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Investigating brief motor imagery for an ERD/ERS based BCI

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***Abstract*—This study establishes the effectiveness of event related synchronisation (ERS) features for a system paced brain computer interface (BCI). In particular, the relationship between the duration of motor imagery (MI) and the quality of the features extracted from the ERS is investigated. To this end, two groups of users performed brief (2s) or sustained (4s) MI, and offline single trial BCIs were validated on each group based on features extracted from the EEG before, during and after MI. The BCIs were designed to recognise two intentional control tasks and a no-control state. Cross-validated results indicate that brief MI leads to more informative ERS features than sustained MI.**

I. INTRODUCTION

Brain computer interfaces (BCIs) are an active field of biomedical signal processing research, with the direct goal of providing communication and control pathways for severely disabled patients [1]. The canonical BCI relies on interpreting electroencephalogram (EEG) characteristics in order to control, for example, a cursor, a speller, or an automated wheelchair [2–4].

Motor imagery (MI) BCI consists in classifying imagined movements, typically of the individual hands, based on the spatial distribution of power in particular frequency bands of the EEG during the event related desynchronisation (ERD) complex. The focus of much of the recent literature has thus centered on improving ERD based BCIs via more sophisticated spatial filters [5], adaptive classifiers [6] and methods to reduce the effects of the inter-session [7] or inter-subject [8] variability of the EEG.

The ideal MI BCI can be defined as requiring all the following: high accuracy in order for the user to be able to use the system without frustration, a large number of recognisable tasks to maximise the throughput of the system, a short training/calibration period so that the user may use the system online without numerous/long calibration sessions, a short setup time with regards to placing the sensors on the user, and finally self-paced operation is desirable for numerous MI based applications, such as navigation.

One type of BCI which has been described recently is the "Beta-rebound" based BCI, which effectively uses the event related synchronisation (ERS) features that occur following the termination of MI [9–11]. Such a system has a function analogous to a button press, in that a single intentional control (IC) task, such as feet movements, is distinguished from a no-control (NC) state. The advantages of this type of system are a very short calibration period, a short setup time due to requiring few electrodes, and self-paced operation.

Here, the concept of a "Beta-rebound" BCI is extended into an ERD/ERS BCI, which can distinguish between 2 IC tasks and has NC support, i.e. a 2-task system-paced BCI [12]. A key aspect of creating an ERD/ERS BCI is designing the experiment in such a way that the ERD and ERS features are informative. However, many studies discuss real movements [13, 14], or are limited to MI in a single IC task [15]. Recent results found that the beta rebound associated with MI exhibits more lateralisation in EEG activity following brief cues rather than sustained cues [16]. This implies that greater accuracy can be achieved in differentiating 2 tasks in an ERD/ERS BCI if brief cues are utilised. To validate this hypothesis, data from two groups of subjects were used, with one group performing brief MI and the other performing sustained MI.

This article compares the use of brief MI and sustained MI for use in an ERD/ERS based BCI, and is organised as follows: in section 2, the experimental protocol is presented, in which the process of obtaining data for the short MI experiment is explained. An ERD/ERS BCI algorithm is proposed in section 3, and the subcomponents of the algorithm are discussed. Results comparing brief MI to sustained MI are presented in section 4 and the results of the group performing brief MI are analysed in greater detail. Finally, a discussion of the findings and further work can be found in section 5.

II. EXPERIMENTAL PROTOCOL

This study reports results from two groups of subjects, one group performing brief MI, whereas the other performed sustained MI. For both groups the IC tasks available to the user were left hand, right hand and both feet. The brief MI data consisted of data from 10 subjects recorded at INRIA Sophia Antipolis, who were presented 2s cues during the experiment. The format for each trial is shown in Figure 1. One block consisted of 10 presentations of each task, followed by a brief pause of 1-2 minutes. Subjects first performed 1 block of real movements in order for them to become familiar with the format of the trials. The subjects then performed 10 blocks of MI, which are used as part of this study. The data recording and cue presentations were performed using OpenVibe [17]. The mean number of trials per subject used in this experiment was 357 for the brief MI group.

