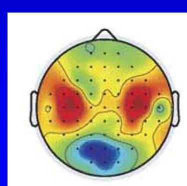
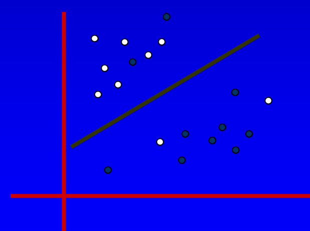
Lecture 3

Non-Invasive and Semi-Invasive Brain Computer Interfaces





Today's Menu

- Wrap up of Machine Learning for BCI
  - Classification
  - Cross-Validation
- EEG-based BCIs
  - Types of EEG responses
  - Case Studies of EEG-based BCIs
- ECoG-based BCIs

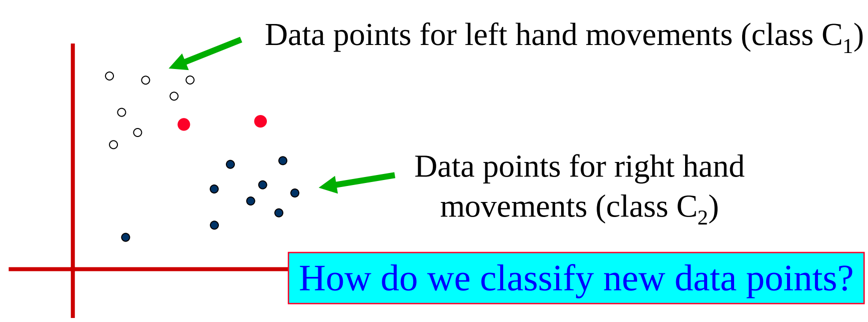
Motivation: Why classification?

- Last lecture: Regression
  - Useful for mapping neural activities to *continuous ouputs* (e.g., cursor position or robotic arm position)
- Many BCI applications require selecting 1 out of N commands or menu choices. E.g.,
  - Word spellers: select 1 out of 26 letters
  - Menu with icons: select 1 out of N icons
  - Semi-autonomous robot: select 1 out of N high-level commands
- Classification techniques can used to classify a given brain signal into 1 of several classes
  - Simplest case: 2 classes ⇨ **binary classification**

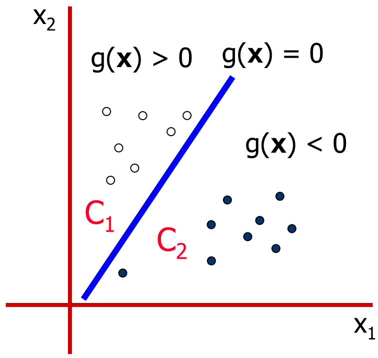
Binary Classification: Example

Suppose BCI is used to move a 1D cursor left or right

Want to use brain signals for Imagined left hand movement vs. Imagined right hand movement



Binary Classification: Linear Classifiers



Find a line (in general, a hyperplane) (**w**, b) separating the two sets of data points:

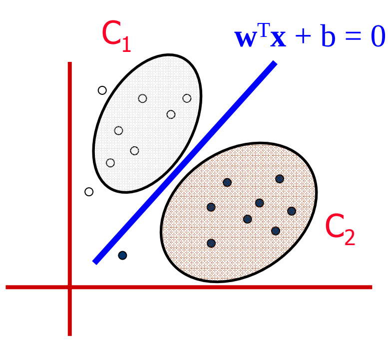
$g(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + b = 0$, i.e.,

$w_1x_1 + w_2x_2 + b = 0$

For any new point **x**, choose:

class C_1 if $g(\mathbf{x}) > 0$ and class C_2 otherwise

Probabilistic Interpretation



Assume each class is a *Gaussian cloud*

$P(\mathbf{x}|C_i) = N(\mu_i, \Sigma)$, i = 1,2

w can be computed as follows:

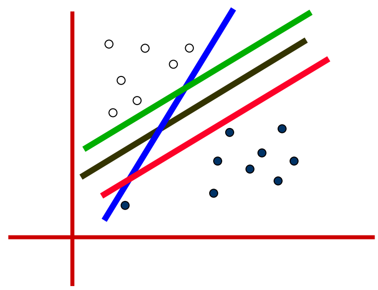
$$\mathbf{w} = \Sigma^{-1}(\mu_2 - \mu_1)$$

(similarly for b)

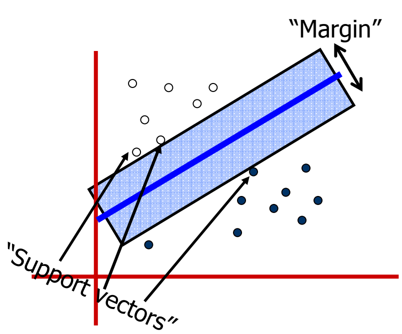
Can show that $g(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + b = \log \frac{P(C_1|\mathbf{x})}{P(C_2|\mathbf{x})}$

which is the log odds of class C_1

Which line to choose?



