

AR-PCA-HMM Approach for Sensorimotor Task Classification in EEG-based Brain-Computer Interfaces

Ali Özgür Argunşah*[†]

[†]Champalimaud Neuroscience Programme
at Instituto Gulbenkian de Ciência
Oeiras, Portugal
argunshah@igc.gulbenkian.pt

Müjdat Çetin*

*Faculty of Engineering and Natural Sciences
Sabancı University
İstanbul, Turkey
mccetin@sabanciuniv.edu

Abstract—We propose an approach based on Hidden Markov models (HMMs) combined with principal component analysis (PCA) for classification of four-class single trial motor imagery EEG data for brain computer interfacing (BCI) purposes. We extract autoregressive (AR) parameters from EEG data and use PCA to decrease the number of features for better training of HMMs. We present experimental results demonstrating the improvements provided by our approach over an existing HMM-based EEG single trial classification approach as well as over state-of-the-art classification methods.

Keywords-BCI, EEG, HMM

I. INTRODUCTION

Electroencephalography (EEG) based Brain-Computer Interface (BCI) systems are a new development in the field of applied neurophysiology. These systems are being developed in order to enable people who cannot carry out normal motor functions, such as Amyotrophic Lateral Sclerosis (ALS) and Tetraplegic patients, to control computer based devices.

EEG is a time series signal. EEG-based BCI research is aimed at the development of signal processing and pattern recognition techniques to find specific patterns, for performing particular actions, using features extracted from this time series signal. During the imagining of motor actions, the frequency structure of the EEG signal changes through time [1]–[3]. There are four different motor imagery tasks in the data we have used (see section III-A). A different region in the brain is responsible for each of these tasks. Although, there is a correspondence between recording electrodes and brain regions, it is not one-to-one due to the volume conduction effect of the brain tissues that make the electrical signal spread all over the brain [4].

When a subject does not process a sensory input or produce a motor output, primary sensory or motor cortical areas display a 8-12 Hz activity known as the μ rhythm [1]. The μ rhythm

decreases with movement, preparation of movement or imagination of that movement [3], particularly in contra-lateral areas of the brain to the limb movement. This decrease is called event-related desynchronization (ERD). Similarly increased rhythm is called event related synchronization (ERS) and often appears after movement [3]. Various machine learning algorithms have been used by BCI community such as linear classifiers, neural networks, nonlinear Bayesian classifiers, nearest neighbor classifiers and the combinations of any of the above [5]–[7] to characterize the ERD and ERS patterns recorded during different movement experiments. In this study, using data from different electrodes corresponding to motor imagery related brain regions for different tasks, we have modeled the evolution of the frequency structure of the signal over time using HMMs.

Hidden Markov Models (HMM) are dynamic classifiers used in a variety of fields, most widely in the field of speech recognition [8]. An HMM is a kind of probabilistic automaton that can provide the probability of observing a given sequence of feature vectors. An HMM involves probabilities for transition between the states, as well as conditional probability densities of the observed feature vectors, given the underlying states. HMMs have been applied to the classification of 2-class temporal sequences of BCI features [9], [10] and even to the classification of raw EEG [11]. Although they are not very widespread within the BCI community, they seem as promising classifiers for BCI systems.

In this paper, an HMM-based classifier based on autoregressive (AR) features is used within the context of BCI for the first time. AR features are good frequency estimators however their rather high dimensions are problematic in the learning of the HMM parameters during training. To overcome this problem, we have proposed an approach based on principal component analysis (PCA) to reduce the dimensions of AR features, making them more suitable for HMM classifiers. This is the major technical contribution of this paper. Finally, this study applies HMM-based classification on a 4-class BCI problem for the first time. We evaluate our approach based on the BCI Competition IV-2a dataset, and demonstrate the

This work was supported by the Scientific and Technological Research Council of Turkey under Grant 107E135, by a Turkish Academy of Sciences (TUBA) Distinguished Young Scientist Award and by a TUBA Graduate Fellowship.

improvements it provides over existing techniques (see Table D).

