Computational EEG Analysis for Characterizing Cognitive Activity: Methods and Applications

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Computational EEG Analysis for Characterizing Cognitive Activity: Methods and Applications

Outline

- 1. Introduction to the first functional brain imaging modality EEG
- 2. History of EEG analysis
 - I. ERP, Power spectral analysis
 - II. Source localization
 - III. Separation of EEG signals by Independent Component Analysis
- 3. Electromagnetic Spatiotemporal Independent Component Analysis (EMSICA)
- 4. Multi-subject spatiotemporal independent source imaging

Introduction



EEG powered by BCILAB | SIFT

Introduction



- To look the working structure and function of living human brain

High-density 128 channels EEG + structure MRI



EEG Lab, Institute of Statistical Science, Academia Sinica

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Anatomical structure from MRI

• what changes are happening in real time in the brain

Electroencephalography (EEG)

- the first functional brain imaging modality



Introduction - Electroencephalography (EEG)

• Electroencephalogram (EEG). Glutmate is the major excitatory neurotransmitter in the brain.



Neuroscience: Exploring the Brain Fourth, North Americ Edition by Bear, Mark F., Connors, Barry W., Paradiso, Mich (2015)

Computational EEG Analysis



→ Machine learning

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History of EEG analysis



The history of EEG analysis

Fra 1. 50s - looking at ripples on the paper



Fra 1. 50s - looking at ripples on the paper

- How could you identify EEG by looking at the ripple?
- Inhibitory <-- --> excitatory function



History of EEG analysis



The history of EEG analysis

Fra 2. 60s - Event Related Potential (ERP) analysis



functional recording of brain activity < events, participant's experiences

The history of EEG analysis

Fra 2. 60s - Event Related Potential (ERP) analysis



Nature Reviews | Neurology

History of EEG analysis - ERSP



The history of EEG analysis

Fra 3. Spectral perturbation analysis

1993. Scott Makeig defined
 broadband event-related spectral
 perturbation (ERSP) measure

1993. fMRI research - blood oxygenation level-dependent (BOLD) recording (Ogawa, et. al 1992, Bandettini, et. al. 1993)



EEG form young adults with Asperger's Syndrome



- significant difference in the N400 component
- differentiate the affective and cognitive functions

(Tsai & Liou, et al., 2013. Chien, Liou, & Tsai, et al., 2016) 18

Conventional EEG Analysis



EEG Methods for the Psychological Sciences

Cheryl L Dickter Paul D Kieffaber **December 20, 2013**

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Chapter 1 – Introduction to Social Neuroscience Chapter 2 – From Cortex to Computer: The Principles of Recording EEG Chapter 3 – The EEG Laboratory Chapter 4 – Getting Started with Data Analysis: Data Pre-Processing Chapter 5 – Time-Domain Analysis Chapter 6 – Frequency-Domain Analysis Chapter 7 – Time-Frequency Analysis Chapter 8 – Current Domains & Future Directions

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History of EEG analysis



Source imaging in EEG

 Perform inverse solutions in an event-related latency interval relevant to average event-related potential (ERP) measures (e.g., the latency range including the P1, N1, P2, N2, P300, N400 ERP peaks).

Conventional approach:



Schematic presentation of **dipole** sources.



If you have many of these neurons, the electric field can be summed up and seen on the scalp.

Dipole source localization: solves $A_B = G(\{\gamma_k, \theta_k\})$

Distributed source imaging: solves $A_B = LB$

Neuroscience: Exploring the Brain Fourth, North Americ Edition by Bear, Mark F., Connors, Barry W., Paradiso, Mich (2015)

EEG --- mixture of underlying cortical sources

Average ERPs ← multiple distributed sources

 Studies applying ICA (Independent Component Analysis) to individual subject data have found that time courses of average ERPs in cognitive tasks are generated by multiple distributed sources with overlapping scalp topographies.



(Makeig et al., 2002, 2004; Moores et al., 2003).

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 $x^{(t)}$

- ICA explains what (independent) processes are involved in the cognitive tasks
- Source analysis method models where the possible sources of these processes occur.



Source decomposition → localization:



The equivalent dipole sources (Onton
 NI2005, Makeig-Autism2009, Cogn2007, Russian's 2010)
 or source current density (e.g., Congedo et al., 2010; De Lucia et al., 2010; Ponomarev et al., 2010)
 can be localized to represent the generators of these components.