Support Vector Machines (SVMs)



Choose hyperplane with largest margin

Facilitates generalization to new data points

Can be shown: margin = 2/ w^Tw

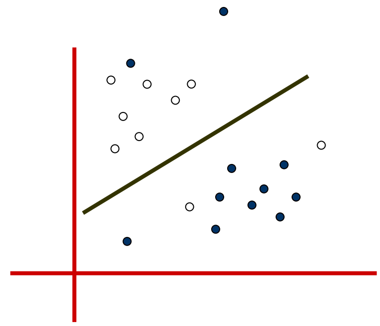
Maximize margin subject to the followi[ng]

$w^Tx_i + b > +1$ for class1 points,

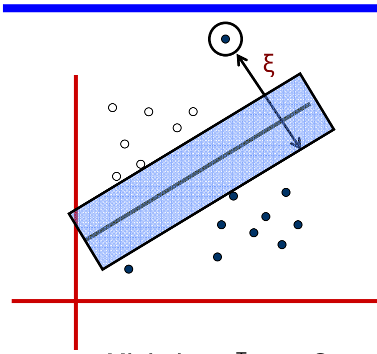
$w^Tx_i + b < -1$ for class2 points.

Solved with Quadratic Programming.

What if data is not linearly separable?



Approach 1: Soft Margin SVMs



Allow *errors* ξ_i (deviations from margin)

Trade off margin with errors.

Minimize $w^T w + C \sum_i \xi_i$ *subject to:*

$w^T x_i + b + \xi_i > +1$ for class1 points,
$w^T x_i + b - \xi_i < -1$ for class2 points, **and** $\xi_i > 0$

Approach 2: Kernel-based SVMs

- **Idea**: Project data to a higher dimensional space and use linear classifier to separate data
  - E.g., 1D mixture of points can be linearly separated in 2D
- Remember trick used for polynomial regression?
  - Replace inputs with functions of inputs:

$$x \leftarrow \Phi(x)$$

- Compute a *linear* classifier in the "higher-dimensional space" of Φ

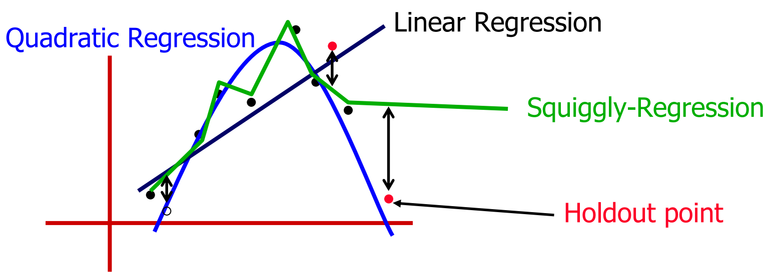
SVMs: Kernel Trick

- **Problem**: What if the high dimensional projection function $\Phi(\mathbf{x})$ is too complicated to compute?
- **Insight:**
  - No need to compute $\Phi(\mathbf{x})$ explictly!
  - Classification only requires $g(\mathbf{x}) = \mathbf{w}^T\Phi(\mathbf{x})$
  - Can show $g(\mathbf{x})$ only requires *scalar products*: $\Phi(\mathbf{x_i})^T\Phi(\mathbf{x})$
- **Kernel trick:** Define a *kernel function* $k(\mathbf{x},\mathbf{y}) = \Phi(\mathbf{x})^T\Phi(\mathbf{y})$
  - Can use (almost) arbitrary kernel functions, where the equivalent Φ space cannot be represented
  - E.g., $k(x,y) = \exp(-(x-y)^2/2\sigma^2)$

Multi-Class Classifiers

- What if we have more than 2 classes (say M classes)?
  - E.g., Move robot forward, backward, left, right, stop, etc.
- Approach 1: Train M classifiers
  - Class C_1 vs. all others, C_2 vs. all others, and so on
  - Given x, choose class C_i with max value for $g_i(x)$
- Approach 2: If not linearly separable, train M(M-1)/2 *pairwise* classifiers:
  - Class C_i vs. Class C_j for every pair i, j
  - Given x, choose class C_i with max value for $\Sigma_j g_{ij}(x)$

Overfitting and Generalization



Question: Which line is the best fit?
Squiggly line *overfits* the data ⇒*Won't generalize* to new data
Solution: *Hold out* some of the points, test performance on the held-out points
What if points held out are bad (uncharacteristic of new data)?

