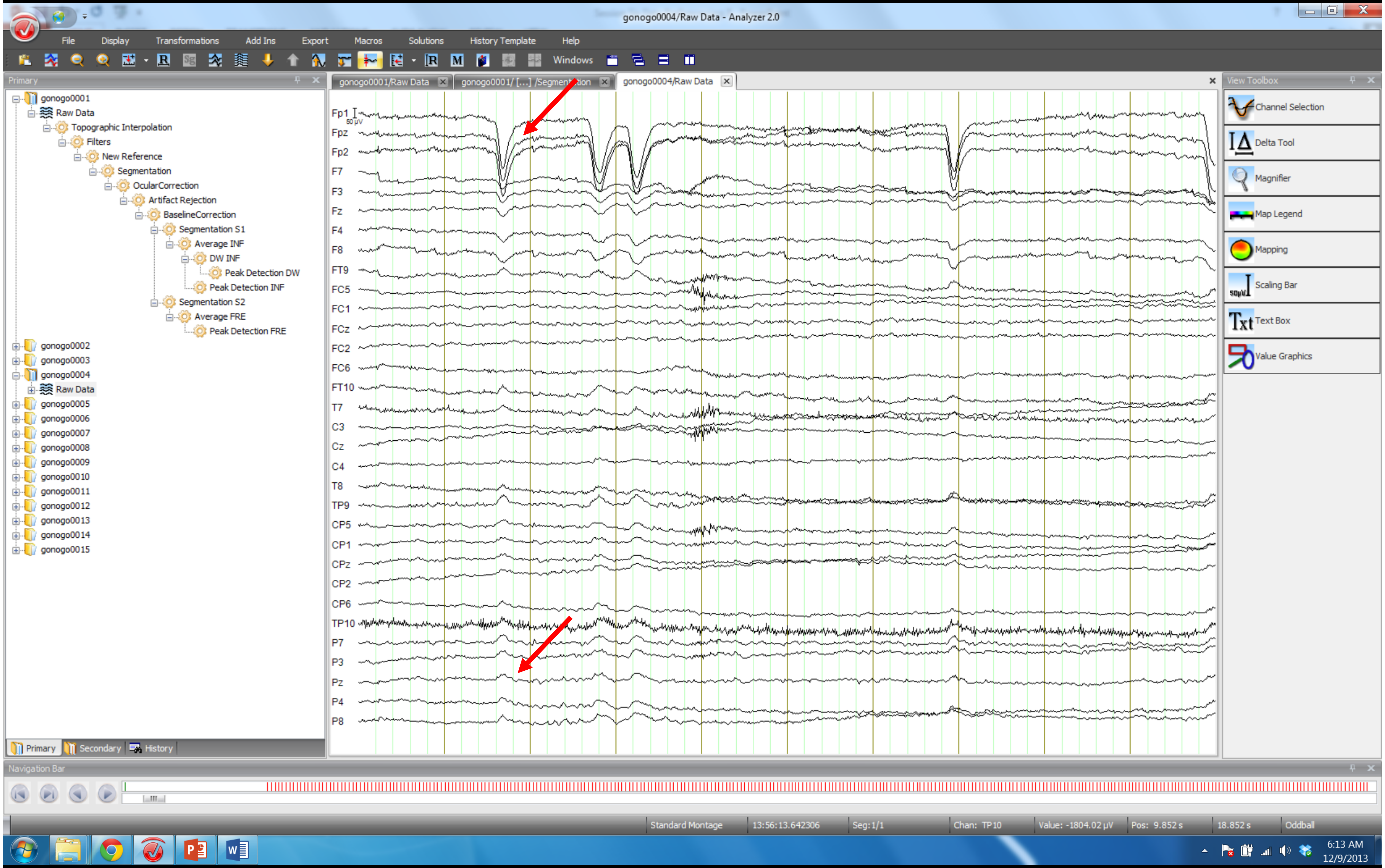
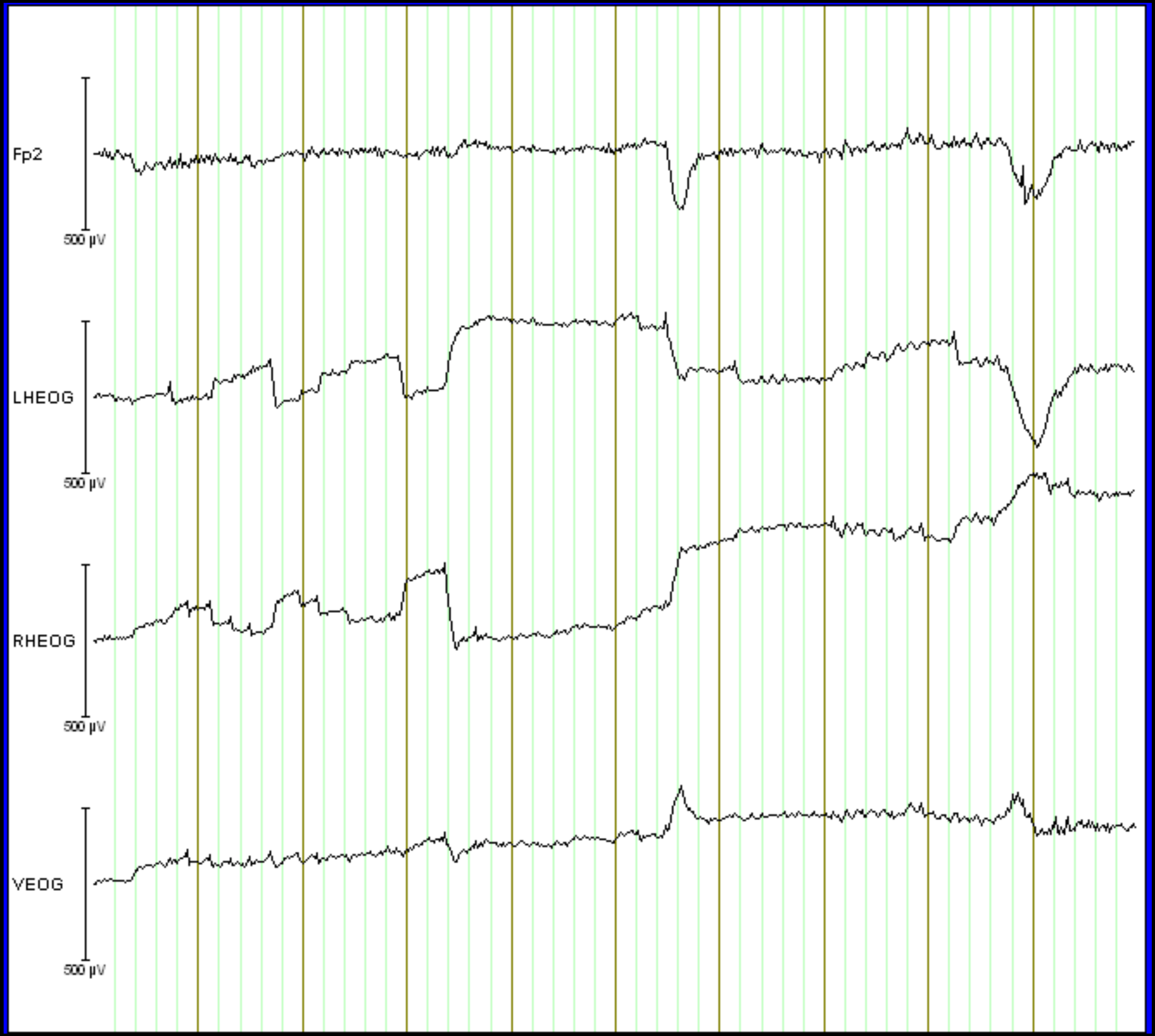
Ocular Correction

The issue with ocular correction is simple…


gonogo0004/Raw Data - Analyzer 2.0
File
Display
Transformations
Add Ins
Export
Macros
Solutions
History Template
Help
Windows
Primary
gonogo0001
Raw Data
Topographic Interpolation
Filters
New Reference
Segmentation
OcularCorrection
Artifact Rejection
BaselineCorrection
Segmentation S1
Average INF
DW INF
Peak Detection DW
Peak Detection INF
Segmentation S2
Average FRE
Peak Detection FRE
gonogo0002
gonogo0003
gonogo0004
Raw Data
gonogo0005
gonogo0006
gonogo0007
gonogo0008
gonogo0009
gonogo0010
gonogo0011
gonogo0012
gonogo0013
gonogo0014
gonogo0015
Primary
Secondary
History
gonogo0001/Raw Data
gonogo0001/ [...] /Segmentation
gonogo0004/Raw Data
Fp1
50 µV
Fpz
Fp2
F7
F3
Fz
F4
F8
FT9
FC5
FC1
FCz
FC2
FC6
FT10
T7
C3
Cz
C4
T8
TP9
CP5
CP1
CPz
CP2
CP6
TP10
P7
P3
Pz
P4
P8
View Toolbox
Channel Selection
Delta Tool
Magnifier
Map Legend
Mapping
Scaling Bar
Text Box
Value Graphics
Navigation Bar
Standard Montage
13:56:13.642306
Seg: 1/1
Chan: TP10
Value: -1804.02 µV
Pos: 9.852 s
18.852 s
Oddball
6:13 AM
12/9/2013


Fp2
500 µV
LHEOG
500 µV
RHEOG
500 µV
VEOG
500 µV

Blinks

Blinks impact data across the entire scalp due to signal propagation.

The magnitude of the blink is much greater than the underlying neural activity, hence the signal at that point in time is lost, or at best, blurred.

What to do?

1. Instruction

Instruct participants to try and minimize blinking, or to blink during rest breaks.

Critique:

Is this now a dual task paradigm?

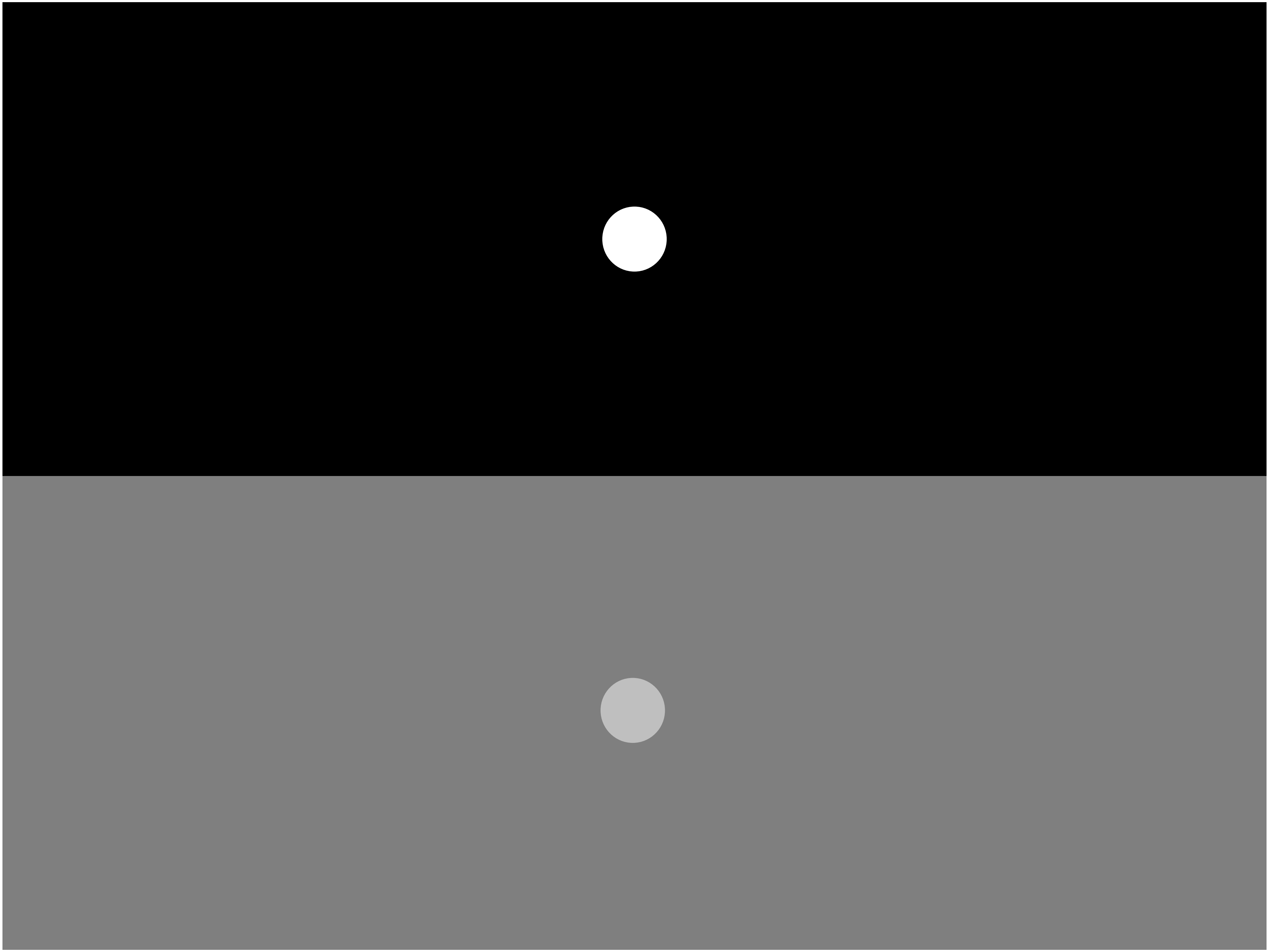
What to do?

2. Environment

Adjust stimuli and lighting to avoid high contrasts.

Critique:

Sleepiness



What to do?

3. Removal

Simply remove all trials from analysis with blinks in them.

Critique:

Data Loss

Systematic Blinking

What to do?

4. Correction

Use a correction method to “remove” the blinks and “interpolate” the missing data.

Critique:

Data Interpolation

Systematic Blinking

With Ocular	Without Ocular
22	44
8	27
5	136
1	18
8	105
24	40
6	91
12	150
22	67
5	68