The sustained MI data consisted of 4 subjects performing MI for a duration of 4s, and was obtained from a publicly available dataset from BCI competition 4 (dataset 1, training data, artificial data subjects were removed from the group) [18]. The format of each trial for the sustained MI group differs in that the ERD block lasted 4s, no cross was shown during ERS, and the inter-trial rest period was fixed at 2s. For more

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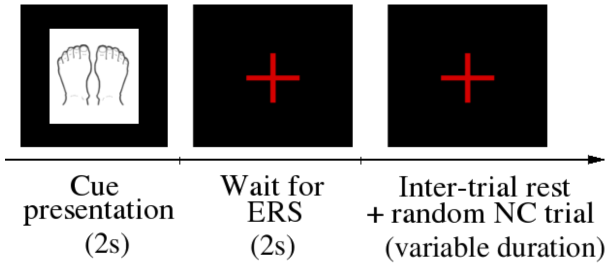

Fig. 1. Cue presentation format for the brief MI group. Note that a fixation cross is displayed at all times other than during the cue presentation.

information on this dataset, the interested reader is directed to [19]. The mean number of trials per subject used in this experiment was 321 for the sustained MI group.

For both groups, 5 fold cross-validation, with contiguous folds, was employed to obtain an estimate of performance. Identical model and feature selection routines were employed in the training stage of both groups, all of which were performed offline using Matlab. For each group, 4 variations of the algorithm were tested, based on features obtained from different time windows with respect to the cue. The timing information of the windows is shown in Figure 2. For each group, BCI algorithms were designed based on features from the ERD, ERD+ERS, pre-stimulus+ERD+ERS and ERS only.

III. Methods

The overall design of the system is given in Figure 3. For each trial, a spectrogram was extracted for each channel (C3, Cz, C4 in this case). The most discriminant features from the spectrogram coefficients were determined in training, as detailed below, in order to reduce the high dimensionality of the feature space. The optimal feature vectors were then analysed by two cascaded SVM classifiers to determine whether the trial corresponded to one of 2 tasks (determined in training) or the NC task. The first SVM was used to determine whether data was from the NC-class or one of the IC classes (data from both IC classes were pooled together in training), and if an IC task was detected, the second SVM determined whether the data belonged to IC task 1 or IC task 2.

The preprocessing of stage was identical for both datasets. First the data was downsampled by a factor of 2, from 256 to 128Hz for the brief MI group and from 200 to 100Hz for the sustained MI group. A bandpass filter was then applied to retain only the activity in the 4-40Hz band. Note that only referential channels C3, Cz and C4 are employed by the BCI.

The parameter selection stage of the training algorithm was used to determine which 2 of the 3 MI tasks were most separable (The 2 MI tasks were pre-selected for the sustained group). Subsequently, the parameters of the algorithm, such as the number of features to be retained and the SVM training parameters, were selected. Every parameter was selected to maximise the 5x5 cross fold validated training accuracy, that is, the cross-fold validation procedure was repeated 5 times with random sampling of each fold. Accuracy was calculated as the percentage of correctly classified trials across all three classes employed in testing.

The spectrograms were based on short time Fourier transforms with 1s windows and 75% overlap between windows, resulting in a resolution of 1Hz in the frequency axis and a 0.25s in the time axis. The spectrogram coefficients used as features were limited to the 8-30Hz range. T-tests were used for feature selection, by performing 2 way t-tests of the spectrogram coefficients between 2 classes. Features were then selected if their corresponding p-value was below a threshold, set during parameter selection. Note that in this way, 2 distinct feature sets were computed, one for NC vs both tasks and one for task1 vs task2. Finally, the C parameters of each linear SVM were set during parameter selection.

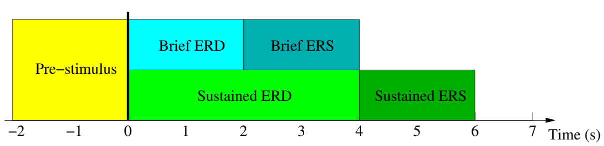

Fig. 2. Timing information for the cued trials.

IV. Results

A. Brief vs sustained imagination

The accuracies of the algorithms are presented in Table I. Note that a large increase in accuracy over the ERD features is observed for the ERD/ERS features in the brief MI group, however ERD/ERS features result in only minor improvements over ERD features for the sustained MI group. For both the brief and sustained MI groups, the addition of pre-cue features did not result in any increase in accuracy.

In the brief MI group, it can be seen that using only ERD features or only ERS features yield commensurable results. In contrast, the sustained MI group results show that the ERD features alone are more informative than the ERS features. Moreover, the discriminative information of the ERS features after sustained imagination is predominantly redundant, as only a minor improvement in accuracy is observed between ERD and ERD/ERS for the sustained MI group.

B. ERD/ERS BCI with brief MI

The ERD/ERS BCI with brief MI being the main focus of this study, the results of this algorithm are analysed in detail in this section. First, it should be noted that there is a high variability in the accuracies obtained in the brief MI group. Two subjects achieved accuracies of approximately 50%, while accuracies above 80% were obtained for 4 other subjects, resulting in a standard deviation of 14.2% for the mean accuracy of 72.1%.

