Asynchronous BCI Control of a Robot Simulator with Supervised Online Training

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Abstract. Due to the non-stationarity of EEG signals, online training and adaptation is essential to EEG based brain-computer interface (BCI) systems. Asynchronous BCI offers more natural human-machine interaction, but it is a great challenge to train and adapt an asynchronous BCI online because the user's control intention and timing are usually unknown. This paper proposes a novel motor imagery based asynchronous BCI for controlling a simulated robot in a specifically designed environment which is able to provide user's control intention and timing during online experiments, so that online training and adaptation of motor imagery based asynchronous BCI can be effectively investigated. This paper also proposes an online training method, attempting to automate the process of finding the optimal parameter values of the BCI system to deal with non-stationary EEG signals. Experimental results have shown that the proposed method for online training of asynchronous BCI significantly improves the performance.

Keywords: Adaptation, asynchronous BCI, brain-computer interface, online training, automated learning.

1 Introduction

A brain-computer interface (BCI) is a communication system in which an individual sends commands to the external world by generating specific patterns in brain signals and a computer detects and translates the brain signal patterns into commands that accomplish the individual's intention. BCI systems can be categorised into systems operating in cue-paced (synchronous) or self-paced (asynchronous) mode. The majority of the existing EEG-based BCI systems are synchronous [1]-[3], in which the analysis and classification of brain signals is locked to predefined time windows. This means that users are supposed to generate commands only during specific periods determined by the BCI system. The advantage of synchronous BCI systems is that the onset of mental activity is known in advance and associated with a specific cue or trigger stimulus, and thus any signal outside the predefined time windows is treated as idling and ignored by the BCI system. On the other hand, asynchronous BCI systems offer a more natural mode of human-machine interaction than synchronous BCIs [4]-[9]. In asynchronous BCIs, no cue stimulus is used, the users

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control the BCI output whenever they want by intentionally performing a specific mental/cognitive task, and the EEG signals have to be analysed and classified continuously. The disadvantage of asynchronous BCI is that the lack of indications of the user's control intention and timing brings about challenges in asynchronous BCI design and performance evaluation.

It is well-known that EEG signals, particularly in EEG-based BCI systems, are non-stationary. The non-stationarities may be caused by the subject's brain conditions or dynamically changing environments. To some extent, a realistic BCI system has to be trained online and adaptive even in application phases where the true labels of ongoing EEG trials are unknown [10]-[17]. It is a great challenge to train and adapt an asynchronous BCI online because the user's control intention and timing are usually unknown to the BCI system. Existing methods for obtaining the user's control intention and timing in asynchronous BCI are to analyse continuous EEG data consisting of defined cue-triggered mental states (simulated asynchronous BCI) [4], use self-report by subjects [5][6], rely on subjects to perform a predefined sequence of mental tasks [5][7], or analyse real movement EEG data recorded along with time stamp of actual movements [8][9]. It should be noted that the above methods are not so suitable for online training purpose, except for the latter approach which assumes that the imagined movements will have enough similarity to actual movements. However, realistic BCI applications should be based on motor imagery or other mental activities rather than real movements.

This paper proposes a novel motor imagery based asynchronous BCI control of a simulated robot in a specifically designed environment, which is able to provide user's control intention and timing during online experiments, so that online training and adaptation of motor imagery based asynchronous BCI can be effectively investigated. This paper also proposes an online training method, attempting to automate the process of finding the optimal parameter values of the BCI system to deal with non-stationary EEG signals. Experiments have been conducted, producing promising results on performance improvement of asynchronous BCI by online training in terms of accuracy and deviation of real paths from optimal paths.

2 Methods

2.1 BCI Experiment Setup

The experiments were carried out with able-bodied subjects who sat on an armchair at 1m distance in front of a computer screen. The EEG recording was made with a g.tec amplifier (Guger Technologies OEG Austria). Five bipolar EEG channels using 10 electrodes, as shown in Fig. 1, were measured over C3 (FC3 vs. CP3), C1 (FC1 vs. CP1), Cz (FCz vs. CPz), C2 (FC2 vs. CP2), and C4 (FC4 vs. CP4). The EEG was sampled at 250Hz.

