threshold for a number of samples equal to the dwell time. After that, the classifier output was ignored (suppressed) during the refractory period. An event was counted as positive if it was detected during the IC and as negative in any other case.

The IC period for continuos processing was changed since it can occur at any time in an asynchronous system. The IC intervals were shifted from the ones obtained through the ERD/ERS maps and were the same for all subjects. The new intervals ranged from 2 to 4 s for ERD and from 3 to 4 s for ERS. Note that the new intervals include the time of the cue and the beep. However, the patterns from this period were used to train the rest class during the classifier training and therefore should not elicit an event.

Measuring the performance of the asynchronous simulation, which is based on events, is different from measuring the performance during the training phase (which was based on segments). The main problem is the definition of the maximum number of events. In this simulation, the maximum number of positive events is given by the total number of trials, namely 30 for each run. On the other hand, the false positive events are difficult to measure. In this work, this number was computed as

$$\sum_i \left\lfloor \frac{\mathrm{NC}_i}{\mathrm{DT} + \mathrm{RP}} \right\rfloor ,$$

all values in samples, NC_i corresponds to the length of the no control (NC) period in trial i which includes all data points except for those inside the IC period. With all definitions solved, the performance was measured in terms of the TPR and FPR. The values of threshold and dwell time were selected at the maximum value of TPR. To achieve an acceptable performance with an asynchronous brain switch, the values of FPR were allowed to be as high as 0.10.

2.3.2. Asynchronous simulation

The remaining two MI runs were described with the same logarithmic band power methods and classified by the ME-trained SVMs. The values of the threshold, dwell time and refractory period were included and the performance was measured with the TPR

Table 1
TPR and FPR in the training phase with ME data for ERD and ERS separately (columns 1–5), and TPR for the calibration phase (columns 6–7). All TPRs corresponding to a classification accuracy greater than 80% are boldface. Naive subjects are marked with an asterisk (*).

ID	ERD		ERS		Calibration (TPR)	
	TPR	FPR	TPR	FPR	ERD	ERS
S1	**0.52**	0.14	**0.73**	0.07	0.13	**0.70**
S2*	0.29	0.18	**0.52**	0.09	0.13	0.33
S3*	0.28	0.22	0.17	0.15	0.00	0.00
S4*	0.36	0.18	**0.43**	0.13	0.23	**0.43**
S5	**0.46**	0.23	**0.70**	0.21	0.30	**0.77**
S6	**0.36**	0.18	**0.84**	0.09	0.33	0.37
S7	**0.67**	0.06	**0.66**	0.09	**0.70**	0.10
S8	**0.92**	0.04	**0.37**	0.15	**0.60**	0.37
S9	**0.58**	0.12	**0.76**	0.03	0.17	**0.97**
$\bar{X}$	0.49 ± 0.21	0.15 ± 0.07	0.58 ± 0.22	0.11 ± 0.05	0.29 ± 0.23	0.45 ± 0.31

and FPR. This processing is equivalent to an on-line implementation of the BCI system.

3. Results

Tables 1 and 2 summarize the performance of all participants in this study. In Table 1, the TPR and FPR values for the training stage with all three runs of ME (final SVM) are shown. The last two columns of this table show the TPR values obtained during the calibration of the post-processing parameters (in this stage the FPR was fixed to be less than or equal to 0.1).

Table 2 lists the TPR and FPR for the simulation of an asynchronous BCI with the last two runs of MI. In both tables, the results that achieved an acceptable performance, i.e., a classification accuracy greater than 80% (ME) or TPR–FPR greater than or equal to 0.40 (MI), are presented with boldface.

In Table 3, the phenomenon (ERD or ERS) associated with the highest TPR is shown for each subject and type of motor task. This table also includes the values of the IC time windows and dwell time used.

For comparison purposes, an ERD/ERS map was computed with the data from MI for every subject, see Fig. 3 for the ERD/ERS maps of all subjects for each motor task. Every map was computed with the methods described above and all trials available from ME or MI.

4. Discussion

In this work, we have shown that a brain switch can be implemented by training a classifier with ME and then applying it directly to MI data with only a minor threshold calibration phase. Moreover, the classification of MI was continuously performed in the simulation of an asynchronous BCI.

Table 2
TPR and FPR values from the simulation of an asynchronous brain switch. A boldface TPR corresponds to the case where TPR–FPR ≥ 0.40.

ID	ERD		ERS	
	TPR	FPR	TPR	FPR
S1	0.05	0.06	**0.63**	0.09
S2	0.12	0.08	**0.50**	0.10
S3	0.50	0.48	0.47	0.41
S4	0.23	0.11	0.25	0.09
S5	0.17	0.10	**0.68**	0.13
S6	0.23	0.14	0.25	0.13
S7	**0.57**	0.09	0.12	0.18
S8	**0.55**	0.15	0.37	0.10
S9	0.25	0.11	**0.88**	0.02
$\bar{X}$	0.30 ± 0.19	0.15 ± 0.13	0.46 ± 0.24	0.14 ± 0.11

Our approach proved to be successful because both motor tasks (MI and ME) result in similar ERD/ERS patterns (as expected). This can be seen from the TPR and FPR values shown in both Tables 1 and 2. The use of a classifier from ME applied to MI data can be seen as a measurement of similarity between the patterns of both tasks.

