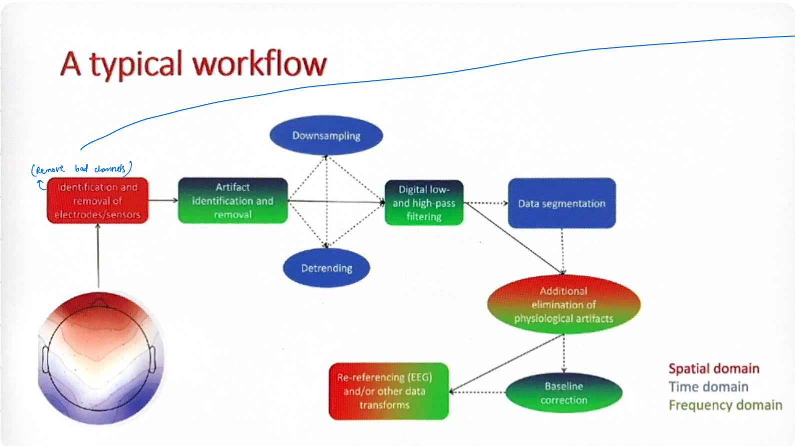
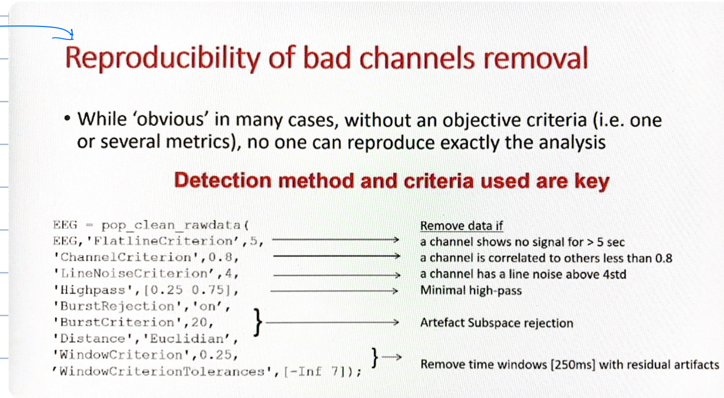
1) Cyril Pernet (Intro)

· Standards
- BIDS
- IFCN
- OHBM COBIDAS

* Github Repo starred
(cpernet / EEGPreprocessing_Not_so_Basic)





2) Li Dong (UESTC, China) → content by Dezhong Yao → talk on REST

· n electrodes
- n-1 channel record.
- 1 ref elect.

→ Diff. gives potential

$$\left.\begin{aligned} x_1 - x_n &= y_1 \\ x_2 - x_n &= y_2 \\ &\vdots \\ x_{n-1} - x_n &= y_{n-1} \end{aligned}\right\}$$

$\underbrace{\text{n-1 eq}^n \text{ but n unknowns}}_{\text{problems}}$

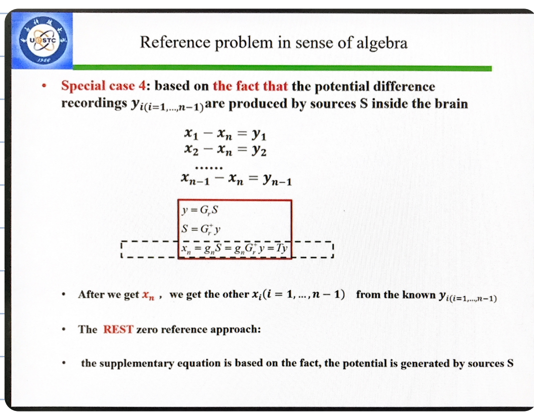
1) Special case 1: take x_n potential be 0 (ref. elect. $x_n = 0$)
(unipolar reference assumptn)

2 Special Case 2: $\sum_{i=1}^{n} x_i = 0$ → sum of all channels is 0
(Average ref. assumptn ⇒ AR)

Practical Meaning: Avg of all channel over sculp is zero

3) Special Case 3: sum of 2 ears = 0, $x_i(\text{left}) + x_j(\text{right}) = 0$
(Linked-ears or Mastoids assumptn ⇒ LM)

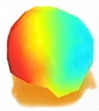
4) Special Case 4:
(REST assumptn)
↓
Reference Electrode Standardization Technique
(Yao, 2001)



→ Resonable

Not Reasonable → "Why the assumptn is correct in all these cases?"

