11020ISA 557300

Brain Computer Interfaces: Fundamentals and Application

Lecture Week 13. ERP-based BCIs

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Today's Agenda

ERP-based BCIs

- Stimulus-evoked activity
- P300
- SSVEP
- RSVP

Online course

https://meet.google.com/fba-uxbj-mdo

EEG-based BCIs

Modulating the response of large neural populations

- Subject training over a period of time → self-paced (*asynchronous BCI*)
  - voluntarily initiate control
  - utilize some form of imagery (motor or cognitive)

- External stimuli → *Stimulus-based (synchronous BCIs)*
  - stereotypical brain responses

Which is easier to be built?

Two major types of BCIs

Invasive BCIs

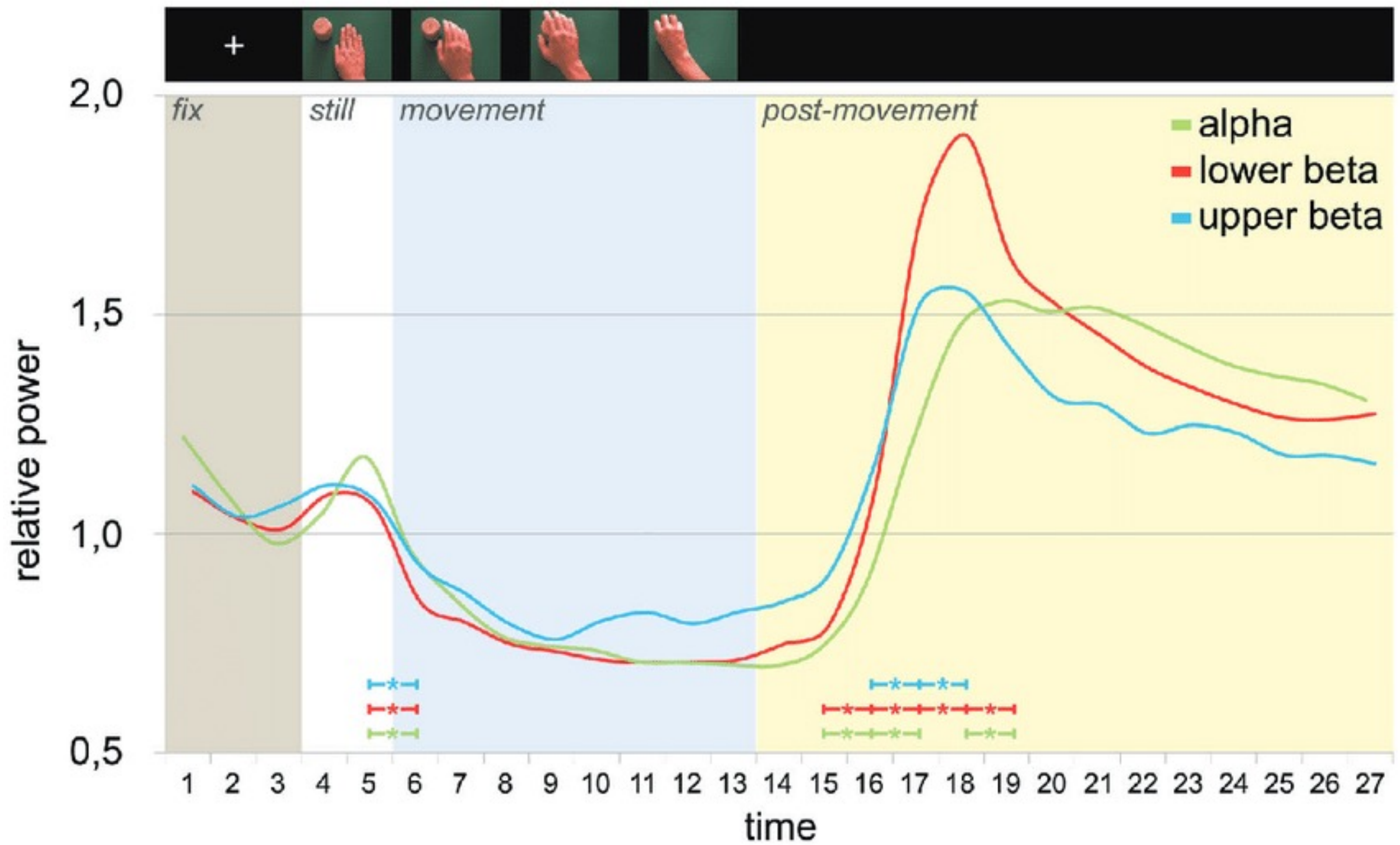
Noninvasive BCIs

- Only record from the brain and translate the neural data into control signals for output devices.
- Only stimulate the brain and cause certain desired patterns of neural activity in the brain.
- Both record and stimulate the brain

Oscillatory Potentials and ERD

Performs movement or imagines performing a movement

– mu (8–12 Hz) or beta band (13–30 Hz) decreases i.e., event-related desynchronization (ERD)



Brain Responses Useful for Building BCIs

Conditioned Responses

Population Activity

Imagined Motor and Cognitive Activity

Stimulus-Evoked Activity

- Brain activity generated in response to certain stimuli
- P300 (or P3) in EEG, an event-related potential (ERP), over the parietal lobe
- The exact neural mechanisms responsible for the P300 are as yet unclear

Other common types of evoked potentials

Steady state visually evoked potential (SSVEP)

- Visual cortex
- A visual stimulus flickering at a certain frequency
- Peaks in the power spectrum at the same frequency

N100 (or N1)

- Frontal and Central regions
- Usually followed by P200 (N1-P2 complex)
- Sudden and loud noise

Other common types of evoked potentials

N400

- Central and Parietal sites
- Incongruent inputs
- Similar to an *error potential* (ErrP)

Stimulus-Evoked Potentials

A “rare” stimulus can evoke a potentials with a positive peak at 300 ms after the stimulus is presented.

- auditory, visual, or somatosensory forms.

visually evoked potentials (VEPs)

- SSVEP

auditory evoked potentials (AEPs)

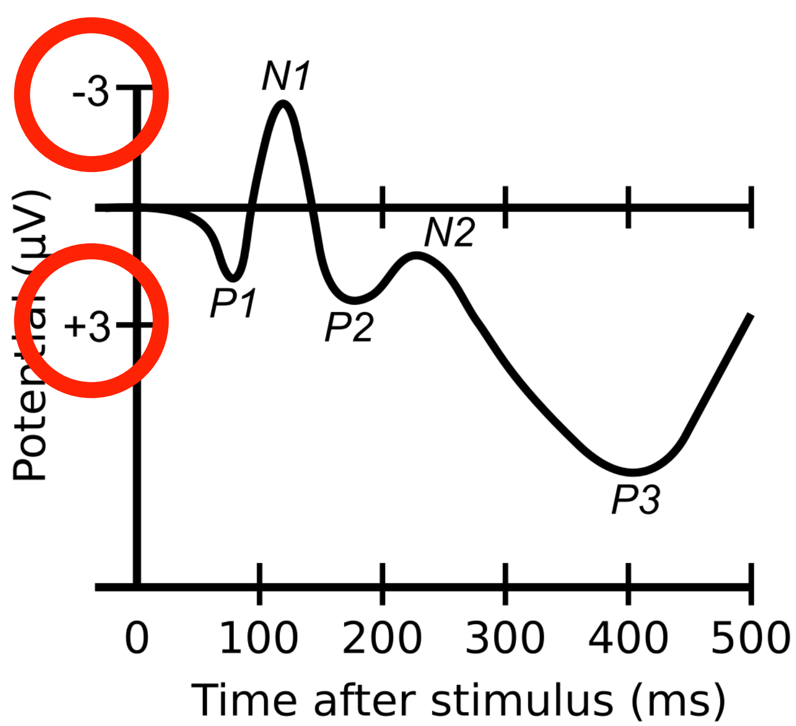
somatosensory evoked potentials (SSEPs)

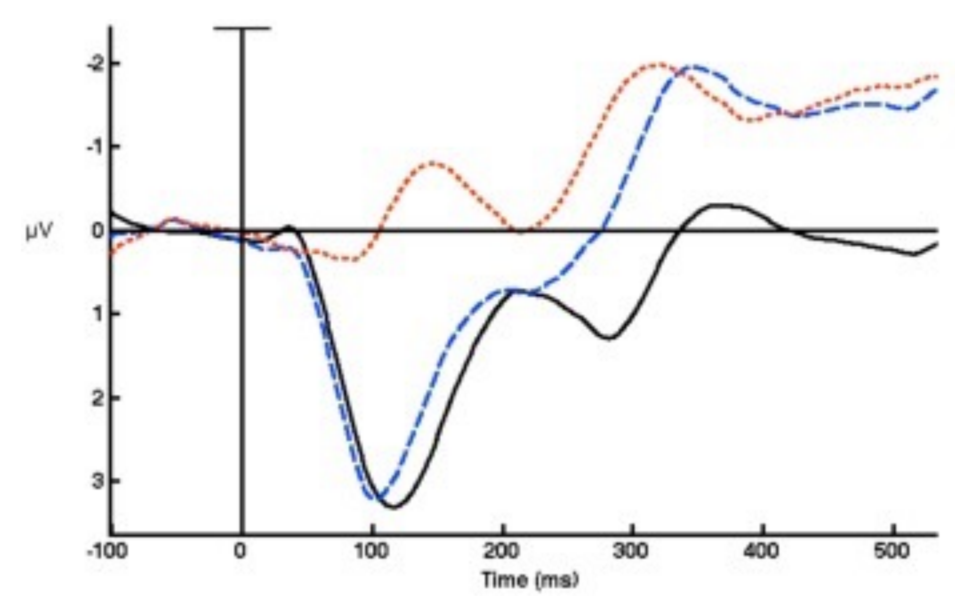
The P300 Potential (250 to 500 ms)

Stimulus must be rare and unpredictable but relevant.

Amplitude of P300

- how relevant the stimulus is
- varies inversely with the probability of stimulus
- decision making





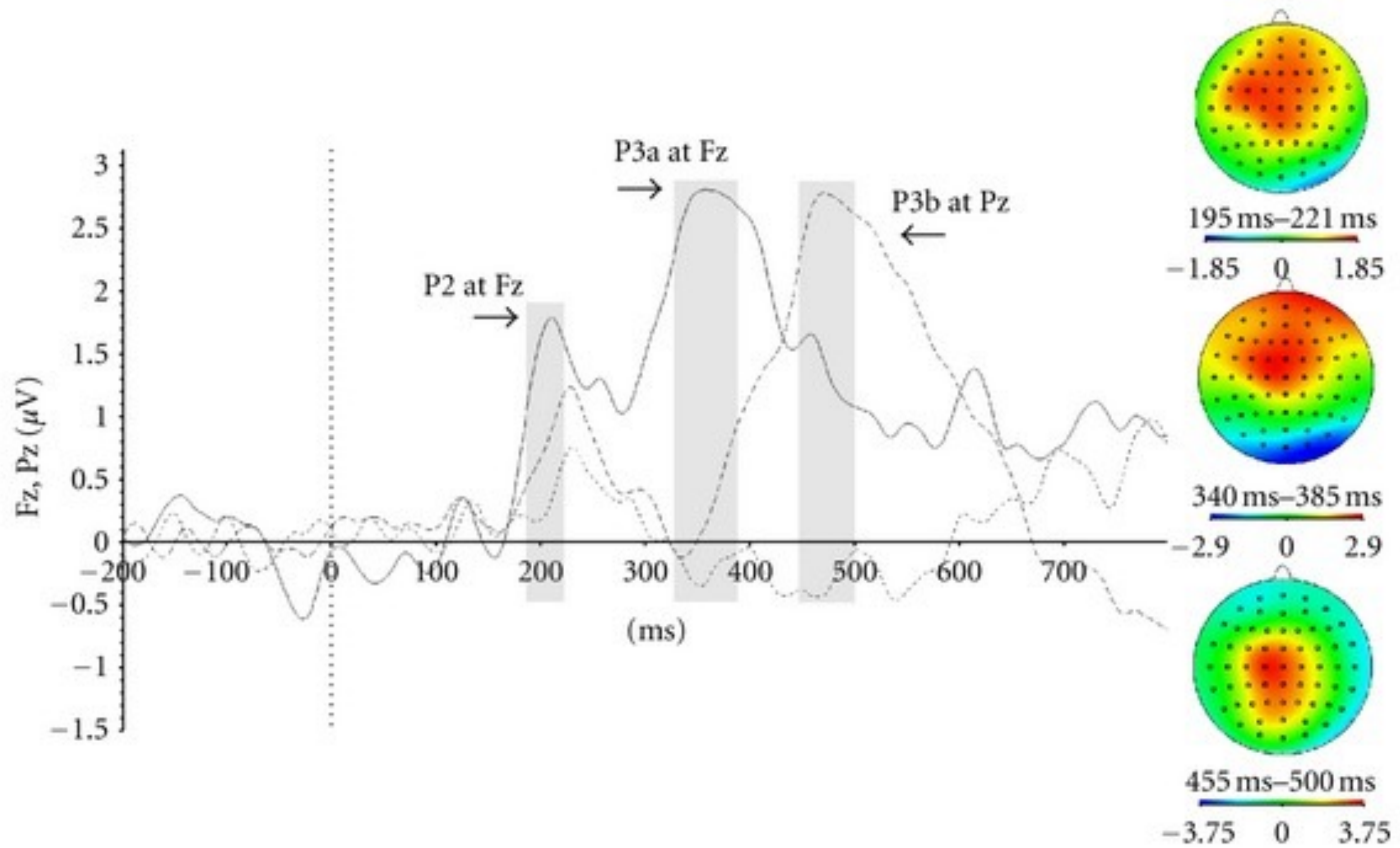
P3a (or novelty P3)

maximum amplitude over frontal/central electrode sites

peak latency in the range of 250-280 ms

associated with

- engagement of attention (especially the orienting, involuntary shifts to changes in the environment)
- processing of novelty

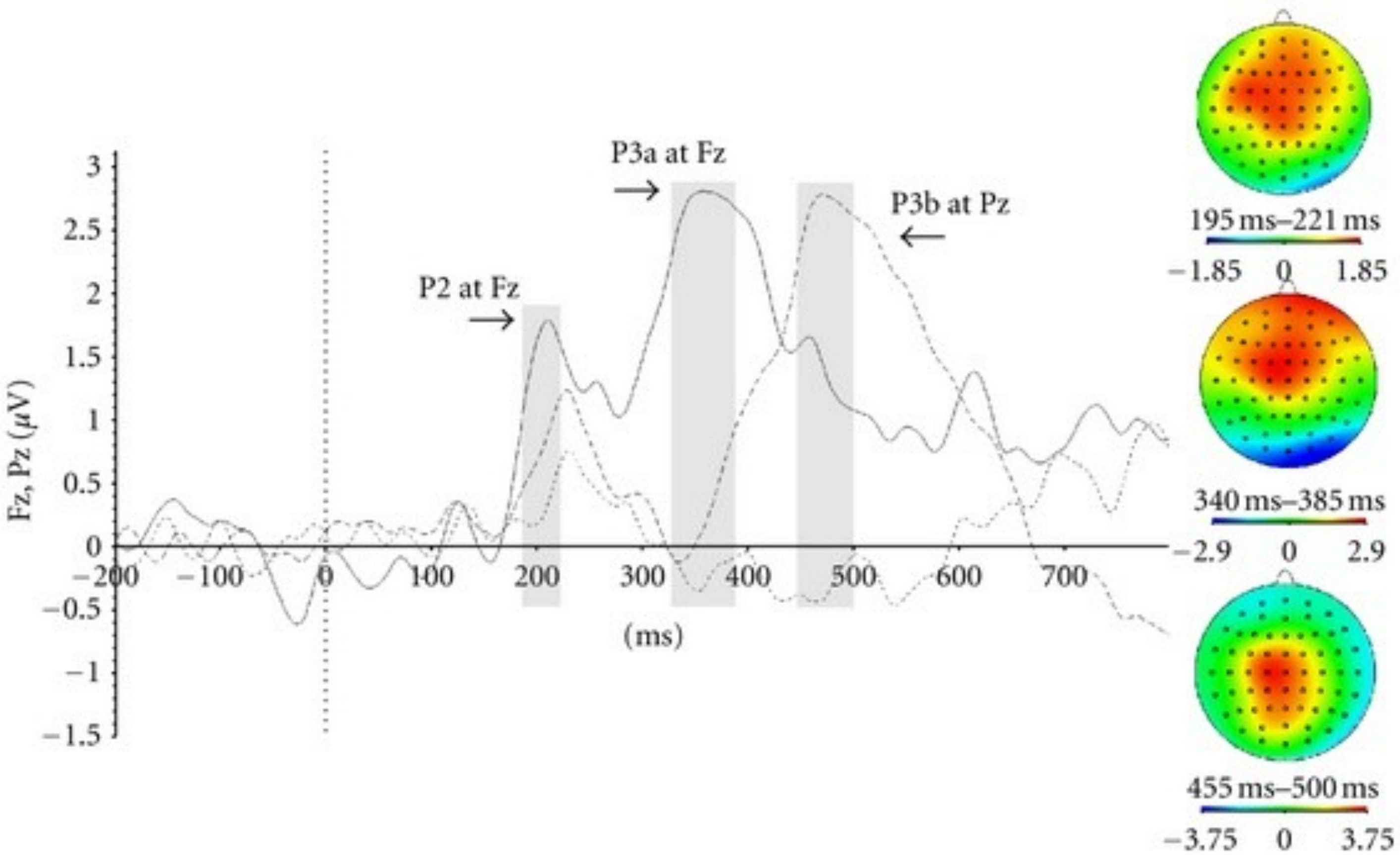


P3b

peaks at around 250–500 ms, over parietal brain areas.

The P3b has been a prominent tool used to study cognitive processes, especially psychology research on **information processing**.

The P3b can also be used to measure how demanding a task is on cognitive workload.



BCI "speller
based on "Oddball paradigm"

Farwell and Donchin (1988)

- 26 letters + symbols/commands
- Focusing attention on the target letter
- Rows and columns of the matrix repeatedly flash in random order

Choose one letter or command

A	G	M	S	Y	*
B	H	N	T	Z	*
C	I	O	U	*	TALK
D	J	P	V	FLN	SPAC
E	K	Q	W	*	BKSP
F	L	R	X	SPL	QUIT

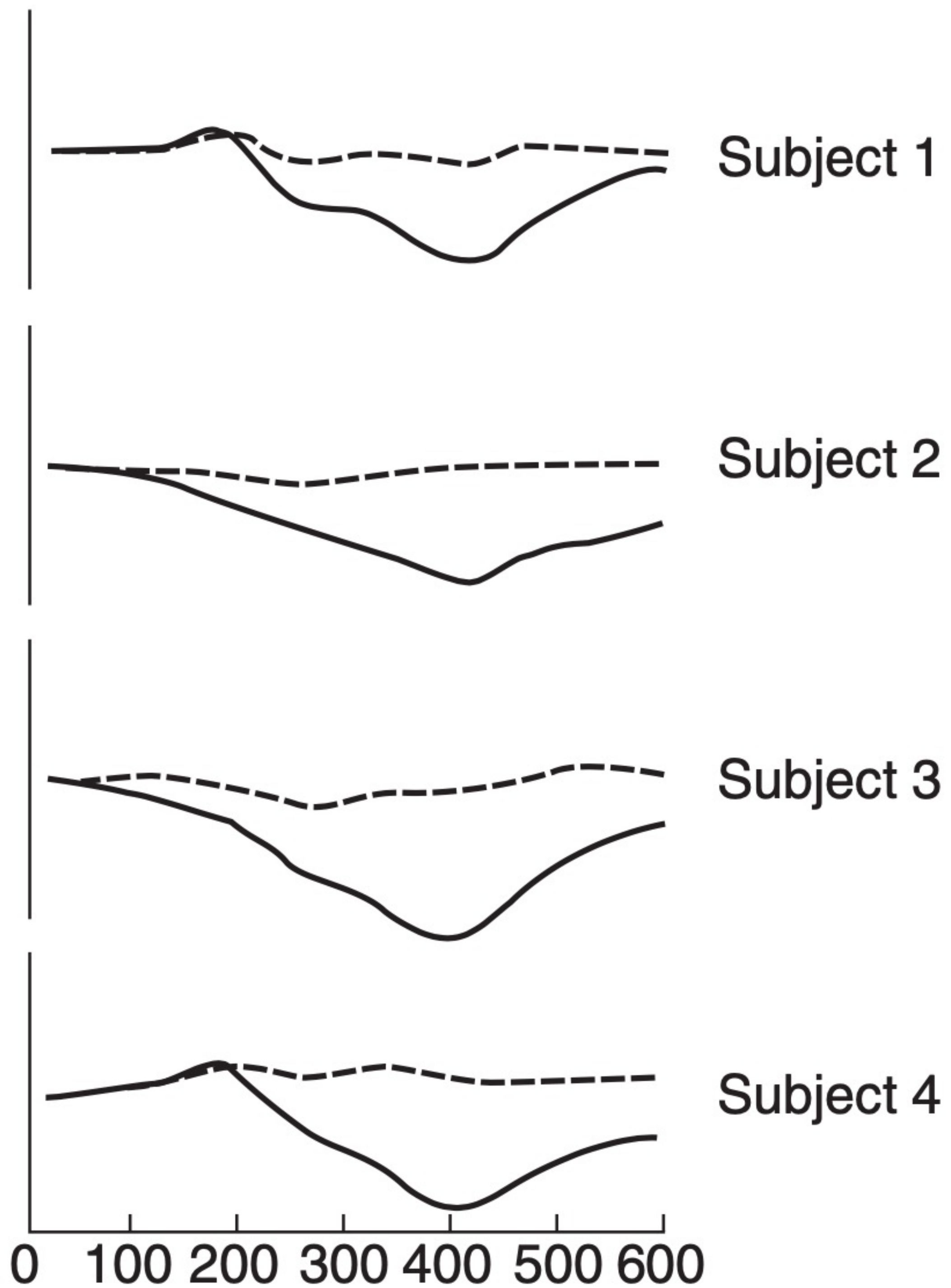
BCI “speller based on “Oddball paradigm”

Containing a subject’s chosen letter → a large P300 generated.

Linear discriminate analysis classifier

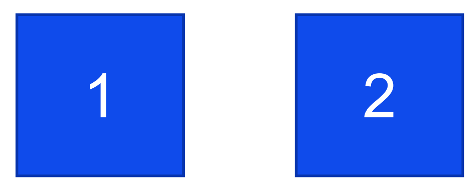
Speed-accuracy trade-off:

Higher the number of flashes, the better the accuracy, but …



Steady State Visually Evoked Potential (SSVEP)

continuously fluctuating stimuli (with repetition rate > 5 Hz)



Focus attention on the button corresponding to your choice.

