Representing and Classifying EEG in Mental Task BCI

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Goals of this research exam

- Goals of this research exam:
  1. Specific type of Brain-Computer Interface
  2. Critically review literature
  3. Representing EEG signals
  4. Classifying these representations
  5. Potential pros and cons
  6. Gaps in research
  7. Promising avenues for future research
- Emphasis on EEG representations
- Use this knowledge for building next generation BCI

Outline

1. Introduction
2. Frequency-Domain Representations
   - Power Spectral Densities
   - Continuous Wavelet Transforms
   - Phase-Locking Values
   - Classifiers
3. Time-Domain Representations
   - Time-Delay Embedding
   - Linear Autoregressive Models
   - Nonlinear Time-Series Models
   - Classifiers
4. Summary
5. Conclusions

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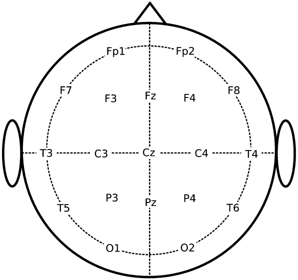
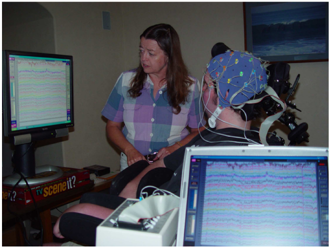
Mental Task Brain-Computer Interfaces

- Brain Computer-Interfaces (BCI)
  - Direct communication between brain and computer
  - No physical interaction required
  - Assistive technology
  - Perhaps become commonplace?
- BCI do not yet perform well enough
- Not practical for everyday use
- One potential approach combines:
  1. Electroencephalography (EEG)
  2. Mental Tasks (MT)
  3. Machine Learning

Electroencephalography

- Electroencephalography (EEG) for monitoring brain activity
- Measures electrical fields using surface electrodes
- Advantages of EEG
  - Non-invasive
  - Relatively affordable
  - Portable
  - High temporal resolution
- Disadvantages of EEG
  - Low signal-to-noise ratio
  - Low spatial resolution
  - Effort to apply cap





Mental Tasks

- Mental Tasks (MT) for communication protocol
- For example:
  - Imagine moving left hand: move left
  - Imagine moving right hand: move right
  - Visualize rotating cube: move up
- Advantages of MT
  - Stimulus-Free
  - Asynchronous & Spontaneous
  - User can adapt
  - Diverse patterns
- Disadvantages of MT
  - Asynchronous & Spontaneous
  - No single type of brain activity

Machine Learning

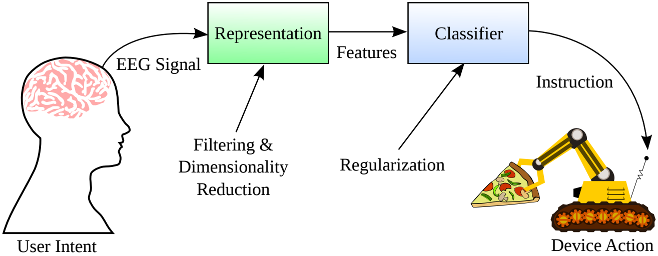
- Machine Learning (ML) for identifying Patterns in EEG that discriminate mental tasks

- This is difficult:
  1. Human brain is complex!
  2. Everyone is unique
  3. Humans multi-task
  4. Spatiotemporal patterns
     - Across electrodes
     - Through time
  5. Low signal-to-noise ratio

- Also important:
  1. Accuracy
  2. Speed
  3. Robustness to noise
  4. Adapt to users

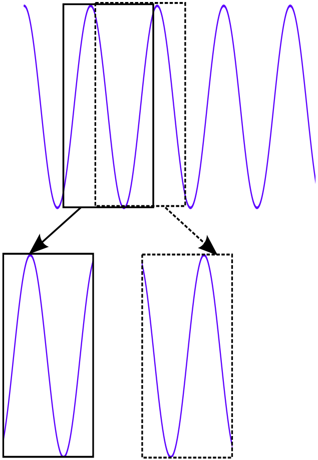
Representations and Classifiers

- Machine Learning consists of two major parts
  1. Representation captures important patterns
  2. Classifier maps features from representation to instructions
- Noise and undesirable information handled in
  1. Representation: filtering & dimensionality reduction
  2. Classifier: regularization