2.2 Offline Training

A simple synchronous BCI paradigm, proposed by the Graz BCI Lab [3], was used to record data for training classifiers offline before online experiments. The subjects were asked to imagine left versus right hand movements. The experiment consisted of

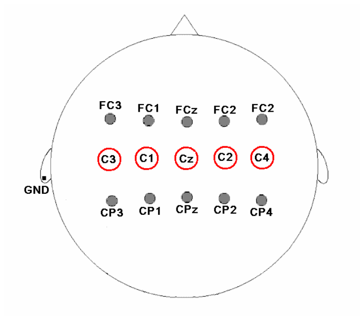

Fig. 1. Five bipolar electrode positions

6 runs with 40 trials each. In each trial the subjects relaxed until a green cross appeared on screen at t = 2s (s for second). At t=3s, a red arrow (cue) pointing either left or right direction appeared on screen for 2 seconds. The subject's task was to respond to the arrow by imagine left or right hand movements until the green cross disappeared at t = 8s. The order of left and right cues was random, and there was a random interval of 2~3 seconds between trials.

Logarithmic band power features were extracted from EEG signals and used to classify the imagery movements into left or right class. Two frequency bands that give good separation were manually selected for each subject. Using the selected frequency bands, EEG signals were digitally bandpass filtered, squared, averaged over a 1 second sliding window, and a natural logarithm was then applied to obtain the features. Using the extracted features and their corresponding class labels (from the cue signals), two linear discriminant analysis (LDA) classifiers were trained, with one to distinguish left imagery movement from others (right imagery movement or no imagery movement) and the other to separate right imagery movement from others.

It was shown in the BCI competition 2003 and 2005 that LDA performs as well as (sometimes even outperforms) non-linear classifier, and almost all the winning classifiers are linear [18]. Therefore, we chose to use LDA in our design.

2.3 Online Asynchronous Event Detection

During online asynchronous BCI experiments, the extracted features, which are related to the user's control intent, were continuously classified by the offline trained LDA classifiers and used to control a robot simulator that is described in detail in section 2.4. The online asynchronous event detection system used in the experiments is shown in Fig. 2, which works as follows. LDA outputs below a threshold will be set to zero. If a LDA output, used as a class's confidence value, is above the threshold long enough (>Dwell_Length), the dwell requirement of an event onset is met, a class (either left or right) will be selected as a command to control the simulated robot, and a refractory period will be switched on at the same time to reject new class/action to be triggered until the refractory period ends. The threshold and dwell mechanism plus refractory period are effective methods for reducing false positive rate. Refractory period also introduce a competition mechanism for the two LDA classifiers because selection of one LDA's output will reject the other LDA's output during the refractory period. A simple principle of 'first come first serve' is used here for the class selection. The idea of using dwell and refractory period for asynchronous event detection was first introduced in [4] for offline event-by-event analysis of simulated asynchronous BCI, and then used in [19] for binary detection of beta oscillation. Here we use dwell and refractory period for online detection of imagery movements in real asynchronous BCI systems.

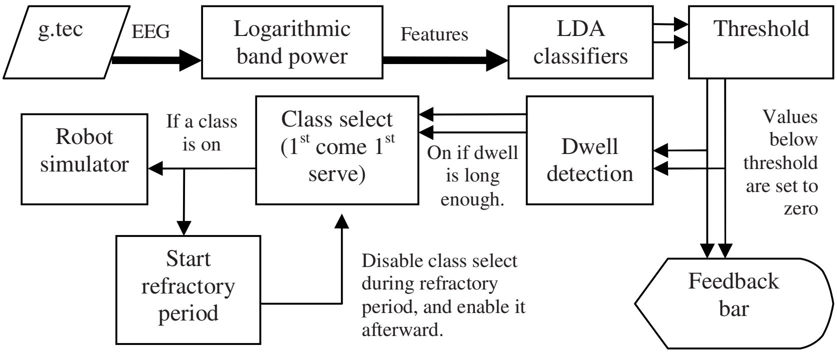

Fig. 2. An online asynchronous event detection system

It is important that the thresholds and dwell lengths are chosen for each class and each subject separately in order to optimise the performance of the whole system. This can be achieved by trial-and-error method or offline Receiver Operating Characteristic (ROC) optimisation. It is because EEG signals are non-stationary that it is also important to adapt these parameters by online training or adaptation. In the following sections an online training method is described, which adapts the threshold and dwell length values when false positive command is detected.

