Senadeera, Manisha, Maire, Frederic, & Rakotonirainy, Andry
(2015)
Turning gaming EEG peripherals into trainable brain computer interfaces.
In Renz, J & Pfahringer, B (Eds.) *AI 2015: Advances in Artificial Intelligence: 28th Australasian Joint Conference, Proceedings [Lecture Notes in Computer Science, Volume 9457].*
Springer, Switzerland, pp. 498-504.

https://doi.org/10.1007/978-3-319-26350-2_44

Turning Gaming EEG Peripherals into Trainable Brain Computer Interfaces

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Abstract. Companies such as NeuroSky and Emotiv Systems are selling non-medical EEG devices for human computer interaction. These devices are significantly more affordable than their medical counterparts, and are mainly used to measure levels of engagement, focus, relaxation and stress. This information is sought after for marketing research and games. However, these EEG devices have the potential to enable users to interact with their surrounding environment using thoughts only, without activating any muscles. In this paper, we present preliminary results that demonstrate that despite reduced voltage and time sensitivity compared to medical-grade EEG systems, the quality of the signals of the Emotiv EPOC neuroheadset is sufficiently good in allowing discrimination between imaging events. We collected streams of EEG raw data and trained different types of classifiers to discriminate between three states (rest and two imaging events). We achieved a generalisation error of less than 2% for two types of non-linear classifiers.

Keywords: EEG, Machine Learning, Device Control, BCI, K-nearest Neighbors, SVM

1 Introduction

Attempts to decipher the brain and interface it with hardware can be traced back to the 1970's when Brain Computer Interface (BCI) research started [24]. BCI devices and methods enable their users to have their brain activity monitored. These devices were in the past confined to the medical arena however in recent years, technological advances have significantly lowered the price of these devices and allowed for the development of non-medical applications [14,15]. An important factor in the usability of EEG devices is their setup and calibration time. New EEG biosensors are easier to operate to the point that they are even used in games to offer novel experience to players [15].

In this paper, we investigate the capabilities of one such device, the Emotiv EPOC neuroheadset [3]. This headset comes with the ability to extract raw EEG

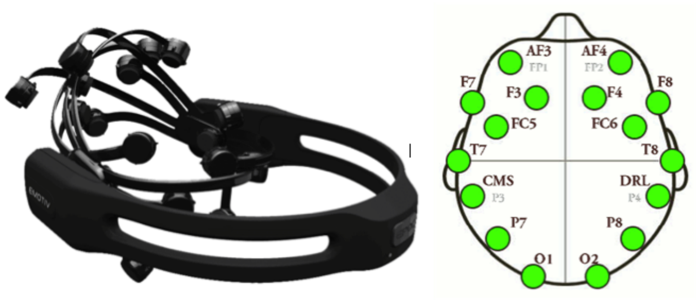

Fig. 1. Left: the Emotiv EPOC headset. Right: the location of its electrodes. The CMS and DRL electrodes act as reference nodes [3].

data from 14 sensors, positioned according to the 10/20 International System, as pictured in Figure 1.

We tried a variety of classifiers using standard machine learning techniques to determine whether it was possible to discriminate between three different mental states. Section 2 retraces briefly the evolution of BCI technology. Section 3 describes the experimental methodology. Section 4 presents experimental results.

2 Related Work

This section briefly reviews the history of BCI.

2.1 Pioneering Days of EEG

Hans Berger The German psychiatrist Hans Berger was researching temperature changes in the cortex of dogs when he first became interested in the electrical activity of the brain [2, 10]. Berger later on became the first person to monitor and record human brain activity from the cortical surface of a 17-year-old undergoing brain surgery [8] thus conducting the first electroencephalography on humans [10, 23]. Berger developed the theory of changes in physiological sleep, coined the "on and off effect", noted the psychological significance of different EEG patterns, and investigated the applications of EEG [8, 10] as well.

EEG Frequencies EEG waves are obtained using electrodes attached to the scalp. These sensitive electrodes pick up postsynaptic potentials, created by inhibitory and excitatory potentials in the dendrites of neurons in the cerebral cortex [21]. Berger suggested that the complex EEG was composed of two fundamental waveforms: the larger α waves correlated with mental activity, and the smaller β waves associated with the metabolic activities of cortical tissue [10]. This observation was refined and led to the identification of five frequency ranges [16]. Each range corresponds to a particular state of mind as indicated in Table 1.

