Discriminating Mental Tasks Using EEG Represented by AR Models

Charles W. Anderson[1] and Erik A. Stolz[2] and Sanyogita Shamsunder[2]

Abstract—**EEG signals are modeled using single-channel and multi-channel autoregressive (AR) techniques. The coefficients of these models are used to classify EEG data into one of two classes corresponding to the mental task the subjects are performing. A neural network is trained to perform the classification. When applying a trained network to test data, we find that the multivariate AR representation performs slightly better, resulting in an average classification accuracy of about 91%.**

I. Introduction and Background

If different mental states can be reliably detected solely on the basis of EEG, then a new means of communication for paralyzed persons can be developed with which, for example, a wheelchair could be controlled. This difficult pattern recognition problem is primarily one finding a signal representation that captures information related to the mental state of a person in a way that is invariant to time and subject.

This paper describes the results of experiments that were performed as part of a larger project in which a wide variety of EEG signal representations are being tested. Each is applied to EEG data obtained from recordings of subjects performing several mental tasks. Representations are evaluated according to how well the EEG samples can be classified as examples of the correct mental task.

Univariate (scalar) and multivariate (MV) AR models were used to extract the features of our AR representations. Various features based on this model were classified with a feedforward neural network using the backpropagation training algorithm. Discrimination was performed between a single pair of tasks. It was found that multivariate AR coefficient features resulted in the best classification percentages when averaged over all subjects.

Single channel recordings are somewhat typical of psychiatric and sleep research, because there are noticeable changes in brainwave activity during a seizure, for example, and the different stages of sleep. For other problems, however, the multi-channel EEG must be recorded because single-channel brainwaves do not provide enough information to be used alone. One must look at activity distributed over the entire scalp in order to detect brain state changes. To date, very little work has been performed regarding multivariate models of multi-channel EEG data. However, a few researchers have studied multivariate AR models applied to other areas of EEG research, such as psychiatric disorders [1], synchronization [2], and spatial smoothing of EEG [3].

II. Modeling and Classification

Subjects were seated in a sound controlled booth with dim lighting. Six electrode positions were recorded using an Electro-Cap elastic electrode cap: C3, C4, O1, O2, P3, and P4 according to the 10-20 system of electrode placement [4]. The signals were filtered to 0.1 - 100 Hz. Data was recorded for 10 seconds during each task and each task was repeated five times per session. Most subjects attended two such sessions recorded on separate weeks. Repeating the tasks several times on different occasions gives a measure of intra-subject variability.

For this paper we analyzed the data from four subjects, each performing two tasks: the *Baseline Task*, for which the subjects were not asked to perform a specific mental task, but to simply relax as much as possible, and the *Math Task*, for which the subjects were given nontrivial multiplication problems, such as 49 times 78, and were asked to solve them without vocalizing or making any other physical movements.

The scalar AR model coefficients were extracted from the six channels using the Burg method [5]. The multivariate AR model coefficient matrices from all six channels were calculated using a multivariate extension of the Levinson algorithm [6]. Although AIC yielded an order of two [7], a sixth order AR was used; a previous study [8] with similar data resulted in good performance using a scalar AR model of order six.

The neural network classifier is trained using standard error backpropagation. We only considered networks with a single hidden layer, but varied the number of hidden units. Cross-validation was used to control for the overfitting in the following way. The data was divided into ten partitions and eight parts were randomly chosen to train the network classifier and the remaining ninth and tenth parts were designated as validation and test sets. After each epoch, or pass through the training data, the squared error on the ninth part was calculated. After the network had converged, the network's weights at the epoch having the lowest validation set error were saved. The generalization ability of this network was tested by calculating

[1]Dept. of Computer Science, Colorado State University, Fort Collins, CO 80523, anderson@cs.colostate.edu
[2]Dept. of Electrical Engineering, Colorado State University, Fort Collins, CO 80523

	Number of Hidden Units		
	1	2	5
Subject 1	93.4 $\pm$ 1.5	93.6 $\pm$ 1.5	93.6 $\pm$ 1.5
Subject 2	96.7 $\pm$ 1.7	96.7 $\pm$ 1.6	96.1 $\pm$ 1.7
Subject 3	80.9 $\pm$ 2.5	80.7 $\pm$ 2.6	82.5 $\pm$ 2.6
Subject 4	91.0 $\pm$ 2.0	91.0 $\pm$ 2.0	90.0 $\pm$ 2.1
Average	90.5 $\pm$ 1.9	90.5 $\pm$ 1.9	90.6 $\pm$ 2.0

