Modeling and Classification of EEG by Forecasting with Recurrent Artificial Neural Networks

Elliott Forney

Colorado State University
Brain-Computer Interfaces Group

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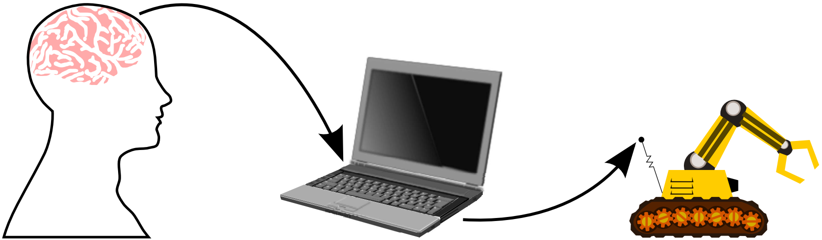
Outline

1. Introduction to EEG-Based Brain-Computer Interfaces

2. Recurrent Artificial Neural Networks

Brain-Computer Interfaces

- Brain-Computer Interface (BCI)
- Direct channel of between brain and machine
- Bypasses innate motor-based means of communication
- Control a computerized device using only thoughts!



Uses for BCI

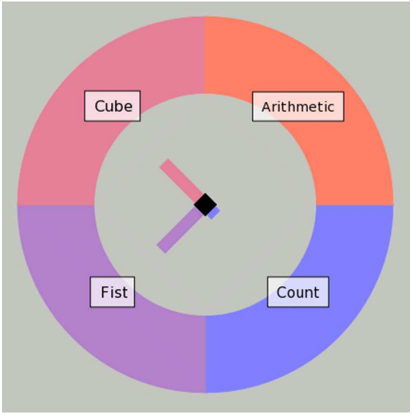
- BCI have many potential uses
- Reestablish communication with people who are Locked-in
  - ALS, stroke, traumatic brain injury
- Assistive technology
  - electric wheelchairs, computers, telephones
- Everyday devices
  - video games, monitoring emotional states

Electroencephalography

- We use Electroencephalography (EEG) to measure brain activity
- Non-invasive, portable, relatively inexpensive
- Superficial & noisy signals

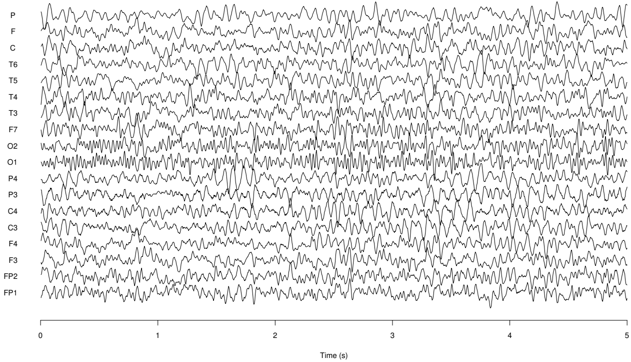
Imagined Mental Tasks

- Imagined mental tasks
- Associate instruction with mental task
- Only covert attention
- Cumbersome at first
- Both user and computer can learn to improve



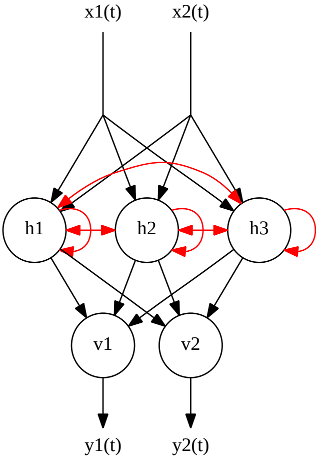
EEG classification is difficult

- The brain is complex!
  - billions of neurons, trillions of synapses, electrochemical interactions
- EEG is also complex and patterns are both spatial and temporal

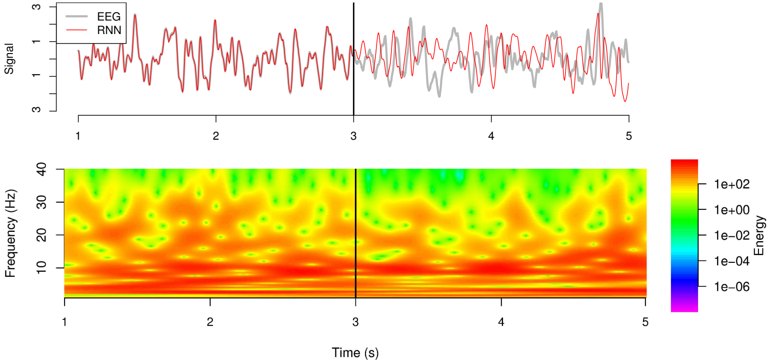


Recurrent Artificial Neural Networks

- Recurrent Artificial Neural Networks (RNN)
- Simple computational units/neurons
- Weighted interconnections
- Feedback connections allow for memory
- Train by adjusting connection weights
- Can learn complex spatio-temporal patterns

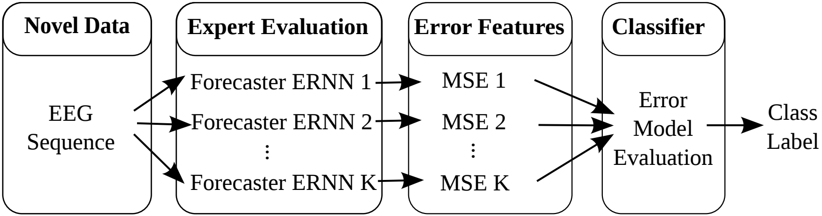


- RNN are able to forecast/model EEG well
- Placing a feedback loop between RNN input and output produces an iterated/autonomous system
- Forecasting left of 3s iterated to the right



Classification by Forecasting

- Generative approach to classification
  - separate ERNN to forecast each class
  - each network is an expert on its class
  - novel EEG labeled by applying each RNN and assigning label associated with lowest forecasting error



Classification Accuracy (Four-Tasks)

Subject	Disability	Hidden units	Classification accuracy	Information transfer rate
A	able-bodied	5	53.5%	16.0bpm
B	able-bodied	8	50.0%	12.5bpm
C	C4 quadriplegia	14	67.5%	34.5bpm
D	C1 quadriplegia	21	36.9%	3.0bpm
E	multiple sclerosis	17	27.9%	0.2bpm
Mean		**13.0**	**47.2%**	**13.2bpm**

- Other state-of-the-art approaches achieve roughly 13-38 bits per minute (bpm) before user feedback
- We achieve between 0-35bpm
- Too few subjects to draw firm conclusions
- Encouraging that Subject C obtained best results

Thanks!