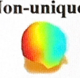
REST (reference electrode standardization technique) (Yao, 2001)



- With theoretical zero reference
  X=GS (1)
- With an actual reference r
  $Y=G_r S$ (2)
- From eq.(2), we have
  $S=G_r^+ Y$ (3)
- Combining eqs.(1) and (3), we have
  $X=GS=GG_r^+Y=TY$
  X=TY (4)
- source S is adopted as a bridge to link Y and X, actually we do not need to know S, but to know G and G_r, which are determined by the positions of sources and the electrodes

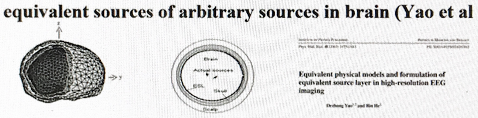
REST (reference electrode standardization technique) (Yao, 2001)

- Non-uniqueness of EEG inverse (Helmholtz,1853)



Y= G(1)S(1)
= G(2)S(2)
....

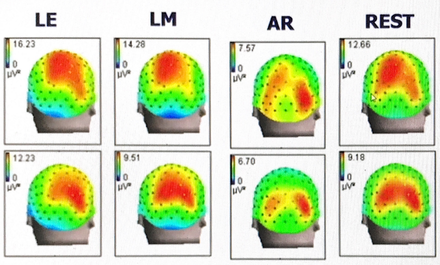
- Principle of equivalent sources
  S(1) and S(2) are equivalent sources of each other in producing the same scalp potential
- Dipole layer on the cortical surface
  may be the equivalent sources of arbitrary sources in brain (Yao et al 2013)



- Based on equivalent dipole layer on the cortical surface
  G, G_r^+, and $T=GG_r^+$ are known
  X=TY (4) is realizable

Adv. of REST → generalized across head sizes
→ " " electrode cap
→ Relative error is much smaller than AR

Power Spectra of EEG (qEEG)



Alpha-1
7.5 - 9.5Hz

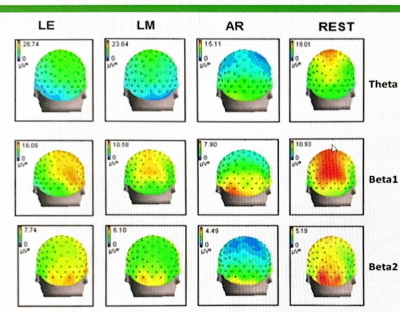
Alpha-2
10.0-12.5Hz

Power maps of the EEG recordings with different references. The power is analysed by FFT with 2 s epochs free of artefacts.

Current practices:
Clinic: linked ears(LM) are common in qEEG
Psychology: LM and AR are widely adopted

Yao, et al, Physiol Meas, 2005, 26:173

Power Spectra of EEG (qEEG)



4-7Hz
13-23Hz
24-34Hz

Current practices:
Clinic: linked ears(LM) are common in qEEG
Psychology: LM and AR are widely adopted