Table 1: % Correct Using Scalar AR Coefficients

	Number of Hidden Units		
	1	2	5
Subject 1	87.4 $\pm$ 1.8	87.7 $\pm$ 1.9	88.3 $\pm$ 1.9
Subject 2	93.9 $\pm$ 2.7	94.2 $\pm$ 2.4	94.2 $\pm$ 2.3
Subject 3	85.4 $\pm$ 1.3	86.0 $\pm$ 1.4	87.0 $\pm$ 1.7
Subject 4	95.8 $\pm$ 1.5	96.3 $\pm$ 1.3	96.2 $\pm$ 1.3
Average	90.6 $\pm$ 1.8	91.1 $\pm$ 1.8	91.4 $\pm$ 1.8

Table 2: % Correct Using MV AR Coefficients

the error on the test set. Thus, 90% of the data was used to train the network and select the best network weights, while 10% of the data was used to test the performance.

III. Results

AR coefficients were estimated for all one second windows (256 points), overlapping by 1/2 s. and not including any which run through an eye blink. The classification results are given in Table 1 for various numbers of hidden units. The results were averaged over 30 runs, each run with different combinations of train, test, and validate sets. The total number of feature vectors for each subject was about 300, except subject 2 which had about half this amount. The validate and test sets each contained 10% of the total number of feature vectors, with the rest in the training set. Shown alongside the classification rates are the 90% confidence intervals. One can see that a net with one hidden unit in the hidden layer does almost as well or the same as the others, although the difference is very small. This suggests that our feature sets are approximately linearly separable. For all subjects except subject 3, the classification percentages are above 90%. Subject 3 features classify at least 10% worse than the other subjects. Overall, an average of 90.6% classification is achieved across all subjects using five hidden units in the neural net.

The next classification experiment involved training the neural net on the multivariate AR coefficients. A sixth order model and six channels results in a feature vector of size 216. As before, the network was trained and tested using various numbers of hidden units. The results are given in Table 2. The results are more consistent here with subject 3 having the worst classification percentage at 87.0% and subject 4 having the best at 96.2% using five hidden units. Averaging over all subjects we find a classification rate of 91.4% with five hidden units. The percentages are the best with five hidden units which may indicate that there is some non-linearity in the decision region. However, the differences are still very small and not statistically significant.

Looking at the subjects individually, subject 3 has the worst results over all experiments. On the other hand, subjects 2 and 4 perform consistently over 90% for all experiments. One can see when looking at the averages across subjects that the multivariate AR coefficients give the best classification accuracies at 91.4%, but not by much.

IV. Discussion

These results indicate that the difference in performance among the various representations is not that great. However, if in the future many subjects are to be tested and computation time is an issue, the scalar AR coefficients appear to be the best choice. If a single subject is to be studied, a variety of representations should be implemented to find the one which gives the best results.

To improve our results, we are investigating the effect of averaging the output of the classifier over consecutive windows. Another possible way of improving the results is to downsample the data prior to estimating the AR models in order to capture longer time dependencies. Increasing the number of channels to the 19 given by the 10/20 system might also dramatically improve the results, since more areas of the brain are most certainly involved in the execution of these tasks than the central, parietal, and occipital regions.

Acknowledgments

The work of the first two authors was supported by the National Science Foundation through grant IRI-9202100.

References

[1] A.C. Tsoi, D.S.C. So, and A. Sergejew, "Classification of Electroencephalogram Using Artificial Neural Networks," *Neural Information Processing Systems 6,* pp. 1151-1158, 1994.

[2] P.J. Franaszczuk,K.J. Blinowska, and M. Kowalczyk, "The Application of Parametric Multichannel Spectral Estimates in the Study of Electrical Brain Activity," *Biological Cybernetics,* vol. 51, pp. 239-247, 1985.

[3] J.C. Jimenez, R. Biscay, and O. Montoto, "Modeling the Electroencephalogram By Means of Spatial Spline Smoothing and Temporal Autoregression," *Biological Cybernetics,* vol. 72, pp. 249-259, 1995.

[4] H. Jasper, "The Ten Twenty Electrode System of the International Federation," *Electroencephalography and Clinical Neurophysiology,* vol. 10, pp. 371-375, 1958.

[5] S.M Kay, *Modern Spectral Estimation: Theory and Application,* Prentice-Hall, 1988.

[6] M.B. Priestly, *Spectral Analysis and Time Series,* Academic Press, 1981.

[7] Erik A. Stolz, "Multivariate Autoregressive Models for Classification of Spontaneous Electroencephalogram During Mental Tasks", MS Thesis, Dept. of EE, CSU, Fort Collins, CO, 80523, May, 1995.

[8] Z.A. Keirn and J.I. Aunon, "A New Mode of Communication Between Man and His Surroundings," *IEEE Transactions on Biomedical Engineering,* vol. 37, no. 12, pp. 1209-1214, 1990.