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It is known that spectral features of the EEG itself and the mutual information between features and condition exhibit a clear time structure during the motor imagery used to control a BCI. Though using this time structure might boost performance, most BCIs use instantaneous classification. Among the few current approaches are time-dependent Neural Nets and Hidden-Markov Models (HMM). We used data from five subjects of which three were from the BCI Competition. We compared HMM performance to a base line of instantaneous classifiers (Linear model and kNN). We also created HMMs with- and without the ability to use the time structure. By comparing these variants of the HMM we describe the temporal nature of data from EEG-based BCI trials. A Flat HMM without time structure resembles a mixture model of Gaussians; a second variant discards information by estimating the observation distributions from all the data rather than from data per movement condition. Here, only the transition probabilities are estimated from disjoint subsets corresponding to conditions. With the limited number of subjects differences between the HMM and base line methods were too small to attain significance. Performance on real data also varied very little between the variants of the HMM. However, difference in performance was highly significant on artificial data with a known time structure. The small differences we found indicate that a HMM is not superior to an instantaneous classifier for this type of data. From the comparison of the performance of HMM variants on real data and on artificial data we conclude that the data is mostly linearly separable, and that the temporal structure in the EEG pattern does not appear to be informative. However, we expect that a modelling approach using HMMs may still have benefits, e.g. in rejecting non task-related brain states.

Time structure of EEG-based cursor control in a brain-computer interface (BCI) using machine-classification methods

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BACKGROUND

- **There is time structure in motor EEG:** Neuper et al. [3] showed time-variance of event-related desynchronization.
- We found time-variant correlation between EEG power difference (C4-C3) and target (L/R) in BCI trials.
- On average a trial exhibits a **non stationarity** (See Fig. 1)
- The time-dependency can also be observed in *single* trials.

➔ If a BCI trial entails pseudo-motor control
...it exhibits a detailed, informative time function
....and HMMs should outperform instantaneous classification.

DATA

- Data comprised 5 subjects, 3 from BCI competition.
- We present results on 2 subjects performing motor imagery to control a cursor on a screen.
- Cursor motion based on mu-power (10Hz) difference between C3 and C4.

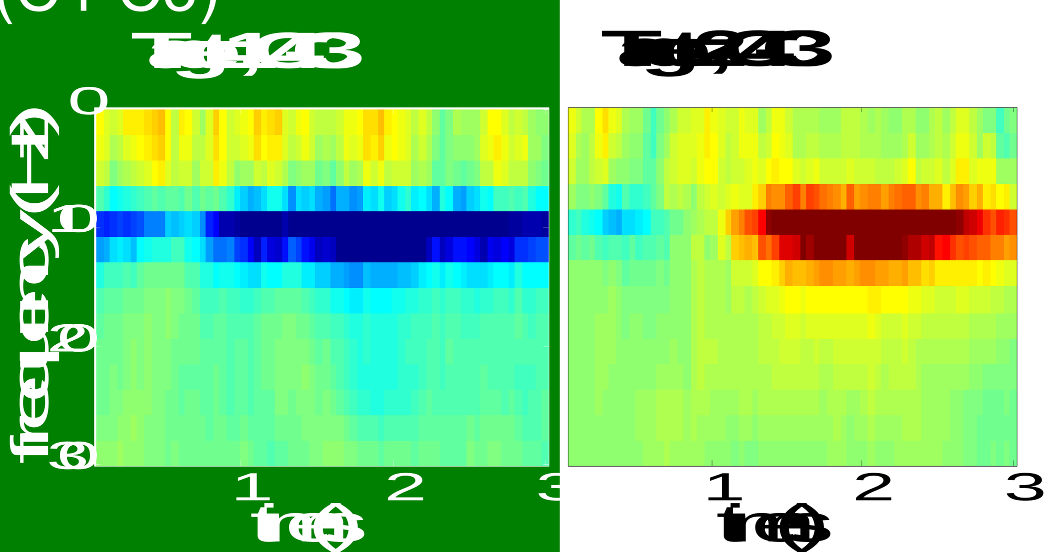

Figure 1. Average difference spectrograms of two conditions. There is a clear time dependency of spectral powers, especially in the mu band (around 10Hz). *n=175 and n=129 for targets 1 and 2 respectively.*

1. Do HMMs outperform instantaneous classification?

- Two **instantaneous** classifiers:
  - k Nearest Neighbours (**kNN**)
  - Linear Model (**LM**)
- **HMM** models time structure as an evolution through discrete states.

- Performance of HMM, LM and kNN compared.
- Difference between methods **not** significant. (See Fig. 2)
- Also: **no effect** of the number of states on HMM performance.