Table 1. EEG Frequency Bands

Band	Frequencies	State of Mind
δ	0.5-4 Hz	Deep dreamless sleep
θ	4-7.5 Hz	Dreamlike, drowsy, meditative
α	8-13 Hz	Relaxed, conscious
β	14-26 Hz	Relaxed but focused, alert, thinking and aware of surroundings
γ	30-40 Hz	Active thinking and information processing

2.2 Brain Computer Interfaces

Although EEG has been primarily used for medical applications such as diagnosing sleep disorders or epilepsy, they have also enabled BCI applications [18, 22]. The simplest form of BCI is switching. This can be achieved through blinking, or the acts of having the eyes open or closed [19]. EEG-based BCI can also be controlled by means of steady state visual evoked potentials, P300 evoked potentials and motor imagery. Many BCI systems share the architecture shown in Figure 2 where an EEG data stream is fed to a classifier whose output is then used to generate control commands.

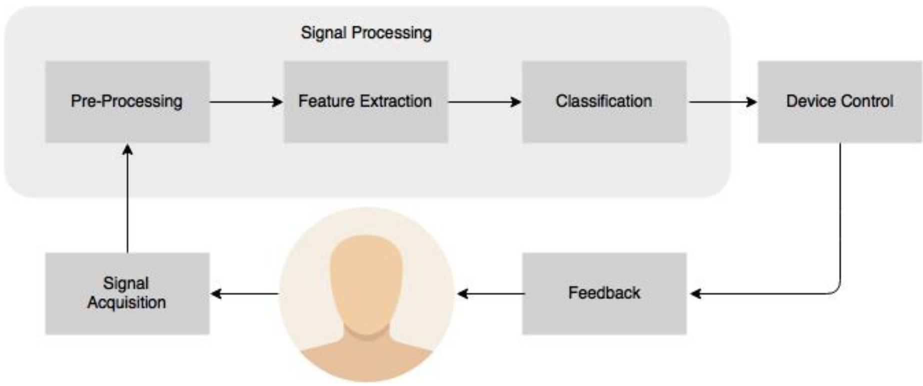

Fig. 2. Architecture of a BCI with feedback loop. The generated output command is displayed to the user as feedback.

P300 Evoked Potentials P300 brainwaves were first discovered by Sutton in 1965 and are evoked via a visual stimulus that a user concentrates upon while different non-target stimuli are also presented [20]. The P300 signal is evoked 250 to 500 ms after the subject detects the target stimulus among the several non-target stimuli [4, 13]. The P300 speller is a device that operates on the P300 evoked potentials. The device presents 36 letters in a 6 x 6 matrix. Each row or column flashes up in turn and the subject concentrates on a particular letter that they wish to write. When the selected letter is lit up, a signal is evoked in the brain and appears in the EEG data [4].

Steady State Visual Evoked Potentials Steady State Visual Evoked Potentials (SSVEP) are the responses evoked from visual stimulus at different frequencies. The SSVEP characteristic increases activity in the EEG signal at the stimulus frequency. An example of SSVEP applications in BCI are demonstrated by Guneysu and Akin who used the SSVEP induced by observing LED lights flashing at different frequencies to control a humanoid robot to draw a square [5].

Motor Imagery Motor imagery is the act of mentally imagining a particular action. Imagining the movement of limbs induces significant changes in the cortical area [7]. This in turn results in changes in potentials allowing for measurements to be made with electrodes. A key component of utilising motor imagery for BCI control is training. Within a few days a tetraplegic patient can learn to control a hand orthosis with mental imaging of left and right hand movements as was demonstrated by Pfurtscheller and Neuper [12].

2.3 Invasive and Non-Invasive BCI

BCI controls can be both via invasive and non-invasive methods. Invasive methods involve directly implanting BCI technologies onto the grey matter of the brain. In 1998 Kennedy implanted the first BCI object to produce a high quality signal into the outer layer of a human neocortex. Conducted on a patient with locked-in syndrome, the recorded signals were transmitted and processed to drive a computer cursor [9].

Due to the costly and dangerous nature of invasive methods, interest exists in non-invasive ones, however these are more sensitive to noise and have lower signal resolution. Nevertheless advances in technology, lower costs, ease of portability and no requirement for surgery has stimulated the development of non-invasive BCI control methods [17, 21, 25].