Cross-Validation

- Repeat for different subsets of held-out points:
  For each choice of held-out points:
  - Fit model on remaining points
  - Evaluate error on held-out points
  - Add to total error score (this is the *generalization error*)
- Choose model with *least generalization error*

Types of Cross-Validation

- Leave-one-out cross-validation: *Each point* is held out once, model trained on remaining points, tested on held out point, and cycle repeated for all points.
- K-fold cross-validation: Split data into *k* blocks. *Each block* is used as hold out set.

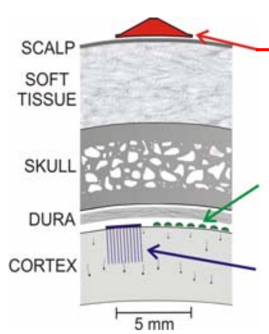
Now that you know something about machine learning techniques, let's get back to BCIs

Rest of this Lecture:

Non-Invasive and Semi-Invasive BCIs

(EEG and ECoG-based BCI)

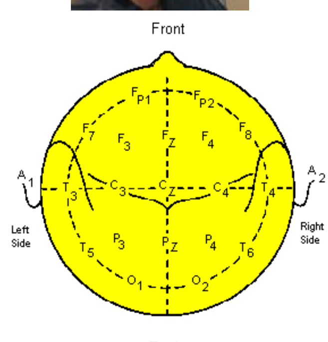
Non-Invasive BCIs: EEG-based Systems



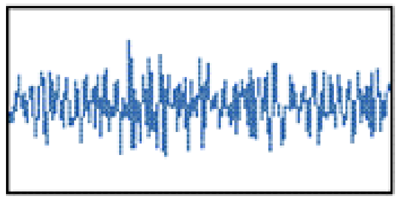
Picture courtesy of Wadsworth Center

EEG (scalp)

"10-20" convention for scalp electrode placement



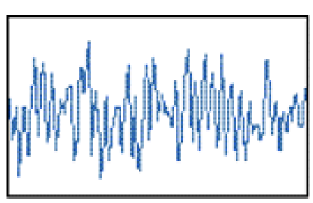
EEG is noisy but correlates with brain activity



Beta waves: Associated with *alertness* and heightened mental activity

(From Scientific American, 1996)

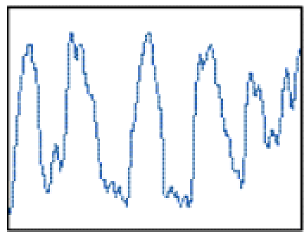
EEG is noisy but correlates with brain activity



Alpha waves: Associated with unfocusing attention (*relaxation*)

(From Scientific American, 1996)

EEG is noisy but correlates with brain activity



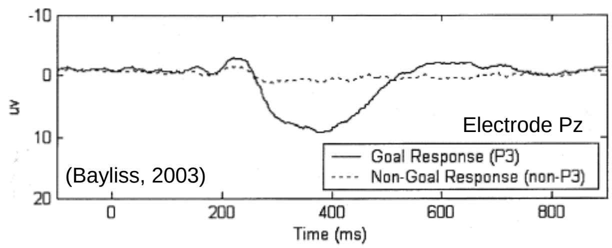
Delta waves: Associated with *deep sleep*

(From Scientific American, 1996)

Using EEG for BCI: Two Types of Responses

- Event Related Potentials (ERPs) or Evoked Potentials (EPs)
  - Particular stimulus causes an EEG response (e.g., P300 in response to sudden visual appearance of a target object)
  - Response had characteristic features
  - Need to average raw EEG responses across many stimulus presentations to see the signal over noise
- Event Related Desynchronization/Synchronization (ERD/ERS): Change in power in specific frequency-bands
  - Perform (or imagine) motor action
  - Average *spectral features* across presentations
  - Characteristic suppression/increase in power

ERP Example: The P300



- Characteristic EEG signal caused by a discrete event
  - Can be visual or auditory event
  - Spontaneous response (a mental "a-ha")
  - Latency of ~300ms
  - Clearly seen in averages over many trials, stronger for rarer/attended-to events, stronger in the midline electrodes

