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Brainwaves Research Lab.

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

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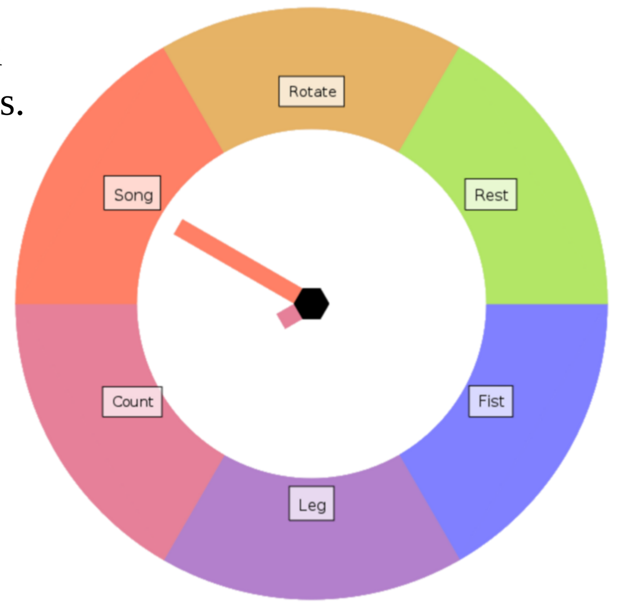
Mental Task BCI Communication Paradigm

The Mental Task (MT) BCI communication paradigm may provide fluid, asynchronous control for BCI users.



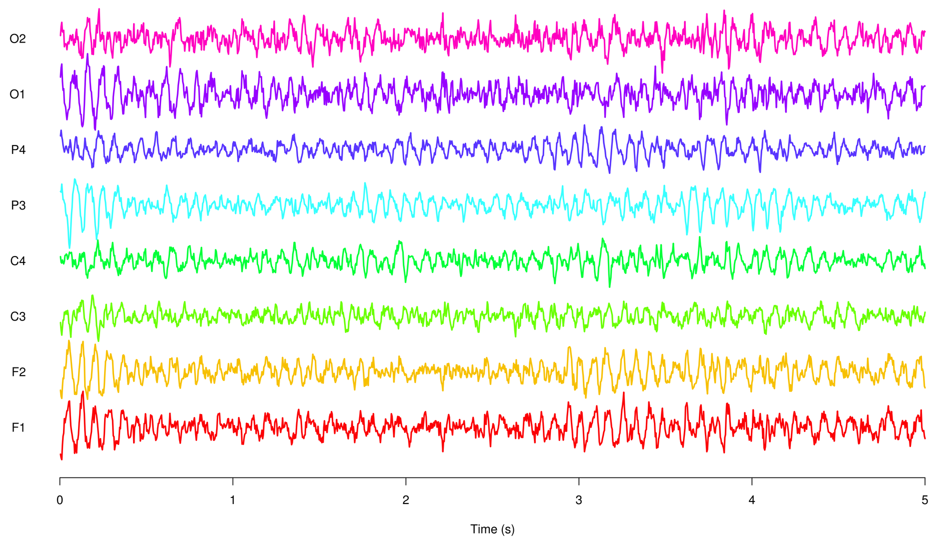
For example, a user might silently sing a song to move a computer cursor to the left or silently count backward to move the cursor to the right.

The MT approach does not require external stimuli and may yield more diverse EEG patterns emanating from more distinct cortical sources than Motor Imagery alone.

However, current approaches for representing EEG patterns and classifying MT do not yet deliver high adequate performance for use in practical, robust BCI.

Capturing Patterns in Spontaneous EEG

Methods that rely on Fourier or Wavelet Transforms have problems with non-stationarity and capturing spatial patterns and phase synchronization.



Methods that rely on Time-Delay Embedding suffer from problems with high-dimensionality.

We believe that these problems may be overcome by using Artificial Recurrent Neural Networks to capture the dynamics of EEG signals and, ultimately, perform classification for use in BCI.

