TWINBRAIN

Mobile Brain/Body Imaging (MoBI) Workshop

TwinBrain Workshop 1.0:

Berlin Mobile Brain/Body Imaging Labs

MoBI meets Android: Current Developments and Future Directions

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@Berlin Mobile Brain/Body Imaging Lab, TU Berlin, 25-27 May 2021

ZRS

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```
function training(self, target, iter, trainingSteps)

    % Get the learning rate for this iteration from the schedule,
    % treat the first 60% with first learning and so on
    if iter/trainingSteps < 0.6
        learningRate = self.learningRateSchedule(1);
    elseif iter/trainingSteps < 0.8
        learningRate = self.learningRateSchedule(2);
    else
        learningRate = self.learningRateSchedule(3);
    end

    % Forward pass
    node_output = innerFunction(self);
    % "descend" the error surface. this error can be used
    % to asses the goodness of the network, it is not used
    % for learning purposes
    % error = 0.5*((node_output - self.targets(example))^2);

    % Backward pass.
    % Create d_k
    derivative = node_output*(1-node_output);
    d_k = (derivative) .* (node_output - target);

    % Apply it -> adapt the weights to learn
    self.weights = self.weights + learningRate * (-1) * d_k
    self.bias = self.bias + learningRate * (-1) * d_k;

    %fprintf('Done training!\n');
end

function final_test(self, target)
    %fprintf('\tWeights: \t= \t%.2f\n', self.weights);
    node_output = innerFunction(self);