Using the P300 in BCIs: Speller Application

- Rows and columns flashed in random order
- Subject focuses on particular letter
- EEG responses for each flash of row/column averaged
- Training Period: Fix a letter, train a classifier to classify subject's P300 (correct row/col versus all others)
- After training, use classifier to figure out which row & column generated P300

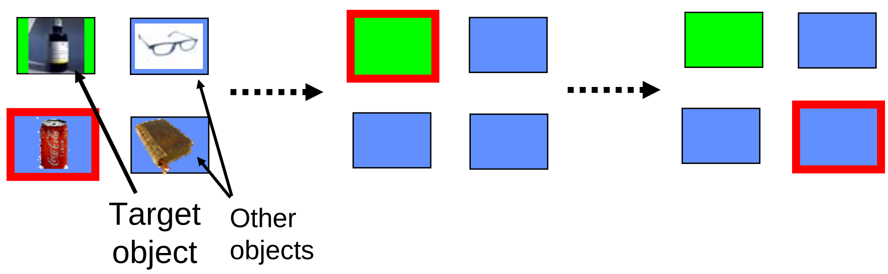
(Farwell & Donchin, 1988)

Using the P300 in BCIs: Robot Application

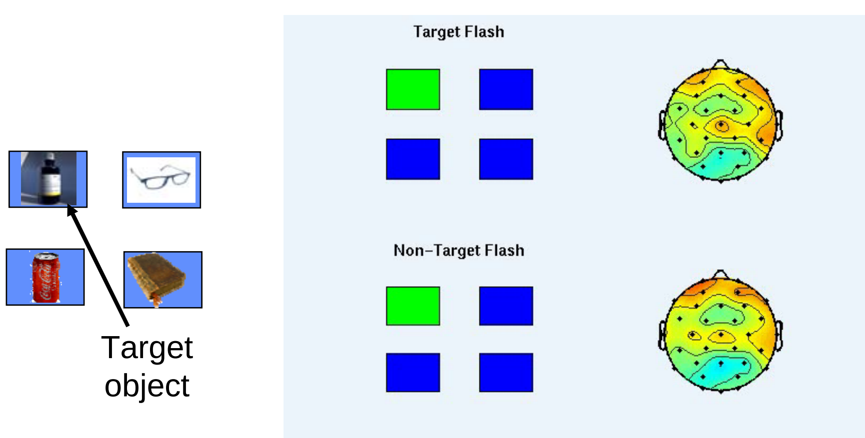
P300 can be used to select an object for a robot to pick up and bring to a specific location

Images of Objects from Robot's camera

Borders flash one at a time in random order

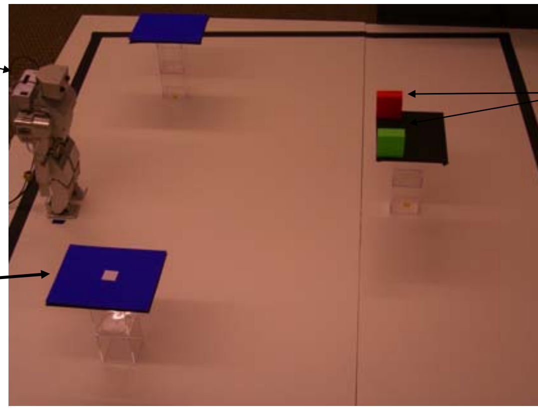


Example P300 Response



Support Vector Machine (SVM) classifies EEG as P300 or not

Using the P300 in BCIs: Robot Application



(CBS News Video)

Another Application: Cortically-Coupled Computing

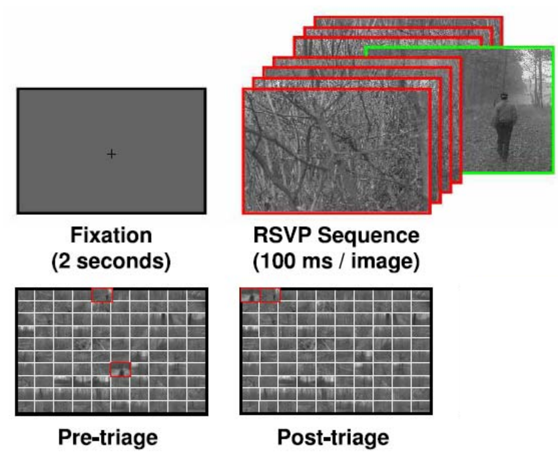
Suppose we want to search an image database for images containing some object (say, people)

Further, you want to do this *really fast (search 100 images within 10 seconds)*

How could we do it?