EEG in the occipital region oscillates at the stimulus frequency.

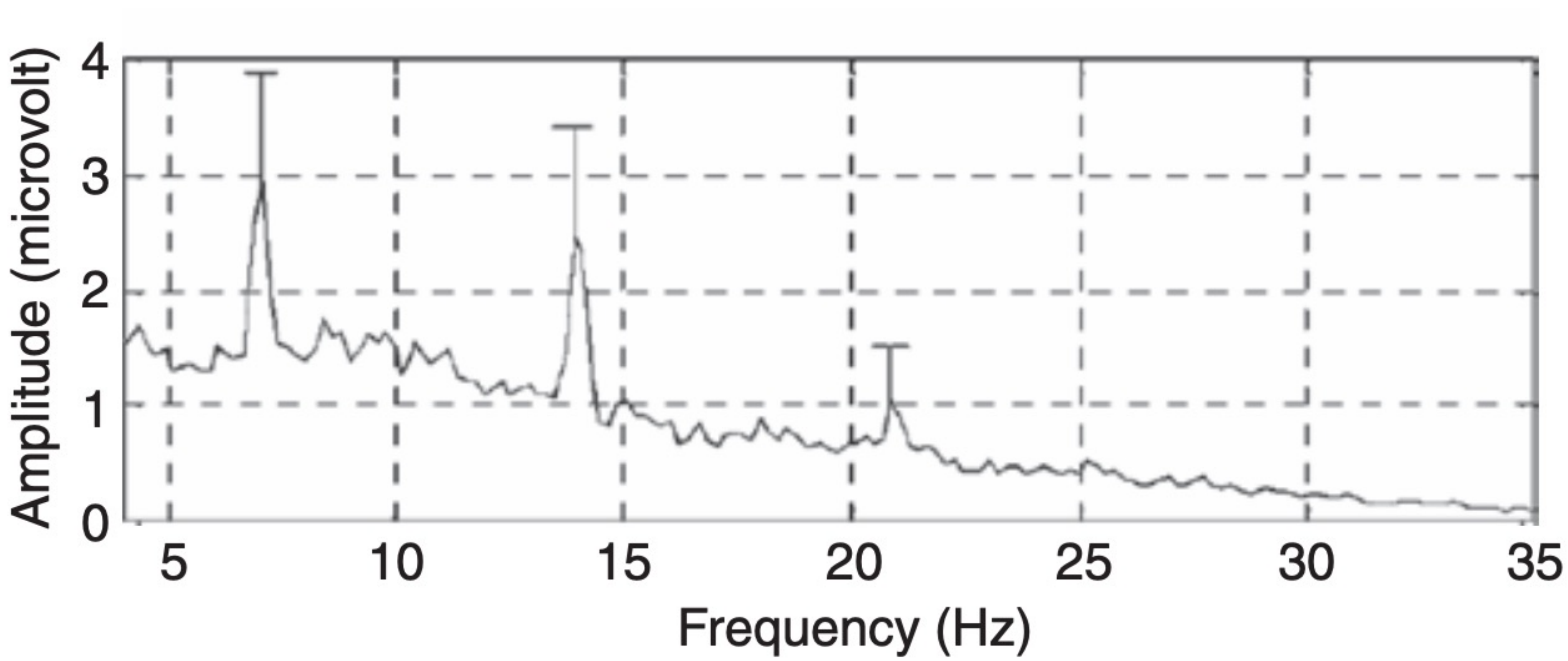
So, how to extract EEG features?

Steady State Visually Evoked Potential (SSVEP)

SSVEP evoked by 7 Hz visual stimulation

FFT

Peaks at 7 Hz and its harmonics



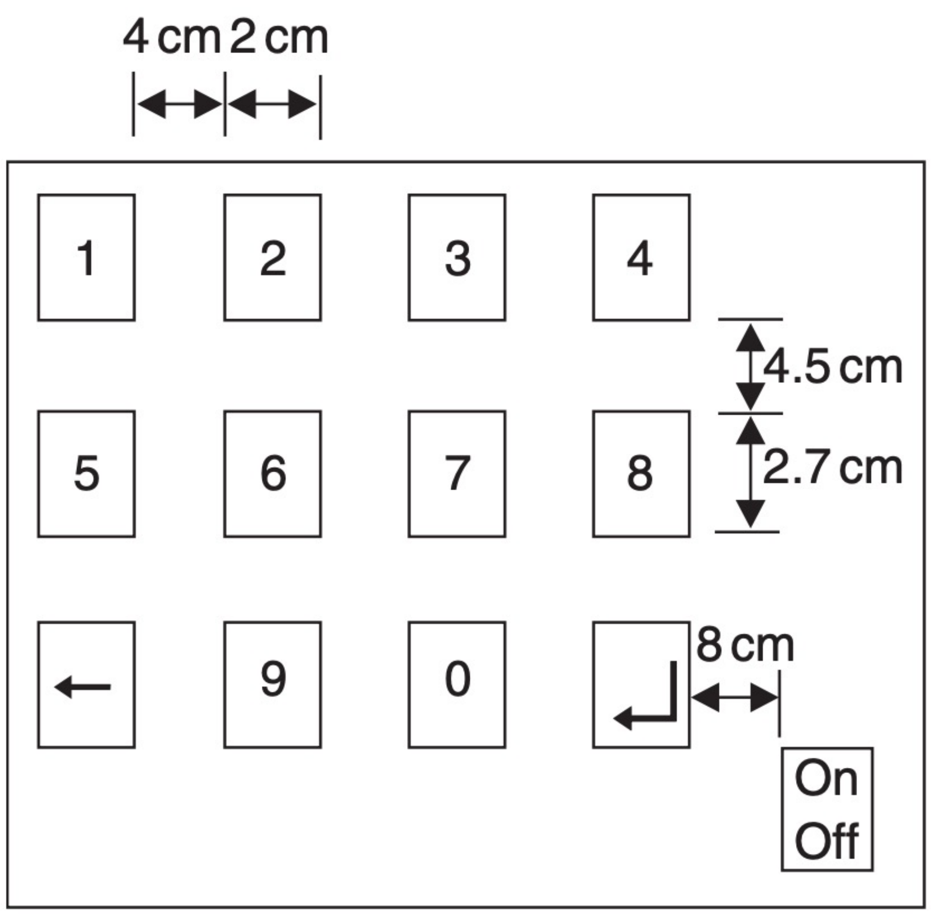
Steady State Visually Evoked Potential (SSVEP)

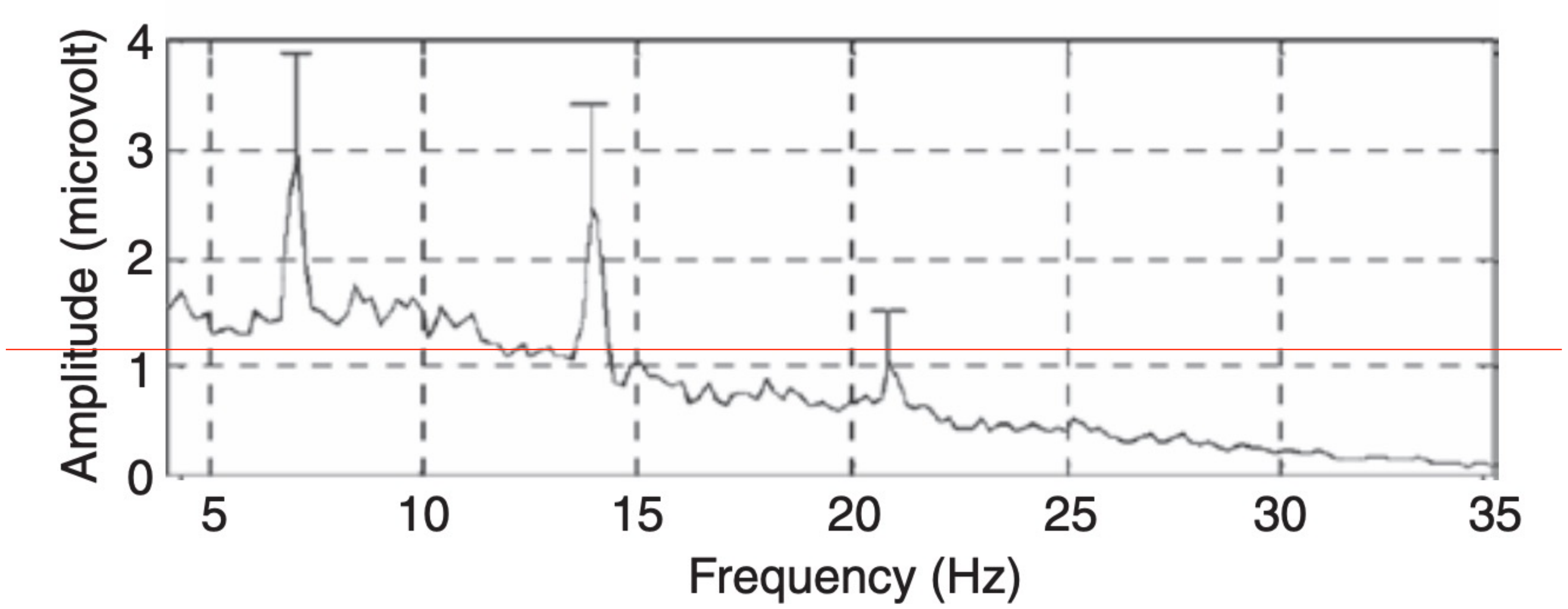
6-14 Hz

FFT was performed every 0.3s to compute the amplitude spectrum

Sum(amplitude and harmonics) vs mean of amplitude spectrum

SSVEP-based method can obtain the highest information transfer rate





BCI using SSVEP

4-command SSVEP BCI demo (by paweu)

BCI using SSVEP

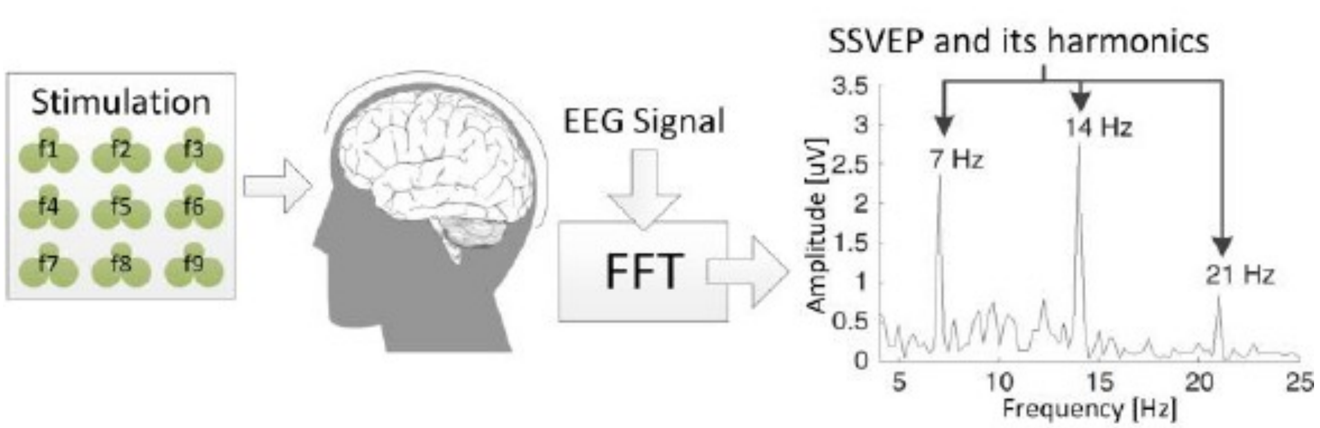
SSVEP-Based Brain-Computer Interface (BCI) System for Real-Time Application (by University of Malta)

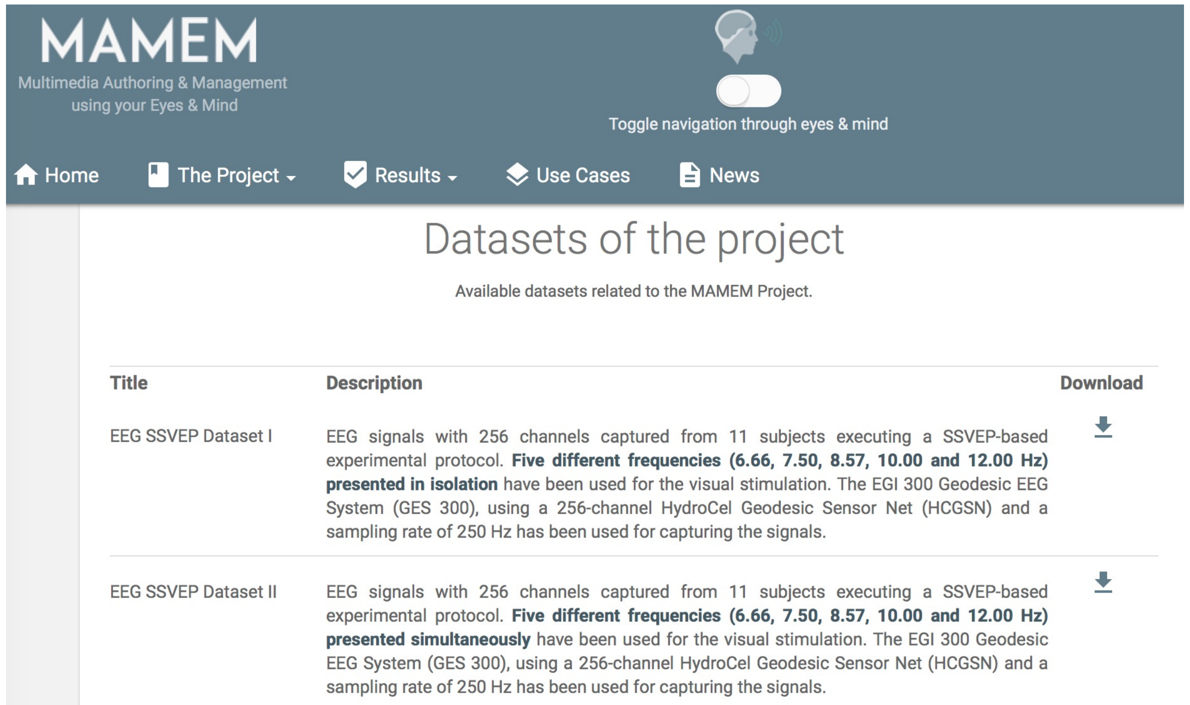
Exercise: SSVEP

Step 1. Select one of SSVEP datasets
https://www.mamem.eu/results/datasets/

Step 2. Apply FFT to analyze the power spectrum of EEG activity in response to the visual stimuli

Step 3. Try to build a classifier that can help you distinguish five different frequencies



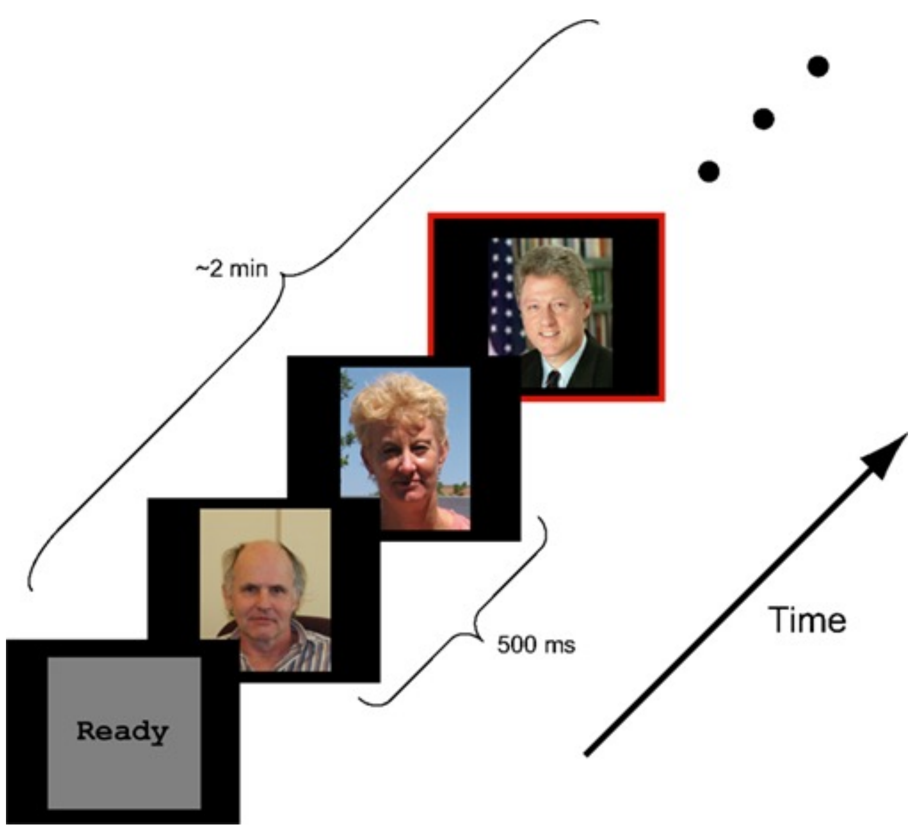


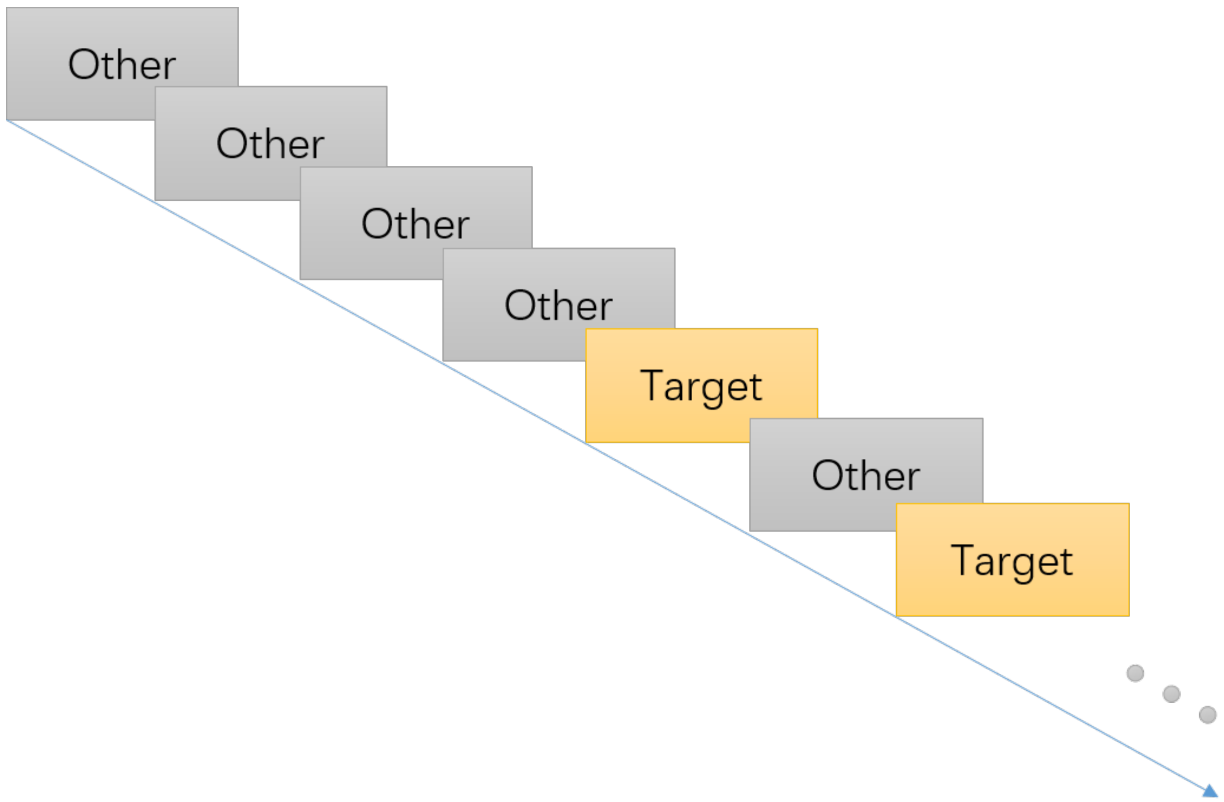
Rapid Serial Visual Presentation (RSVP)

Examine the temporal characteristics of attention

The RSVP paradigm requires participants to look at a continuous presentation of visual items which is around 10 items per second.

The targets are placed inside this stream of continuous items. They are separate from the rest of the items known as distracters.