   % fprintf('For input = %.1f, output = %.2f (target=%i)\n'
   %     self.inputs, node_output, target);
   s = ['Input was ', num2str(self.inputs), ' output = ', nu
end

function result = innerFunction(self)
   result =  self.sigma(self.weights * self.inputs' + self.b
end
```

MoBI meets Android

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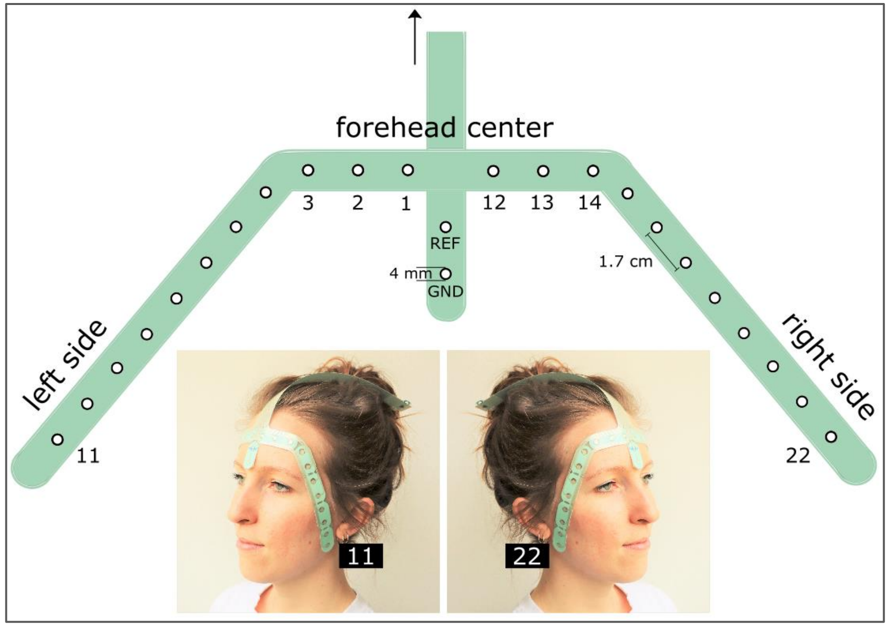


Two Topics Today

mobile EEG
&
new Android Apps

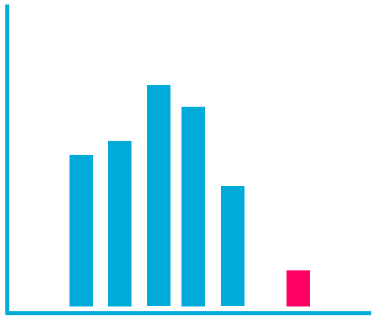
artifact handling
&
Riemannian ASR

Artifacts: Signal or Noise?

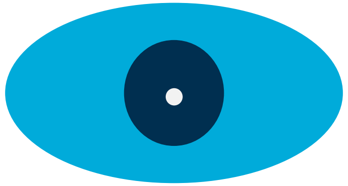
– outlier

– unwanted signal

– deviant



– context specific



Types of Artifacts in EEG

– biological

– technical

Artifact Subspace Reconstruction (ASR)

– online artifact handling method

– no validation, complicated

– my adaptation: Riemannian ASR

Kothe, Mullen (2013)
Swartz Center for Computational Neuroscience, San Diego, USA
Chang (2018,2019)

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ASR toolbox versus ASR algorithm

clean_rawdata
clean_artifacts
clean_flatlines
clean_drifts
[clean_channels]
clean_asr → calibration / processing
[clean_windows]

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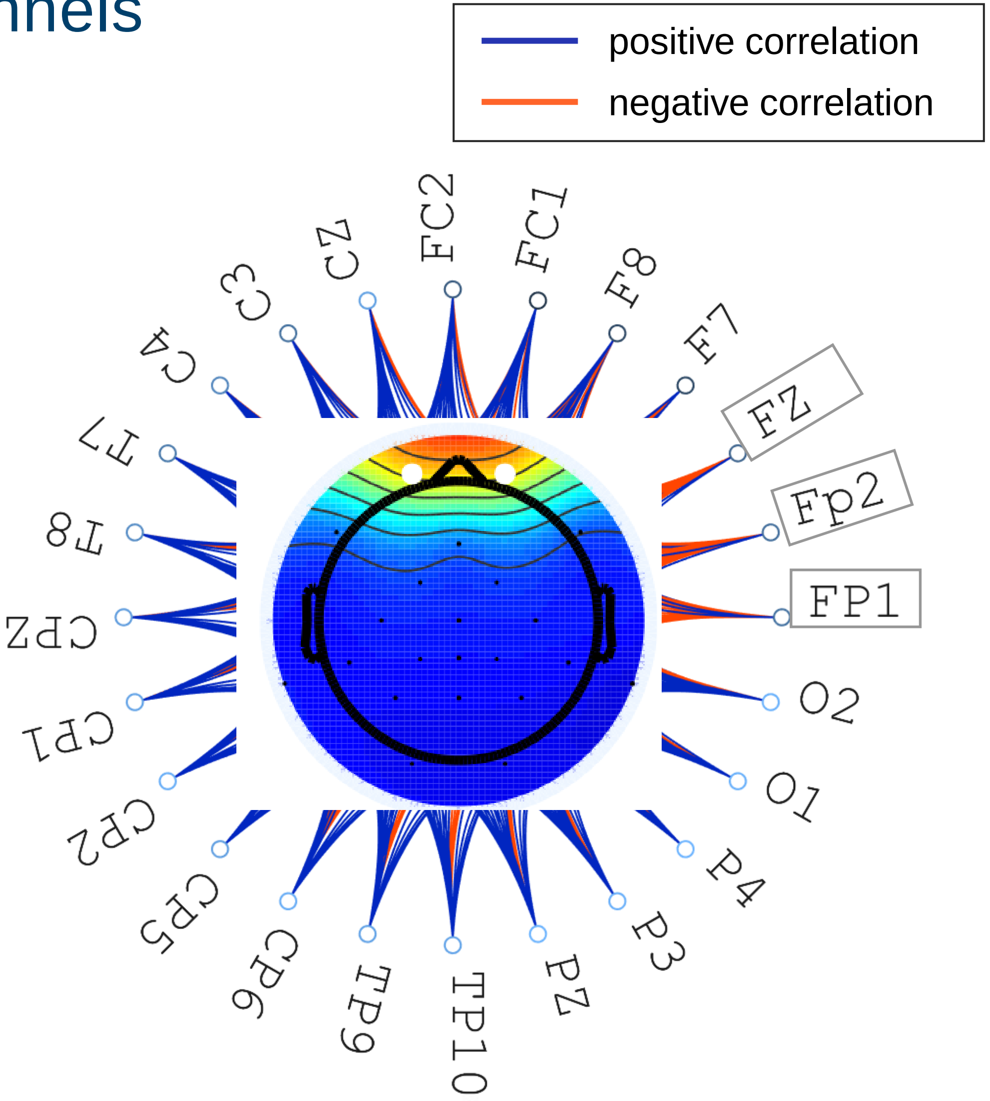
Correlational Structure over Channels

- consider an eye blink
- covariance matrices
- correlational structure is very regular
- locally captured artifacts break correlation structure
- detection based on asymmetry in correlation