Common Correction Techniques

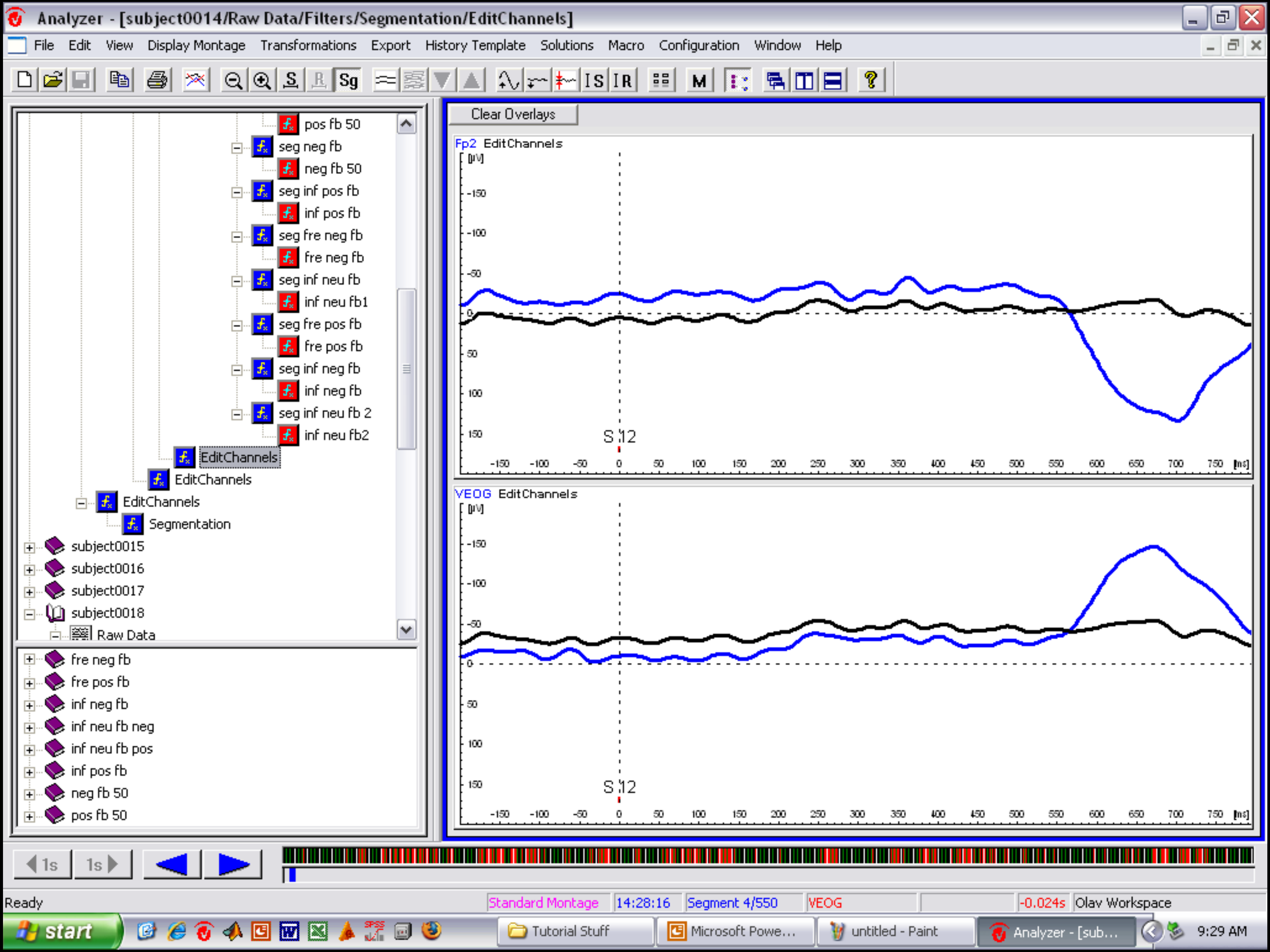
Gratton and Coles

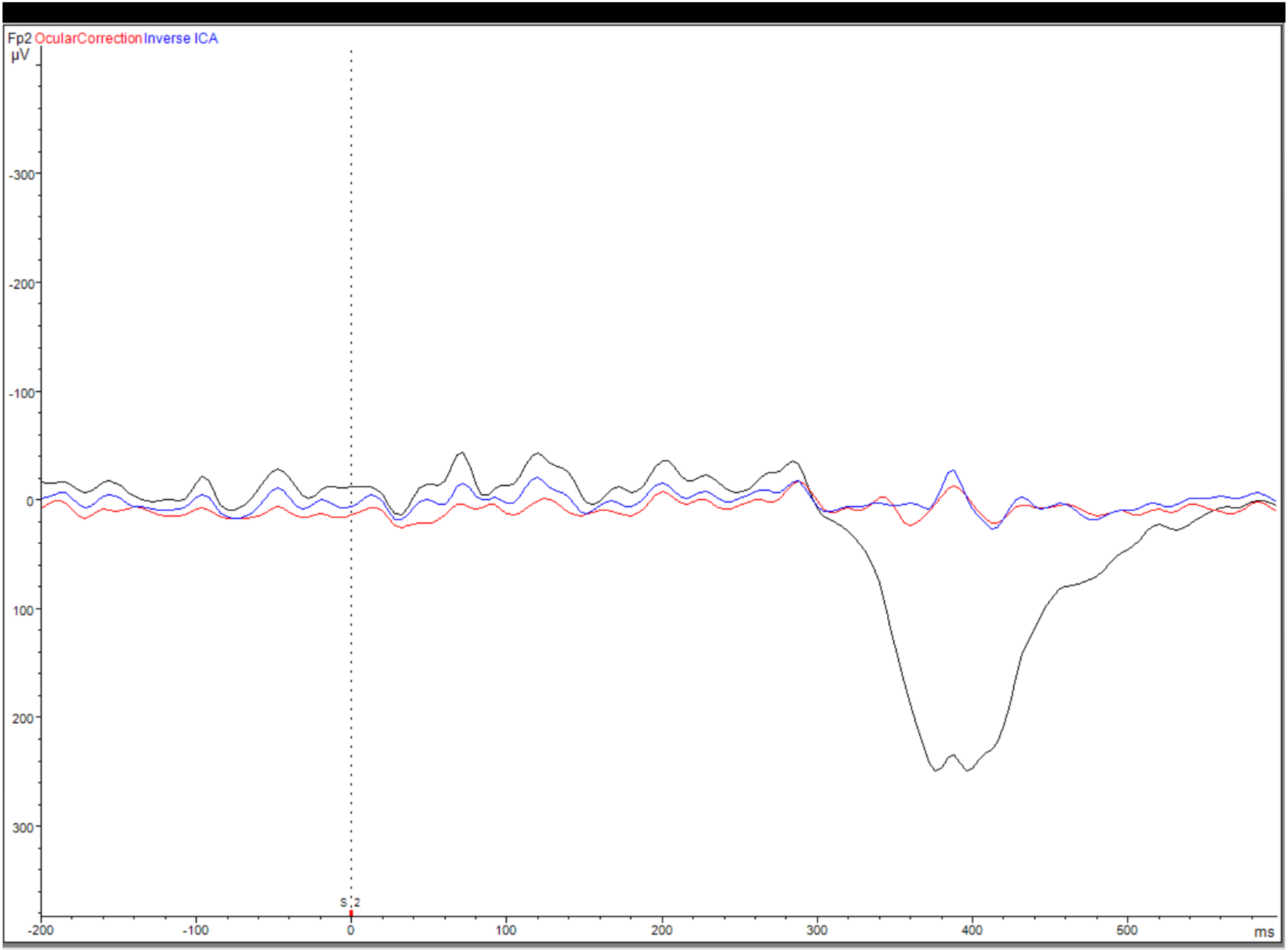
The GC technique uses EOG channels to identify blinks – based on slope and amplitude criterion. Then, a regression approach is used to estimate the missing data and interpolate it. Scaling factors are used to correct for blink amplitude corrections across the scalp.

Common Correction Techniques

Independent Component Analysis

ICA is a more complex correction procedure (we will discuss it Friday in depth) that uses the ICA solution to identify components that capture variance in the data. Those that capture variance associated with blinks can be subtracted from the data itself to “remove” the blink.


Analyzer - [subject0014/Raw Data/Filters/Segmentation/EditChannels]
File
Edit
View
Display Montage
Transformations
Export
History Template
Solutions
Macro
Configuration
Window
Help
pos fb 50
seg neg fb
neg fb 50
seg inf pos fb
inf pos fb
seg fre neg fb
fre neg fb
seg inf neu fb
inf neu fb1
seg fre pos fb
fre pos fb
seg inf neg fb
inf neg fb
seg inf neu fb 2
inf neu fb2
EditChannels
EditChannels
EditChannels
Segmentation
subject0015
subject0016
subject0017
subject0018
Raw Data
fre neg fb
fre pos fb
inf neg fb
inf neu fb neg
inf neu fb pos
inf pos fb
neg fb 50
pos fb 50
Clear Overlays
Fp2 EditChannels
[µV]
-150
-100
-50
0
50
100
150
S 12
-150 -100 -50 0 50 100 150 200 250 300 350 400 450 500 550 600 650 700 750 [ms]
VEOG EditChannels
[µV]
-150
-100
-50
0
50
100
150
S 12
-150 -100 -50 0 50 100 150 200 250 300 350 400 450 500 550 600 650 700 750 [ms]
1s
1s
Ready
Standard Montage
14:28:16
Segment 4/550
VEOG
-0.024s
Olav Workspace
start
Tutorial Stuff
Microsoft Powe...
untitled - Paint
Analyzer - [sub...
9:29 AM


Fp2
OcularCorrection
Inverse ICA
µV
-300
-200
-100
0
100
200
300
S 2
-200
-100
0
100
200
300
400
500
ms

What to do?

5. Short Segments

-200 to 400	13
-200 to 600	40
-200 to 800	64
-200 to 1000	84

Ocular Correction Demonstration

ICA

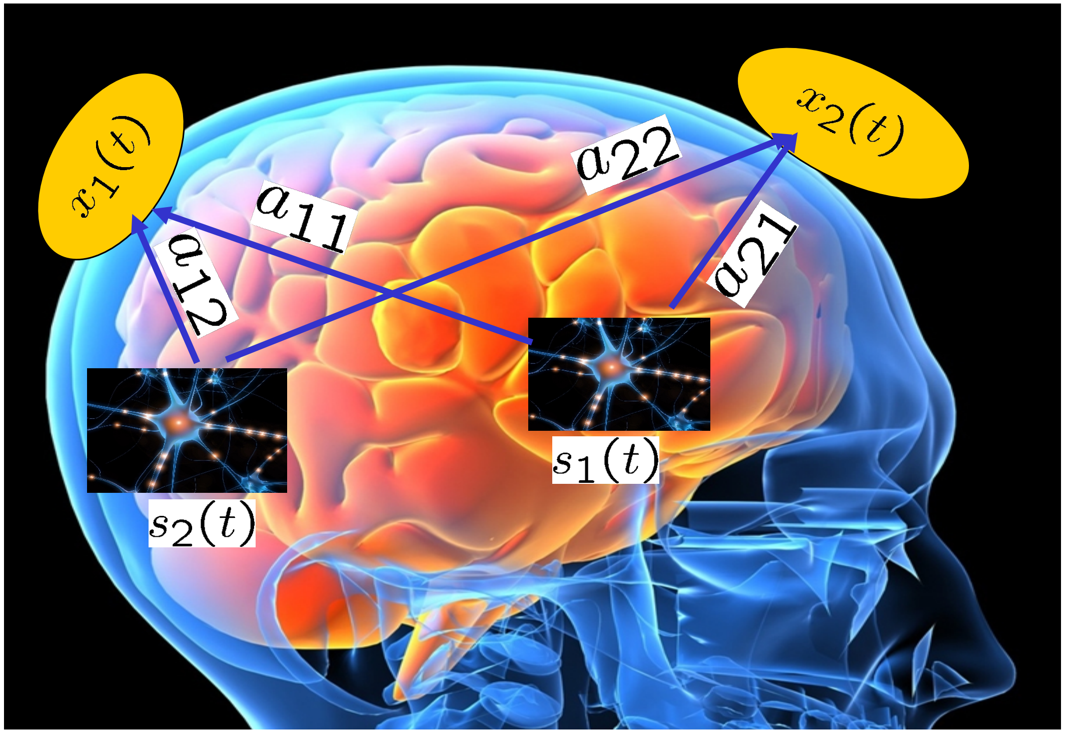
ICA

ICA has been primarily used in EEG research to correct ocular artifacts but can be used to isolate spatial components as well.

Independent Component Analysis

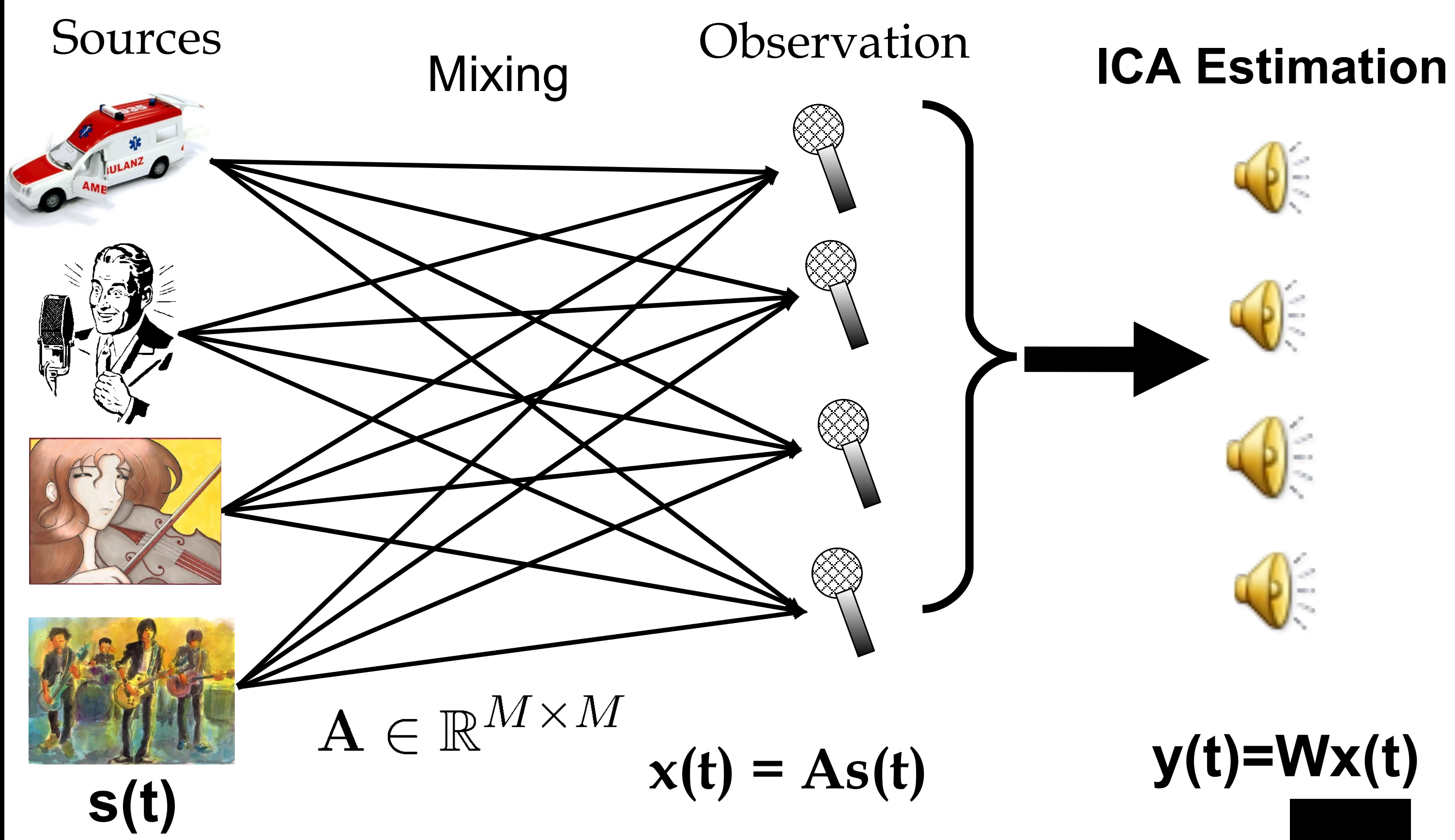
$$\begin{aligned} x_1(t) &= a_{11}s_1(t) + a_{12}s_2(t) \\ x_2(t) &= a_{21}s_1(t) + a_{22}s_2(t) \end{aligned}$$

Goal: Estimate $\{s_i(t)\}$,
(and also $\{a_{ij}\}$)



The Cocktail Party Problem

SOLVING WITH ICA



Sources

Mixing

Observation

ICA Estimation

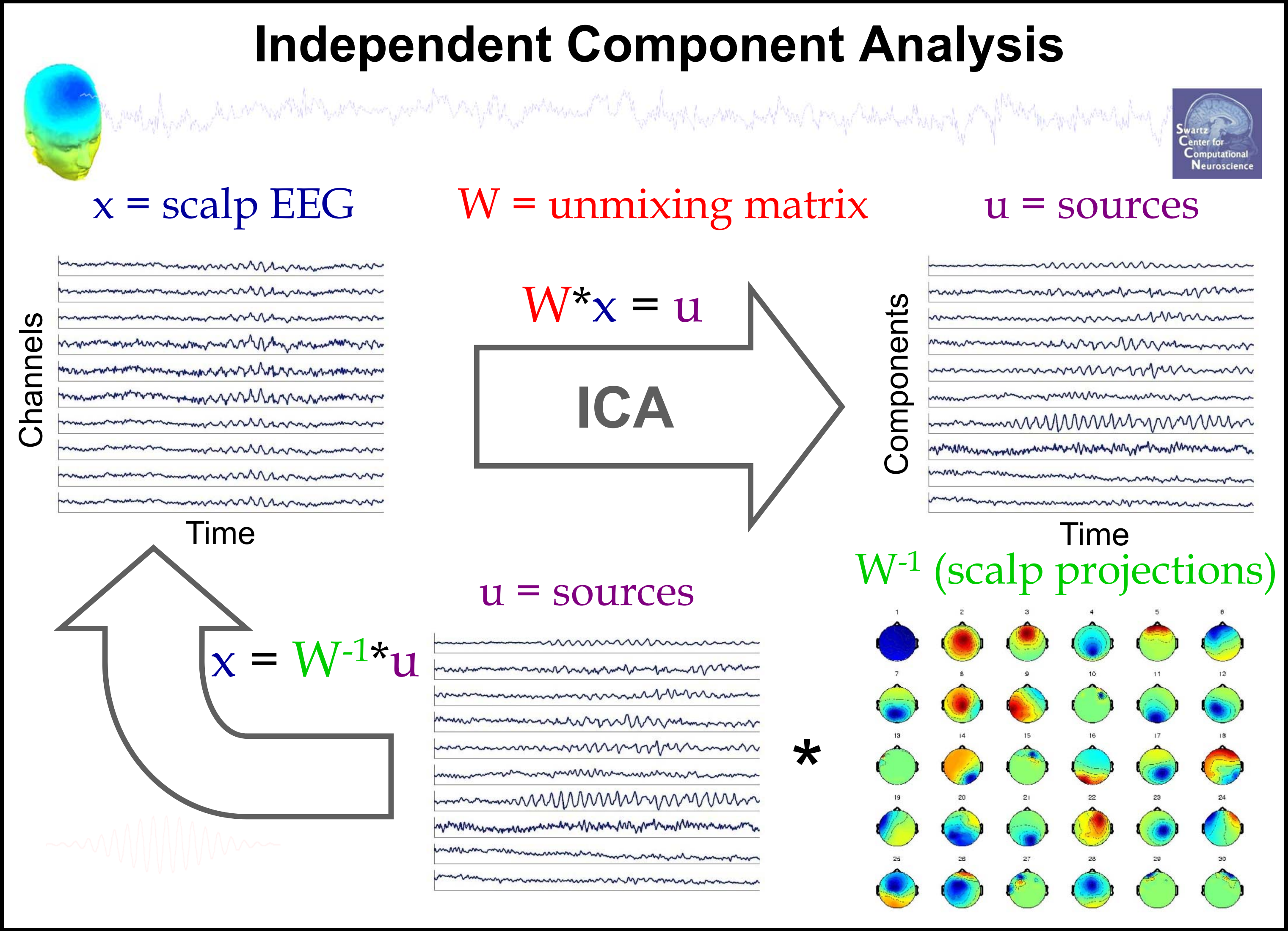
$\mathbf{A} \in \mathbb{R}^{M \times M}$

$\mathbf{x(t) = As(t)}$

$\mathbf{y(t)=Wx(t)}$

$\mathbf{s(t)}$

[redacted]



