Mental-Task BCIs using Convolutional Networks and Transfer Learning

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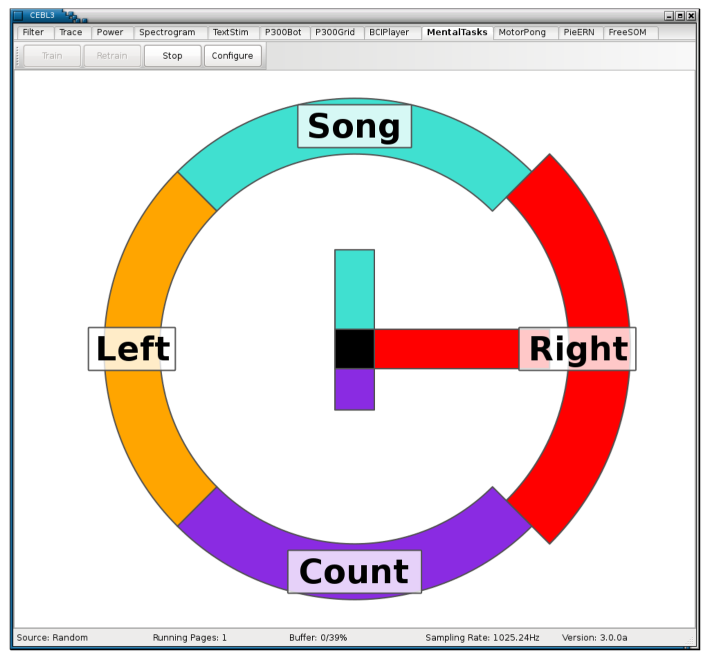
Mental-Task Brain-Computer Interfaces



Constructing Brain-Computer Interfaces (BCIs) that achieve smooth, continuous control remains challenging

Especially with more than two degrees of freedom

In order to control devices like
- -mouse cursors
- -wheelchairs
- -prostheses
- -robotic assistants

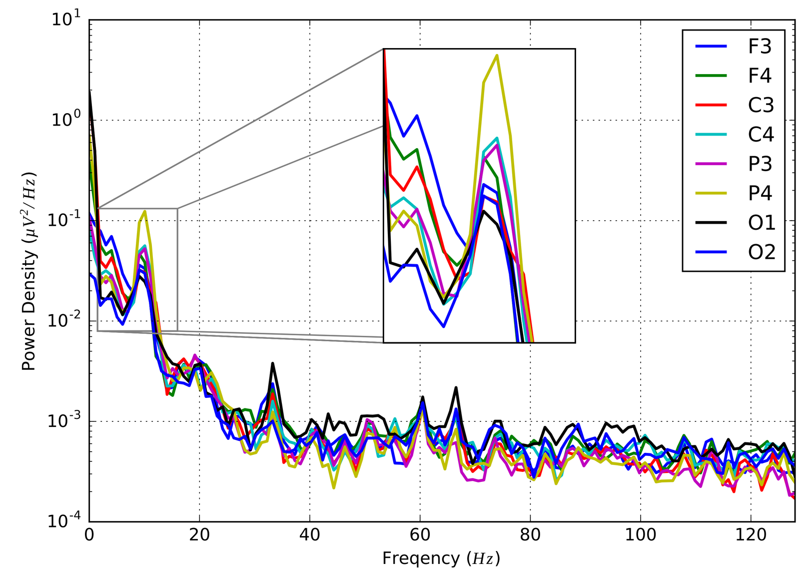
BCI's must
- -not be time-locked (asynchronous)
- -not require external stimuli (stimulus-free)
- -provide fluid state transitions

We believe that Mental-Task (MT) BCIs are well suited for this role

For example:
- -Imagine left-hand movement moves cursor left
- -Imagine right-hand movement moves cursor right
- -Silently sing a song moves cursor up
- -Count backward from 100 moves cursor down

This may become second nature after prolonged use and adaptation by both the user and the BCI system

Current Approaches



Power-Spectral Densities (PSDs) and Common Spatial Patterns (CSP) are often used for classifying these types of EEG signals.