Example

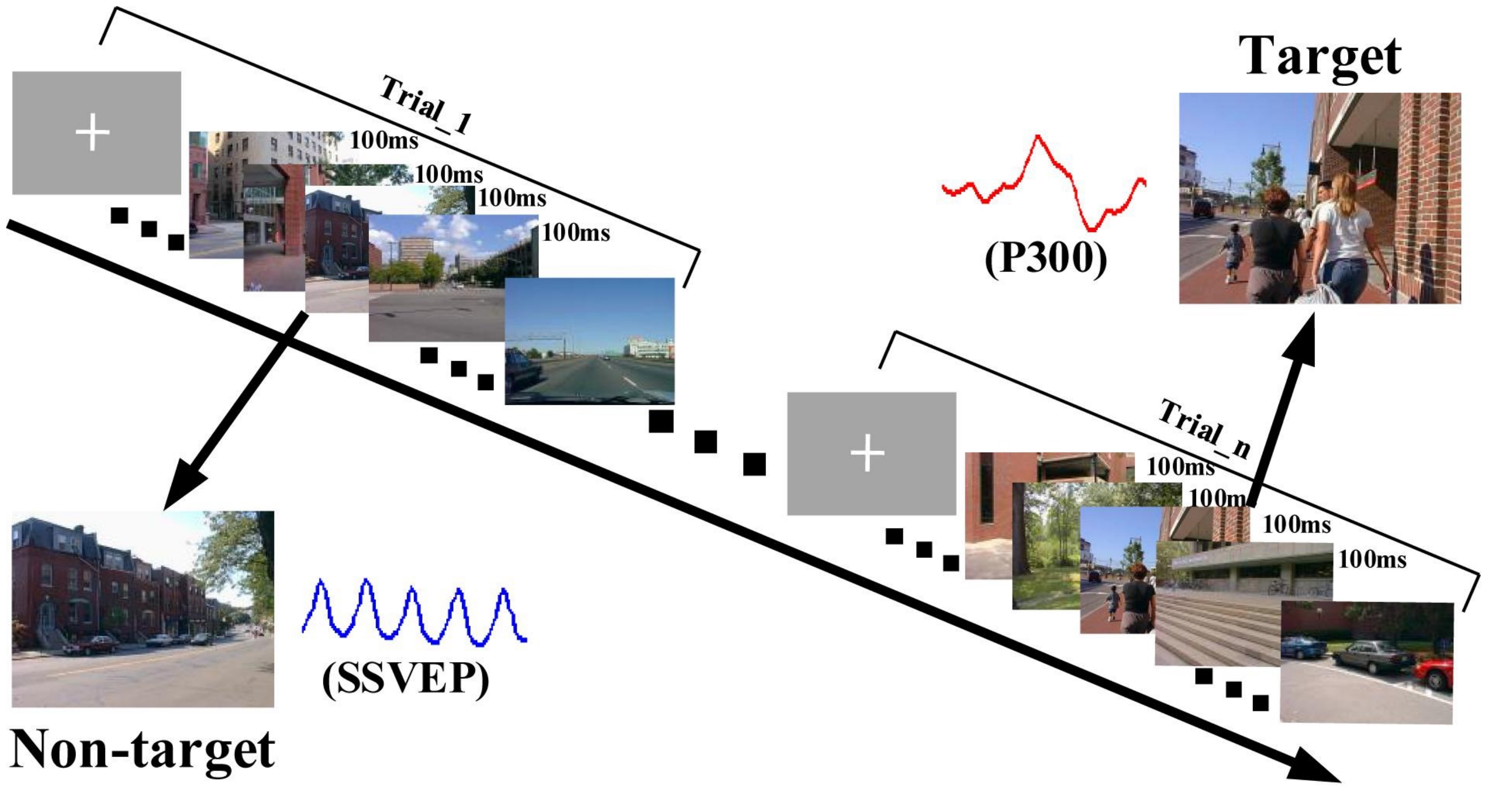
RSVP Keyboard TM (by CogSysLab atNEU)

A Benchmark Dataset for RSVP-Based Brain–Computer Interfaces

Zhang et al. (2020), http://bci.med.tsinghua.edu.cn/download.html

Images: Computer Science and Artificial Intelligence Library of MIT University

target (with human) vs. non-target (without human)



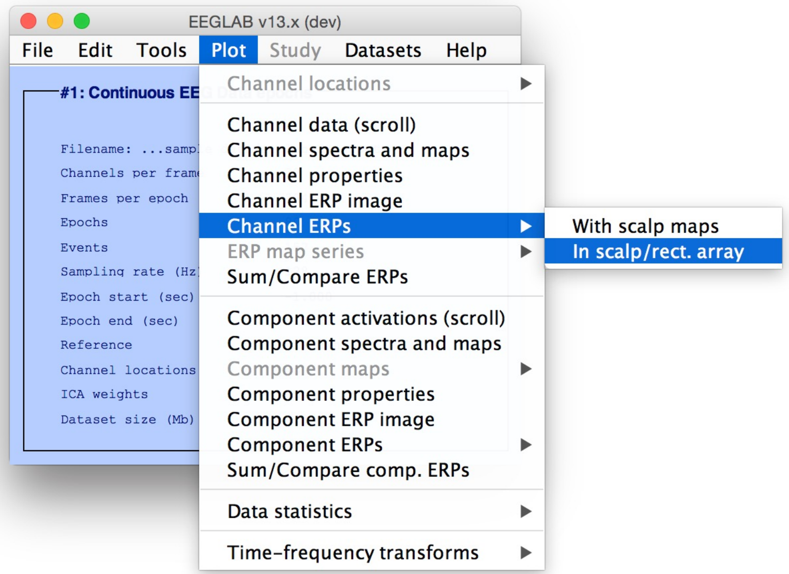
Auditory Evoked Potentials

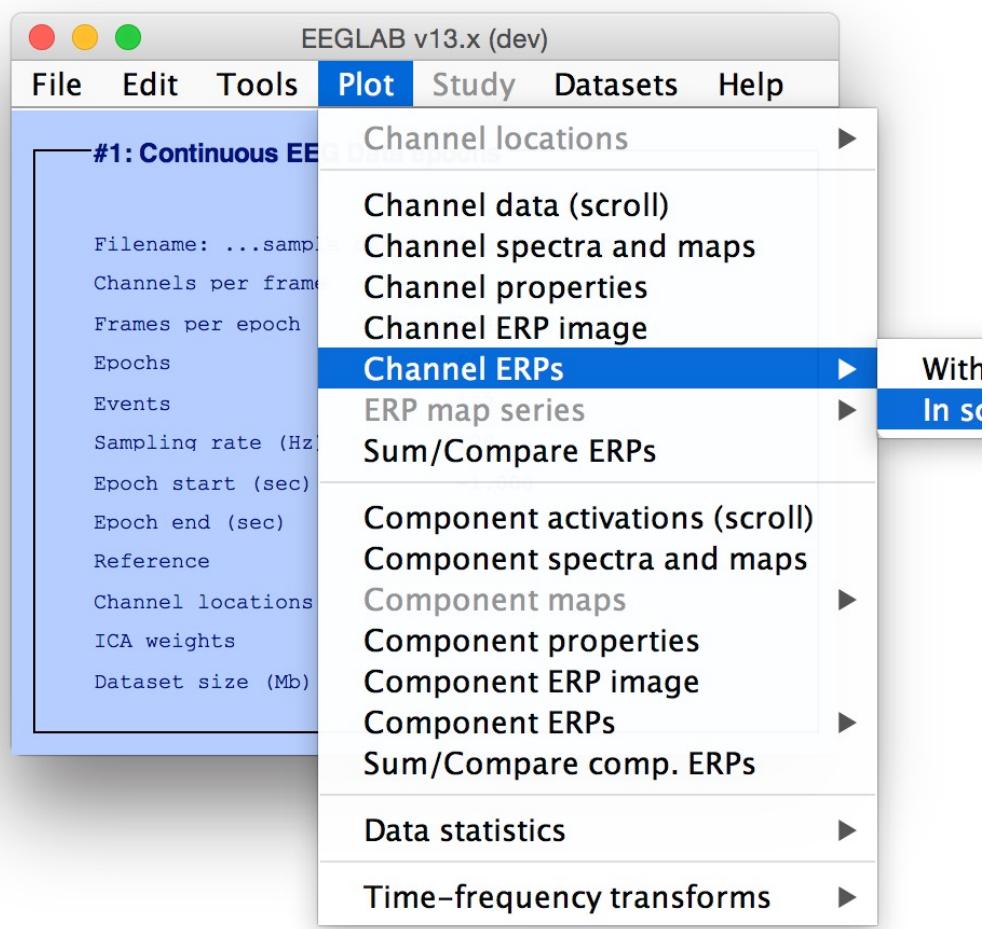
Replace visual stimuli with auditory stimuli → auditory oddball paradigm

- 50 ms square-wave beeps
- Frequent non-target beeps + occasional target beeps
- Paying attention to the target stimuli (by counting)

- 39-ch EEG signals, unmixed using ICA, and classified using a linear SVM → 5-15% error rate

Tutorial: ERP


EEGLAB v13.x (dev)
File Edit Tools Plot Study Datasets Help
#1: Continuous EE
Filename: ...samp
Channels per fram
Frames per epoch
Epochs
Events
Sampling rate (Hz
Epoch start (sec)
Epoch end (sec)
Reference
Channel locations
ICA weights
Dataset size (Mb)
Channel locations
Channel data (scroll)
Channel spectra and maps
Channel properties
Channel ERP image
Channel ERPs
ERP map series
Sum/Compare ERPs
Component activations (scroll)
Component spectra and maps
Component maps
Component properties
Component ERP image
Component ERPs
Sum/Compare comp. ERPs
Data statistics
Time-frequency transforms
With scalp maps
In scalp/rect. array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Filename: ...samp
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Time-frequency transforms
With
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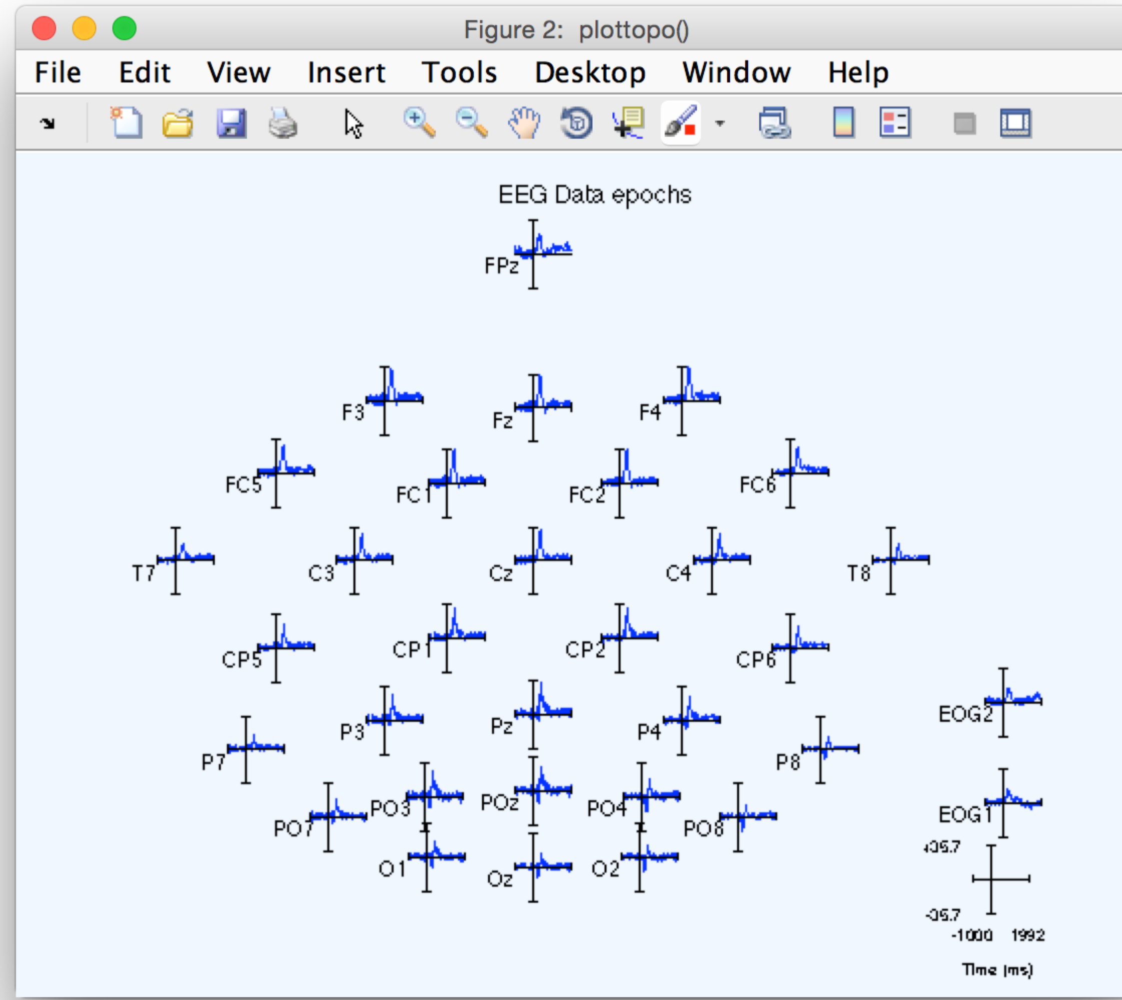
Figure 2: plottopo()
File Edit View Insert Tools Desktop Window Help
EEG Data epochs
FPz
F3 Fz F4
FC5 FC1 FC2 FC6
T7 C3 Cz C4 T8
CP5 CP1 CP2 CP6
P7 P3 Pz P4 P8
PO7 PO3 POz PO4 PO8
O1 Oz O2
EOG2
EOG1
+36.7
-36.7
-1000 1992
Time (ms)

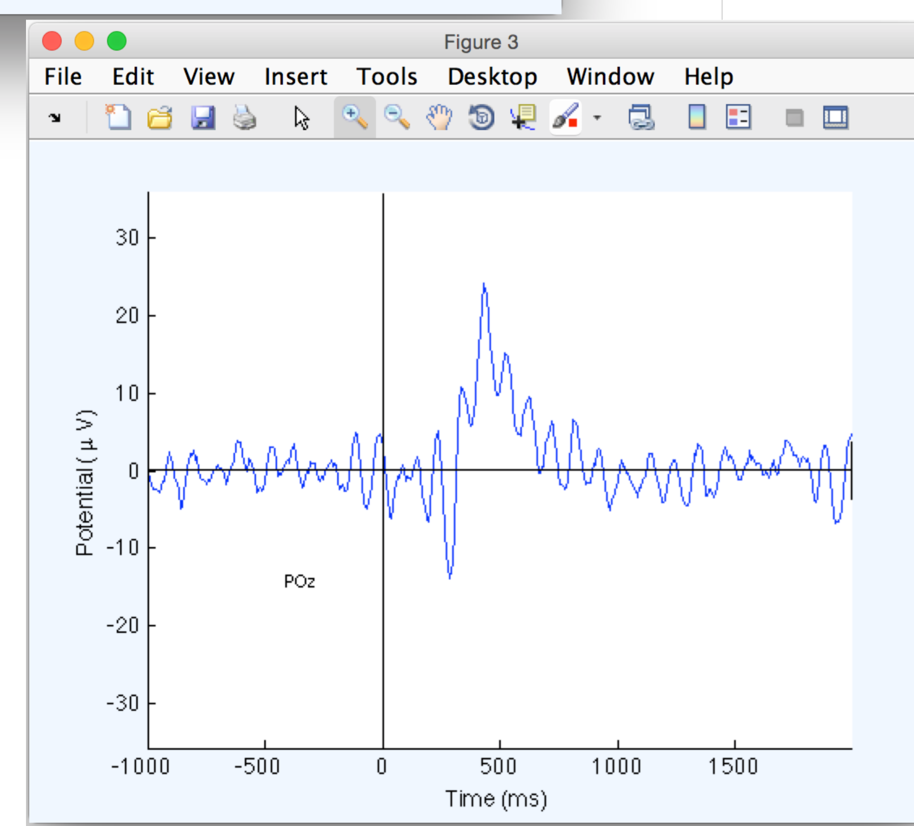
Figure 3
File Edit View Insert Tools Desktop Window Help
30
20
10
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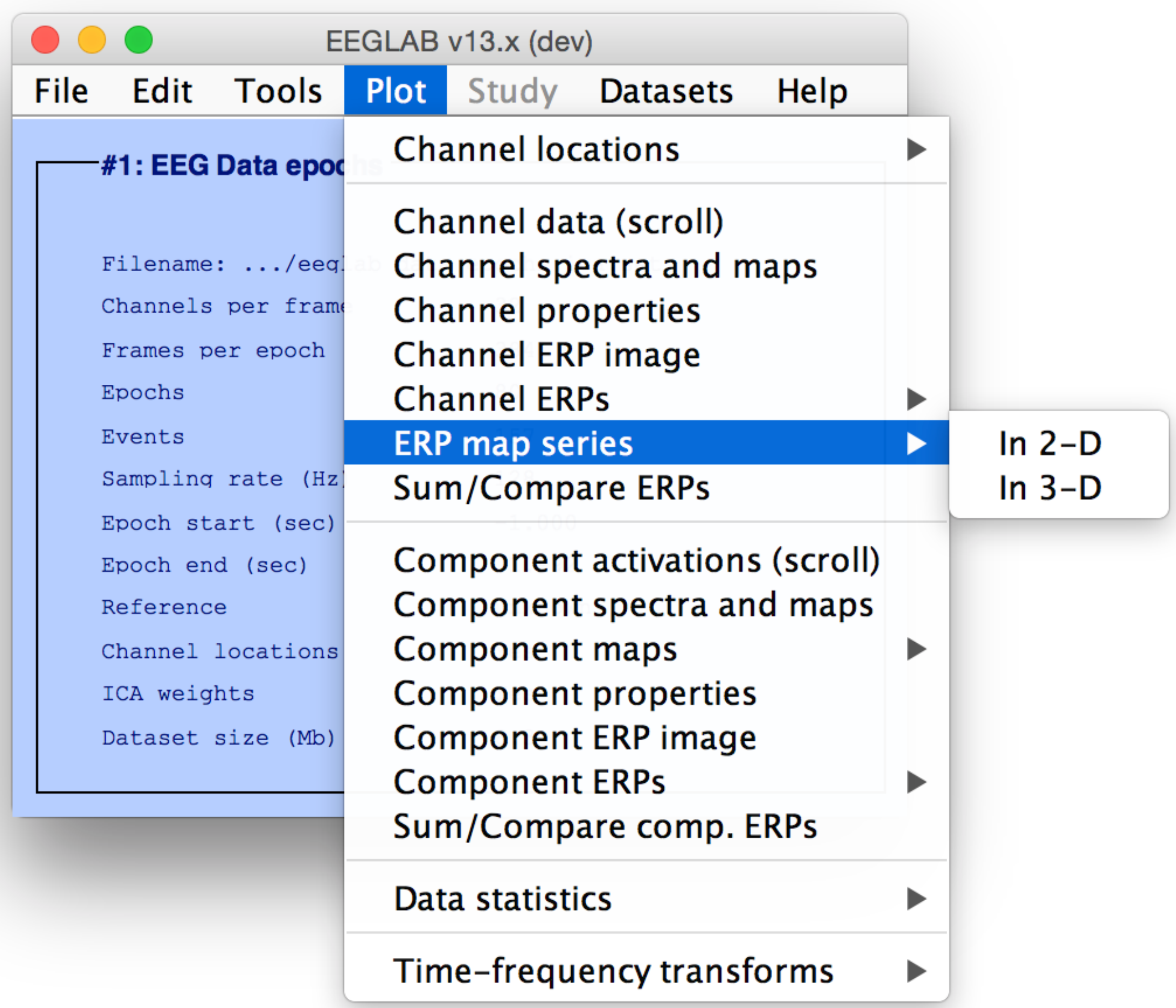
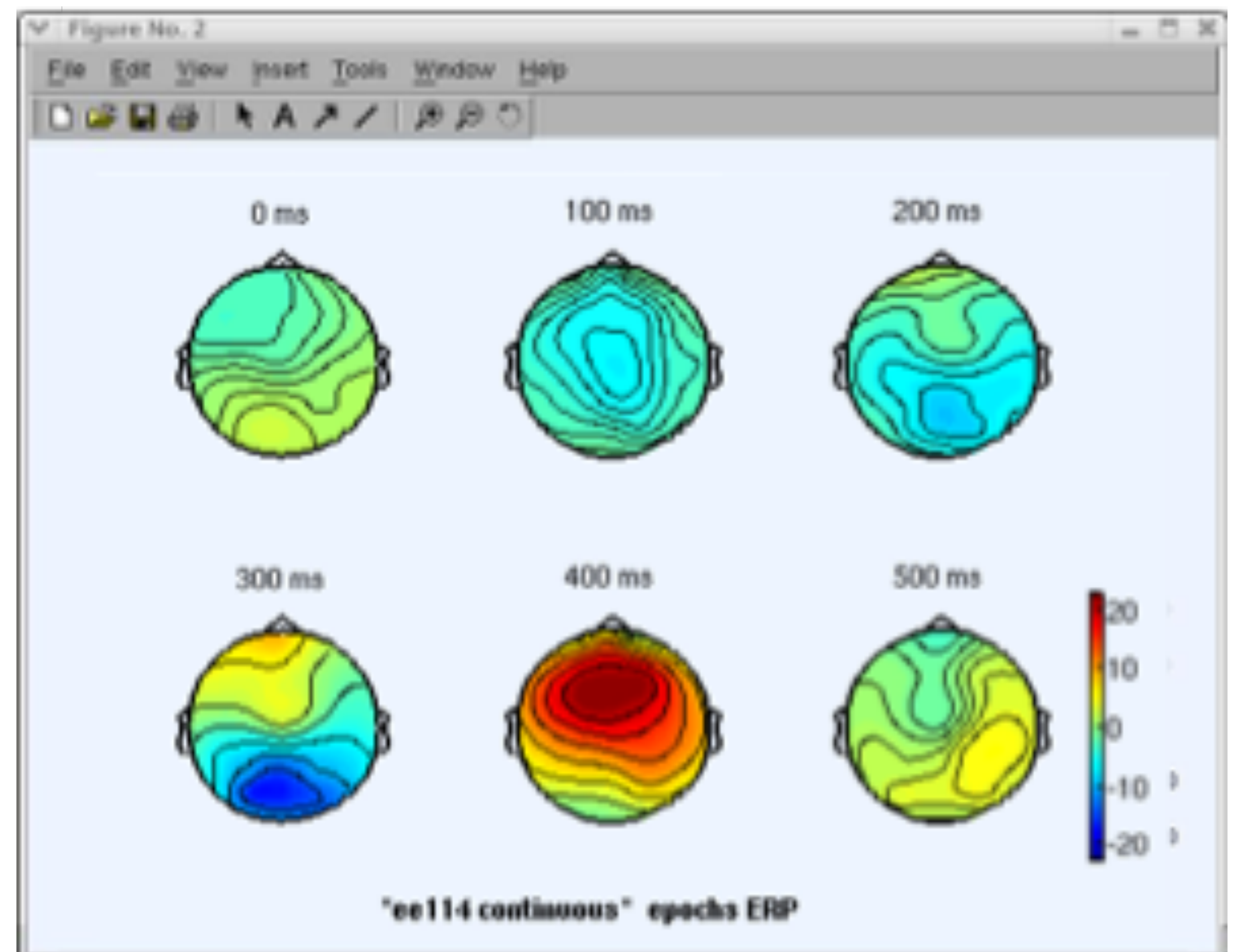
-10
-20
-30
Potential (µ V)
POz
-1000 -500 0 500 1000 1500
Time (ms)