Group	ERD	ERD/ERS	PRE+ERD/ERS	ERS only
Brief	63.7 ± 9.6	72.1 ± 14.2	70.7 ± 15.1	58.9 ± 15.4
Sustained	69.0 ± 4.9	71.2 ± 4.1	70.8 ± 4.8	51.9 ± 3.2

TABLE I

Accuracies obtained in 5 fold cross-validation testing.

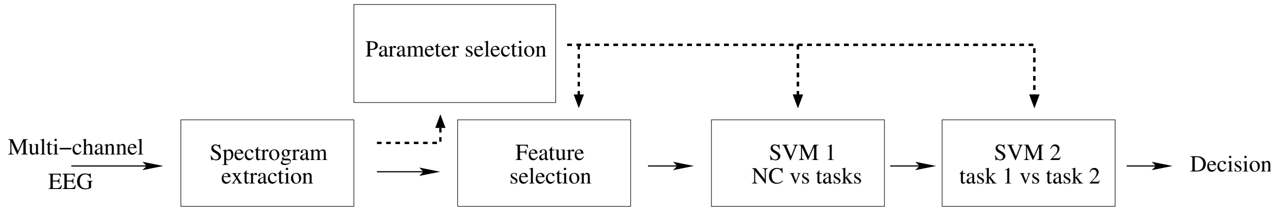

Fig. 3. Block diagram of BCI algorithm. Dashed lines correspond to training stage.

The mean sensitivity of the NC class over all subjects was 75%, while the sensitivity averaged over both IC tasks was 69.8%. Over all subjects and all folds, the proportion of pairs of tasks chosen was 20% for LH&RH, 30% for LH&F and 50% for RH&F, for a dataset composed of 80% right-handed subjects and 20% left-handed subjects. It was observed that for any given subject, no single pair of IC tasks was persistently selected over all 5 cross validation folds, which suggests that more than 2 IC tasks may be differentiated using the proposed feature representation.

Average spectrograms are plotted for one subject from the brief MI group in Figure 4, in order to help the reader visualise the ERD/ERS complex which is being exploited by the system. An accuracy of 82.7% was achieved for this subject. The spectrograms are arranged according to channels horizontally and according to tasks vertically, with time 0 corresponding to the onset of the 2 second cue. For the NC trials, it is clear that neither ERD nor ERS occurs as the subject does not perform MI. A 2s ERD followed by a 2s ERS is clearly visible on all channels for both left hand MI and right hand MI. However, it can be seen that there is relatively more suppression of mu and beta rythms during ERD and a larger beta rebound in the contralateral side of each MI task. This is particularly visible in the spectrograms for right hand MI, where the suppression and rebound of beta rythms is particularly clear in C3, but less obvious in C4. It should be noted that the number of features retained by the algorithm after feature selection was 246 for NC versus both tasks, and 155 for task 1 versus task 2.

V. Significance and Further Work

The results of this study provide two interesting conclusions. First, in comparing brief MI to sustained MI, it was observed that the inclusion of ERS features resulted in a significant increase in accuracy for the brief MI group, but only a marginal increase in accuracy for the sustained group. These results, the first in single trial analysis, thus confirm previous reports that brief MI leads to more lateralisation of ERS [16].

