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INSTITUTE OF NEUROLOGY IMAGINING DEPARTMENT

UCL

Statistical Parametric Mapping for MEG/EEG

Data pre-processing

Catharina Zich

30th May – 2nd June

scientific reports

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Article | Open Access | Published: 09 February 2023

EEG is better left alone

Arnaud Delorme

Scientific Reports **13**, Article number: 2372 (2023) | Cite this article

John T. Johnson, PhD @johnatl@fossto... @Joh... · Feb 14 ···
That's fine for ERPs and people who aren't behaving and are motionless. Throw in some time-frequency and kinematics and you'll be crying for artifact subspace reconstruction (Kothe & Jung, 2014), and adaptive mixture of independent component analyzers (Palmer, 2011).

Abstract

Automated preprocessing methods are critically needed to process the large publicly-available EEG databases, but the optimal approach remains unknown because we lack data quality metrics to compare them. Here, we designed a simple yet robust EEG data quality metric assessing the percentage of significant channels between two experimental conditions within a 100 ms post-stimulus time range. Because of volume conduction in EEG, given no noise, most brain-evoked related potentials (ERP) should be visible on every single channel. Using three publicly available collections of EEG data, we showed that, with the exceptions of high-pass filtering and bad channel interpolation, automated data corrections had no effect on or significantly decreased the percentage of significant channels. Referencing and advanced baseline removal methods were significantly detrimental to performance. Rejecting bad data segments or trials could not compensate for the loss in statistical power. Automated Independent Component Analysis rejection of eyes and muscles failed to increase performance reliably. We compared optimized pipelines for preprocessing EEG data maximizing ERP significance using the leading open-source EEG software: EEGLAB, FieldTrip, MNE, and Brainstorm. Only one pipeline performed significantly better than high-pass filtering the data.

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PSYCHOPHYSIOLOGY

SPR SOCIETY FOR PSYCHOPHYSIOLOGICAL RESEARCH

ORIGINAL ARTICLE

Variations in ERP data quality across paradigms, participants, and scoring procedures

Guanghui Zhang, Steven J. Luck

First published: 07 February 2023 | https://doi.org/10.1111/psyp.14264

ELSEVIER

International Journal of Psychophysiology

Volume 111, January 2017, Pages 80-87

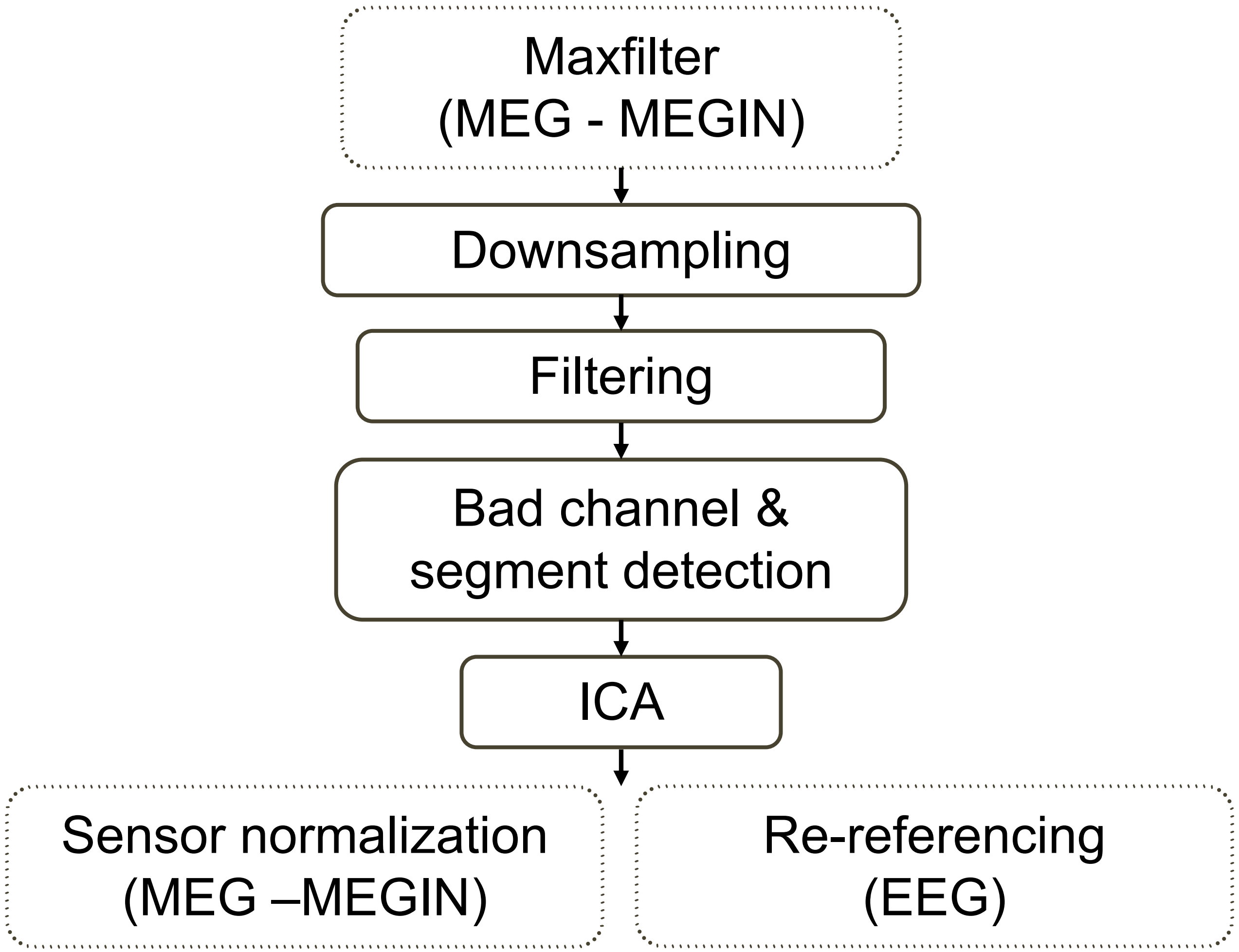
Rigor and replication in time-frequency analyses of cognitive electrophysiology data

Michael X Cohen

EEGManyPipelines: Robustness of EEG results across analysis pipelines

Johannes Algermissen[1,*], Niko A. Busch[2,*], Elena Cesnaite[3,*], Nastassja L. Fischer[4,*], Claudia Gianelli[5,*], Joshua D. Koen[6,*], Tom R. Marshall[7,*], Muhammad Samran Navid[1,8,*], Gustav Nilsonne[9,*], Annalisa Pascarella[10,*], Tuomas Puoliväli[11,*], Mehdi Senoussi[12,*], Darinka Trübutschek[13,*], Mikkel C. Vinding[14,15,*], Andrea Vitale[16,*], Yu-Fang Yang[17,*], and Jeremy Yeaton[18,*]

Data pre-processing: Overview



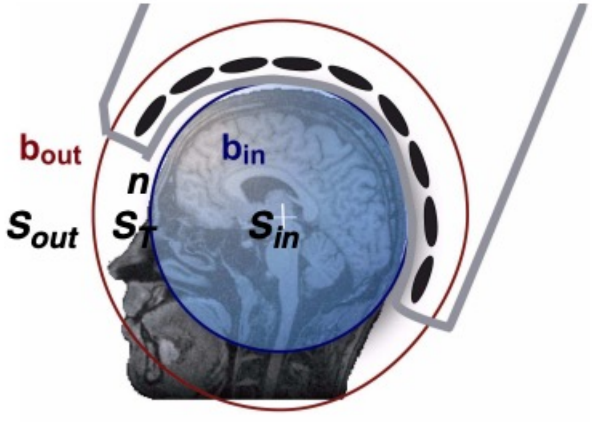
SSS & Maxfell filtering (MEG - MEGIN Neuromag)

- A program provided by MEGIN (but see also MNE-Python)

- **Signal-Space Separation** (SSS) separates components attributable to sources inside a sphere within the sensors array (the internal components), and components attributable to sources outside of a sphere of sensors.

- **Maxwell** filtering is a related procedure that omits the higher-order components of the internal subspace, which are dominated by sensor noise.

MaxFilter User's Guide
Taulu et al., 2005
Taulu & Kajola, 2005
Taulu & Simola, 2006



$b = b_{in} + b_{out} + n$

SSS & Maxfell filtering (MEG - MEGIN Neuromag)

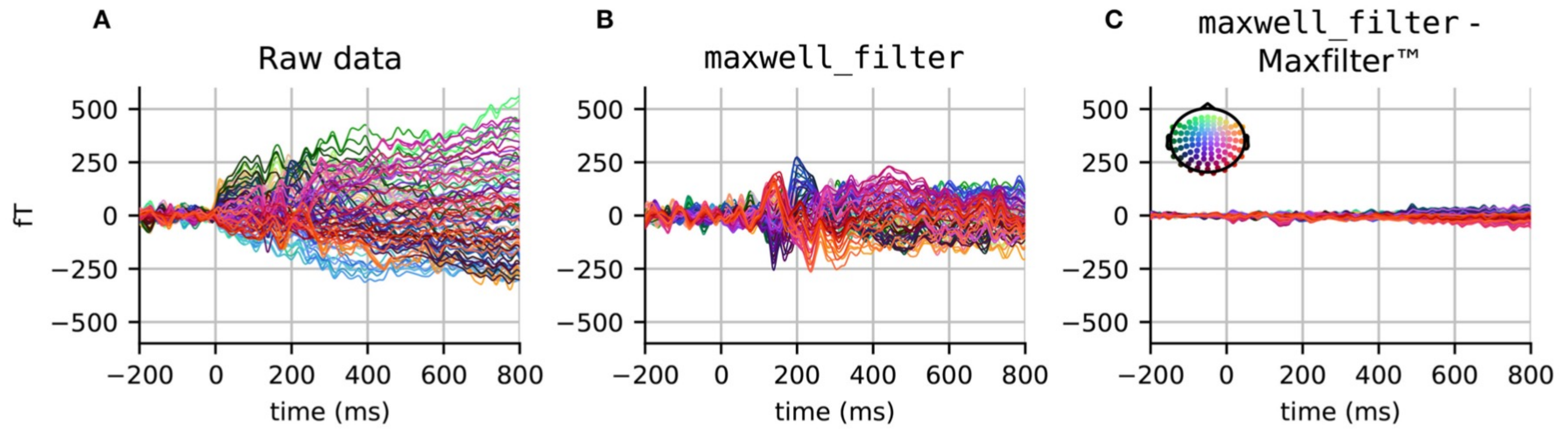
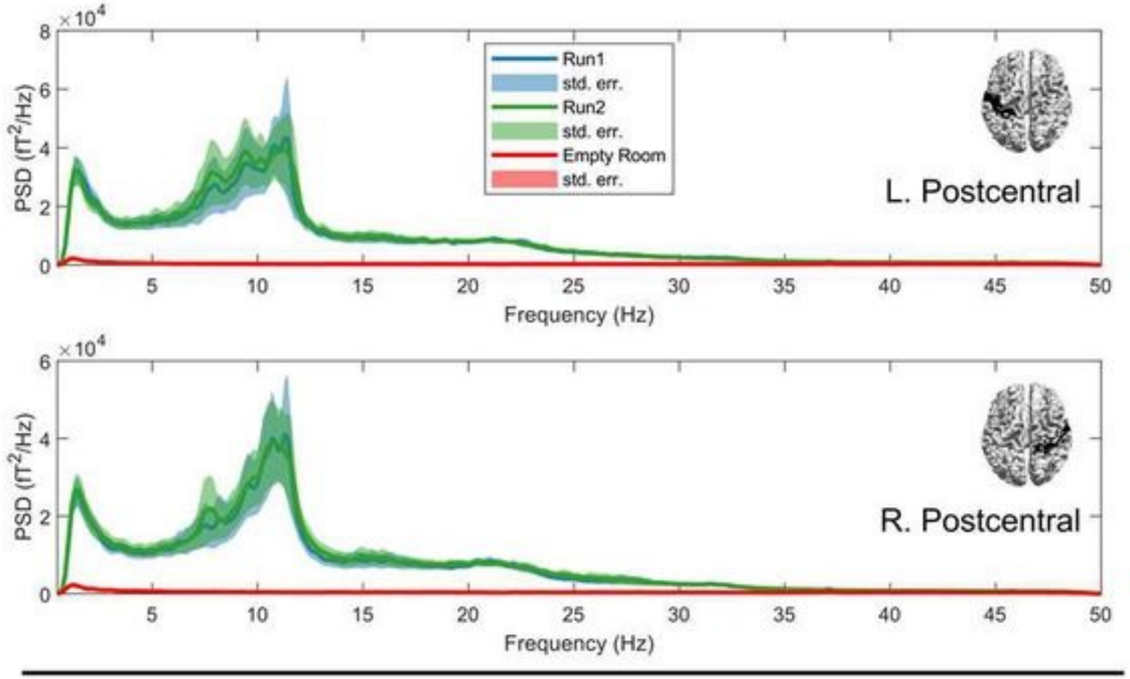


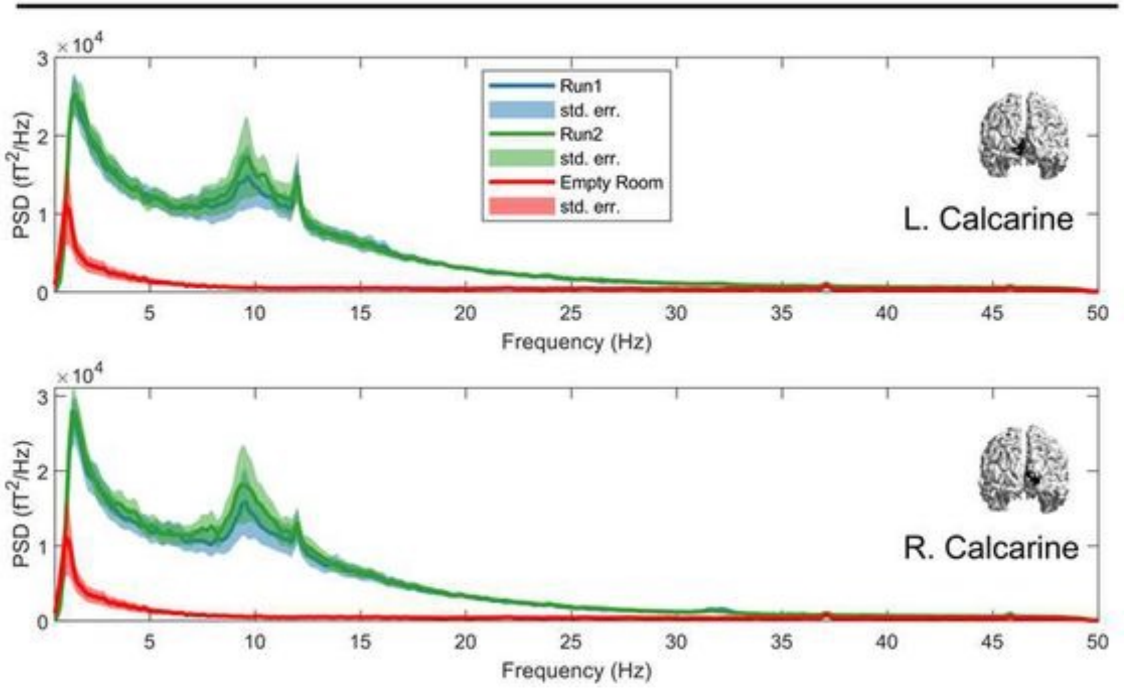
FIGURE 1 | Evoked responses (filtered between 1 and 40 Hz) in the magnetometer channels from **(A)** unprocessed data, **(B)** data processed with `maxwell_filter` in MNE, and **(C)** the difference between data processed using `maxwell_filter` and Elekta MaxFilter (TM). The colors show the sensor position, with (x, y, z) sensor coordinates converted to (R, G, B) values, respectively.