Capturing Spatiotemporal Patterns

- Representation should capture
  1. Spatial patterns: across electrodes
  2. Temporal patterns: through time
- EEG is non-stationary
  - Characteristics change over time
- Capture temporal information at high resolution
- Temporal invariance
  - Insensitive to small shifts in time



Organization

- We will look at:
  1. Undesirable information
  2. Spatial patterns
  3. Temporal patterns
- Pros: ▲
- Cons: ▼

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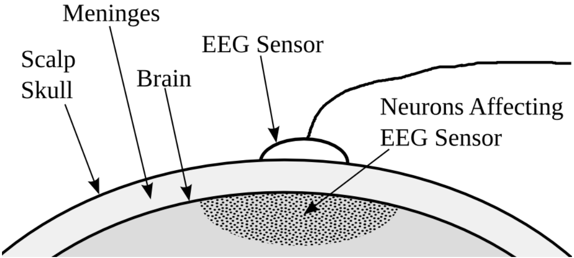
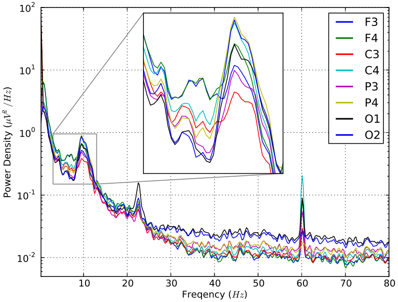
Frequency-Domain Representations

- Frequency-domain representations describe EEG in terms of oscillatory components
- EEG is commonly analyzed in the frequency-domain
- EEG measures synchronized firing of action potentials
- Research shows synchronized firing when idle
- Straightforward to interpret



Power Spectral Densities

- Power Spectral Densities (PSD) represent EEG in terms of power density across a range of frequencies
- Achieved using Discrete Fourier Transforms
  - Sum of sines and cosines on complex plane
- Welch's method for smoothing

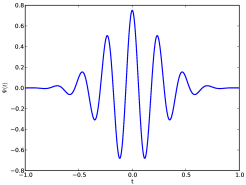


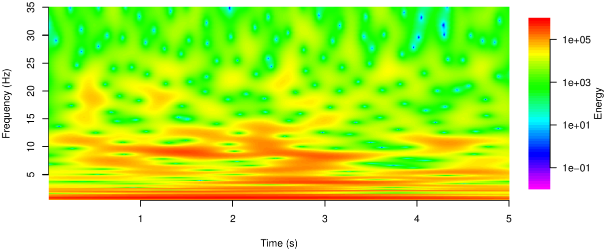
Power Spectral Densities

- Undesirable information:
  1. Welch's Method: Frequency smoothing ▲
  2. Trade-off between resolution and smoothing ▲▼
- Spatial Information:
  1. Power across channels ▲
  2. Not phase ▼
- Temporal Information:
  1. Power vs. Frequency is time invariant ▲
  2. Sinusoids are not good for non-stationary patterns ▼
     - Use windows to overcome
     - Leads to low temporal resolution

Continuous Wavelet Transforms

- Continuous Wavelet Transforms (CWT) represent EEG in terms of wavelets
- Response localized near zero
- Multiplication acts as a filter
- Can determine energy content over time



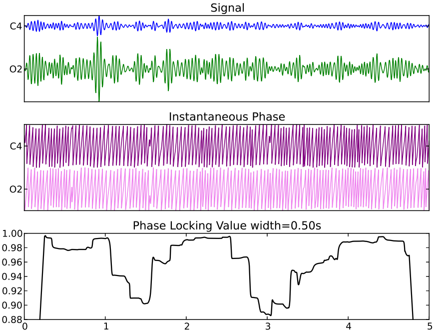


Continuous Wavelet Transforms

- Undesirable information:
  1. Frequency and temporal smoothing via wavelet choice ▲▼
  2. Resolution is parameterized ▲
- Spatial information:
  1. Energy across channels ▲
  2. Not phase (could be used) ▼
- Temporal information:
  1. Energy vs. Frequency is time invariant ▲
  2. Can localize energy in time ▲
     - Better temporal resolution than PSD
     - Better for non-stationary patterns

