 DOI:10.3217/978-3-85125-260-6-148

A Stimulus-Free Brain-Computer Interface Using Mental Tasks and Echo State Networks

E. Forney[1], C. Anderson[1], W. Gavin[2,3,4], P. Davies[3]

[1]*Department of Computer Science;* [2]*Department of Human Development and Family Studies;*
[3]*Department of Occupational Therapy, Colorado State University, Fort Collins, CO, USA;*
[4]*Institute of Language Brain & Behavior, University of Canterbury, Christchurch, NZ*

Correspondence: Elliott Forney, Colorado State University, 1873 Campus Delivery, Fort Collins, CO 80523, USA.
E-mail: idfah@cs.colostate.edu

Abstract. We propose an EEG classification algorithm for the mental task BCI paradigm that uses Echo State Networks (ESN). In this approach, ESN are used to model the dynamics of EEG during each of several mental tasks. Classification is performed by applying several of these models and assigning the class label associated with the ESN that produces the lowest forecasting error. Experiments performed on 14 subjects using a portable EEG system achieve information transfer rates as high as 15 bits-per-minute with four tasks and 21 bits-per-minute for two tasks.

Keywords: Brain-Computer Interface, Electroencephalography, Recurrent Neural Network, Echo State Network, Mental Task

1. Introduction

The mental task paradigm for operating brain-computer interfaces (BCI) allows a user to issue instructions to the system by performing one of several predetermined mental tasks [Keirn and Aunon, 1990]. For example, a user might silently sing a song to move a cursor to the left or visualize a geometric figure to move it to the right. This approach does not require external stimuli and may yield discriminable signals with high degrees of freedom. When combined with user practice and machine learning, we believe that this approach may yield fluid, second-nature control.

In previous work, we proposed a generative EEG classification algorithm for use with the mental task paradigm that uses Recurrent Artificial Neural Networks [Forney and Anderson, 2011; Forney, 2011]. Here, we extend this work to use a fast and powerful recurrent network architecture known as Echo State Networks (ESN) [Jaeger, 2003]. We then explore the performance of this system on data recorded in a controlled laboratory environment as well as in home environments with users that have severe motor impairments.

2. Modeling and Forecasting EEG Signals

First, we show that ESN are capable of accurately modeling EEG signals. This is done by training an ESN to forecast an EEG signal a single step ahead in time given only the current signal value as input. When applied to an 8-channel EEG signal with a sampling frequency of 256 Hz and a bandwidth of 4–100 Hz, this technique achieves a root-mean squared error as low as 7 % of the signal range.

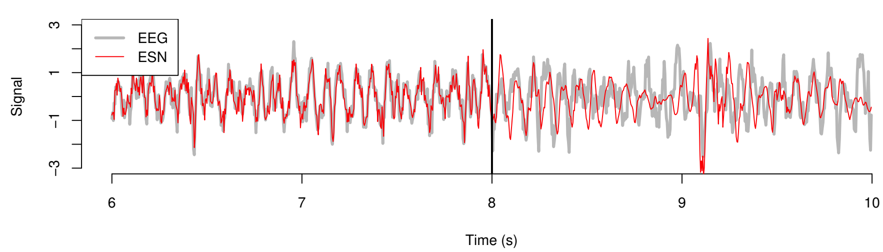

Figure 1: *A trace illustrating an ESN transitioning from forecasting to an iterated model at the 8-second mark.*

To further support our claim that ESN are able to capture the dynamics of EEG, we also explore iterated models. In this approach, a feedback loop is placed from the outputs to the inputs of a trained ESN so that it autonomously produces artificial signals. In Fig. 1, we see the transition from forecasting, before the 8-second mark, to an autonomous signal, after the 8-second mark. These autonomous signals have rich dynamics that are not clearly periodic. A spectral analysis confirms that they contain transient frequencies generally matching those in the underlying EEG.