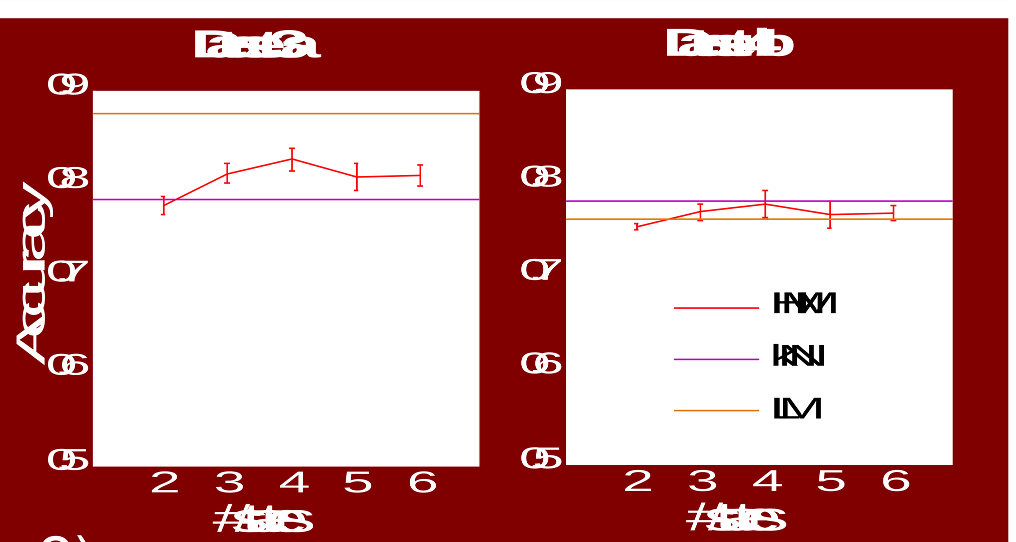

Figure 2. Comparison of performance of HMM and instantaneous classifiers on BCI data of two subjects.

2. Double check: using the HMM for detailed time-structure analysis

- Artificial data: For two conditions (◊, ○)
- Process described by two features evolving through three states
- Three types of time structure (See Fig. 3)

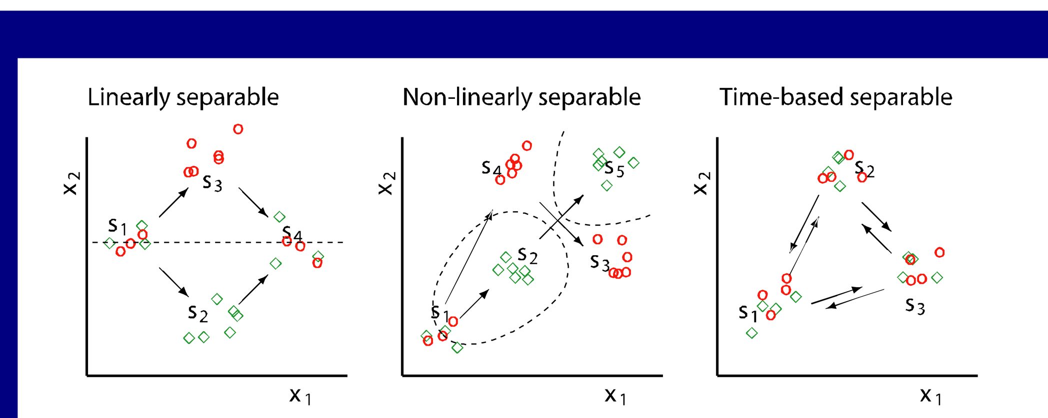

Figure 3. Three different types of time structure in two-dimensional feature space. Arrows indicate transitions between states.

- **FlatHMM** does not use transition matrix, i.e. a Mixture of Gaussians.
  ➔ **no** time information.
- **CSHMM** uses same observation distributions for both conditions.
  ➔ **only** time information.