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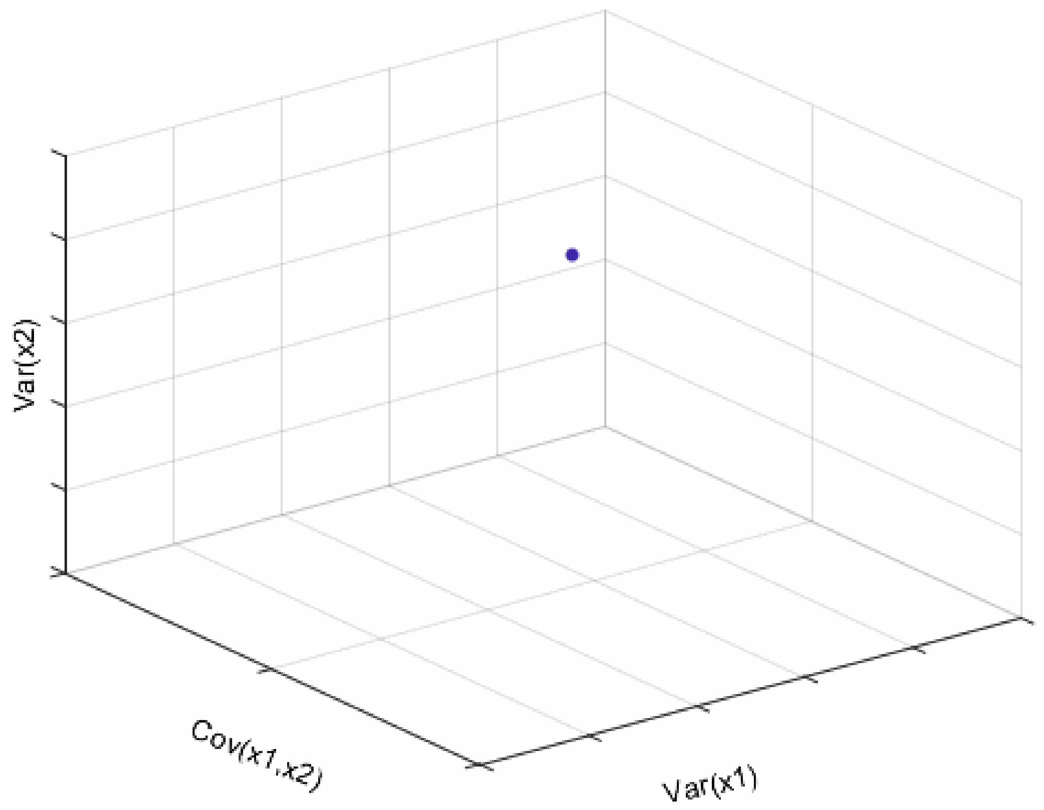
Correlational Structure over Time

- correlation for 2 channels $x1, x2$
- every point is a covariance matrix for one segment in time
- most points form a neighbourhood
- outliers: possible artifact

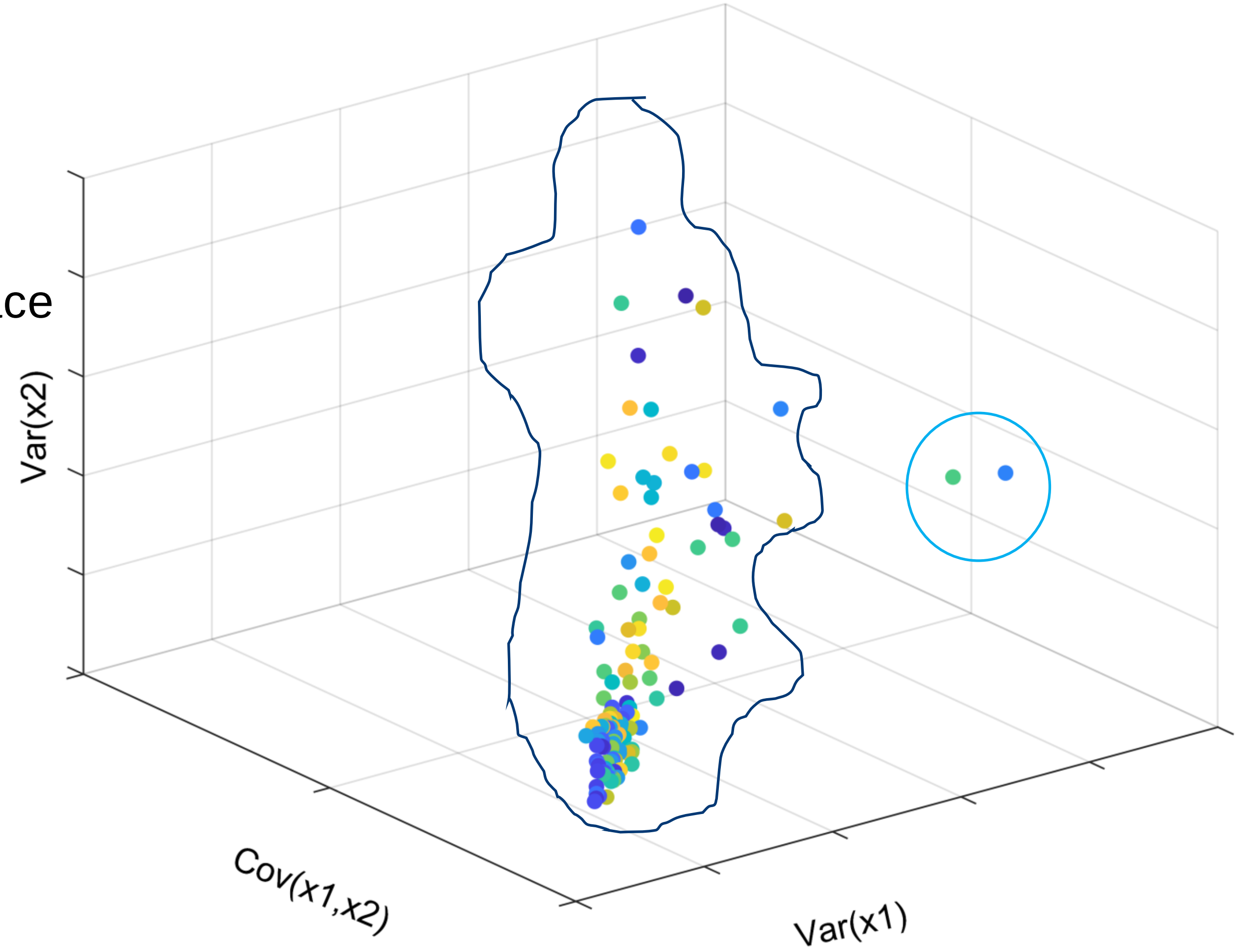


ASR: Detection of Outliers

– neighbourhood defined during training

– threshold

– for more channels: curved space



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Riemannian Methods in EEG Data

- covariance matrices are symmetric positive definite matrices (SPD)
- SPD matrices form curved space
- straight line distance is imprecise

- → ASR might not detect some data points as artifacts!

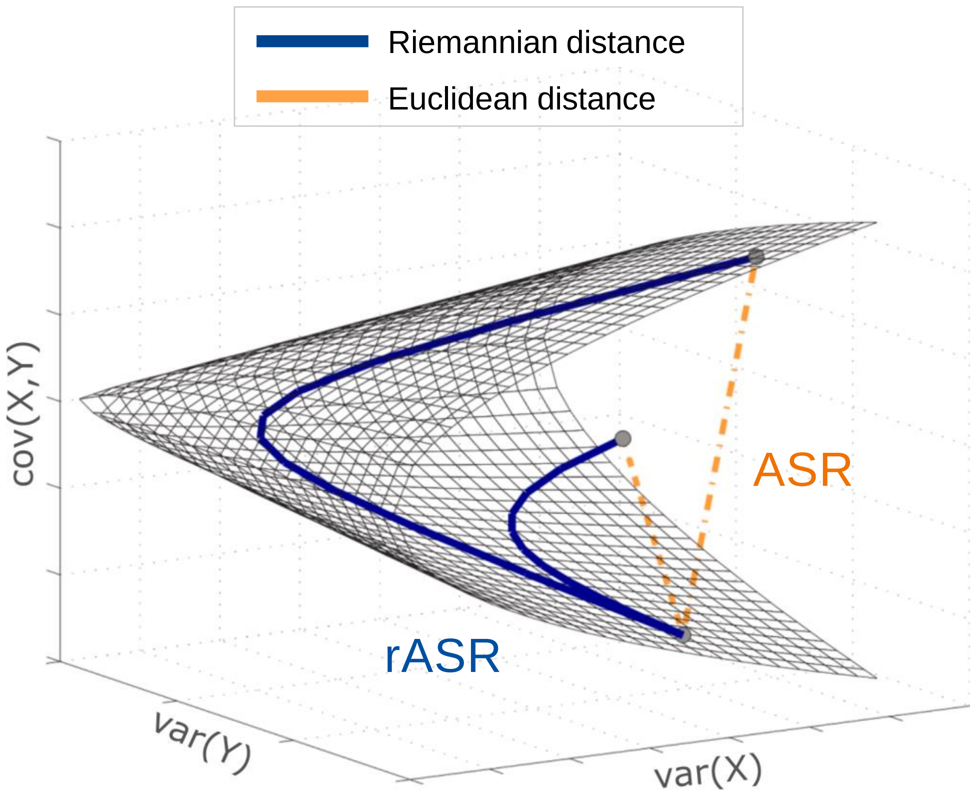

Figure adapted from Yger et al., 2015

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Results: Cap-EEG Sensitivity

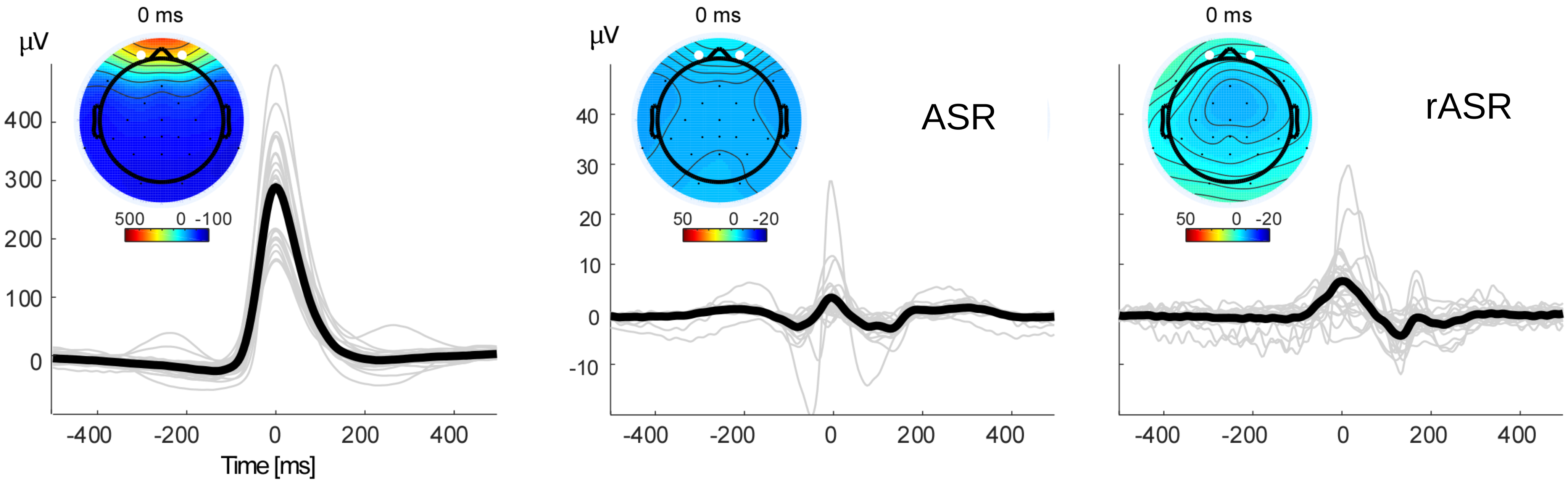

Figure adapted from Blum et al., 2019

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Results: Cap-EEG Specificity

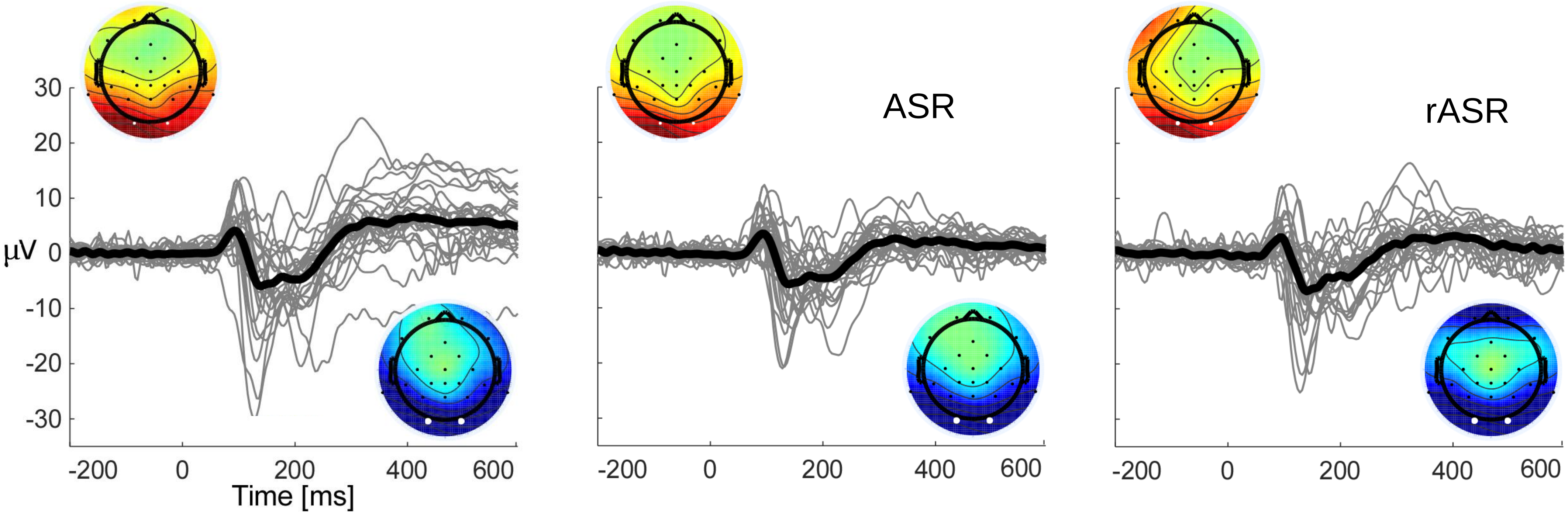
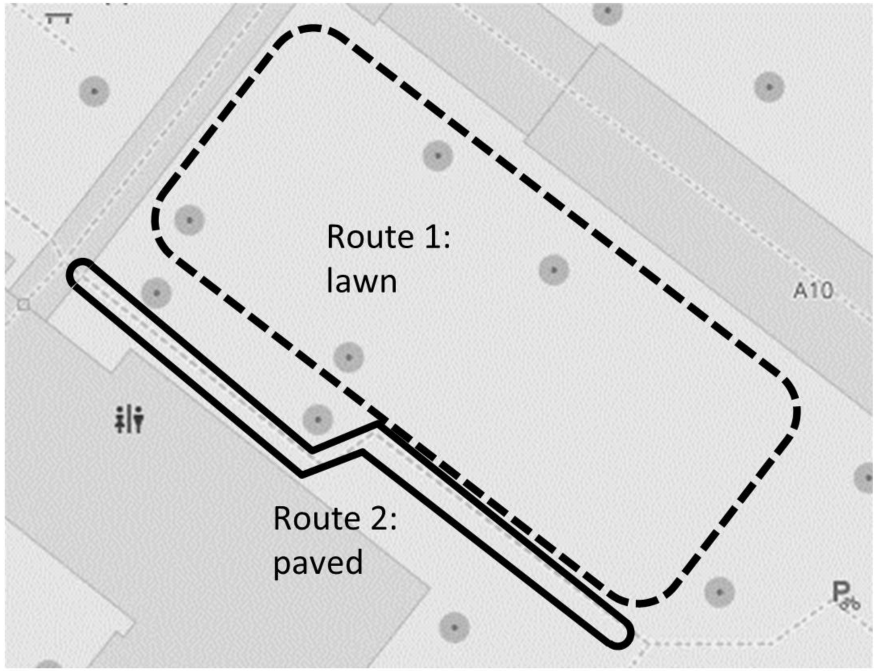


Figure adapted from Blum et al., 2010

Movement Artifact: ASR vs. ICA

- adapted from
Jacobsen et al., 2020



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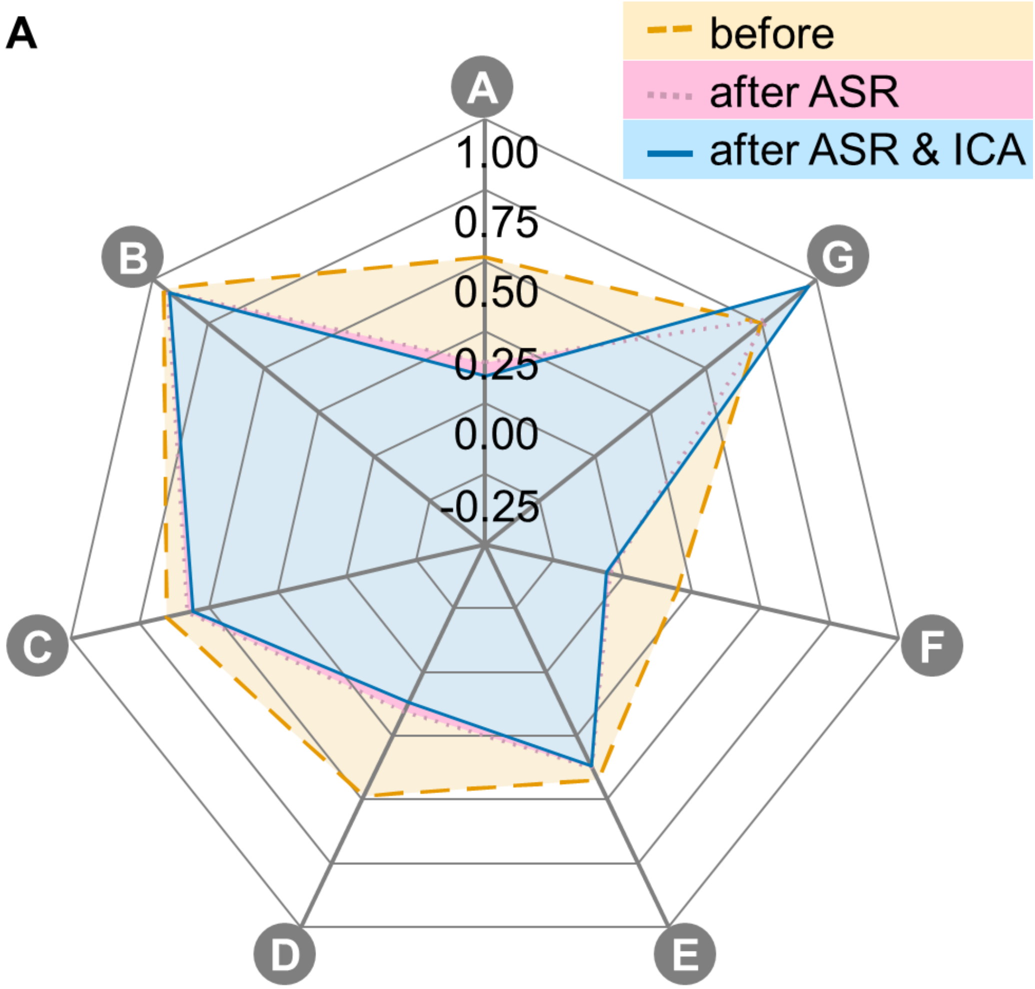
Artifact footprint

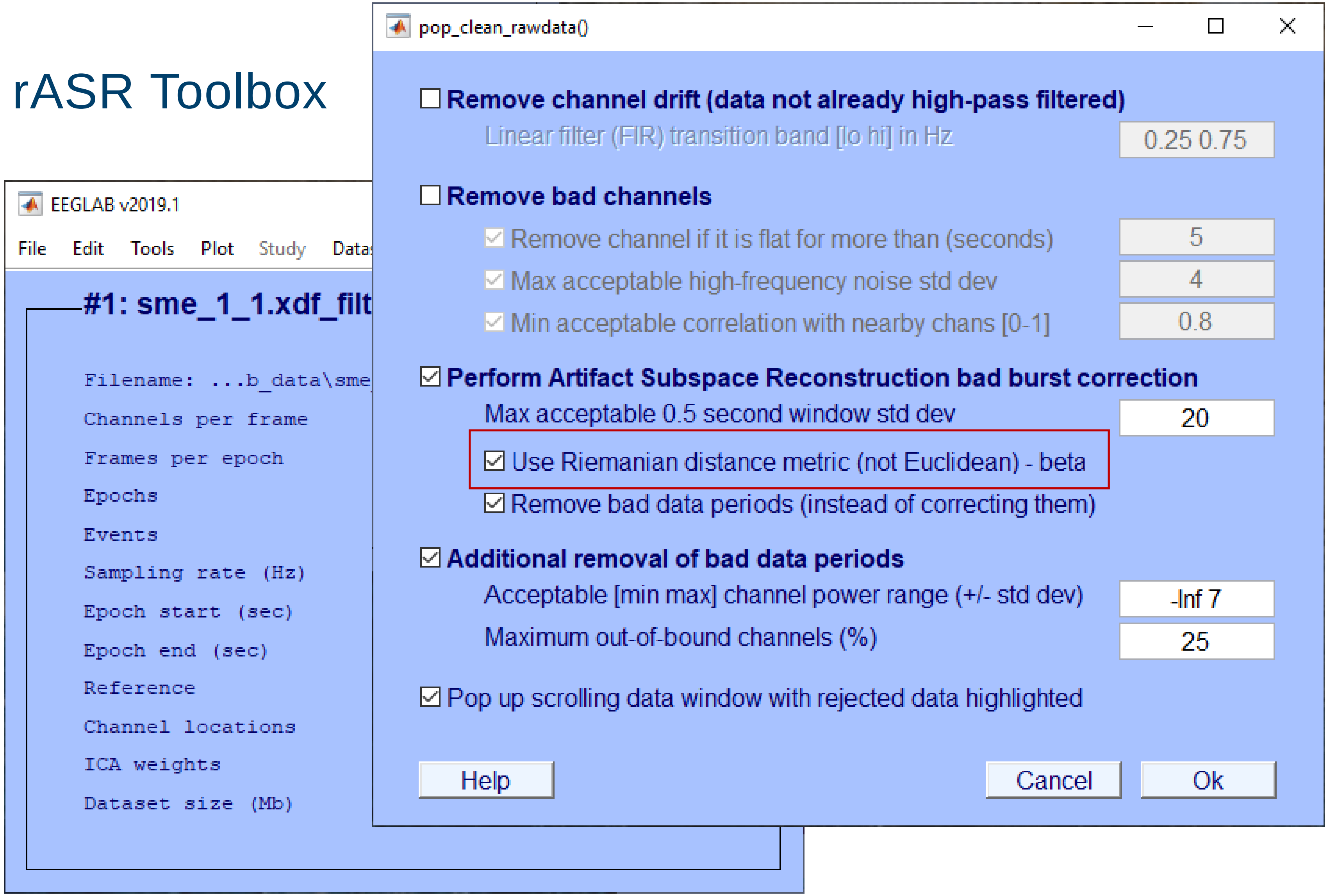


Ferris
Nordin
Wagner
Seeber

ASR - Discussion

- training data make the difference!