3. Classification of Mental Tasks

Next, we use the models described in the previous section to construct a generative classifier. This is done by training a separate ESN to forecast sample EEG recorded during each mental task. We then have an ESN associated with each mental task that can be viewed as an expert at modeling the corresponding EEG. Previously unseen EEG is labeled by applying each ESN and selecting the class label associated with the model that produced the lowest forecasting error.

Table 1: *Subjects without impairments in our lab.*

	2-Tasks		4-Tasks	
Subject	CA (%)	IT (bpm)	CA (%)	IT (bpm)
01	85.00	11.70	62.50	13.54
02	80.00	8.34	42.50	3.15
03	90.00	15.93	55.00	8.82
04	95.00	21.41	65.00	15.34
05	65.00	1.98	45.00	4.06
06	95.00	21.41	62.50	13.54
07	70.00	3.56	40.00	2.34
08	95.00	21.41	62.50	13.54
09	75.00	5.66	53.13	7.79
Mean	83.33	12.38	54.24	9.12

Table 2: *Subjects with impairments in their homes.*

	2-Tasks		4-Tasks	
Subject	CA (%)	IT (bpm)	CA (%)	IT (bpm)
10	40.00	0.00	27.50	0.07
11	70.00	3.56	55.00	8.82
12	50.00	0.00	15.00	0.00
13	87.50	13.69	56.25	9.54
14	60.00	0.87	37.50	1.65
Mean	61.50	3.63	38.25	4.02

Finally, we evaluate our classifier on EEG recorded from 14 subjects using g.tec's portable g.MOBILab+/g.GAMMAsys with eight active electrodes. Nine subjects had no disabilities and recording took place in a laboratory. Five subjects had severe motor impairments and recording took place in their homes. Following cues on a computer screen, each subject performed four mental tasks: *silently count backward from 100 by 3s, imagine left hand clenching, visualize a rotating cube and silently sing a song*. Five repetitions lasting 10 seconds were recorded for each task totaling 200 seconds of EEG per subject. The data was split 60/40 into training and test partitions and all parameters were tuned using cross-validation over the training partition. We first classify all four mental tasks and then only the two tasks with the best validation performance. Class labels are assigned at two-second intervals. We measure classification accuracy (CA) in percent correct as well as information transfer rate (IT) in bits-per-minute (bpm).

In Table 1 and Table 2 we summarize the final test results of these experiments. Many subjects outperform the random CA of 50 % for two tasks or 25 % for four tasks. Performance varies greatly, however, with some subjects achieving IT as high as 21.41 bpm and others achieving an IT of zero. A comparison of mean classification accuracy using t-tests with pooled variance also suggests significantly higher performance among subjects without disabilities in the laboratory than among those with disabilities in their homes ($p_{\text{2-task}} = 0.017, p_{\text{4-task}} = 0.047$).

4. Discussion

We have introduced a BCI that uses ESN to classify EEG in the mental tasks paradigm. Using this approach, we have observed information transfer rates that are competitive with the state-of-the-art. However, the modest classification accuracies obtained suggest that further refinements may be necessary for interactive use.

Acknowledgments

This work was partially funded by The National Science Foundation, Grant Number 1065513.

References

Forney, E. (2011). Electroencephalogram classification by forecasting with recurrent neural networks. Master's thesis, Department of Computer Science, Colorado State University, Fort Collins, CO.

Forney, E. and Anderson, C. (2011). Classification of eeg during imagined mental tasks by forecasting with elman recurrent neural networks. *Int Joint Conf Neural Net (IJCNN)*, pages 2749–2755.

Jaeger, H. (2003). Adaptive nonlinear system identification with echo state networks. In *Advances in Neural Information Processing Systems (Proceedings of NIPS 15)*, volume 15, pages 593–600. MIT Press.

Keirn, Z. and Aunon, J. (1990). A new mode of communication between man and his surroundings. *IEEE Trans Biomed Eng*, 37(12):1209–1214.