Phase-Locking Values

- Phase-Locking Value (PLV) is a measure of phase synchronization between two signals
- Uses instantaneous phase
  - 1 for unchanging phase difference
  - 0 for randomly changing phase difference
- Typically used with PSD



Phase-Locking Values

- Undesirable information:
  1. Increases dimensionality ▼
     - $O(N^2)$ channel pairs
     - More if divided into frequency bands
- Spatial information:
  1. Captures changes in phase ▲
  2. Not constant phase shifts ▼
  3. Combined with PSD ▲
- Temporal information:
  1. Moving average of phase changes
  2. Combined with PSD ▲

Classifiers for Frequency-Domain Representations

- Bayesian Classifiers are common:
  - Linear Discriminant Analysis (LDA)
  - Quadratic Discriminant Analysis (QDA)
  - Mixture of Gaussians
- Assumptions are rarely verified
- Support Vector Machines (SVM)
  - Good results with CWT
  - Linear kernels worked as well as Nonlinear
- Classifiers rely heavily on representations
  - Regularization parameters neglected
  - Linear classifier as regularization
  - Other classifiers should be explored

Frequency-Domain Discussion

- Frequency-domain representations are good for capturing periodic components in EEG
  1. Insensitive to shifts in time
  2. Wealth of research in EEG
  3. Straightforward to visualize
- Challenges:
  1. Difficulty with non-stationary patterns
     - Argument seems strong for CWT over PSD
  2. Often omit phase information
     - Yet to be fully addressed
  3. Not well-suited for non-periodic patterns

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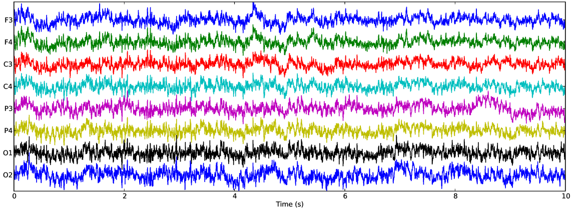
Time-Domain Representations

- Time-domain representations are a function of time
- Difficult to interpret for spontaneous EEG
- Time-domain representations may allow
  - Other forms of removing undesirable information
  - Capturing non-periodic patterns
  - Modeling EEG signals directly
- Challenging to incorporate temporal information



Time-Delay Embedding

- Time-Delay Embedding (TDE) captures temporal information by including past signal values
- Embedding dimension is number past values to include
- Overlap is number of repeated values

$$X = \{\overbrace{X_1, X_2, X_3}^{\text{Embedding Dimension: 3}}, X_4, \overbrace{X_5}^{\text{Overlap: 1}}, X_6, X_7, \ldots, X_n\}$$

$$Y = \left\{ \begin{bmatrix} X_3 \\ X_2 \\ X_1 \end{bmatrix}, \begin{bmatrix} X_5 \\ X_4 \\ X_3 \end{bmatrix}, \begin{bmatrix} X_7 \\ X_6 \\ X_5 \end{bmatrix}, \ldots, \begin{bmatrix} X_n \\ X_{n-1} \\ X_{n-2} \end{bmatrix} \right\}$$

Time-Delay Embedding

- Undesirable information:
  1. Increases dimensionality ▼
  2. Linear transforms can be used ▲
     - Largely beyond scope
     - See written exam for more
- Spatial information:
  1. Raw signal values across electrodes ▲
- Temporal information:
  1. Raw signal values through time ▲
     - Limited by embedding dimension ▼
     - Trade-off with dimensionality ▼
  2. Not time invariant ▼
     - Overlap can help
     - Trade-off with redundant information