2.4 A Robot Simulator and Its Specifically Designed Environment

During online training, in order to detect whether there is false positive command generated by the BCI system, information about the user's control intention and timing is needed. For this purpose, a robot simulator that runs in a specifically designed environment, as shown in Fig. 3, is proposed and implemented for online asynchronous BCI experiments.

The environment is filled with hexagon grid, and robot movements are railed to the grid line. The robot simulator executes 2 commands: "turn left then move forward to the next node" or "turn right then move forward to the next node", thus the event detection system operates in 2 class mode. The task of the BCI control is to drive the simulated robot to a given target position. There is no obstacle in the environment, but the user is supposed to drive towards the target all the time. An explicit instruction is given to subjects: *At each node the user should always turn the robot to the direction that the target is located.* In the scenario given in Fig. 3, according to the above instruction, the ideal sequence of commands to control the robot from "start" to the 1st target should be: left, right, left, right, left, right, left, right, right, left, left, right and right. It is unnecessary for subjects to plan the whole sequence in advance, as long as the subjects follow the instruction at each node. The simulator executes every detected command, including false positive ones, but the result of a false positive event will not affect future events in evaluation. This is because the correctness of each event is evaluated locally.

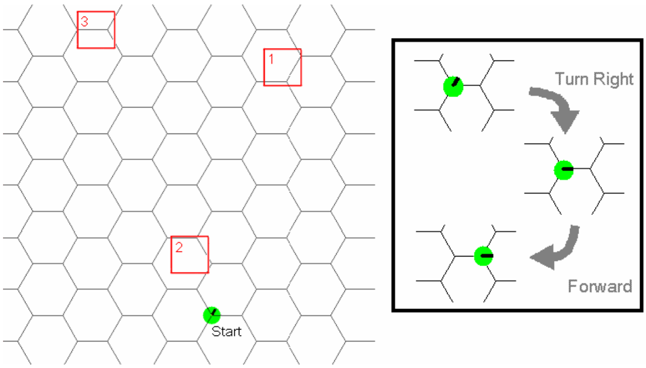

Fig. 3. (left): Hexagon grid, where the circle with a heading indicator represents the robot and the squares are targets. (right): Illustration of a "turn right then move forward to the next node" command executed.

By assuming a subject will follow the instruction, it is possible to predict what command the subject tries to send or what motor imagery movement the subject tries to perform at each node. This prediction can be used to check whether the event/command detected by the BCI is true positive or false positive. This is particularly useful for online training and performance evaluation of asynchronous BCI systems.

The key part of the user's intent prediction is the calculation of the target direction at each node. Since the robot position and target position are known. The current direction of the robot, *CD*, and the target direction, *TD,* with respect to the centre of the robot can be calculated by:

$$CD = \operatorname{atan2}(X2 - X1, Y2 - Y1) \; .$$
$$TD = \operatorname{atan2}(TX - X1, TY - Y1) \; . \tag{1}$$

where (*X1,Y1*) is the centre of the robot, (*X2,Y2*) is the robot heading point, and (*TX,TY*) is the target location. Prediction can be obtained by comparing the values of *CD* and *TD*. However, because the output of *atan2* lies in the closed interval $[-\pi, \pi]$, simple comparison is only valid when both *CD* and *TD* are >0 or <0. To avoid this limitation, *CD* and *TD* are rotated together to the point where *CD* is aligned to the axis of $-\pi/\pi$, as shown in Fig. 4.

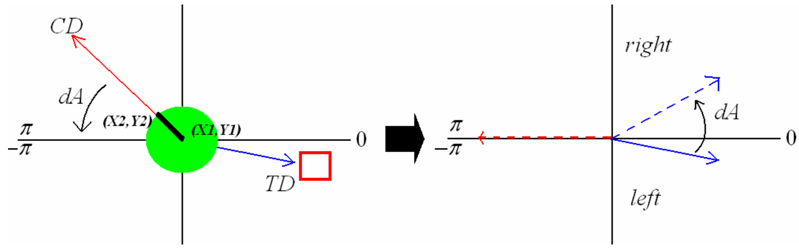

Fig. 4. Rotation of *CD* and *TD* for making a prediction

The rotation angle is as follows:

$$dA = \begin{cases} \pi - CD & CD > 0 \\ -\pi - CD & CD \leq 0 \end{cases} . \tag{2}$$