- global artifacts
- processing delay
- spatial coverage of channels

Results: rASR Toolbox



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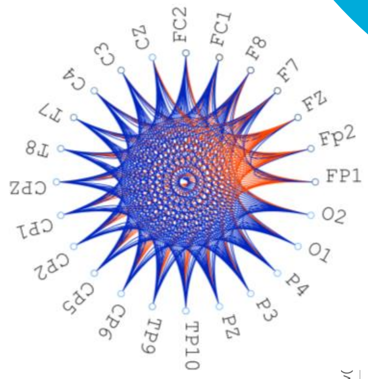
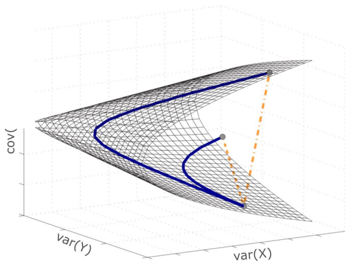
Two Topics Today





mobile EEG
&
new Android Apps

artifact handling
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Riemannian ASR

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Mobile EEG and Current Developments

- LSL
- continuous data no markers
  - combining EEG with additional sensors

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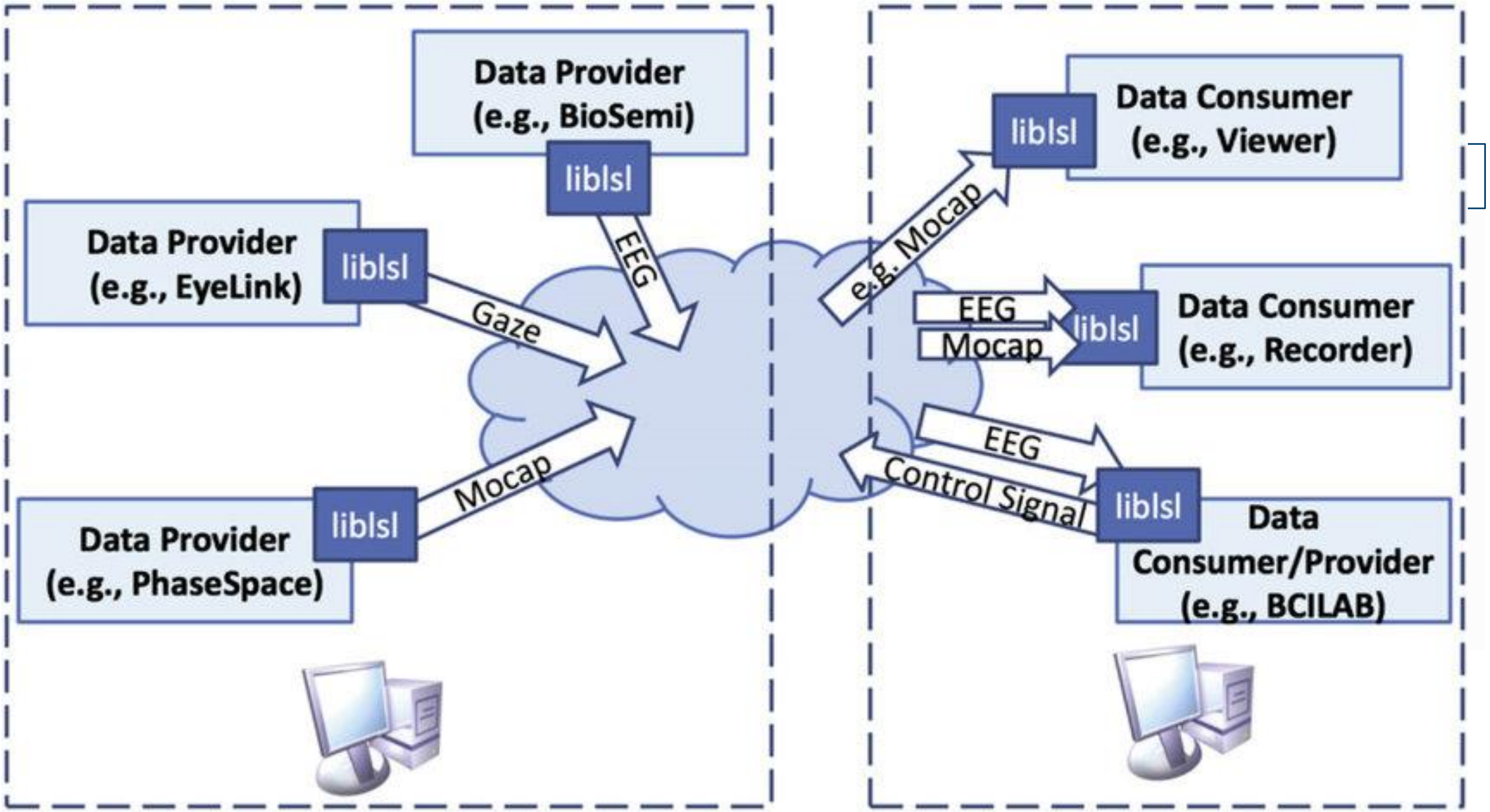
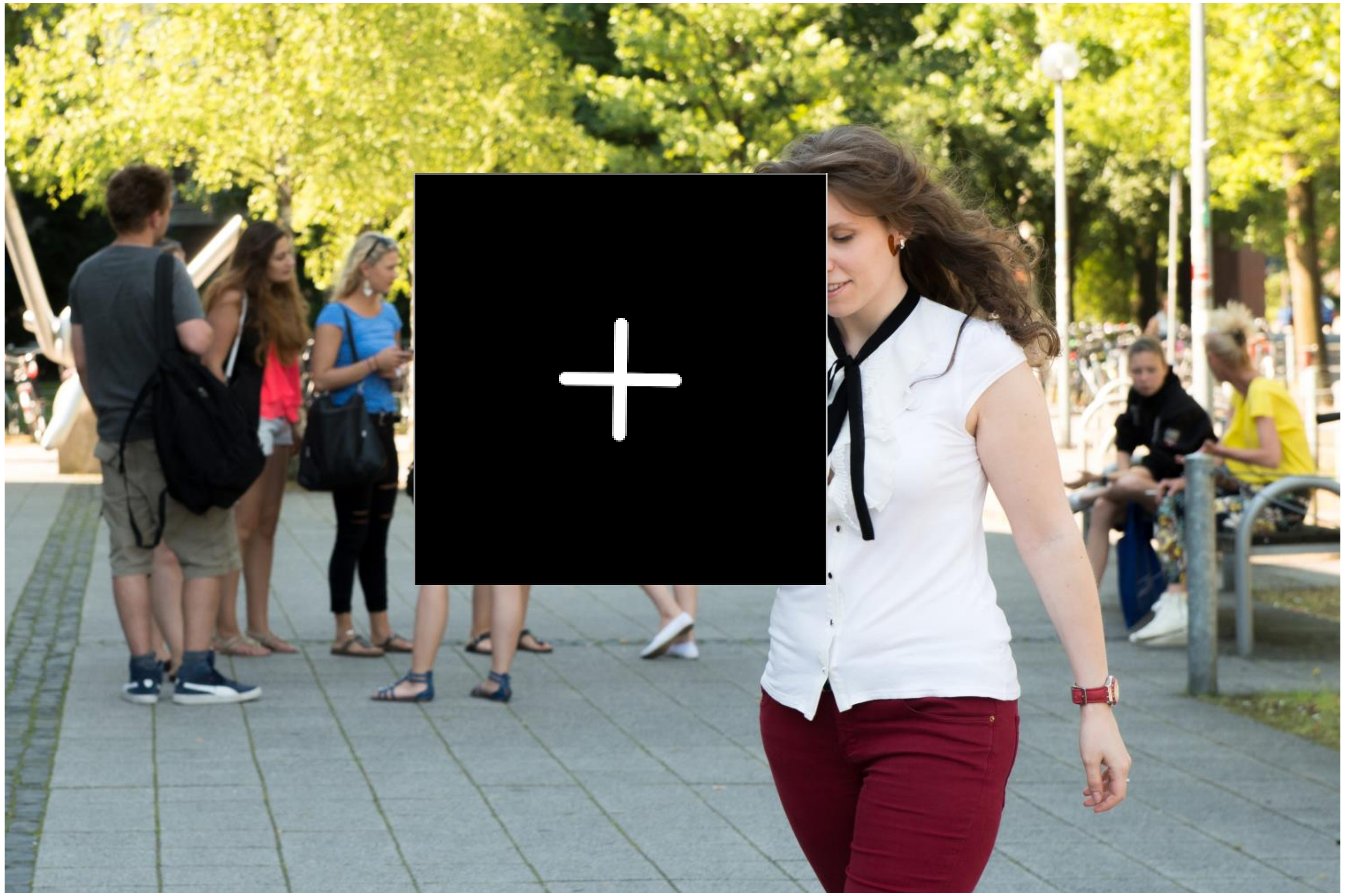
LabStreamingLayer



Gramann (2014)

Markerless EEG



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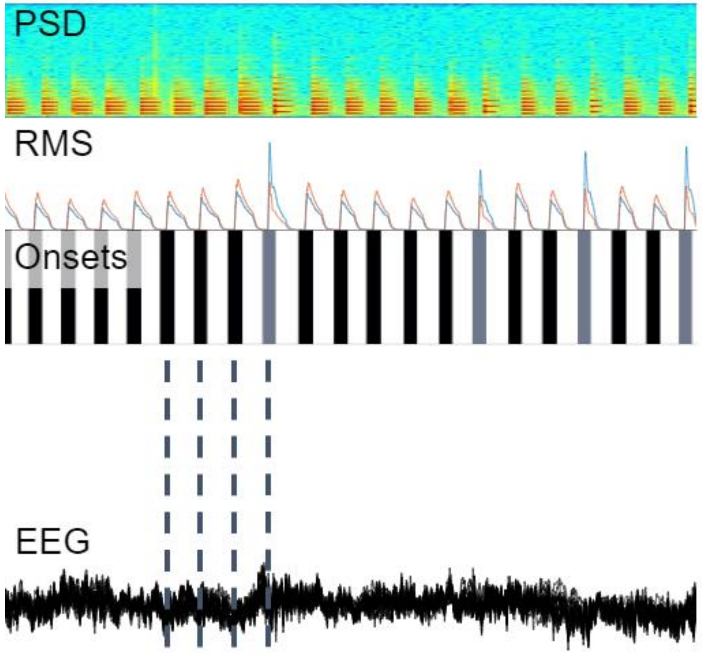
Real-time audio processing of real-life soundscapes for EEG analysis: The AFEx Android App