Independent Component Analysis

x = scalp EEG

W = unmixing matrix

u = sources

$W*x = u$

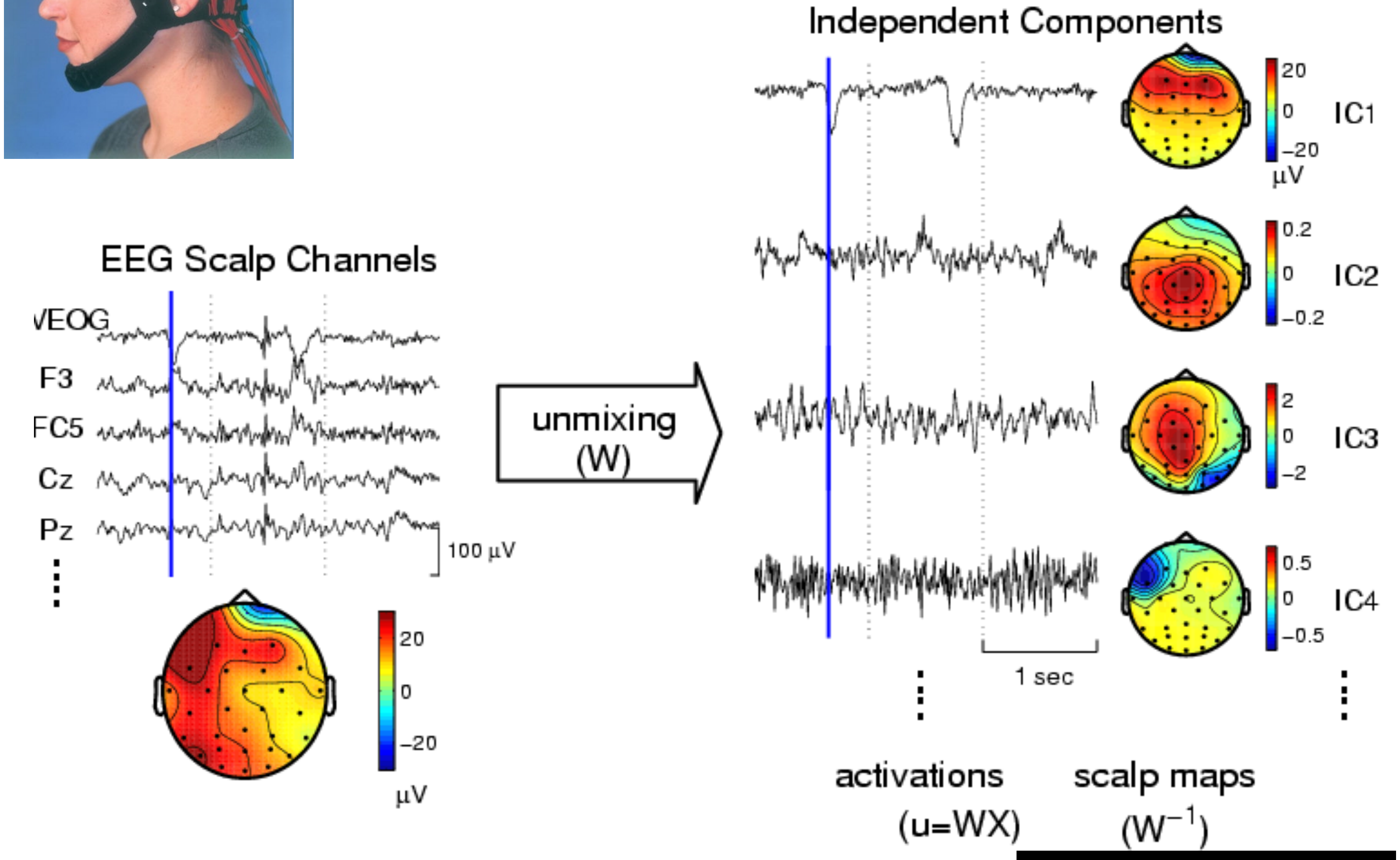
ICA

u = sources

$x = W^{-1}*u$

W^{-1} (scalp projections)

ICA decomposition



EEG Scalp Channels

unmixing
(W)

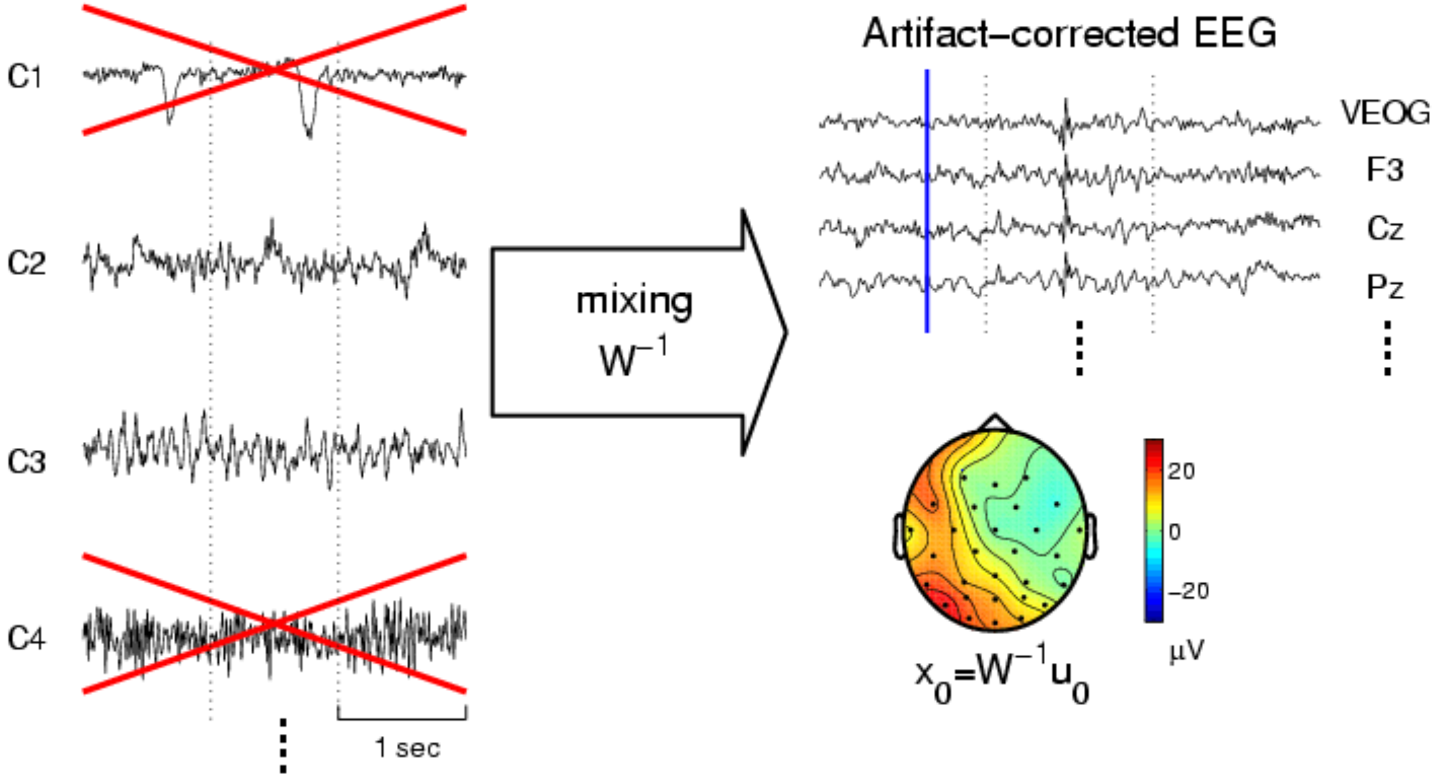
Independent Components

activations
(u=WX)

scalp maps
(W^{-1})

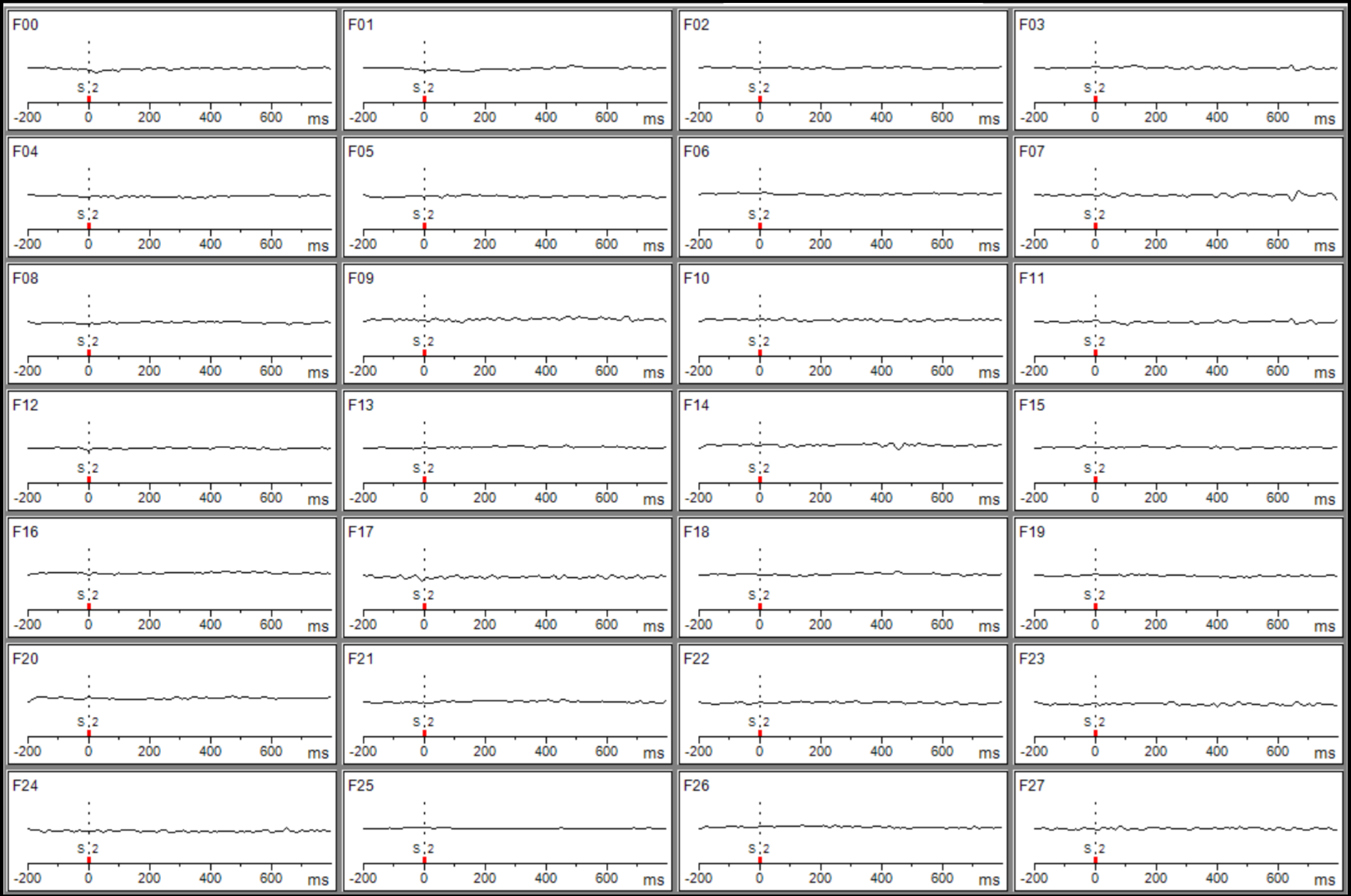
[redacted]

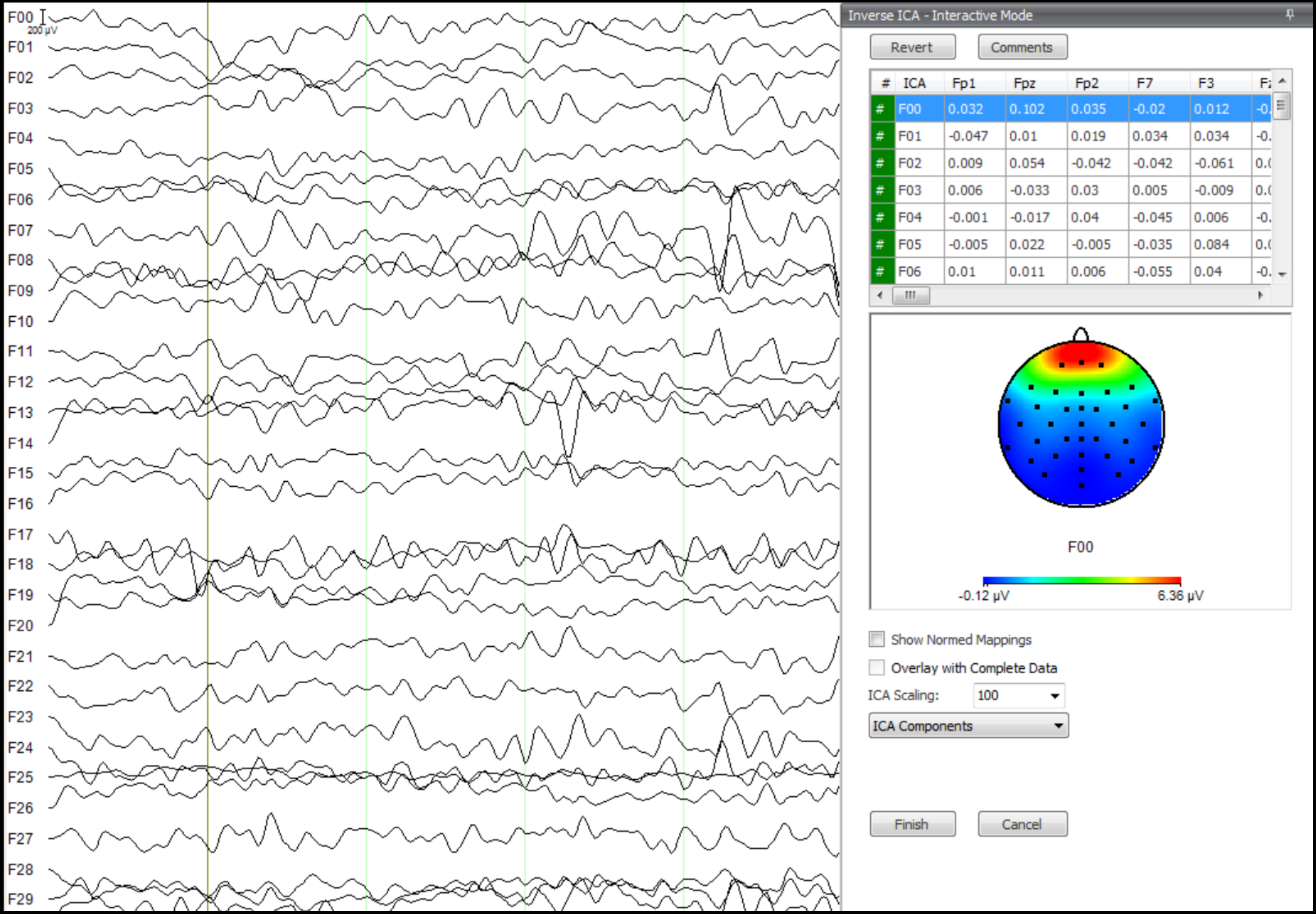
Summed Projection of Selected Components



[redacted]

What It Looks Like


F00
S 2
-200 0 200 400 600 ms
F01
S 2
-200 0 200 400 600 ms
F02
S 2
-200 0 200 400 600 ms
F03
S 2
-200 0 200 400 600 ms
F04
S 2
-200 0 200 400 600 ms
F05
S 2
-200 0 200 400 600 ms
F06
S 2
-200 0 200 400 600 ms
F07
S 2
-200 0 200 400 600 ms
F08
S 2
-200 0 200 400 600 ms
F09
S 2
-200 0 200 400 600 ms
F10
S 2
-200 0 200 400 600 ms
F11
S 2
-200 0 200 400 600 ms
F12
S 2
-200 0 200 400 600 ms
F13
S 2
-200 0 200 400 600 ms
F14
S 2
-200 0 200 400 600 ms
F15
S 2
-200 0 200 400 600 ms
F16
S 2
-200 0 200 400 600 ms
F17
S 2
-200 0 200 400 600 ms
F18
S 2
-200 0 200 400 600 ms
F19
S 2
-200 0 200 400 600 ms
F20
S 2
-200 0 200 400 600 ms
F21
S 2
-200 0 200 400 600 ms
F22
S 2
-200 0 200 400 600 ms
F23
S 2
-200 0 200 400 600 ms
F24
S 2
-200 0 200 400 600 ms
F25
S 2
-200 0 200 400 600 ms
F26
S 2
-200 0 200 400 600 ms
F27
S 2
-200 0 200 400 600 ms