2.4 EEG Technology

The study of EEG began with the development of mirror and strong galvanometers with the ability to respond to a time constant less than several seconds [2]. Du Bois-Reymond developed non-polarizable electrodes from clay which were used for many years for animal and human EEG recordings [1]. In 1875 Caton first recorded electrical activity in the exposed brains of animals and Berger the first human EEG recordings with an Edelmann galvanometer [2, 10].

In current times, the technology of EEG has undergone further developments after entering the digital age. Through the commercialisation of EEG headsets for applications such as game control and artistic experimentation, products such as NeuroSky, Mindflex, and the device used in this study, the Emotiv EPOC neuroheadset, are finding new roles outside the medical professions.

3 Stimulus Classification with the Emotiv EPOC

In order to test the suitability of the Emotiv EPOC headset as a BCI device with multiple control outputs, an experiment was set up to record EEG signals from three subjects (the authors of this paper). Subjects were shown three different types of visual stimuli and data were collected with an Emotiv EPOC headset. Several classifiers were investigated as will be explained in the following sections.

3.1 Experimental Setup

The three tasks the subjects performed were

- **Neutral**: Watching a white screen for 10 seconds
- **Push**: Watching a blue cube being pushed away from the subject for 5 seconds
- **Pull**: Watching a blue cube being pulled towards the subject for 5 seconds

Screen shots of the cube being pushed and pulled are displayed in Figure 3 and Figure 4. The cube animation starts at the same size and then becomes either larger (Pull) or smaller (Push).

Fig. 3. Animation of the Cube Pull

Fig. 4. Animation of the Cube Push

The following standard protocol was followed when preparing subjects for data collection.

1. Subjects were asked to confirm that they were not feeling any drowsiness or discomfort (such as headaches or pain) prior to conducting the experiment.
2. The Emotiv sensors were moistened with saline drops and connected to the headset.
3. The Emotiv headset was fitted onto the subject. Positioning of the sensors were corrected with the assistance of Emotiv EPOC sensor software until all sensors displayed on the console turned 'green' indicating a strong connection and correct positioning.
4. Subjects sat comfortably in a chair facing a computer screen during the experiment. They were advised to remain in a passive state and not interact with any of the equipment used in the experiment as well as to follow instructions as advised by the experimenter. Subjects were also advised to limit blinking and head movements (whilst undertaking a recording) to reduce the interference of artifacts.

3.2 Data Collection

All data was collected in one sitting for each subject. Detailed below are the steps the experimenter followed to record the EEG signals produced by the subjects undertaking the tasks during the experiment.

Collecting Raw EEG data The headset undertakes sequential sampling at 128 Hz for each sensor with Analog to Digital Conversion of the data. Located in the headset are digital notch filters at 50 Hz and 60 Hz and a built-in digital 5th order sinc filter. The raw data is transmitted in packets via Bluetooth 2.4 GHz band from the neuroheadset to a USB dongle [3]. The protocol followed for the data recording was the same for each subject. The experiment was conducted in a quiet room to reduce the influence of external distractions. Two applications were run during the experiment, the visual stimulus and the EEG signal recording applications.

1. During the experiment subjects were exposed to each of the 3 scenarios. Prior to being shown the scenario, the subject was made aware of the upcoming scenario. As well as this, prior to the display of a scenario, the recording application was prepared by selecting the scenario being recorded as well as selecting the duration to record a signal for (5 seconds or 10 seconds for the neutral scenario).
2. Each scenario was displayed for 7 seconds (or 12 seconds for the neutral scenario) and recording of the EEG signal evoked began approximately 1 second after the start of the stimulus (recording activation was started manually). This was done in order to remove any impulse signals that may be observed in the data as a result of the sudden start of a stimulus.
3. Subject was notified upon the completion of a scenario recording.

4. Multiple recordings for each scenario were made. Recordings were made until subject expressed discomfort from the neuroheadset or until a suitably sized data set was accumulated.

Table 2 displays the total recording duration for each task and subject.