neli neurophysiology of everyday life

Martin Bleichner's Group



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RECORD-A and SEND-A

- Android applications
- enable completely mobile **LabStreamingLayer** setups

- SEND-A
  - LSL streams from smartphone sensors
- RECORD-A
  - record all incoming LSL streams to xdf

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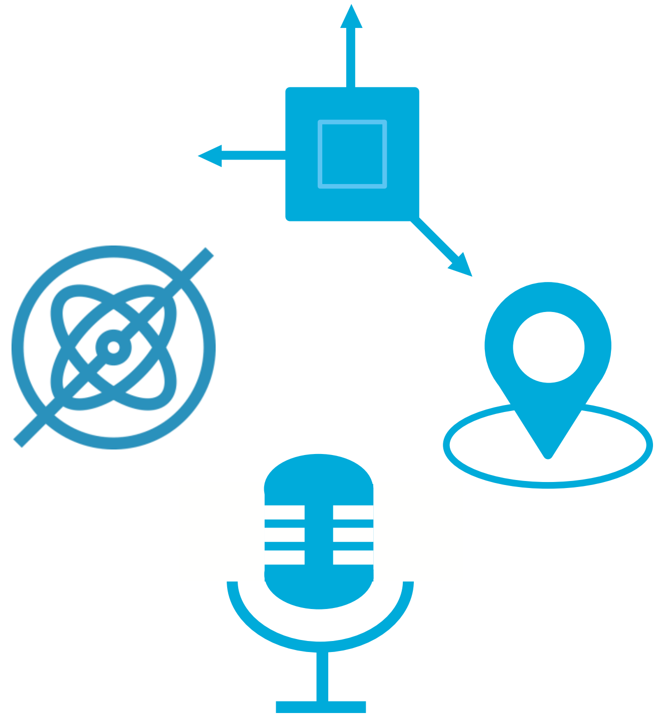
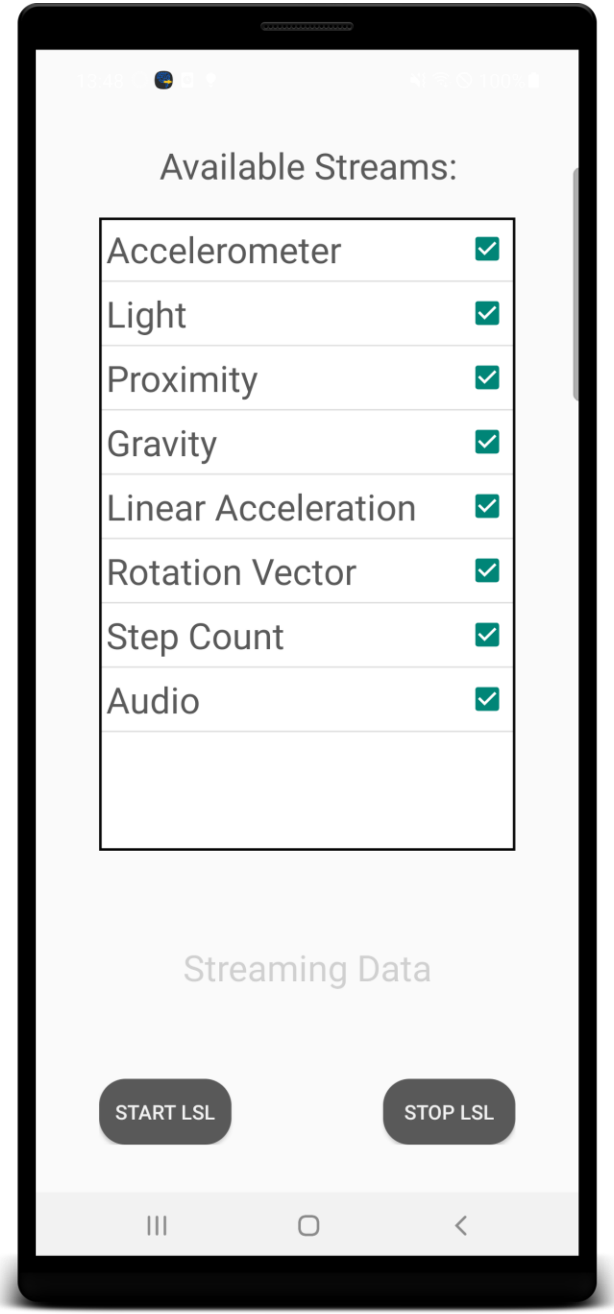
SEND-A




Available Streams:
Accelerometer
Light
Proximity
Gravity
Linear Acceleration
Rotation Vector
Step Count
Audio
Streaming Data
START LSL
STOP LSL

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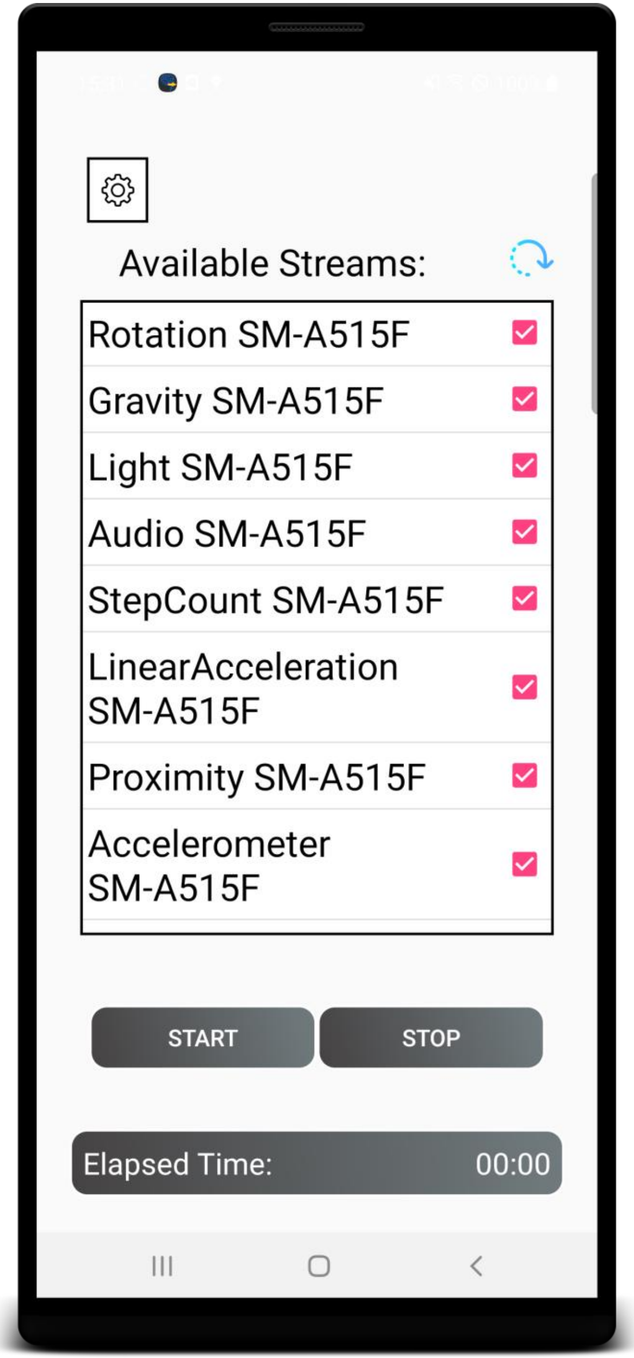
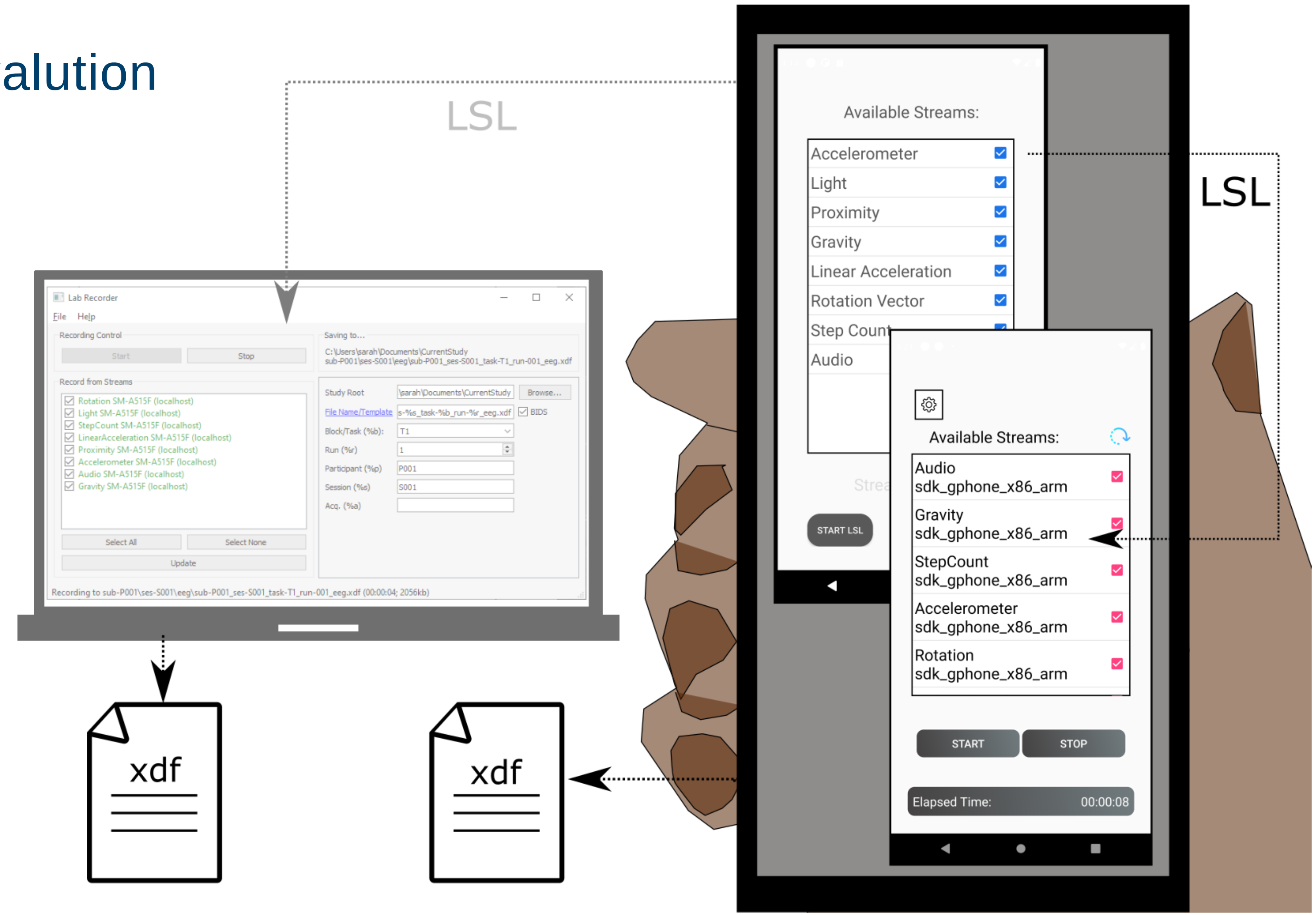
RECORD-A



Evalution


LSL
Lab Recorder
File Help
Recording Control
Start
Stop
Saving to...