Answer: Use your brain!

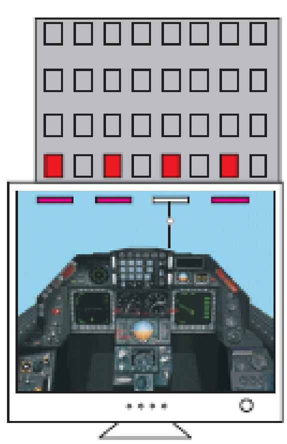
Cortically-Coupled Computing



(Gerson, Parra, & Sajda, 2006)

- Tell subject to watch out for people
- Show images rapidly (100 ms/image)
  - Images with people will generate P300
- Train a classifier to classify EEG as target image or not
- Classify images based on classifier output
- ~90% accuracy reported

Another EP: Steady State Visually Evoked Potential (SSVEP)



- Flickering light source causes evoked EEG responses of same and higher/sub-harmonic frequencies in visual cortex
- Each frequency = 1 choice (e.g., 6,7,8,…Hz)
- Subject looks at chosen flickering light source
- Frequency domain analysis of EEG or classification used to infer subject's choice
- Accuracy up to 95% for 4 choices

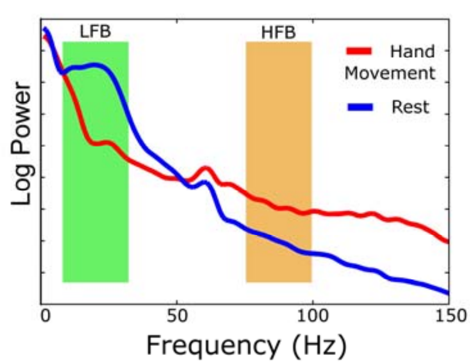
These BCIs are all locked to a stimulus…

Can we build EEG BCIs that allow voluntarily initiated commands?

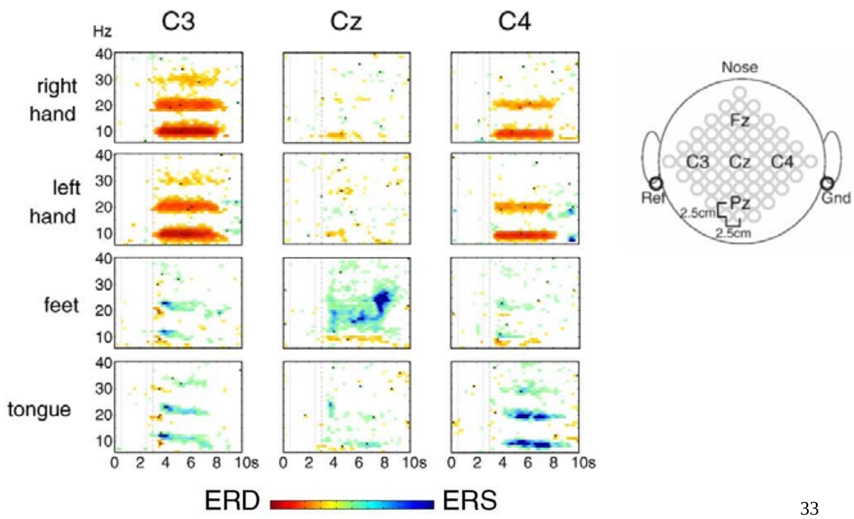
Yes, by classifying imagined movements (based on ERD/ERS)

Event-Related (De)Synchronization (ERD/ERS)

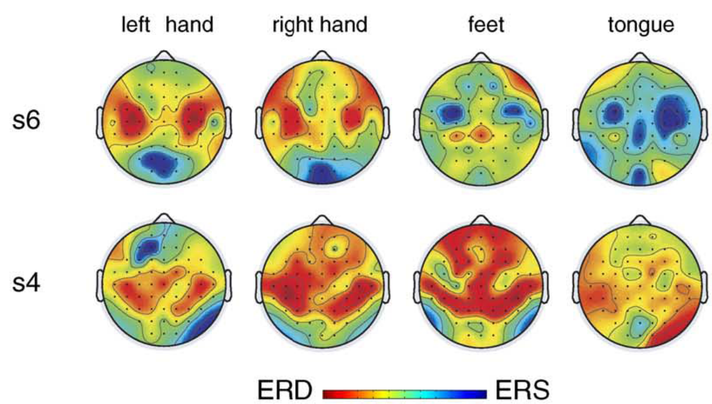
- ERD/ERS: Characteristic change in oscillatory nature of EEG signal due to voluntary motor activity or imagery
  - suppression or increase in power in certain frequency bands, e.g., mu band (8-12 hz)