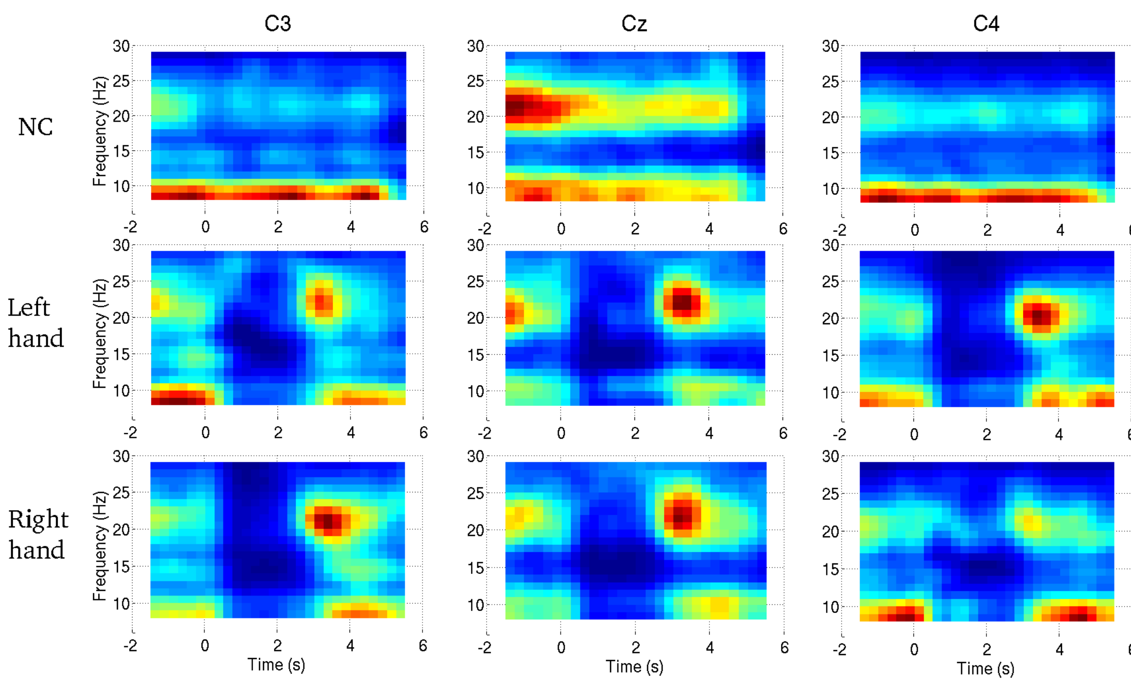

Fig. 4. Average spectrograms in all 3 electrodes for subject 6 of the brief MI group during NC and while performing left hand and right hand movement imagination.

The second conclusion of this study comes from the analysis of the ERD/ERS BCI with brief MI. A mean cross validation accuracy of 72.1% was obtained, despite the fact that 2 subjects with low accuracy were present in the group. This suggests that an ERD/ERS BCI with brief MI is realisable for most subjects without the need for prolonged subject training.

One question of particular importance, which is not answered here, is the influence of feedback on the ERS. As has been shown here, longer MI leads to less informative ERS features due to reduced lateralisation of the beta rebound. However, in an online implementation, the subject would need to perform MI and then wait approximately 2s for the algorithm to acquire the ERS features before a decision can be made. Whether this waiting (or anticipation) period modulates the ERS complex must therefore be established by carrying out a follow-up experiment online.

As discussed in the results section, the pair of IC tasks chosen in training was not persistent over all cross validation folds. This indicates that any IC task can be differentiated from at least one other IC task and NC. This observation suggests that a similar approach could be used to discriminate between all 3 IC tasks and a NC state with good results.

The BCI presented here is a system paced algorithm, i.e. a trial structure exists and NC trials are supported. Ideally, the BCI would support self-paced operation, for example in a navigation scenario the multiple IC tasks could be mapped to motion and direction commands. However, the system currently requires MI of exact duration, due to the spectrogram features and training of the SVM, i.e. 2s of ERD are expected. This condition could be relaxed by modelling the duration of the ERD and ERS probabilistically. Such a paradigm has previously been proposed [20].

Alternatively, such a system could be used for correction or labelling of decisions, when a user receives immediate feedback based only on ERD. In other words, the user performs motor imagery and receives feedback from a BCI based on ERD, however a second BCI is used to classify the ERD/ERS following the termination of motor imagery to provide a secondary decision, provided that the ERS is not corrupted by the feedback of the ERD BCI. This secondary decision could then be used for error correction, or as a label for adapting the ERD classifier or simply to monitor performance.

VI. CONCLUSION

A 3-class BCI using 2 IC tasks and a NC state was proposed based on ERD and ERS features. It was demonstrated that employing brief MI led to more informative ERS features in contrast to sustained MI, for which the addition of ERS features did not significantly improve results. The brief MI results indicated that an ERD/ERS based BCI is a feasible control interface for subjects to use with limited training, with 8 out 10 subjects obtaining cross-fold validation accuracies above 65% for a 3 task paradigm. Further work will focus on validating these results through online testing and improving the functionality of the BCI.

REFERENCES

[1] J. Millán, R. Rupp, G. Müller-Putz, R. Murray-Smith, C. Giugliemma, M. Tangermann, C. Vidaurre, F. Cincotti, A. Kübler, R. Leeb *et al.*, "Combining brain–computer interfaces and assistive technologies: state-of-the-art and challenges," *Frontiers in Neuroscience*, vol. 4, 2010.

[2] J. Wolpaw, N. Birbaumer, D. McFarland, G. Pfurtscheller, and T. Vaughan, "Brain-computer interfaces for communication and control," *Clinical Neurophysiology*, vol. 113, pp. 767–791, 2002.

[3] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kübler, J. Perelmouter, E. Taub, and H. Flor, "A spelling device for the paralysed," *Nature*, vol. 398, no. 6725, pp. 297–298, 1999.

