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Feasibility of using time domain parameters as online therapeutic BCI features

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Abstract

Feature extraction and selection is a major issue in brain computer interfaces. In an electroencephalogram based brain computer interface bandpower features are widely used. Time domain parameters (TDP) are other features which have not been extensively tested in online brain computer interfaces. In this study with eight naive subjects, it is shown that the time domain parameters (TDP) are suitable online features for a motor imagery based therapeutic brain computer interface. ERD/ERS maps were compared between trials selected as motor imagery-active and those rejected when using TDP as features. The ERD/ERS maps of the trials selected with the TDP method show ERD mainly in the 8-12 Hz frequency band on the hemisphere corresponding to the hand the subjects were imagining to move. There were significantly stronger ERDs in the trials that were selected than in those rejected.

1 Introduction

In electroencephalogram (EEG) based brain computer interface (BCI), it is important to extract the appropriate feature suitable for classifying EEG arising from different cognitive tasks. Typically the bandpower features are extracted from the EEG and used in the online classification. These features are easy to compute and require minimum number of EEG electrodes minimizing setup time. This advantage makes the bandpower method suitable especially for therapeutic BCI where setup time must be minimized. The bandpower features are well established and researchers can target physiologically relevant frequency bands when using it as features for therapeutic BCI. However the need to select a user specific narrow frequency bands can be an issue. Firstly because the user specific bands are known to vary for the same user. Secondly due to the uncertainty principle, estimating narrow band spectral powers must be dubious within short time windows.

The time domain parameters (TDP) [2] are features which do not require the selection of narrow frequency bands. In addition TDP target the most time varying EEG features. TDP features have been shown to outperform bandpower [2]. However to be suitable for therapeutic BCI, TDP must be able to select physiologically relevant frequencies despite the use of a wide band filtered signal. Furthermore, the current authors could only find one report [2] on the use of TDP in online BCI; more investigation is required before using TDP on patients.

The aim of this study is to assess the suitability of using TDP for online therapeutic BCI by analysing the time-frequency components of EEG classified into two classes using TDP. It is shown that despite using wide band, TDP target the relevant frequency band.

2 Methods

Eight BCI naive subjects took part in this study after giving their informed consents. The study was approved by the university ethic committee.

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To obtain an initial classifier, a subject performed the motor imagery (MI) of closing and opening of the left and the right hand (20 trials for each hand). During these tasks EEG was recorded, using the g.USBamp (GTEC, Austria) from three pairs of bipolar electrodes, namely Fc3-Cp3, Fcz-Cpz and Fc4-Cp4. The input signal from the amplifier was bandpass filtered (5^{th} order Butterworth) online between 0.5 to 30 Hz. The TDP of the filtered data were computed.

The TDP features were computed in a similar way as that described by Vidaurre and colleagues [2]. This is shown graphically on Figure 1. The feature was used to compute initial

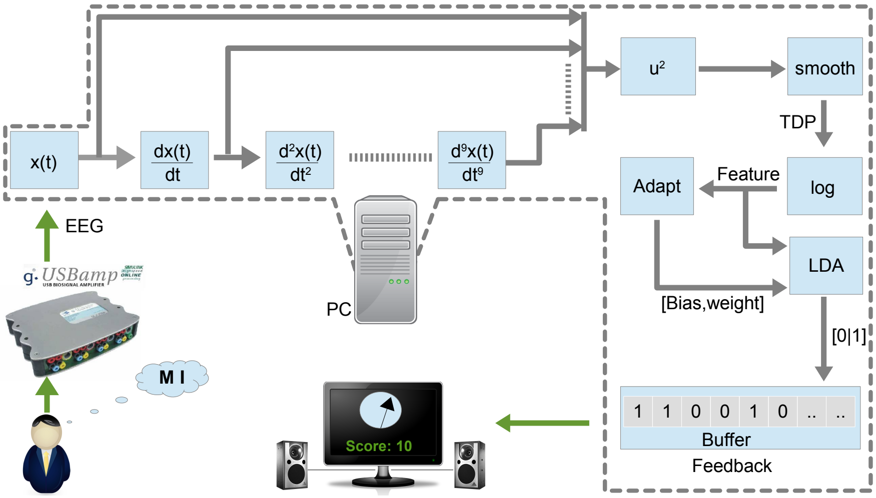

Figure 1: BCI setup showing the computation of TDP

linear discriminant analysis classifier to discriminate right hand movement MI from resting state. This initial classifier was saved for online use. These steps were all integrated into a graphical user interface.

In the online classification, TDP features were estimated using Simulink's difference blocks (see Figure 1). Each sample of the signal in the feature space was binary classified either as an 'Active' or 'Relaxed' state using the initial classifier computed offline. The 'Active' state occurred when the subject attempted opening and closing of the right hand MI while the 'Relaxed' state corresponded to a resting period. The classifier output ('1' or '0' for 'Active' or 'Relaxed' respectively) was then buffered for a variable length of time up to a maximum of 3 s or 768 samples. An 'Active' state was detected when the buffer was filled with a chosen percentage of 'Active' state. The length of the sub-buffer, usually 1.5-2 s long, was determined for the subject and optimized to significantly reduce false positives which was reported by the subject. The difficulty of the BCI was set to 50% determined using the equation, $d = bf/B$, where d is the difficulty, b is the sub-buffer length, B is the maximum buffer length (set to 3 s) and f is the percentage filling of the sub-buffer that activates the 'Active' state. For example when $b = 2s$, f was set to 75%.

The initial classifier was updated online using the fixed rate supervised mean and covariance adaptation methods described elsewhere [1].