More information about the similarity of these two phenomena can be obtained from the ERD/ERS maps in Fig. 3. When analyzing these maps, three cases can be observed, both for ERD and ERS: (i) the pattern disappears, (ii) the pattern increases (time/frequency span) or (iii) the pattern decreases. Another pair of (de)synchronization-specific changes can be identified, (a) for ERD the pattern overlaps with the event-related potential evoked by the cue and (b) for ERS the pattern changes with the enhancement or attenuation of harmonics. From the results, it can be seen that the performance of the system is sensitive to the changes in the ERD/ERS patterns, as expected.

For the ERD-based classification, only two subjects (S7 and S8) achieved an acceptable performance for the continuous processing. It can be seen from their corresponding ERD/ERS maps that the ERD patterns changed from ME towards MI mostly with differences in the width of the pattern. The highest drop of performance (for subject S8) can be attributed to the reduced bandwidth of the pattern and the new ERD pattern around 10 Hz. On the other hand, for ERS-based subjects S1, S2, S5 and S9, the TPR values did not drop by more than 0.10 from ME to MI. The results are also supported by the differences in the ERS patterns (Fig. 3). Thus, these results clearly show that our method succeeds in 6 out of 9 subjects.

Subjects S3, S4 and S6 need to be discussed in further detail. First, subject S3 did not exhibit highly significant ERD/ERS patterns neither in the ME nor in the MI task. This is shown by the TPR and FPR values in all tables. Second, the ERD patterns from subject S4 were slightly shifted from 24 Hz in ME towards 21 Hz in MI and the ERD pattern around 25 Hz disappeared. Although this frequency

Table 3
Most important phenomenon (ERD or ERS) during ME and MI and post-processing parameter values.

ID	Training		Calibration/evaluation		
	Phenomenon	IC (s)	Phenomenon	DT (samples)	Threshold ($p_{(x)}$)
S1	ERS	3–4	ERS	100	0.15
S2	ERS	4.5–5.5	ERS	75	0.15
S3	ERS	3.5–4.5	–	25	0.15
S4	ERS	3.5–4.5	–	100	0.29
S5	ERS	3.5–4.5	ERS	62	0.22
S6	ERS	4–6	–	100	0.22
S7	ERD	5–6	ERD	62	0.66
S8	ERD	4–5	ERD	100	0.56
S9	ERS	4–5	ERS	75	0.24

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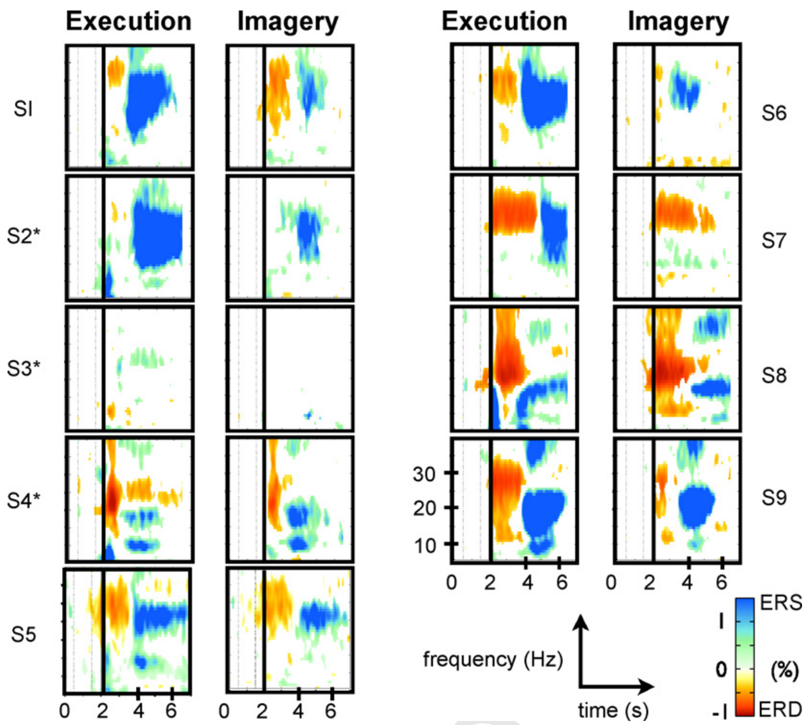

Fig. 3. ERD/ERS maps for all subjects. Similar patterns can be appreciated for all subjects in both ME and MI. The maps represent the statistical significance of ERD and ERS across all trials. Naive subjects are marked with an asterisk (*).

shift is small, it affects the performance, reducing the TPR from 0.36 to 0.23 while improving the FPR from 0.18 to 0.11. The changes in ERS patterns and its classification are more evident with a decrease in performance from (TPR) 0.43 to 0.25. This is probably caused by the ERD around 25 Hz that overlaps with the ERS IC during ME (training stage). In these two cases, the subjects were naive and had no previous knowledge of their own patterns.

