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Non-Invasive Brain-Computer Interfaces using Echo State Networks

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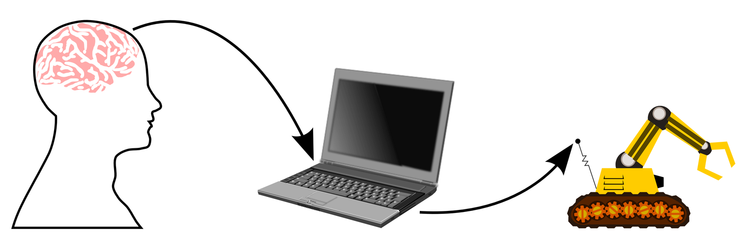
Non-Invasive Brain-Computer Interfaces

Brain-Computer Interfaces (BCI) are devices that allow users to control computer systems by voluntarily altering their mental state.



Non-Invasive BCI typically use Electroencephalography (EEG) to monitor brain activity while a machine learning algorithm identifies the user's mental state by searching for patterns in the EEG signals.

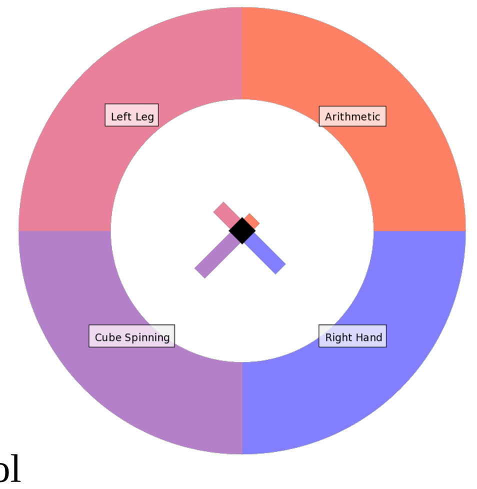
Since BCI bypass the motor-based mechanisms that ordinarily drive human communication, they are of interest to those afflicted with severe motor impairments such as quadriplegia and locked-in syndrome.

BCI may eventually be used in everyday human-computer interaction.

We propose a method for constructing BCI that uses Echo State Networks to forecast and ultimately classify spontaneous EEG signals produced during several imagined mental tasks.

Controlling BCI with Imagined Mental Tasks

In the present work, we are investigating BCI that users control by performing one of several predetermined mental tasks.



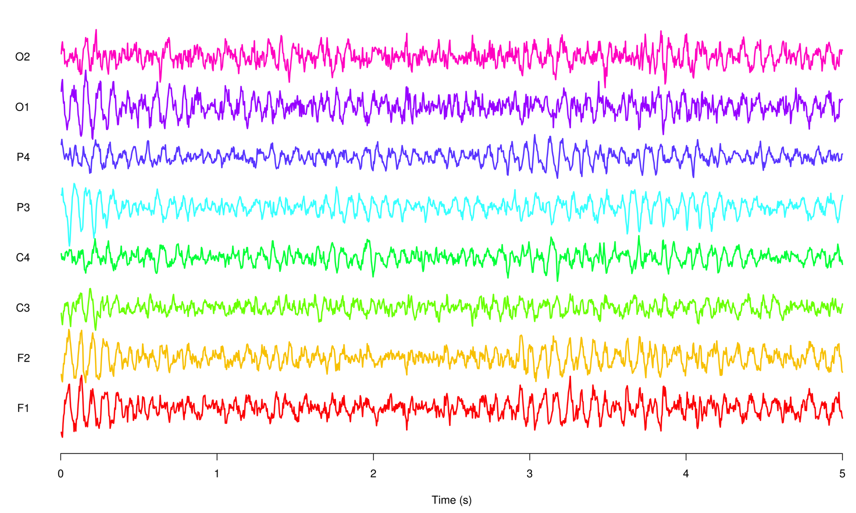
For example, a user may silently sing a song to move a computer cursor to the left or silently count backward to move the cursor to the right.

Unlike many other BCI approaches, using imagined mental tasks does not require external stimuli.

We believe that this approach may eventually allow fluid, continuous control that is second nature for experienced users.

Participants and Data Collection

Data was collected from 14 participants for offline analysis at a later time.



Nine participants had no known medical conditions or motor impairments and recording took place in a laboratory environment.