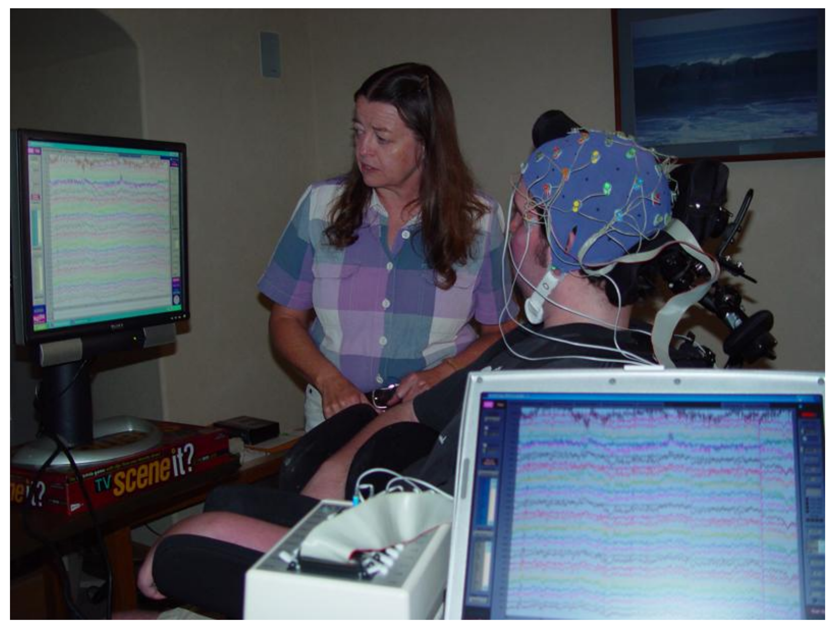
These networks can be non-linear and have memory and state, allowing them to capture complex spatiotemporal patterns.

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.



Impairments were caused by one of: high-level spinal cord injury, multiple sclerosis, or cerebral palsy.

EEG was recorded using the portable 8-channel g.tec g.MOBILab+ with g.GAMMASys active electrodes at sites F3, F4, C3, C4, P3, P4, O1, O2 with an earlobe reference.

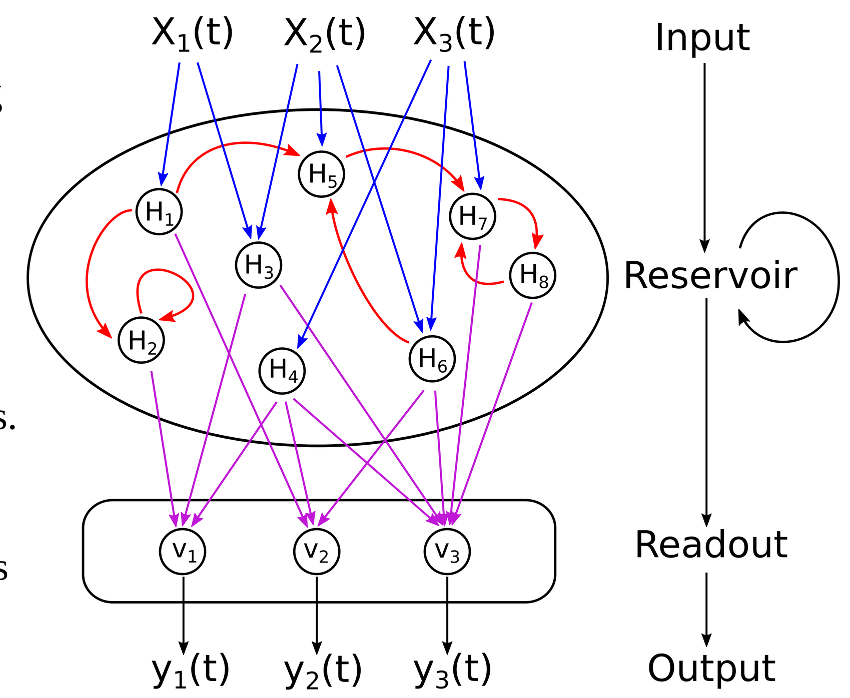
The EEG signals have a sampling frequency of 256Hz and were preprocessed using a bandpass filter from 4-100Hz, a notch filter at 60Hz and a common average reference.

Each participant performed four mental tasks following a queue on an LCD computer screen.