Visualize data measures



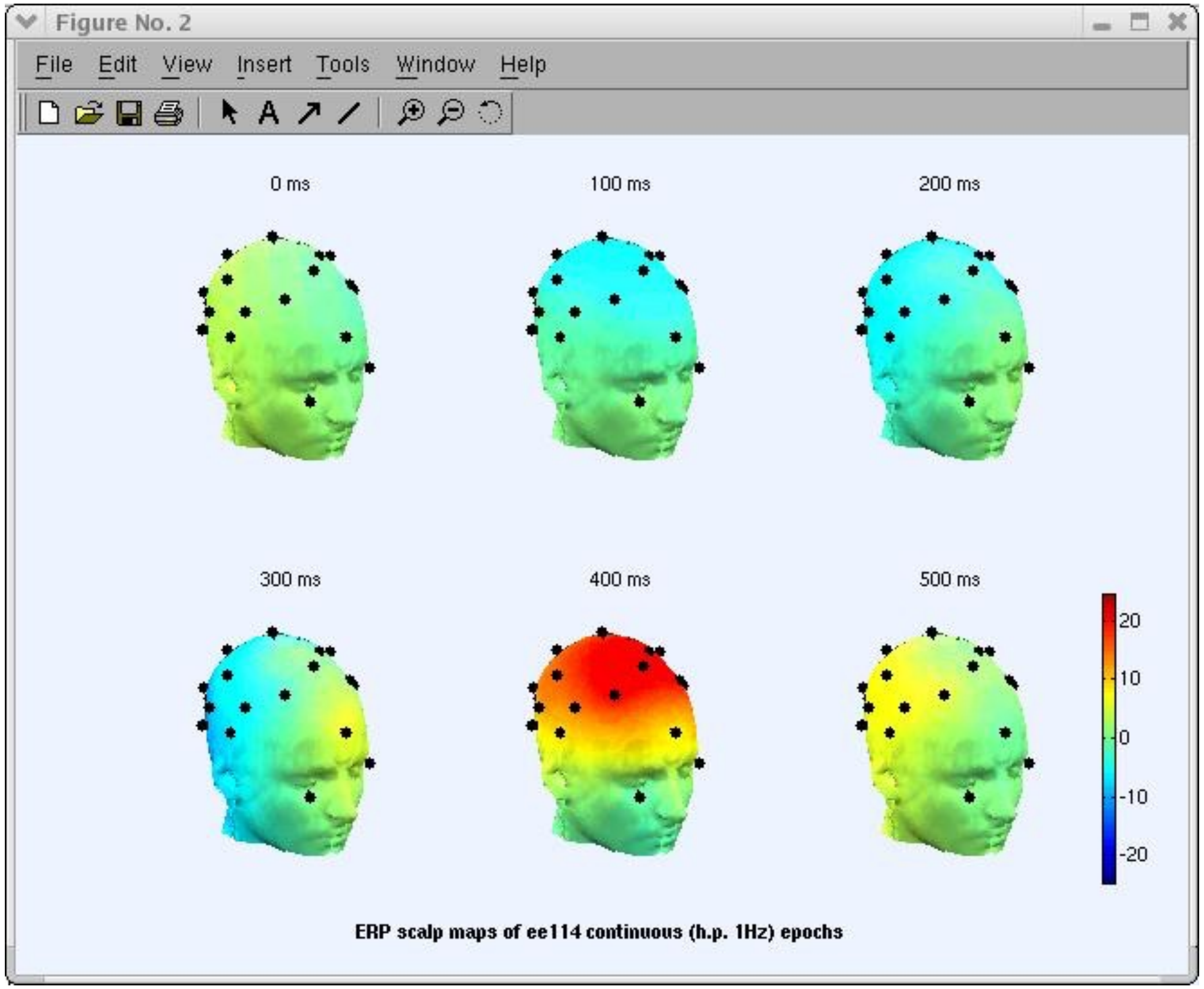


Manually plot a topography

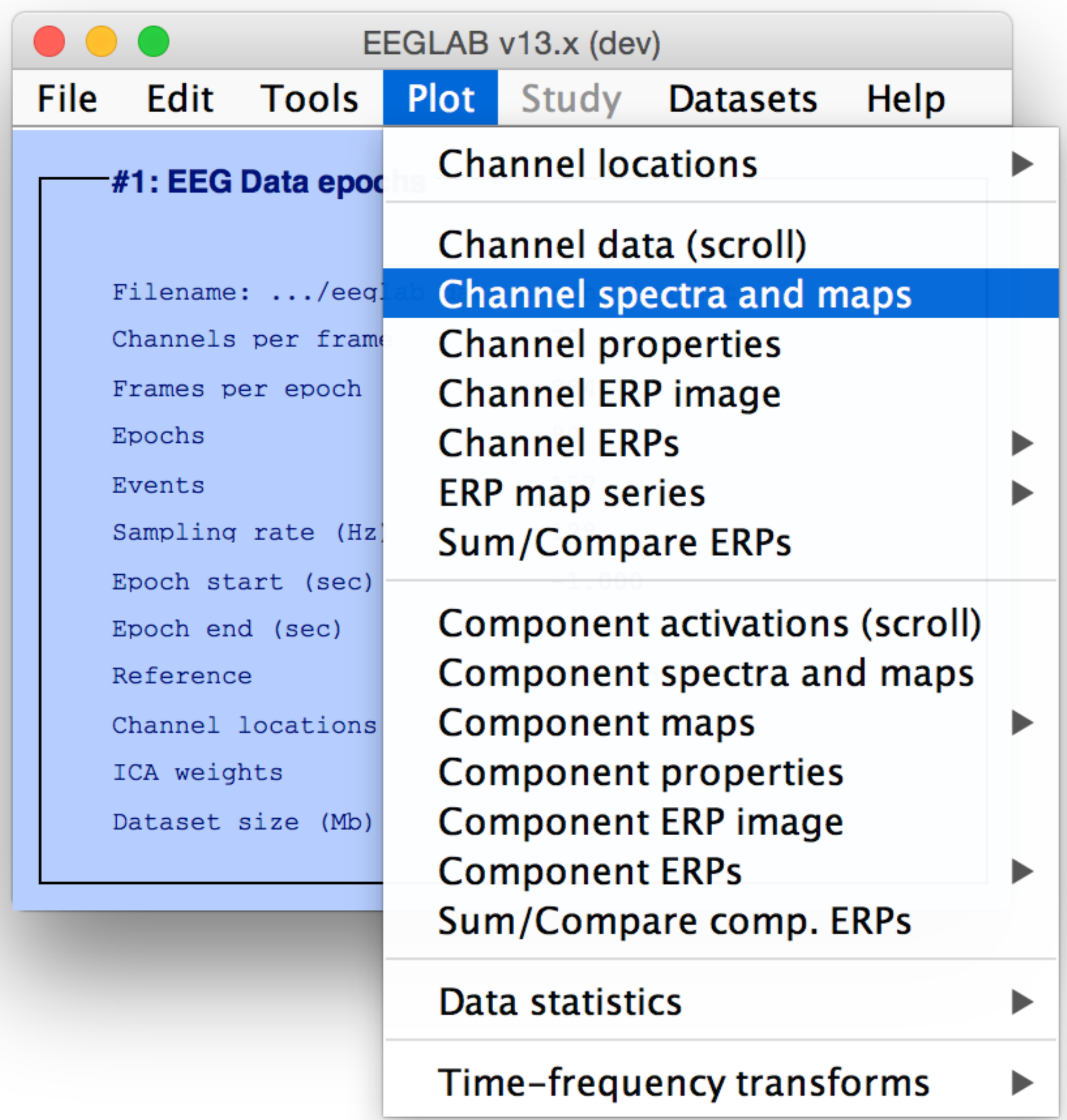
```
chanlocs = struct('labels', {'FP1' 'FP2' 'F7' 'F3' 'FZ' 'F4' 'F8' 'FT7' 'FC3'
'FCZ' 'FC4' 'FT8' 'T3' 'C3' 'CZ' 'C4' 'T4' 'TP7' 'CP3' 'CPZ' 'CP4' 'TP8' 'T5'
'P3' 'PZ' 'P4' 'T6' 'O1' 'OZ' 'O2'});

chanlocs = pop_chanedit(chanlocs);

topoplot(EEG.data(:, 1000), chanlocs);
```