Jas et al., 2018

MEG - Empty room recording

- Useful for MEG data, especially resting state data

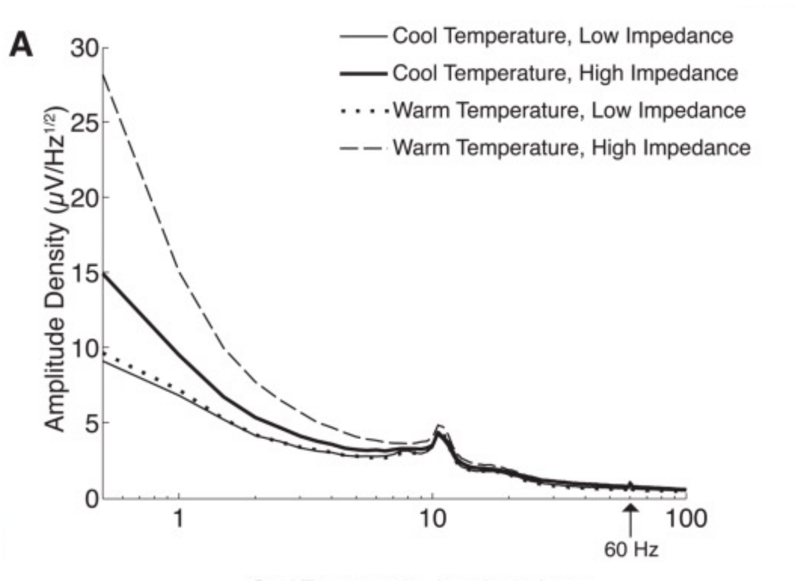


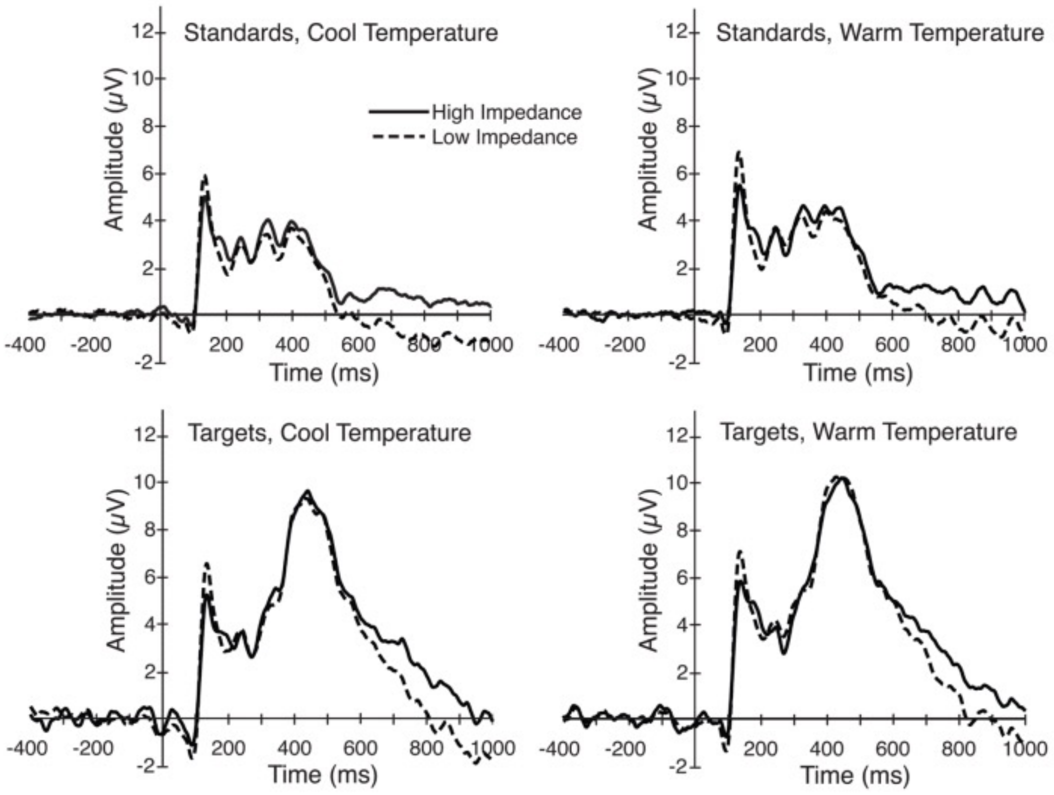


Rier et al., 2022

Impedances - EEG

- Higher impedance = lower SNR
- Impedances up to 10 kΩ are usually acceptable, but values below 5 kΩ are recommended.





Kappenman & Luck, 2010

(Down)Sampling

Sampling is the conversion of a continuous signal (e.g., brain activation in time & space) to a sequence of discrete sample (discretisation).

Why is it important?

- Digital signal processing can only handle discrete numbers (finite precision).
- Sampling can provide the information necessary while allowing efficient processing.

Sampling

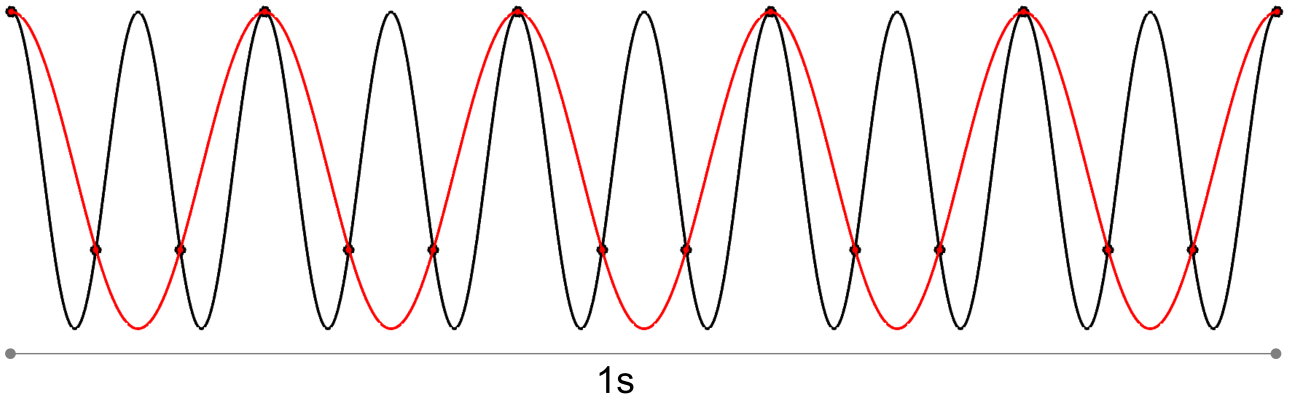
Convenient to sample equidistantly, i.e. neighbouring samples have the same 'distance to each other

Sampling Rate/Frequency: How densely are samples taken?
100 samples per second → 100 samples/s → 100 Hz
10 samples per centimetre → 10 samples/cm

Sampling Interval/Distance: How far apart are the samples?
100 Hz → (1/100)*1s = 0.01 s = 10 ms
10 samples/cm → (1/10)*1 cm = 0.1 cm = 1mm

Sampling depth (quantisation), **Sampling range**, **Resolution/precision**

Sampling - Aliasing



Signal frequency = 10 Hz
Sampling Frequency = 1000 Hz

Aliased Frequency = 5 Hz
Sampling Frequency = 15 Hz

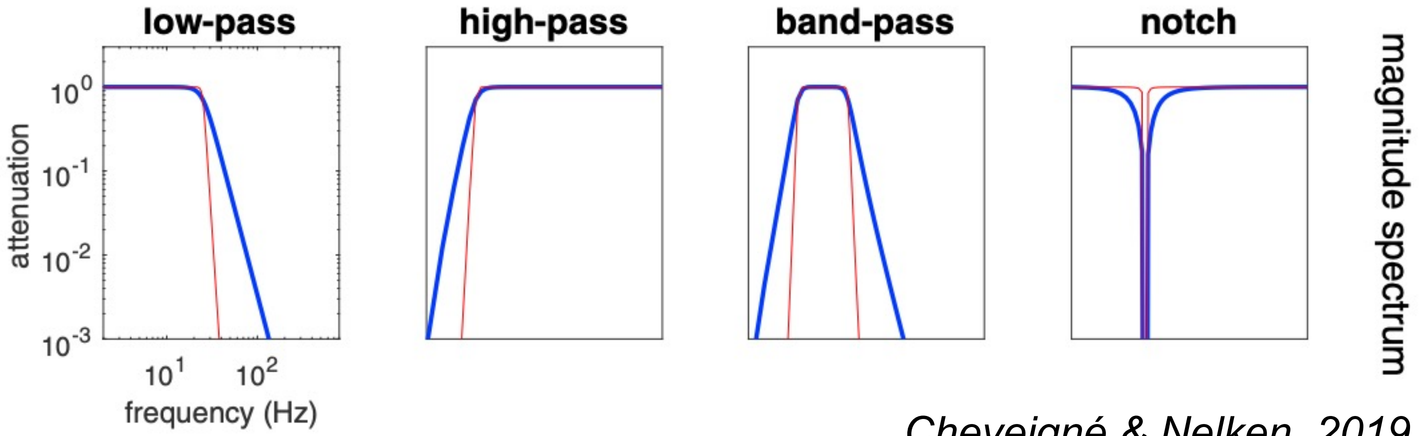
Nyquist – Shannon Sampling Theorem:
If you sample a signal with a sampling rate of **X** Hz, make sure the signal doesn't contain frequencies above **X/2** Hz.

Nyquist Frequency = half of the sampling rate of a discrete signal.

The **highest** frequency in the signal should be **smaller** than the Nyquist Frequency.

Filter

- Filters are temporal models that restrict the frequency range of dynamics that are observable in a time series.
- We typically use filters to:
  - reduce low frequencies (= high-pass filter; e.g., <1Hz)
  - reduce high frequencies (=low-pass filter; e.g., >90Hz)
  - reduce electrical line noise (=notch filter/band-stop filter; e.g., 50/60Hz)
  - focus on a frequency range of interest (= band-pass filter; e.g., 13-30Hz)