However, these approaches have a limited ability to capture some types of patterns:
- -spatiotemporal
- -nonlinear
- -nonstationary

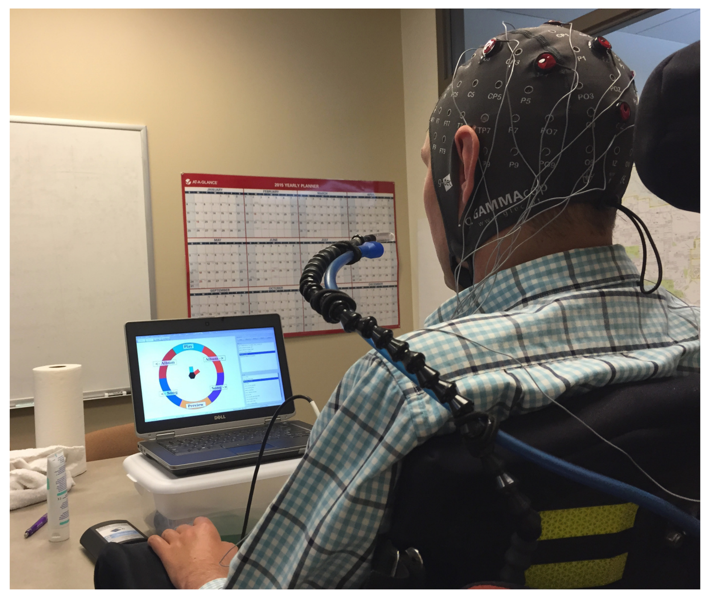
Susceptible to over fitting

Require extensive manual engineering and tuning

Not well suited for smooth control

PSDs along with Linear Discriminant Analysis (LDA) achieves good performance among these methods and will serve as our baseline classifier

Participants and Data Collection



EEG collected from 14 participants

10 with no disabilities, recorded in a well-vetted laboratory environment

Four participants have severe motor impairments, recorded in their home environments

Each participant performed four tasks:
- -Silently count backward from 100 by 3
- -Imagine making a right-handed fist
- -Visualize a rotating Rubik's Cube
- -Silently sing a favorite song