Example ERD Maps: over time



Example ERD Maps: over space



Fraction of increase/decrease in [10-12]Hz band power between 5.5 and 6.5s of trial, for subjects s6 & s4

Using ERD/ERS for BCI

- Train a classifier to classify ERD/S maps for different imagined movements (e.g., left hand vs. tongue movement)
- Use trained classifier to classify new data
  - Subject uses imagined movements to issue commands (e.g., cursor up or down)
- Alternately, can also directly map magnitude of ERD/S to magnitude of cursor movement
- A user uses ERD to control a cursor select from icons in a menu (μ rhythm control, 64 channels EEG, Wadsworth group in New York)

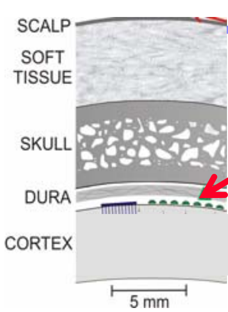
Weaknesses of EEG BCIs

- Very low signal-noise ratio: Best BCIs only manage 20-30 bits/min
- Artifacts and noise
  - muscle movement, eye blink, head shake, ambient 60Hz noise >> signal
  - recordings from any 2 sessions *qualitatively* similar but *quantitatively* very different
- Lack of thorough understanding of EEG
  - only 2-3 reliably reproducible phenomena available for use in BCIs
- Signal attenuation between brain and scalp fundamentally limits range of useful control signals that can be extracted

Can we do better with “semi-invasive” BCIs?

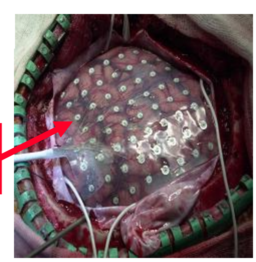
Electrocorticographic BCIs

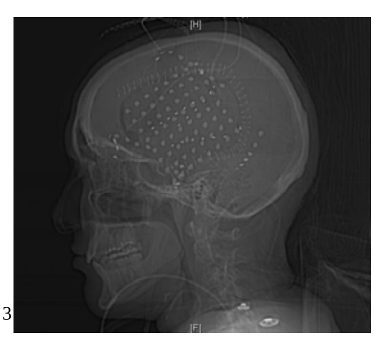
Electrocorticography (ECoG)



Picture courtesy: Wadsworth Center

Grid of ECoG Electrodes



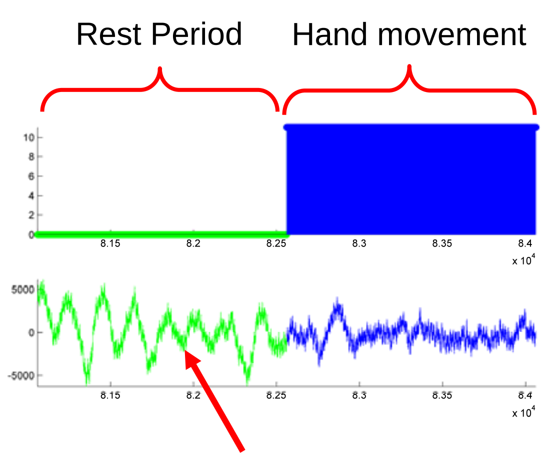


Patient Population and Setup

(from Seattle Times)

- Epileptic patients implanted with ECoG for finding source of seizures
- All experiments at bedside
- All patients located at epilepsy center at Harborview Medical Center, Seattle, WA

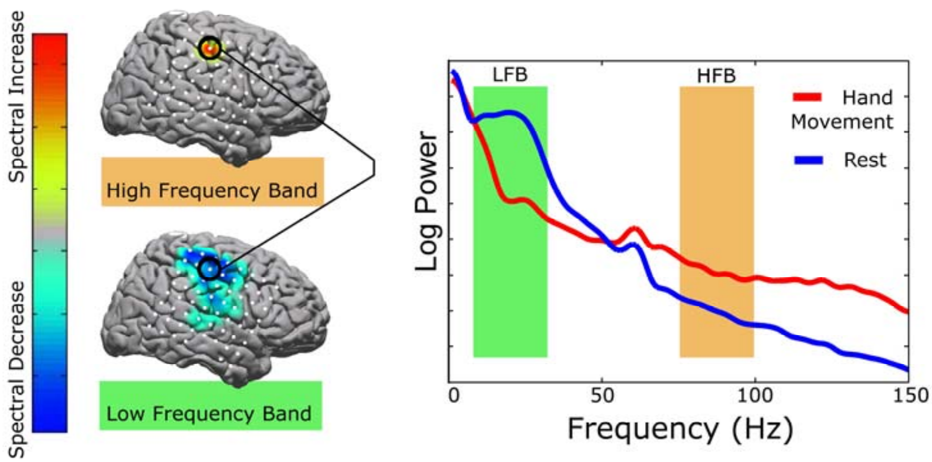
ECoG signals can indicate what task is being performed