Linear Autoregressive Models

- Raw EEG can be modeled directly
- Attempt to capture the dynamics of the signal
- Autoregressive (AR) models use a linear combination of previous values

$$\mathbf{A}_t = \sum_{i=0}^{p} \mathbf{C}_i \mathbf{A}_{t-i} + \mathbf{R}_t$$

  - **A** are model values
  - **C** are model coefficients
  - **R** are residuals
  - p is order

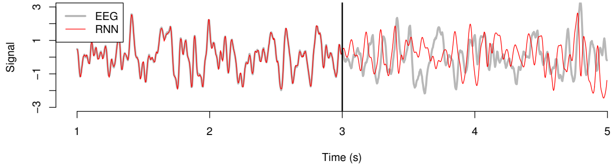
- AR coefficients define the model
- Classification typically uses only the coefficients

Linear Autoregressive Models

- Undesirable information:
  1. Represented by model coefficients ▲
  2. Linear filter ▲▼
- Spatial information:
  1. Linear combination of signal values ▲
- Temporal information:
  1. Linear combination of past values ▲
  2. Insensitive to time shifts ▲
  3. Limited by model order ▼

Nonlinear Time-Series Models

- EEG signals may not be a linear process
- Nonlinear models using Artificial Neural Networks
- Feedforward networks
  - Nonlinear combination of past values
- Recurrent networks
  - Feedback connections give memory
- Forecasting errors used for classification



Nonlinear Time-Series Models

- Undesirable information:
  1. Filters unpredictable information ▲
     - can be tuned
- Spatial information:
  1. Nonlinear combination of signal values ▲
- Temporal information:
  1. Nonlinear combination of past values ▲
  2. Model dynamics insensitive to time shifts ▲
  3. Limited network and optimization ▼
- Slow to train ▼

Classifiers for Time-Domain Representations

- LDA and QDA are most common
- Artificial Neural Networks (ANN)
  - Few hidden units, nearly linear
  - Outperform LDA and QDA with TDE
- Time-Series Models
  - Representation and classifier not distinct
  - Nonlinear outperform linear AR
- Appear to rely less on representation
  - Less prior knowledge of patterns
  - Difficulty visualizing

Discussion of Time-Domain Representations

- Time-domain representations are capable of capturing patterns that are
    1. Spatial
    2. Temporal
    3. Non-periodic
    4. Non-stationary
- Many methods for removing undesirable information
- Challenges:
    1. Interpretation
    2. Temporal invariance
    3. Long-term patterns

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Summary of All Representations

	Representation	Undesirable Information	Spatial Information	Temporal Information	Temporal Invariance
Frequency-domain	PSD	Frequency smoothing	Power but not phase	Low resolution windows	Yes
	CWT	Frequency and temporal smoothing	Energy but not phase	High resolution localized	Yes
	PLV	Increased dimensionality	Some phase but no amplitude	Moving average	Yes
Time-domain	TDE	Increased dimensionality Linear transforms	Yes	Limited by embedding	No
	AR Models	Linear Filter	Linear	Linear and limited by model order	Yes
	ANN Models	Nonlinear Filter	Nonlinear	Limited by embedding	Yes
	RNN Models	Nonlinear Filter	Nonlinear	Limited by network or optimization	Yes

Within-Study Performance Comparisons

- Great... but how do these methods compare in practice?
- Major gap in research is a lack of direct comparisons
- Within-study comparisons suggest:
  1. PSD+PLV wins over PSD (conflicting)
  2. CWT+SVM, linear kernels as good as radial-basis and polynomial kernels (regularization)
  3. TDE+ANN wins over TDE+LDA and TDE+QDA
  4. Time-series+ANN+LDA wins over AR coefficients
- Few subjects and tasks
- Small performance differences