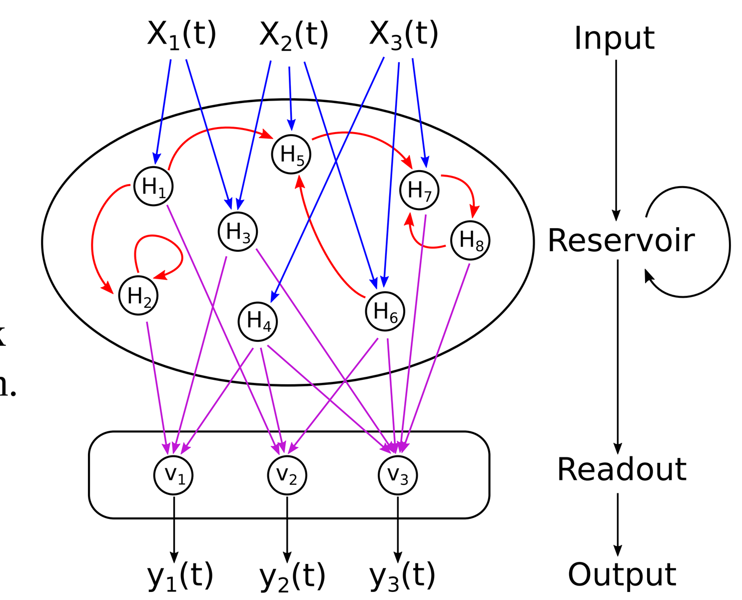
Five participants had severe motor impairments and recording took place in their homes in order to replicate real-world operating conditions.

Each participant performed four imagined mental tasks following a queue on an LCD computer screen:
1. Silently sing a song, 2. Imagine making a fist, 3. Visualize a rotating cube, 4. Silently count backward.

The EEG signals have a sampling frequency of 256Hz and were preprocessed using a bandpass filter from 4-100Hz, a notch filter at 60Hz and a common average reference.

Echo State Networks

Echo State Networks (ESN) are recurrent artificial neural networks that are capable of learning complex spatiotemporal patterns.



ESN have two layers with weighted connections.

The first layer is called the reservoir and consists of hundreds or thousands of sparsely connected neurons including recurrent feedback connections. The reservoir uses a hyperbolic tangent transfer function.

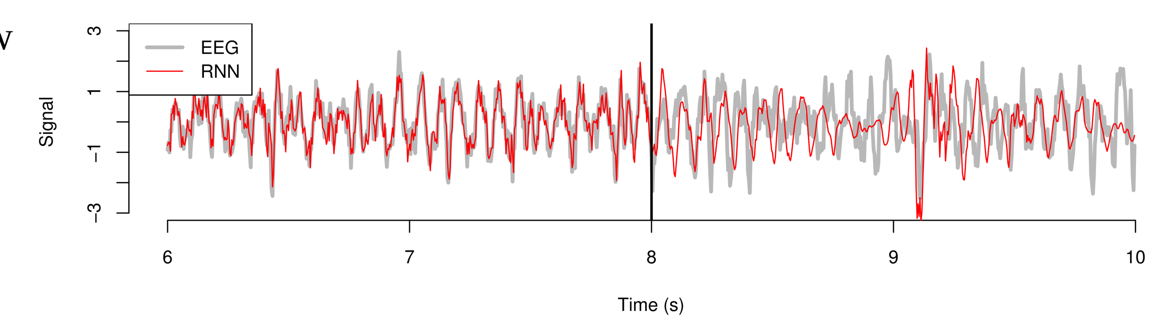
The second layer is called the readout layer and is densely connected with no recurrent connections and a linear transfer function.

ESN are remarkable in that the reservoir weights and connectivity are chosen randomly. The only way that the reservoir is tuned is by scaling the reservoir weights to have a given spectral radius, choosing a connectivity value and scaling the input weights to fall within a given range.

The readout layer is trained using linear regression with a ridge regression penalty.

Forecasting EEG

Our first experiments seek to determine how well ESN are able to forecast EEG signals.



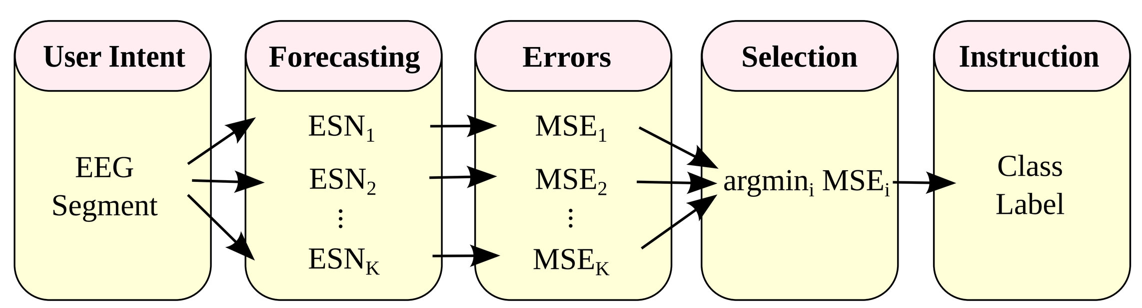
ESN trained to continually predict the next value of an EEG signal are able to achieve errors less than 7% of the signal range.

