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Specificities of ERD lateralization during motion execution

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ABSTRACT

When creating motor imagery brain-computer interfaces (BCI), there is a problem with the accuracy of determining which limb made the movement. The accuracy of the classifiers is no more than 80-85%. In this work, we examined this problem from the point of view of the well-known phenomenon of lateralization during motor movements. Several different algrorithms were used to investigate proportion of contralateralization and ipsilateralization based on event related desynchronization/synchronization (ERD/ERS) calculations using EEG data gathered throughout motor function related experiment.

Keywords: BCI, brain function lateralization, EEG, ERD, KDE

1. INTRODUCTION

Brain-computer interfacing is a technology that uses a non-muscular way to interact with the world.[1,2] The development of brain-computer interfaces is an urgent problem in neuroscience.[3–8] Since decoding brain signals is a complex task, such technologies require high computing power.[6,9–12] That is why these technologies started to emerge only 30 years ago. In recent years, several studies on brain-computer interface (BCI) topics only tend to increase.[13,14] BCI captures the electrical signals directly from the brain and forwards them into electronic devices for further analysis and interpretation. Scientists argue it could potentially become a treatment for people with disabilities and could be used to operate the prostheses.[15–19] It can also be used in an educational environment, as it increases the efficiency of acquiring knowledge.[20–22] One of the fundamental challenges in adopting BCI is the lack of precision of the classifiers (80-85%). That is why a lot of studies on sensorimotor BCI are aimed at solving this problem.[23–27] We hypothesize that this problem is more fundamental than we think and could be linked to the appearance of a spontaneous ipsilateral motor pathway.

In this paper, we investigate the motor pathways using the phenomena of event related desynchronization (ERD) in alpha band. This events in primary motor cortex are commonly considered as the biomarkers of motor function activation.[28,29] We have developed several easily interpretable algorithms for ERD detection to determine occurrences of contralateral and ipsilateral pathways of motor function activation and compared their proportion to accuracy of sensorimotor BCI.

2. METHODS

Experimental procedure: 15 healthy volunteers participated in the experiment. Each of them sat in a comfortable chair in front of the display and performed either right or left-hand clenching, according to the task on the display. Each trial consisted of recording background activity before action during 5 seconds and activity during the action itself during 5 seconds correspondingly. Before the experiment, we recorded rest-state activity for 30 seconds.

EEG data were recorded using a 48-channel NVX-52 amplifier. 32 standard Ag/AgCl electrodes placed according to the international 10-10 system. EEG was digitized with a signal sampling frequency of 1 kHz and filtered in the frequency range 1-70 Hz, and a 50 Hz notch filter was applied. We used independent component analysis (ICA) for eys blinking and heartbeat artifacts removal procedure. The remaining artifacts were removed manually.

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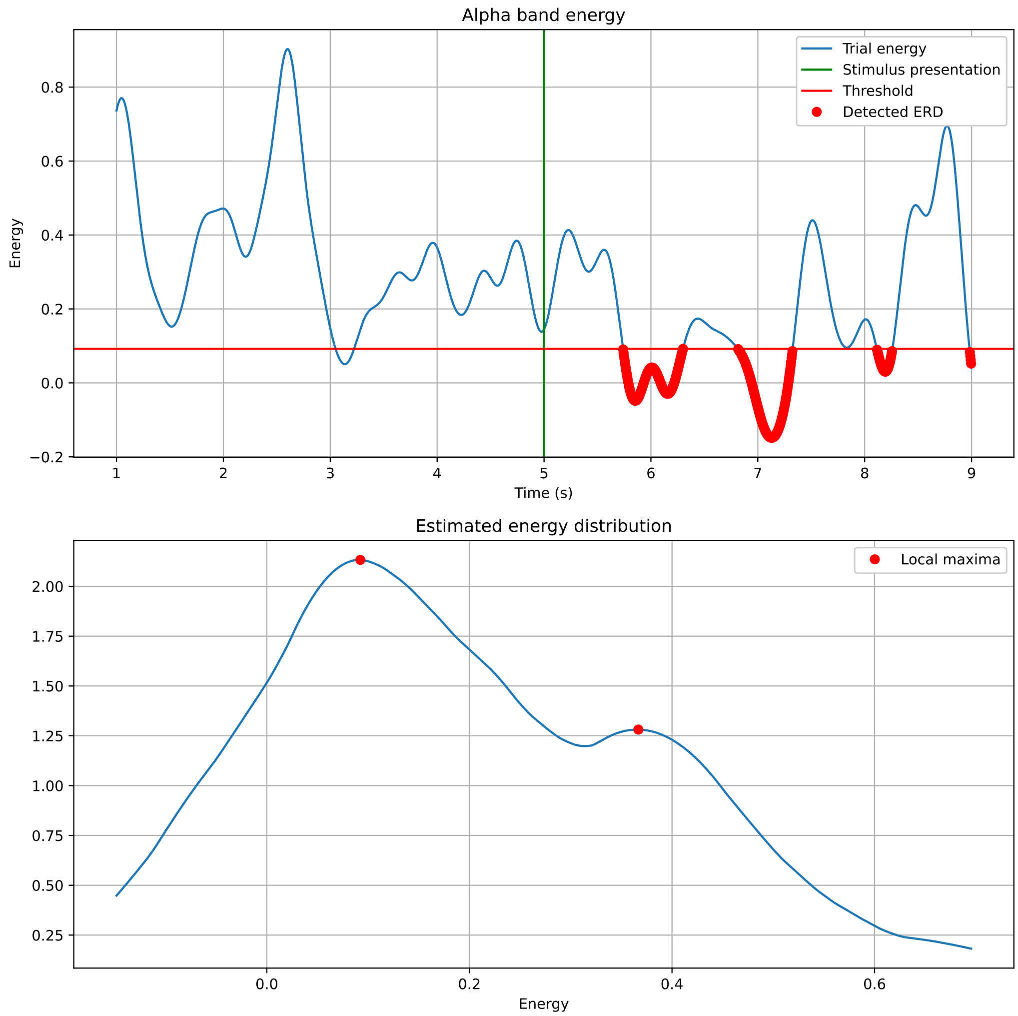