Table 2. Recording Durations

	Subject A	Subject B	Subject C
Neutral	100 sec	100 sec	80 sec
Push	75 sec	100 sec	100 sec
Pull	75 sec	100 sec	100 sec

3.3 Signal Preprocessing and Classification

The processing pipeline for exploiting the trained classifiers was illustrated in Figure 2. The main steps involved for training and testing the different classifiers are described below:

1. **Load Raw EEG Data:** Upon receiving the data packets from the Emotiv headset, all raw EEG data for each subject was extracted via the data recording application and loaded into the Python workspace as a Numpy matrix.
2. **Concatenate Samples:** As was discussed in the experiment setup section, each task was timed for 5 or 10 seconds, and all samples of the same task were concatenated
3. **Extract the 14 EEG Channels:** From these concatenated task data from each subject, information which was not relevant to the study, like the inertial measurement unit (IMU) data, was removed so that only data from the 14 EEG sensors remained. This created a data matrix with 14 columns with each row corresponding to a time sample (at a rate of 128 samples per second).
4. **Preprocessing:** A question of interest of this study was to determine if any preprocessing of data had an impact in improving the classification rate of a signal. We tried principal component analysis and data normalisation (using the mean and standard deviation).
5. **Training and Test Set:** After optional preprocessing, the data was divided into a training set and a test set.
6. **Building Classifier:** Each classifier used in this study was built using the training set. Cross validation of the model was conducted.
7. **Testing:** Once the classifier was trained its performance was evaluated using the test set from Step 5. The generalisation capabilities of the trained classifiers are measured by the percentage of test data points correctly classified.

Linear and non-linear classifiers were trained on the collected datasets. The linear classifiers tested were *linear discriminant analysis*, *logistic regression* and *linear support vector machines.* The non-linear classifiers tested included *k-nearest neighbors*, *decision trees* and *support vector machines* with *Gaussian kernels.*

4 Experimental Results

In this section, we report on the performance of the different classifiers for the classification task of the three stimuli. We also discuss the effect of preprocessing.

4.1 Preprocessing

All classifiers tested benefited from centering and scaling the data to unit variance. All results reported are on the dataset centered and scaled to unit variance. Scaling was essential for the success of non-linear SVM classifiers.

For some noisy datasets, performing principal components analysis (PCA) and projecting the input vectors on the first few principal components that explain a given percentage of the variance of the data can in theory reduce the noise in the data and improve the performance of a classifier. We tried to reduce the dimensionality of the input vectors by projecting them on the first few principal components that explain 95% of the variance of the data, but classifiers trained on this subspace performed worse.

In summary, for our dataset, centering and scaling was beneficial and applied systematically. However, PCA preprocessing did not help.

4.2 Support Vector Machine

There is a parameter C, common to all SVM kernels, that controls how smooth the decision surface between classes is. This parameter trades off misclassification of training examples against the simplicity of the decision surface. The larger C is, the more emphasis is put on classifying all training examples correctly, whereas a smaller C will make the decision surface smoother.

SVM - Linear Kernel Table 3 displays the accuracy results for a SVM with a linear kernel trained on the dataset of Subject B with a 3 fold cross-validation for different values of the regularisation parameter C. From this table, it can be noted that the best accuracy does not exceed 54%. A random classifier would score around 33% because we have three classes. The same procedure was repeated for the other subjects and led to very similar results.

The performance of other classifiers based on linear frontiers like *linear discriminant analysis* and *logistic regression* was slightly worse (around 50%).

Table 3. Subject B - SVM (Linear Kernel)

	C = 0.1	C = 1.0	C = 10	C = 100
Score 1	0.540000	0.538125	0.536250	0.536172
Score 2	0.538516	0.536328	0.538047	0.538125
Score 3	0.536563	0.539609	0.539531	0.539609

SVM - Gaussian Kernel Table 4 displays the accuracy for a SVM with a Gaussian kernel trained on the data of Subject B for different values of the regularisation parameter C. The best choice of C is 1000, giving an accuracy rate of 97%.

Table 4. Subject B - SVM (Gaussian Kernel)

	C = 0.1	C = 1.0	C = 10	C = 100	C = 1000	C = 10000
Score 1	0.754766	0.865313	0.926875	0.959609	0.971354	0.967839
Score 2	0.756406	0.865234	0.930547	0.959297	0.972786	0.969531
Score 3	0.752578	0.863047	0.931016	0.960703	0.969661	0.969141

The experiment was repeated for the other subjects and led to the same choice for C. Gaussian SVM's were then trained for all three subjects with a 10 fold cross validation. The results are presented in Table 5. The average accuracy values were 99.76%, 97.30% and 98.13% for Subject's A, B and C respectively.