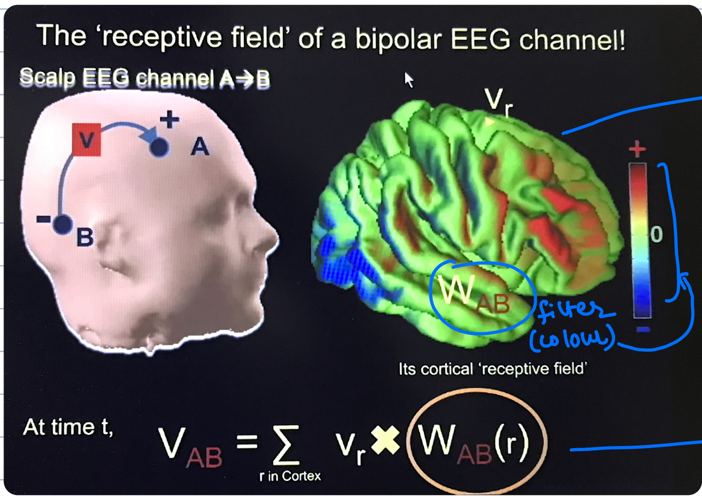
Yao Pedro etal BT 2019

Install REST (EEGLAB Plugin version)

- To install REST, download the zip file (http://www.neuro.uestc.edu.cn/rest/ or
- https://sccn.ucsd.edu/eeglab/plugin_uploader/plugin_list_all.php)
- Unzip and place the folder in the 'plugins' folder of your existing EEGLAB installation (so something like ~/eeglab14_1_0b/plugins/REST_reference_v1.1_20190818/eegplugin_rest.m exists).

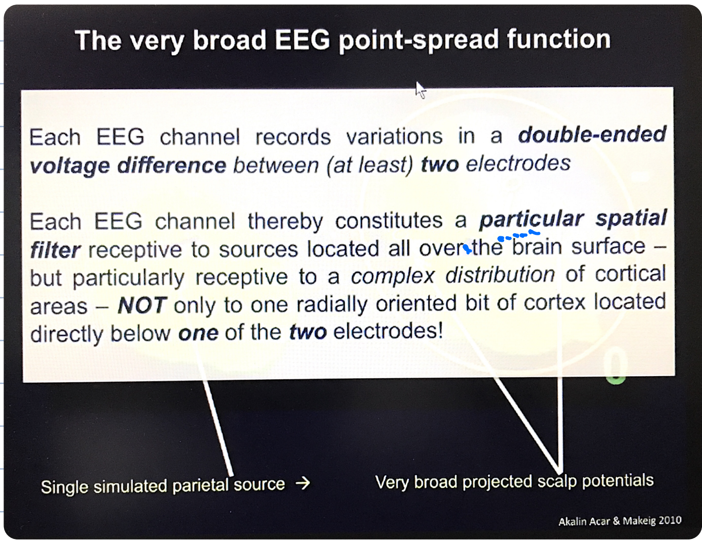
Dong, L., et al. (2017). "MATLAB Toolboxes for Reference Electrode Standardization Technique (REST) of Scalp EEG." Front Neurosci 11.

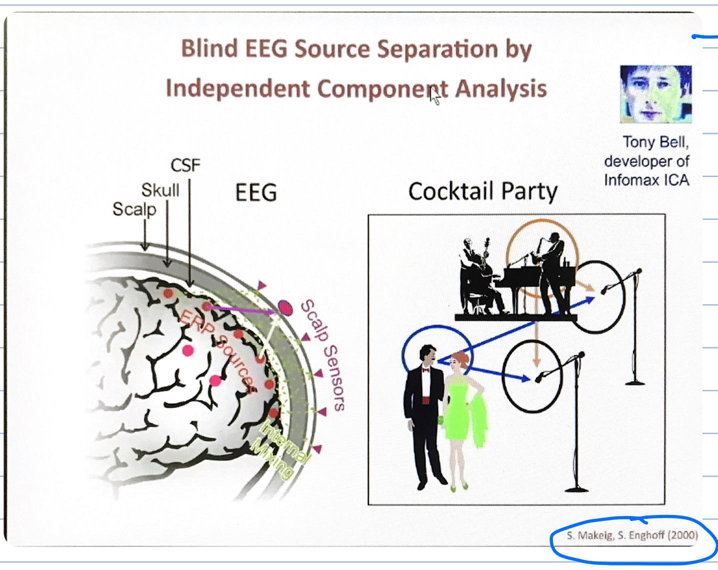
3) Scott Makeig → talk on ICA



→ A-B channel is sensitive to activities in all the voxels which are not green
⇓
each EEG channel is a spatial filter, which is messy, because it is not dominated by a single cortical area.