II. AR-PCA-HMM FOR CLASSIFICATION

A. Autoregressive Features

AR parameter estimation is one of the most commonly used techniques to extract frequency related EEG features. The p^{th} order autoregressive (AR) model describes an EEG signal $y_k(t)$ at channel (electrode) k as:

$$y_k(t) = a_{1,k}y(t-1) + a_{2,k}y(t-2) + \dots + a_{p,k}y(t-p) + E(t)$$

Here, $a_{i,k}$ denotes the i^{th} order AR parameter modeling the EEG signal at channel k and $E(t)$ is white noise with zero mean and finite variance. There is a direct correspondence between the AR parameters and the autocorrelation function of the process, and this correspondence can be inverted to determine the parameters from the autocorrelation function using the Yule-Walker equations. We have estimated AR parameters for each EEG channel that we have used for this study using least-squares (LS) estimation. We have calculated parameters for each single trial in overlapping windows. Four EEG channels were used namely C_3, C_4, C_z, P_z . These channels correspond to the electrodes which are likely to provide informative measurements about motor tasks. We have the feature matrix F for each trial after the estimation:

$$F = \begin{bmatrix} a_{1,C_3}(1), & \dots, & a_{1,C_3}(M) \\ \vdots & & \vdots \\ a_{p,C_3}(1), & \dots, & a_{p,C_3}(M) \\ a_{1,C_4}(1), & \dots, & a_{1,C_4}(M) \\ \vdots & & \vdots \\ a_{p,C_4}(1), & \dots, & a_{p,C_4}(M) \\ a_{1,C_z}(1), & \dots, & a_{1,C_z}(M) \\ \vdots & & \vdots \\ a_{p,C_z}(1), & \dots, & a_{p,C_z}(M) \\ a_{1,P_z}(1), & \dots, & a_{1,P_z}(M) \\ \vdots & & \vdots \\ a_{p,P_z}(1), & \dots, & a_{p,P_z}(M) \end{bmatrix}_{4p \times M}$$

Here $a_{i,k}(m)$ is the AR parameter at the m^{th} window and M is the number of overlapping windows. From now on, each column of F will be represented as f_m^c if data are labeled and as f_m if the data are not labeled, where $m \in [1, \dots, M]$ and $c \in [1, \dots, 4]$, with c denoting the class label.

B. Principal Component Analysis

PCA is an orthogonal linear transformation that maps the data into a new space, so called eigenspace, such that the elements of the transformed data are uncorrelated with each other.

Let f_m be the $r = 4p$ dimensional feature vector with zero mean and covariance matrix Σ . Eigenvalues and eigenvectors can be calculated using eigendecomposition:

$$\Lambda_m = W_m \Sigma_m W_m^T$$

where W_m^T is the eigenvector matrix of the covariance matrix Σ_m , and Λ_m is the corresponding diagonal matrix of eigenvalues. These eigenvectors in this case are known as the principal components. Consequently, projection to the eigenspace is achieved by

$$z_m = W_m f_m$$

One can reduce the dimension of the feature vector by ordering eigenvalues and selecting the corresponding first s columns of W_m where $s < r$.

We compute one eigenvector matrix for each overlapping window separately. To do that, first we estimate features for each trial using four electrodes as explained in section II-A. Then, we create the following matrix G_m^n for each overlapping window by concatenating the data from same window of different classes:

$$G_m^n = [f_m^1, \dots, f_m^4]_{4,p \times 4}$$

where $n \in [1, \dots, N]$ denotes the trial number and N corresponds to the total number of trials. For the sake of notational simplicity we ignore the dependence of f_m^c on the trial index n . Then, corresponding features from the corresponding windows of each trial are concatenated:

$$H_m = [G_m^1, \dots, G_m^N]_{4,p \times 4.N}$$

For each overlapping window m , we estimate the covariance matrix of f_m as $\hat{\Sigma}_m = H_m^T H_m$. Then W_m is found as the matrix of eigenvectors of $\hat{\Sigma}_m$.