Table 5. SVM (RBF Kernel) with C = 1000

	Subject A	Subject B	Subject C
Score 1	0.998125	0.97161458	0.97991071
Score 2	0.996875	0.97473958	0.98158482
Score 3	0.996875	0.9734375	0.98102679
Score 4	0.9990625	0.97395833	0.98214286
Score 5	0.9978125	0.97213542	0.98353795
Score 6	0.99625	0.96953125	0.98074777
Score 7	0.9971875	0.97421875	0.97684152
Score 8	0.9965625	0.97369792	0.98186384
Score 9	0.99875	0.97421875	0.98465402
Score 10	0.998125	0.97239583	0.98074777
Average	0.9975625	0.972995	0.9813058
Standard Deviation	0.0009035	0.0015052	0.00199649

4.3 Decision Tree

The decision trees performed better than the linear classifiers, but not as well as the Gaussian SVM. Pruning the trees, and limiting the size of their leaves did not help significantly. Using a 10 fold cross validation, the accuracy values were on average 97% for Subject A, 84.8% for Subject B and 88.9% for Subject C.

4.4 K-Nearest Neighbors

The best performance was obtained with the conceptually simplest classifier. The idea behind the nearest neighbor method is to find a predefined number k of training samples closest in distance to the unlabeled query point, and predict the most common label of these k neighbors as the class label of the query point.

Table 6 shows the accuracy values of different k-Nearest Neighbors classifiers using 10 fold cross validation. We observed that that $k = 1$ provides the best results.

Table 6. k Nearest Neighbors

	k = 1	k = 3	k = 5	k = 7
Subject A Avg	0.99996875	0.9995625	0.99946875	0.9993125
Subject A Std	9.375e-05	0.0004677	0.0004204	0.0004146
Subject B Avg	0.991432292	0.987526042	0.984375	0.98145833
Subject B Std	0.0011076	0.00131478	0.00159259	0.00145833
Subject C Avg	0.99199218	0.98858817	0.9863560	0.98334263
Subject C Std	0.00088277	0.00143063	0.00265419	0.002260045

5 Discussion

Collecting data and training classifiers can be time consuming. A natural question to ask is whether a classifier trained on one person generalizes well to other people. The answer is unfortunately negative. For example, the SVM classifier built from Subject B data achieved an accuracy of 97% on this person's test data. However when applied to Subject A and Subject C, the accuracy of the same SVM dropped to 26% and 36% respectively. That is, the classifier performed as badly as random guessing. This observation leads to the conclusion that trained classifiers are not transferable between subjects.

In the future, we would like also to assess the suitability of the Emotiv EPOC neuroheadset for classifying mental workloads. Our interest in assessing mental workloads stems from the road transport field where it is consistently shown that high mental workloads (e.g conversation on a mobile phone) distracts drivers and causes crashes. Identifying the most representative objective measures of mental workload whilst driving is a complex and significant area of research in transport as cognitive workload is a function of situation complexity and driving experience [6, 11]. Mental workload influences the driving performance and its measure can be used to tailor BCI based interventions which will reduce crashes related to driver distractions.

6 Conclusion

In this paper, we demonstrated that the Emotiv EPOC neuroheadset which was primarily designed for use in entertainment, market research and neurotherapy, is also suitable for BCI control systems. We showed that using the sensor values of its 14 electrodes, we can train classifiers to discriminate between three mental states with high accuracy. The best results were obtained with a 1-nearest neighbor classifier achieving a generalisation error of less than 1% across all the subjects. Our experiments on the collected EEG data show that non-linear classifiers perform substantially better than linear classifiers with the highest accuracy of a linear classifier being only 54%. In the future, we plan to explore further the capabilities of the device to determine what is the maximum number of classes that can be discriminated at a given level of accuracy. Our preliminary results are encouraging because they show that the difficult classification task of distinguishing between an object moving closer or moving away can be performed with high accuracy.