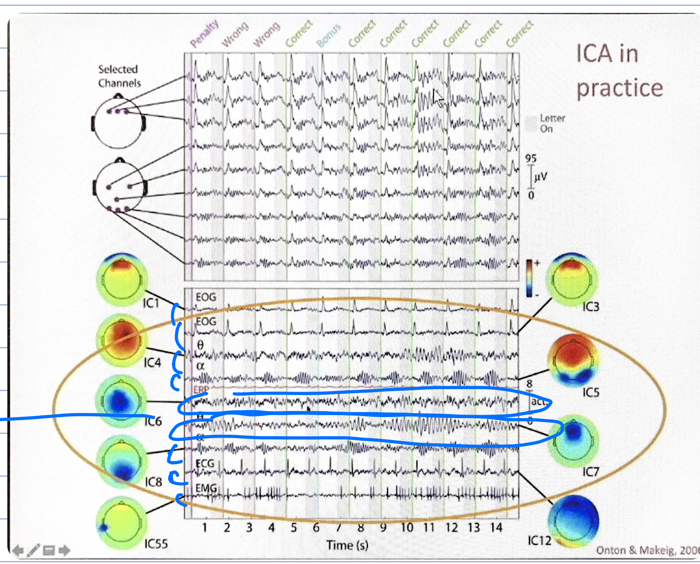
→ Any EEG signal b/w 2 electrodes is sum of voltages at individual voxel weighted according to filter W



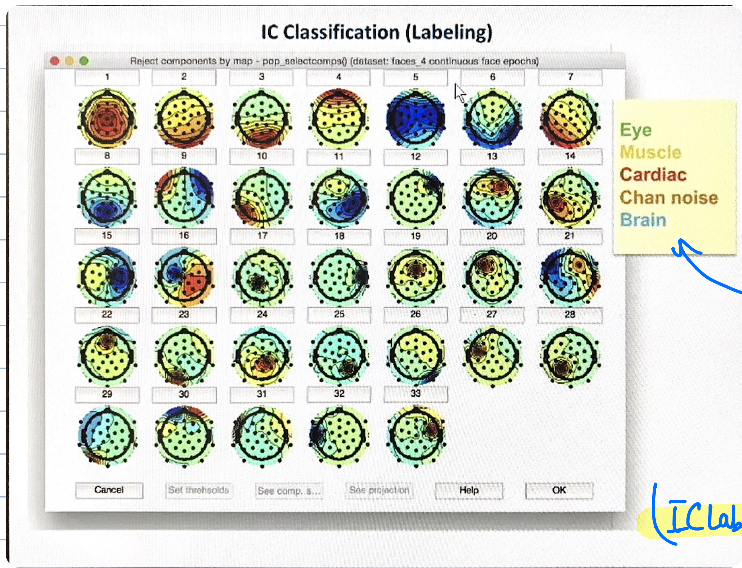


→ wow. Basically using ICA to detect activity at individual sites.

In other words, ICA can find distinct EEG source activities & their simple scalp maps!



because of ICA, we can see that all these final recordings have temporal independence (you don't see common signal between α & θ etc)



→ we can get Indep. components of all the different activities leading to EEG signal. But then How to classify them ?

⇒ Machine learning

they performed it (to train ML, labels available at IClabels website)

(IClabel → Luca Pion-Tonachini, 2019)

labeling.ucsd.edu/tutorial

4) Nicloas Langer (Uni Zurich) - effect of data filtering on Automated ICA classifiers, ERP & multivariate analysis

filtering → to improve SNR

Nice perspective of looking why ideal filters is not possible

↳ Any abrupt transitn in one domain (t/ω) requires ∞ number of components in other domain

• Note : FIR filters recommended for most EEG analyses

→ further lecture was too much basics into data filtering (I knew those things)

Effects of filtering on ICA

↓

Biased towards high amplitude & in EEG, low freq has high amp.