After rotation the target direction is updated as follows:

$$TD = TD + dA \ . \tag{3}$$

$$TD = \begin{cases} TD - 2\pi & TD > \pi \\ TD + 2\pi & TD < -\pi \\ TD & -\pi \geq TD \leq \pi \end{cases} . \tag{4}$$

Finally, the prediction of command that the user is supposed to produce at each node can be obtained based on the target direction as follows:

$$predict = \begin{cases} right & TD > 0 \\ left & TD \leq 0 \end{cases} . \tag{5}$$

2.5 Online Training

To further make use of the advantage of the robot simulator and its running environment in online asynchronous BCI experiments, an adaptation scheme was implemented for online training in attempt to find the optimal parameter settings to deal with the non-stationarity of EEG signals. The general idea behind the adaptation scheme is: “If it works, do not change it”, but adaptation is required when false positive is detected. We choose to adapt the dwell and threshold parameters, because they both affect the asynchronous BCI performance greatly.

During the online training period, if the detected event does not match the prediction, the following adaptation will be conducted:

- *Higher threshold and dwell are set for the triggered (false) class to prevent next false detection.*
- *On the other hand, lower threshold and dwell are set for the predicted (but not triggered) class.*

- *If the system cannot detect a command for a certain period, called maximum no control allowance, lower threshold and dwell are set for the predicted class.*

The adaptation will be controlled by learning rates. Another important issue is when to start or stop the training. Without a stopping rule, the adaptation could potentially destroy a well tuned BCI system when a minor false positive event is detected. The start and stop rules are as follows:

- *Training starts at the beginning of the online training period.*
- *Training ends when the number of consecutive true positive detections is over a preset value called #CTP.*
- *Training re-stared when the number of consecutive false positive detections is over a preset value called #CFP.*

How to choose the learning parameters will be explained in the next section in connection with experimental results.

3 Results

The system was tested online with 2 male subjects. Subject 1 had a little BCI experience before, and subject 2 was experienced in synchronous BCI experiment. Several runs of online asynchronous BCI experiments were carried out for each subject. In each run, subjects were asked to drive the robot simulator to reach 3 targets. The robot starting point and target positions were fixed and unchanged between runs in order to compare performances in a fair manner. The scenarios used in the experiments are shown in Fig. 3. However, the subjects saw only one target at a time. The current target disappeared as soon as the robot reached it, and the next target appeared at the mean time. The numbers of true positive (TP), false positive (FP), and events triggered were recorded. The performance is evaluated by accuracy defined as (TP/(TP+FP)) and the total number of events (TP+FP) happened in comparison with the minimum number of events needed (ME). The difference between the total number of events and the minimum number of events indicates the deviation of the real path from the optimal path.

3.1 Performance of the Asynchronous BCI without Online Training

The system was first tested without online training. Each subject performed 2 runs. Prior to the formal experiments, subjects took some trial runs with the present of the experiment conductor, so that the subjects understood the paradigm and requirement, and a suitable parameter setting could be found. For subject 1 (S1), 11-14 Hz and 15-30 Hz bandpass features were extracted from each channel, initial thresholds for the two LDA classifiers were set to 2.0, and initial dwell lengths were set to 1.6 seconds. For subject 2 (S2), frequency bands were chosen as 11-14 Hz and 15-25 Hz, initial thresholds were set to 1.0 for left imagery and 2.0 for right imagery, and initial dwell lengths were set to 1.4 and 1.6 seconds for left imagery and right imagery respectively. The results are shown in Tab.1 (Top).

Table 1. (Top) Performance without online training. (Bottom) Performance with online training. TP: Number of true positive event. FP: Number of false positive events. ME: Minimum number of events required to reach the target. ACC: Accuracy TP/(TP+FP). #A: Number of adaptations during online training. E/Min: Number of events per minute.

