Neuroscience Aspects and Outlook

EEGLAB Workshop 2013, Track B

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Outline

1. Prerequisites
2. Source Signal Feature Extraction
3. Location-Based Prior Knowledge
4. Recent Example: Attention Shifting
5. Outlook
   A. Further Reading
1 Prerequisites
Prerequisites

• Neuroscientifically interpretable BCI models rely on *being able to spatially locate the parameters* and the importance/weight assigned to them by models

• Can be accomplished in multiple ways:
  – Calculate 3d gain field for spatial filters
  – Represent models in terms of localizable signal components
  – Represent models in a very large space of cortical basis vectors (one per patch)
Prerequisites

• Currently in practice the easiest is to utilize spatially localizable components

• Can be done via Independent Component Analysis and Dipole fitting (our choice at SCCN)
Independent Component Analysis

- ICA is a method to learn spatial filters for statistically independent brain sources in an unsupervised manner (i.e. no need for labels)
- Basic idea is to learn a square filter matrix $W$ such that the filtered signal components are statistically maximally independent
Independent Component Analysis

- There are dozens of ways to implement it – currently best for EEG are extended Infomax and AMICA
- Surprisingly, many ICs have dipolar scalp topographies
- Can be practically localized via dipole fitting
2 Source Signal Feature Extraction
Source Signal Feature Extraction

• Source components need no further spatial filtering, so features can be extracted directly from them, including:
  – spectral measures
  – non-linear temporal measures
  – higher-order (inter-component) features

• Since ICs are statistically independent, only a sparse set of components is relevant for any given (BCI or other) question – allows for sparsity assumptions
Component Spectral Features

- Fourier spectrum
  - Windowed DFT/FFT
  - Welch spectral estimation
  - Multi-taper spectral estimation

- Between Component Features
  - Coherence
  - Phase Locking Value
  - Effective Connectivity
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- Time/Frequency representations
  - Short-Time Fourier Transform (STFT)
  - Continuous Wavelet Transform (CWT)
  - Discrete wavelet transform (DWT)
  - Time-frequency distributions
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Integrating Structural Prior Knowledge

• Amounts to side assumptions about the data
  • For example:
    – Spatial smoothness (correlation)
    – Sparsity, group sparsity
    – Shared latent structure between parameters
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• For example:
  – Spatial smoothness (correlation)
  – Sparsity, group sparsity
  – Shared latent structure between parameters
  – Kernels for non-linear features
  – “Dictionaries” of known (learned) features
  – Per-trial parameters (e.g. outlyingness, time shift)
3 Location-based Prior Knowledge
Source-Space Modeling

- If IC sources are localized using, e.g., dipole fitting or NFT, parameters ($\theta$) have a location
Integrating Quantitative Prior Knowledge

• If weights have an associated location (refer to a localized signal components), anatomical prior knowledge can be used

• For example, reweight the regularizing penalty based on probability of source being located inside a particular brain area

• Brain atlases: Talairach, LONI
Integrating Empirical Prior Knowledge

- Information gathered from other subjects can be factored into a given model (e.g., add an extra penalty or Bayesian prior).
- Having spatially localized parameters enables location-dependent priors and spatial coregistration or alignment of multi-subject data.
4 Recent Example: Attention Shifting
Experimental Task

- 38 subjects (2 age groups, ignored here)
- 32 channels EEG
- Stimulus stream: Targets (20%) & Non-Targets (80%), randomly interleaved order (100-400ms onset-to-onset SOA)
- Some delivered visually (bright and dark rectangles), others delivered acoustically (beeps and boops)
- Sporadically (6600ms onset-to-onset): **Instructions to switch to another sensory modality** ("LOOK" / "HEAR"), bimodal delivery
- Other blocks at beginning/end of experiment, ignored here
- Ca. 260 switch trials total per subject
Analysis Goal

• Build a classifier that can determine the directionality of a subject’s attention switch (auditory to visual or visual to auditory)
• Parameterize the model in a way that is interpretable from a neuroscience perspective
• Evaluate its performance (mis-classification rate)
1. Signal Decomposition