- Song: Silently sing a favorite song.
- Fist: Imagine making a left-handed fist.
- Cube: Visualize a computer screen tumbling in 3D.
- Count: Silently count backward from 100 by 3's.

Echo State Networks

Echo State Networks (ESN) are recurrent neural networks that are fast and often good at modeling complex dynamical systems and time-series.



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 tanh transfer function.

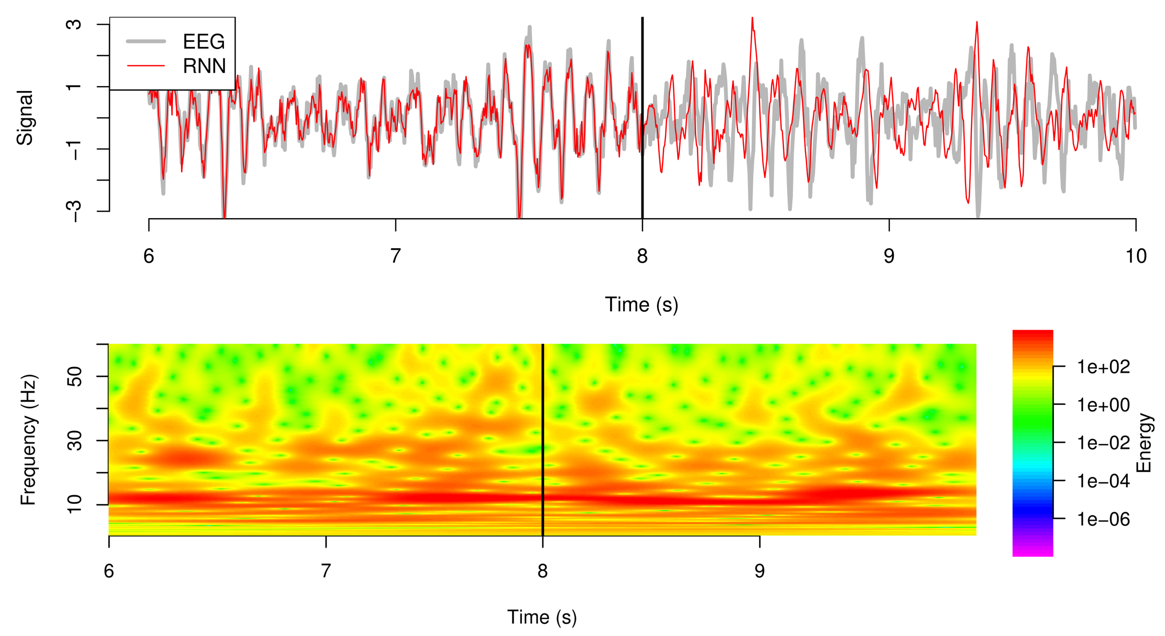
The second layer is called the readout layer and is densely connected with no recurrent connections. The readout layer uses a linear transfer function.

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 probability and scaling the input weights to fall within a given range.

The readout layer is trained using linear regression with a Tikhonov regularization 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.

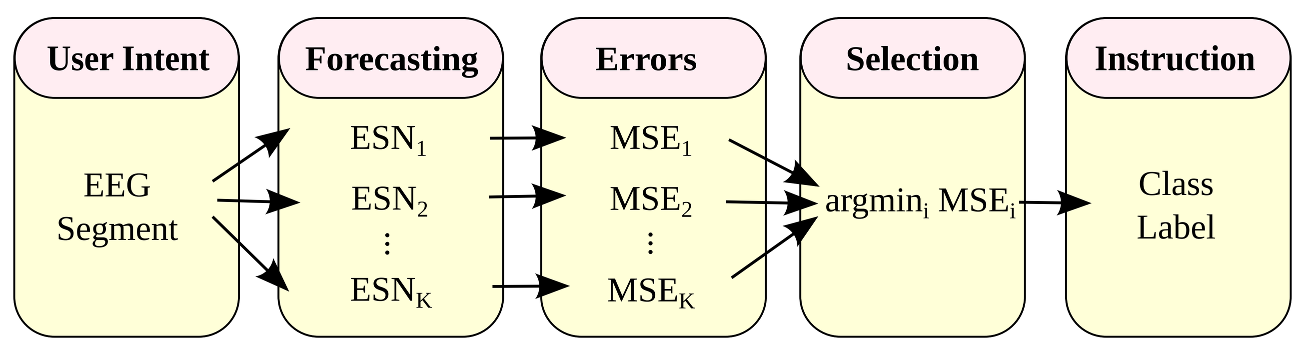
Next, ESN that are trained to forecast EEG in this way are allowed to run autonomously, also called an iterated model, using their previous predictions as the network inputs.