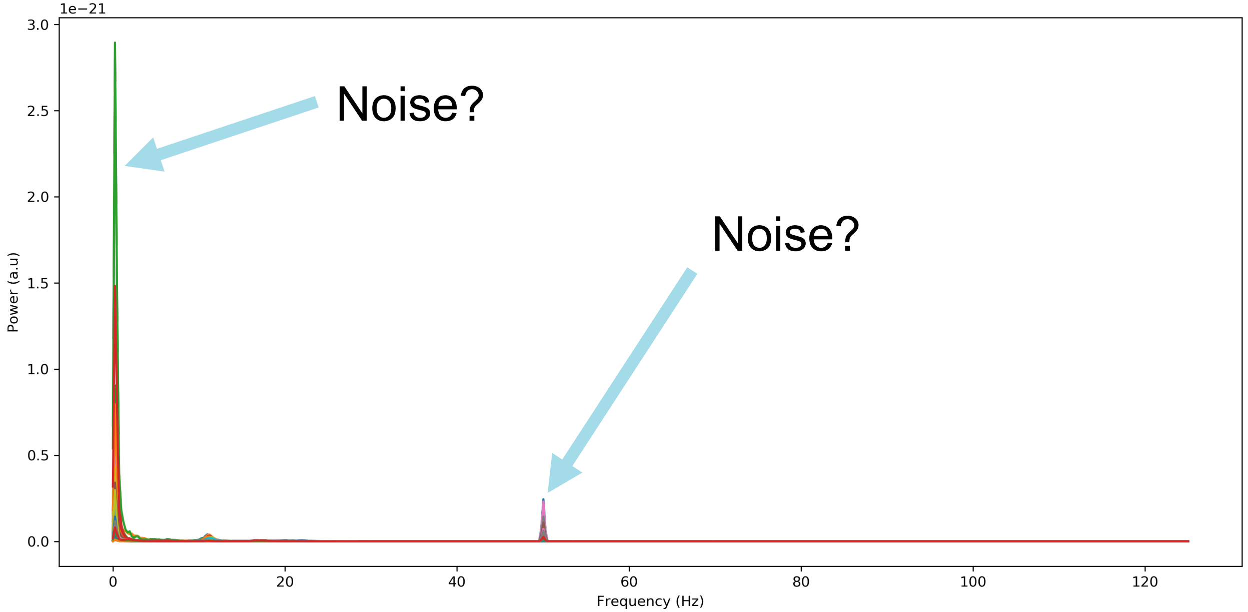


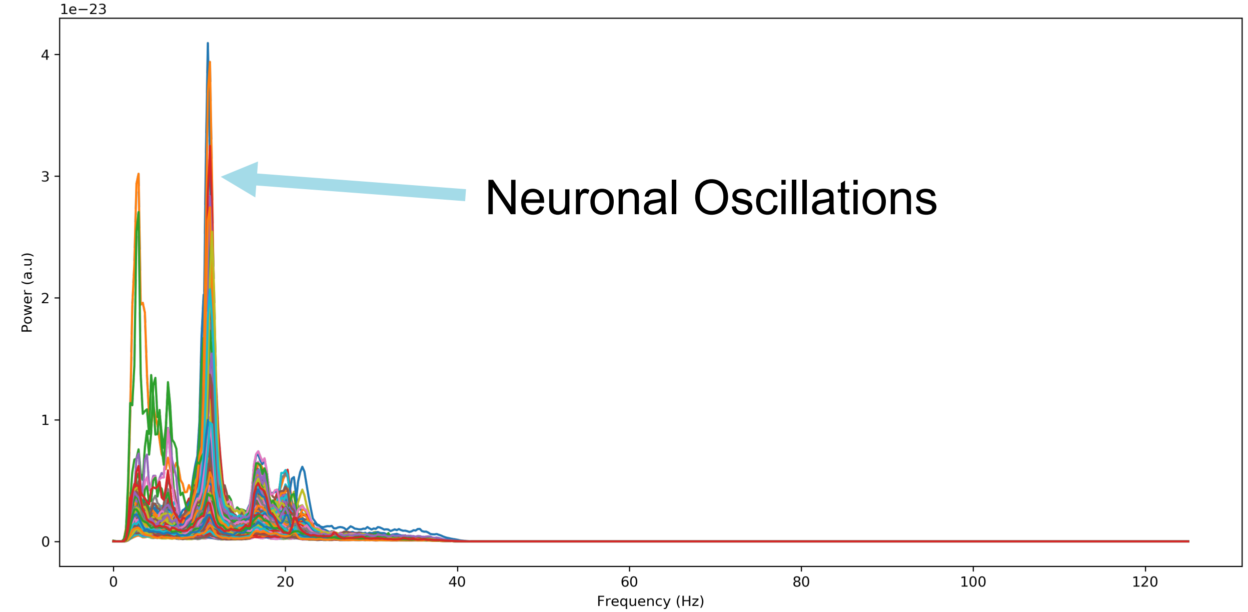
Cheveigné & Nelken, 2019

Filter

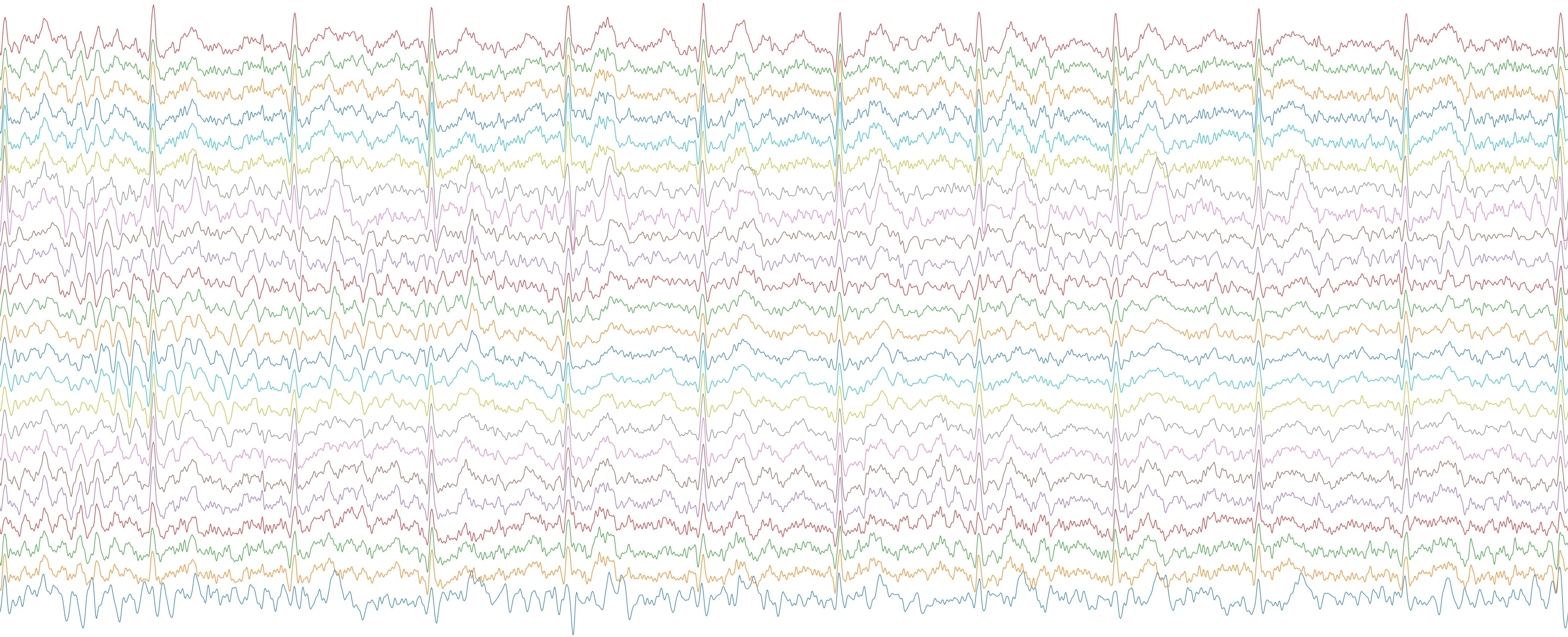
We typically use filters to reduce very low (<1Hz), very high (variable, typically 40Hz+) frequencies and electrical line noise (50Hz).

Order: low-pass filter, down-sample, high-pass filter

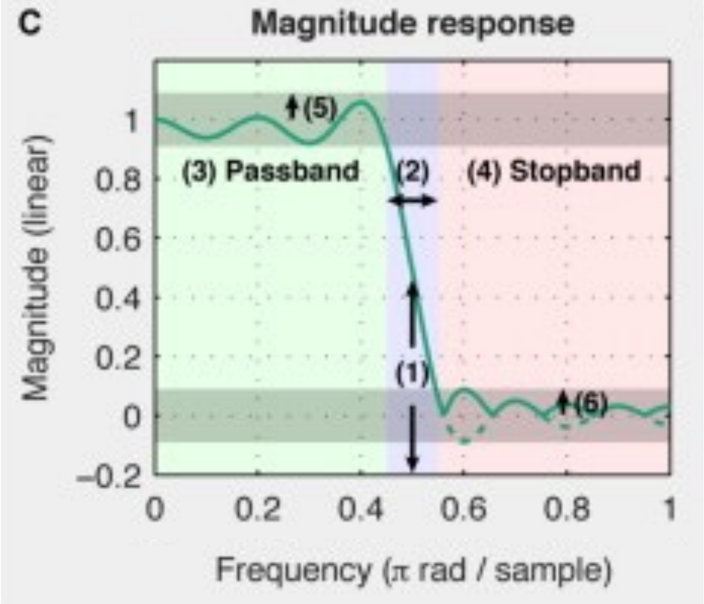




Filter



Filter



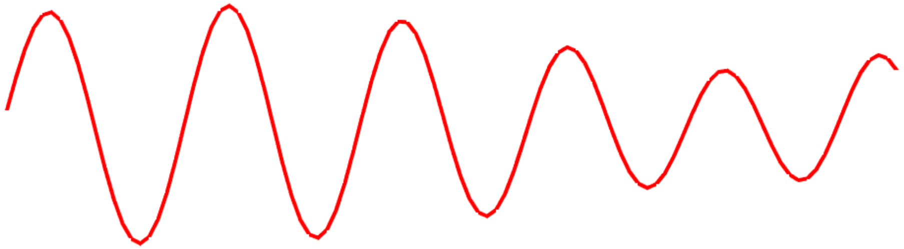
Widmann et al., 2015

Order 18 linear-phase low-pass finite impulse response [FIR] The cutoff frequency (1) in the center of the transition band (2) separates passband (3) and stopband (4). The deviation from designed passband (one) and stopband magnitude (zero) is described by passband ripple (5) and stopband attenuation (6).

```
srate = 500;
forder = 5;
freqs = [1 40]
[b,a] = butter(forder,freqs./srate);
fvtool(b, a, 'fs', srate)
```

Filter

- Filters common and powerful, but complex.
- Filtering can ‘generate’ oscillations.



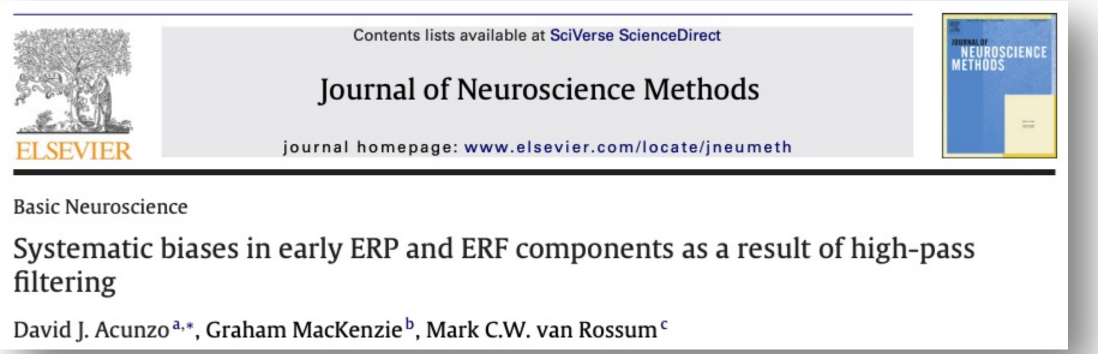
```
srate = 100;
twin = 60;
forder = 5;

x = randn(twin*srate,1);
figure;
subplot(2,1,1);hold on
plot(x,'k','Linewidth',2);
xlim([100 200]);axis off ;


subplot(2,1,2);hold on;
[b,a] = butter(forder,[8 12]./srate);
y1 = filtfilt(b,a,x);
plot(y1,'r','Linewidth',2);
xlim([100 200]);axis off ;
```

Filter

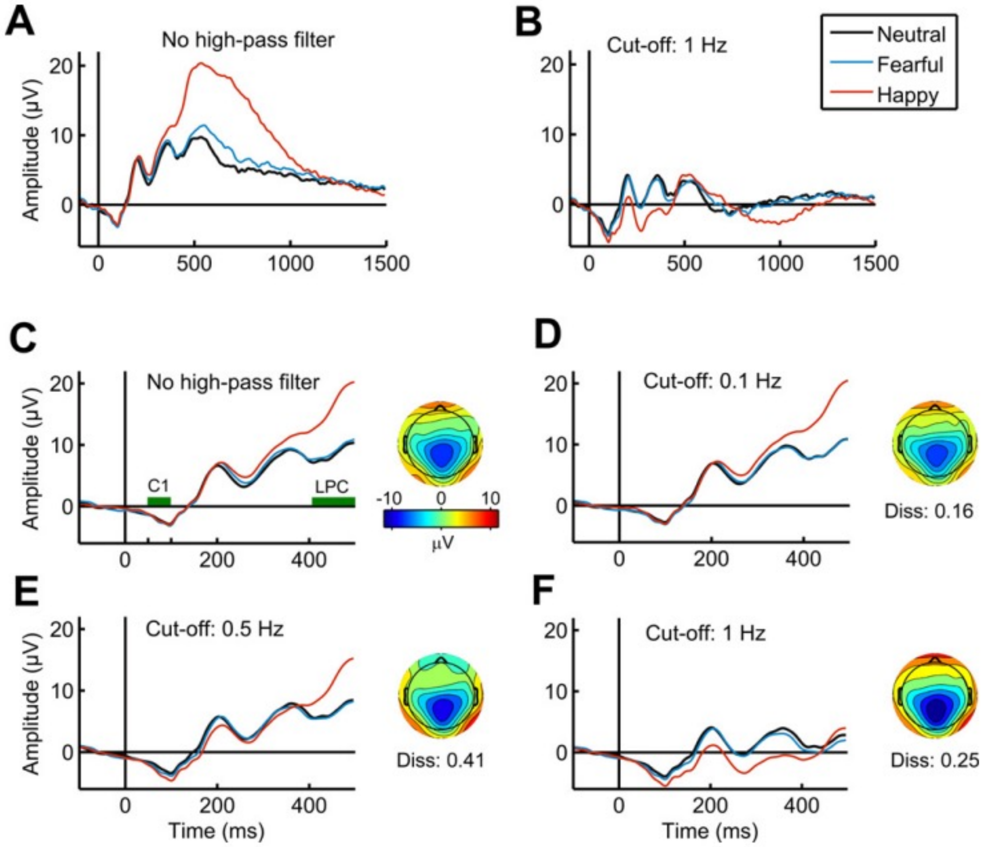
- Filters common and powerful, but complex.
- Filtering can distort the signal.


Contents lists available at SciVerse ScienceDirect
Journal of Neuroscience Methods
journal homepage: www.elsevier.com/locate/jneumeth

Basic Neuroscience

Systematic biases in early ERP and ERF components as a result of high-pass filtering

David J. Acunzo[a,*], Graham MacKenzie[b], Mark C.W. van Rossum[c]



Filter

- The optimal filter strongly depends on your specific data and questions.
- General rule: Filter as much as necessary, but as little as possible.