Each task performed for 10s and 5 repetitions

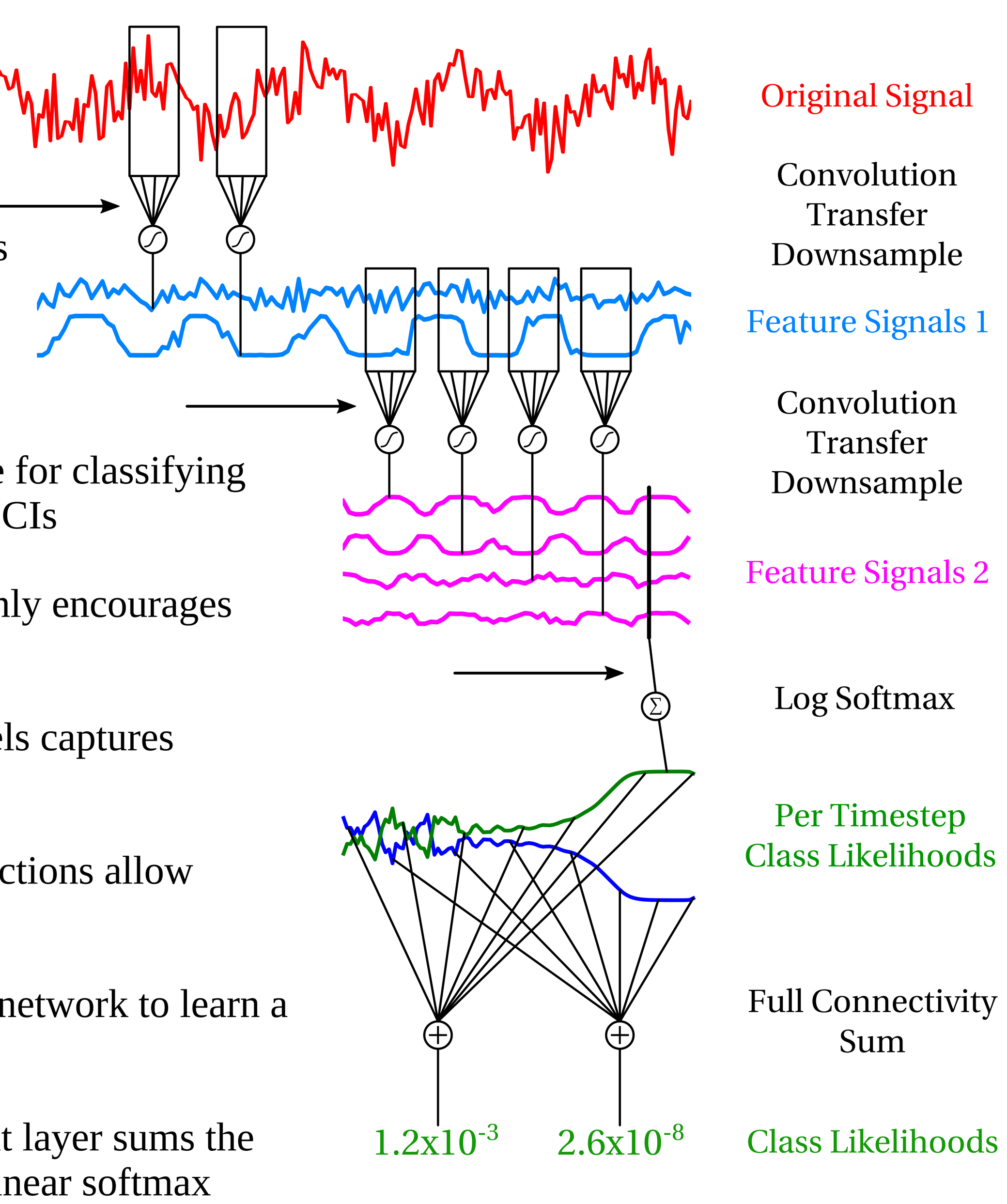
200s of EEG data per subject

Data were split into 2s segments

Four repetitions used for training and model selection via cross-validation

Final repetition used for testing

Convolutional Networks with Label Aggregation



Multilayer (deep) Convolutional Neural Networks (CNNs) are state-of-the-art for a number of machine learning problems

We propose a CNN architecture for classifying EEG signals in asynchronous BCIs

Convolution across time axis only encourages time invariance

Full-connectivity across channels captures spatial patterns

Hyperbolic tangent transfer functions allow modeling of nonlinear patterns

Multiple layers encourages the network to learn a hierarchy of multiscale patterns

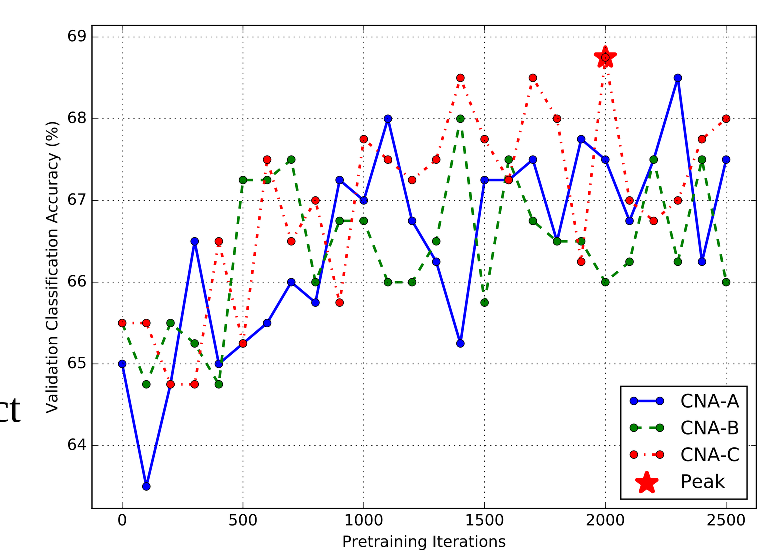
Label aggregation at the readout layer sums the log likelihoods produced by a linear softmax