ECoG Signal from an electrode

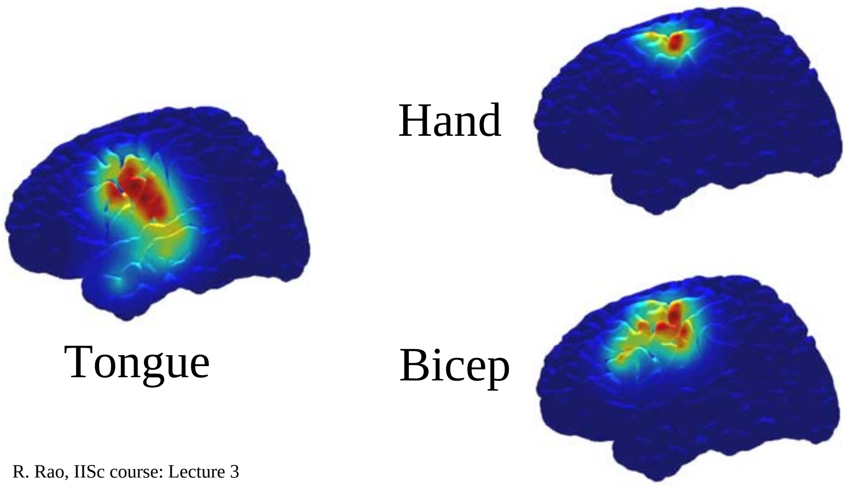
(work of grad student Kai Miller)

Movement causes ERD and ERS



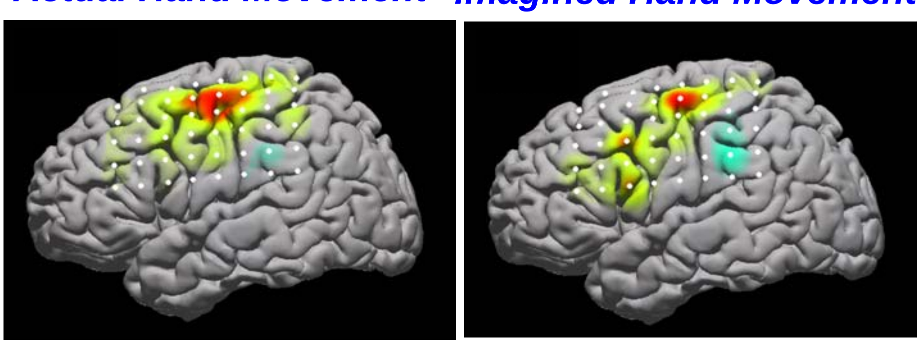
Example of ECoG during Movement

ERS for Different Movements are Spatially Separated



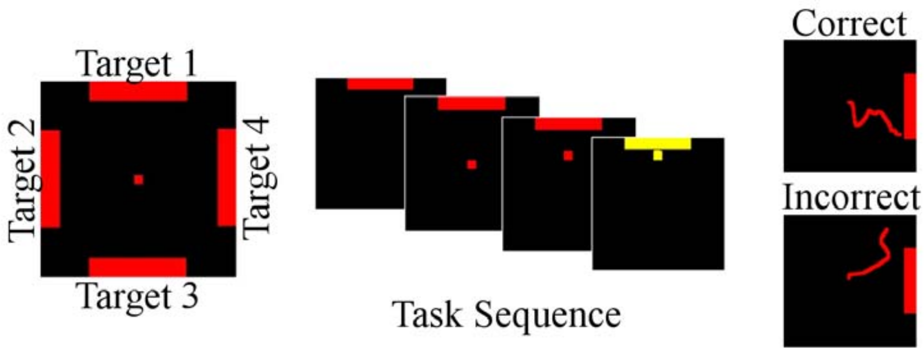
Imagined Movements can be Distinguished

Actual Hand Movement ***Imagined Hand Movement***



Can we use imagined movements to control objects such as a cursor on a screen?