⇓

low freq. have most influence on ICA

• Recommedation - Compute ICA on EEG data which are at least 1Hz High pass filtered

→ But the problem is 1Hz HPF causes distortn in Event Related Potential (ERP)

Solutn : Temporal Filtering

1) Calculate ICA
2) Remove Artifactual ICA
3) Apply ICA weight & sphere matrix to retain IC's to 0.1 Hz HPF data

- Recommendatⁿ → Use 2 Hz HPF & 40 Hz LPF for IC label (Pion-Tonachini et al. 2019)

Because such dataset was used to train the model

But again, 2 Hz HPF also causes distortⁿ in ERP

∴ follow the same solutⁿ as previously.

Automagic : Standarized Preprocessing toolbox

↳ github.com/methlab UZH/automagic (Pedroni et al., 2019)

5) Data Normalizatⁿ & its impact on source modelling & multivariate Analysis

- Multivariate models Boost SNR

1) Consider 2 EEG signal,

$$x_1(t) = 2s(t) + n(t)$$
$$x_2(t) = \underbrace{s(t)}_{\text{source}} + \underbrace{n(t)}_{\text{noise}}$$

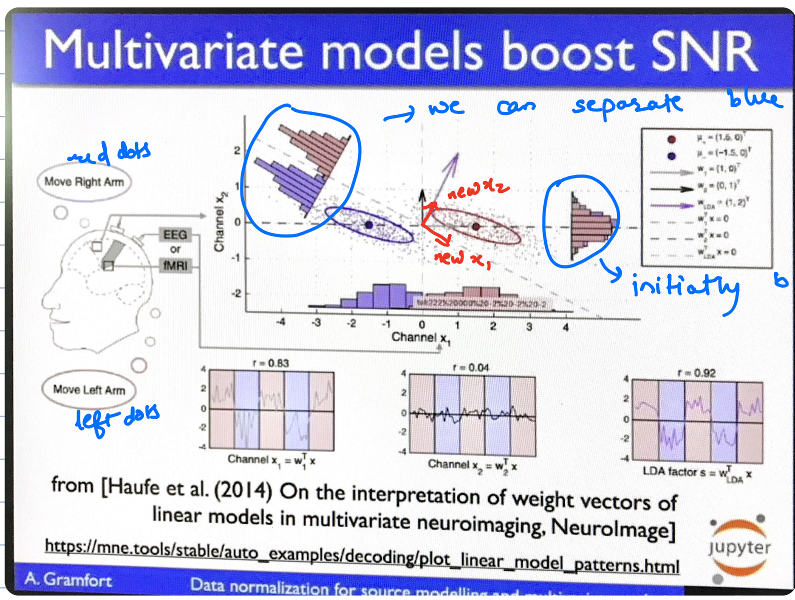
$\Rightarrow$ $x_2(t) - x_1(t) = s(t)$ → ONLY SIGNAL remains!

$\Rightarrow$ By subracting the signals, one can ↑ SNR

2) Signal Subspace Projector - improves SNR.

the last example was basic, this is similar analogy, we use linear combinatⁿs of multiple signals to remove noise

eg:



→ we can separate blue & red dots by using Linear combination (with required weights)

initially blue isn't separated from red

Notation

$M = M/EEG = \begin{bmatrix} \quad & \quad & \quad \end{bmatrix}$

→ one column = one time instant (time)

→ one row = one sensor (space)

$M \in R^{N \times T}$

6) EEG devices : what's out there for which application

Portable EEG systems — openBCI (github.com/openBCI)

Avoid Artifacts : 1) subject shouldn't swing (produces swinging artifact)

2) Muscles should be relaxed
↳ otherwise we get artifacts

3) No eye moments should be there (blink artifact in front channel)

4) Don't touch electrical systems

EEG data acquisition and appropriate data pre-processing: not so basic after all.