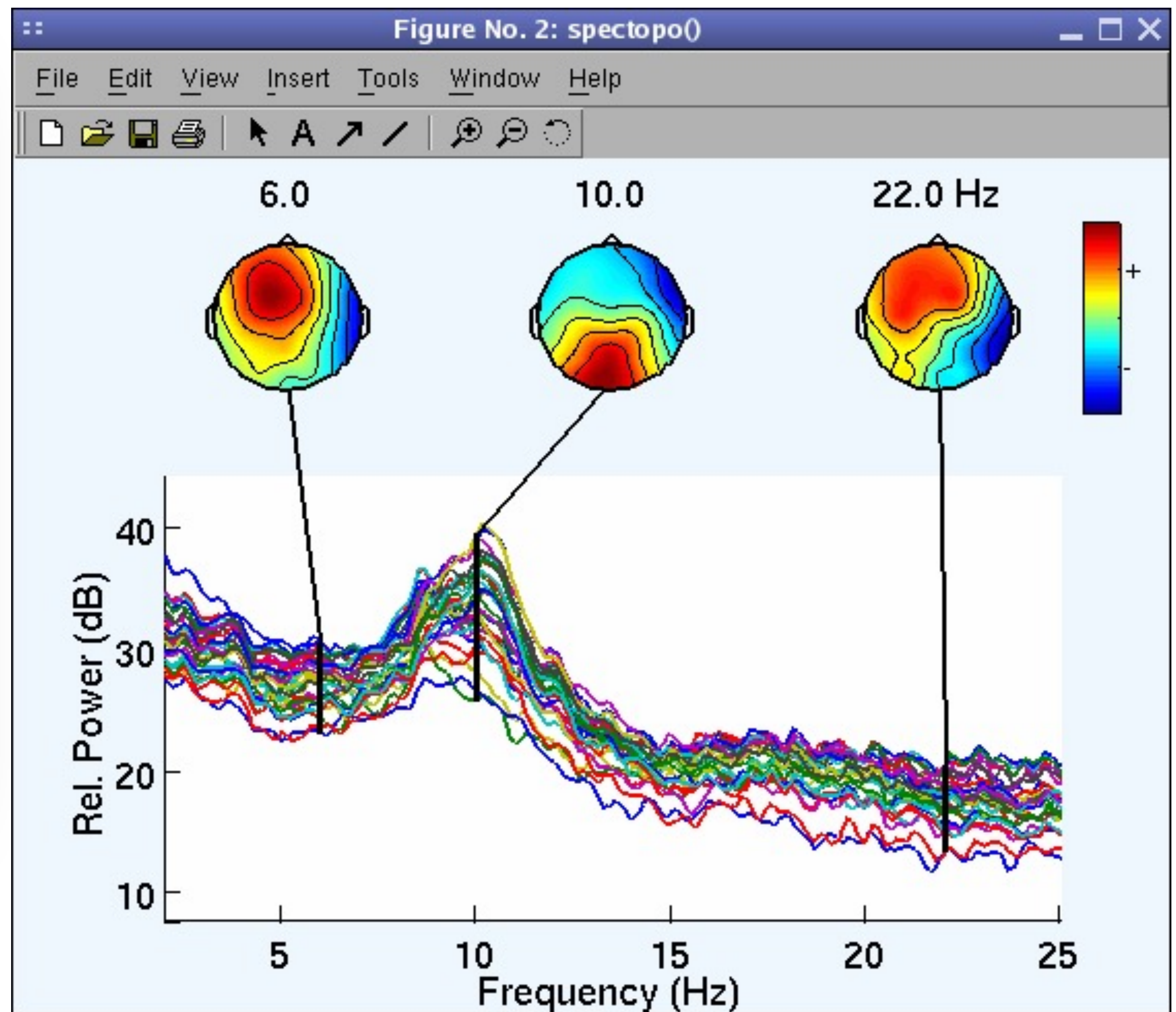
Visualize data measures

headplot.m



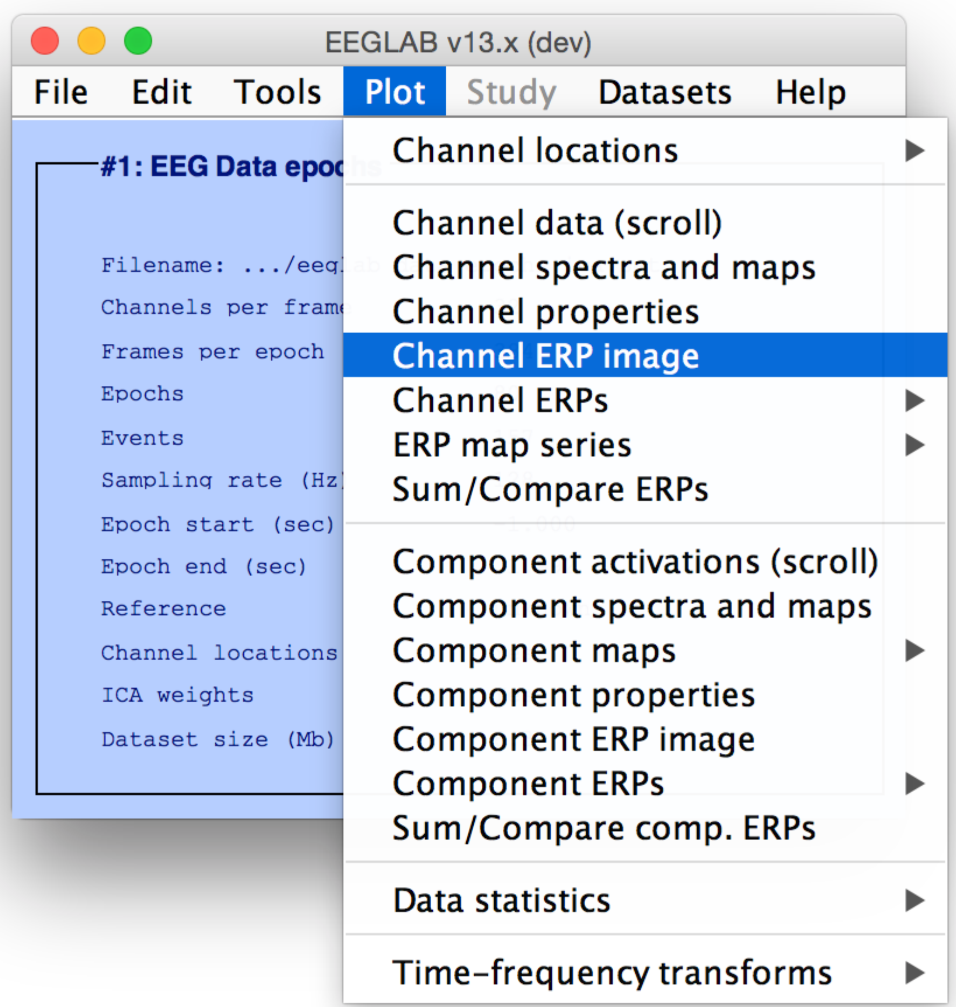
Plot data spectrum and maps

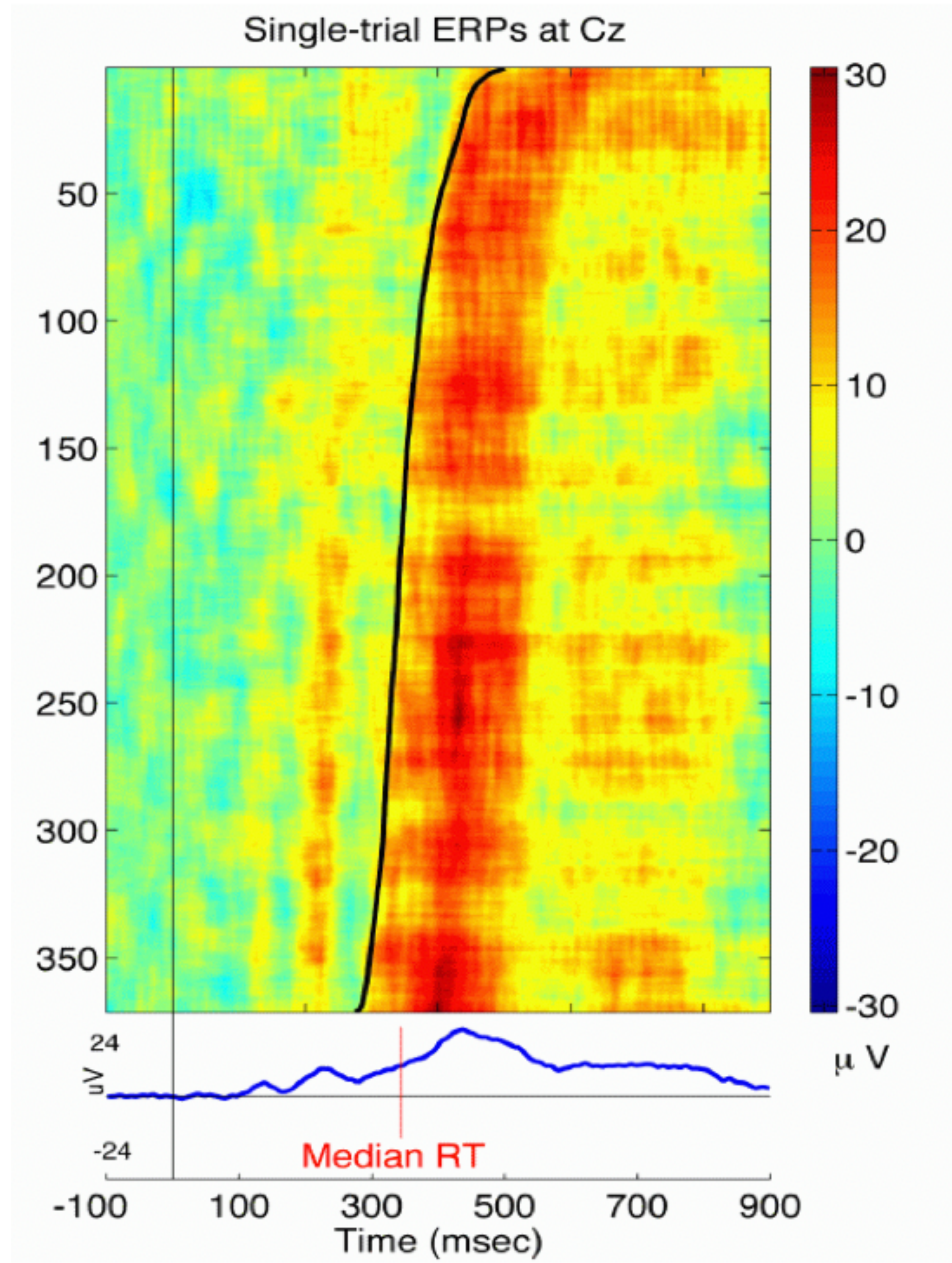




Plot channel ERPimage

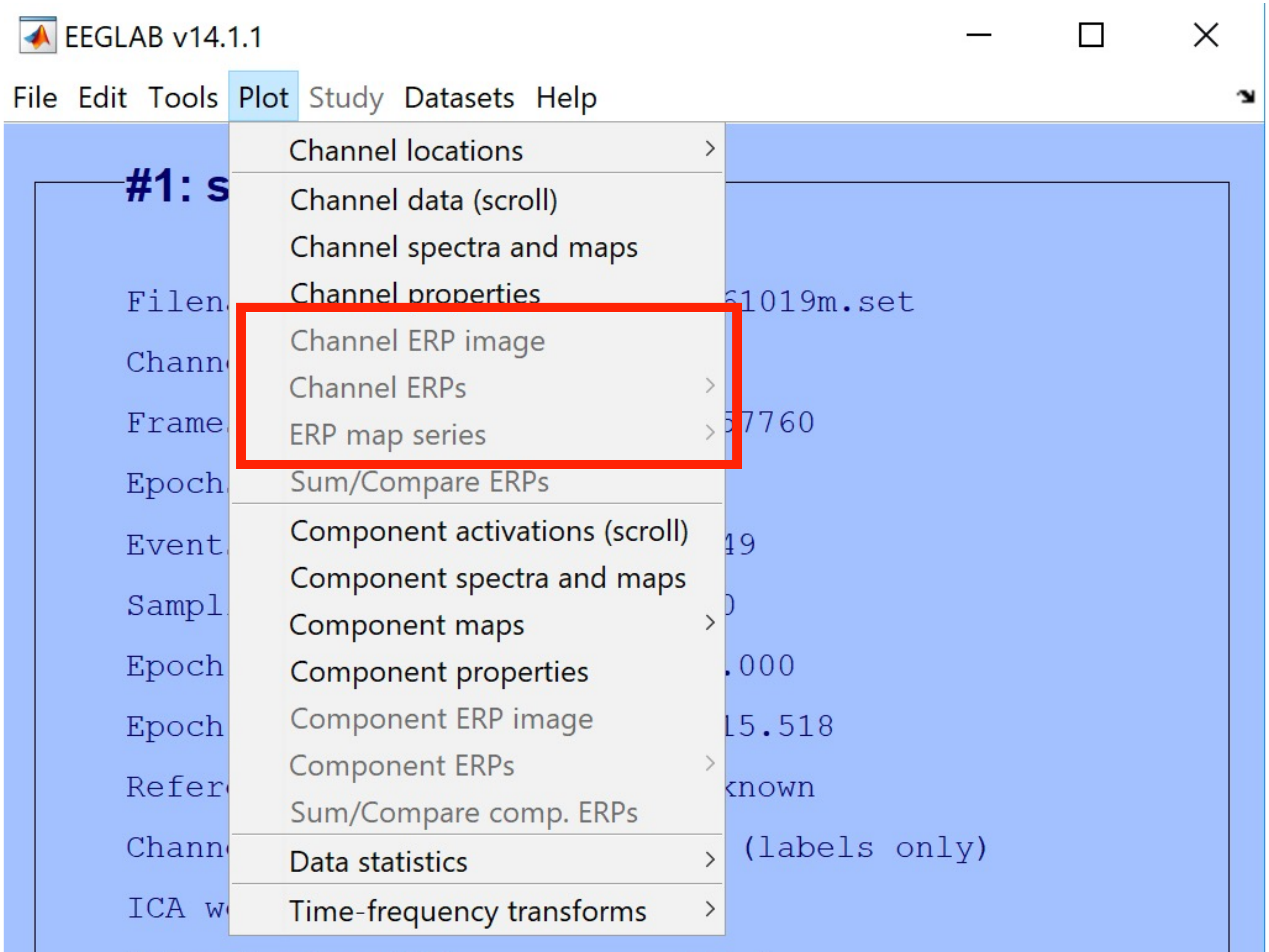
ERP: event-related potentials





Reaction Time

EEG.event.latency


EEGLAB v14.1.1
File Edit Tools Plot Study Datasets Help
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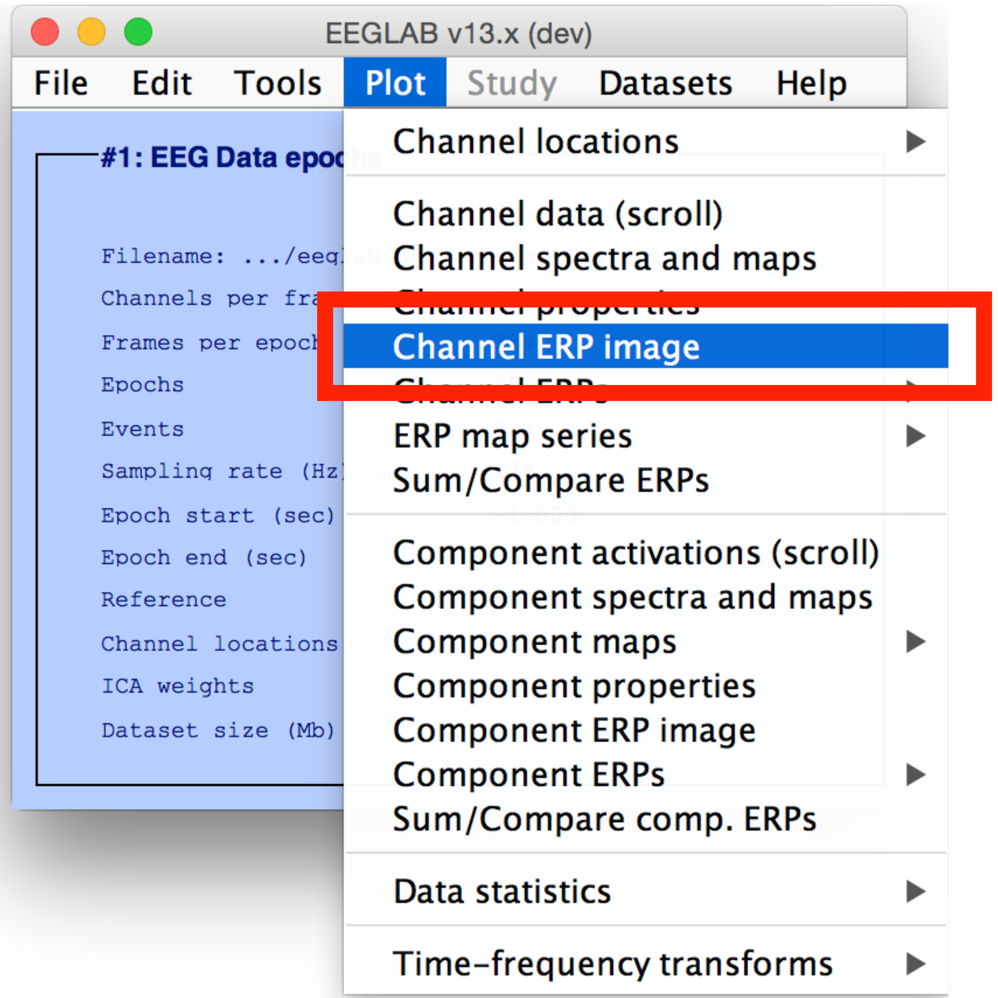
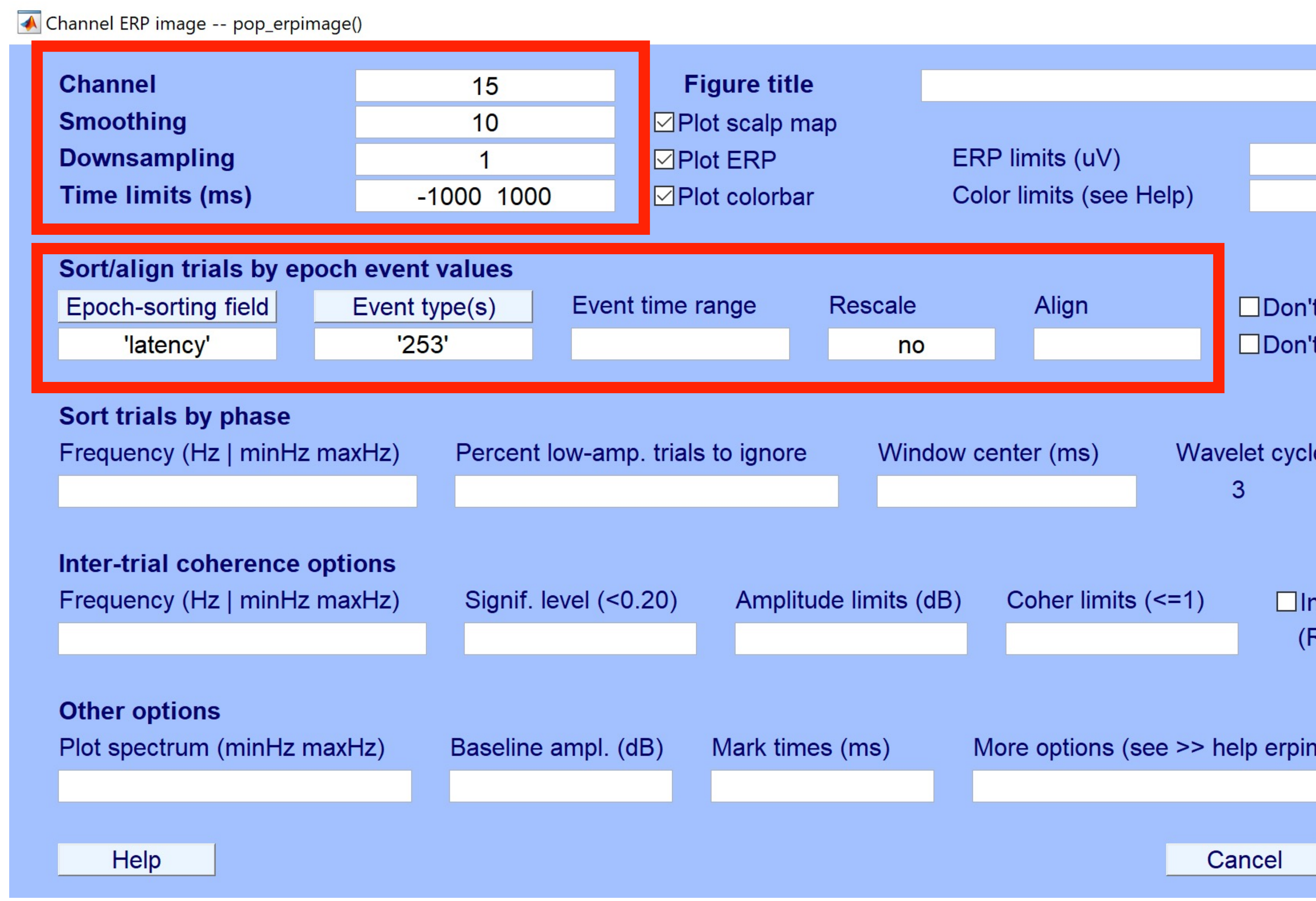
(labels only)
Channel locations
Channel data (scroll)
Channel spectra and maps
Channel properties
Channel ERP image
Channel ERPs
ERP map series
Sum/Compare ERPs
Component activations (scroll)
Component spectra and maps
Component maps
Component properties
Component ERP image
Component ERPs
Sum/Compare comp. ERPs
Data statistics
Time-frequency transforms

Plot a RT-sorted ERPimage






EEGLAB v14.1.1
File Edit Tools Plot Study Datasets Help
Channel locations
Channel data (scroll)
Channel spectra and maps
Channel properties
Channel ERPs
With scalp maps
In scalp/rect. array
ERP map series
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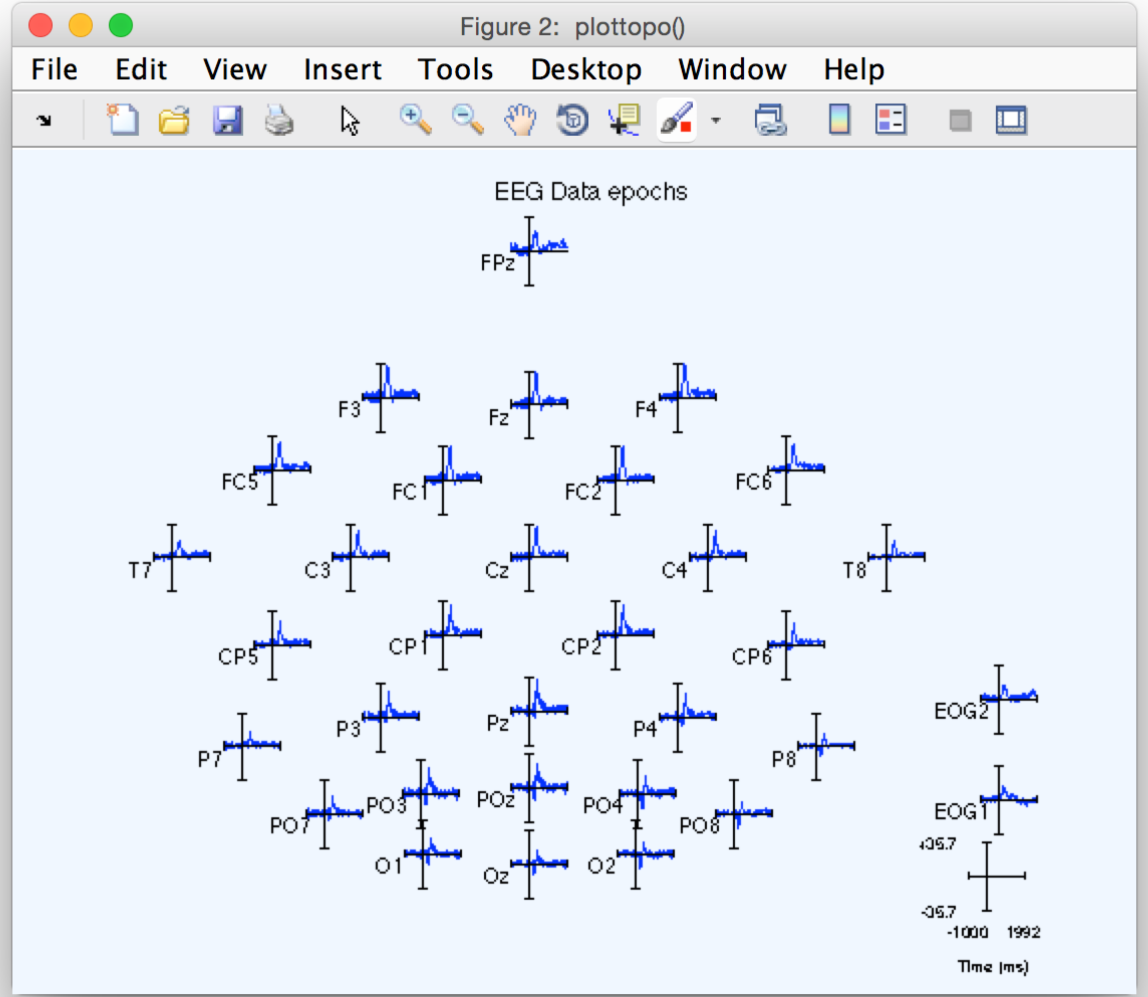
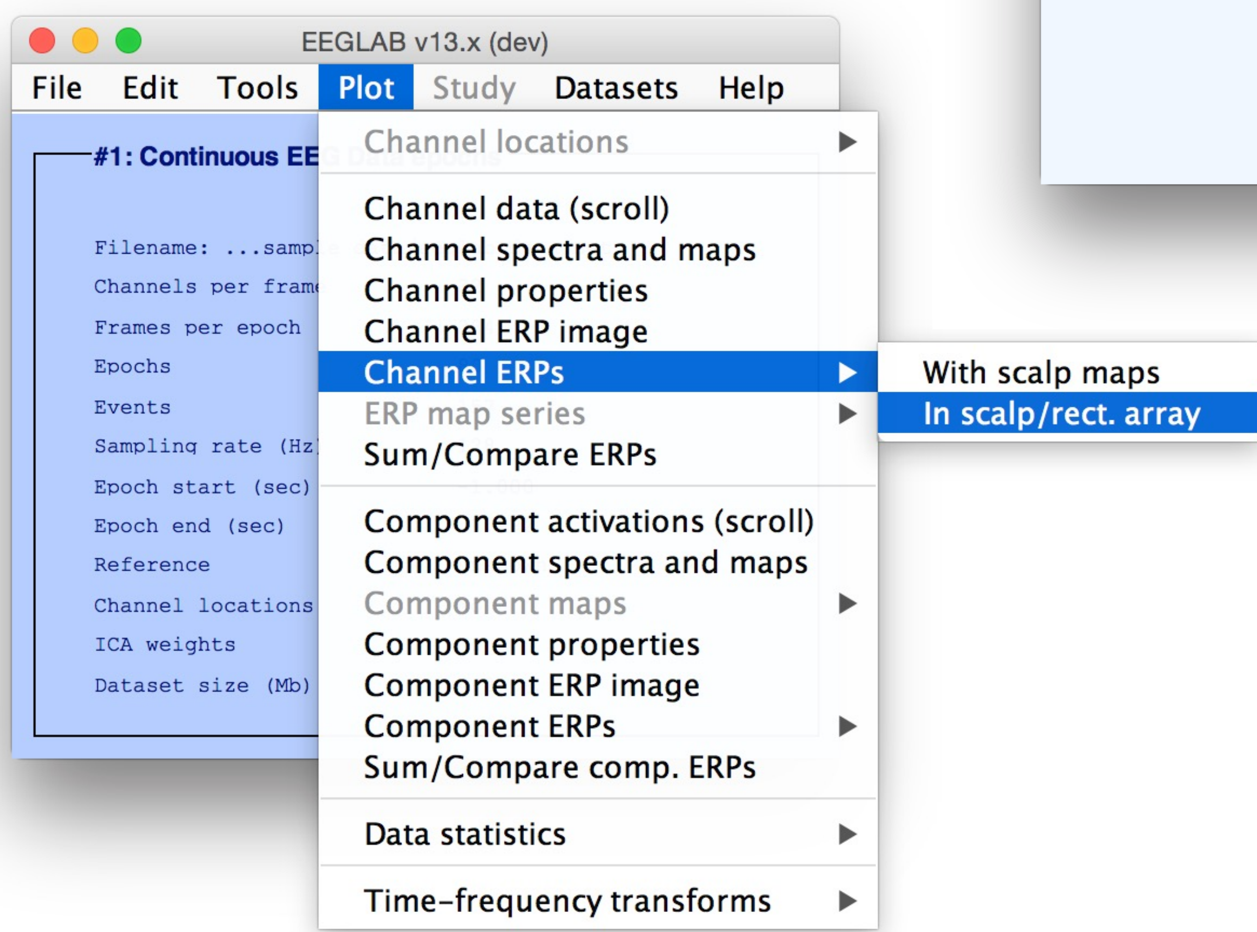
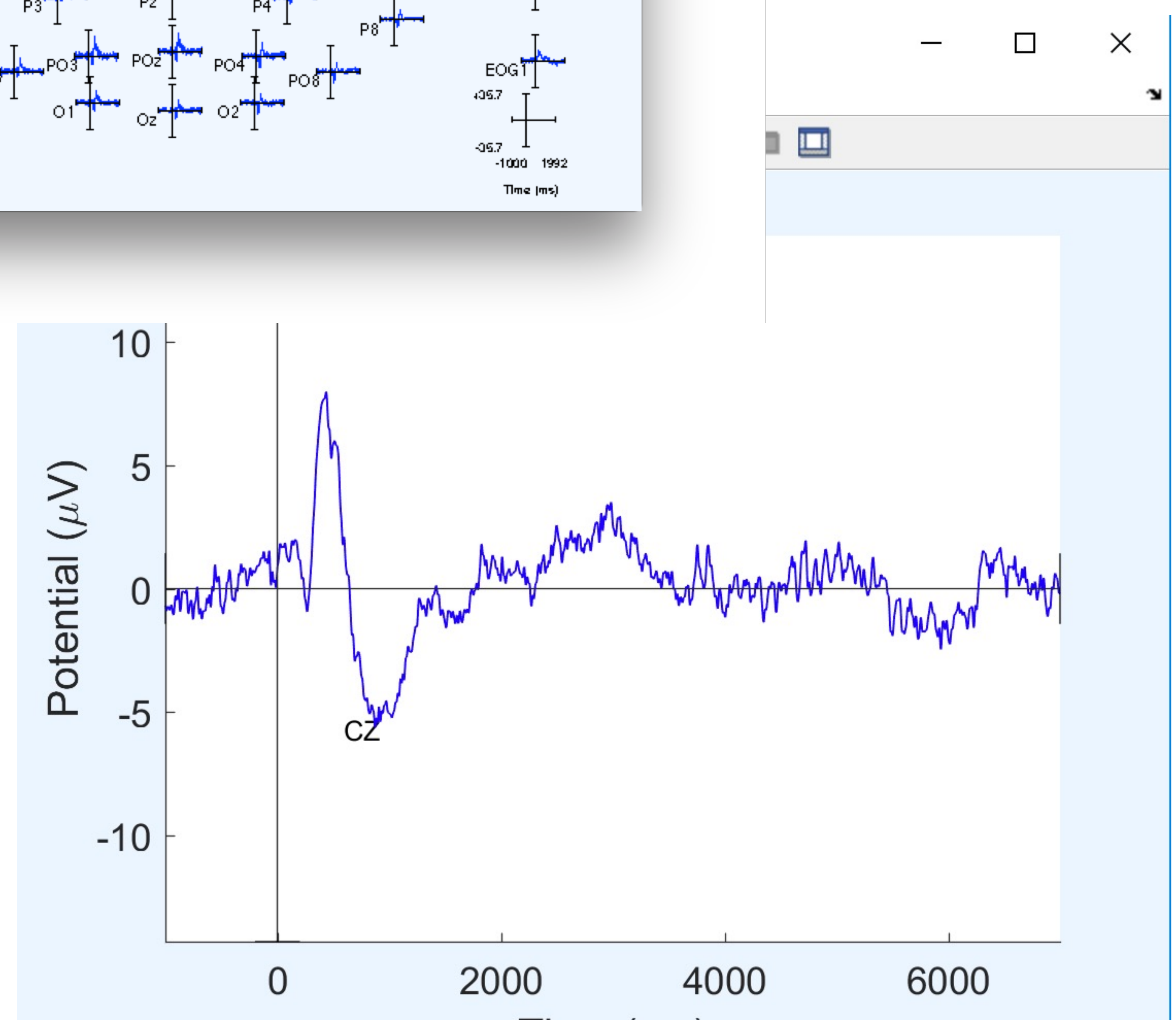
Component activations (scroll)
Component spectra and maps
Component maps
Component ERPs
Data statistics
d epochs
61019m.set
Dataset size (Mb)
Figure 2: timtopo()
File Edit View Insert Tools Desktop Window Help
1028
460 ms
552 ms
Potential (µV)
Latency (ms)

Visualize data measures







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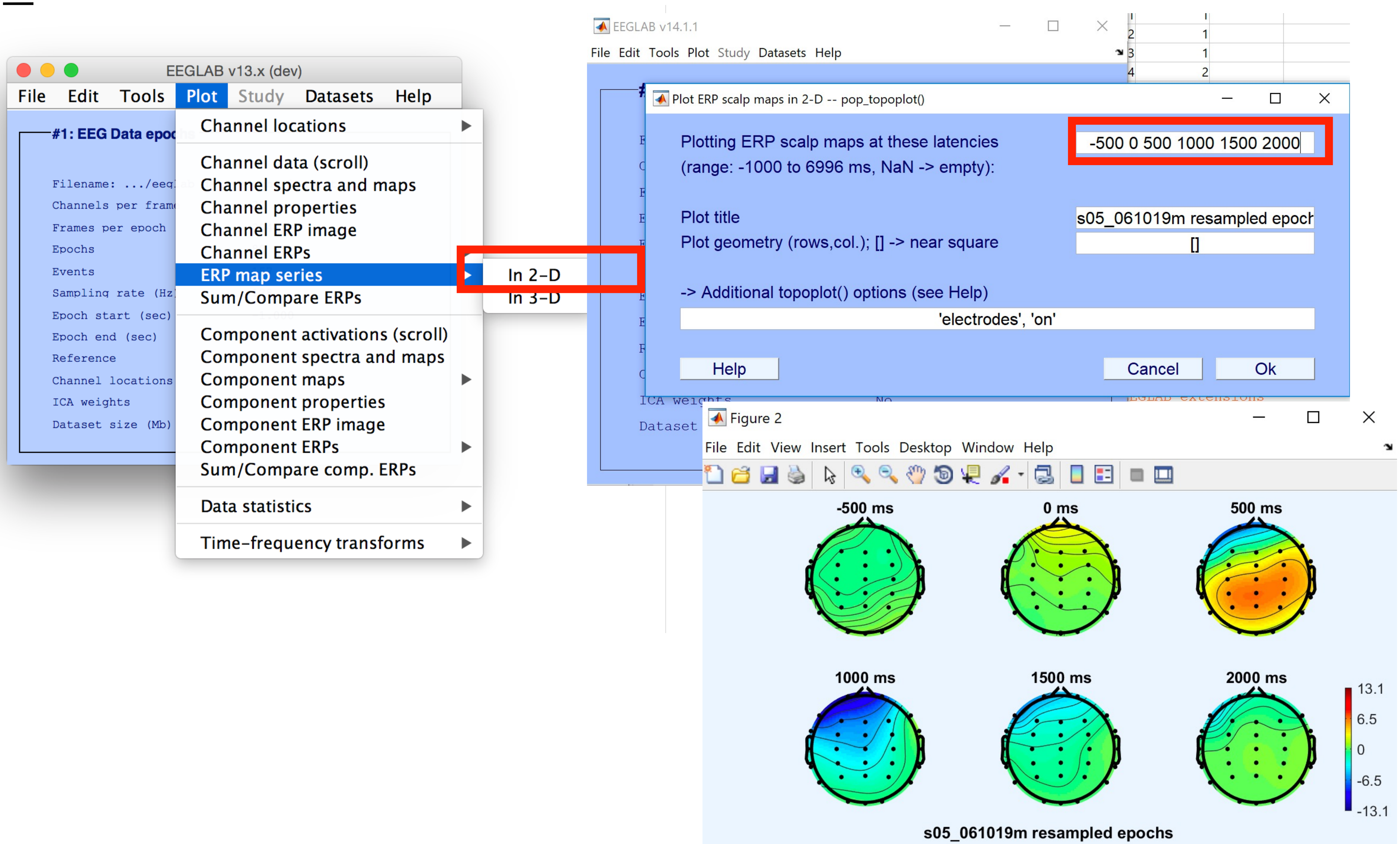