Neuron *Supports open access*

PRIMER | VOLUME 102, ISSUE 2, P280-293, APRIL 17, 2019

Filters: When, Why, and How (Not) to Use Them

Alain de Cheveigné • Israel Nelken

Open Archive • DOI: https://doi.org/10.1016/j.neuron.2019.02.039 • Check for updates

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Journal of Neuroscience Methods

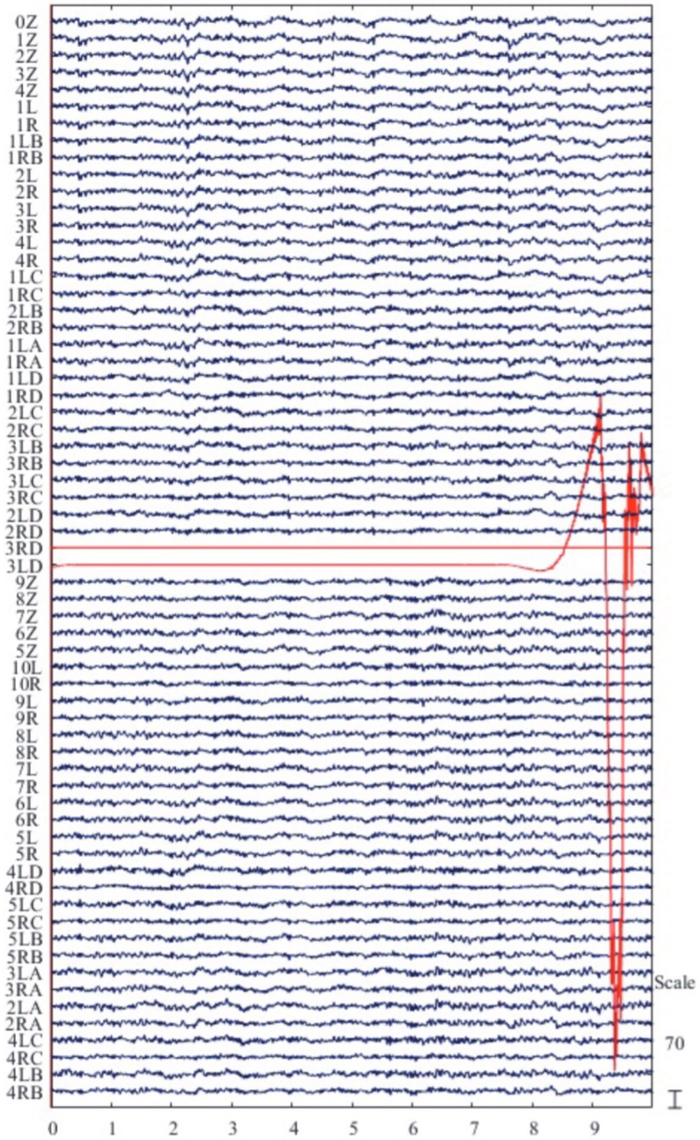
Volume 250, 30 July 2015, Pages 34-46

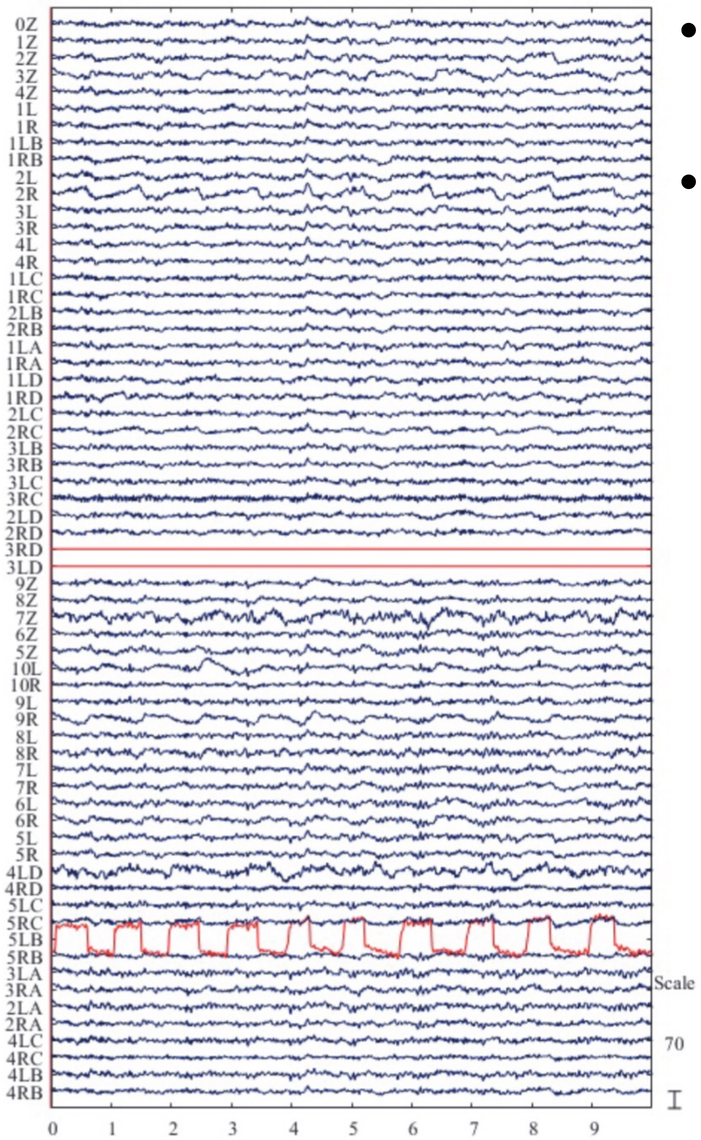
Basic Neuroscience

Digital filter design for electrophysiological data – a practical approach

Andreas Widmann [a], Erich Schröger [a], Burkhard Maess [b]

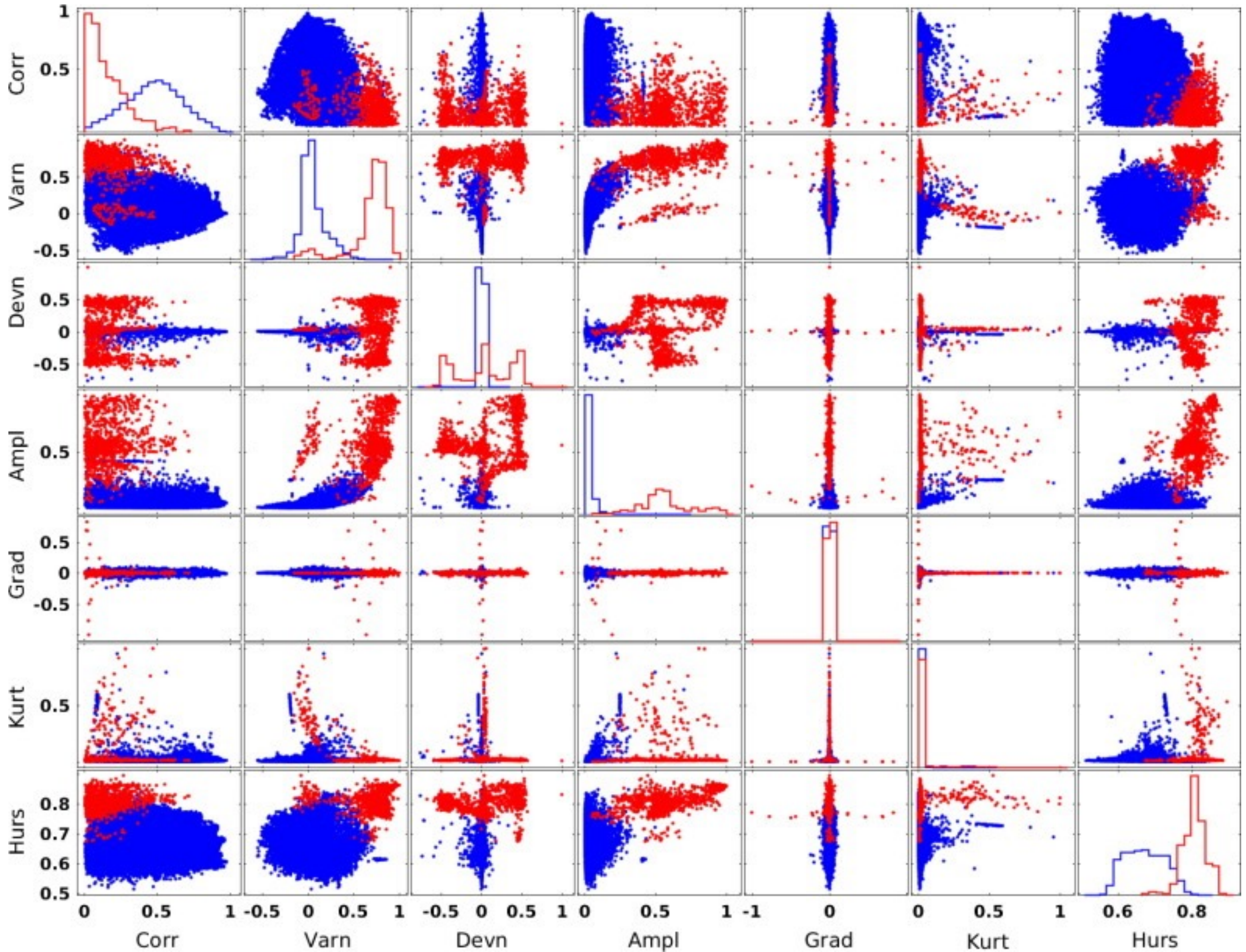
Bad channels





- Drifts, lost good contact, malfunctioning
- Detect & remove or interpolate (reduced dimensionality)

Bad channels

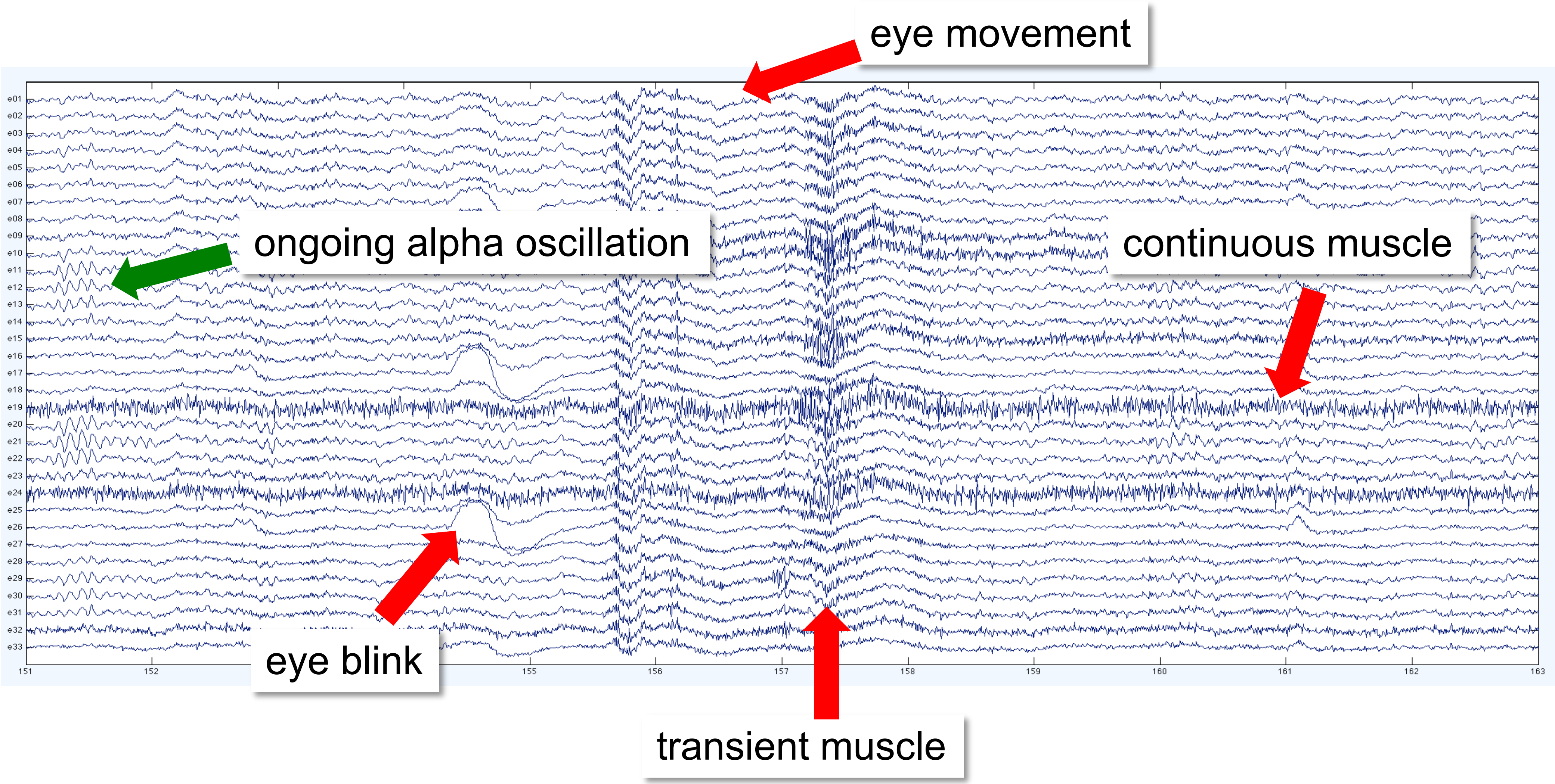


Correlation (Corr)
Variance (Varn)
Deviation (Devn)
Amplitude (Ampl)
Gradient (Grad)
Kurtosis (Kurt)
Hurst exponent (Hurs)

Tuyisenge et al., 2018

Dealing with artifacts

Signals are a mixed bag of signals from brain and non-brain sources and the environment.



Dealing with artifacts

Two types of Artifacts

- Nonstereotypical Artifacts
- Sterotypical Artifacts

The sources can be environmental, physiological, or even neural.