Above top, we see an ESN forecasting EEG before 8s and an iterated model after 8s.

Above bottom, we see a spectrogram of the iterated model generated using a continuous wavelet transform. ESN with 1000's of hidden units and a high spectral radius generate iterated models that appear similar to true EEG. Simpler networks tend to dampen or oscillate at a single frequency.

Classification by Forecasting

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.

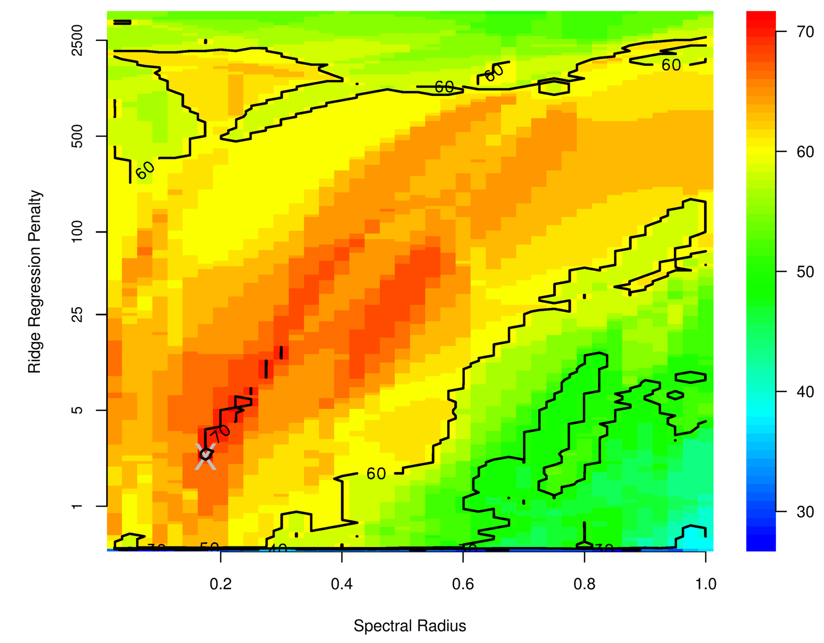
Each ESN can then be viewed as an expert at forecasting EEG from each task.

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

For performance and consistency, a single reservoir is used with multiple readout layers.

Regularization

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

The Tikhonov regression penalty can prevent the readout layer from being strongly influenced by only a few neurons in the reservoir.

Above, we see that there is interplay between these parameters and an optimal combination.

These hyper-parameters are subject-specific and are found using a 6-fold cross validation over the first 60% of the EEG data. Final classification results are found using the remaining 40% test partition.

Results and Conclusions

We now evaluate the performance of our BCI on 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 a 2-task problem using the tasks that performed best during cross-validation.

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

A t-test shows significantly higher classification accuracy in the laboratory (p2-task = 0.017, p4-task = 0.047).

Table 1: Classification Accuracies.

	Subject	4-Tasks (%)	2-Tasks (%)
WO/ Impairment	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
W/ Impairment	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

Table 2: Information Transfer Rates.

	Subject	4-Tasks (bpm)	2-Tasks (bpm)
WO/ Impairment	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
W/ Impairment	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

In Table 2, we present the information transfer rates in bits per minute (bpm).

These information transfer rates appear competitive with other BCI systems.

However, performance varies widely between subjects with some failing to achieve any information transfer.

Although these results are encouraging, BCI users would likely find them frustratingly low. Better performance is still required for a practical system.

Future Work

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

Filtering, preprocessing artifact rejection may improve performance.

Other forecasting approaches should be explored and directly compared to ESN.