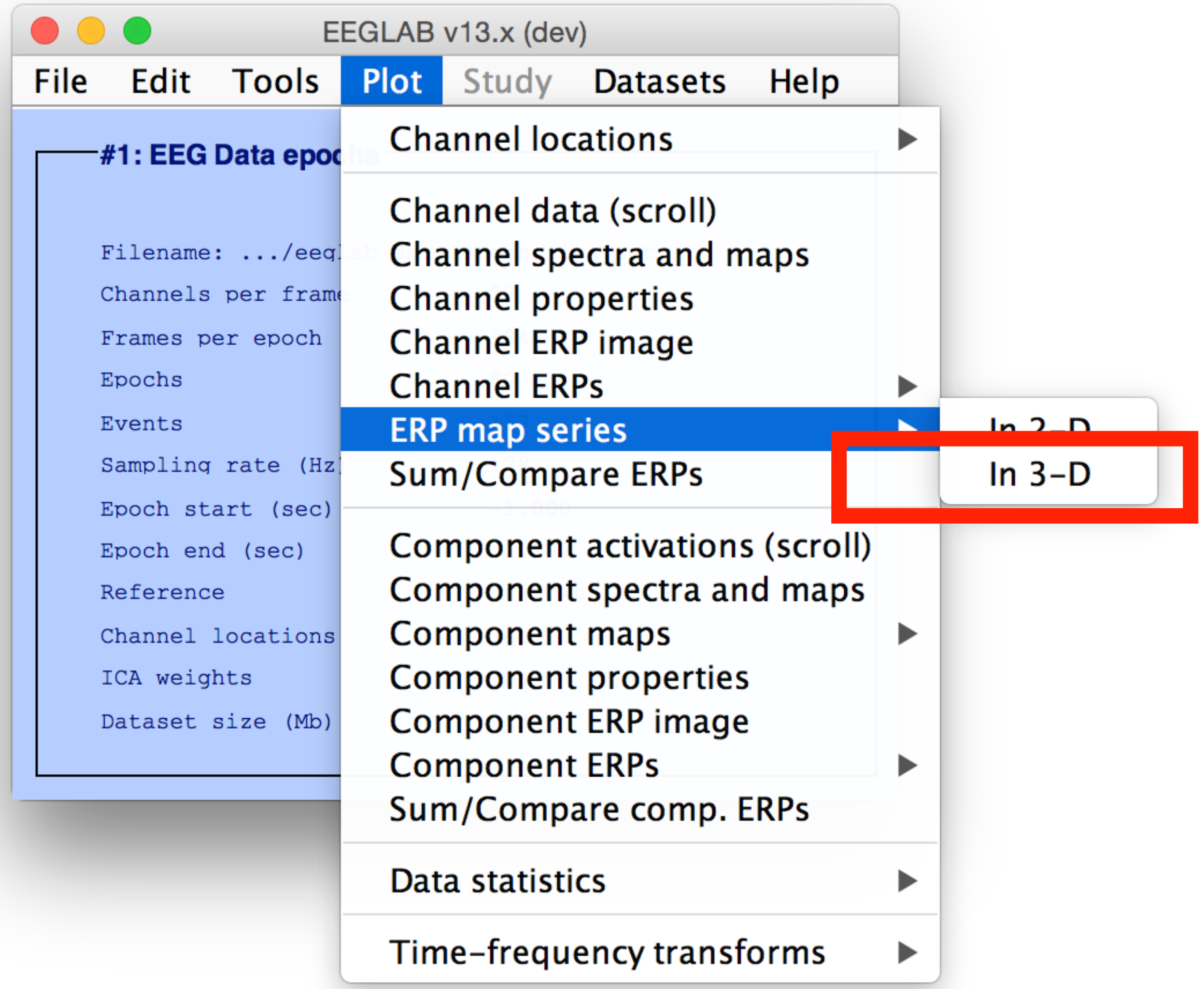

EEGLAB v13.x (dev)
File Edit Tools Plot Study Datasets Help
#1: EEG Data epoc
Filename: .../eeg
Channels per frame
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Sampling rate (Hz
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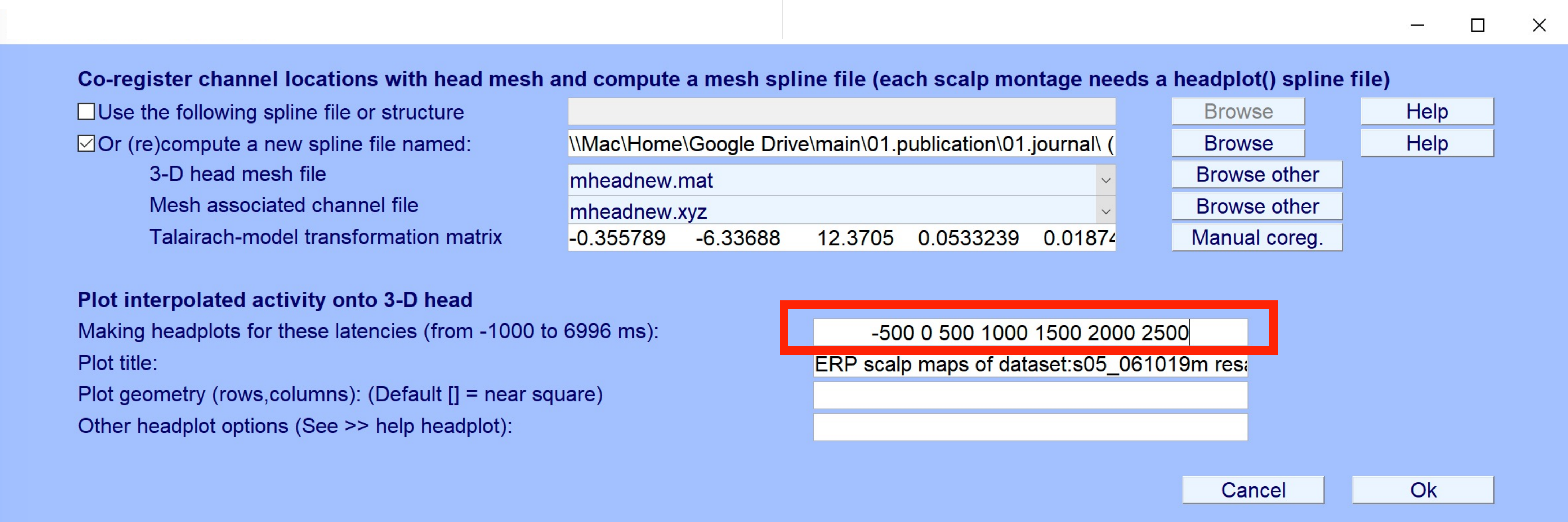
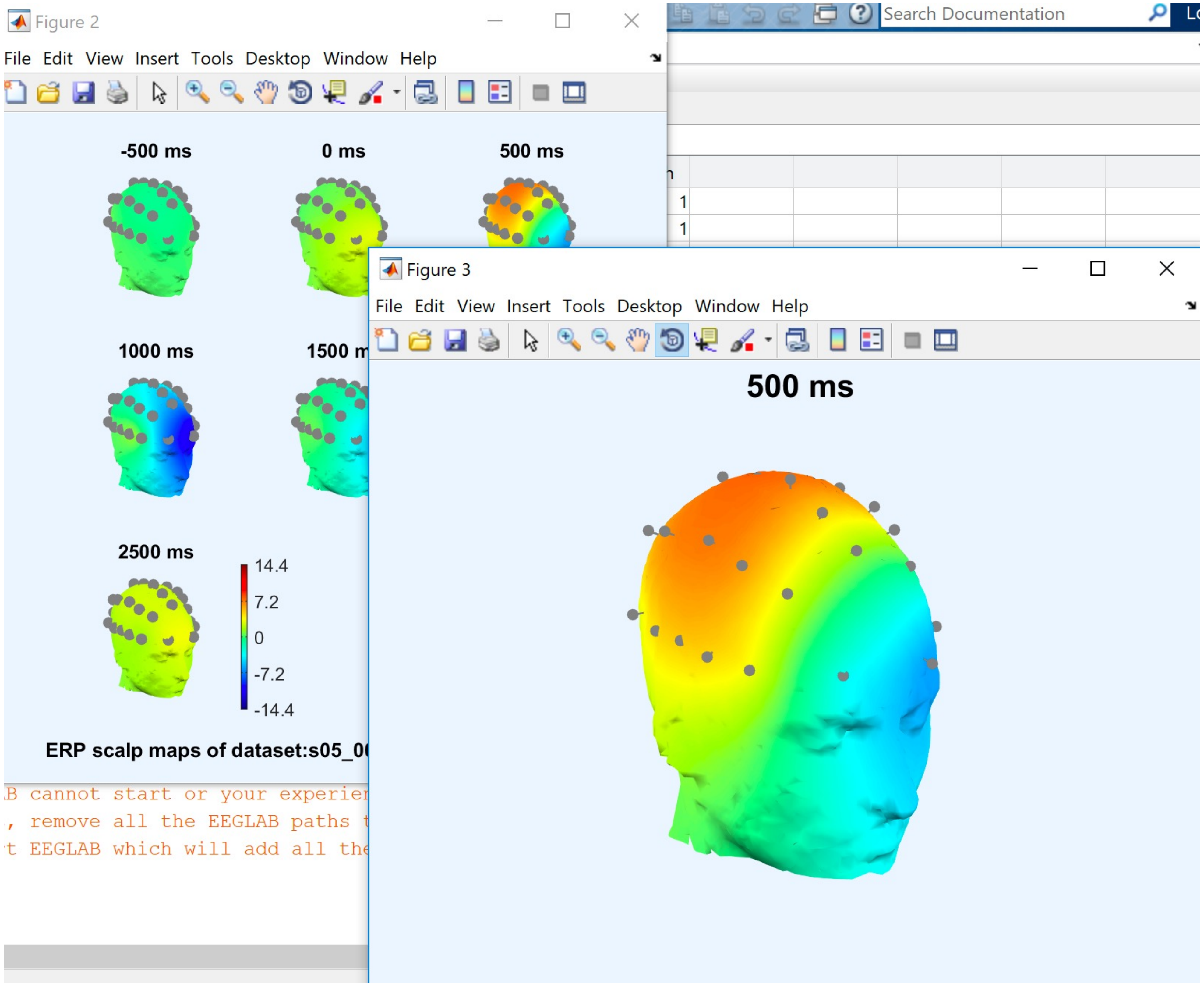
Sum/Compare comp. ERPs
Data statistics
Time-frequency transforms
In 2-D
In 3-D



Co-register channel locations with head mesh and compute a mesh spline file (each scalp montage needs a headplot() spline file)
Use the following spline file or structure
Or (re)compute a new spline file named:
\\Mac\Home\Google Drive\main\01.publication\01.journal\ (
3-D head mesh file
mheadnew.mat
Mesh associated channel file
mheadnew.xyz
Talairach-model transformation matrix
-0.355789 -6.33688 12.3705 0.0533239 0.01874
Browse
Help
Browse
Help
Browse other
Browse other
Manual coreg.
Plot interpolated activity onto 3-D head
Making headplots for these latencies (from -1000 to 6996 ms):
-500 0 500 1000 1500 2000 2500
Plot title:
ERP scalp maps of dataset:s05_061019m resa
Plot geometry (rows,columns): (Default [] = near square)
Other headplot options (See >> help headplot):
Cancel
Ok

Visualize data measures



2D vs 3D

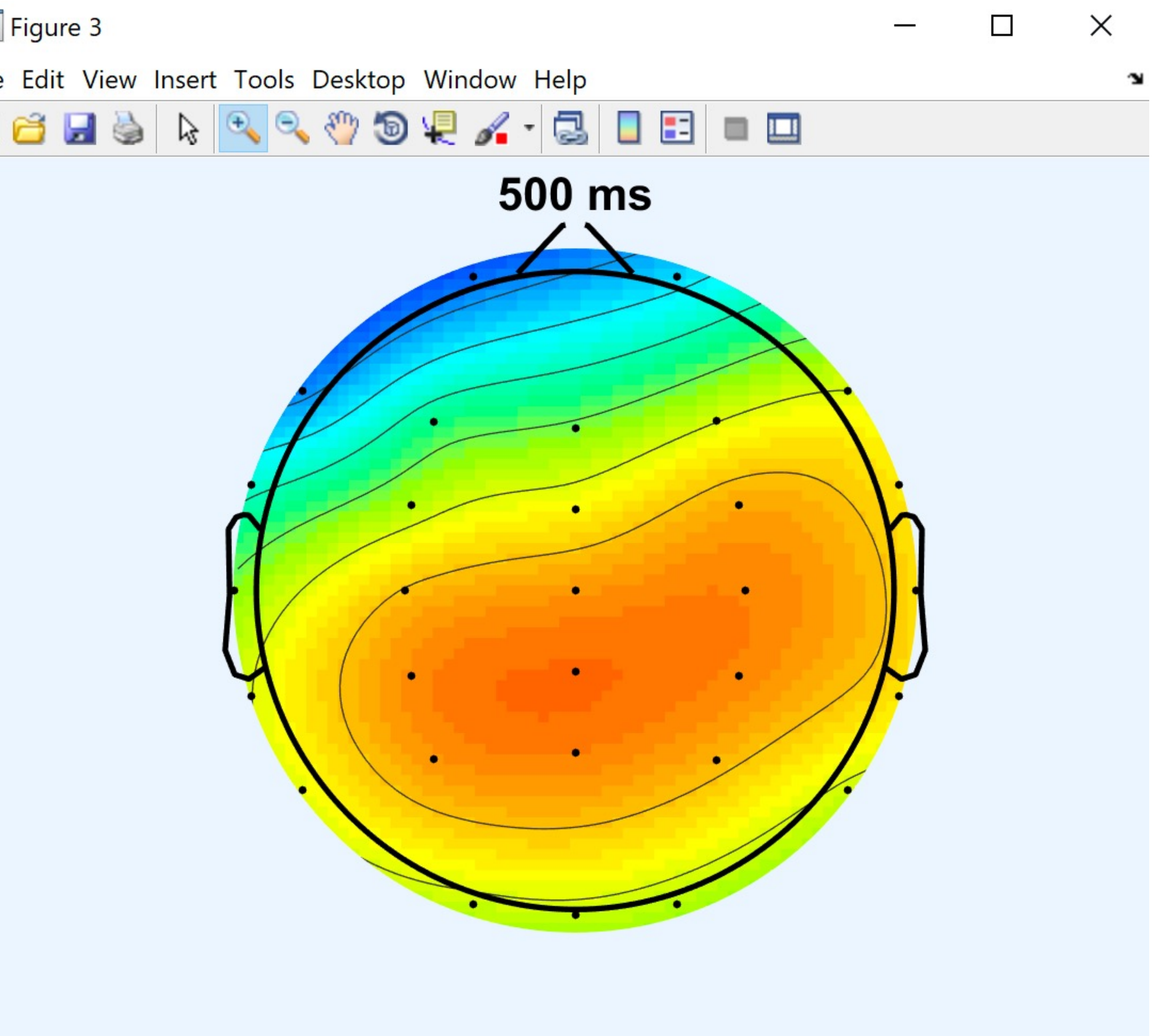


Figure 3
Edit View Insert Tools Desktop Window Help
500 ms

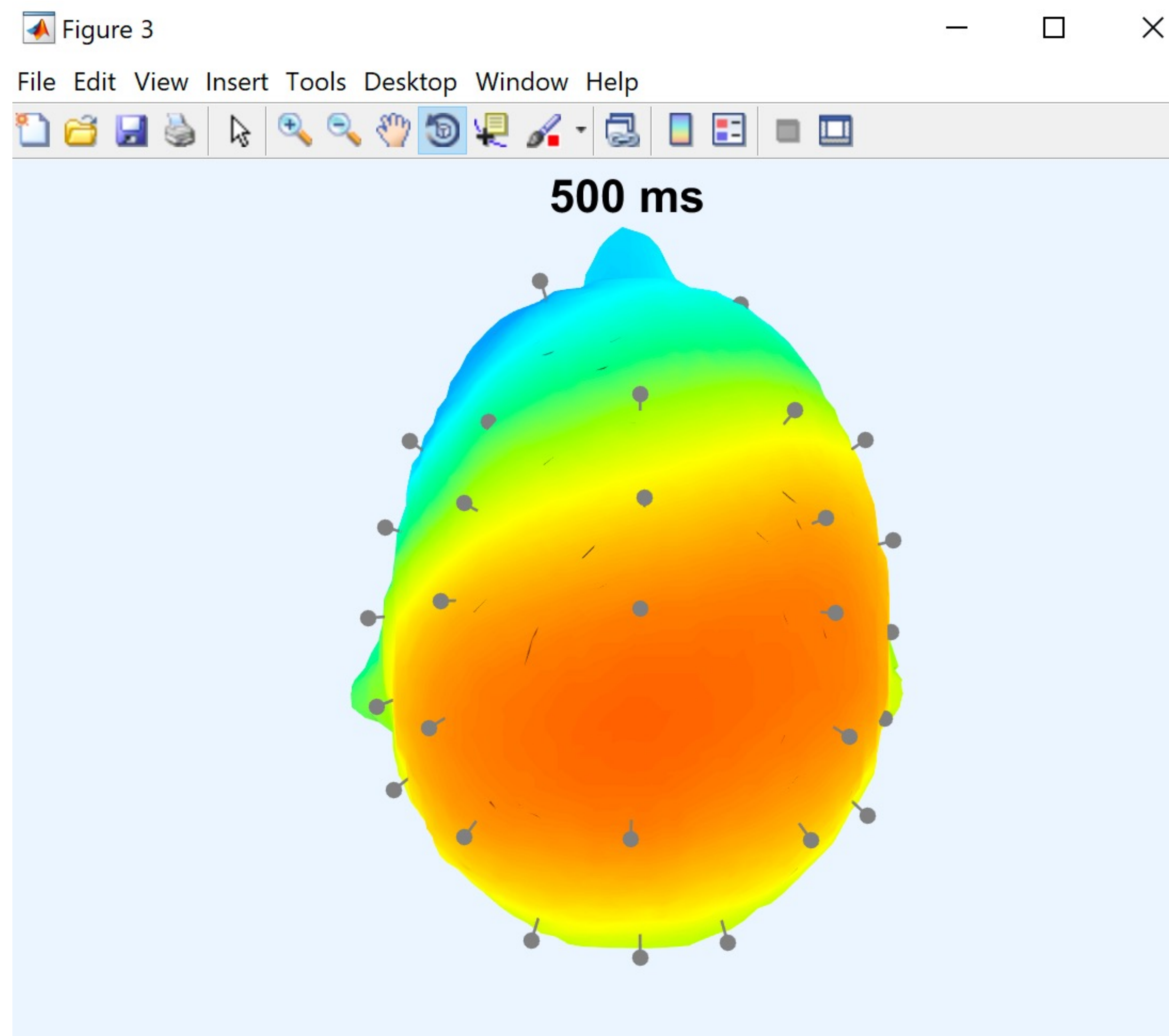
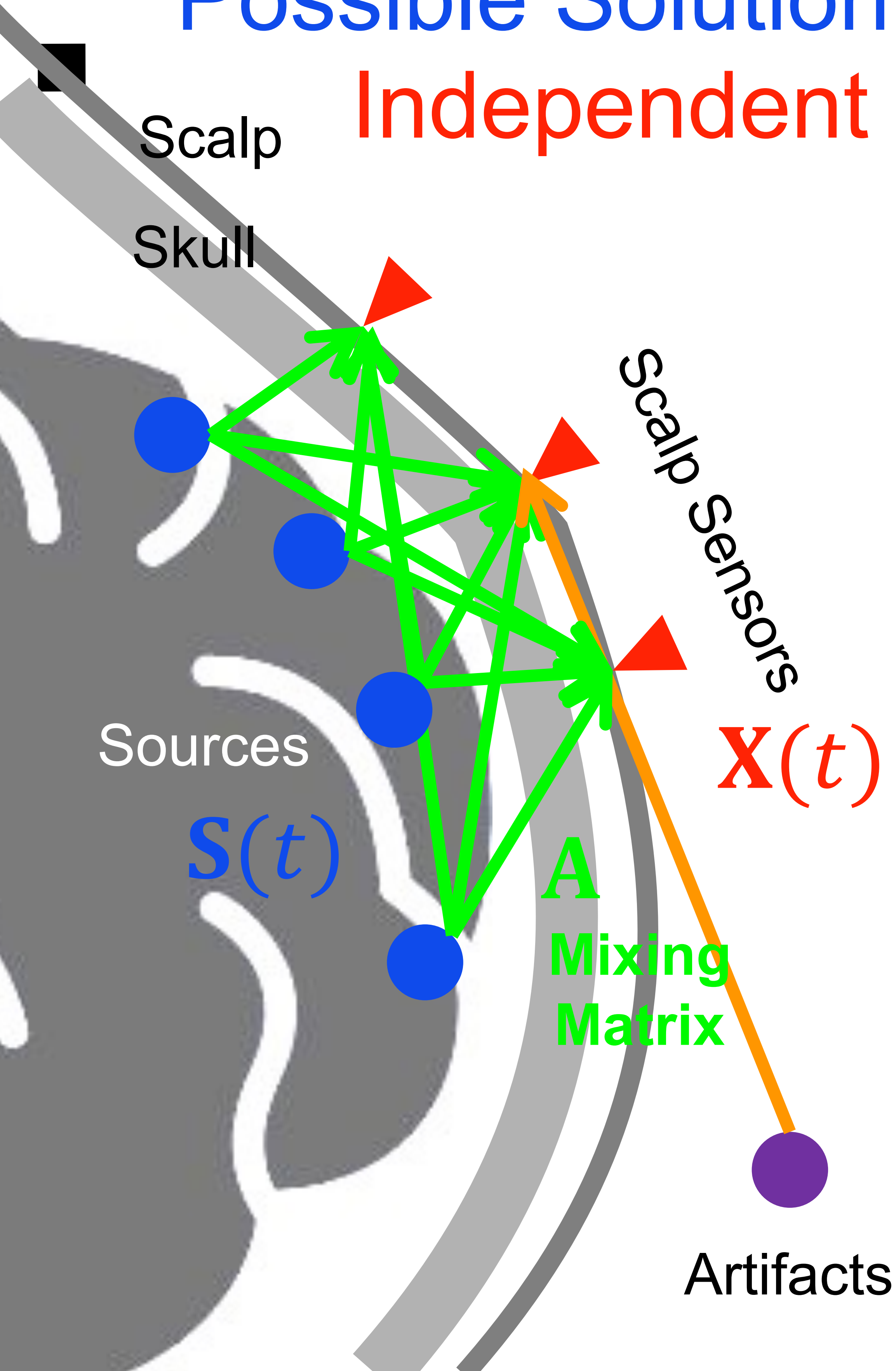


Figure 3
File Edit View Insert Tools Desktop Window Help
500 ms

Possible Solution – Independent Component Analysis



The signal recorded can be considered as a linear mixture of underlying neural generators

$$\mathbf{A}\times\mathbf{S}(t) = \mathbf{X}(t)$$

Assume that Sources are statistically independent from each.

