Assessing Non-stationarities in BCI data

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Non-stationarities and long-term changes of EEG-data play an important role in real-world BCI applications. We investigate, whether it is possible to separate the changes due to training from other effects. For this purpose, we investigate 1080 trials of a single subject, recorded in 3 sessions á 9 runs.

Introduction:

Nonstationarities and long-term changes can have various origins (e.g. awareness, motivation, environment, but also effects due the BCI feedback etc.) and are not easy to capture. In this work, the non-stationarities are studied in detail.
The short-time changes reflect mostly the class-related differences; almost all BCI-studies report these changes. These short-term changes are well represented by the time-course of the performance measure [1,2]. Fig. 1 displays the time courses of the error rate and the mutual information, reflecting the class-related changes within each trial.

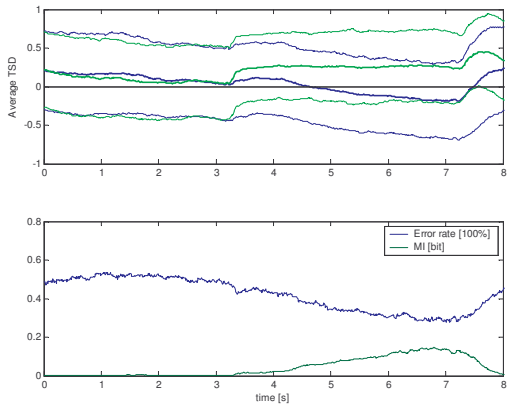

Figure 1: Short-term changes (within one trial). The first subplot shows the average (and standard deviation) of the classification output for both classes. Below are shown the time course of the error rate and the mutual information.

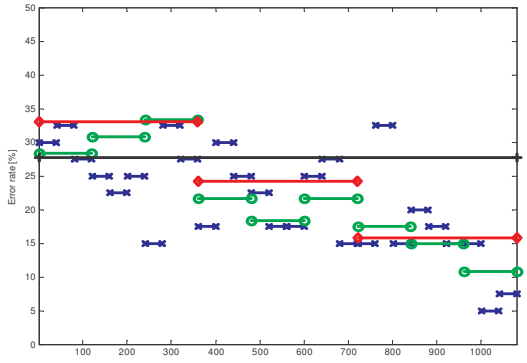

Figure 2: *Error rate of different partitions. Partition results of 27x40 (x, blue), 9x120 (o, green), 3x360 (<>, red) and 1x1080 (+,black) trials are shown.*

Data:

We applied this method to investigate the performance on various recording lengths. 1080 trials (3 sessions á 9 runs á 40 trials) from cue-based BCI data were investigated. These 1080 trials were partitioned into 27 segments with 40 trials each. From each partition, the time-course of the error rate, the mutual information and the kappa coefficients were calculated using AAR(3) parameters of two bipolar channels C3 and C4, Linear Discriminant Analysis (LDA) and a trial-based Leave-One-Out cross-validation was used. BIOSIG (2005) was used for data analysis.

Number of partitions	Trials per partition	Error rate [%] MI [bits]
27	40	21.4 % ± 1.4 0.243 bit ± 0.032
9	120	21.9 %± 2.5 0.266 bit ± 0.072
3	360	24.4 %± 5.0 0.235 bit ± 0.123
1	1080	27.7 % 0.148 bit

Table 1: *Error rate* and *Mutual information of different partitions. On average, the mutual information of short segments is larger.*

Results:

The results show the performance of different partitions of the data. The average performance of the 27 segments was statistically significant better than the classification result using all 1080 trials.

The difference can not solely be explained by the improved separability due to feedback training. Some other non-stationarity must be present.

Discussion and Conclusion:

In summary, a method of testing for non-stationarities has been implemented and applied to BCI data. Several types of non-stationarity name, short-term, long-term due to feedback training and non-specific long-term changes have been observed and quantified.

References:

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Schlögl A., Neuper C. Pfurtscheller G. Estimating the mutual information of an EEG-based Brain-Computer-Interface. *Biomedizinische Technik* 47(1-2): 3-8, 2002
BIOSIG - an open source software library for biomedical signal processing. 2003-2005. available online: http://BIOSIG.SF.NET

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