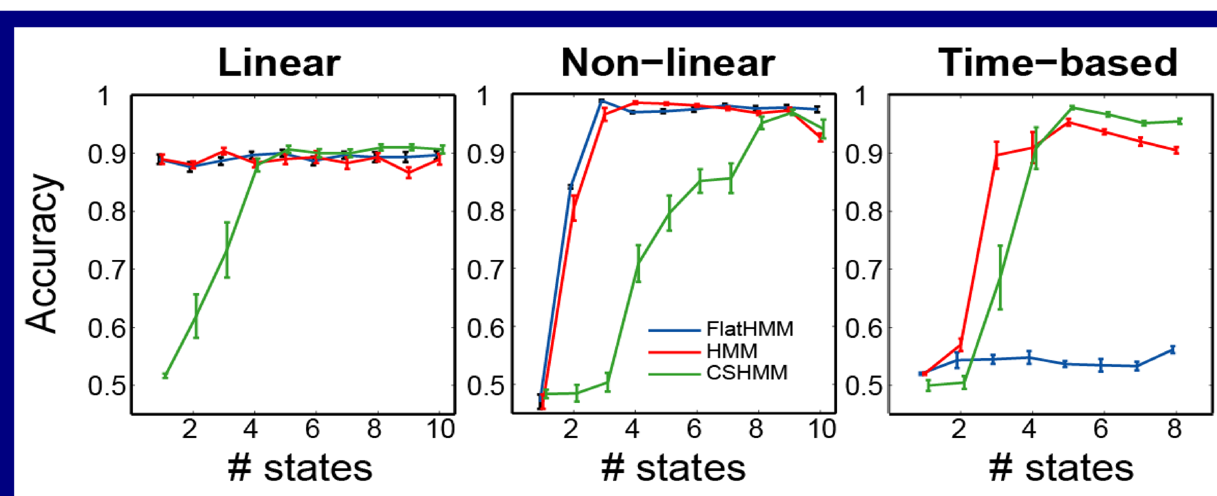

Figure 4. Performance of the three types of models (HMM, FlatHMM & CSHMM) on the three types of time data (linearly-, non-linearly and time-based separable)

- HMMs are **well able** to find time structure in artificial data (See Fig. 4)

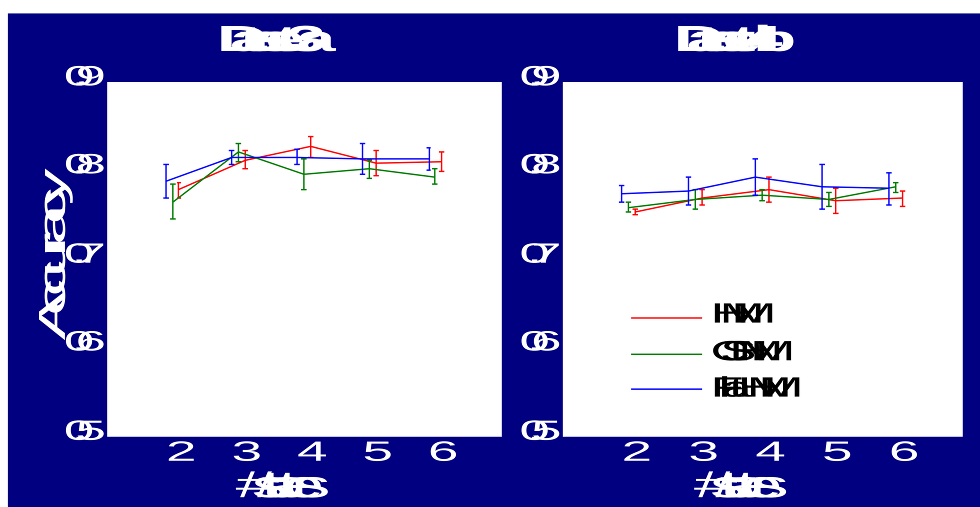

Figure 5. Performance of the three types of models on real BCI data from two subjects. Note the small differences compared to Fig. 4.

- Real EEG data: No difference between models FlatHMM vs CSHMM vs HMM:
  dataset 3a: $F(2, 75) = 2.09$, $p = .13$
  dataset 4b: $F(2, 75) = 2.87$, $p = .06$

CONCLUSION

- **No difference** between instantaneous and time-function based methods (n=2 subjects)
- **But:** more data & more subjects needed!

CONCLUSIONS

- EEG power C3-C4 mu-band power in binary BCI trials is primarily linearly separable (in line with Garrett [4])
- Time structure itself bears no task-relevant information, but there may be waxing and waning (Fig. 1) of decidability.

➔ **Hypothesis:** During these BCI trials there is no pseudo-motor control but modulated observation probabilities of spectral powers: $p(y,t|x)$, $x,y \in \{L,R\}$.

References

[1] A. Schlögl, C. Neuper and G. Pfurtscheller, "Estimating the mutual information of an EEG-based Brain-computer interface" in Biomedizinische Technik vol. 47, pp. 3-8, 2002.

[2] E. Haselsteiner and G. Pfurtscheller, "Using time-dependent neural networks for EEG classification" in *IEEE Transactions on rehabilitation engineering* vol. 8, pp. 457-463, 2000.

[3] C. Neuper and G. Pfurtscheller, "Event-related dynamics of cortical rhythms: frequency-specific features and functional correlates" in *International Journal of Psychophysiology* vol 43, pp.41-58, 2001.

[4] D. Garrett, A. Peterson, C.W. Anderson and M. H. Thaut, "Comparison of linear, nonlinear and feature selection methods for EEG signal classification" in *IEEE Transactions on rehabilitation engineering* vol. 11, pp.141-144, 2003.