Figure 1: The illustration of KDE algorithm work

Since we were interested in event-related synchronization/desynchronization events, we applied wavelet transform to the raw signal in order to get the time-frequency representation of the signal. We chose wavelet transform over Fourier transform due to higher time-frequency resolution.[30] The number of cycles was sticked to the frequency range. For the frequency-time analysis, we have chosen 8 Hz-14 Hz frequencies, since they cover the alpha band and mu band, in particular. This frequency band always arises in motor function activation studies.[31–33] We calculated mean energy for the selected band and performed percent correction using recorded rest-state data. Our next step was to localize ERD in time and estimate its power.

We have implemented two different algorithms for ERD time localization and estimation of its value. The main idea of the kernel density estimation (KDE) algorithm is adaptive thresholding. To find the needed threshold, we need to accomplish several steps of preprocessing. The essential step is the signal probability distribution function estimation. As the name of the algorithm implies, we used a neighbor-based approach, namely kernel density estimation (KDE).[34] Despite the fact that the most popular kernel for use in KDE is the Gaussian kernel,[35] we rejected it due to the problem with high smoothing. Psychophysiological data occurs to have high variance, therefore we needed a more sensitive tool. Our final choice was Epanechnikov kernel[36] since it is optimal in a mean square error sense.[37] We have manually fine-tuned kernel parameters on different EEG datasets related to motor function activation.

Using the estimated PDF function we were finally able to find a threshold for our signal. To do so, we calculated the local maxima of PDF. The rationale for doing so lies in the idea, that ERD will last longer than random decline caused by fluctuations of the signal. The needed threshold will correspond to the first local maxima of the PDF. This threshold will indicate, which parts of the signal correspond to ERD (Fig. 1). We pick the first appropriate part of the time series, calculate the meantime and value of it. These values will depict ERD for a single trial.

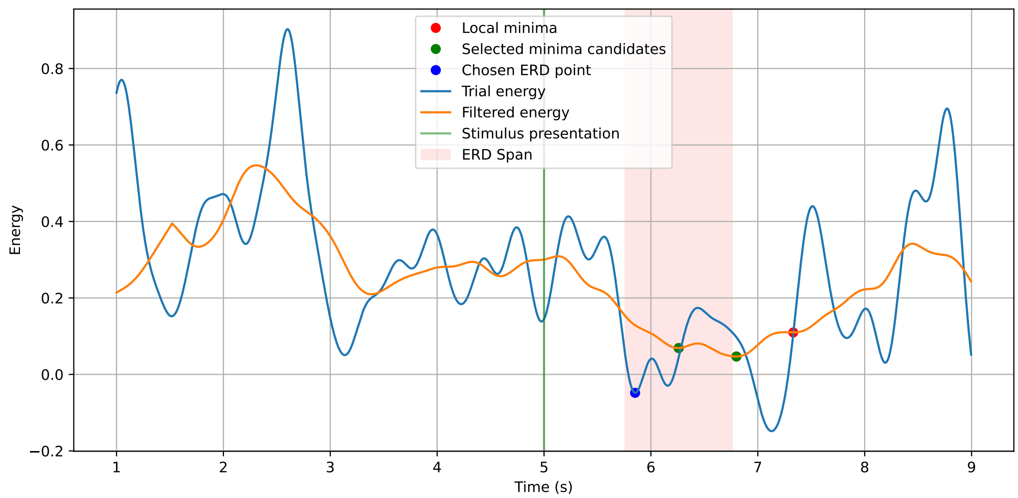


Figure 2: The illustration of local minima algorithm work

The mechanism for the second algorithm is simpler. First, we apply filtering using a forward-moving average to reduce the effect of the high variance of the signal. Second, we find all local minima of the filtered signal. We reject all time points, which were found in the interval of the first 10 ms. Then, we normalize the corresponding values of these points by adding the minimal value of the points. We reject all points, which corresponding values are higher than 0.95 of the mean value of selected points. This step is needed to reduce the false alarm rate and remove candidate points corresponding to random fluctuations. Then, we pick the earliest candidate point and reject others. If there are no more candidate points for ERD, we pick the global minima on the filtered signal. After that step, we search for global minima of the original time series in the time region near the selected candidate point (Fig. 2). The size of the region is defined as 1 s.