	Start to 1st target					1st to 2nd target					2nd to 3rd target				
	TP	FP	ME	ACC	E/Min	TP	FP	ME	ACC	E/Min	TP	FP	ME	ACC	E/Min
S1 - 1st run	17	6	11	73.91%	6.48	7	1	8	64.71%	8	21	12	10	63.64%	5.59
S1 - 2nd run	9	2	11	81.82%	7.02	10	3	8	76.92%	6.19	23	10	11	69.70%	6.19
S2 - 1st run	10	3	11	76.92%	7.5	9	1	8	90.00%	6.98	12	4	10	75.00%	8.65
S2 - 2nd run	11	2	11	84.62%	5.74	8	0	8	100%	7.74	15	5	10	75.00%	3.82
S1 Average=	13	4		77.87%	6.75	8.5	2		70.82%	7.10	22	11		66.67%	5.89
S2 Average=	11	2.5		80.77%	6.62	8.5	0.5		95.00%	7.36	14	4.5		75.00%	6.24

	Start to 1st target (Online Training)						1st to 2nd target					2nd to 3rd target				
	TP	FP	ME	ACC	#A	E/Min	TP	FP	ME	ACC	E/Min	TP	FP	ME	ACC	E/Min
S1 - 3rd run	10	5	11	66.67%	7	6.08	12	5	8	75.59%	7.03	12	3	11	80.00%	7.69
S1 - 4th run	9	2	11	81.82%	2	7.1	9	3	8	75.00%	7.74	10	2	10	83.33%	7.13
S2 - 3rd run	11	3	11	78.57%	3	6.51	9	1	8	90.00%	7.69	10	2	10	83.33%	4.07
S2 - 4th run	14	3	11	82.35%	3	7.56	8	1	8	88.89%	4.25	11	2	11	84.62%	4.38
S1 Average=	9.5	3.5		74.25%	4.5	6.59	11	4		75.30%	7.39	11	2.5		81.67%	7.41
S2 Average=	13	3		80.46%	3	7.04	8.5	1		89.45%	5.97	11	2		83.98%	4.23

3.2 Performance of the Asynchronous BCI with Online Training

The above experiment was repeated, except that the first part of the experiment (from start to the 1st target) was used for online training. During online training, the system adapts the thresholds and dwell lengths based on the method described in Section 2. The initial parameter settings were the same as used in 3.1. The learning rates for threshold and dwell adaptation were set to 0.25 and 0.14 seconds respectively for both subjects. Maximum no control allowance was set to 20 seconds. *#CTP* and *#CFP* were set to 5 and 3.

The results are given in Tab.1 (Bottom), which show that Subject 1 produced significantly better performance after online training. For instance, the averaged accuracy of the 3rd part of the experiment (from the 2nd target to the 3rd target) is significant improved, increased from 66.67% to 81.67%, and the number of events detected (TP+FP) is greatly reduced (close to optimal). The 2nd part of the experiment also shown improvement with averaged accuracy increased from 70.82% to 75.30% with a slightly higher number of events detected. However, first part of the experiment (start to 1st target) cannot be compared, because target position was known to the BCI system during online training.

The result from Subject 2 has also shown some improvement after online training, but not as significant as Subject 1. The reason could be that Subject 2 was very experienced in imagery arm movements, and did not make many mistakes during online training. Hence, the number of adaptations (#A) was small. Nevertheless, the averaged accuracy of the 3rd part of the experiment (from the 2nd target to the 3rd target) was increased from 75% to 83.98%.

For readers who are interested in more detailed results, some playback videos of the above online asynchronous BCI experiments are available from http://cswww.essex.ac.uk/staff/jqgan/IDEAL2007_VIDEOS/.

4 Conclusion

This paper has presented an asynchronous BCI system with online training for control of a simulated robot. Taking up the challenge in online training of asynchronous BCI systems, this paper has proposed a novel method for providing information about class labels (user's control intention and timing), which is essential for training and adapting asynchronous BCIs so as to improve the performance. This paper has also developed a method for online adaptation of the thresholds and dwell lengths of the classifiers in asynchronous BCI systems. Initial experimental results have shown the effectiveness of the proposed methods. More experiments will be conducted to further justify the methods. The current work is limited to 2 classes. The proposed experimental paradigm can be easily extended to multiple classes. Further research will be focused on online asynchronous BCI adaptation, including adaptation of all the parameters of the LDA classifiers and unsupervised adaptation during online testing when event labels are unavailable.