Aina Puce, Dr Co Organizer
Indiana University
Psychological & Brain Sciences
Bloomington, IN
United States

Cyril Pernet, Dr Organizer
University of Edinburgh
Center for Clinical Brain Sciences
Edinburgh, Scotland
United Kingdom

EEG is nearly a century old and, until recently, the data pre-processing flow was common, with small incremental steps toward more standardized methods. With the recent advent of new devices, new computational methods for pre-processing (Bayesian approaches and machine learning) and new biophysical (source reconstruction) and statistical analyses (GLM, MVPA, connectivity), there are now many modern options available with different impacts on different analytic pathways, yet most researchers are not aware of this and do not make use of these modern tools. This educational session aims to address this gap, bringing modern data acquisition and digital pre-processing analysis technology to all EEG researchers, a topic not previously covered at OHBM. The learning outcomes are: (1) learning the relative pros and cons of different available EEG acquisition systems (2) gaining a theoretical understanding of the key pre-processing steps: re-referencing, filtering, artefact removal (including using ICA with automated labelling), and data normalization procedures. While a half-day session does not allow enough time for practicals, the audience response system will be used throughout and a dedicated GitHub repository will be made available to provide a working knowledge of what will be presented.

Objective

- distinguish the different EEG hardware and know the pros and cons
- understand the key preprocessing steps and how this impact on reproducibility

Target Audience

- the primary target audience are newcomers to MEG-EEG
- the secondary target is experienced MEEG researcher who needs to update knowledge a new pre-processing tools

Presentations

The impact of pre-processing on reproducibility.

8:00 AM - 8:35 AM
This 15 min presentation will introduce the notion of workflows and present the different key steps in EEG preprocessing and how different methods impact results, limiting reproducibility if not fully described – as suggested in the COBIDAS MEEG report. This presentation will serve as an introduction to the different topics addressed during the session. The audience response system will be used throughout the presentation via pools/MCQ asking the audience to think about the impact of a different approach on results/reproducibility (~ 1/3 of the presentation time, 5 min).

Presenter

Cyril Pernet, Dr, University of Edinburgh
Center for Clinical Brain Sciences
Edinburgh, Scotland
United Kingdom

EEG devices: What's out there and for which application?

EEG systems have made the transition from laboratory based large behemoths to portable units with small numbers of electrodes for use in naturalistic settings - giving scientists many choices for how to perform EEG recordings. That said, choice of EEG system and analysis approach depends on the scientific question being asked. I will present EEG examples previously recorded from different commercially available systems - these data will be made available on the course repository. I will use the audience response system for an MCQ 'artifact quiz' to get the audience to identify some more common as well as some more esoteric artifacts (~1/4 of the presentation time; 10 min). I will also perform a physical demonstration of a portable EEG system to show some of the data acquisition issues users face in environments outside the laboratory. Finally, I will also contrast and compare some characteristics of the hardware and discuss suitability for particular applications, e.g., the lab versus natural settings, and also consider what consequences the chosen EEG hardware may have for a desire to subsequently re-reference the data, or on the choice to perform analyses in sensor versus source space. Ref: Lau-Zhu et al. Dev Cogn Neurosci 2019 Hari & Puce MEG-EEG Primer 2017

Presenter

Aina Puce, Dr, Indiana University
Psychological & Brain Sciences
Bloomington, IN
United States

EEG re-referencing: Common average referencing should not be your default.