Inverse ICA - Interactive Mode

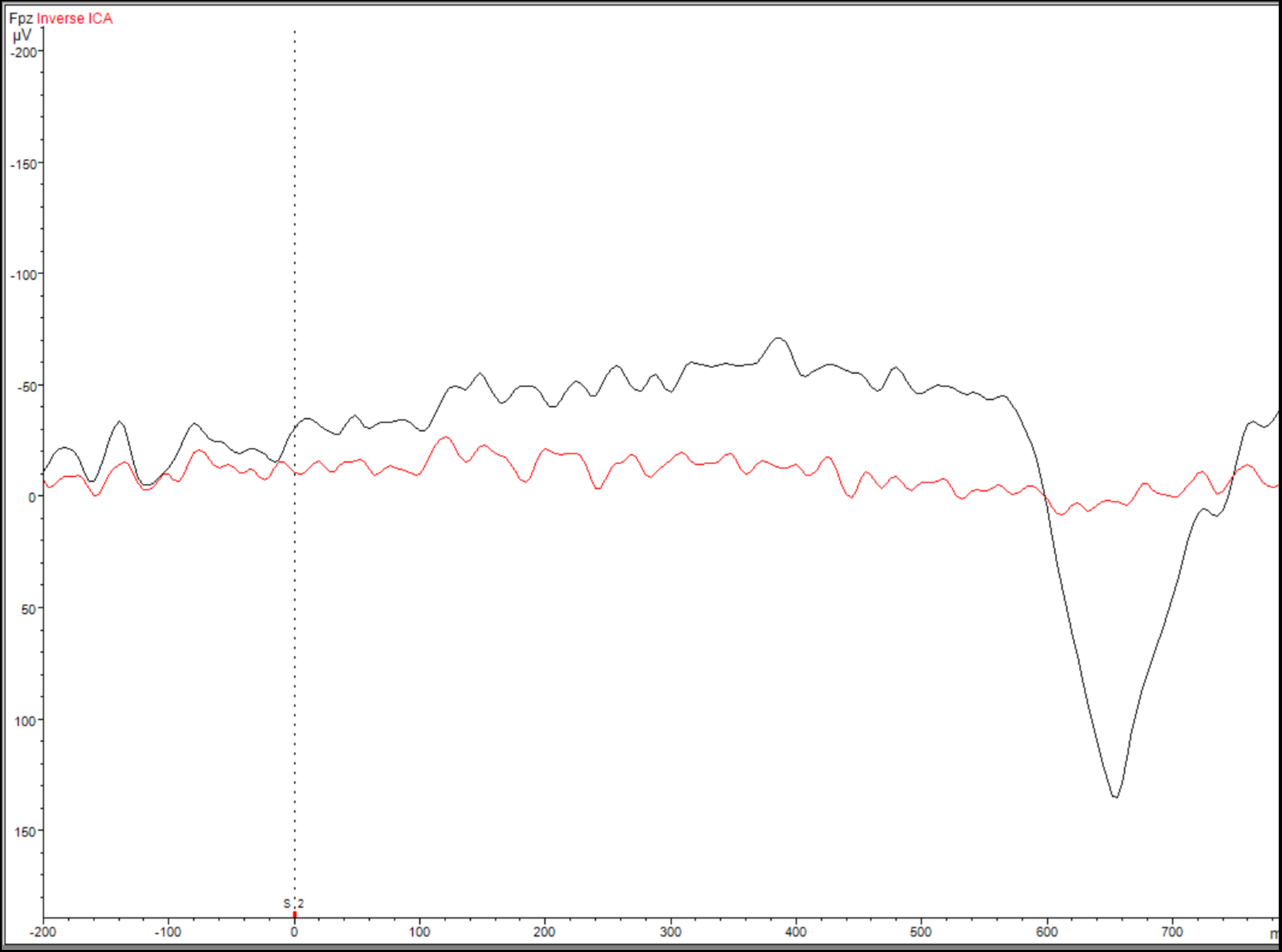
#	ICA	Fp1	Fpz	Fp2	F7	F3	F
#	F00	0.032	0.102	0.035	-0.02	0.012	-0.
#	F01	-0.047	0.01	0.019	0.034	0.034	-0.
#	F02	0.009	0.054	-0.042	-0.042	-0.061	0.0
#	F03	0.006	-0.033	0.03	0.005	-0.009	0.0
#	F04	-0.001	-0.017	0.04	-0.045	0.006	-0.
#	F05	-0.005	0.022	-0.005	-0.035	0.084	0.0
#	F06	0.01	0.011	0.006	-0.055	0.04	-0.

☐ Show Normed Mappings

☐ Overlay with Complete Data

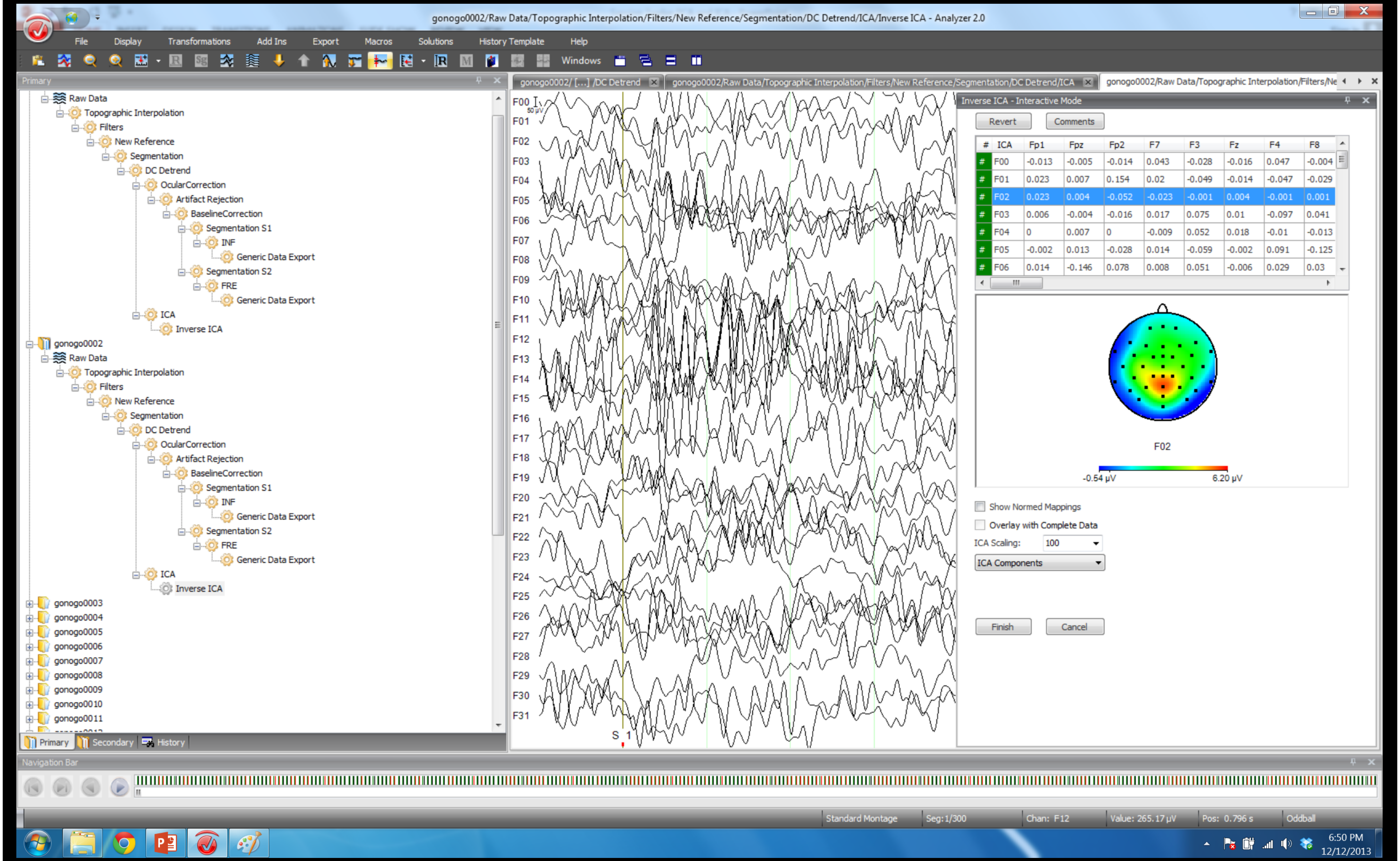
ICA Scaling: 100

ICA Components


Fpz Inverse ICA
µV
-200
-150
-100
-50
0
50
100
150
S 2
-200
-100
0
100
200
300
400
500
600
700
m

ICA and EEG

More recently it has been proposed to do the reverse, only keep components with a topography that is of interest.



gonogo0002/Raw Data/Topographic Interpolation/Filters/New Reference/Segmentation/DC Detrend/ICA/Inverse ICA - Analyzer 2.0

Inverse ICA - Interactive Mode

#	ICA	Fp1	Fpz	Fp2	F7	F3	Fz	F4	F8
#	F00	-0.013	-0.005	-0.014	0.043	-0.028	-0.016	0.047	-0.004
#	F01	0.023	0.007	0.154	0.02	-0.049	-0.014	-0.047	-0.029
#	F02	0.023	0.004	-0.052	-0.023	-0.001	0.004	-0.001	0.001
#	F03	0.006	-0.004	-0.016	0.017	0.075	0.01	-0.097	0.041
#	F04	0	0.007	0	-0.009	0.052	0.018	-0.01	-0.013
#	F05	-0.002	0.013	-0.028	0.014	-0.059	-0.002	0.091	-0.125
#	F06	0.014	-0.146	0.078	0.008	0.051	-0.006	0.029	0.03

F02

-0.54 µV 6.20 µV

☐ Show Normed Mappings

☐ Overlay with Complete Data

ICA Scaling: 100

ICA Components

Standard Montage | Seg: 1/300 | Chan: F12 | Value: 265.17 µV | Pos: 0.796 s | Oddball

Continuous or Segmented Data

ICA will work on continuous or segmented data.

If you want to remove ocular artifacts continuous data is fine but you may want to train the ICA on a subset of the data.

If you use full data then looking for components of interest can be very difficult.

Continuous or Segmented Data

If you want to use ICA on segmented data you need to ensure you use a sufficient amount of data that does include artifacts.

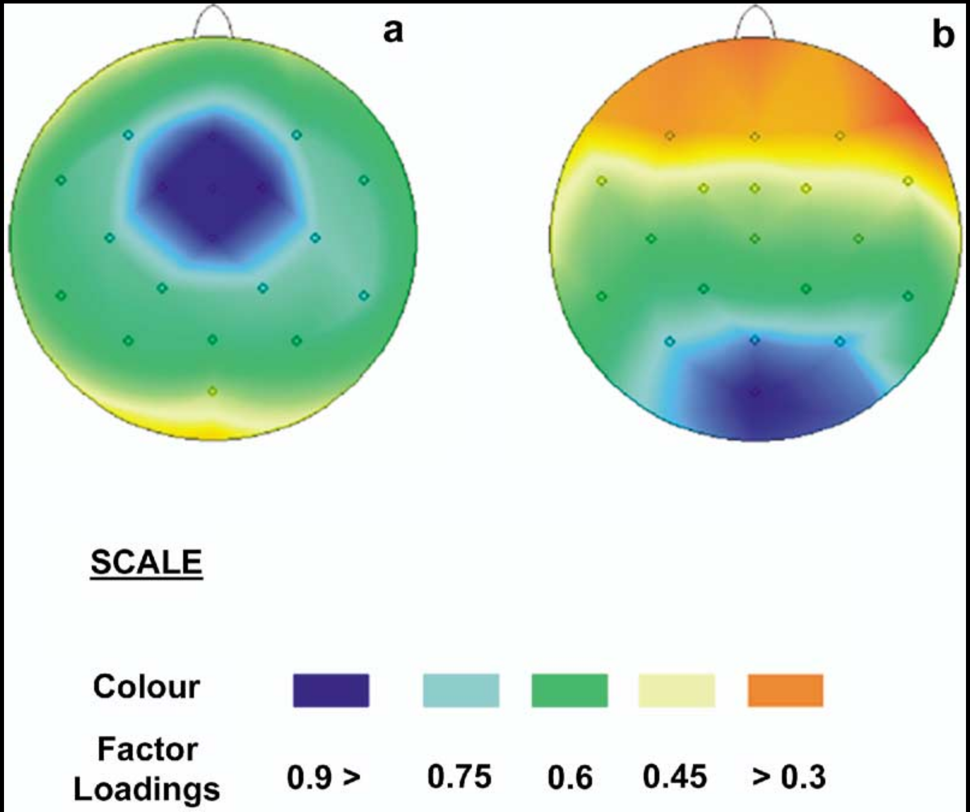
ICA Demonstration

PCA

The data we are working with is very complex and we are making some very broad and simple assumptions to estimate properties of the data and/or correct/adjust/remove bits of the data.

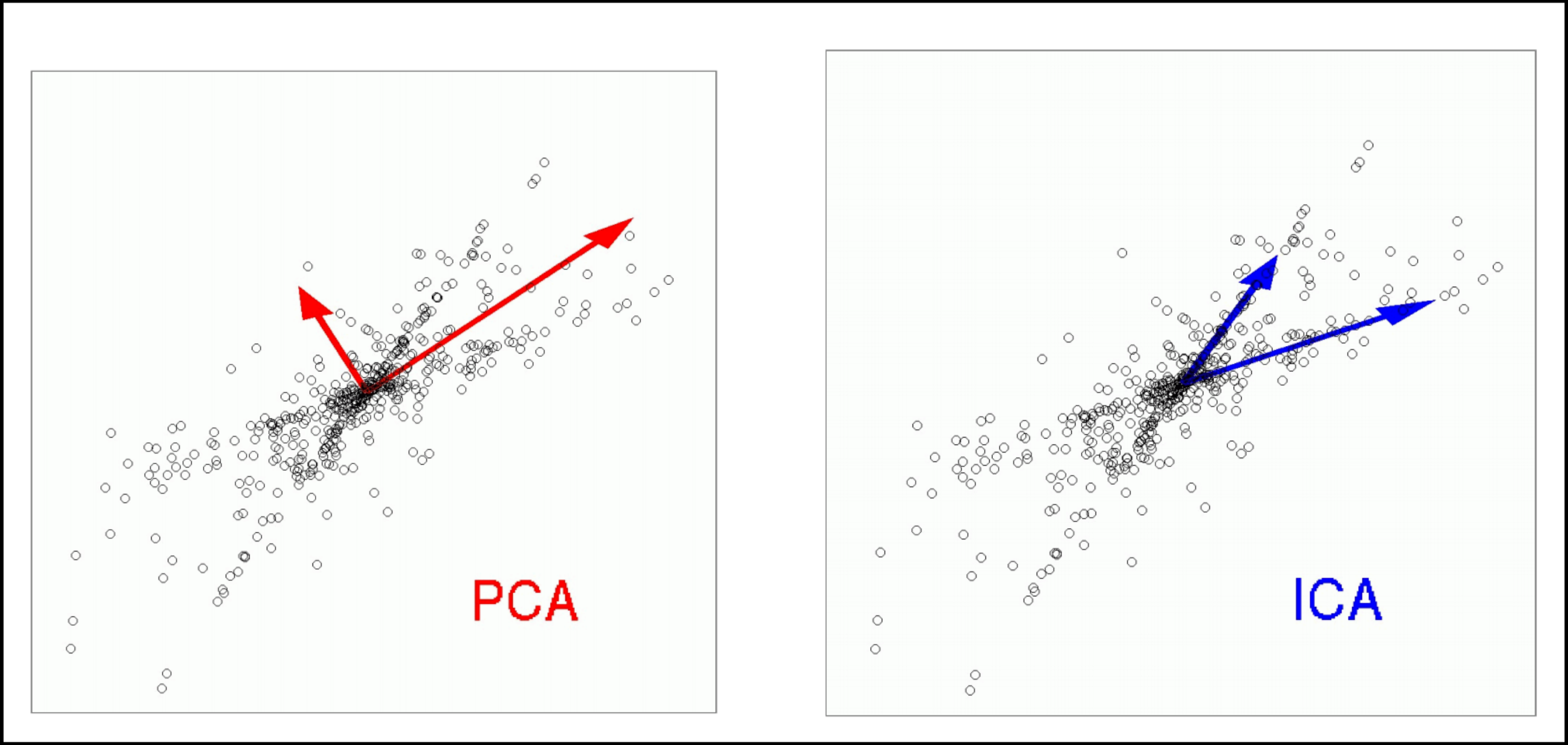
What do they do?

PCA reduces the data into a series of "components".



PCA

Utilizes the first and second moments of the measured data, hence relying heavily on Gaussian features.


PCA
ICA

PCA and EEG

PCA is typically used in EEG research to identify spatial, temporal, and/or spatial-temporal components in the data.