Reduces free parameters to avoid over fitting and improve generalization

Provides flexibility in interface design and is well suited for smooth control

The network weights are optimized using backpropagation and Scaled Conjugate Gradients

Transfer Learning



Initializing the network's weights using a model trained over a larger group of subjects improves performance

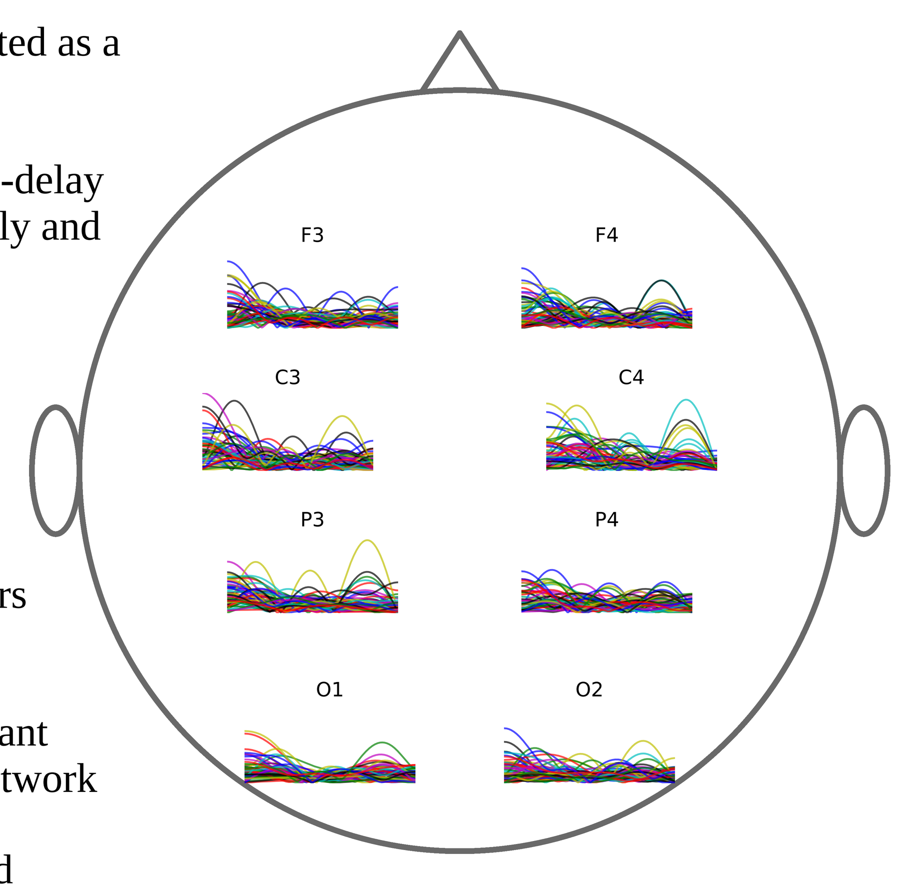
Can be viewed as a form of transfer learning and pretraining

In our experiments, we first train a model over the first 10 subjects except for the current subject

The model is the further fine-tuned using the training data for the subject at hand

The improvements that result from transfer learning suggest there is some commonality in the structure of EEG signals across participants that is useful for classifying mental tasks

CNNs as Nonlinear Finite Impulse Response Filters



Each layer of our CNNs can be interpreted as a Finite Impulse Response (FIR) filter

This process is also equivalent to a time-delay embedding followed by a matrix multiply and transfer function

These filters are multivariate, nonlinear and have learned weights

Although challenging to interpret fully, Fourier transforms can be used to gain insights into the properties of these filters