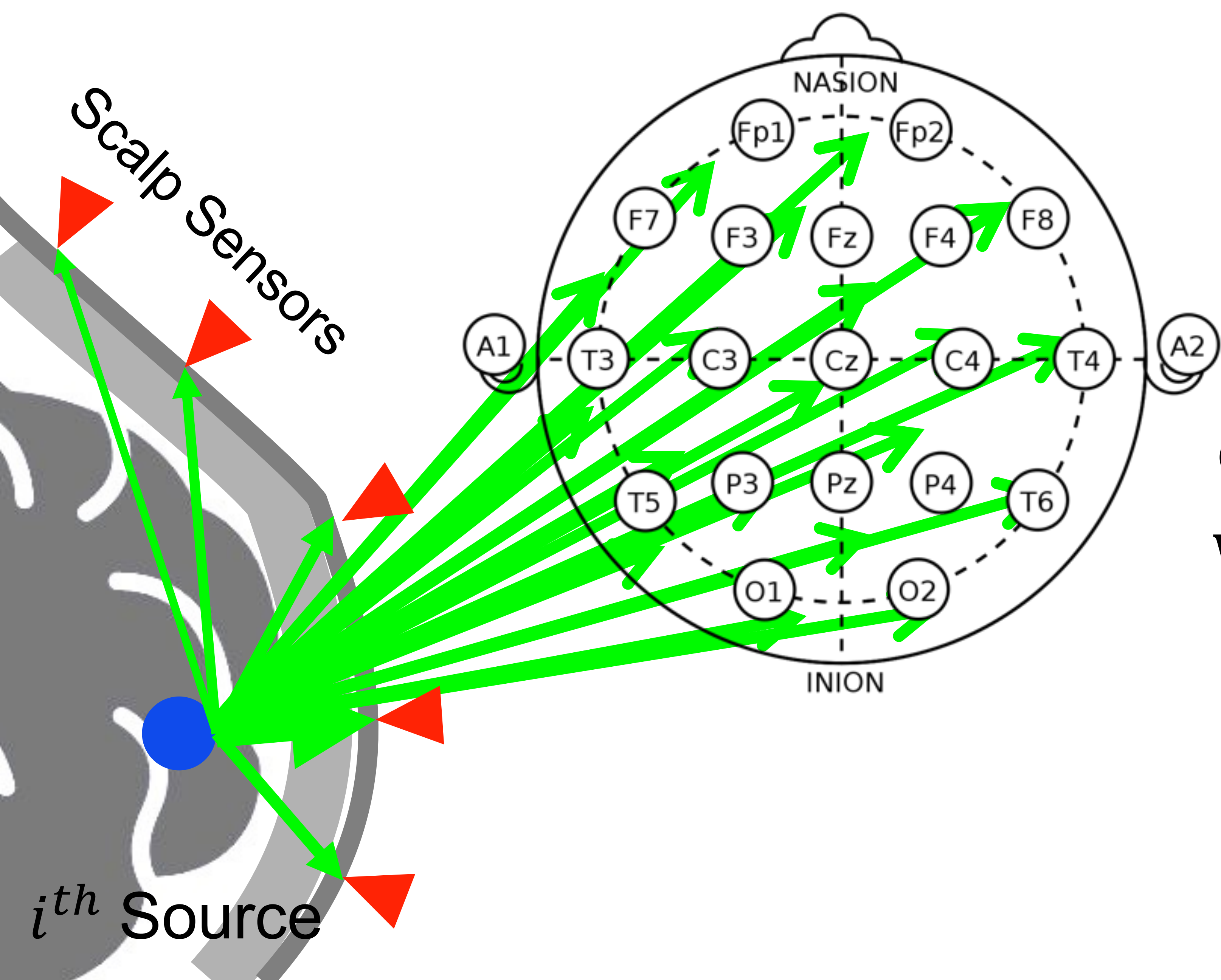
$$\mathbf{W}\times\mathbf{X}(t) = \hat{\mathbf{S}}(t)$$

Unmixing Matrix

Independent Component Analysis finds an unmixing matrix $\mathbf{W}$ to maximize some objective function that measures **independence of the estimated components**

Independent Component Analysis (ICA)

Unmixes the uncertainty of WHAT from that of WHERE!



$$\mathbf{W} \times \mathbf{X}(t) = \hat{\mathbf{S}}(t)$$

$$\mathbf{X}(t) = \mathbf{W}^{-1} \times \hat{\mathbf{S}}(t)$$

Inverse of Unmixing Matrix

Given n sensors,

$$\mathbf{W}^{-1} = \Lambda$$

$$= \begin{bmatrix} \lambda_{11} & \cdots & \lambda_{1i} & \cdots & \lambda_{1n} \\ \lambda_{21} & \cdots & \lambda_{2i} & \cdots & \lambda_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \lambda_{n1} & \cdots & \lambda_{ni} & \cdots & \lambda_{nn} \end{bmatrix}$$

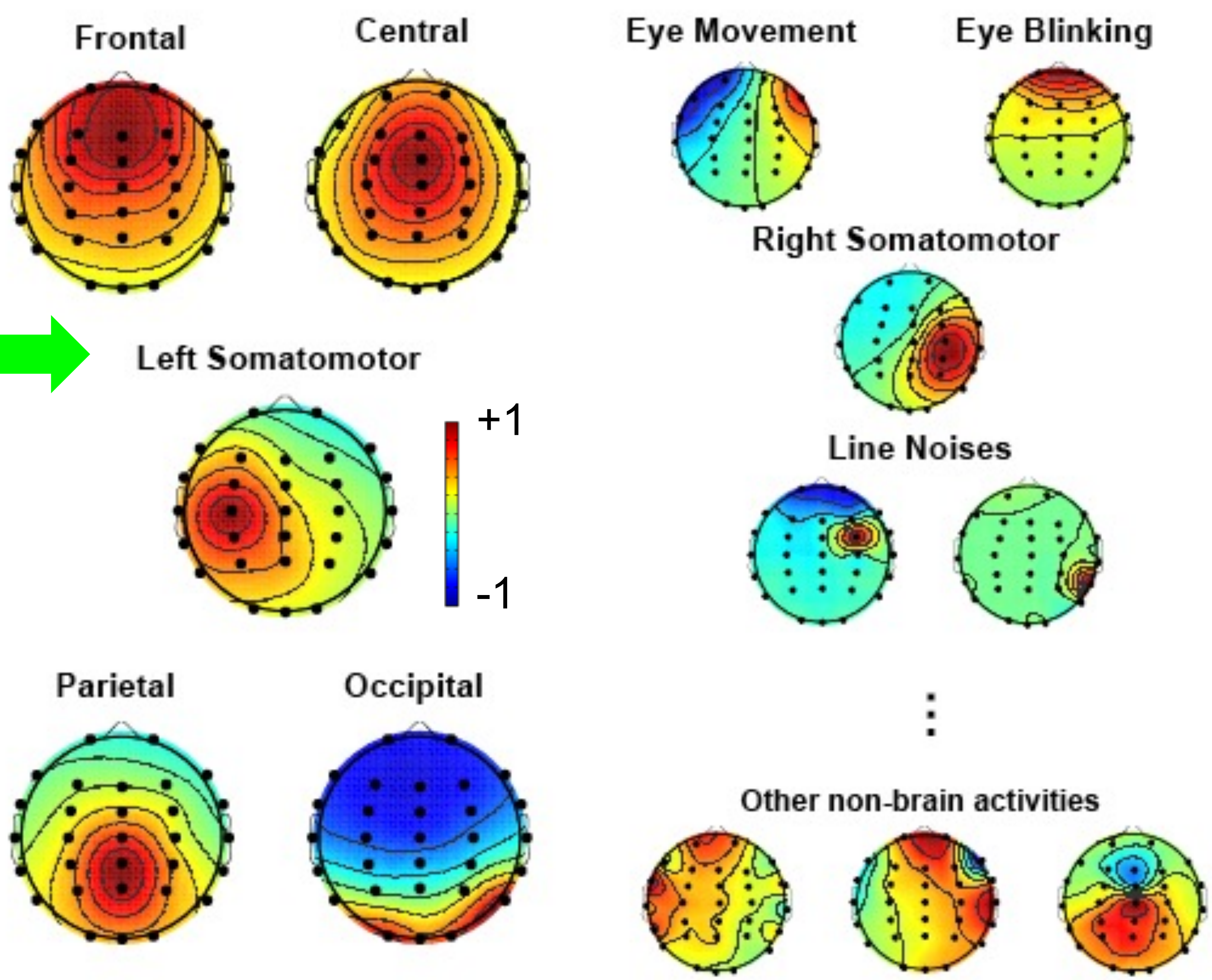
Independent Component Analysis (ICA)

$$\mathbf{X}(t) = \mathbf{W}^{-1} \times \hat{\mathbf{S}}(t)$$

$$\mathbf{W}^{-1} = \Lambda$$

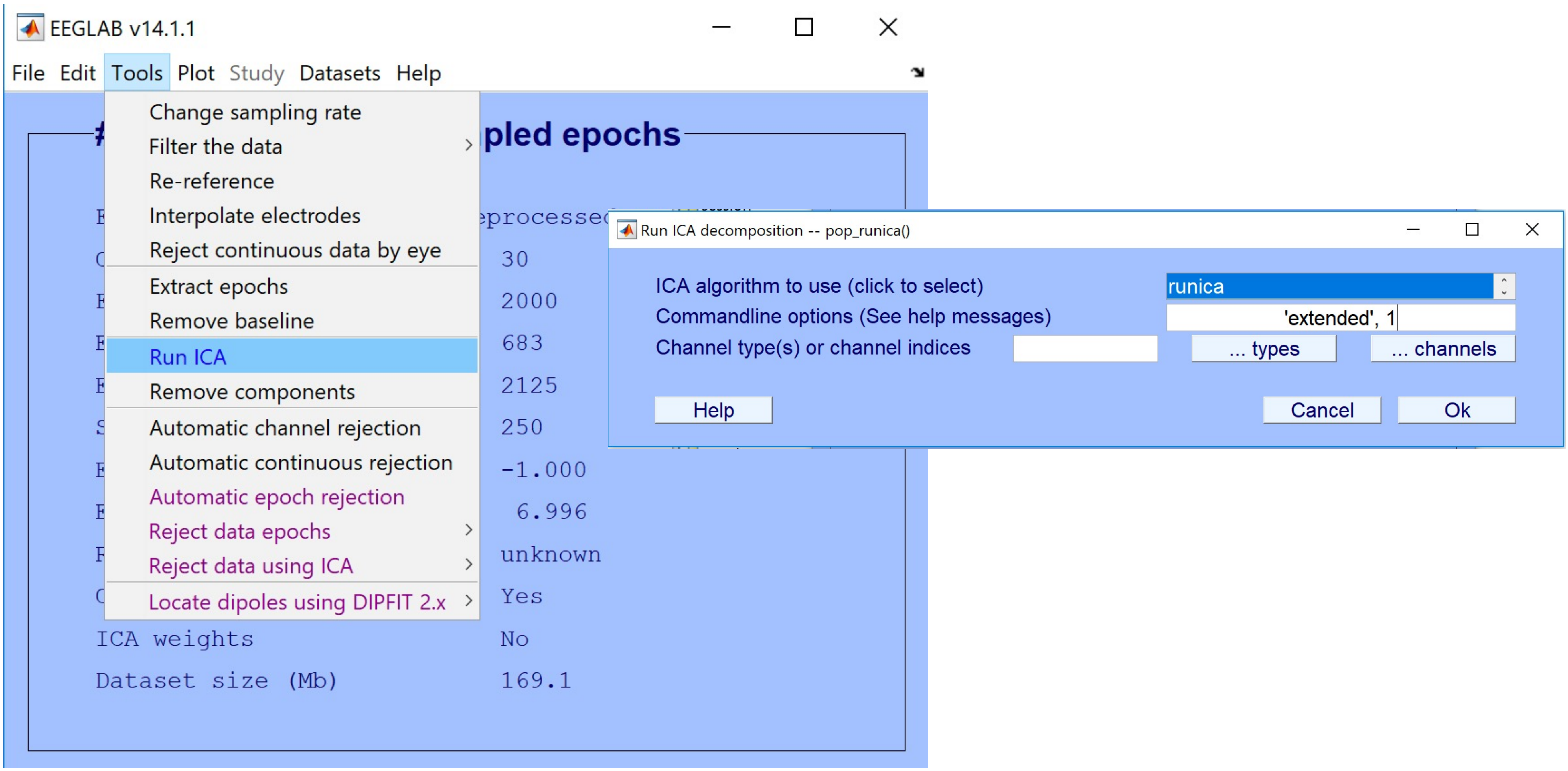
$$= \begin{bmatrix} \lambda_{11} & \cdots & \lambda_{1i} & \cdots & \lambda_{1n} \\ \lambda_{21} & \cdots & \lambda_{2i} & \cdots & \lambda_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \lambda_{n1} & \cdots & \lambda_{ni} & \cdots & \lambda_{nn} \end{bmatrix}$$

$$\begin{bmatrix} \boldsymbol{X_1}\ (t) \\ \vdots \\ \boldsymbol{X_n}\ (t) \end{bmatrix} = \mathbf{W}^{-1} \times \begin{bmatrix} \hat{\mathbf{S}}_{\mathbf{1}}\ (t) \\ \vdots \\ \hat{\mathbf{S}}_{\boldsymbol{n}}\ (t) \end{bmatrix}$$



CH Chuang*, CS Huang, LW Ko, & CT Lin, 'An EEG-based perceptual function integration network for application to drowsy driving', *Knowledge-Based Systems* 2015, 80, 143-152.

EEGLAB



EEGLAB v14.1.1
File Edit Tools Plot Study Datasets Help
pled epochs
Change sampling rate
Filter the data
Re-reference
Interpolate electrodes
Reject continuous data by eye
Extract epochs
Remove baseline
Run ICA
Remove components
Automatic channel rejection
Automatic continuous rejection
Automatic epoch rejection
Reject data epochs
Reject data using ICA
Locate dipoles using DIPFIT 2.x
30
2000
683
2125
250
-1.000
6.996
unknown
Yes
ICA weights
No
Dataset size (Mb)
169.1
Run ICA decomposition -- pop_runica()
ICA algorithm to use (click to select)
runica
Commandline options (See help messages)
'extended', 1
Channel type(s) or channel indices
... types
... channels
Help
Cancel
Ok

```
Kurtosis will be calculated initially every 1 blocks using 6000 data points.
Decomposing 1517 frames per ICA weight ((900)^2 = 1366000 weights, Initial learning rate will be 0.001, block
Learning rate will be multiplied by 0.98 whenever angledelta >= 60 deg.
More than 32 channels: default stopping weight change 1E-7
Training will end when wchange < 1e-06 or after 512 steps.
Online bias adjustment will be used.
Removing mea
Final traini
Computing the
Starting wei
Sphering the
Beginning IC                                     ...
Warning: Usi                                     RAND, RANDI, and RANDN to use legacy random number
generators.  This syntax is not recommended.  See Replace Discouraged Syntaxes of rand and randn to use RNG
to replace the old syntax.
> In runica (line 830)
  In pop_runica (line 399)
Lowering learning rate to 0.0009 and starting again.
Lowering learning rate to 0.00081 and starting again.
Lowering learning rate to 0.000729 and starting again.
```

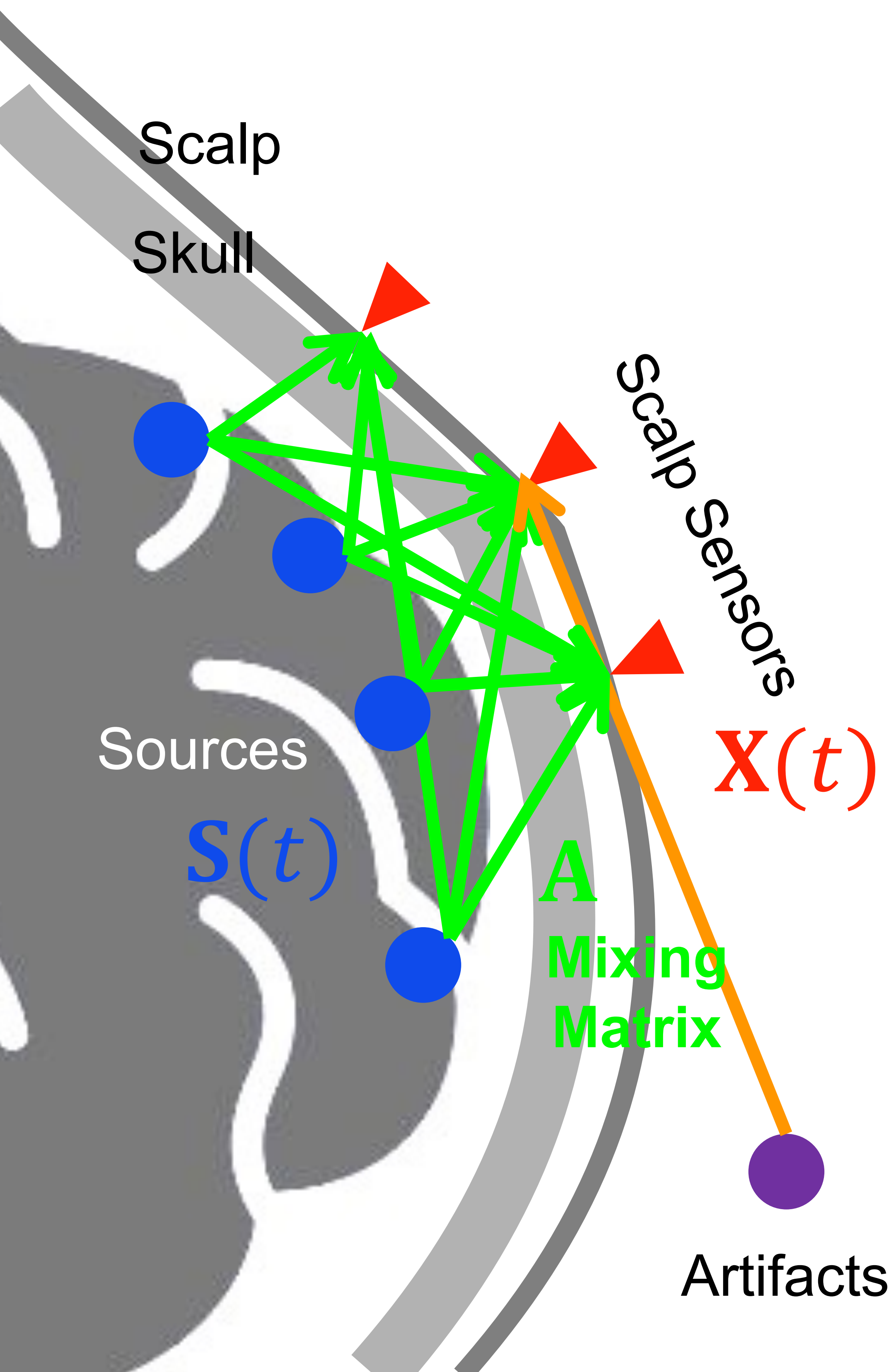
Press button to interrupt runica()

Interupt

```
ommand Window
step 48 - lrate 0.000019, wchange 0.60102712, angledelta 137.4 deg
step 49 - lrate 0.000019, wchange 0.45452005, angledelta 169.7 deg
step 50 - lrate 0.000018, wchange 0.48941163, angledelta 170.1 deg
step 51 - lrate 0.000018, wchange 0.04110124, angledelta 75.0 deg
step 52 - lrate 0.000018, wchange 0.40831810, angledelta 115.8 deg
step 53 - lrate 0.000017, wchange 0.73758322, angledelta 167.0 deg
step 54 - lrate 0.000017, wchange 0.05327091, angledelta 144.9 deg
step 55 - lrate 0.000016, wchange 0.02706516, angledelta 124.5 deg
step 56 - lrate 0.000016, wchange 0.01631103, angledelta 104.6 deg
step 57 - lrate 0.000016, wchange 0.02201465, angledelta 120.1 deg
step 58 - lrate 0.000016, wchange 0.33487233, angledelta 113.6 deg
step 59 - lrate 0.000015, wchange 0.10354193, angledelta 33.3 deg
step 60 - lrate 0.000015, wchange 0.01142147, angledelta 95.9 deg
step 61 - lrate 0.000015, wchange 0.01723309, angledelta 100.1 deg
step 62 - lrate 0.000015, wchange 0.01847892, angledelta 145.3 deg
step 63 - lrate 0.000014, wchange 0.56760624, angledelta 94.6 deg
step 64 - lrate 0.000014, wchange 0.03602543, angledelta 110.7 deg
step 65 - lrate 0.000014, wchange 0.03381547, angledelta 142.6 deg
step 66 - lrate 0.000013, wchange 0.01898318, angledelta 114.5 deg
step 67 - lrate 0.000013, wchange 0.00898991, angledelta 122.3 deg
step 68 - lrate 0.000013, wchange 0.01130301, angledelta 123.4 deg
>>
```

EEG.icaact?

xmax	1.9960
times	1x750 double
data	30x750x683 single
icaact	[]
icawinv	30x30 double
icasphere	30x30 double
icaweights	30x30 double
icachansind	1x30 double



$$\mathbf{A} \times \mathbf{S}(t) = \mathbf{X}(t)$$

Unmixing Matrix

$$\mathbf{W} \times \mathbf{X}(t) = \hat{\mathbf{S}}(t)$$

$$\mathbf{X}(t) = \mathbf{W}^{-1} \times \hat{\mathbf{S}}(t)$$

Inverse of Unmixing Matrix

Given n sensors,

$$\mathbf{W}^{-1} = \Lambda = \begin{bmatrix} \lambda_{11} & \cdots & \lambda_{1i} & \cdots & \lambda_{1n} \\ \lambda_{21} & \cdots & \lambda_{2i} & \cdots & \lambda_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \lambda_{n1} & \cdots & \lambda_{ni} & \cdots & \lambda_{nn} \end{bmatrix}$$

xmin	-1
xmax	1.9960
times	*1x750 double*
data	*30x750x683 single*
icaact	*[ ]*
icawinv	*30x30 double*
icasphere	*30x30 double*
icaweights	*30x30 double*
icachansind	*1x30 double*

icaact??

The Infomax ICA algorithm first "sphere" the data (remove correlation) and then performs ICA.