In the online BCI there were 30 trials in total divided into three runs of 10 trials each. A trial started at t= -3 s with a cross sign on the screen facing the subject. At t=0 s an execution cue in form of an arrow pointing to the right was shown on the screen and the subject was instructed to perform right hand MI until a text and sound feedback were given. The feedback

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included an acknowledgment text on the screen and a reward sound played to the subject when the 'Active' state was detected. If the 'Active' state was not detected after about 6.5 s following the execution cue onset, a text was shown and a sound was played to reflect the subject's failure for that trial. The subjects were also provided with a continuous feedback in form of a scale that moves counter clockwise when imagery was detected.

Of interest were the time-frequency characteristics of the trials selected as 'Active' state (Detection) and those not selected (No Detection) when using TDP as BCI features. Therefore ERD/ERS analysis was carried out by first separating the trials from all subject and all runs into 'Detection' and 'No Detection' groups. The resulting ERD/ERS maps were compared between the two groups of trials using statistical nonparametric method with Holm's correction for multiple comparisons at p=0.05.

3 Results and discussions

Table 1 shows the initial classifier accuracy, and the detection rate (true positive) per subject. The naive subjects improved the detection rate from run 1 and 2 to run 3 because they got better with experience. No false positive was reported because the subjects were imagining as soon as the execution cue was shown and the false positive was significantly reduced when the BCI difficulty was set.

Subjects	Initial classifier (% accuracy)	% rate (run 1 and 2)	% rate (run 3)
1	83	75	100
2	97	0	30
3	78	10	40
4	75	50	100
5	85	40	90
6	83	50	100
7	83	15	50
8	90	61	47

Table 1: The initial classifier accuracy and detection rate

Figure 2 shows the ERD/ERS maps of the right hand MI when 'Active' state was detected (first column) and when it was not detected (second column). The third column shows in frequency and time the statistical differences between column one and two for each channel. After the onset of the execution cue, ERD could be seen in all three channels suggesting that the subjects were performing MI. Visually inspecting the ERD/ERS shows that there are more ERD for the Detection group than for No Detection group. However the differences in ERD is only statistically significant in channel location Fc3-Cp3 as shown by the shaded area on the first row, third column in Figure 2. This is a desirable result because this channel is on the left hemisphere which represents the right hand which the subjects were imagining to move. The time-frequency statistical differences appears predominantly within the 8-12 Hz frequency range which is the so called μ-band known to show ERD within the motor areas during MI. There are also small differences in the 12 -30 Hz range. It is an interesting result that the physiologically relevant frequency band is more active in the Detection group despite having not selected narrow frequency bands in this range. Despite the No Detection group showing ERD in the low frequency range they were still not selected. It was possible that the μ-band has

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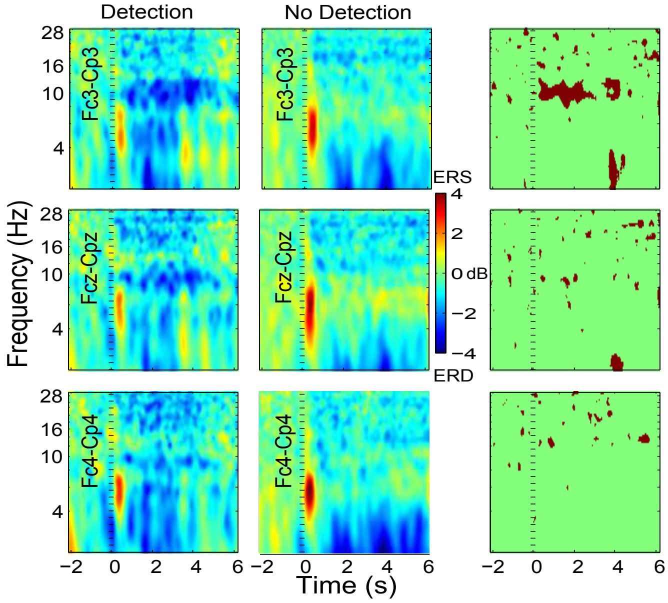

Figure 2: ERD/ERS maps of the right hand MI for when 'Active' state was detected (column 1) and when it was not detected (column 2). The column 3 shows the time-frequency statistical differences between column one and two (p=0.05 with Holm's correction). The execution cue was shown at t=0 ms. (Generated with EEGLAB, http://sccn.ucsd.edu/eeglab).

the most time varying activities during the cognitive tasks making it likely to be selected by the TDP. The statistical difference on Fc3-Cp3 at t=4 s is due to the ERD in the low frequencies in the No Detection group.

There were many failed trials because the subjects were naive, no training was given, they had short time to perform the MI and only 20 trials were used to compute the initial classifier although it was updated online to compensate for the low number of trials. However this is a more realistic BCI as we tend to move it out of the laboratory and also use it in our rehabilitation programmes.

4 Conclusions

TDP eliminates the requirement to select a user specific frequency band allowing for a more generalised BCI classifier. It is easy to compute and require minimum EEG electrodes. The current result shows that TDP features are suitable in online therapeutic BCI because they target the physiologically relevant frequency band.

References

[1] Alois Schlögl, Carmen Vidaurre, and Klaus-Robert Muller. *Brain-Computer Interfaces: Revolutionizing Human-Computer Interaction*, chapter Adaptive Methods in BCI Research An Introductory Tutorial, pages 131–356. Springer, 2010.

[2] Carmen Vidaurre, Nicole Krämer, Benjamin Blankertz, and Alois Schlögl. Time domain parameters as a feature for EEG-based brain–computer interfaces. *Neural Networks*, 22(9):1313–1319, 2009.