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References

1. Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G., Vaughan, T.M.: Brain-Computer Interfaces for Communication and Control. Clinical Neurophysiology. 113, 767–791 (2002)
2. Birbaumer, N., Ghanayim, N., Hinterberger, T., Iversen, I., Kotchoubey, B., Kubler, A., Perelmouter, J., Taub, E., Flor, H.: A Spelling Device for the Paralyzed. Nature 398, 297–298 (1999)
3. Pfurtscheller, G., Neuper, C.: Motor Imagery and Direct Brain-Computer Communication. Proc. IEEE 89, 1123–1134 (2001)
4. Townsend, G., Graimann, B., Pfurtscheller, G.: Continuous EEG Classification during Motor Imagery - Simulation of an Asynchronous BCI. IEEE Trans. on Neural Syst. & Rehab. Eng. 12(2), 258–265 (2004)
5. Birch, G.E., Bozorgzadeh, Z., Mason, S.G.: Initial On-Line Evaluations of the LF-ASD Brain-Computer Interface with Able-Bodied and Spinal-Cord Subjects Using Imagined Voluntary Motor Potentials. IEEE Trans. Neural Syst. & Rehab. Eng. 10(4), 219–224 (2002)
6. Millán, J.d.R., Mouriño, J.: Asynchronous BCI and Local Neural Classifiers: An Overview of the Adaptive Brain Interface Project. IEEE Trans. on Neural Syst. & Rehab. Eng. 11(2), 159–161 (2003)
7. Roberts, S., Penny, W.: Real-Time Brain Computer Interfacing: A Preliminary Study Using Bayesian Learning. Medical & Biological Engineering and Computing 38(1), 56–61 (2000)
8. Mason, S.G., Birch, G.E.: A Brain-Controlled Switch for Asynchronous Control Applications. IEEE Trans. on Biomedical Engineering 47(10), 1297–1307 (2000)

9. Krauledat, M., Dornhege, G., Blankertz, B., Curio, G., Müller, K.-R.: The Berlin Brain-Computer Interface for Rapid Response. Biomed. Tech. 49(1), 61–62 (2004)
10. Sun, S., Zhang, C.: Adaptive Feature Extraction for EEG Signal Classification. Medical and Biological Engineering and Computing 44(10), 931–935 (2006)
11. Tomioka, R., Dornhege, G., Aihara, K., Müller, K.-R.: An Iterative Algorithm for Spatio-Temporal Filter Optimization. In: 3rd International Workshop on Brain-Computer Interfaces, Graz, pp. 22–23 (2006)
12. Grosse-Wentrup, M., Gramann, K., Buss, M.: Adaptive Spatial Filters with Predefined Region of Interest for EEG Based Brain-Computer Interfaces. In: Schoelkopf, B., Platt, J.C. (eds.) Advances in Neural Information Processing Systems 19 (NIPS), MIT Press, Cambridge, MA (2007)
13. Farquhar, J.: Learning Optimal EEG Features Across Time, Frequency and Space. In: Schoelkopf, B., Platt, J.C. (eds.) Advances in Neural Information Processing Systems 19 (NIPS), MIT Press, Cambridge, MA (2007)
14. Millán, J.d.R.: On the Need for On-Line Learning in Brain-Computer Interfaces. In: IJCNN. International Joint Conference on Neural Networks, Budapest, pp. 2877–2882 (2004)
15. Buttfield, A., Ferrez, P.W., Millán, J.d.R.: Towards a Robust BCI: Error Potentials and Online Learning. IEEE Trans. on Neural Syst. & Rehab. Eng. 14(2), 164–168 (2006)
16. Sykacek, P., Roberts, S., Stokes, M.: Adaptive BCI Based on Variational Bayesian Kalman Filtering: An Empirical Evaluation. IEEE Trans. on Biomedical Engineering 51(5), 719–729 (2004)
17. Vidaurre, C., Schlögl, A., Cabeza, R., Scherer, R., Pfurtscheller, G.: Study of On-Line Adaptive Discriminant Analysis for EEG-Based Brain Computer Interfaces. IEEE Trans. on Biomedical Engineering 54(3), 550–556 (2007)
18. Blankertz, B., Müller, K.-R., Krusienski, D.J., Schalk, G., Wolpaw, J.R., Schlögl, A., Pfurtscheller, G., Millán, J.d.R., Schröder, M., Birbaumer, N.: The BCI Competition III: Validating Alternative Apporaches to Actual BCI Problems. IEEE Trans. on Neural Syst. & Rehab. Eng. 14(2), 153–159 (2006)
19. Kanoh, S., Scherer, R., Yoshinobu, T., Hoshimiya, N., Pfurtscheller, G.: Brain Switch" BCI System Based on EEG During Foot Movement Imagery. In: 3rd International Workshop on Brain-Computer Interfaces, Graz, pp. 64–65 (2006)