This presentation (40 min) will examine the history of EEG reference electrodes, what is the EEG reference problem and describe the Reference Electrode Standardization Technique (REST, http://www.neuro.uestc.edu.cn/rest/). REST is applied as a re-referencing technique to transform multi-channel EEG data to an approximate zero reference one. Its use has increased in the EEG/ERPs community around the world in recent years. I will discuss the performance of REST, and review reference recommendation and present tools for applying REST. The audience response system will be used throughout the presentation via pools/MCQ asking the audience to think about the impact of a different approach on REST reference (~ 10%, 5 min of the presentation time). Data will be made available on the course repository to test the effect of re-referencing. Ref: Nunez & Srinivasan, Electric Fields of the Brain 2006 Yao, 2017 Brain Topography 30, Yao et al., 2019 Brain Topography 32 Dong et al., 2017 Front. Neurosci., 30

Presenter

Dezhong Yao, University of Electronic Science and Technology of China Chengdu, n/a
China

ICA for artefact removal: Crowd sourced machine learning to the rescue.

A difficulty in using independent component analysis (ICA) to analyze EEG data is that the independent component (IC) source processes it identifies as making the most temporally independent contributions to the scalp-recorded channel data isolate the activities of functionally and temporally distinct brain as well as non-brain source processes. Through experience, one can learn to associate ICs with various source processes (eye or muscle activity, line noise, single-channel artefact, brain activity), or as (typically small) ICs without clear association to these categories. I will present how machine learning can be used to model this association probabilistically (cf. Frolich et al 2014) and will illustrate automated labelling using ICLabel (Pion-Tonachini et al 2019), an efficient tool trained on features computed for over 100k ICs in the Swartz Center data library, many then labeled by volunteer ('crowdsource') users of the ICLabel website (iclabel.ucsd.edu). I will illustrate using the website and EEGLAB (sccn.ucsd.edu/eeglab), which the audience may use to follow along if they wish. During the talk, the audience response system will be used to assess their understanding of ICA and IC classification (~ 10%, 5 min).

Presenter

Scott Makeig, University of California San Diego San Diego, CA
United States

Data filtering and its impact on univariate and multivariate analyses

Filtering is a ubiquitous step in M/EEG data preprocessing that can considerably affect results. Besides the intended effect of the attenuation of signal components considered as noise, filtering can also produce unintended adverse filter effects and artifacts. In the literature, questionable “standard” filter parameters are commonly applied, and filter details are often incompletely reported, compromising replicability. In this lecture (40 min), I will introduce digital filter design including the most relevant filter parameters, properties and their interpretation. The aim is to provide practical guidelines on how to design appropriate filters for specific applications. I focus on the implications and side effects of frequency filtering of broadband time (and frequency) domain signals. I will demonstrate how to evaluate and visualize filter effects on test and real M/EEG signals. I will give strategies for recognizing potential filter distortions in event-related data and discuss relations to other operations, such as baseline correction and time-frequency analysis. Relevant best practices from the COBIDAS MEEG report will be discussed during the lecture. The audience response system will be used throughout the lecture to present MCQs (10%, ~5 min) identifying common-sense conceptions and misconceptions on data filtering and potential distortion of results. I will provide documented code to illustrate basic principles, filter design and evaluation using test and real signals, and to reproduce most of the figures. These will be made available on the course repository. Ref: Rousselet, 2012; Widmann & Schröger, 2012; Widmann et al. 2015, Maess et al., 2016a,b, Alday, 2018, van Driel et al., 2019

Presenter

Nicolas Langer, University of Zurich Zurich, Switzerland
Switzerland

Data normalization and its impact on source modelling and multivariate analysis

Processing tools to analyze physiological signals such as EEG or MEG are grounded on statistical assumptions. One such typical assumption concerns what we call 'noise' and how we statistically model it. In this lecture, I will cover the data normalization step that is often referred to as spatial whitening. I will detail some of the challenges and solutions that exist to deal with this variant of data normalization. This will include examining the problem of covariance estimation from limited data, as well as the problem of data with reduced rank due to preprocessing. This lecture will be illustrated with Python notebooks based on the MNE software. Attendees will have access to notebooks on the course repository on GitHub and will be able to run them during the course, e.g. using Binder. Ref: Engemann & Gramfort, 2015, Guggenmos et al., 2018

Presenter

Alexandre Gramfort, Dr, INRIA Paris, n/a
France