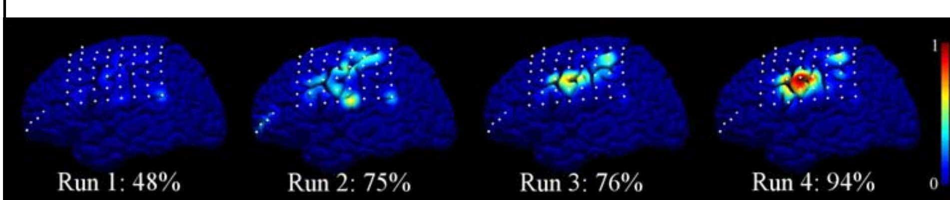
Cursor Task



Cursor movement proportional to change in power in high frequency band (70-100 Hz) for different movements

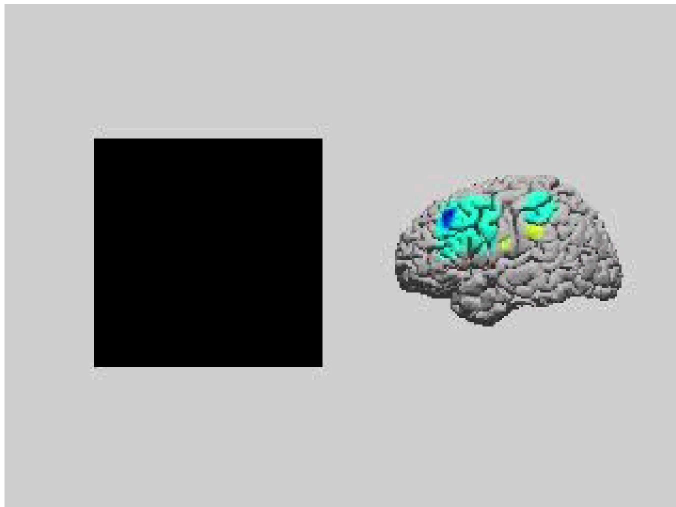
Patient learning to control a cursor through imagined speech

Move cursor up = imagine saying the word "move"
Move cursor down = do nothing (relax)

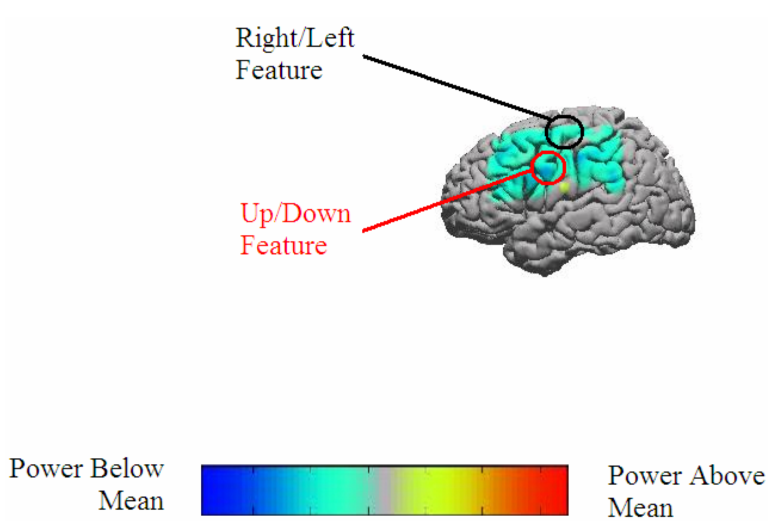


Patient gets progressively better at cursor control

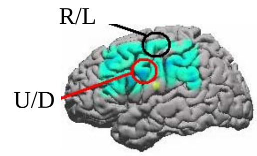
1D Cursor Control using Imagined Speech

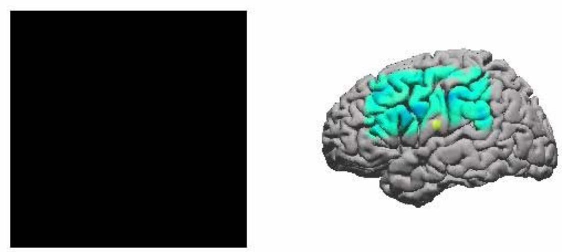


Example of 2D Cursor Control



Example of 2D Cursor Control





Can we do better by going inside the brain and directly recording from neurons?

Next time:

Invasive BCIs

(Rats, monkeys, humans)