At the end of the day…

DIMENSION REDUCTION

As opposed to having a bunch of channels/time points you have a "spatial component" or a "temporal component"

Dimension Reduction
Before PCA

Channels x Time x Conditions x Participants

4 Dimensions

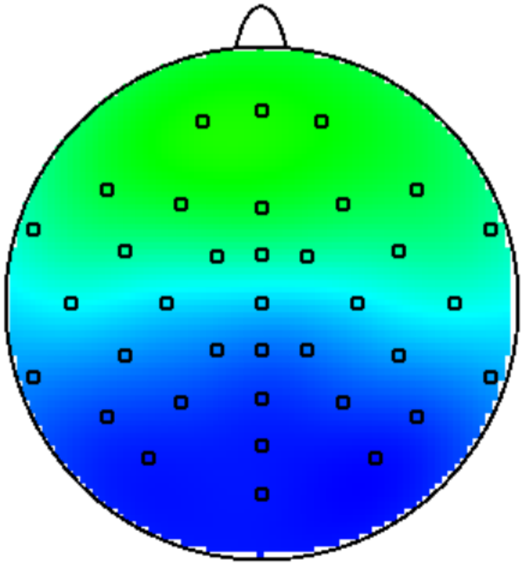
Dimension Reduction
After Spatial PCA

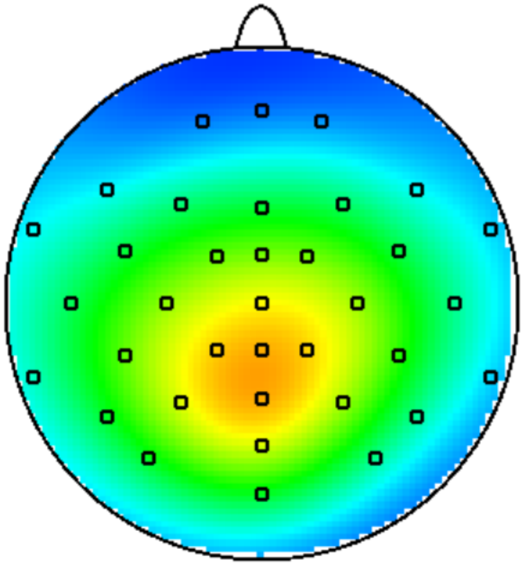
Time x Conditions x Participants

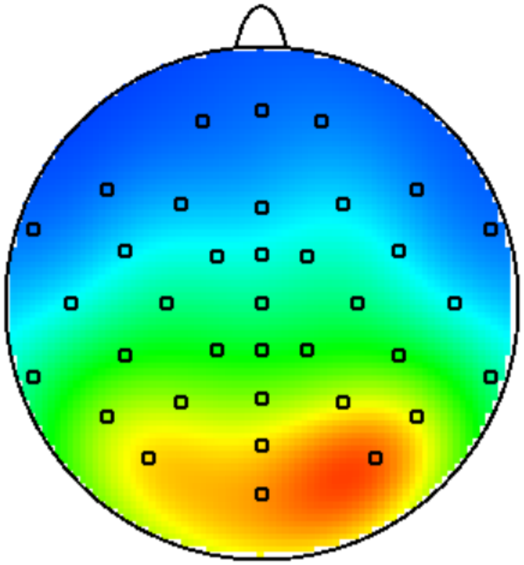
3 Dimensions

for each Spatial Factor

Spatial Factors



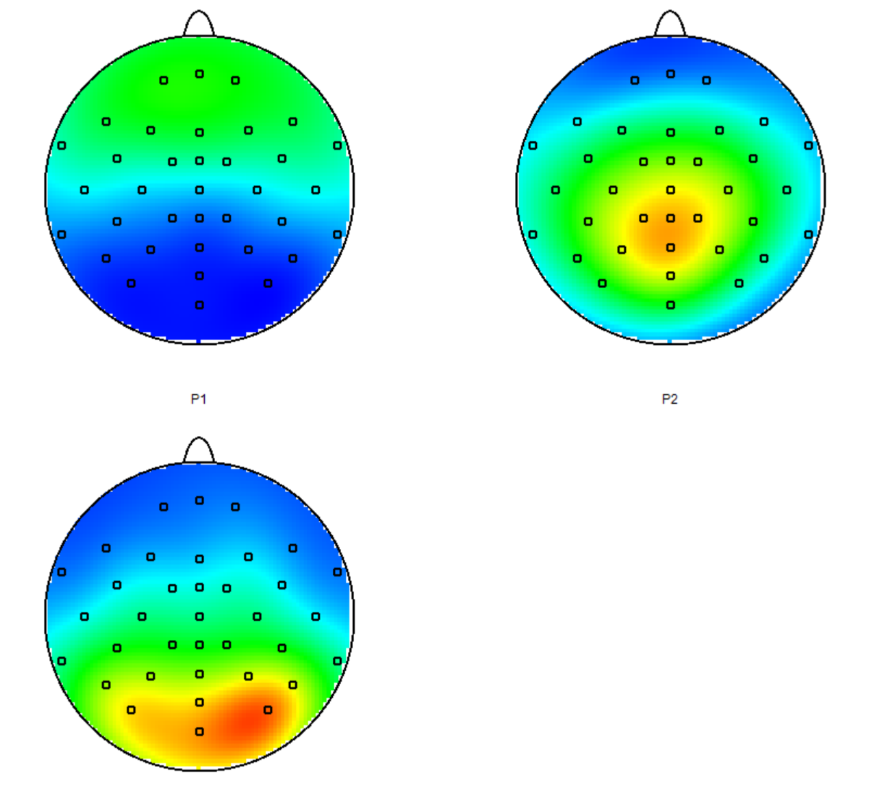




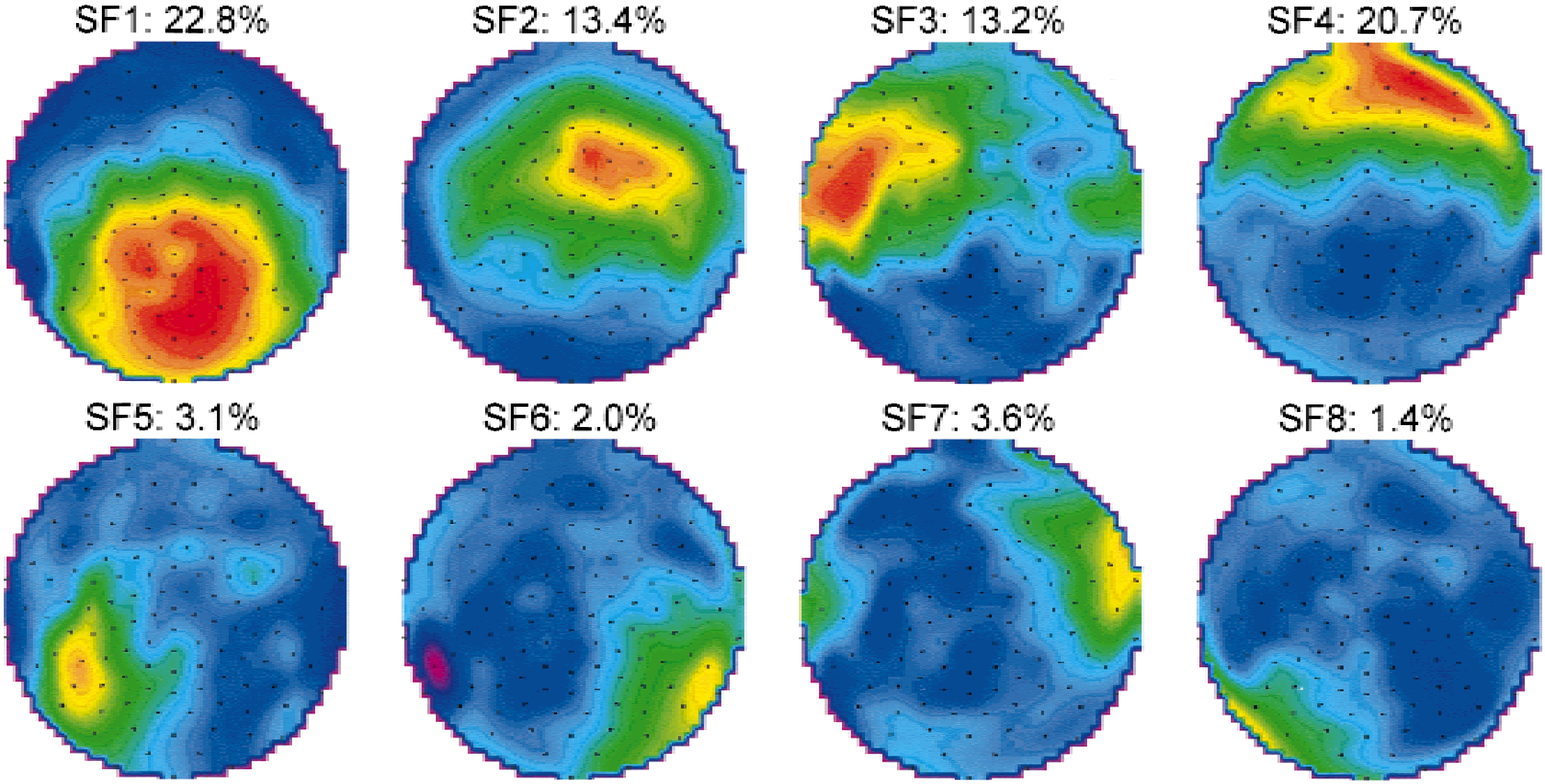
Spatial Factors:
Each factor will have loadings or weights that when plotted topographically show the spatial components.

What is a Spatial Component?

Component	Fpz	Fz	FCz	Cz	Cpz	Pz	POz	Oz
1	0.1	0.4	0.9	0.8	0.4	0.3	0.2	0.1
2	0.1	0.1	0.1	0.1	0.4	0.7	0.5	0.2
3	0.9	0.5	0.2	0.1	0.1	0.1	0.1	0.1



Spatial Factor Loadings (Virtual Electrodes)



SF1: 22.8%

SF2: 13.4%

SF3: 13.2%

SF4: 20.7%

SF5: 3.1%

SF6: 2.0%

SF7: 3.6%

SF8: 1.4%

But how is the data reduced?

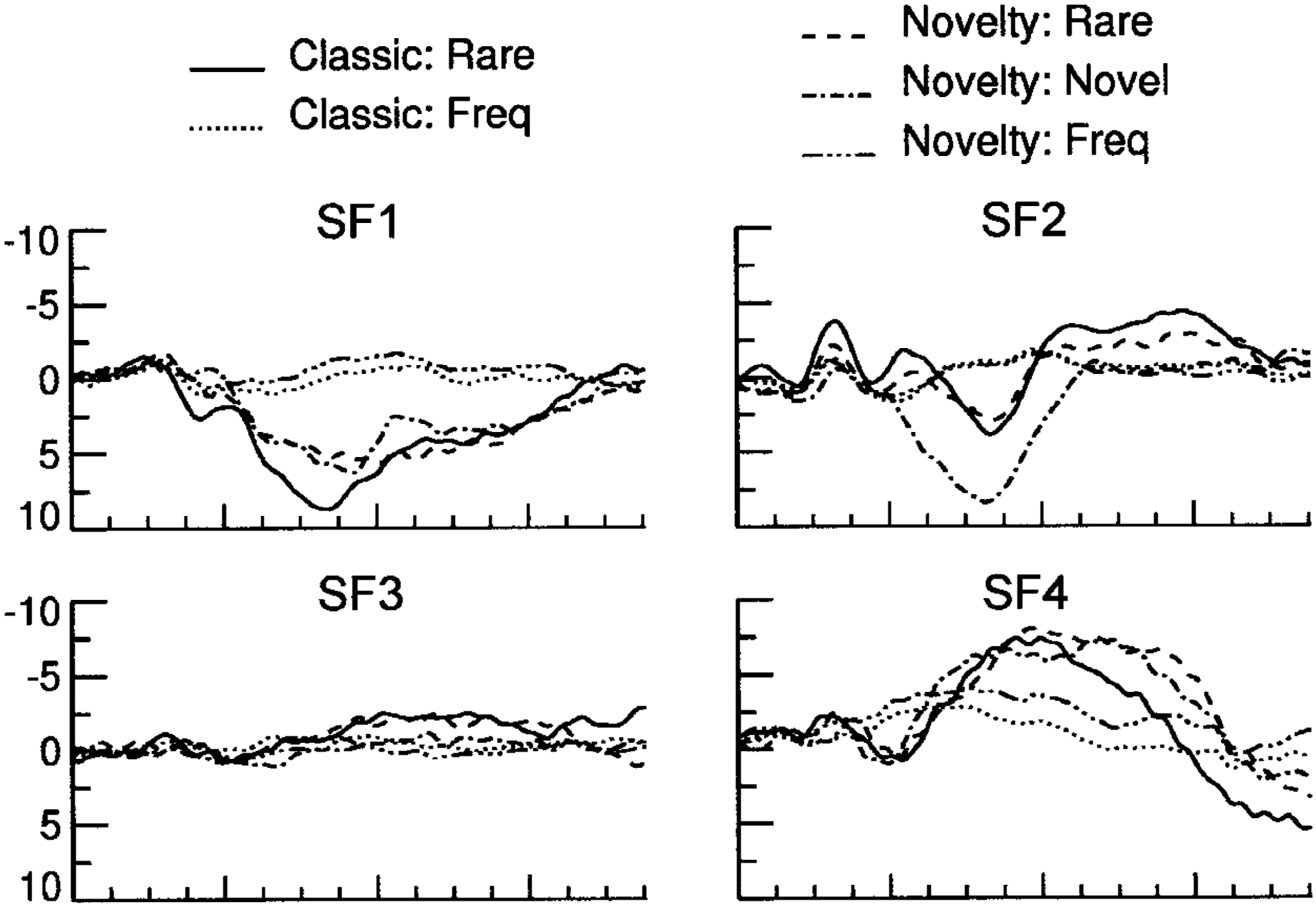
The component weighting matrix (loadings) are multiplied with the data to create component scores.

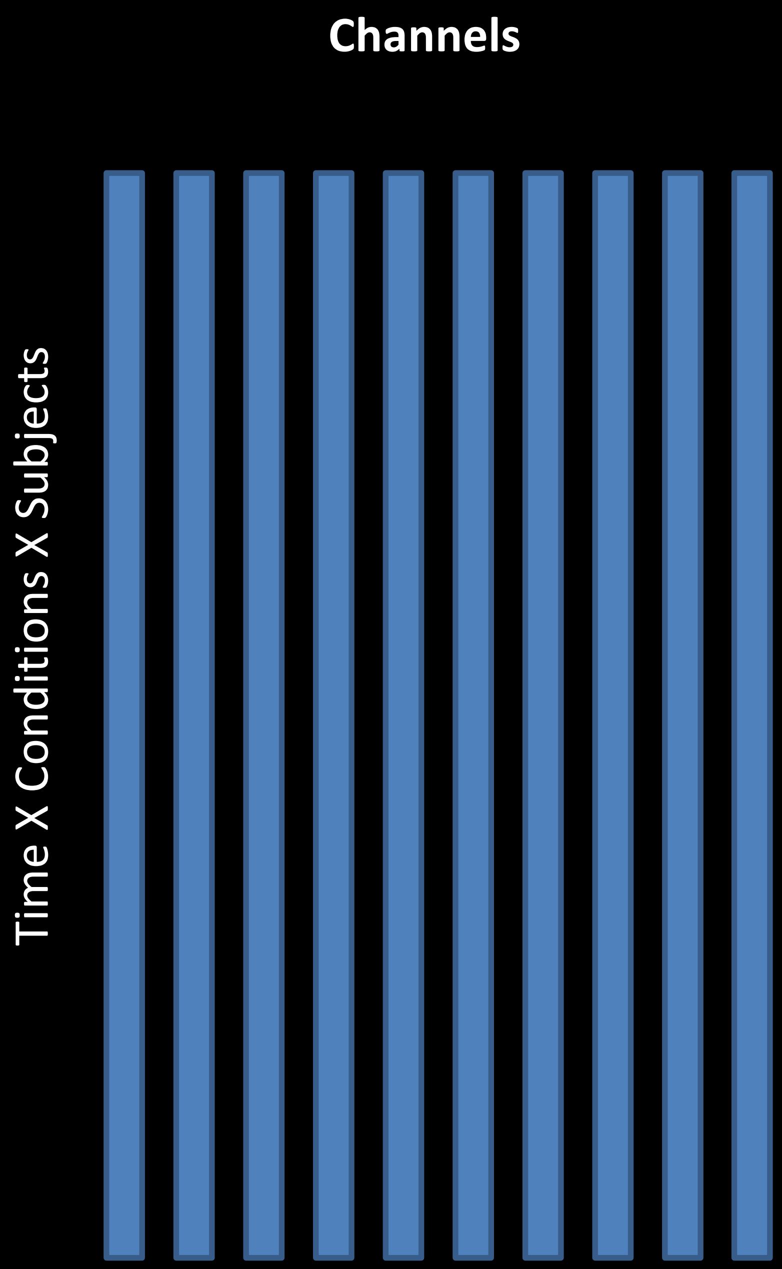
Think of it this way, each point in time for each condition for each subject would be weighted by that component relative to the original data value present.

Virtual ERPs

Once this is done, you can reshape the scores back into the original data format, but with the dimensionality greatly reduced.