Two philosophies on how to deal with Artifacts:

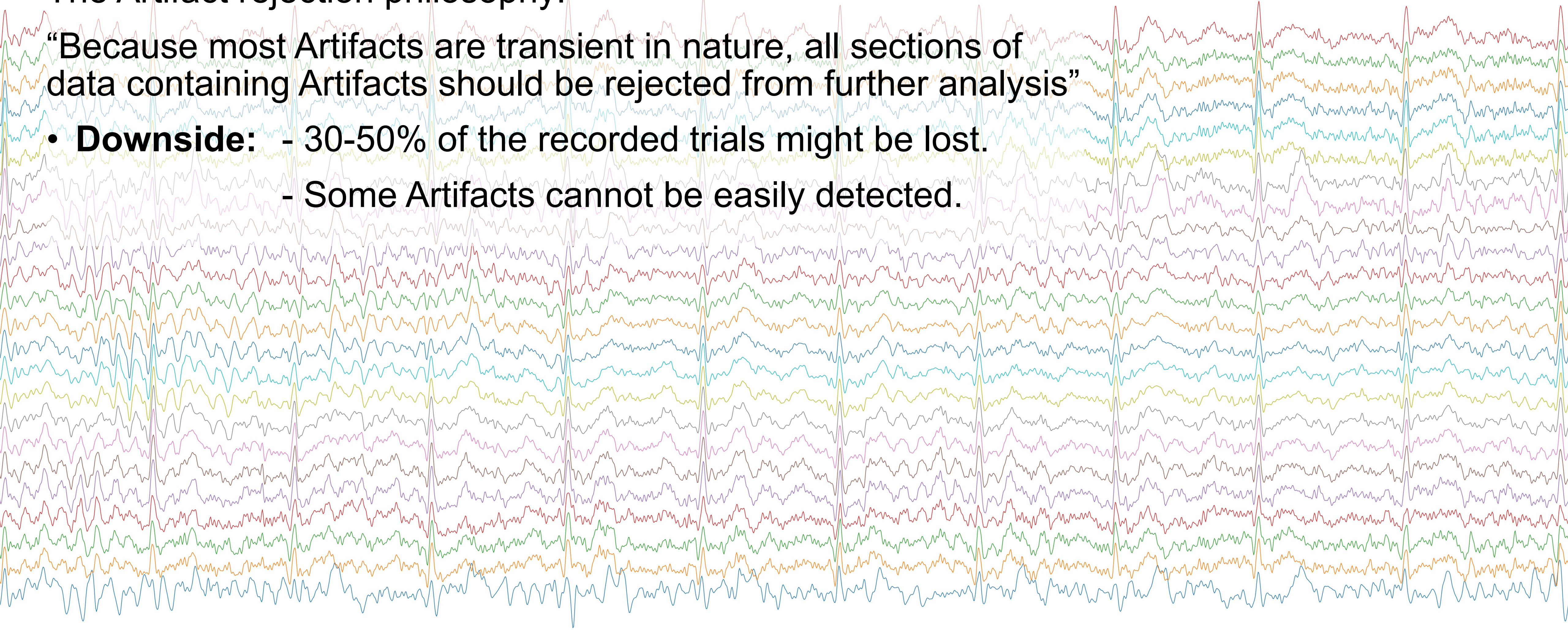
- Artifact rejection: Reject data containing Artifacts → data loss
- Artifact correction/attenuation: Statistical correction of Artifacts → data transformation; avoid over-/ under-correction

Dealing with artifacts

The Artifact rejection philosophy:

"Because most Artifacts are transient in nature, all sections of data containing Artifacts should be rejected from further analysis"

- **Downside:** - 30-50% of the recorded trials might be lost.
  - Some Artifacts cannot be easily detected.



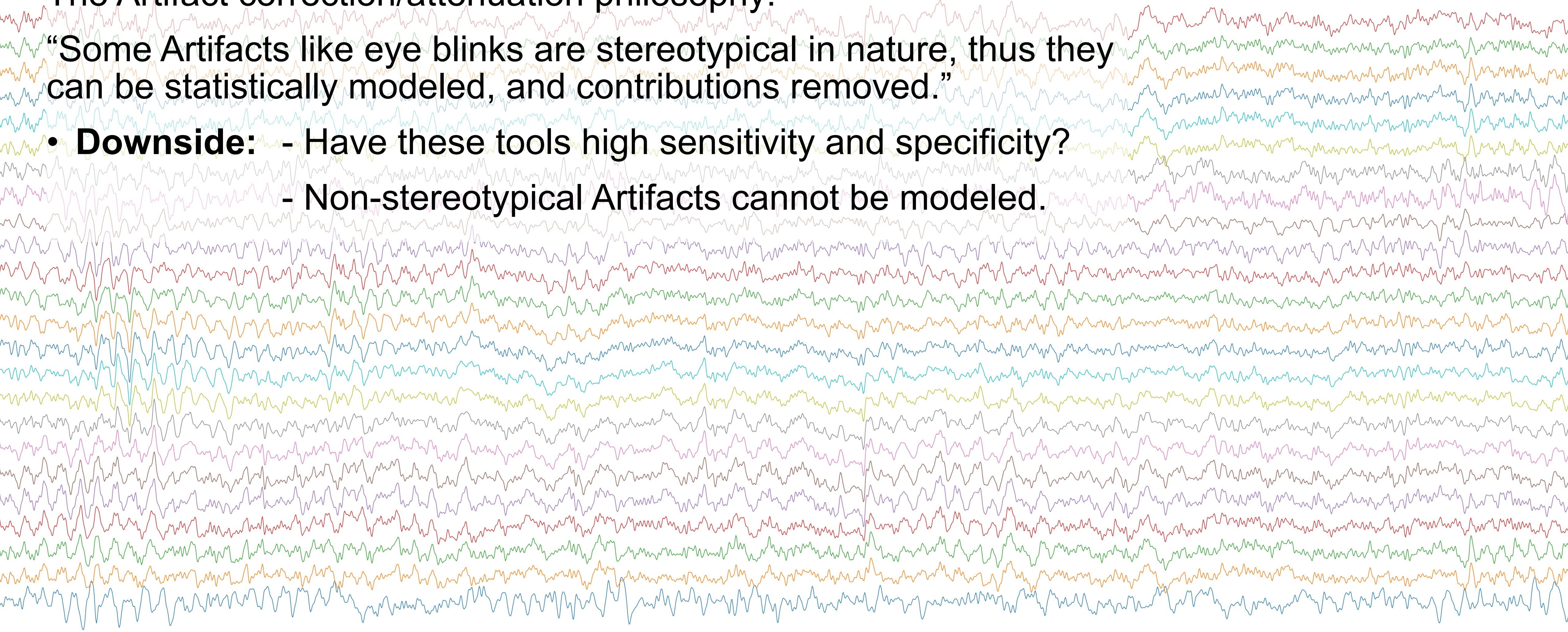
Dealing with artifacts

The Artifact correction/attenuation philosophy:

"Some Artifacts like eye blinks are stereotypical in nature, thus they can be statistically modeled, and contributions removed."

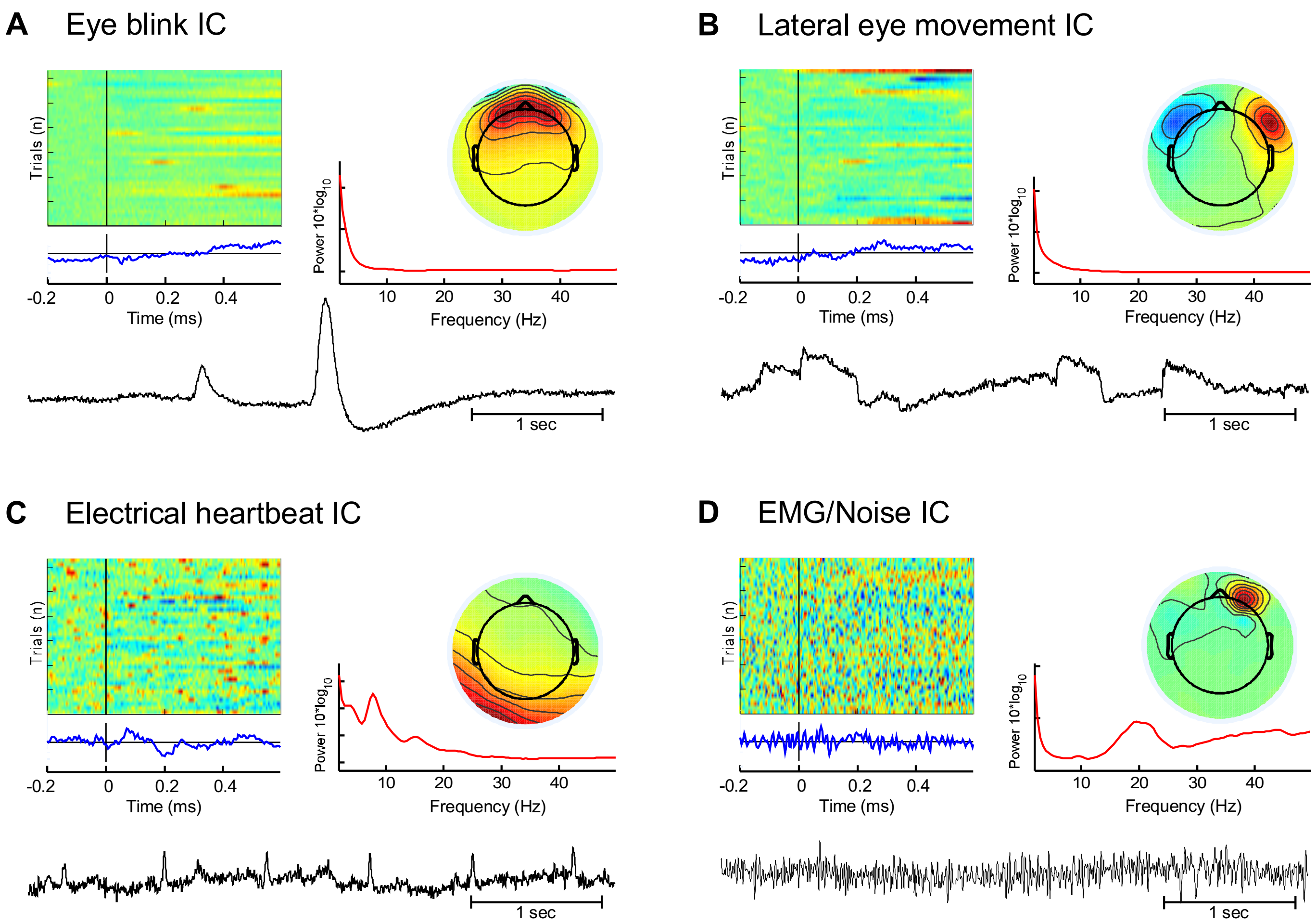
- **Downside:** - Have these tools high sensitivity and specificity?

  - Non-stereotypical Artifacts cannot be modeled.



Dealing with artifacts - ICA

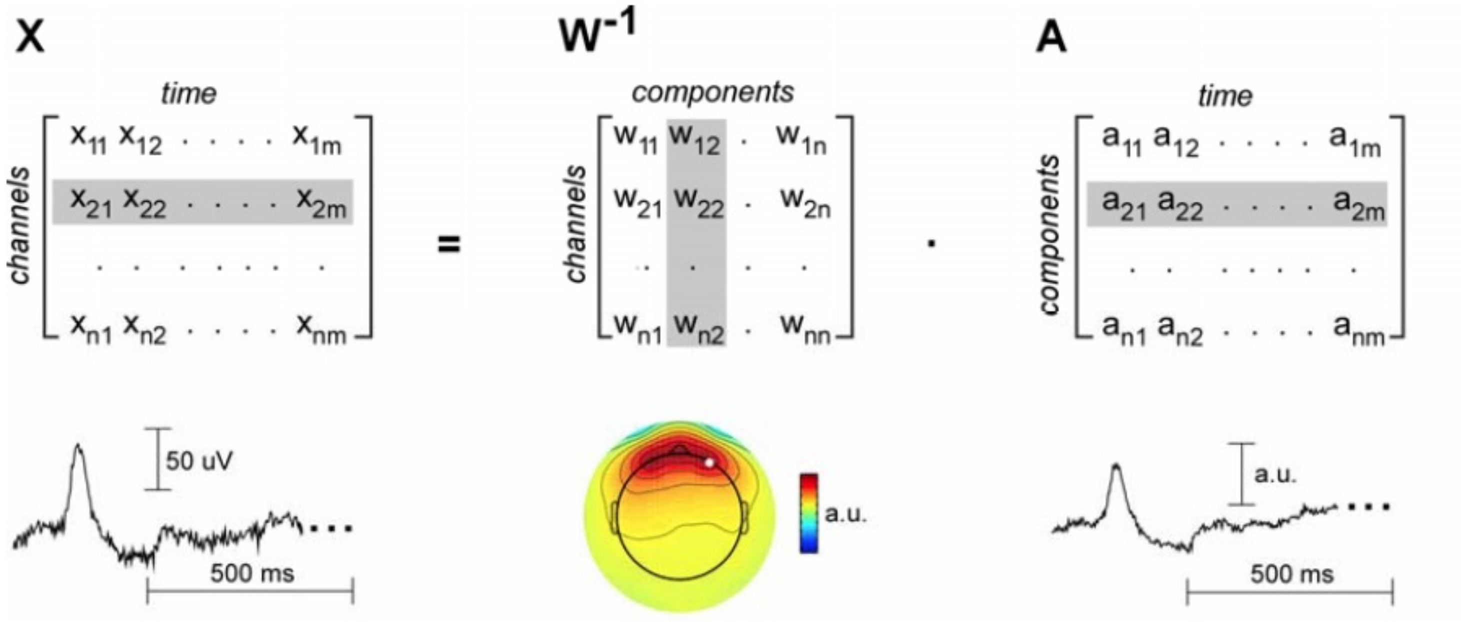
Stereotypical artifacts have typical signatures.



Debener et al., 2010

Dealing with artifacts - ICA

Un-mixing overview.