An interesting case is subject S6. The differences in ERD-based classification are obvious, because the pattern disappears almost completely from ME to MI (Fig. 3), but the ERS pattern does not present dramatic changes that could lead to a bad performance. The ERS patterns presented in this subject are similar to the ones present in subjects S1 and S2. A closer look to the individual runs made evident that this subject was not able to produce an ERS pattern for all cue-based MI trials, thus making it impossible to detect any command during the expected IC.

One way to overcome the problems related to pattern shifts or new harmonics during MI is the use of narrow bands for the feature extraction as used in [19,27]. However, this requires previous knowledge of the MI patterns. The methods presented in this work make use of the ME for training the classifier and one single run (30 trials) of MI to adjust the bias, although this threshold could be estimated from ME data alone. A method that uses direct comparisons between the patterns from ME and MI should lead to a better performance of the ME-trained classifiers. Another improvement could be the combination of both classifiers by a simple product as presented in [20].

In comparison with current work, two recently published papers show results for an asynchronous BCI with ME detection (namely wrist extension and finger flexion, respectively). In the work of Bai et al. [6], an accuracy of about 90% is achieved for ME and around 75% for MI. These results are similar to the ones presented in this work. During ME training, the accuracy values were above 80% for eight subjects (Table 1). In the second work by Fatourechi et al. [28], three different motor-related brain potentials were used to detect ME. An average performance of 0.56 for the TPR (with a minimum FPR of 0.05) is reported. In our case, 7 out of 9 subjects achieved a TPR greater than 0.50 with different values of FPR. Five of these subjects (S1, S2, S5, S7 and S9) showed a similar performance for the continuous processing of the MI recordings.

A study published by Morash et al. [29] reports on the cue-based classification of the ERD/ERS prior to the execution/imagination of four different motor tasks (left hand, right hand, tongue and right foot rotation). In this study, eight naive subjects participated in a cue-based task and the time–frequency patterns were analyzed in both conditions (execution/imagination). For the foot movement execution/imagination, one subject showed no patterns before the cue and five subjects had a classifiable ERD while the other two subjects had an ERS pattern. Classification results were in the range of 60–80% for ME and 55–70% for MI (six subjects during the testing phase). A large electrode array with 29 electrodes and more complex spatial filtering (independent component analysis) were used.

As opposed to the studies mentioned above, where highly dense electrode arrays were used, only one Laplacian derivation from Cz was used in this study for all subjects. Two other papers from Mason and Birch [4] and Birch et al. [30] present a brain switch approach with the use of 9 electrodes in bipolar configurations, the use of a low frequency feature (1–4 Hz) and wavelets for feature extraction. In the second paper, the use of such a brain switch with spinal cord injured patients proved to work with a low FPR ($\leq$ 1%). The main differences to our approach are that we use less EEG channels, simpler features and train the classifiers with ME data; it is clear that, since our design is based on ME, this methodology can not be used to create a brain switch for patients. It is instead a simple way to train a BCI for home applications by healthy users.

It is worth noting that our classifiers were trained in a general way for all subjects with the same number of features and only one Laplacian EEG channel. The time interval for labeling of the classes was selected based on the ERD/ERS maps. Optimization was carried out for classifier training and post-processing parameters

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only. In the subset of naive subjects, only one of the three participants presented no significant patterns during MI and a weak beta ERS during ME. The remaining two subjects had similar patterns in both cases, but the changes in the patterns led to a bad performance during the asynchronous simulation. It can be expected that feedback and subject training with MI tasks would help these subjects to increase their performance. At the same time, the FPR can be further improved by updating the threshold with the new MI data.

Although beyond the scope of this work, the importance of ERS is notable for the MI task; this is in accordance with the findings reported in [17]. A closer look at ERS and its changes will be the subject of further studies.

This brain switch could also be useful in a “hybrid” BCI. The brain switch has a low false positive rate, but also suffers from a low information throughput. Our group is combining a brain switch with an SSVEP BCI for control of an orthosis, which could capitalize on the advantage of both types of BCIs. Other future directions involving “hybrid” BCIs also merit exploration [31].

5. Conclusions

The methods presented in this work are an important step towards an asynchronous BCI system that can be used outside the lab. A simple strategy to train a robust classifier is given and the asynchronous performance shows an acceptable level of control for six out of nine subjects (TPR $\geq$ 0.50). Further studies on the characteristics of ERD/ERS and the stability from ME to MI may lead to the use of simpler classifiers, thus improving the information transfer rate and reducing the time needed to train the classifiers.

No feature selection was used and all the parameters were derived from the data. The use of automatic methods for the definition of the IC from the ERD/ERS maps and adaptation of the classifiers to the changes in ERD/ERS patterns during MI would lead to an auto-configurable, subject-specific system. Furthermore, the presentation of feedback and update of the classifiers would improve the performance.

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