Record from Streams
Rotation SM-A515F (localhost)
Light SM-A515F (localhost)
StepCount SM-A515F (localhost)
LinearAcceleration SM-A515F (localhost)
Proximity SM-A515F (localhost)
Accelerometer SM-A515F (localhost)
Audio SM-A515F (localhost)
Gravity SM-A515F (localhost)
Select All
Select None
Update
Study Root
Browse...
BIDS
xdf
xdf
LSL
Available Streams:
Accelerometer
Light
Proximity
Gravity
Linear Acceleration
Rotation Vector
Step Count
Audio
START LSL
Available Streams:
Audio
sdk_gphone_x86_arm
Gravity
sdk_gphone_x86_arm
StepCount
sdk_gphone_x86_arm
Accelerometer
sdk_gphone_x86_arm
Rotation
sdk_gphone_x86_arm
START
STOP
Elapsed Time:
00:00:08

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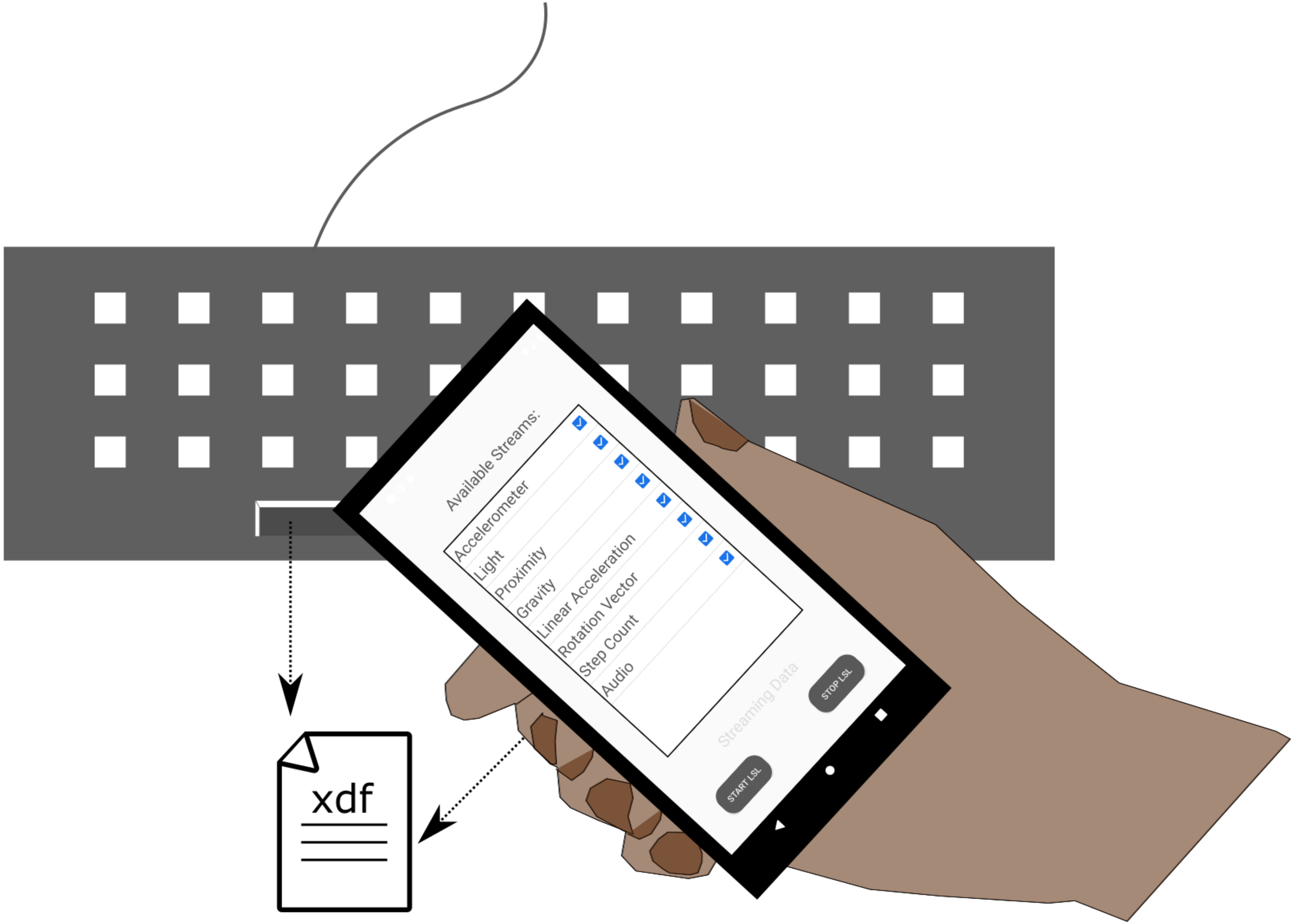
Timing



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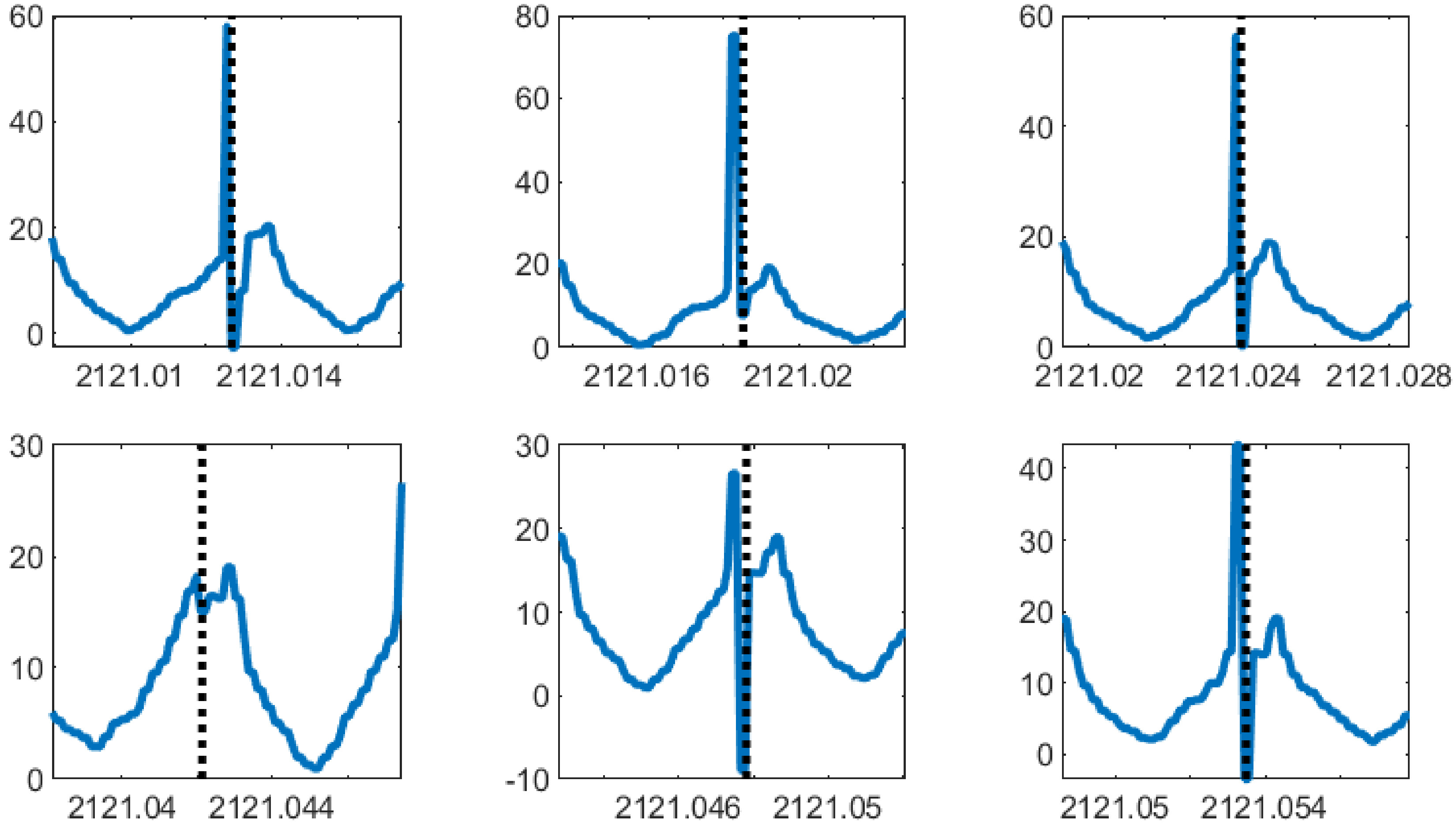
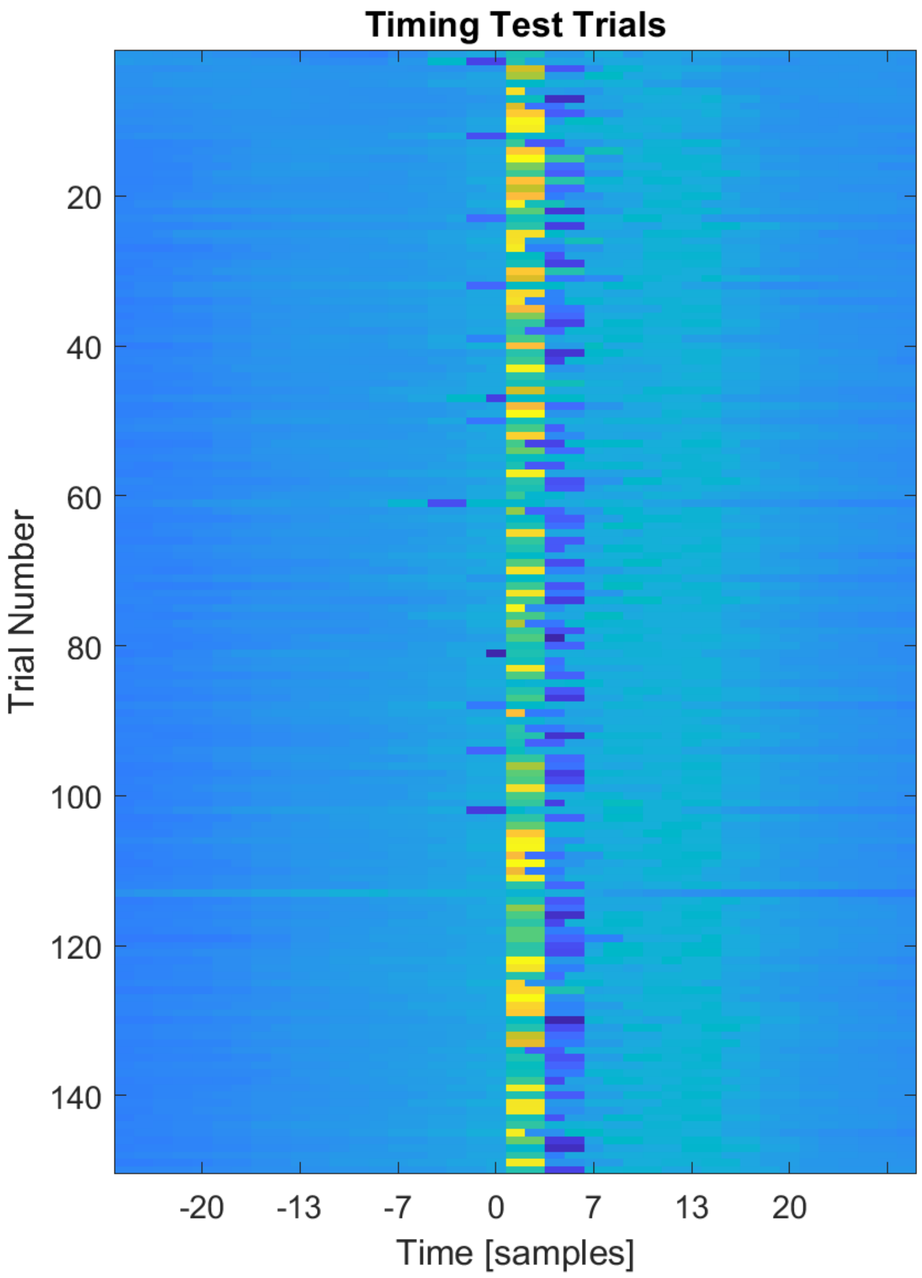