[4] F. Galán, M. Nuttin, E. Lew, P. Ferrez, G. Vanacker, J. Philips, and J. Millán, "A brain-actuated wheelchair: Asynchronous and non-invasive brain-computer interfaces for continuous control of robots," *Clinical Neurophysiology*, vol. 119, no. 9, pp. 2159–2169, 2008.

[5] M. Kawanabe, C. Vidaurre, S. Scholler, and K. Müller, "Robust common spatial filters with a maxmin approach," in *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*. IEEE, 2009, pp. 2470–2473.

[6] C. Vidaurre, C. Sannelli, K. Müller, and B. Blankertz, "Machine-learning-based coadaptive calibration for brain-computer interfaces," *Neural Computation*, vol. 23, no. 3, pp. 791–816, 2011.

[7] M. Sugiyama, M. Krauledat, and K. Müller, "Covariate shift adaptation by importance weighted cross validation," *The Journal of Machine Learning Research*, vol. 8, pp. 985–1005, 2007.

[8] S. Fazli, F. Popescu, M. Danóczy, B. Blankertz, K. Müller, and C. Grozea, "Subject-independent mental state classification in single trials," *Neural networks*, vol. 22, no. 9, pp. 1305–1312, 2009.

[9] G. Pfurtscheller and T. Solis-Escalante, "Could the beta rebound in the EEG be suitable to realize a "brain switch"?" *Clinical Neurophysiology*, vol. 120, pp. 24–29, 2009.

[10] J. Fruitet, M. Clerc, and T. Papadopoulo, "Preliminary study for an hybrid BCI using sensorimotor rhythms and Beta rebound," in *International Journal of Bioelectromagnetism*, vol. 13, 2011, pp. 70–71.

[11] O. Bai, P. Lin, S. Vorbach, M. K. Floeter, N. Hattori, and M. Hallett, "A high performance sensorimotor beta rhythm-based brain–computer interface associated with human natural motor behavior," *Journal of Neural Engineering*, vol. 5, no. 1, p. 24, 2008.

[12] S. Mason, J. Kronegg, J. Huggins, M. Fatourechi, and A. Schlögl, "Evaluating the performance of self-paced brain computer interface technology," 2006, neil Squire Soc., Vancouver, BC, Canada, Tech. Rep.

[13] N. Erbil and P. Ungan, "Changes in the alpha and beta amplitudes of the central eeg during the onset, continuation, and offset of long-duration repetitive hand movements," *Brain research*, vol. 1169, pp. 44–56, 2007.

[14] F. Cassim, W. Szurhaj, H. Sediri, D. Devos, J. Bourriez, I. Poirot, P. Derambure, L. Defebvre, and J. Guieu, "Brief and sustained movements: differences in event-related (de) synchronization (ERD/ERS) patterns," *Clinical neurophysiology*, vol. 111, no. 11, pp. 2032–2039, 2000.

[15] Y. Jeon, C. Nam, Y. Kim, and M. Whang, "Event-related (de) synchronization (ERD/ERS) during motor imagery tasks: Implications for brain-computer interfaces," *International Journal of Industrial Ergonomics*, 2011.

[16] C. Nam, Y. Jeon, Y. Kim, I. Lee, and K. Park, "Movement imagery-related lateralization of event-related (de) synchronization (ERD/ERS): Motor-imagery duration effects," *Clinical Neurophysiology*, vol. 122, no. 3, pp. 567–577, 2011.

[17] Y. Renard, F. Lotte, G. Gibert, M. Congedo, E. Maby, V. Delannoy, O. Bertrand, and A. Lécuyer, "Openvibe: An open-source software platform to design, test, and use brain–computer interfaces in real and virtual environments," *Presence: Teleoperators and Virtual Environments*, vol. 19, no. 1, pp. 35–53, 2010.

[18] C. Brunner, R. Leeb, G. Müller-Putz, A. Schlögl, and G. Pfurtscheller, "BCI competition 2008–Graz data set A," *Institute for Knowledge Discovery (Laboratory of Brain-Computer Interfaces), Graz University of Technology*, 2008.

[19] B. Blankertz, G. Dornhege, M. Krauledat, K.-R. Müller, and G. Curio, "The non-invasive berlin brain-computer interface: Fast acquisition of effective performance in untrained subjects," *NeuroImage*, vol. 37, no. 2, pp. 539–550, 2007.

[20] J. Doležal, J. Šťastny, and P. Sovka, "Exploiting temporal context in high-resolution movement-related EEG classification," *Radioengineering*, vol. 20, no. 3, pp. 666–676, 2011.