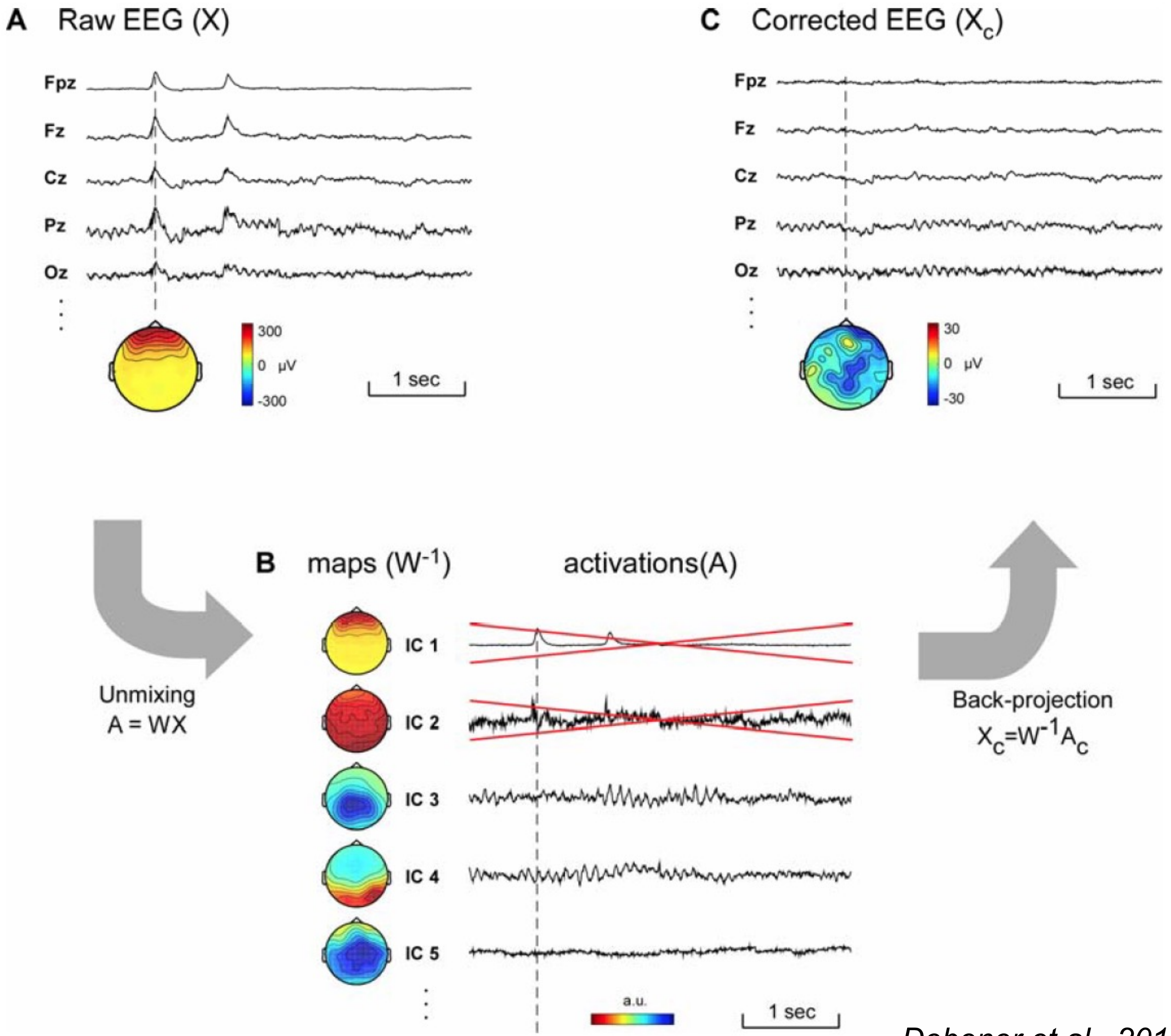


Debener et al., 2010

X	raw data (channels x frames)
W	un-mixing weights (channels x components)
A	component activations (components x frames)

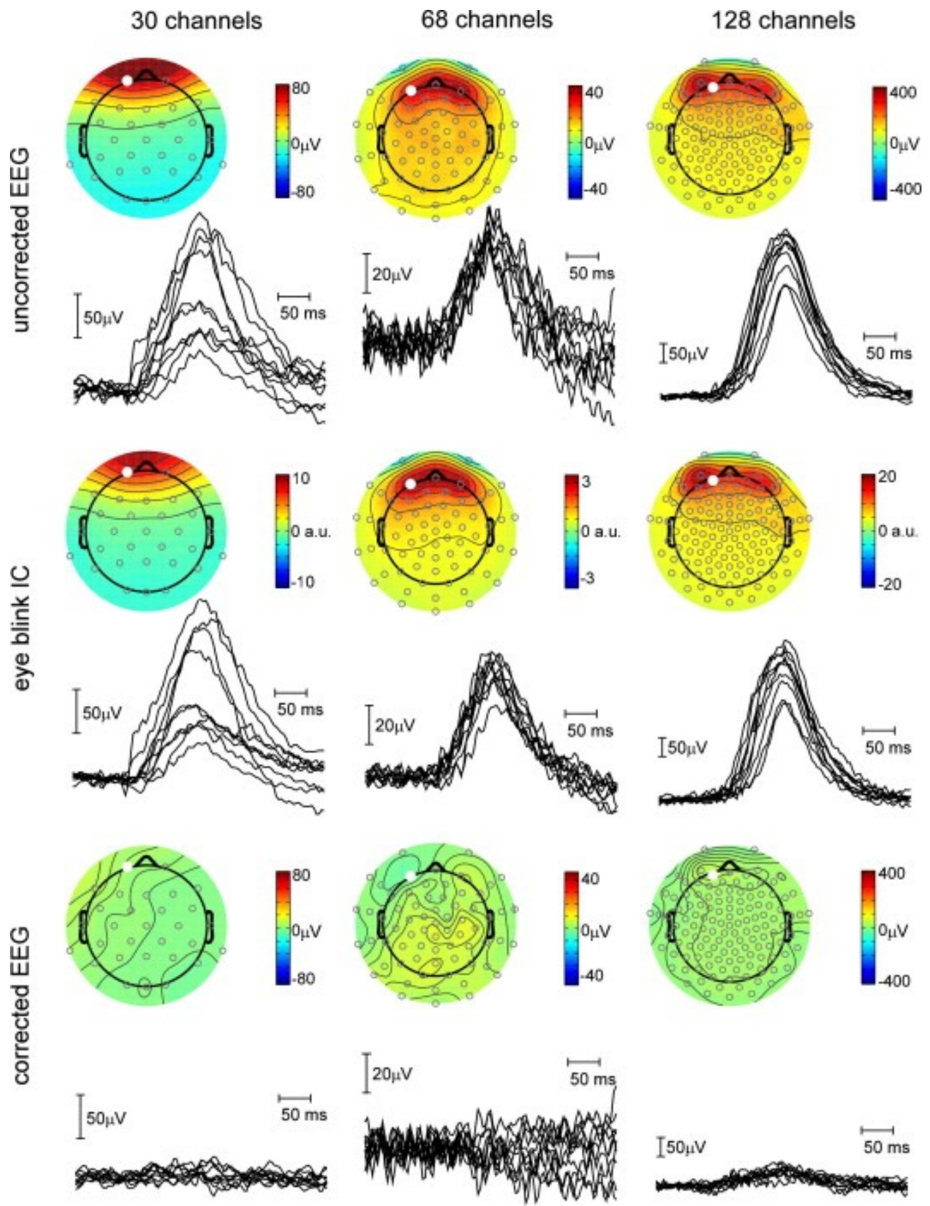
Dealing with artifacts - ICA

Back-projection overview



Debener et al., 2010

Dealing with artifacts



Viola et al., 2009

Dealing with artifacts - ICA

(Semi-)Automatic detection of IC's

Contents lists available at ScienceDirect

Clinical Neurophysiology

journal homepage: www.elsevier.com/locate/clinph

ELSEVIER

Semi-automatic identification of independent components representing EEG artifact

Filipa Campos Viola [a,b], Jeremy Thorne [a,b], Barrie Edmonds [c], Till Schneider [d], Tom Eichele [e], Stefan Debener [a,b,*]

Winkler *et al. Behavioral and Brain Functions* 2011, **7**:30
http://www.behavioralandbrainfunctions.com/content/7/1/30

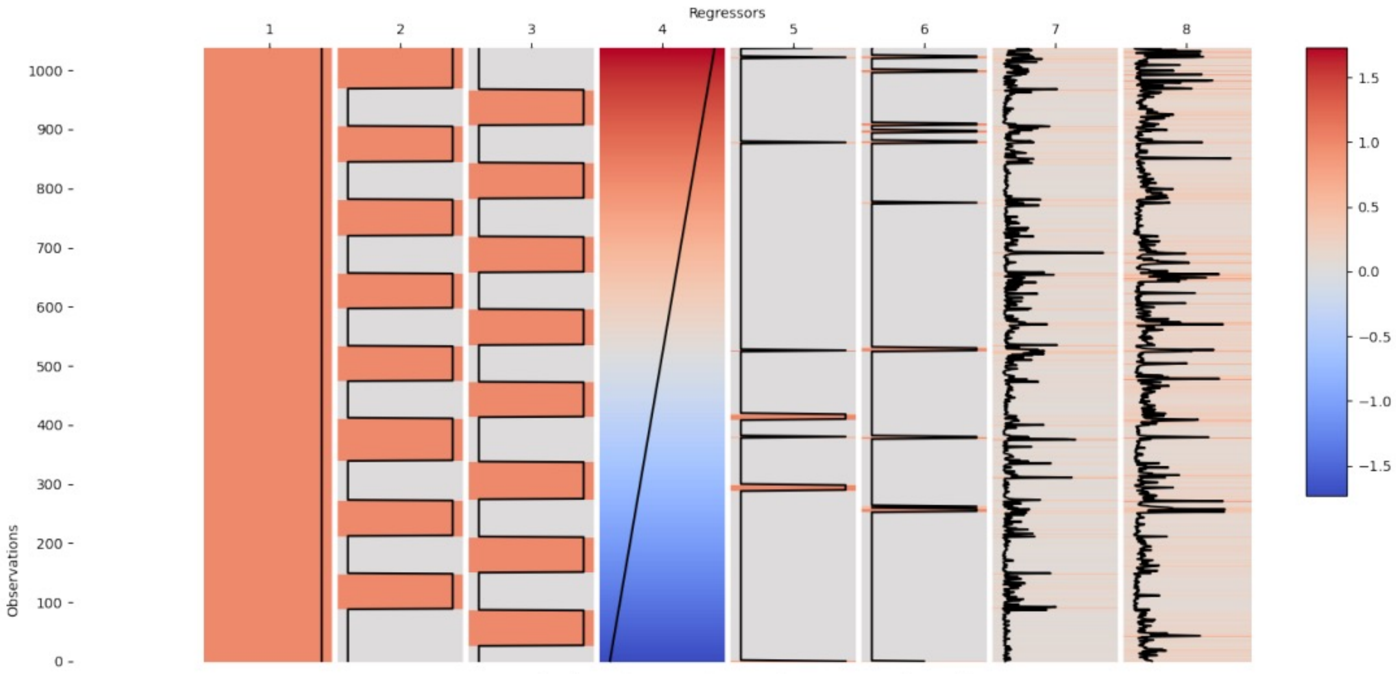
BBF BEHAVIORAL AND BRAIN FUNCTIONS

METHODOLOGY Open Access

Automatic Classification of Artifactual ICA-Components for Artifact Removal in EEG Signals

Irene Winkler[*], Stefan Haufe and Michael Tangermann

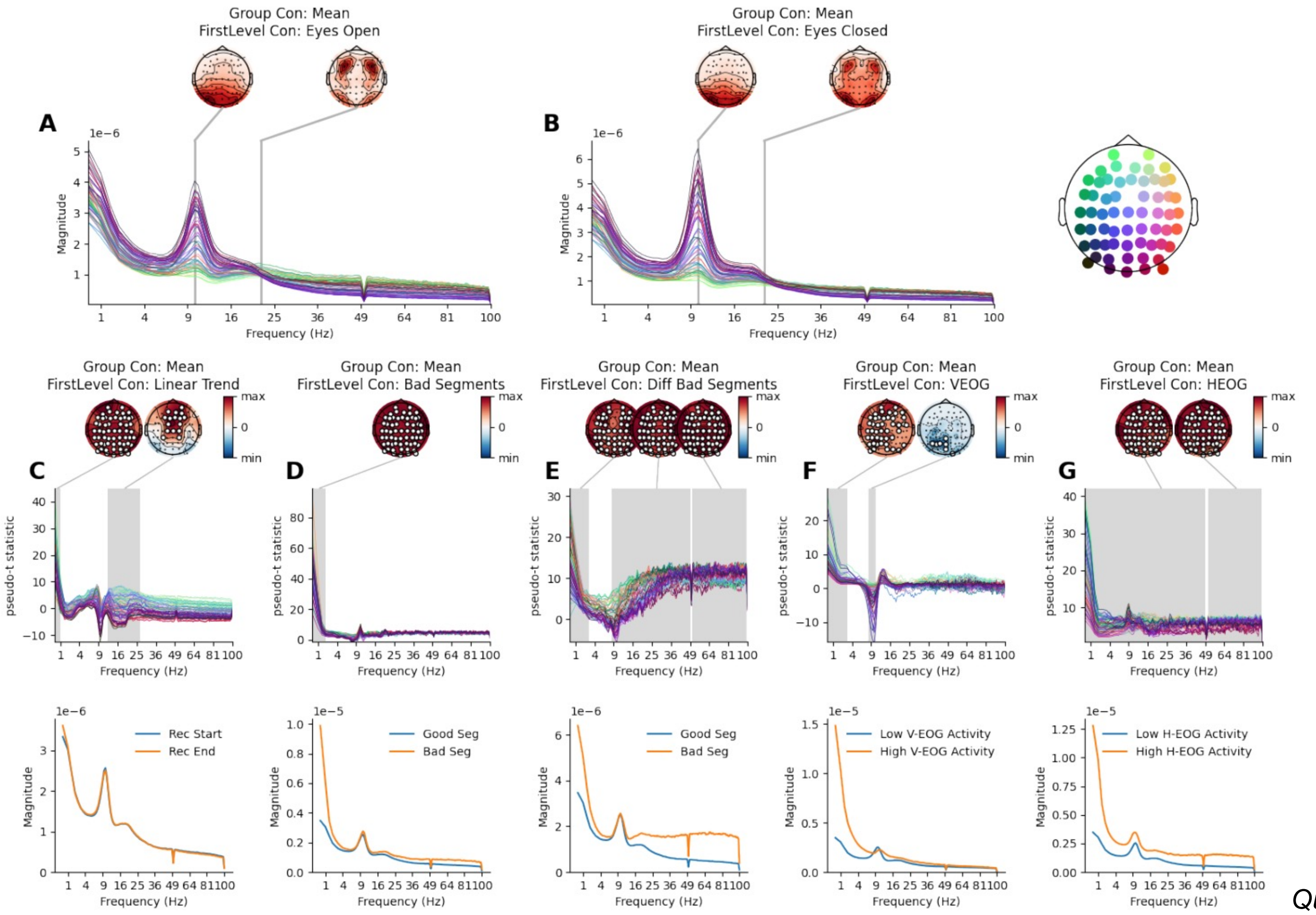
Dealing with artifacts - GLM



	Constant	Eyes Open	Eyes Closed	Linear Trend	Bad Segs	Bad Segs Diff	V-EOG	H-EOG
C1: OverallMean	1.0	0.496	0.479	0.0	0.0	0.0	0.0	0.0
C2: RestMean	0.0	0.5	0.5	0.0	0.0	0.0	0.0	0.0
C3: Eyes Open AbsEffect	1.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0
C4: Eyes Closed AbsEffect	1.0	0.0	0.5	0.0	0.0	0.0	0.0	0.0
C5: Open > Closed	0.0	1.0	-1.0	0.0	0.0	0.0	0.0	0.0
C6: Constant	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
C7: Eyes Open	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
C8: Eyes Closed	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
C9: Linear Trend	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
C10: Bad Segs	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
C11: Bad Segs Diff	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
C12: V-EOG	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
C13: H-EOG	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