So the inverse weight matrix EEG.icawinv is equal to

EEG.icawinv = pinv(EEG.icaweights*EEG.icasphere);

$$\mathbf{W}\times\mathbf{X}(t) = \hat{\mathbf{S}}(t)$$

$$\mathbf{X}(t) = \mathbf{W}^{-1}\times\hat{\mathbf{S}}(t)$$

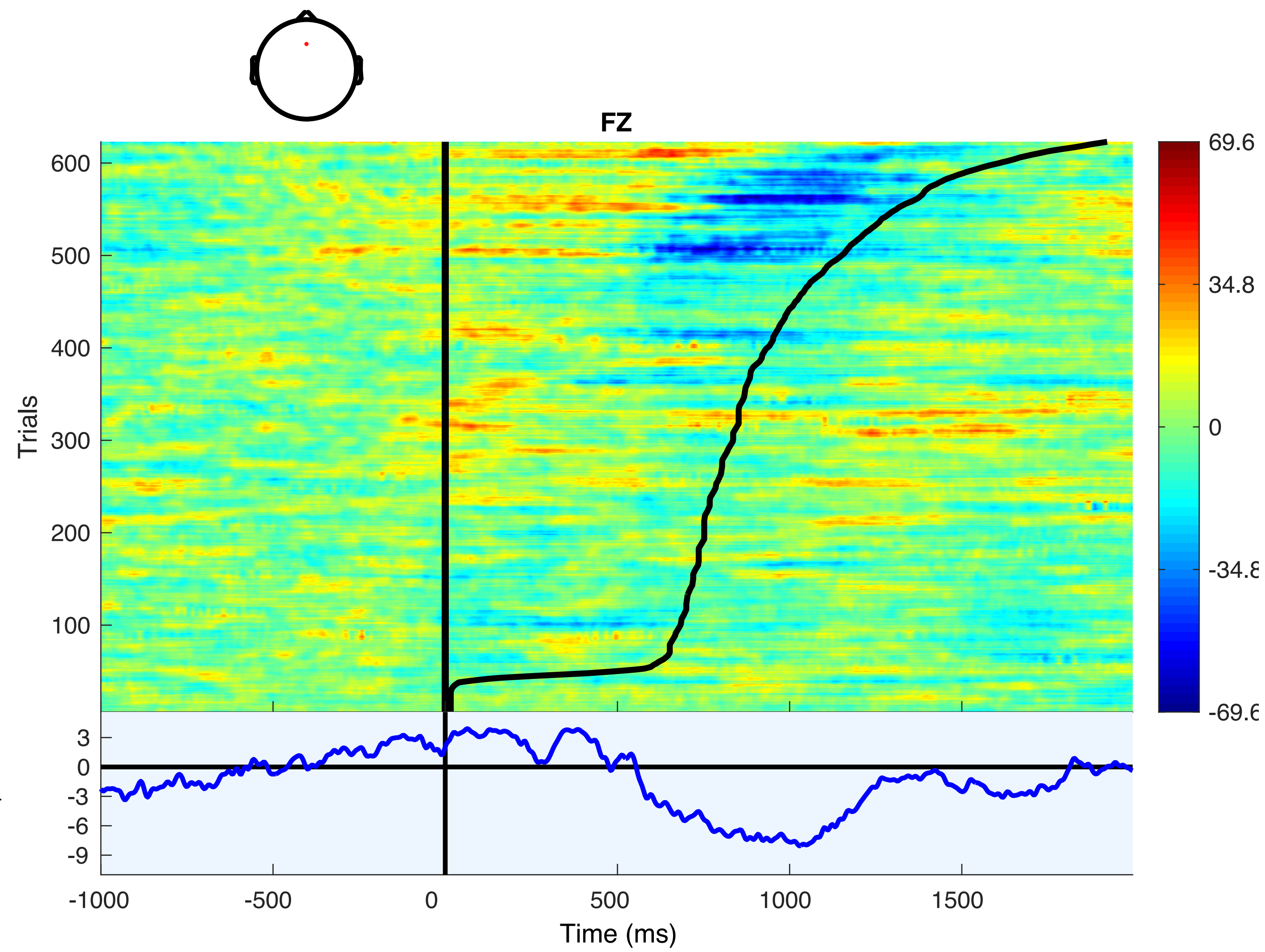
$$\mathbf{X}(t) = \mathbf{W}^{-1}\times\hat{\mathbf{S}}(t)$$

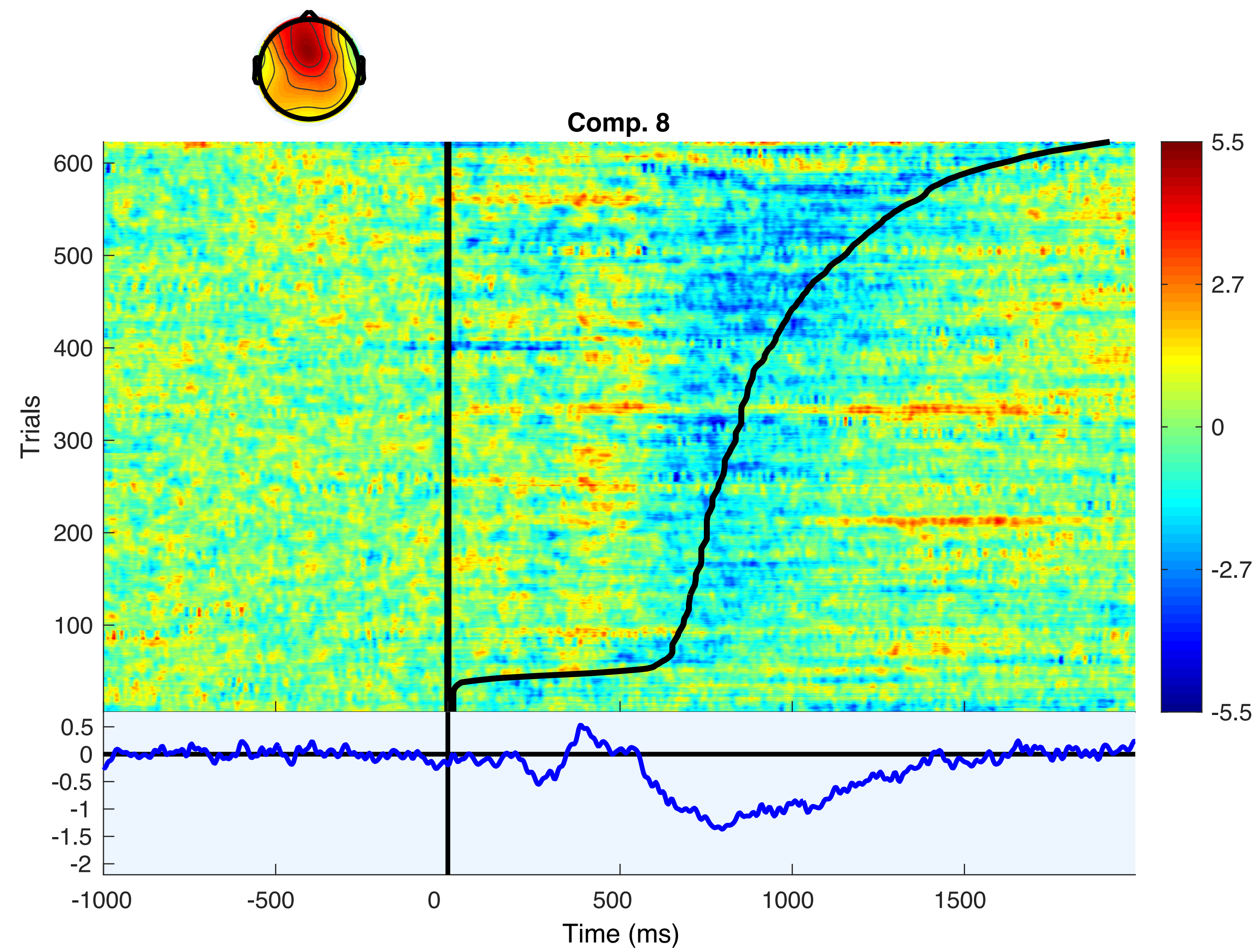
$$\mathbf{W}\times\mathbf{X}(t) = \hat{\mathbf{S}}(t)$$

Inverse of Unmixing Matrix

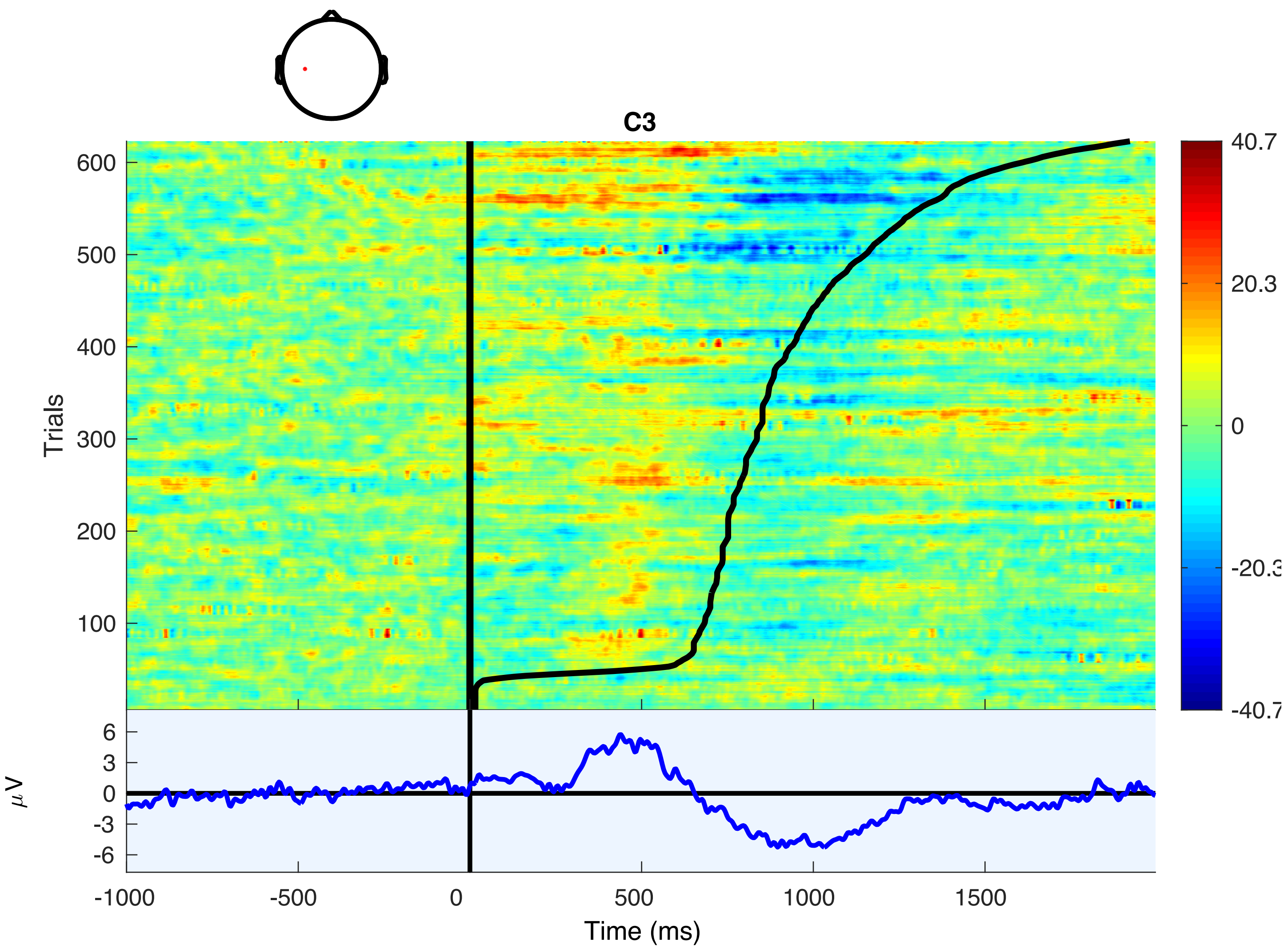
Channels domain
vs.
Component domain

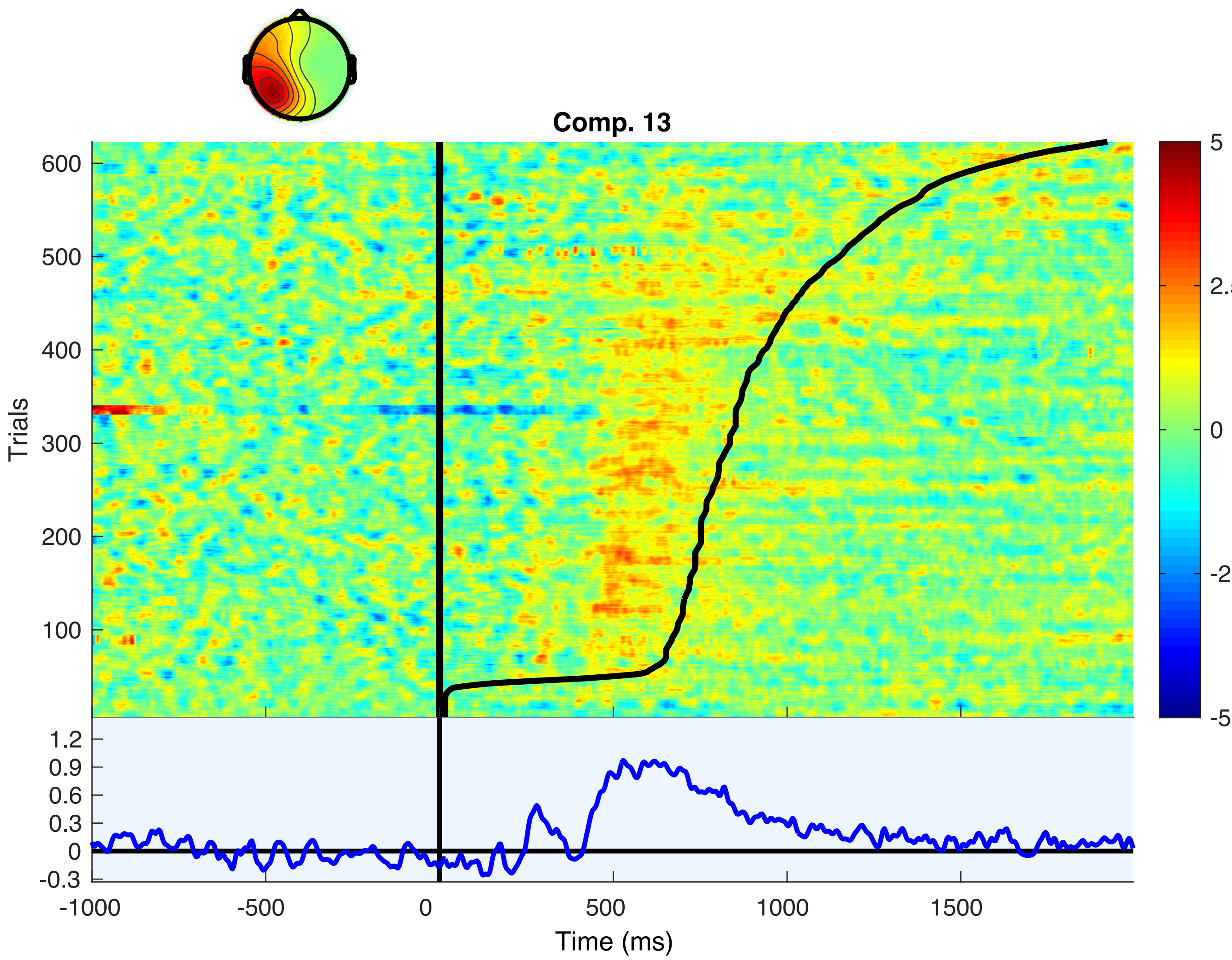
Frontal


FZ
Trials
600
500
400
300
200
100
69.6
34.8
0
-34.8
-69.6
3
0
-3
-6
-9
-1000
-500
0
500
1000
1500
Time (ms)

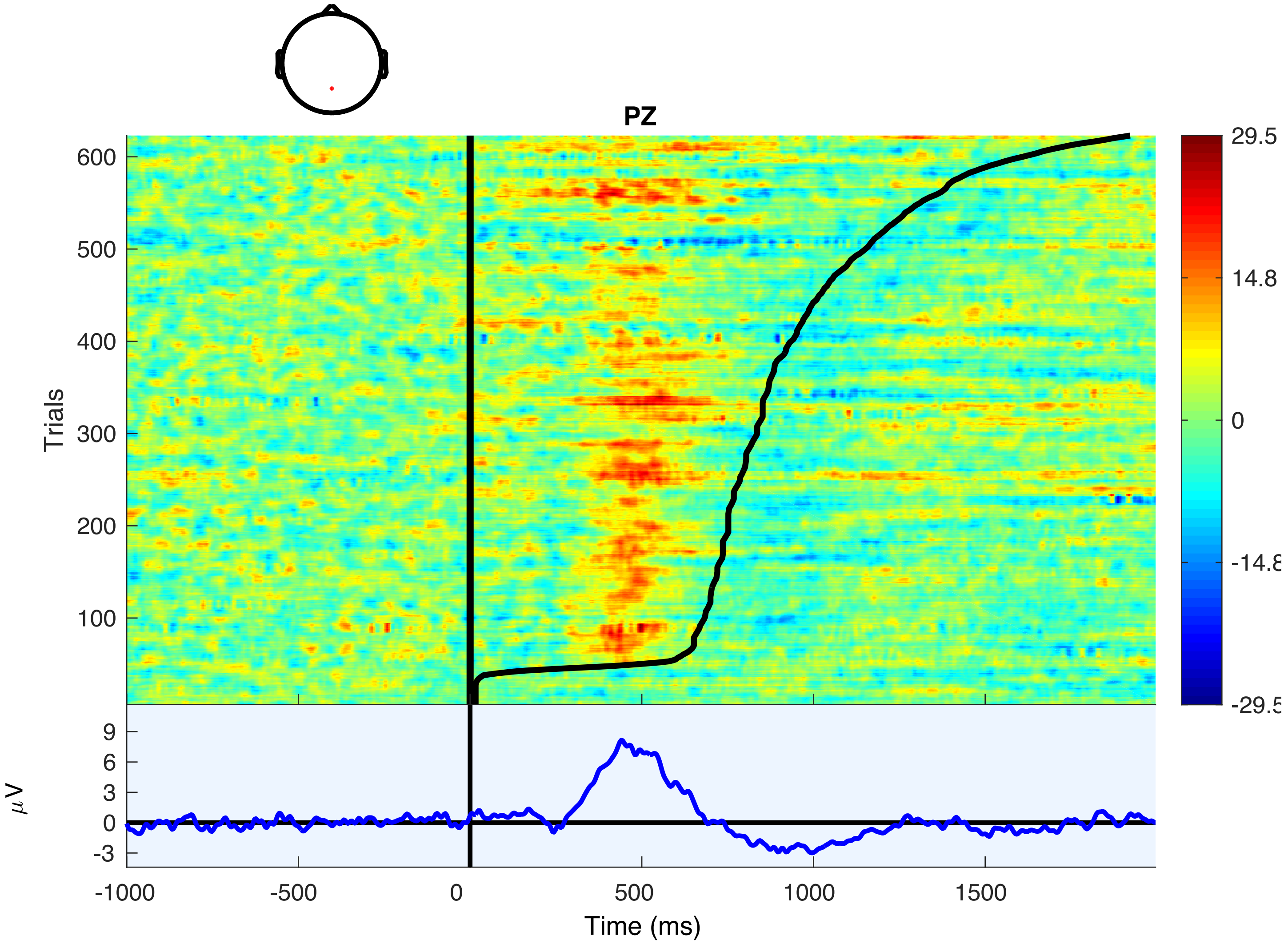

Comp. 8
Trials
600
500
400
300
200
100
5.5
2.7
0
-2.7
-5.5
0.5
0
-0.5
-1
-1.5
-2
-1000
-500
0
500
1000
1500
Time (ms)

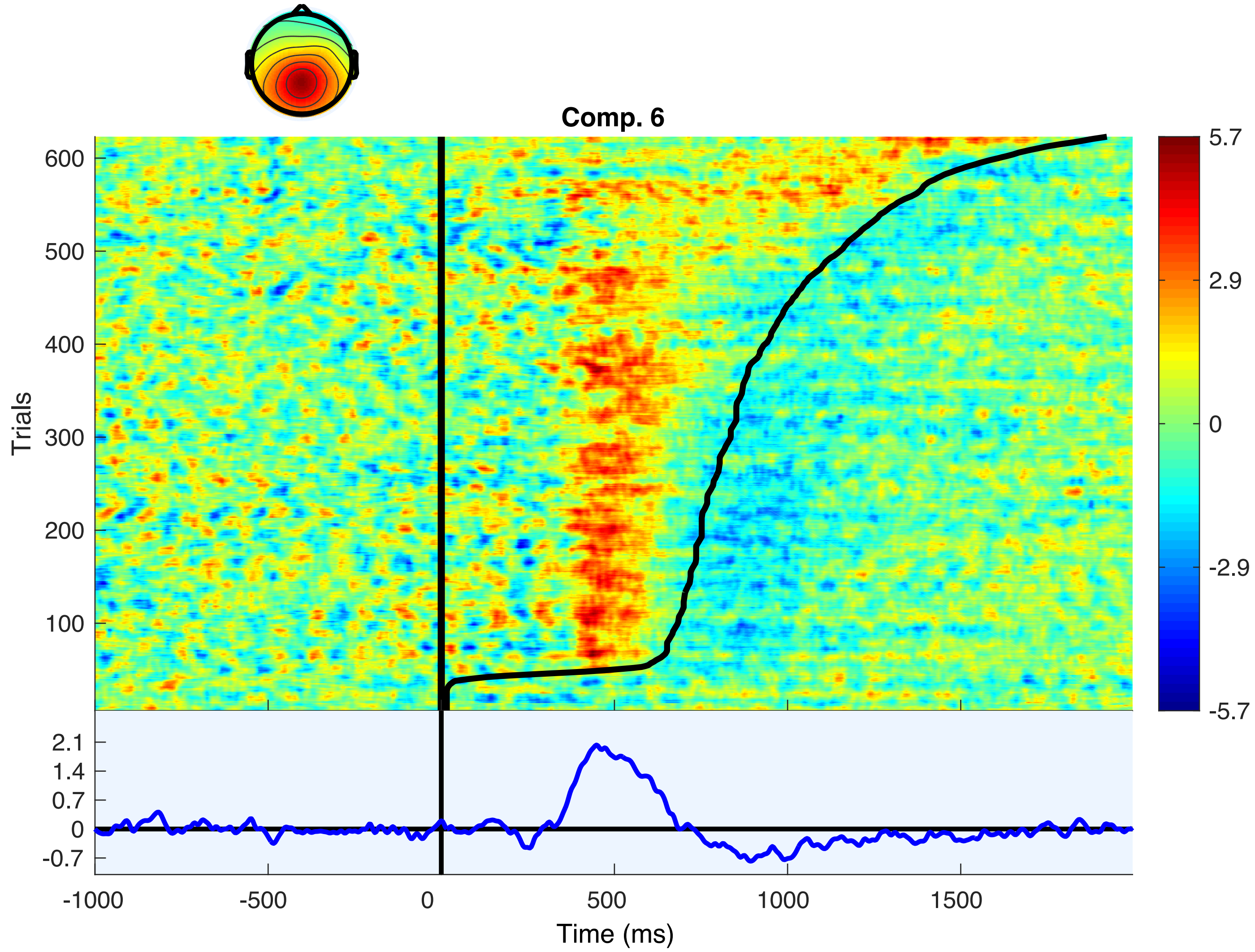
Left motor


C3
Trials
600
500
400
300
200
100
40.7
20.3
0
-20.3
-40.7
µV
6
3
0
-3
-6
-1000
-500
0
500
1000
1500
Time (ms)


Comp. 13
Trials
600
500
400
300
200
100
5
0
1.2
0.9
0.6
0.3
0
-0.3
-1000
-500
0
500
1000
1500
Time (ms)

Parietal


PZ
Trials
600
500
400
300
200
100
29.5
14.8
0
-14.8
-29.5
μV
9
6
3
0
-3
-1000
-500
0
500
1000
1500
Time (ms)


Comp. 6
Trials
600
500
400
300
200
100
5.7
2.9
0
-2.9
-5.7
2.1
1.4
0.7
0
-0.7
-1000
-500
0
500
1000
1500
Time (ms)