THE OXFORD-PUTNEY BCI SYSTEM

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Abstract

Recent BCI research carried out in our groups has focused on two aspects. The main BCI contributions focus on improving standard machine learning approaches by utilizing probabilistic principles. We also design experimental settings which can be used for reliable user-machine communication and user assistance.

Probabilistic models for BCI systems

Probabilistic models can be used to describe many models that have been applied to offline and adaptive BCI systems. Examples are Hidden Markov models, that have been successfully applied to BCI systems ([OGNP01]). Probabilistic models have also been quite popular tools in the machine learning and statistics community. Recently these communities have, in particular, come up with algorithms that allow inference of very complex models. Hence we can benefit from those findings that allow us to extend these classical time series models. We have recently evaluated two such generalizations in the context of BCI systems. Coupled HMM's are generalizations of ordinary HMM's, where two hidden state sequences are probabilistically coupled using arbitrary lags. In ([RGR02]) these models have been applied to movement planning and shown to outperform classical HMM's.

Another modification of HMM's was proposed in [SR02]. Probabilistic principles suggest that classifications based on extracted features have to regard those as *latent variables*. Hence inference and predictions are required to marginalize over this latent space. We applied this model to classification of different cognitive tasks. These experiments have shown that integrating out feature uncertainty significantly outperforms classifications obtained when conditioning on feature estimates.

Probabilistic models can also be used to describe algorithms for adaptive BCI systems. A method which proposes such an approach is shown in [SRS], this workshop. The method uses variational Kalman filtering to infer an adaptive *nonlinear* BCI-classifier. Variational methods are attractive for BCI systems because compared with Laplace approximations (as e.g. used by [PR99]), they allow for more flexibility and, as opposed to particle filters, they still provide a parametric form of the posterior. A parametric form of the posterior is important since it allows efficient implementations. Results with the variational Kalman filter classifier suggest that it significantly outperforms the corresponding offline method. Consequently, our current research direction aims to obtain adaptive methods that implement the ideas we found to be useful for offline BCI systems.

BCI-Applications and experimental issues

We are currently working on two different applications. On one hand we are interested in the classical man machine communication channel. Experiments reported in [CSS + 01] compare the communication bandwidth that can be achieved using different cognitive tasks. It was found that other task pairings result in slightly better correct classification rates as the classical imagined motor task. The main conclusion is that we might significantly increase the bit rate of the BCI system by using more than two cognitive tasks.

Our second project's aim is to develop an immediately effective brain computer interface. Using adaptive inference techniques, we obtain a system that does not require training before the system can be applied. To achieve this we detect and classify *state changes* in the motor cortex areas of the brain which are associated with movement planning. Another major focus of this project is to investigate the effect of different biofeedback mechanisms. As part of this study we look at audio and tactile as well as visual forms of feedback and evaluate the effect on the overall system performance.

References

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