Timing Data



All Timing Events



End

– artifact correction is important

– know your data

– add information to your data

– don’t be afraid to go completely mobile

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Hearing4all

Bundesministerium für Bildung und Forschung

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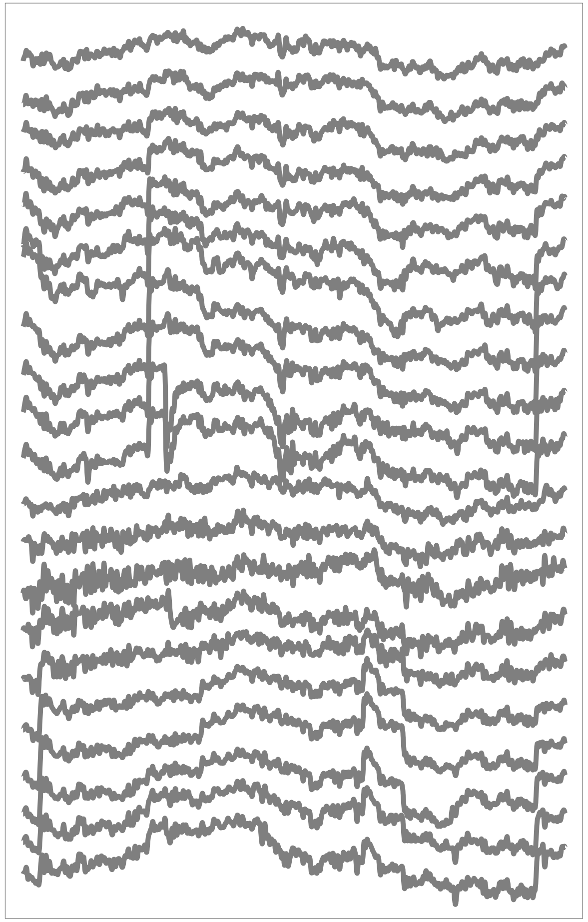
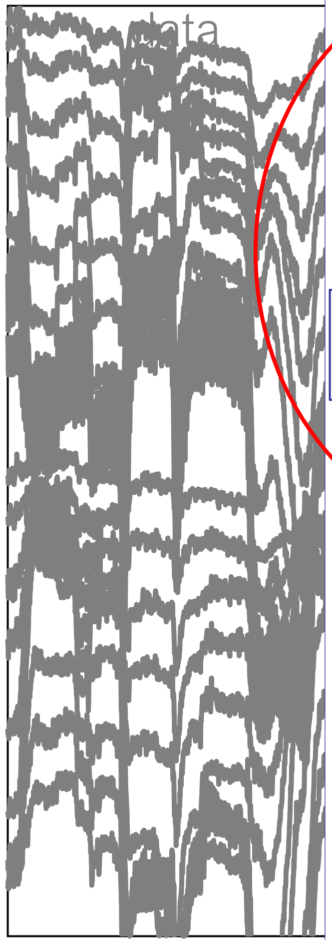
calibration data



← 1 min →

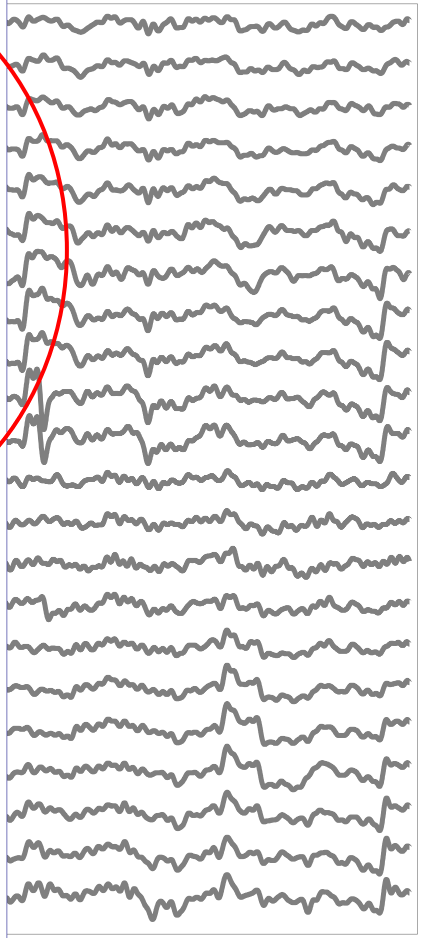
- compute sample covariance matrix
- compute mixing matrix
- decompose mixing matrix
- compute statistical properties in component space
- save these in threshold matrix

uncorrected data



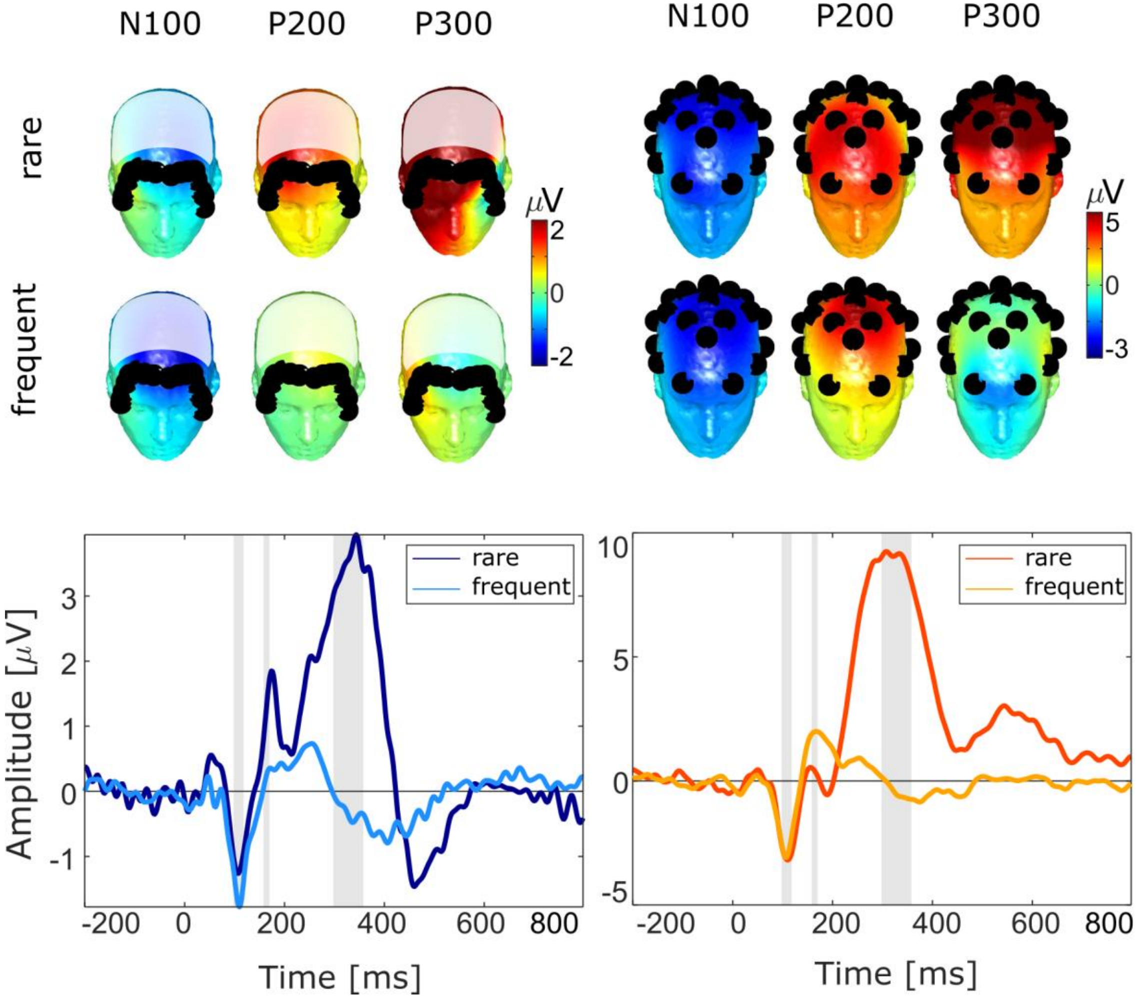
- compute sample covariance matrix
- decompose sample covariance matrix
- choose clean components using threshold matrix
- reconstruct data segment