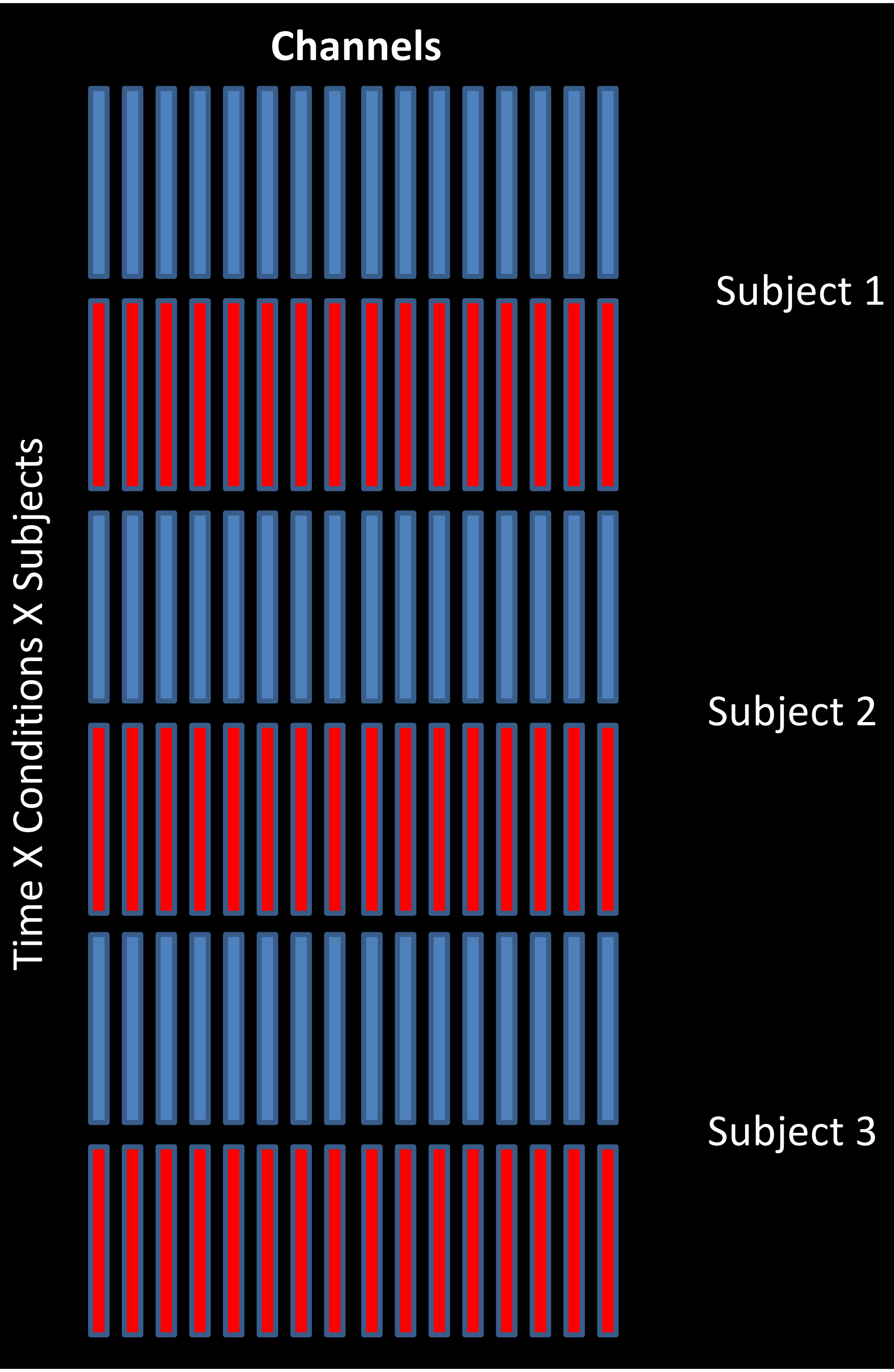
Virtual ERPs: “Attend” Tasks (SF1-8)





Channels

Time X Conditions X Subjects



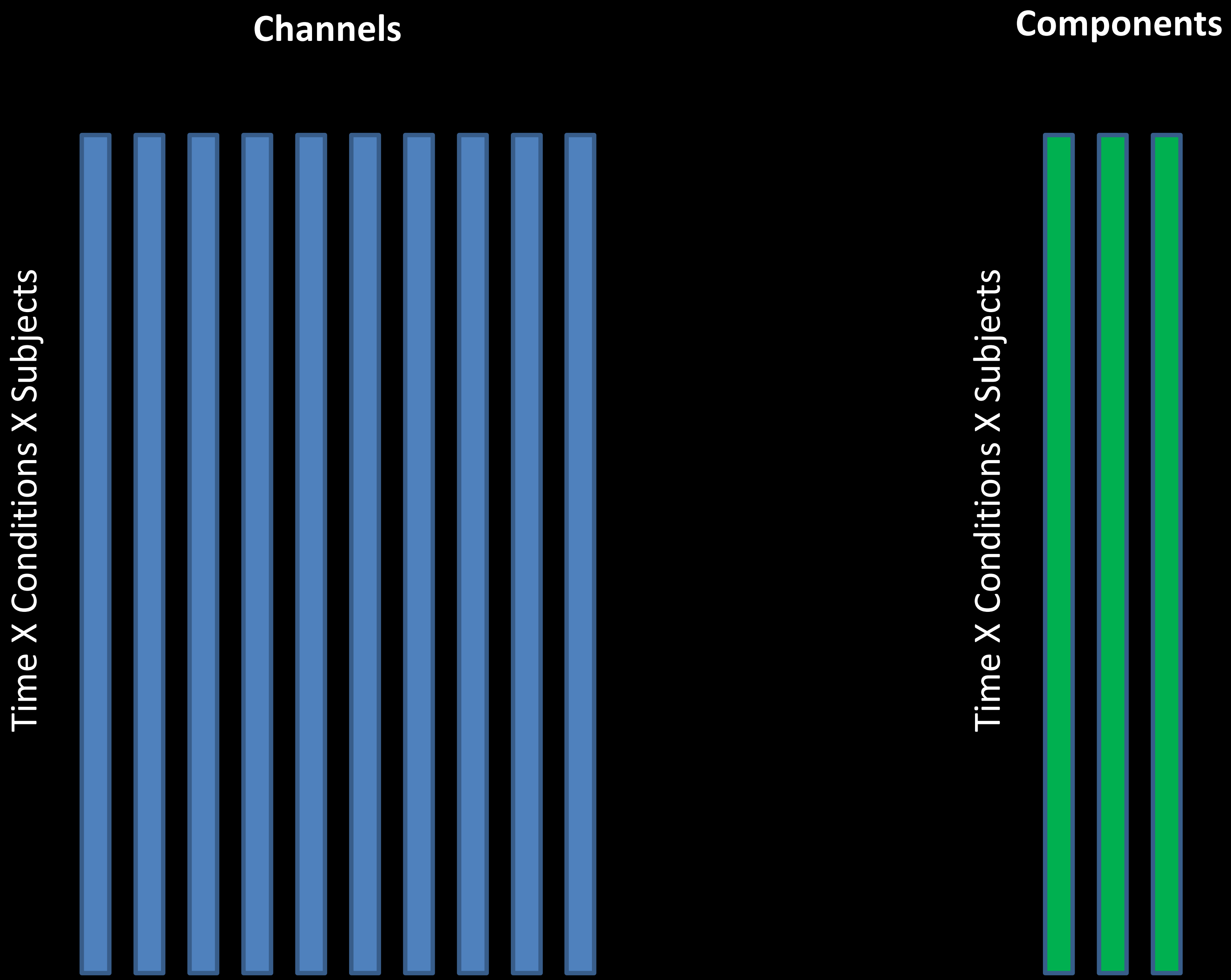
Channels

Time X Conditions X Subjects

Subject 1

Subject 2

Subject 3

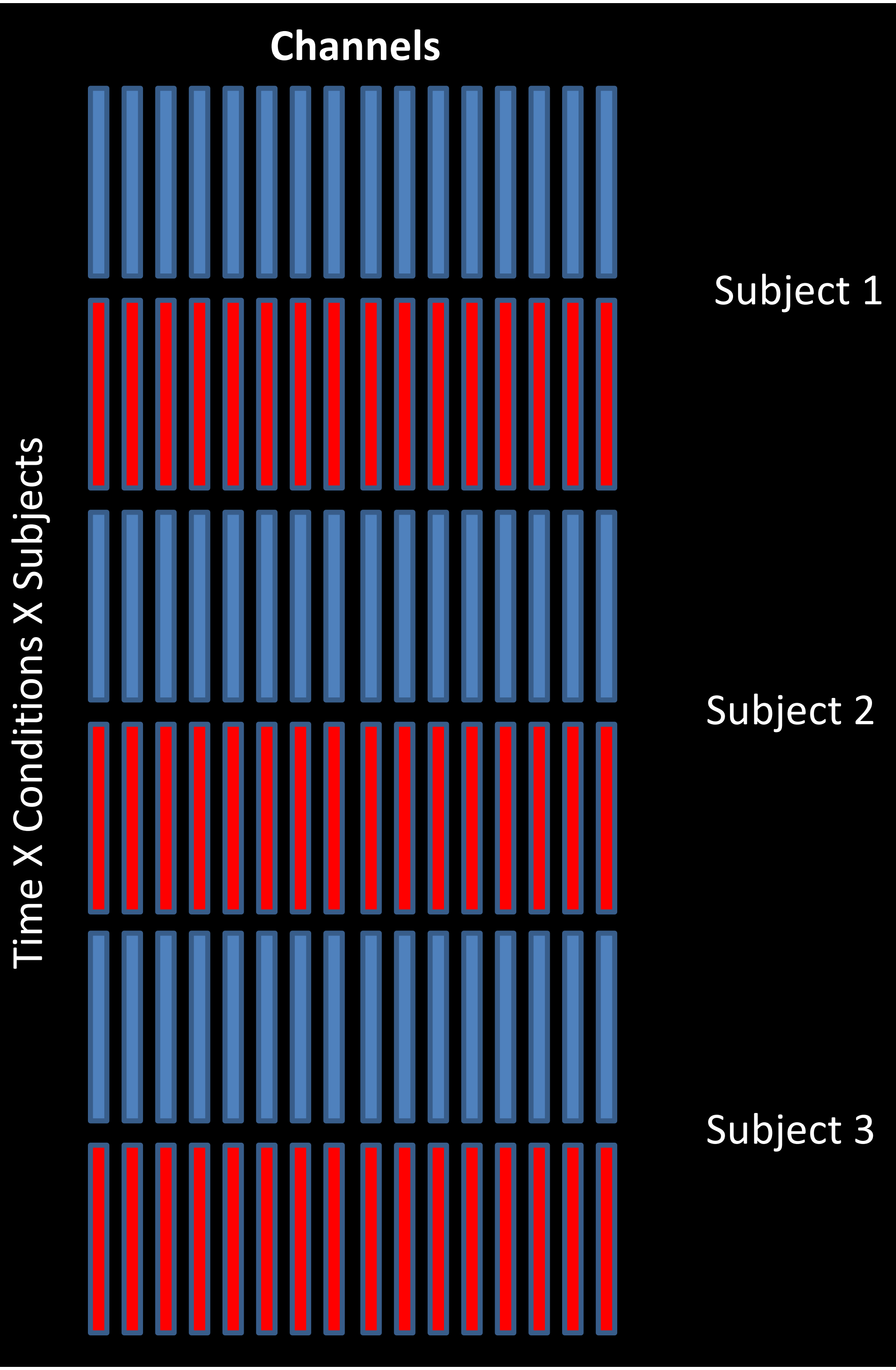


Channels

Time X Conditions X Subjects

Components

Time X Conditions X Subjects



Channels

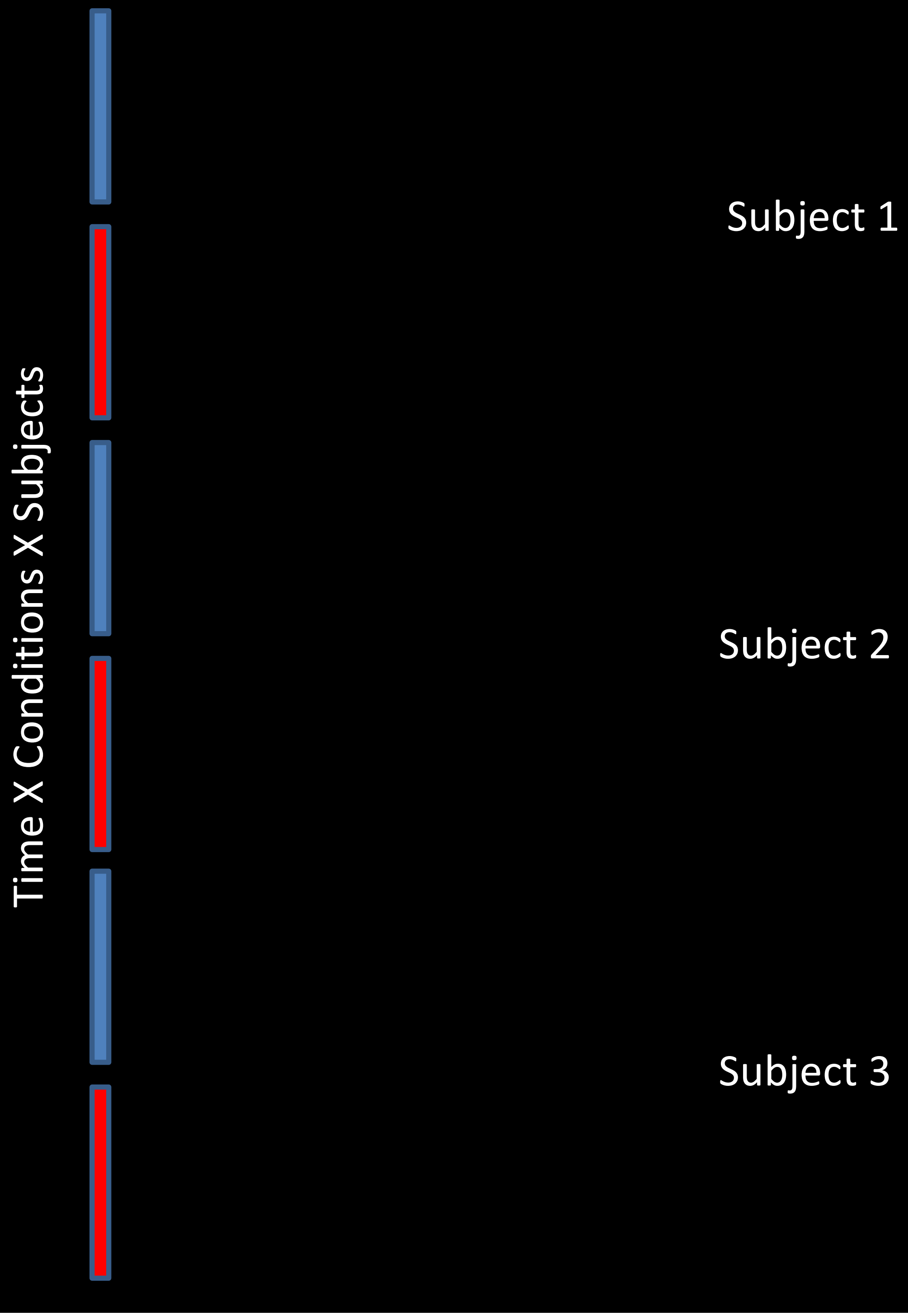
Time X Conditions X Subjects

Subject 1

Subject 2

Subject 3

Component 1 Scores



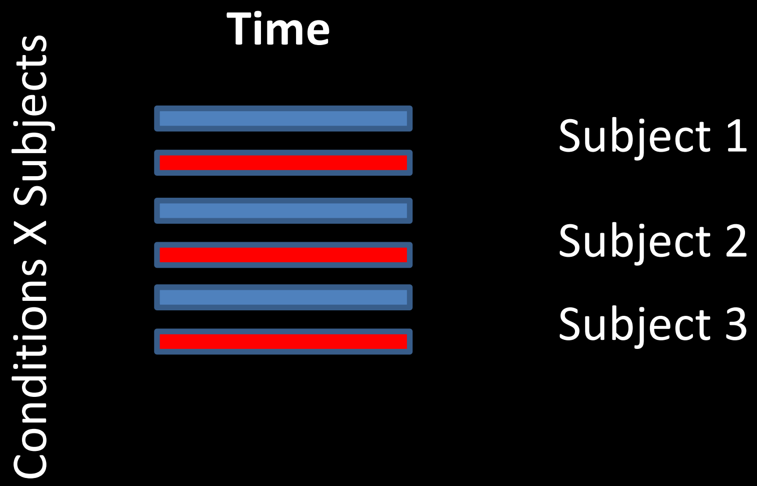
Time X Conditions X Subjects

Subject 1

Subject 2

Subject 3

Virtual ERPs



Time

Conditions X Subjects

Subject 1

Subject 2

Subject 3

Temporal PCA

The same logic as Spatial PCA but with Time Points as the DV.