References

1. Akst, J.: The body electric, 1840s (2014), http://www.the-scientist.com/?articles.view/articleNo/41258/title/The-Body-Electric--1840s/
2. Collura, T.F.: History and Evolution of Electroencephalographic Instruments and Techniques. J. Clin. Neurophysiol. 10(4), 476–504 (1993)
3. Emotiv Systems: Emotiv EPOC / EPOC+ (2014), https://emotiv.com/epoc.php
4. Farwell, L.A., Donchin, E.: Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroen. Clin. Neuro. 70(6), 510–523 (1988)
5. Guneysu, A., Akin, H.L.: An SSVEP based BCI to control a humanoid robot by using portable EEG device. vol. 2013, pp. 6905–6908. IEEE, United States (2013)
6. Hood, D., Joseph, D., Rakotonirainy, A., Sridharan, S., Fookes, C.: Use of Brain Computer Interface to Drive: Preliminary Results. In: Proceedings of the 4th International Conference on Automotive User Interfaces and Interactive Vehicular Applications. pp. 103–106. AutomotiveUI '12, ACM (2012), http://doi.acm.org/10.1145/2390256.2390272
7. Jeannerod, M.: The representing brain: Neural correlates of motor intention and imagery. Behav.Brain Sci. 17(2), 187–202 (1994)
8. Karbowski, K.: Hans Berger (18731941). J. Neurol. 249(8), 1130–1131 (2002)
9. Kennedy, P.R., Bakay, R.A.E., Moore, M.M., Adams, K., Goldwaithe, J.: Direct control of a computer from the human central nervous system. IEEE T. Rehabil. Eng. 8(2), 198–202 (2000)
10. Millett, D.: Hans Berger: From Psychic Energy to the EEG. Perspect. Biol. Med. 44(4), 522–542 (2001)

11. Paxion, J., Galy, E., Berthelon, C.: Mental workload and driving. Front. Psychol. 5, 1344 (2014)
12. Pfurtscheller, G., Neuper, C.: Motor imagery and direct brain-computer communication. P. IEEE 89(7), 1123–1134 (2001)
13. Polich, J.: Updating P300: An integrative theory of P3a and P3b. Clin. Neurophysiol. 118(10), 2128–2148 (2007)
14. Prindle, D.: Thoughts into motion: Amazing brain-controlled devices that are already here (2012), `http://www.digitaltrends.com/cool-tech/brain-control-the-user-interface-of-the-future/`
15. Raajan, N.R., Jayabhavani, G.N.: A smart way to play using brain machine interface (BMI). pp. 1130–1135. IEEE (2013)
16. Sanei, S, C.J.: EEG Signal Processing: Fundamentals of EEG signal processing. John Wiley & Sons Ltd (2007)
17. Schlgl, A., Lee, F., Bischof, H., Pfurtscheller, G.: Characterization of four-class motor imagery EEG data for the BCI-competition 2005. J. Neural. Eng. (2005)
18. Sheth, D., Benbadis, R.: EEG in common epilepsy syndromes (2014), `http://emedicine.medscape.com/article/1138154-overview`
19. Singla, R., Chambayil, B., Khosla, A., Santosh, J.: Comparison of SVM and ANN for classification of eye events in EEG. J. Biomed. Sci. Eng. 4(1), 62–69 (2011)
20. Sutton, S., Braren, M., Zubin, J., John, E.R.: Evoked-Potential Correlates of Stimulus Uncertainty. Science 150(3700), 1187–1188 (1965)
21. Szafir, D.: Non-Invasive BCI through EEG: An Exploration of the Utilization of Electroencephalography to create Thought-Based Brain-Computer Interfaces (2010)
22. Vidal, J.J.: Toward Direct Brain-Computer Communication. Annu. Rev. Biophys. Bio. 2(1), 157–180 (1973)
23. Wiedemann, H.R.: The pioneers of pediatric medicine. Eur. J. Pediatr. 153(10), 705 (1994)
24. Wolpaw, J.R., Birbaumer, N., Heetderks, W.J., McFarland, D.J., Peckham, P.H., Schalk, G., Donchin, E., Quatrano, L.A., Robinson, C.J., Vaughan, T.M.: Brain-computer interface technology: a review of the first international meeting. IEEE T. Rehabil. Eng. 8(2), 164–173 (2000)
25. Wolpaw, J.R., McFarland, D.J., Bizzi, E.: Control of a Two-Dimensional Movement Signal by a Noninvasive Brain-Computer Interface in Humans. P. Natl. Acad. Sci. USA 101(51), 17849–17854 (2004)