The pre-transfer gain of the filter in the frequency domain highlights the important frequencies utilized by a single-layer network

A similar analysis suggests sophisticated phase relationships

Results

Analysis of test Classification Accuracy (CA) reveals that:

A single-layer Time-Delay Neural Network (TDNN) outperforms PSDs with LDA

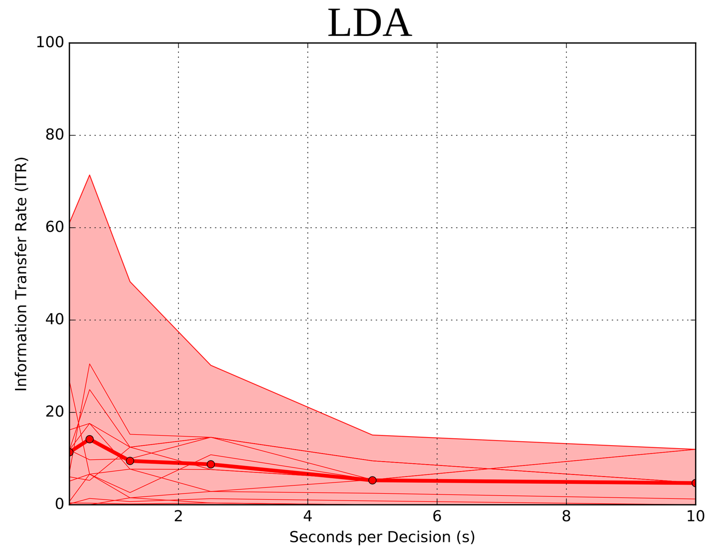
Multilayer CNNs outperform TDNNs only when transfer learning is leveraged

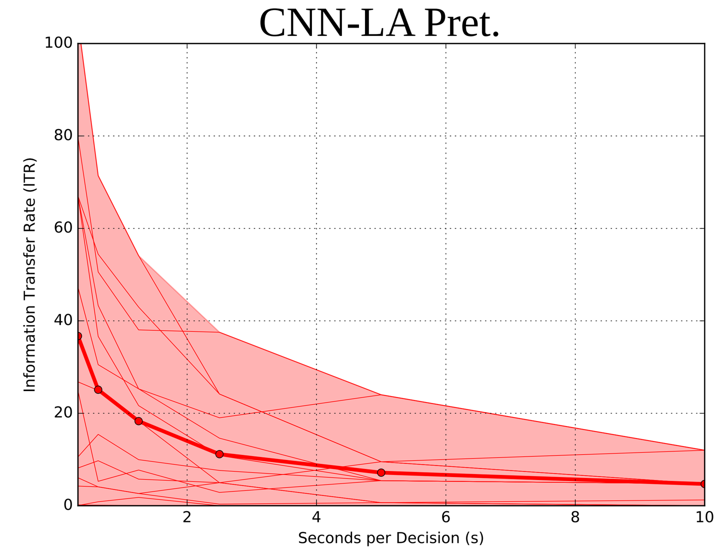
Note that a random classifier would be expected to achieve 25% CA

CNNs with fully connected readout layers perform only slightly better than random

Test Classification Accuracies

	Participant	LDA	TDNN	CNN-LA	CNN-LA Pret.
No Impairment	1	**85.00**	80.00	80.00	**85.00**
	2	55.00	60.00	**70.00**	55.00
	3	40.00	75.00	60.00	**80.00**
	4	55.00	55.00	60.00	**65.00**
	5	70.00	85.00	80.00	**90.00**
	6	**40.00**	30.00	**40.00**	30.00
	7	65.00	**75.00**	70.00	**75.00**
	8	45.00	55.00	40.00	**60.00**
	9	50.00	50.00	45.00	**55.00**
	10	**25.00**	**25.00**	**25.00**	**25.00**
	Mean	53.00	59.00	57.00	**62.00**
Impairment	11	25.00	45.00	45.00	**50.00**
	12	80.00	80.00	**90.00**	**90.00**
	13	25.00	25.00	25.00	**30.00**
	14	**30.00**	25.00	**30.00**	20.00
	Mean	40.00	43.75	**47.50**	**47.50**
All	Mean	49.29	54.64	54.29	**57.86**