First s rows ($s < 4p$) of each overlapping window specific W_m matrix is used and represented as W_m^s to calculate each reduced dimensional feature vector, where s is the number of principal components that we want to reduce the dimension to.

$$j_m^c = W_m^s f_m^c$$

Finally, by concatenating the reduced dimensional feature vectors we get the following reduced dimensional feature matrix J_{train}^c for each class:

$$J_{train}^c = [j_1^c, j_2^c, \dots, j_M^c]_{s \times M}$$

We apply the learned matrix W_m^s for dimensionality reduction of unlabeled test data. For each trial the number of features were reduced from $4p \times M$ to $s \times M$. The values of p and s used in the test data for each subject are shown in Table I.

C. Hidden Markov Model Learning

We learn a different HMM for each of the four classes in our problem. We model the conditional probability densities of the reduced dimensional feature vectors given the underlying states with Gaussian mixtures. For each of these models, we consider two sets of parameters to be learned. The first one, which we denote *model-order parameters* includes the number of states (NoS) of the HMM, the number of Gaussian mixtures (NoGM), the AR model order p , and reduced dimension s (see Table I). We denote the second set of parameters as *model parameters* $\lambda_c = \{\mathbf{A}, \mathbf{B}, \mathbf{\Pi}\}$. Here \mathbf{A} is state transition

probabilities, \mathbf{B} is the means and variances of the observation probability distributions and $\mathbf{\Pi}$ is initial state distributions (see [8]). We split the data into three namely \mathbf{F}_{train}^c (40%), $\mathbf{F}_{validation}^c$ (30%), \mathbf{F}_{test} (30%). For a fixed set of model-order parameters, we learn the model parameters based on training data \mathbf{F}_{train}^c using the expectation-maximization (EM) algorithm so that the likelihood of the observed training sequences is locally maximized. We learn the model-order parameters by maximizing the classification performance on validation data $\mathbf{F}_{validation}^c$. We then test our classification approach on test data \mathbf{F}_{test} based on these learned parameters.

III. EXPERIMENTAL RESULTS

A. Experimental Setup and Data

BCI Competition IV-2a dataset consists of EEG data from 9 subjects. The cue-based BCI paradigm consisted of four different motor imagery tasks, namely the imagination of movement of the left hand (class 1), right hand (class 2), both feet (class 3), and tongue (class 4). Two sessions on different days were recorded for each subject. Each session is consist of 6 runs separated by short breaks. One run consists of 48 trials (12 for each of the four possible classes), yielding a total of 288 trials per session.

The subjects were sitting in a comfortable armchair in front of a computer screen. At the beginning of a trial ($t = 0$ s), a fixation cross appeared on the black screen. In addition, a short acoustic warning tone was presented. After two seconds ($t = 2$ s), a cue in the form of an arrow pointing either to the left, right, down or up (corresponding to one of the four classes left hand, right hand, foot or tongue) appeared and stayed on the screen for 1.25s. The subjects were asked to carry out the motor imagery task until the fixation cross disappeared from the screen at $t = 6$ s. A short break followed where the screen was black again. The paradigm is illustrated in Figure 1b.

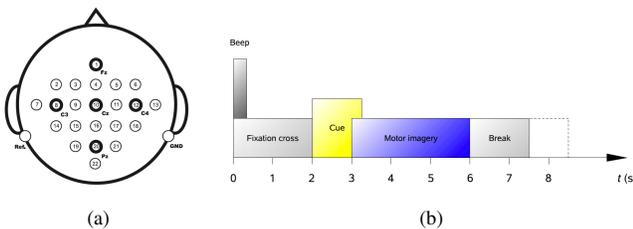


Fig. 1: Electrode Configuration and Timing Scheme

Twenty-two Ag/AgCl electrodes (with inter-electrode distances of 3.5 cm) were used to record the EEG according to the international 10-20 system. All signals were recorded monopolarly with the left mastoid serving as reference and the right mastoid as ground (see Figure 1a). The signals were sampled at 250 Hz and bandpass filtered between 0.5 Hz and 100 Hz. An additional 50 Hz notch filter was enabled to suppress line noise. We have used the first sessions of first 8 of the subjects. These same 8 subjects were also used in [12] and [13].

