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Uncued Brain-Computer Interfaces: a Variational Hidden Markov Model of Mental State Dynamics

Cédric Gouy-Pailler[1]*, Jérémie Mattout[2], Marco Congedo[1] and Christian Jutten[1]

1- GIPSA-lab - Images and Signal Department - CNRS UMR 5216
Joseph Fourier University - Grenoble Institute of Technology - Stendhal University
Domaine Universitaire, BP 46, 38402 Saint Martin d'Hères Cedex - FRANCE

2- INSERM U821 - Dynamique Cérébrale et Cognition
Institut Fédératif des Neurosciences - Université Lyon 1
Centre Hospitalier Le Vinatier, 95 Boulevard Pinel, 69500 Bron - FRANCE

Abstract. This paper describes a method to improve uncued Brain-Computer Interfaces based on motor imagery. Our algorithm aims at filtering the continuous classifier output by incorporating prior knowledge about the mental state dynamics. On dataset IVb of BCI competition III, we compare the performances of four different methods by combining smoothed probabilities filtered by our algorithm/direct classifier output and static/dynamic classifier. We demonstrate that the combination of our algorithm with a dynamic classifier yields the best results.

1 Introduction

Brain-Computer Interfaces (BCIs) aim at providing people suffering from severe motor diseases with a tool to restore communication and movement [1]. Over the past 15 years, many signal processing methods have been developed for the online extraction of relevant information from different kinds of neurophysiological phenomena. A typical example is motor imagery and its resulting somatotopical and frequency-specific brain signals to control 2-dimensional cursors. Many BCI developments showed and rely on the controlateral mu-power ($\sim 10\,\mathrm{Hz}$) desynchronization in the sensorimotor cortex during motor imagery. Such a signal is typically measured using EEG. However, although high classification rates have been achieved in tightly controlled BCI paradigms, those systems have not yet been successfully applied to large patient populations in order to improve the quality of their living. Indeed, a major limitation of most of these systems lies in the cued motor imagery paradigm they use. The users have to send a command within a precise time interval enforced by the computer. Although that operating mode helps extracting user's intent from the noisy and unspecific EEG activity, they are difficult to use in practice and cognitively very demanding.

In order to promote efficient practical BCI systems, a significant effort is currently devoted to uncued paradigms [2]. Dataset IVb of BCI competition III [3] was proposed to encourage such developments although only one research group submitted a response at that time. Such problems can only be tackled by the careful combination of fine and fast methods for each step of the sequential

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treatments, from real-time acquisition of the EEG up to the estimation of the final command. First, spatial filters have to be used to transform the global and unspecific EEG activity measured by an array of scalp sensors onto local and task-related signals; then since motor imagery tasks are known to involve narrow band frequency-specific modulations of some brain activity, the best relevant features have to be provided to the classifier. Finally, this paper proposes that the output of the classifier can be efficiently filtered using a variational Bayesian Hidden Markov Models to decrease false positive and negative rates. This step involves the definition of prior probabilities about the mental state dynamics.

This short paper is organized as follows. In the first section, the paradigm is briefly described. In the next section, we detail the different steps of our method, including the off-line learning of the parameters and the on-line monitoring of mental states. Another section is dedicated to the quantitative comparison between the dynamic version of our approach (HMM) and static one (direct classifier output). The method and results are discussed in the final section.

2 Experimental Paradigm

We just recall the crucial points of the paradigm. An extended description of the dataset can be found on the BCI competition website[1] (BCI competition III, dataset IVb). This data set was recorded from one healthy subject and contains two sessions without feedback. During the first session, visual cues indicated which of the following 2 motor imageries the subject should perform during 3.5 s: (L) left hand, (F) foot. The presentation of target cues were interleaved by periods of random length, between 1.75 and 2.25 s, in which the subject could relax. In the second session the three classes (Left hand, Foot and Rest) were triggered by acoustic stimuli for 1.5 up to 8 s. The recorded 118 channels were digitized at 1000 Hz, band-pass filtered between 0.05 and 200 Hz, and down-sampled at 100 Hz.

3 Methods

3.1 Off-Line Learning of the Model Parameters

Spatial Filters Common Spatial Patterns by Joint Approximate Diagonalization [4] was performed on the calibration dataset (session 1) to determine efficient spatial filters. The covariance matrices of EEG signals $\mathbf{x}(t) \in \mathbb{R}^N$ ($N = 118$ is the number of EEG channels) associated with class "Left hand" and class "Foot" respectively (from $t = 0$ s to $t = 3.5$ s of each trial) are jointly diagonalized. This procedure yields a set of 118 spatial filters out of which $L = 6$ are selected using an Information Theoretic Feature Extraction algorithm [4]. The number of selected features has been chosen by cross-validation based on the calibration session only. Spatial filters are aggregated into a $N \times L$ matrix W. Filtering signals are given by $\mathbf{s}(t) = W^T\mathbf{x}(t)$.