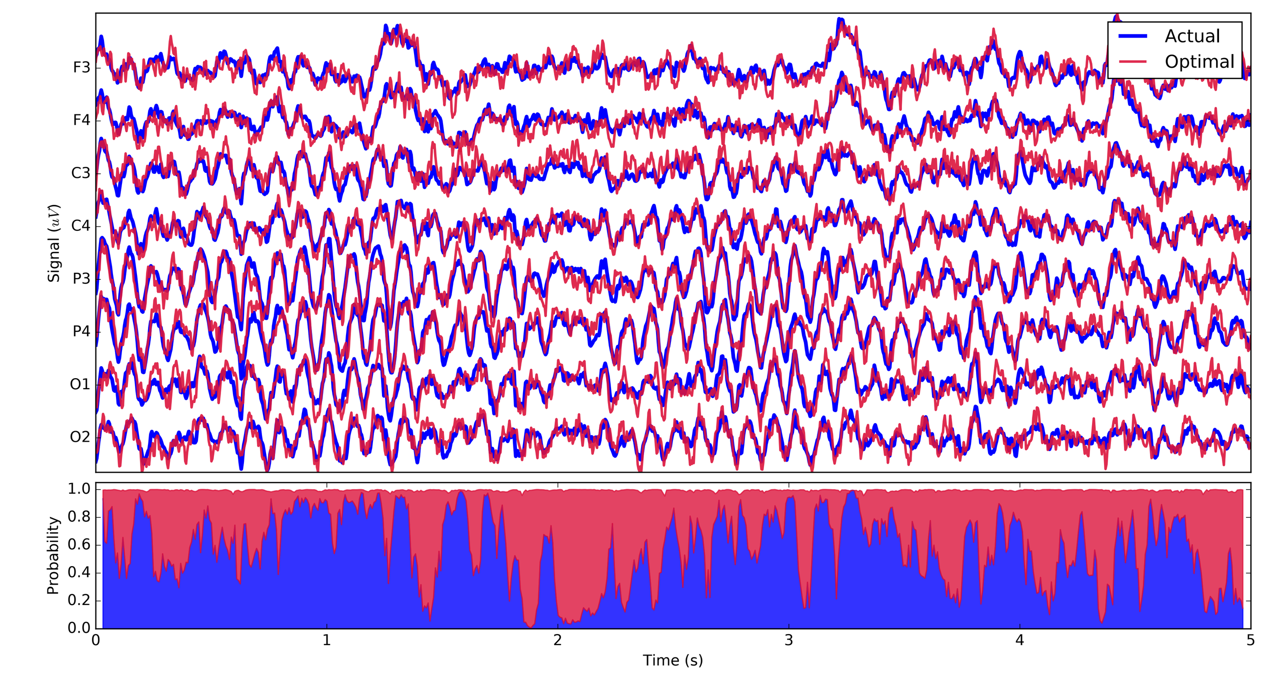




Analysis of information transfer rates in Bits Per Minutes (BPM) show that CNNs hold the largest advantage over PSDs when decisions are made rapidly

Supports our claim that CNNs are well suited for applications that require smooth, continuous control

Learning Optimal Input Sequences



Further insights into the patterns learned by our networks may be found by
- -fixing the network weights and class label
- -using optimization to learn an optimal input sequence

We use the ALOPEX correlative learning algorithm

Seed the input sequence with a known signal segment from the desired class

Often appears to include subtle increases in high frequency information

Conclusions

Convolutional Networks are a powerful tool for classifying EEG signals recorded during imagined mental tasks when label aggregation and transfer learning are incorporated

Various methods are available for analyzing the patterns learned by these networks

Real-time experiments are a next-step toward developing these types of BCI systems