Quinn et al., 2022

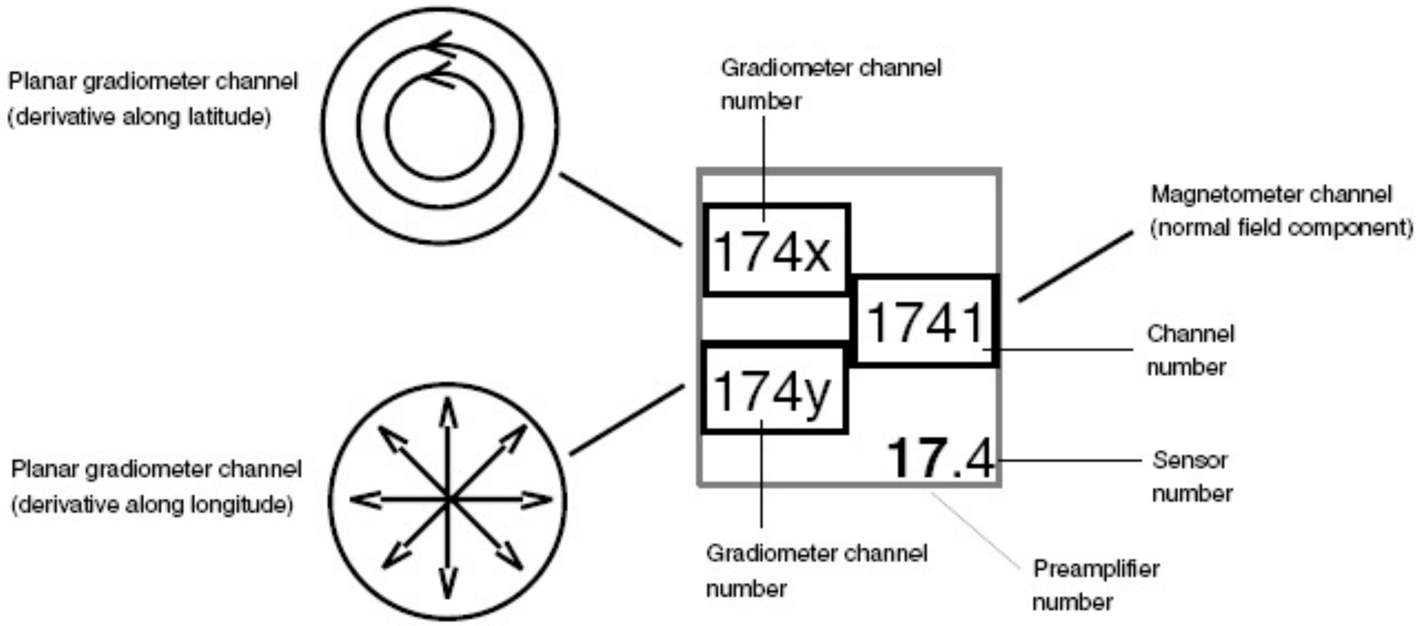
Dealing with artifacts - GLM



Quinn et al., 2022

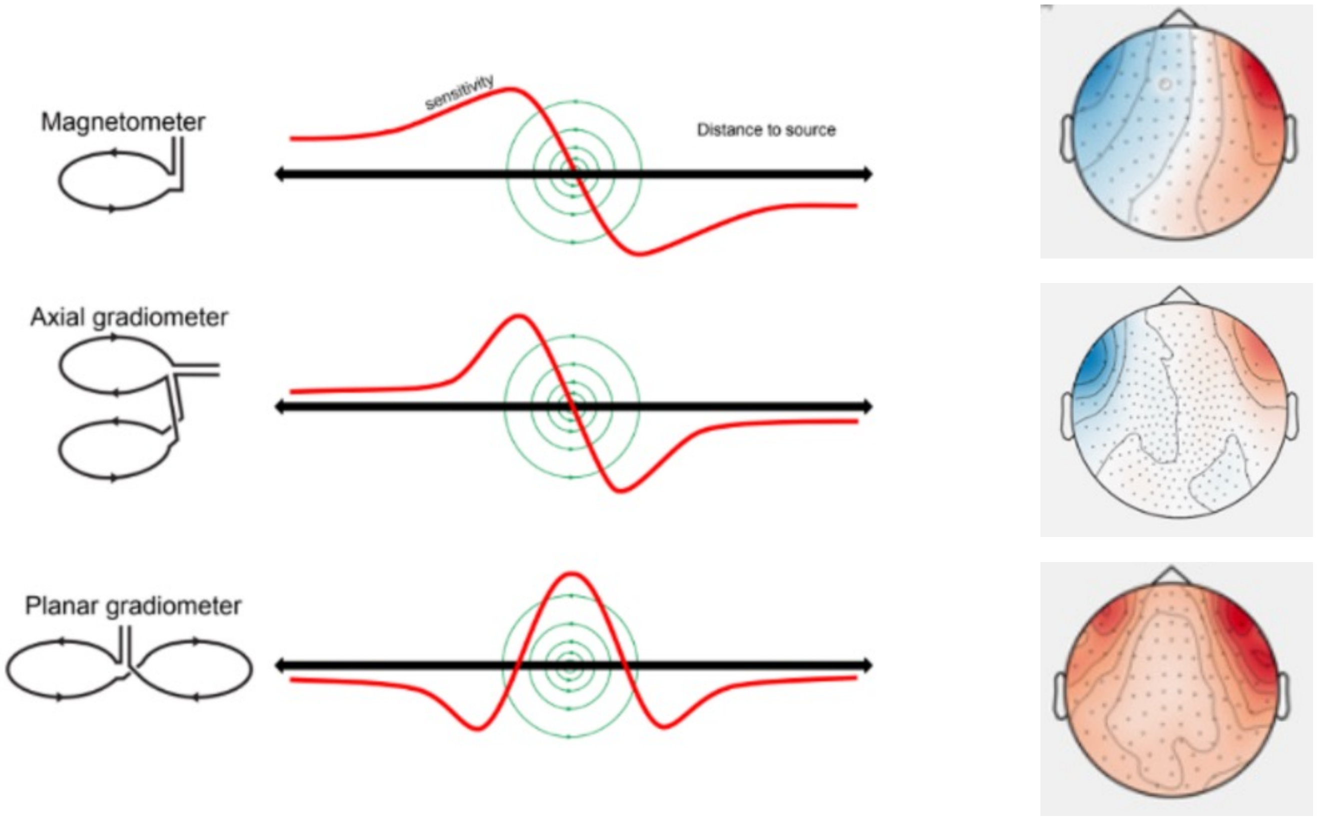
Sensor Normalisation (MEG - MEGIN Neuromag)

- MEGIN Neuromag data have two sensor types, planar gradiometers and magnetometers.



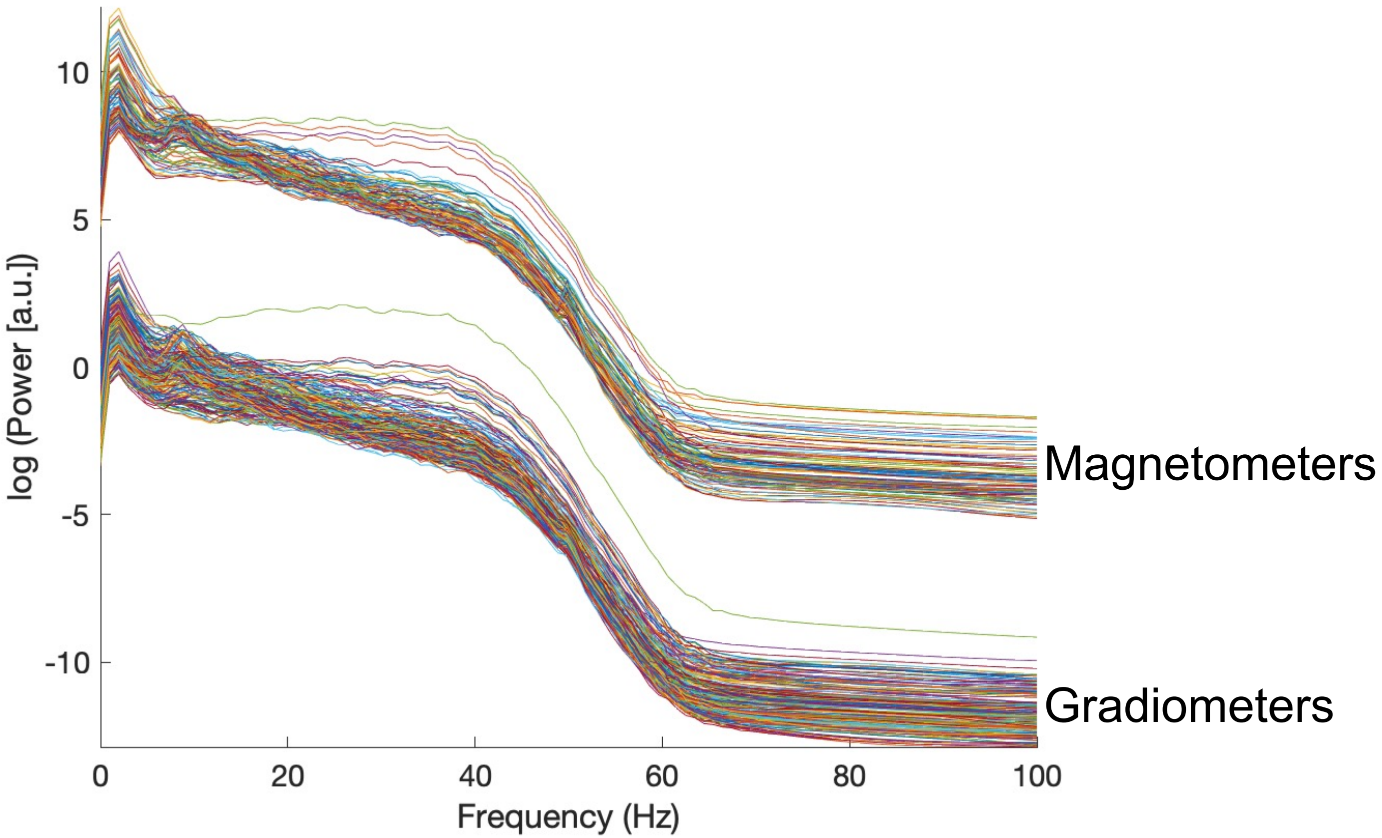
Sensor Normalisation (MEG - MEGIN Neuromag)

- Sensor types have distinct sensitivity profiles.

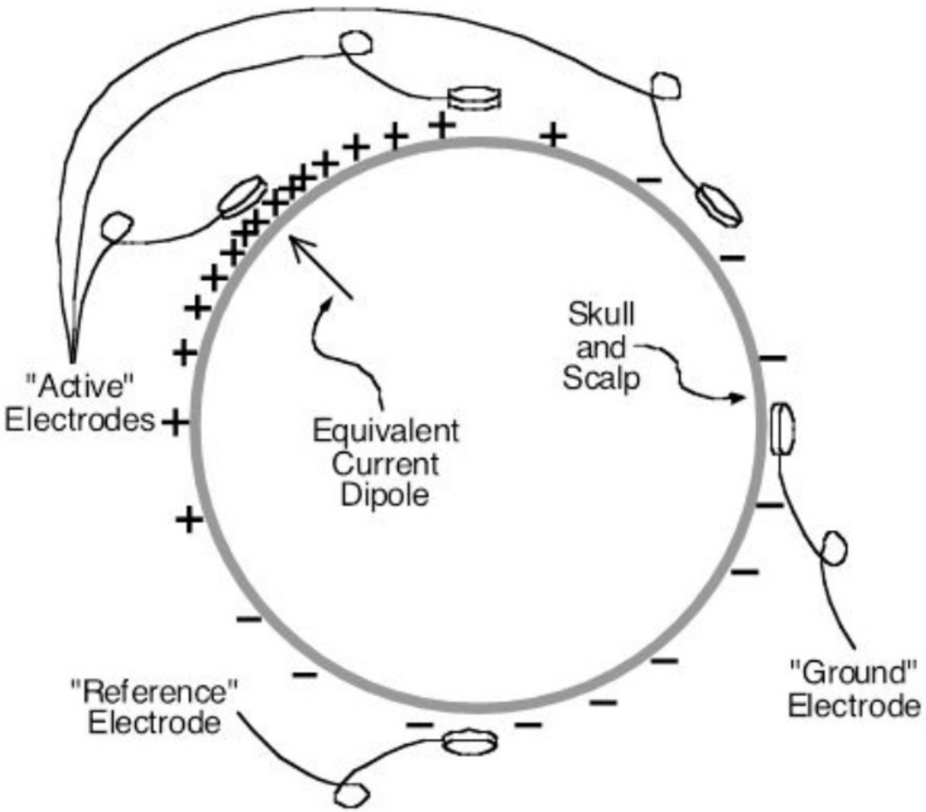


Sensor Normalisation (MEG - MEGIN Neuromag)

- Before beamforming, we would need to normalise these two sensor types so that they can contribute equally to the beamformer calculation.
- This is done by scaling the different sensor types so that their variances over time are equal.