Two-stage ICA

The Issues of Two-stage ICA



ICA model:

 $x^{(t)} = A u^{(t)}$

where A denoting the mixing matrix whose columns can be partitioned into

$$A = [A_A, A_B]$$

$$\begin{array}{l} x_c^{(t)} = A_B \ u_B^{(t)} \\ _{64 \mathrm{xT}} & \mathrm{IxK} & \mathrm{KxT} \end{array}$$

Issues on Two-stage ICA



Parametric source localization:

Two-stage method- solves
$$A_B = G(\{\gamma_k, \theta_k\})$$

128x20 solve 2x3xKx20. K is unknown

Distributed source imaging:

Two-stage method- solves $A_B = LB$ 128x20 solve 12,000x20

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Electromagnetic Spatiotemporal Independent Component Analysis (EMSICA)



Electromagnetal Spatiotemporal Independent Component Analysis (EMSICA)

EMSICA model:

$$x_c^{(t)} = LBs^{(t)}$$

128x600,000 solve 12,000x20

Single-trial, single-stage independent source imaging.

cf. Two-stage ICA: $x_c^{(t)} = A_B u_B^{(t)}$ Two-stage method- solves $A_B = LB$ 128x20 solve 12,000x20



source analysis from IC scalp map $A_B = LB$ IXK

The two-stage ICA/PCA approach, dramatically reduces training data information for source analysis from $x_c^{(t)}$, for t = 1, ..., T, to A_B , where the number of data points are *I*-by-*T* (e.g., 128x600,000) and *I*-by-*K* (e.g. 128x60), respectively, while $T \gg K$.

EMSICA algorithm

To Maximize:

 $p\left(B|x^{(t)},L\right) \propto p(B) \int ds^{(t)} p\left(x^{(t)}|L,B,s^{(t)}\right) p\left(s^{(t)}\right)$

Assume spatial independence + Markov Random Field as prior

Assume temporal independence

• $B \in \mathbb{R}^{J \times K}$: b_{jk} the contribution of the *k*th source component to the *j*th tessellation element on the cortex

• *s*(*t*): the source signal

• *x*(*t*): Single-trial EEG recordings

• L : Leadfield obtained from realistic head model

The learning rule:

$$\Delta B = B \left[B^T \phi(B) - I - (1/\tau) \phi(U) U^T \right]$$
(Topi of all Nour

(Tsai et al., NeuroImage, 2006)

Single-trial, single-stage spatiotemporal independent component analysis

Comp 2 Comp 3 Comp 5 EMSICA components Comp 9 Comp 8 Comp 6 scalp projection Comp 24 Comp 7 active source area (Tsai et al., NeuroImage, 2006)

Identical, what are they equivalent now? How to cluster the components?

History of EEG analysis



2014



Multi-subject group analysis workflow

Cortical surface alignment in multi-subject

spatiotemporal independent source imaging



Multi-subject Cortical surface alignment



Latency-frequency Image Aligning



Multi-subject group analysis workflow

Cortical surface alignment in multi-subject spatiotemporal independent EEG source imaging



(Tsai et al., NeuroImage, 2014)

Results of component clusters



stop signal paradigm





Results of component clusters (cont')





Results of component clusters (cont')



Neuroimaging studies have demonstrated that the anterior cingulate cortex (ACC) is engaged in detecting or dealing with conflict between a stop signal and an intended action [Gehring and Knight, 2000], and that, subsequently, right inferior frontal cortex (rIFC) is involved in suppressing the intended response [Aron et al., 2004], supporting the findings of the involvement of ACC θ and $rIFC\theta$ in this study.

Summary and discussion

- Direct comparison of the scalp maps of ICs or even the location of the equivalent dipole calculated by scalp maps of ICs across subjects may not be scientifically meaningful, because
 - the signal recorded from a scalp electrode is actually a mixture of underlying cortical sources instead of single dipole(s) and
 - the brain geometry can differ between subjects, thus, yields different corresponding leadfields.
- The study presents the cortically evidence-based aligned clustering strategy and validates its effectiveness by applying to investigate the mechanism of activation and inhibition in the stop-signal paradigm.
- To assess the consistency of independent components across subjects, a group analysis method has been proposed by directly compares spatiotemporal independent components in aligned activation brain topography and power spectral patterns over short time intervals in an oscillatory fashion.



Summary: History of EEG analysis



→ Machine learning