B. Results

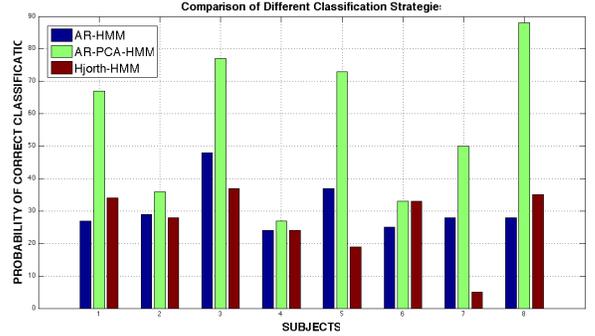


Fig. 2: Performance of the proposed AR-PCA-HMM approach as compared to other HMM-based techniques.

TABLE I: Model-order parameters that gave best probability of correct classification results in validation dataset and used in the test dataset.

Method	Parameters	S1	S2	S3	S4	S5	S6	S7	S8
AR-PCA-HMM	p	14	15	14	14	15	14	15	15
	s	10	8	8	10	10	7	9	8
	NoGM	3	3	3	3	3	2	3	3
	NoS	5	5	5	3	5	5	5	5
AR-HMM	p	9	5	5	8	6	15	13	6
	NoGM	2	1	1	1	2	1	1	3
	NoS	4	2	3	4	1	2	3	3
Hjorth-HMM	NoGM	3	1	3	2	1	1	1	3
	NoS	5	3	1	5	3	1	4	1
AR-Mahal	p	10	8	5	7	9	5	6	9

TABLE II: AR-PCI-HMM vs. State-of-the-art Techniques. $\kappa = (C \times PCC - 1)/(1 - C)$. κ approaches to zero as the PCC approaches to $1/C$ where C is the number of classes.

Feature / Classifier	κ_{mean}	S1	S2	S3	S4	S5	S6	S7	S8
AR-PCA / HMM	.65	.93	.91	.34	.36	.95	.01	.89	.81
FBCSP / Naive Bayes	.57	.68	.42	.75	.48	.40	.27	.77	.75
CSP / LDA-Bayes	.51	.69	.34	.71	.44	.16	.21	.66	.73
CSP / SVM-Voting	.30	.38	.18	.48	.33	.07	.14	.29	.49
CSP / LDA-SVM	.29	.46	.25	.65	.31	.12	.07	.00	.46
CSP / SVM	.28	.41	.17	.39	.25	.06	.16	.34	.45

We show the probability of correct classification (PCC) of our AR-PCA-HMM approach as compared to other HMM-based classifiers including the Hjorth-HMM approach of [14] in Figure 2. For 7 of 8 subjects, our approach achieves the highest PCC. In Table II, we present a comparison of AR-PCA-HMM with the top techniques in BCI Competition IV on this dataset¹, in terms of the κ coefficient. We observe that AR-PCA-HMM achieves the best performance.

¹In our experiments, we have used the first part of the competition data, provided for use in algorithm development.

IV. CONCLUSIONS

In this paper, we have estimated autoregressive (AR) features from EEG data and used principal component analysis (PCA) to decrease the number of features for better training of HMMs to solve the four-class sensory motor EEG-based BCI classification problem. The main idea of the paper was supporting the use of AR features with HMM classifiers for the EEG-based BCI problem.

Results suggest that AR features are better features for HMM based EEG-BCI classifiers and dimension reduction is crucial for EEG classification. Comparison with the state-of-the-art classification methods shows that dynamic structure of the HMMs combined with a good frequency estimator results in better performance than all static classifiers and their combinations.