Across-Study Performance Comparisons

Author	Representation	Classifier	# Tasks	Delay	Accuracy
Keirn	PSD	QDA	2	2s	76–84%
Millán	PSD	Mixture of Gaussians	3	0.5s	>70%
Zhiwei	CWT	Linear SVM	2	1s	67–100%
Zhiwei	CWT	Linear SVM	4	1s	65–92%
Iáñez	CWT	LDA	2	1s	20–60%
Gysels	PLV+PSD	Linear SVM	3	1s	60–75%
Anderson	TDE	ANN	4	3s per correct	
Anderson	TDE+PCA	LDA	5	1-2s	68–78%
Zhang	PSD+ICA	LDA	2	1s	62–86%
Zhang	PSD+ICA	LDA	5	1s	38–69%
Freidrich	TDE+CSP	LDA	4	1s/256	61–72%
Keirn	AR	QDA	2	2s	78–88%
Anderson	AR	ANN	2	1s	88–96%
Curran	AR	Variational Learning	2	1s	63–74%
Coyle	Time-Series+ANN+LDA		2	5s	85–91%
Forney	Time-Series+ERN+Best Fit		2	1s	52–93%
Forney	Time-Series+ERN+Best Fit		4	1s	28–68%
Forney	Time-Series+ESN+Best Fit		2	2s	50–95%
Forney	Time-Series+ESN+Best Fit		4	2s	15–65%

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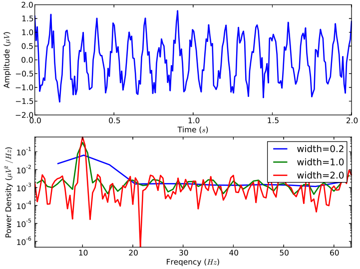
Final Comments

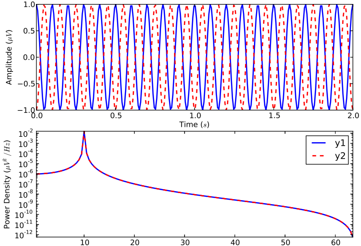
- Research in this field has only begun
- More research is needed:
  1. Direct comparisons
  2. Other classifiers
  3. Parameter exploration
  4. Real-world performance
- Three avenues appear promising:
  1. Continuous Wavelet Transforms with phase
  2. Time-Delay Embedding with Transforms and Regularized Nonlinear classifiers
  3. Nonlinear time-series models using Neural Networks

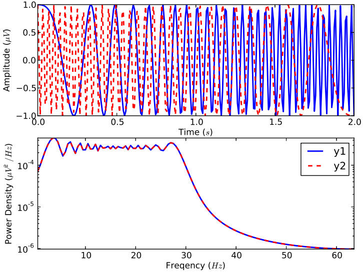
Thanks!

Examples of PSD Limitations

1. Below: no phase information
2. Below & Right: order of frequency change
3. Right: frequency resolution vs. noise

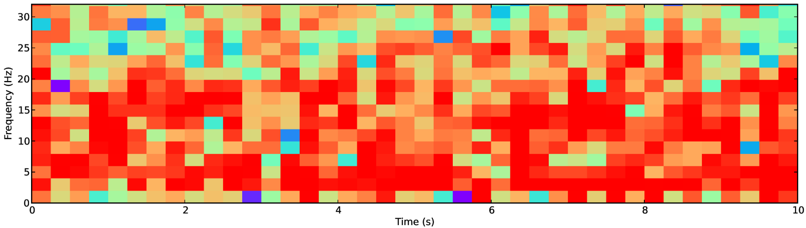


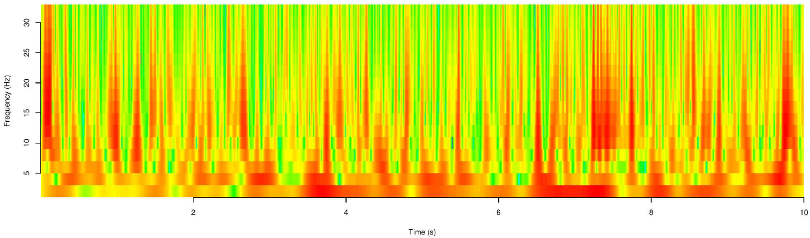




Temporal Resolution of PSD and CWT

- Example comparing temporal resolution of PSD and CWT
  - Different color schemes (python vs R)
  - Same frequency resolution, 2Hz bins
  - Depends on sampling rate, frequency resolution, smoothing





Maximum Signal Fraction