Dimension Reduction
Before PCA

Channels x Time x Conditions x Participants

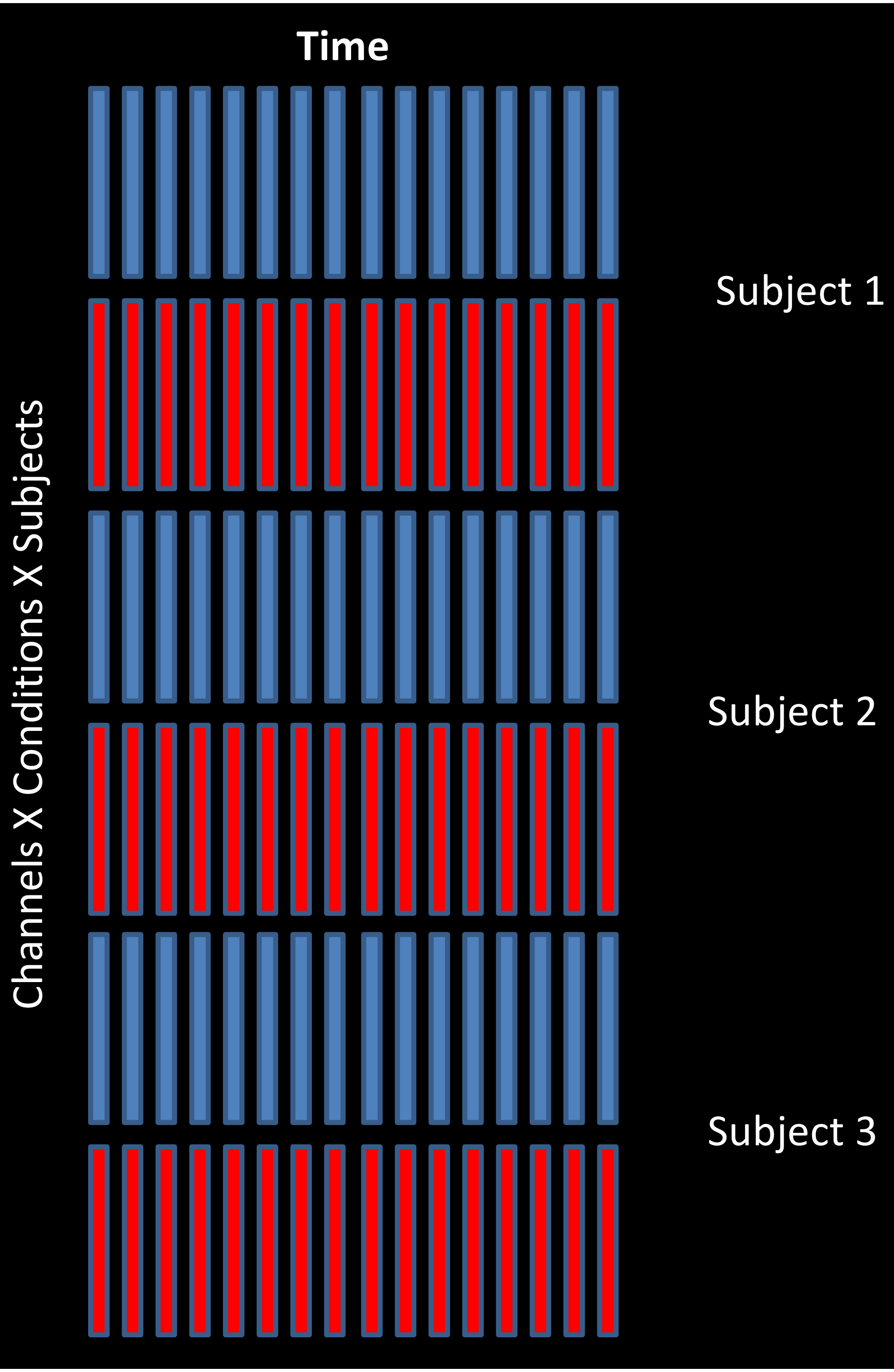
4 Dimensions

Dimension Reduction
After Temporal PCA

Channels x Conditions x Participants

3 Dimensions

for each Temporal Factor



Time

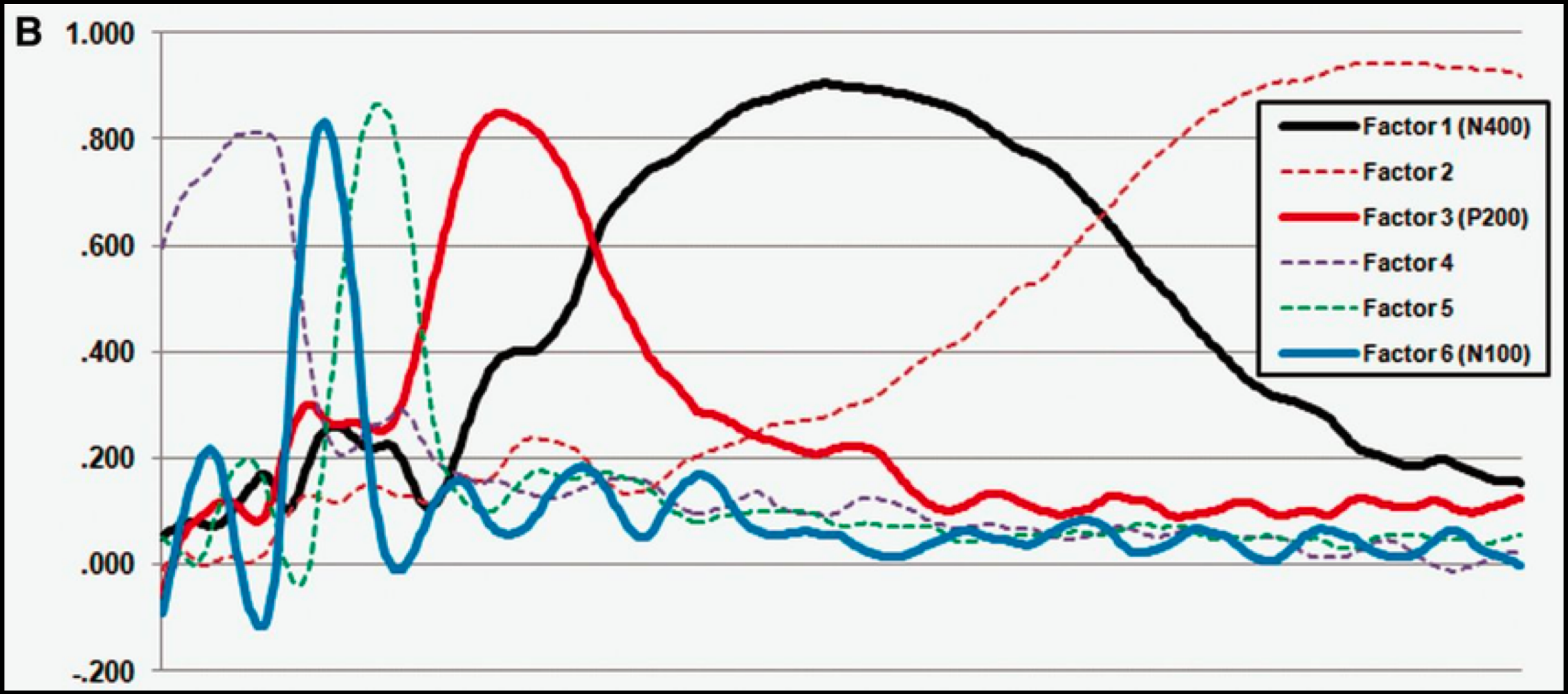
Channels X Conditions X Subjects

Subject 1

Subject 2

Subject 3

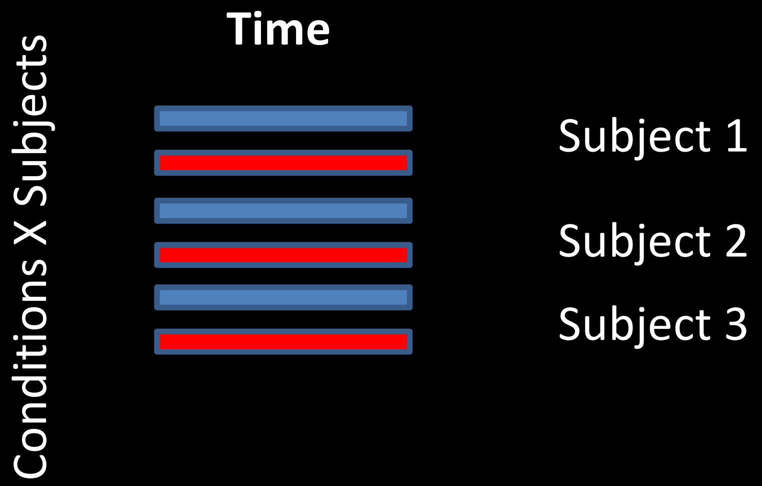
Temporal Factor Loadings



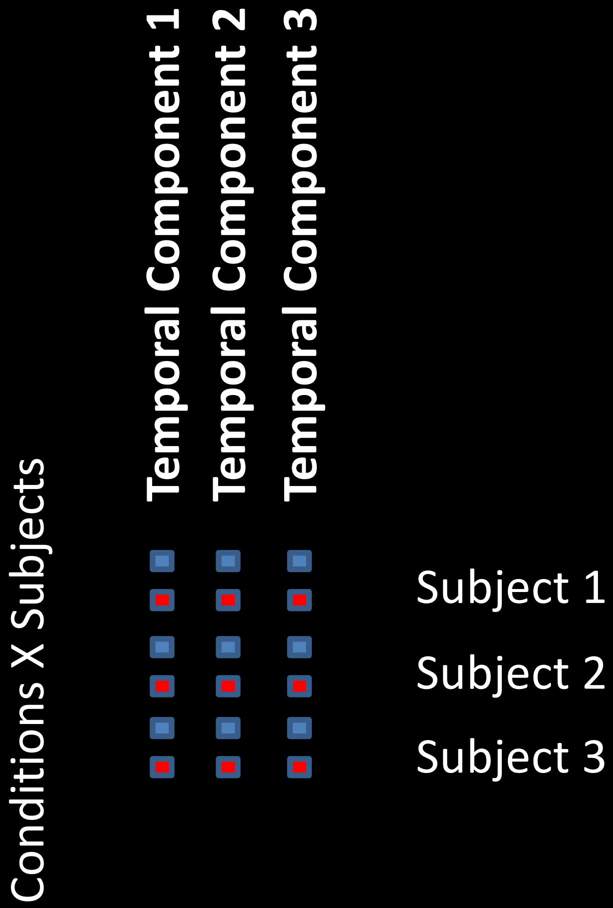
Spatial – Temporal
or
Temporal – Spatial PCA

The logic is simple – you run a PCA on either the spatial or temporal dimension first and then you run a second PCA on the virtual data from one of the factors from the first PCA to reduced the dimensionality further.

Virtual ERPs



The second PCA would collapse the time dimension to a series of factors.
For each factor you would have a score. For example, a factor might be maximal between 200 to 300 ms.
As such, when you reshape the data one last time, you would have a single score for each participant for each condition. The score reflects the value of a single spatial and temporal compoment.



Temporal Component 1

Temporal Component 2

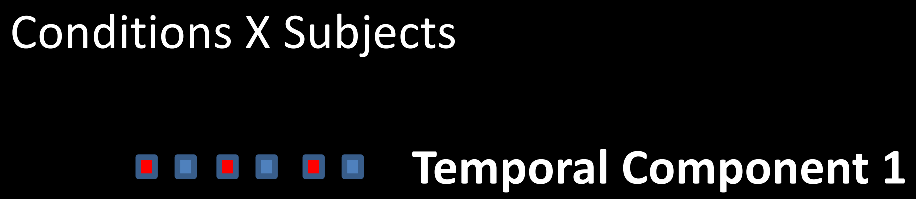
Temporal Component 3

Conditions X Subjects

Subject 1

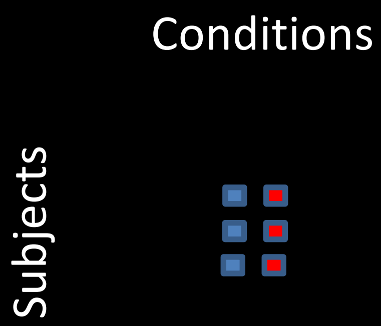
Subject 2

Subject 3



Conditions X Subjects

Temporal Component 1

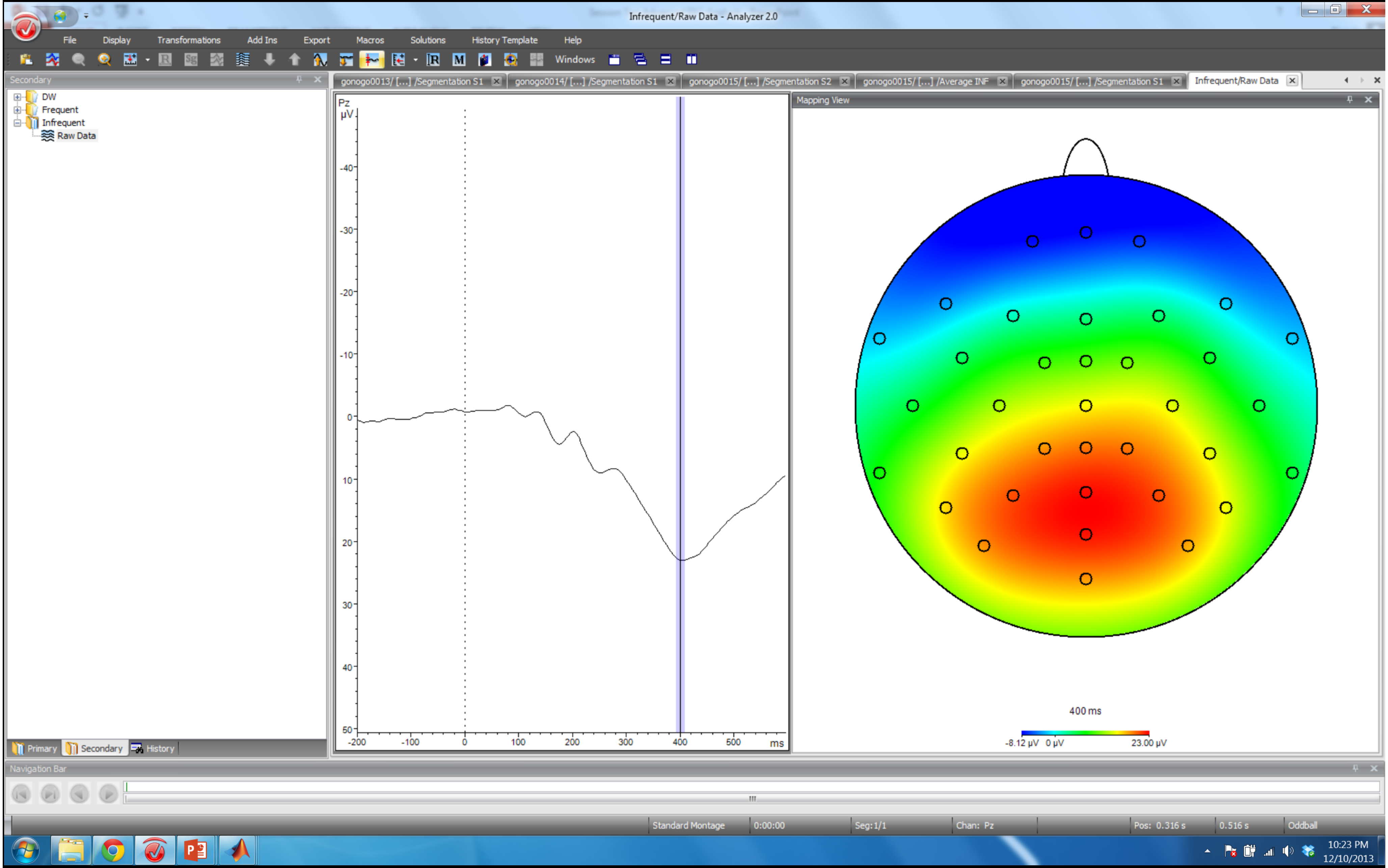


Conditions

Subjects

Source Analysis and a Few Other Tricks

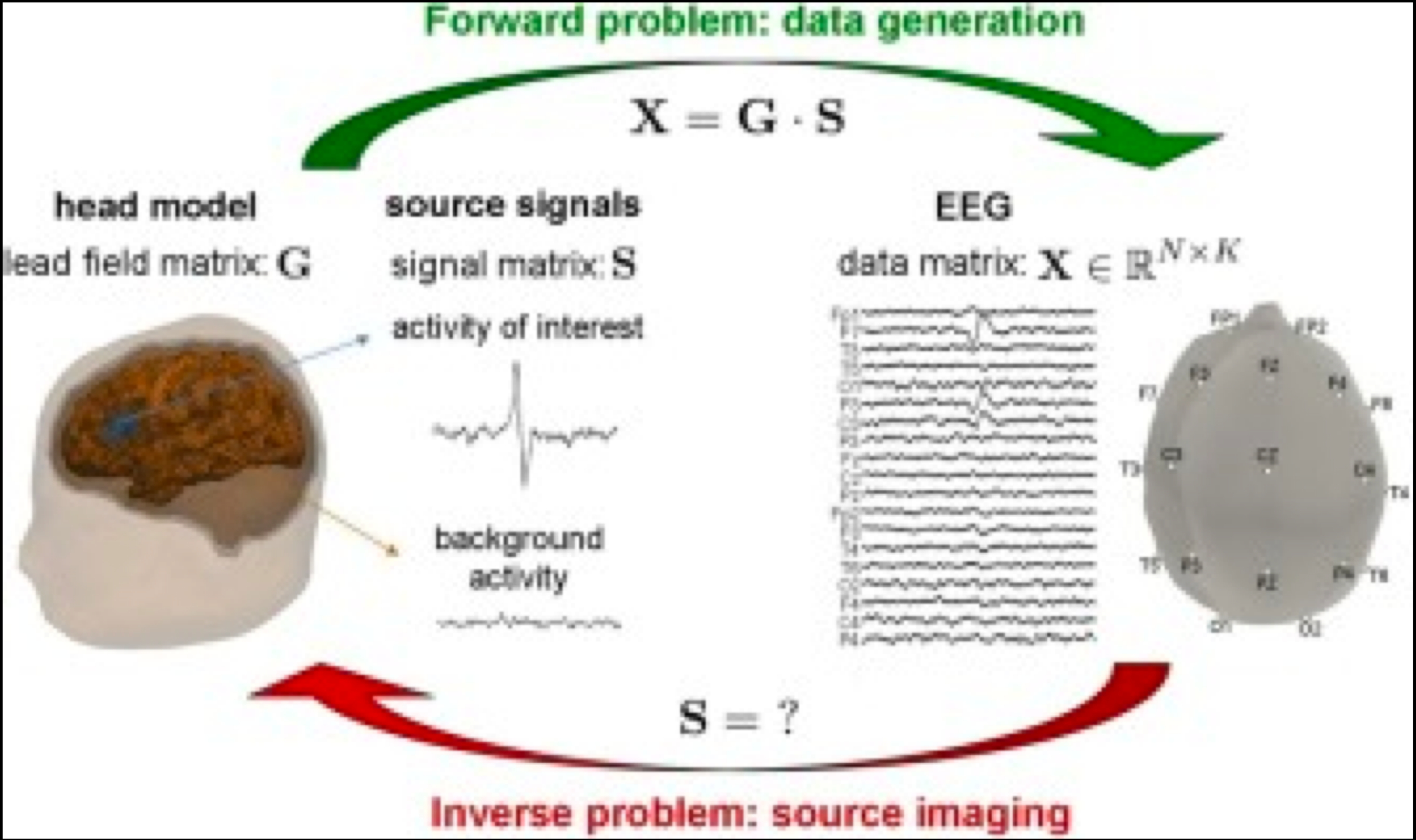
Source Analysis


Infrequent/Raw Data - Analyzer 2.0
File
Display
Transformations
Add Ins
Export
Macros
Solutions
History Template
Help
Windows
Secondary
DW
Frequent
Infrequent
Raw Data
gonogo0013/ [...] /Segmentation S1
gonogo0014/ [...] /Segmentation S1
gonogo0015/ [...] /Segmentation S2
gonogo0015/ [...] /Average INF
gonogo0015/ [...] /Segmentation S1
Infrequent/Raw Data
Pz
µV
-40
-30
-20
-10
0
10
20
30
40
50
-200
-100
0
100
200
300
400
500
ms
Mapping View
400 ms
-8.12 µV
0 µV
23.00 µV
Primary
Secondary
History
Navigation Bar
Standard Montage
0:00:00
Seg: 1/1
Chan: Pz
Pos: 0.316 s
0.516 s
Oddball
10:23 PM
12/10/2013

The Inverse Problem

Simply put, because we do not know the number of dipoles at any given point in time, there are an infinite number of potential solutions for a given scalp topography.