Raw EEG segments / trials → Linear spatial decomposition (multi-model AMICA) → Continuous wavelet time/frequency decomposition (complex Morlet)
2. Predictive Model

• Severely underdetermined without additional side assumptions
• Assumptions here: sparse in components, low-rank in time/frequency
• Also an anatomical prior
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- Severely underdetermined without additional side assumptions
- Assumptions here: sparse in components, low-rank in time/frequency
- Also an anatomical prior
- Can be solved as a single large convex optimization problem:

$$\min_{\theta} \log(1 + e^{-y(\theta X + b)}) + \lambda \sum_{c=1}^{C} \sum_{k=1}^{\text{rank}(\theta_c)} \sigma_k(\theta_c)$$
Results: Classification Accuracy

• Analysis approach
  – 10-fold chronological cross-validation, 5 trials margin between training set and test set
  – Nested cross-validation on training set to optimize the regularization parameter ($\lambda$)
  – ICA and other data statistics only computed on the training set, recomputed for every fold

• Test-set prediction attained: mean **86.4%** correct across all subjects (chance level 50%), $p<0.001$
Results: Full Model Structure
Caveats

• Takes several hours to compute (currently)
• Independent Components are learned without label knowledge – not guaranteed that relevant processes are captured
• Spatial decomposition can be derailed by strong artifacts in the data (get artifact components rather than brain components)
5 Outlook
Open Research Areas

• What are the fundamental accuracy limits imposed by our current EEG sensors?
• How far are we from these limits with our current approaches?
• Need a model that is mathematically optimal (under widely agreeable assumptions) to answer this question empirically
Open Research Areas

• Hierarchical models that include data from multiple people and sessions
• Inclusion of neuroscientific knowledge (from the book and from quantitative sources, e.g., data bases)
• Inclusion of auxiliary data (e.g., MoCap, etc.)
• Designing methods that are entirely principled and optimal
• Designing methods that directly target real-world applications (e.g., robustness)
What We Did Not Cover

• Fully Bayesian approaches (graphical models, variational inference, Bayesian model selection) and connections to optimization
• Existing multi-subject BCI approaches (e.g., Altun 2010, Fazli 2011)
• Beamforming techniques (e.g., Wentrup 2009)
• Connectivity-based approaches (e.g., Daly 2012)
• Non-standard signal features (e.g., Brodu 2012)
Some Concluding Remarks

• Simple and fast methods (e.g., LDA) often work remarkably well (much easier to write a paper if it takes 5 seconds to compute instead of 5 hours)
• But: approaches that take 5 hours today were largely intractable 10 years ago – so new territory to explore
• The importance of assumptions cannot be overstated (as opposed to getting sidetracked with ad hoc algorithms and questions)
• Provably optimal and well-defined methods allow us to directly test our assumptions (with fewer random or unexplained effects)
• It is too easy to evaluate things in not entirely proper ways – ultimately hampers progress, always do it right!
Questions?
Appendix: Further Reading
BCI Papers Worth Reading


BCI Surveys


Interesting Technical Papers


Technical Papers, ct’d

Researchers to Watch

• Klaus-Robert Mueller et al. (TU Berlin) – one of the leading BCI groups
  http://www.bbci.de/publications.html
• Marcel van Gerven et al. (Donders) – BCI and Neuroscience with a Bayesian approach
  https://sites.google.com/a/distrep.org/distrep/publications
• Ryota Tomioka (U Tokyo) – known for some technical achievements
  http://www.ibis.t.u-tokyo.ac.jp/RyotaTomioka
• Karl Friston et al. (UC London) – working on relevant underpinnings for neuroimaging (outside BCI)
  http://www.fil.ion.ucl.ac.uk/Research/publications.html
• Leading Statisticians and Machine Learners: Michael I. Jordan, Andrew Ng, Lawrence Carin, Zoubin Ghahramani, Francis Bach, Geoffrey Hinton, Ruslan Salakhutdinov, Yeh Whye Teh, David Blei, ...