Functional High-Definition Imaging of EEG Brain Dynamics

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The Electromagnetic Forward / Inverse Problem
Phase cones (Freeman)
Avalanches (Plenz)
Electromagnetic source localization using realistic head models → The NFT toolbox
The very broad EEG point-spread function
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Simulated spatially labile (traveling wave) parietal source activity

Akalin Acar & Makeig 2010
Blind EEG Source Separation by ICA

Information-based Signal Processing
ICA is a linear decomposition
Independent Component Analysis of Electroencephalographic Data

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Abstract

Because of the distance between the skull and brain and their different minivis, electroencephalographic (EEG) data collected from any point on the human scalp includes activity generated within a large brain area. This spatial smearing of EEG data by volume conduction does not involve significant time delays, however, suggesting that the Independent Component Analysis (ICA) algorithm of Bell and Sejnowski (1) is suitable for performing blind source separation on EEG data. The ICA algorithm separates the problem of source identification from that of source localization. First results of applying the ICA algorithm to EEG and event-related potential (ERP) data collected during a sustained auditory detection task show: (1) ICA training is insensitive to different random seeds. (2) ICA may be used to segregate obvious artificial ERP components (e.g., speech) from other sources. (3) ICA is capable of isolating overlapping ERP phenomena, including alpha and theta bands and spatially-separable ERP components, to separate ICA channels. (4) Nonstationarities in EEG and behavioral state can be tracked using ICA via changes in the amount of residual correlation between ICA-filtered output channels.
“ICA may be used to segregate obvious artificial EEG component (line and muscle noise, eye movements) from other sources.”

- Makeig et al., 1996
Figure 1: Left: 4.5 seconds of 14-channel EEG data. Right: an ICA transform of the same data, using weights trained on 5.5 minutes of similar data from the same session.
“ICA is capable of isolating overlapping EEG phenomena including alpha and theta bursts and spatially separable ERP components, to separate [ICs].”

- Makeig et al., 1996
ICA in practice

Onton & Makeig, 2006
“ICA training is insensitive to different random seeds,”

[... and can separate out independent components of data with hundreds of channels].

- Makeig et al., 1996
Brain-based, ‘dipolar’ independent components of EEG data are projections of single (dual) cortical patches.
Independent cortical components

- Single dipole component
- Dual-symmetric dipole component
- Equivalent dipoles

Julie Onton & S. Makeig (2006)
THUS → ICA (BSS) decompositions that find components whose time courses are more independent

→ also find more components whose scalp maps are ‘dipolar’!

Thus, the two approaches to constraining the EEG inverse problem, *biophysical* and *statistical*, are directly interlinked.
Why?

Very likely because the physiological assumptions motivating the use of ICA for EEG data are *substantially* correct...
Frontal Midline Theta Process
Anterior Cingulate Cognitive Division

Bush et al., 1999
Similar independent components tend to reappear in different subjects performing the same task.

S. Makeig, 2007
Clustering ICA components

Left mu

Right mu
Equivalent dipole density

Visual Working Memory

Onton et al., 2005
Independent components of EEG data tend to be functionally independent – changes in their activity patterns tend to reflect ‘top-down’ changes in cognitive state and/or cognitive appraisal.

S. Makeig, 2007
Brain processes have evolved and function to optimize the outcome of the behavior the brain organizes in response to perceived challenges and opportunities.

Brains meet the challenge of the moment!
Collections of single trials, even at the source level, are regular, but in multiple ways – so they appear noisy!

Trial-to-trial Variability
1. Display single trials as color-coded horizontal lines (e.g., red is $+\mu V$, blue is $-\mu V$, green is 0).

2. Sort all trials according to some variable of interest (here, subject RT).


Visual Selective Attention Task

15 subjects
$\mu$ - In or Near Right Hand Somatomotor Cortex

$\mu$ - In or Near Left Hand Somatomotor Cortex

S Makeig et al., *PLOS Biology* 2004
FM - In or Near Rostral Cingulate Zone (dACC)

CM - In or Near Motor Cingulate / Supplementary Motor Cortex

S Makeig et al., *PLOS Biology* 2004
Complex event-related dynamics sum to ‘the’ P300
Measure Projection: RSVP Example

N. Bigdely-Shamlo, 2011
A Passive Spatial Navigation Paradigm
A Passive Spatial Navigation Paradigm

Klaus Gramann et al., 2010
‘Turner’ and ‘Nonturner’ subjects use different spatial orienting styles

Klaus Gramann & S. Makeig, 2010
Parietal component clusters

Klaus Gramann et al., 2010
Pre-motor component clusters
Medial prefrontal component clusters

Klaus Gramann et al., 2010
Clusters distinguishing Turners & Nonturners

Klaus Gramann et al., 2010
Visual spatial working memory in young and older adults

V. Bjerre, J. Onton, & S. Makeig, 2006
Young adults – Older adults

V. Bjerre, J. Onton, & S. Makeig, 2006
Changes in distribution of broadband high-frequency EEG power with imagined emotion

EEG & Emotion

Julie Onton & Scott Makeig, Frontiers in Human Neuroscience, 2009
JUST: A quartet suite for flute, violin, cello, and brain

Fourth International BCI Meeting
Asilomar Meeting Grounds, Pacific Grove, CA
June, 2010
Brain imaging during movement – How?

• Current advances in miniaturization, computer power, and information-based signal processing make possible a new imaging modality:

  Mobile Brain/Body Imaging (MoBI)

Concept:

Combine whole-head EEG, eye-gaze tracking, and whole-body motion capture recording in a real-world 3-D environment.
Finding EcoG Sources
(invasive monitoring before surgery for epilepsy)

Number of elements:
Scalp: 10,000
Skull: 30,000
Plastic sheet: 7,000

Akalin Acar et al. 2011
Sources of seizure components
5-model AMICA decomposition (dependent subspaces)