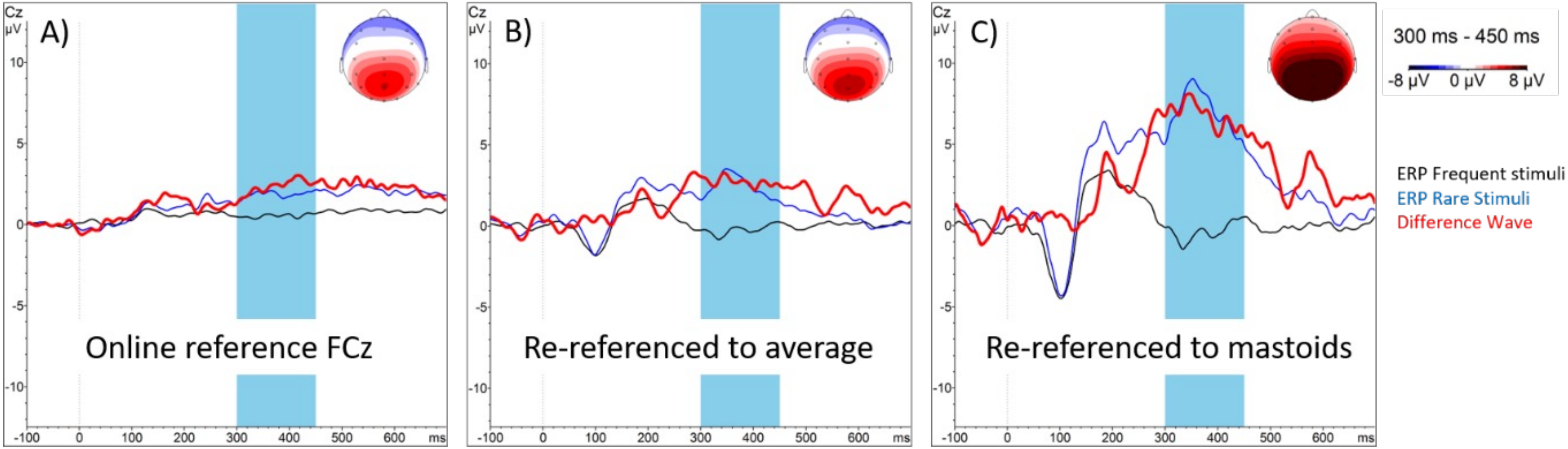


Re-referencing (EEG)



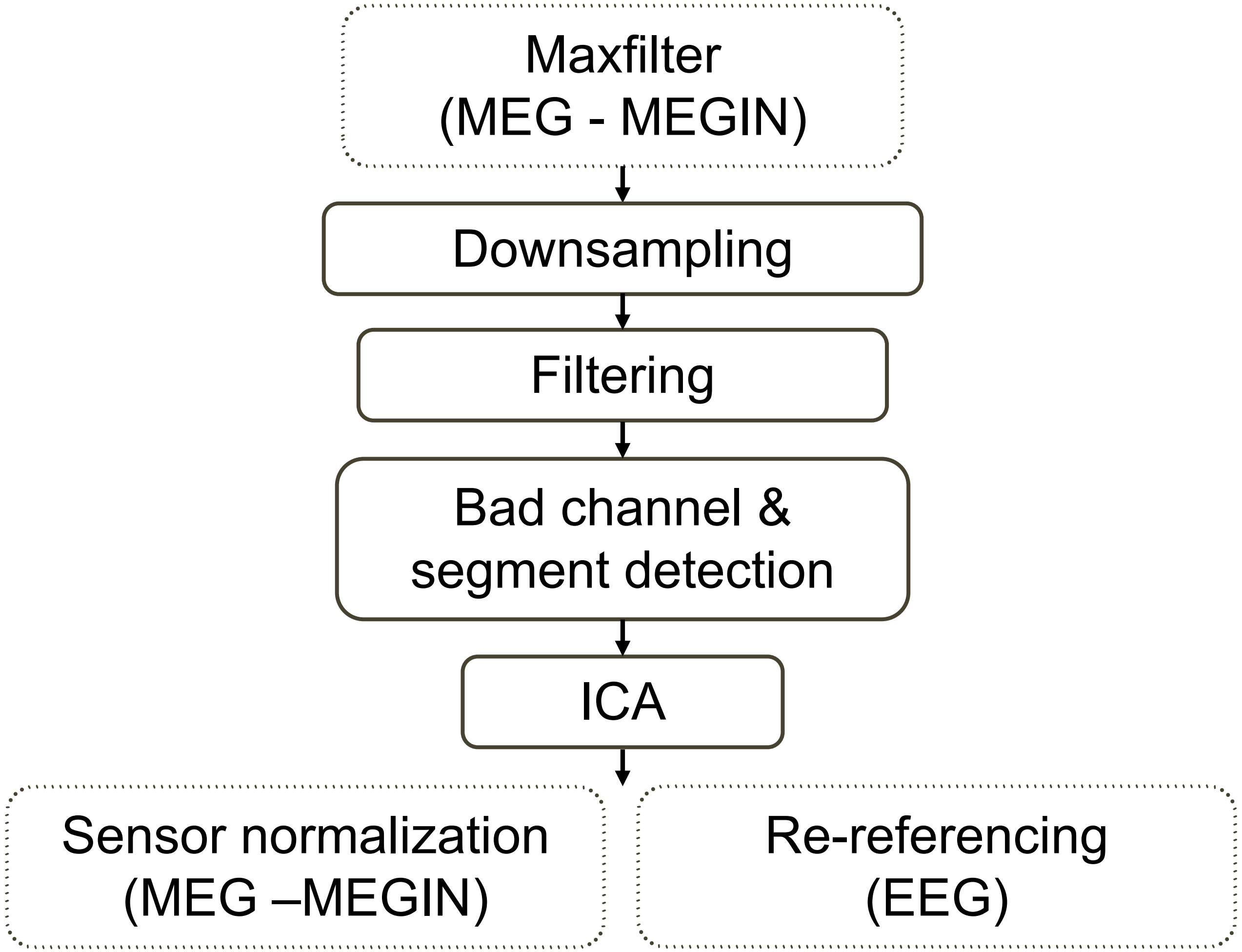
- Voltage is measured between ACTIVE and GROUND [DRL] (A-G)
- Voltage is measured between REFERENCE and GROUND [CMS] (R-G)
- Output is difference between these voltages (A-g)-(R-G) = A-R
- Any noise in common to A and R will be eliminated.

Re-referencing (EEG)



https://pressrelease.brainproducts.com/referencing/

Data pre-processing: Overview



Resources

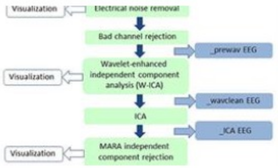
Frontiers in Neuroscience > Brain Imaging Methods > Research Topics > From raw MEG/EEG to publicati...

From raw MEG/EEG to publication: how to perform MEG/EEG group analysis with free academic software

TECHNOLOGY REPORT
Published on 27 Feb 2018

The Harvard Automated Processing Pipeline for Electroencephalography (HAPPE): Standardized Processing Software for Developmental and High-Artifact Data

Laurel J. Gabard-Durnam · Adriana S. Mendez Leal · Carol L. Wilkinson · April R. Levin



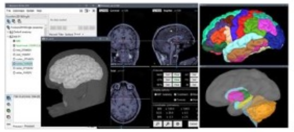
doi 10.3389/fnins.2018.00097

34,410 views 224 citations

METHODS
Published on 08 Feb 2019

MEG/EEG Group Analysis With Brainstorm

François Tadel · Elizabeth Bock · Guiomar Niso · John C. Mosher · Martin Cousineau · Dimitrios Pantazis · Richard M. Leahy · Sylvain Baillet



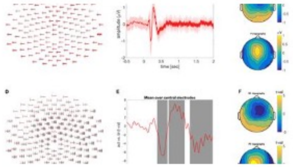
doi 10.3389/fnins.2019.00076

25,477 views 105 citations

ORIGINAL RESEARCH
Published on 09 Oct 2018

FieldTrip Made Easy: An Analysis Protocol for Group Analysis of the Auditory Steady State Brain Response in Time, Frequency, and Space

Tzvetan Popov · Robert Oostenveld · Jan M. Schoffelen



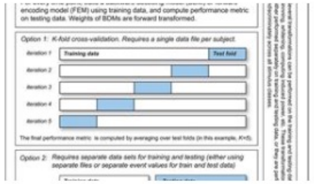
doi 10.3389/fnins.2018.00711

24,401 views 49 citations

METHODS
Published on 03 Jul 2018

From ERPs to MVPA Using the Amsterdam Decoding and Modeling Toolbox (ADAM)

Johannes J. Fahrenfort · Joram van Driel · Simon van Gaal · Christian N. L. Olivers



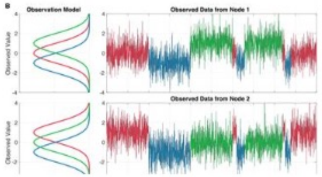
doi 10.3389/fnins.2018.00368

19,591 views 89 citations

ORIGINAL RESEARCH
Published on 28 Aug 2018

Task-Evoked Dynamic Network Analysis Through Hidden Markov Modeling

Andrew J. Quinn · Diego Vidaurre · Romesh Abeysuriya · Robert Becker · Anna C. Nobre · Mark W. Woolrich



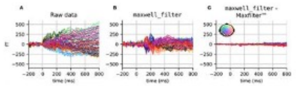
doi 10.3389/fnins.2018.00603

18,384 views 107 citations

METHODS
Published on 06 Aug 2018

A Reproducible MEG/EEG Group Study With the MNE Software: Recommendations, Quality Assessments, and Good Practices

Mainak Jas · Eric Larson · Denis A. Engemann · Jaakko Leppäkangas · Samu Taulu · Matti Hämäläinen · Alexandre Gramfort



doi 10.3389/fnins.2018.00530

17,932 views 74 citations

Resources

NeuroImage
Volume 257, 15 August 2022, 119056

Good scientific practice in EEG and MEG research: Progress and perspectives

Guiomar Niso [a b 1], Laurens R. Krol [c 1], Etienne Combrisson [d], A. Sophie Dubarry [e], Madison A. Elliott [f], Clément François [e], Yseult Héjja-Brichard [g], Sophie K. Herbst [h], Karim Jerbi [i j], Vanja Kovic [k], Katia Lehongre [l], Steven J. Luck [m], Manuel Mercier [n], John C. Mosher [o], Yuri G. Pavlov [p q], Aina Puce [a], Antonio Schettino [r s], Daniele Schön [n], Walter Sinnott-Armstrong [t], Bertille Somon [u]…Maximilien Chaumon [l]

NeuroImage
Volume 65, 15 January 2013, Pages 349-363

Comments and Controversies

Good practice for conducting and reporting MEG research

Joachim Gross [a], Sylvain Baillet [b], Gareth R. Barnes [c], Richard N. Henson [d], Arjan Hillebrand [e], Ole Jensen [f], Karim Jerbi [g], Vladimir Litvak [c], Burkhard Maess [h], Robert Oostenveld [f], Lauri Parkkonen [i j], Jason R. Taylor [d], Virginie van Wassenhove [k l m], Michael Wibral [n], Jan-Mathijs Schoffelen [f o]

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Introductory tutorials

These tutorials cover the basic EEG/MEG pipeline for event-related analysis, introduce the `mne.Info`, events, and `mne.Annotations` data structures, discuss how sensor locations are handled, and introduce some of the configuration options available.

- Overview of MEG/EEG analysis with MNE-Python
- Modifying data in-place
- Parsing events from raw data
- The Info data structure
- Working with sensor locations
- Configuring MNE-Python
- Getting started with mne.Report

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https://mne.tools

Reporting - Examples

“Data were low-pass filtered at 40 Hz (FIR filter, filter order: 100, window type: Hann), downsampled to 250 Hz and high-pass filtered at 1 Hz (FIR filter, filter order: 500, window type: Hann) to remove drifts from the data.”

“Independent Component Analysis (ICA) denoising was carried out using a 30 component FastICA decomposition (Hyvarinen, 1999) on the EEG channels. This decomposition explained an average of 99.2% of variance in the sensor data across datasets. Artefactual components containing blinks were automatically identified by correlation with the simultaneous V-EOG channel. ICA components linked to saccades were identified by correlation with a surrogate H-EOG channel, i.e., the difference between channels F7 and F8. Between 2 and 7 components were rejected in each dataset, with an average of 2.66 across all datasets.”

Reporting - Examples

“Bad segments were identified by segmenting the ICA-cleaned data into arbitrary 2-second chunks (distinct from the STFT time segments) and using the G-ESD algorithm to identify outlier (bad) samples with high variance across channels. An average of 31 seconds of data (minimum 6 seconds and maximum 114 seconds) were marked as bad in this step. This procedure is biased towards low-frequency artefacts due to the 1/f shape of electrophysiological recordings. Therefore, to identify bad segments with high-frequency content, the same procedure was repeated on the temporal derivative of the ICA-cleaned data. An average of 27 seconds of data (minimum 2 seconds, maximum 109 seconds) were marked as bad when using the differential of the data.”

WELLCOME CENTRE FOR HUMAN NEUROIMAGING

INSTITUTE OF NEUROLOGY IMAGINING DEPARTMENT

Statistical Parametric Mapping for MEG/EEG

Data pre-processing

Catharina Zich

30th May – 2nd June