Using the algorithms listed above, we were finally able to calculate lateralization proportion. We used ERD estimated value in channels F3, F4 and C3, C4 for premotor and motor areas, respectively (Fig. 3). For each channel pair, a proportion of ERD values was calculated, C4/C3 and F4/F3 for the right hand and vice versa for the left hand. We have initially labeled time series for each channel based on the following condition: if the proportion exceeds 1.05 (5%), the activity during this trial is labeled as low, if the proportion is below 0.95, then it is labeled as high and the corner case we label as middle. Each trial was marked as bilateral if each channel has the same label, or contralateral if the left channel has been labeled as low unlike the right channel (for the right-hand motion, vice versa for the left hand). The corner case was labeled as ipsilateral.

3. RESULTS

Results reveal not such great difference between right and left hand, around 70-80% and 65-75% of contralateral-bilateral activity in right and left hand, correspondingly (Fig. 4). This may explain errors in BCI hand classification. Showed phenomena needs further investigation. Besides that, results strongly depend on introduced algorithms parameters. They require further fine tuning.

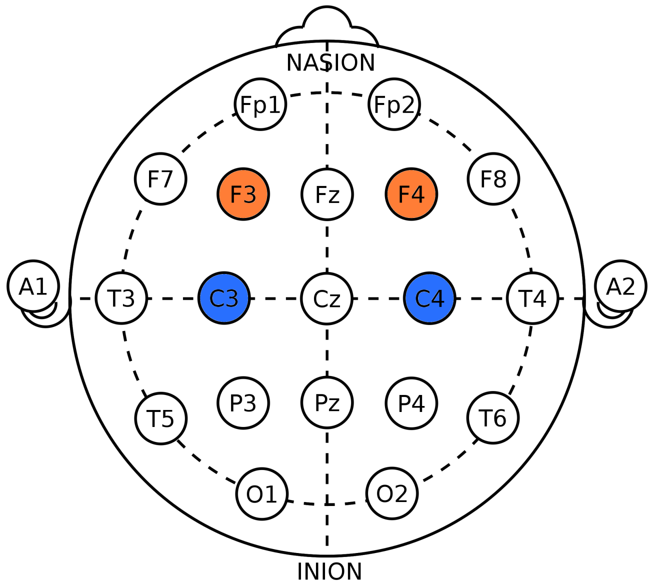
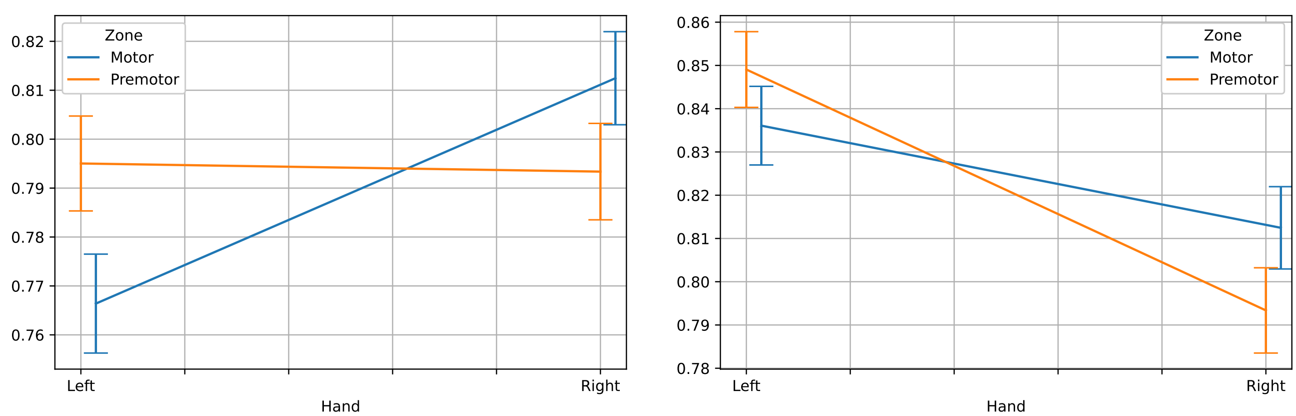


Figure 3: Channel mapping. Orange and blue channels represent premotor and motor area respectively



(a) KDE algorithm results (b) Local minima algorithm results

Figure 4: Proportion of contralateral-bilateral pathways

4. CONCLUSION

Using proposed algorithms we have revealed that the portion of contralateral and bilateral pathways of motor function activation is consistent with BCI classification error. No abnormalities related to lateralization assymetry was found, which is also consistent with the other studies in the field. Based on the results obtained, we can assume that the pattern of motor area activation is inconstant and can vary, which affects the accuracy of the classification. These variations in the patterns may be caused by a deep mechanism of movement execution, which needs further investigation.

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