[1] http://ida.first.fraunhofer.de/projects/bci/competition_iv/desc_1.html

Features Extraction In each trial, the relevant features were taken as the log-energy of the L components of $\mathbf{s}(t)$ in nine different frequency bands (7-9, 9-11,..., 23-25 Hz). The power corresponds to the variance of the 5-order Butterworth filtered signals between $t = 2.5$ s to $t = 3.5$ s as optimized using cross-validation on calibration dataset. This yields $9 \times 6 = 54$ features for each of the 210 trials (105 "Left hand" and 105 "Foot" trials).

Classifier Training Classification is performed using a regularized logistic regression (l_1/l_2 regularization) [5] to estimate a probability of belonging to class "Left hand" or "Foot". We interpret the resulting probability as conditional probabilities of being in class "Left hand" or "Foot" given that the subject is not at rest but indeed intends to send a command. In the following and for simplicity of notations, we omit the ubiquitous conditioning of the probabilities on the actual data segment. By construction, $p(L|A) + p(F|A) = 1$, where A indicates the active state. Cross-validation using the calibration dataset is also used to fix the regularization parameter among a finite set of predefined values.

3.2 On-Line Mental State Monitoring

Testing our approach consists in detecting Left hand and Foot motor imagery from continuous EEG. We insist on the fact that no timing information about the task is known, thus we have to classify successive continuous EEG segments. As segments, we consider overlapping (80 %) windows of 1 s duration. In the absence of any task, segments should be identified as corresponding to a resting period (R). Given a data segment, the above-defined features are extracted after spatial filtering over all channels. Then our two-class classifier applies. Assuming that the subject is being active, it provides us with an estimate of $p(L|A)$ or $p(F|A)$. However, what we are really interested in, since the subject might be at rest, is $p(L)$ or $p(F)$ that relate to $p(A)$ and $p(R)$ by

$$p(R) = 1 - p(A) = 1 - [p(L) + p(F)] \quad . \tag{1}$$

Since $p(L) = p(L, A) = p(L|A).p(A)$ and similarly for $p(F)$, the actual estimated probabilities and the true probabilities of interest are linked by

$$p(L) - p(F) = p(A).\, [p(L|A) - p(F|A)] \quad . \tag{2}$$

Importantly, the final decision should be based on the sign and amplitude of the above difference. Note that if this difference is close to zero, this is either due to close class probabilities (the classifier cannot tell between the two classes, given that the subject is active) or to a high probability that the subject is resting. To distinguish between the active and resting states, another two-class classifier could be used, although the non-active class is difficult to characterize due to a high variability of the EEG signal during rest. In the current study, we consider $p(A)$ as a parameter of the model and denote it as δ. Note that in practice, δ could be set based on our a priori knowledge of the BCI paradigm in use. In other words, given the particular application of the BCI system, one might have a strong prior about the proportion of resting periods, hence δ.

On-line Classifier Updates (Dynamic Classifier) Uncued BCIs suffer from non-stationarities that may come from different reasons (changes in impedance between scalp and electrodes or learning effect by subject). In this paper the adaptive procedure consists in two different steps:

1. the training set size is kept constant but the oldest trials are replaced by newer ones. As the labels of every segments are not known during the test step, the crucial part consists in deciding whether we are sure enough of the cognitive state of the subject to include the segment into the training set. To do so, we model $p(L|A)$ as a beta distribution with shaping parameters recursively updated as a function of $p(L|A)$. This gives theoretical thresholds for $p(L|A)$ and $p(F|A)$ by computing 20-80 quantiles.

2. the classifier is periodically retrained (every 30 s) using the updated training set. This step is made possible in real time because of the computationally efficient logistic regression used in this paper [5].

Variational Mental State Filtering In this paper, we further propose to smooth the estimated mental state dynamics (the estimated posterior class probabilities). This is obtained by incorporating a priori knowledge in a HMM that constrains the state dynamics. The HMM is defined by: (i) a first-order Markov chain on the unobserved discrete variable (the hidden label) l_t, with c possible values ($l_t \in [1..c]$, here $c = 3$); (ii) an observation process in which the labels are observed via a continuous c-dimensional variable $d_t \in \mathbb{I}^c_{(0,1)}$. d_t refers here to the probability of each state at time t. If the state transition matrix T of the Markov process is known, as well as some prior probability densities about each mental state [6], then probability densities $l_t|d_0, \cdots, d_t$ and $l_{t-1}|d_0, \cdots, d_t$ are multinomial densities given below, with shaping parameters α_t and β_t respectively:

$$\left\{ \begin{array}{l} \alpha_t \propto d_t \exp\left(\ln(T^T)\beta_t\right) \\ \beta_t \propto \alpha_{t-1} \exp\left(\ln(T^T)\alpha_t\right) \end{array} \right. , \sum_{i=1}^{c} \alpha_{i,t} = 1 \text{ and } \sum_{i=1}^{c} \beta_{i,t} = 1 \ . \tag{3}$$

By iterating at each time point t the above equations, we can infer the most probable state given the observed/estimated conditional class probabilities and transition matrix: $l_t = \arg\max_{i \in [1..c]} \alpha_{i,t}$.