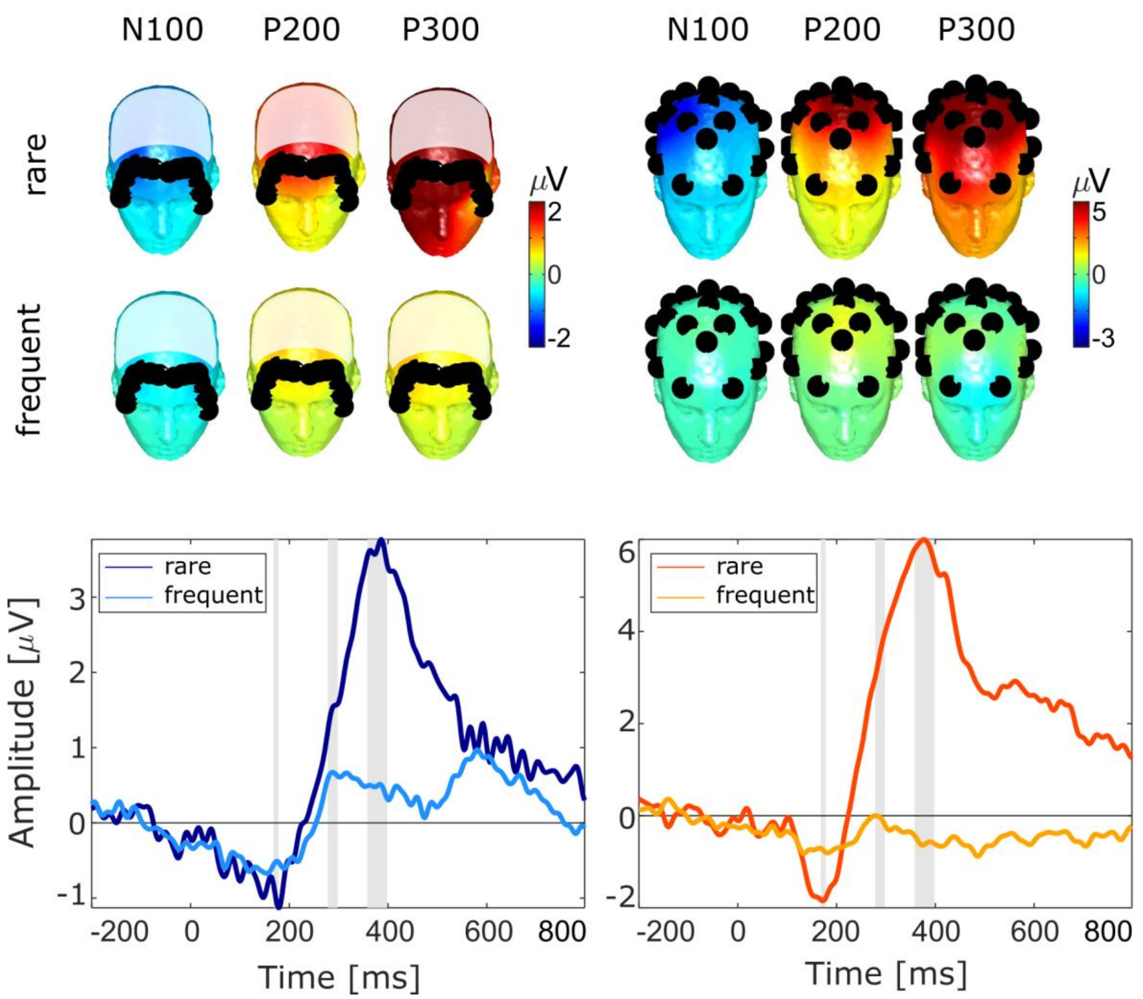
corrected data



Auditory Oddball

Vibrotactile Oddball





- variance of a time series X:

$$\text{var(X)} = \frac{1}{n}\sum_{i=0}^{n}(x_i\ -\ \mu)^2$$

variance in 1 dimension is a positive real number

- covariance between two time series:

$$cov(X,Y) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu_x)(y_i - \mu_Y)$$

- covariance matrix of two time series:

$$C = \begin{pmatrix} var(X) & cov(X,Y) \\ cov(Y,X) & var(Y) \end{pmatrix}$$

variance in n dimensions is a positive matrix

  - where X and Y can denote epochs in EEG measurement, or data from different channels

(symmetric) positive definite matrices

1) a symmetric $n \times n$ real matrix M is positive definite if

$$z^T M\, z$$

is strictly positive for every non-zero column vector of z (energy)

2) all eigenvalues λ of SPD matrices are real and positive