REFERENCES

- [1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control." *Clin Neurophysiol*, vol. 113, no. 6, pp. 767–791, June 2002. [Online]. Available: <http://view.ncbi.nlm.nih.gov/pubmed/12048038>
- [2] C. Neuper, G. Muller, A. Kubler, N. Birbaumer, and G. Pfurtscheller, "Clinical application of an EEG-based brain computer interface: a case study in a patient with severe motor impairment," *Clinical Neurophysiology*, vol. 114, no. 3, pp. 399–409, March 2003. [Online]. Available: [http://dx.doi.org/10.1016/S1388-2457\(02\)00387-5](http://dx.doi.org/10.1016/S1388-2457(02)00387-5)
- [3] G. Pfurtscheller, C. Neuper, G. Muller, B. Obermaier, G. Krausz, A. Schlogl, R. Scherer, B. Graimann, C. Keinrath, D. Skliris, M. Wortz, G. Supp, and C. Schrank, "Graz-BCI: state of the art and clinical applications," *IEEE Trans. on Neural Systems and Rehab. Eng.*, vol. 11, no. 2, pp. 1–4, June 2003.
- [4] J. Holsheimer and B. Feenstra, "Volume conduction and EEG measurements within the brain: A quantitative approach to the influence of electrical spread on the linear relationship of activity measured at different locations," *Electroencephalography and Clinical Neurophysiology*, vol. 43, no. 1, pp. 52–58, 1977. [Online]. Available: <http://doc.utwente.nl/68036/>
- [5] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain-computer interfaces." *Journal of neural engineering*, vol. 4, no. 2, June 2007. [Online]. Available: <http://view.ncbi.nlm.nih.gov/pubmed/17409472>
- [6] D. McFarland and J. Wolpaw, "Sensorimotor rhythm-based brain-computer interface (BCI): feature selection by regression improves performance," *IEEE Trans. on Neural Systems and Rehab. Eng.*, vol. 13, no. 3, pp. 372–379, Sept. 2005.
- [7] W. D. Penny and S. J. Roberts, "Bayesian methods for autoregressive models," in *Neural Networks for Signal Processing X, 2000. Proceedings of the 2000 IEEE Signal Processing Society Workshop*, vol. 1, 2000.
- [8] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," *Proc IEEE*, pp. 257–286, 1989.
- [9] F. Cincotti, D. Mattia, C. Babiloni, F. Carducci, S. Salinari, L. Bianchi, M. Marciani, and F. Babiloni, "The use of EEG modifications due to motor imagery for brain-computer interfaces," *IEEE Trans. Neural Sys. and Rehab. Eng.*, vol. 11, no. 2, pp. 131–133, June 2003.
- [10] B. Obermaier, C. Guger, C. Neuper, and G. Pfurtscheller, "Hidden Markov models for online classification of single trial EEG data," *Pattern Recogn. Lett.*, vol. 22, no. 12, pp. 1299–1309, 2001.
- [11] S. Solhjoo, A. M. Nasrabadi, and M. Golpayegani, "EEG-based mental task classification in hypnotized and normal subjects," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, Jan. 2005, pp. 2041–2043.
- [12] C. Brunner, R. Scherer, B. Graimann, G. Supp, and G. Pfurtscheller, "Online control of a brain-computer interface using phase synchronization," *IEEE Trans. Biomedical Engineering*, vol. 53, no. 12, pp. 2501–2506, Dec. 2006.
- [13] M. Naeem, C. Brunner, R. Leeb, B. Graimann, and G. Pfurtscheller, "Seperability of four-class motor imagery data using independent components analysis," *Journal of Neural Engineering*, vol. 3, no. 3, pp. 208–216, 2006. [Online]. Available: <http://stacks.iop.org/1741-2552/3/208>
- [14] B. Obermaier, C. Munteanu, A. Rosa, and G. Pfurtscheller, "Asymmetric hemisphere modeling in an offline brain-computer interface," *IEEE Trans. on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 31, no. 4, pp. 536–540, Nov 2001.