4 Results

Four different settings are compared in the following. We combine direct classifier output (predicted class is the one with the maximum probability)/predicted mental state l_t given by the HMM with static/dynamic classifier. The transition matrix of the variational filtering is herein imposed by the experimental paradigm timings, namely the windows length and mental states duration. Here we set $T(L,L) = T(F,F) = 0.8$, $T(L,F) = T(F,L) = 0$, $T(R,R) = 0.8$ and $T(L,R) = T(F,R) = 0.2$. As depicted in figure 1, the true and false positive

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rates (TPR and FPR) are used to draw the receiver operating characteristic (ROC) curves, while classification rate shows the performance of the system when the subject is in active state.

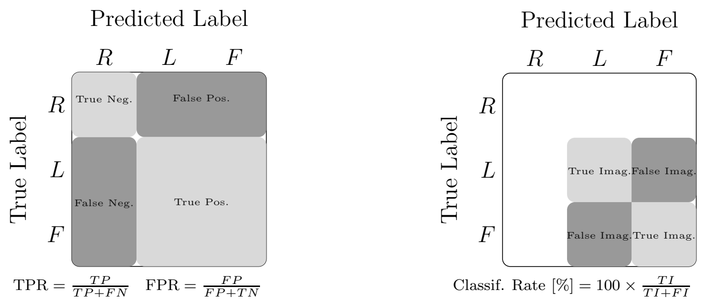

Fig. 1: Performance Measures defined from the confusion matrix.

The performance of the method when varying δ between 0 and 1 are summarized in figure 2.

It can be seen that the use of a static classifier does not result in classification significantly better than chance in case of raw unsmoothed probabilities. The use of vbhmm combined with static classifier yields tiny improvements but is only better than chance for low and high FPR. We observe significant increases of performances by using adaptive versus static classifiers. The combination of vbhmm and the adaptive classifier yields the best results.

5 Discussion and Conclusion

We proposed and demonstrated an original approach to tackle the difficult issue of uncued BCIs. We detailed the steps of this approach, which include spatial filtering, feature extraction in the frequency domain and classification. We quantified the performance of our method and proved that it could be improved by constraining the estimated decisions along time by smoothing the classifier outcome using a Hidden Markov Model of the mental state dynamics. We applied this approach to the continuous control of a 2-dimensional cursor. However, the same methods could apply to another uncued BCI paradigm with different settings that would imply the adjustment of the transition matrix of the HMM and/or an appropriate tuning of the δ parameter. Future directions thus include the development of a principle way to optimize these model parameters based on both the data and prior knowledge of the experimental protocol.

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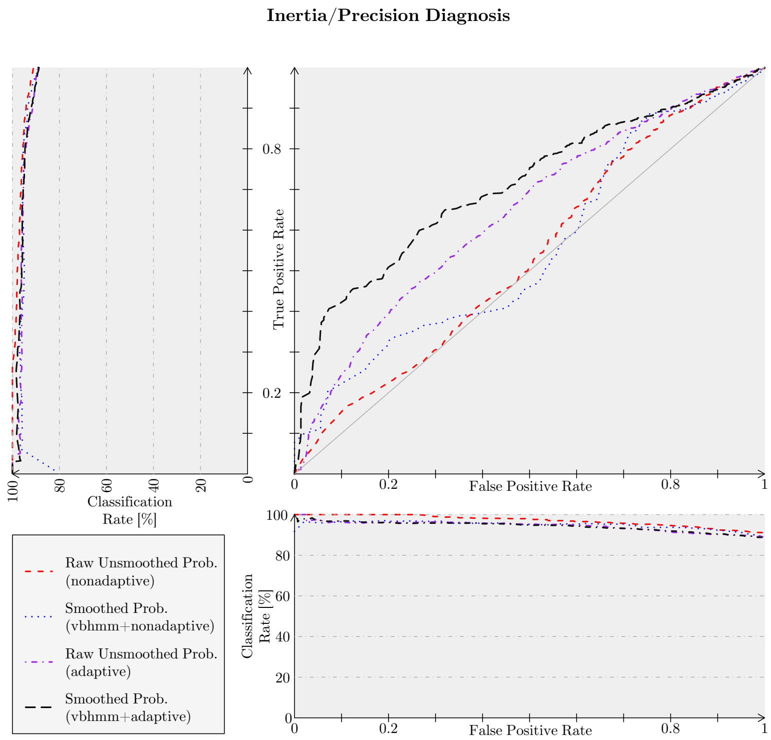

Fig. 2: Inertia/precision diagnosis plot.

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