Next, ESN that are trained to forecast EEG in this way are allowed to operate autonomously, utilizing their previous predictions as the network inputs. These signals are often similar to the true EEG signal.

Above, we see an ESN forecasting EEG before the 8s mark. After 8s, we see an ESN operating autonomously.

Classification by Forecasting

Next, we desire to classify EEG segments so that a BCI can identify the mental task a user is performing.



This is achieved by training a separate ESN to model EEG produced while the subject performs each mental task.

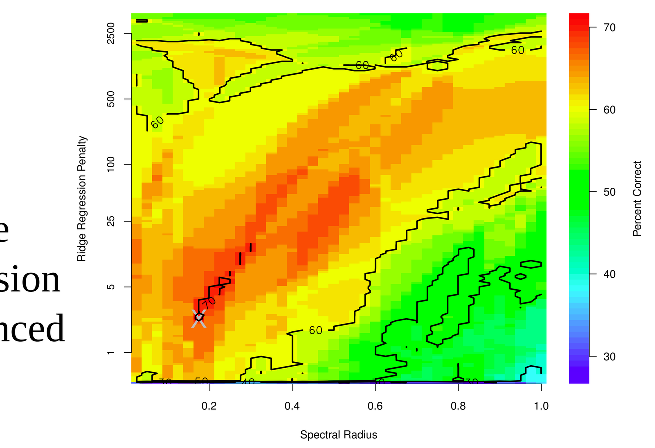
Each ESN can then be viewed as an expert at forecasting EEG from each task.

Previously unseen EEG is labeled by applying each ESN and selecting the label associated with the model that produced the lowest forecasting error.

An instruction to the computer that is associated with the class label can then be executed.

Regularization

In order to prevent our models from fitting noise in the signal or learning any trial-specific patterns, we limit, or regularize, the complexity of our models.



The spectral radius can be viewed as a limit on the length of time that information resonates in the reservoir while the ridge regression penalty can prevent the readout layer from being strongly influenced by only a few neurons in the reservoir.

To the right, we see that there is a sweet-spot for the spectral radius and ridge regression penalty.

These parameters are tuned for each subject using a 6-fold cross validation over the training partition.

Results and Conclusions

We now evaluate the performance of our BCI system by applying these methods to the data recorded from all 14 subjects at the rate of one decision every 2 seconds.

We examine the full 4-task problem as well as looking at the performance of our system when only using each subject's two best-performing tasks.

In Table 1, we see the classification accuracies in percent correct for each subject. Note that we would expect a random classifier to achieve 25% for four tasks and 50% for two tasks.

Classification accuracy varies widely between subjects and reaches a peak of 65% correct for the four tasks and 95% for two tasks.

Table 1: Classification Accuracies.

	Subject	4-Tasks (%)	2-Tasks (%)
Able-bodied	01	62.50	85.00
	02	42.50	80.00
	03	55.00	90.00
	04	65.00	95.00
	05	45.00	65.00
	06	62.50	95.00
	07	40.00	70.00
	08	62.50	95.00
	09	53.13	75.00
	Mean	54.24 ± 7.43	83.33 ± 8.81
Impaired	10	27.50	40.00
	11	55.00	70.00
	12	15.00	50.00
	13	56.25	87.50
	14	37.50	60.00
	Mean	38.25 ± 22.05	61.50 ± 22.77

In Table 2, we see the information transfer rates in bits per minute (bpm) for each subject.

These information transfer rates are competitive with current state-of-the-art BCI systems.

Although the subjects with motor impairments do not perform as well as those without motor impairments, the differences are not statistically significant given our small sample size.

Although these results are encouraging, BCI users would likely find them frustratingly low.

Table 2: Information Transfer Rates.

	Subject	4-Tasks (bpm)	2-Tasks (bpm)
Able-bodied	01	13.54	11.70
	02	3.15	8.34
	03	8.82	15.93
	04	15.34	21.41
	05	4.06	1.98
	06	13.54	21.41
	07	2.34	3.56
	08	13.54	21.41
	09	7.79	5.66
	Mean	9.12 ± 3.90	12.38 ± 6.11
Impaired	10	0.07	0.00
	11	8.82	3.56
	12	0.00	0.00
	13	9.54	13.69
	14	1.65	0.87
	Mean	4.02 ± 5.92	3.63 ± 7.22

Future Work

Interactive and real-time experiments are required in order to fully evaluate these methods.

Filtering and preprocessing techniques may improve performance by attenuating artifacts and noise.

Other forecasting approaches, such as autoregressive models, will be directly compared to ESN.