Source localization techniques try to get around this by using certain assumptions.



Forward problem: data generation

$$\mathbf{X} = \mathbf{G} \cdot \mathbf{S}$$

head model

lead field matrix: $\mathbf{G}$

source signals

signal matrix: $\mathbf{S}$

activity of interest

background activity

EEG

data matrix: $\mathbf{X} \in \mathbb{R}^{N \times K}$

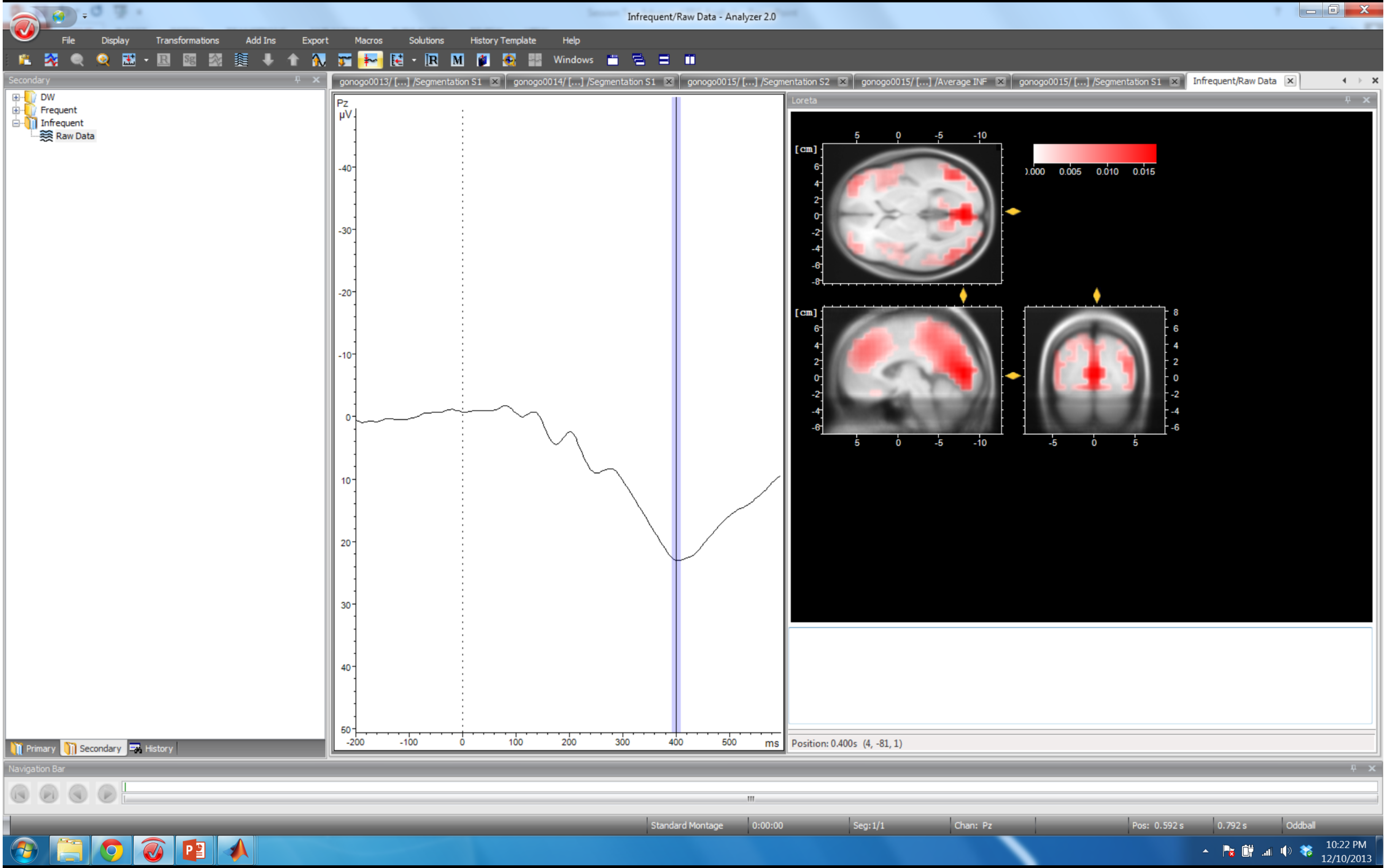
$$\mathbf{S} = ?$$

Inverse problem: source imaging

Discrete vs Distributed Source Solutions

Discrete source solutions focus on dipoles.

Distributed source solutions use dipoles but "consider" whole brain activity.


Infrequent/Raw Data - Analyzer 2.0
File
Display
Transformations
Add Ins
Export
Macros
Solutions
History Template
Help
Windows
Secondary
DW
Frequent
Infrequent
Raw Data
gonogo0013/ [...] /Segmentation S1
gonogo0014/ [...] /Segmentation S1
gonogo0015/ [...] /Segmentation S2
gonogo0015/ [...] /Average INF
gonogo0015/ [...] /Segmentation S1
Infrequent/Raw Data
Pz
µV
-40
-30
-20
-10
0
10
20
30
40
50
-200
-100
0
100
200
300
400
500
ms
Loreta
[cm]
5
0
-5
-10
6
4
2
0
-2
-4
-6
-8
).000
0.005
0.010
0.015
8
Position: 0.400s (4, -81, 1)
Primary
Secondary
History
Navigation Bar
Standard Montage
0:00:00
Seg: 1/1
Chan: Pz
Pos: 0.592 s
0.792 s
Oddball
10:22 PM
12/10/2013

Loreta

The mathematics behind these techniques is beyond the scope of what we are covering here.

In a nutshell, Loreta divides the brain into a number of voxels each containing three perpendicular dipoles (X, Y, Z) and then varies the parameters of these dipoles for each voxel to obtain the observed scalp topography.

Loreta

There are still multiple solutions. So, the determined solution is the one that has the best smoothness – contiguous voxels should have gradual changes in dipole strength.

There are additional constraints such as perpendicular dipoles only, minimum overall source magnitudes, and more…

Be careful…

Loreta has a strong bias towards the midline and towards the cortical surface.

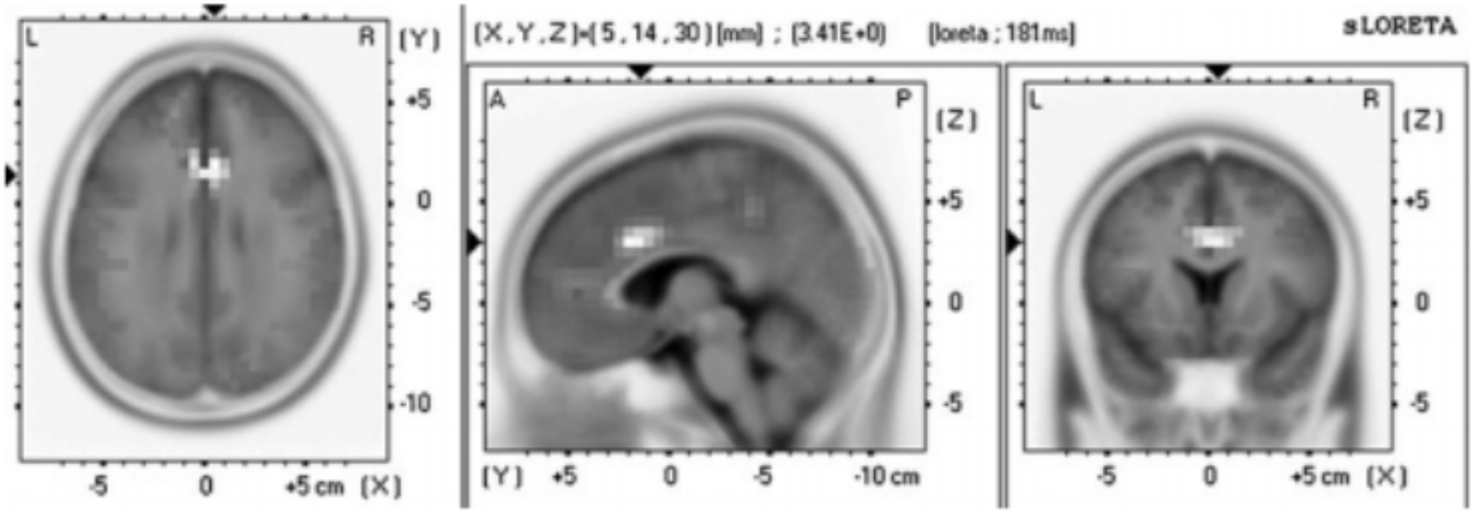
When using a source technique, do not use it like fMRI. At best, it is a confirmation of something we already know from other lines of research.

sLoreta and eLoreta

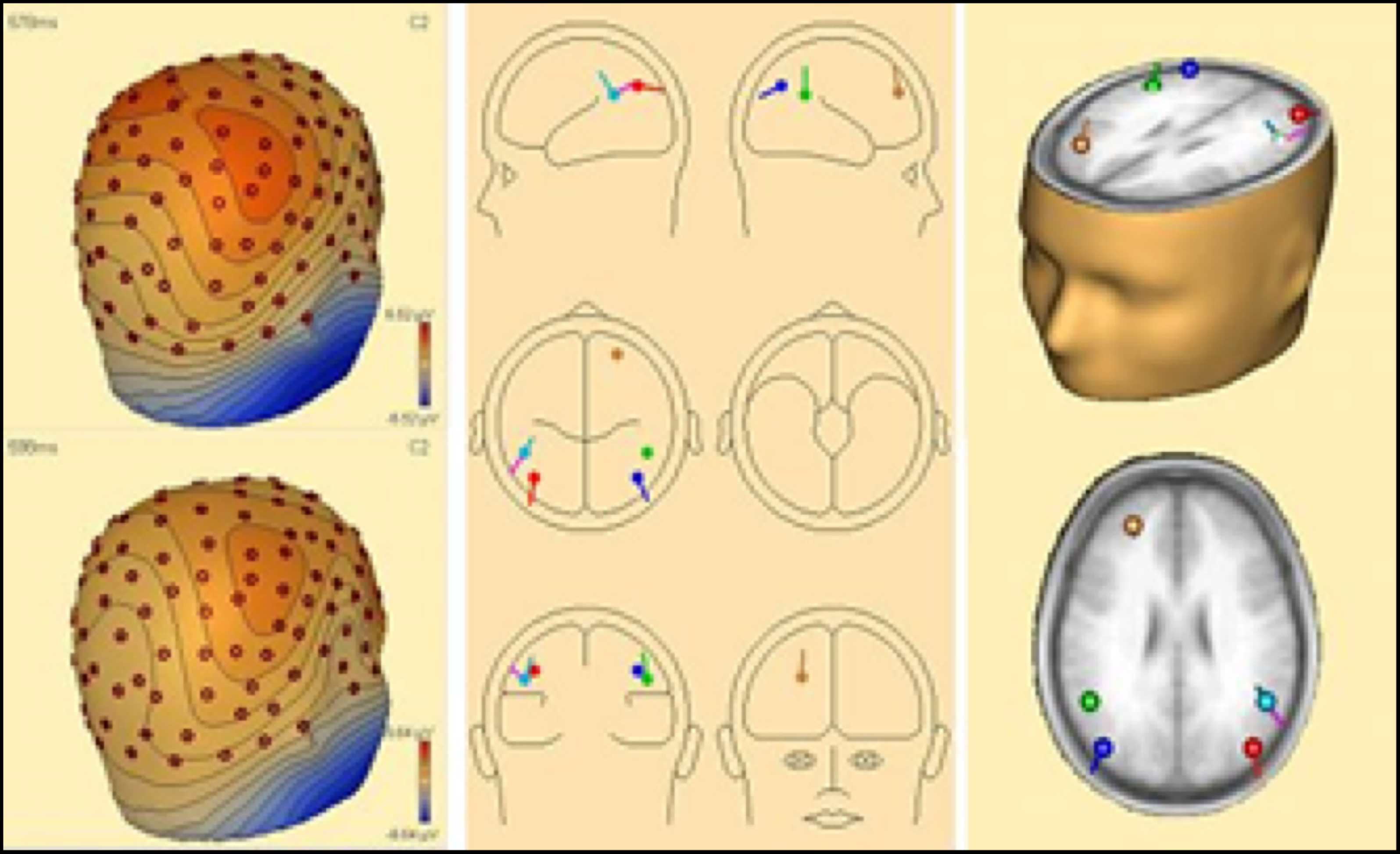
http://www.uzh.ch/keyinst/loreta.htm

Reporting Source Data

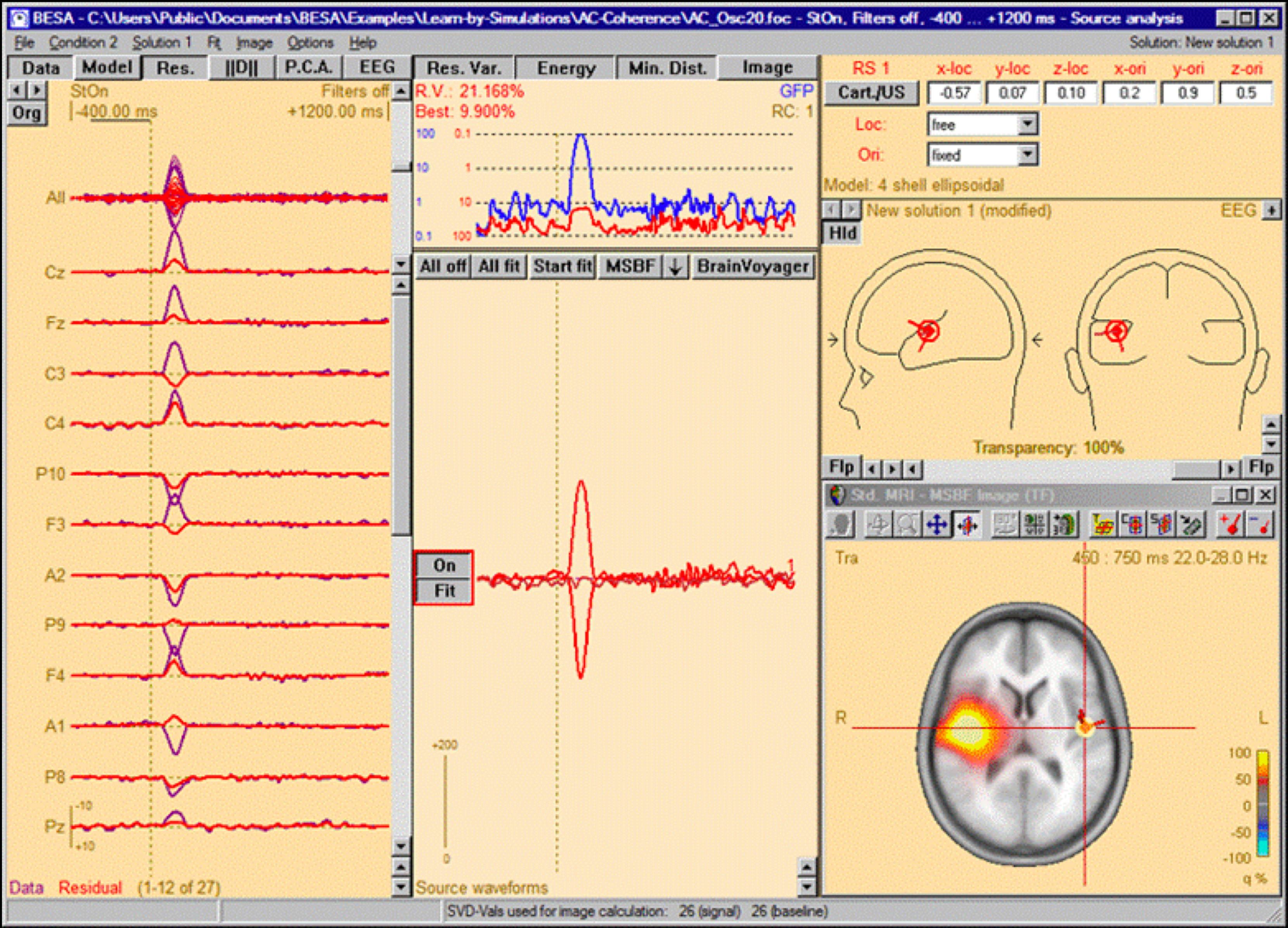
Fig. 4 sLORETA source analysis of self-ownership, as compared with other-ownership, cues at 190–240 ms post-cue-onset. Statistical non-parametric mapping (SnPM) at a significance level of .05 revealed differences localized in Brodmann area 24 (sLORETA value = 34.1) within the cingulate gyrus



BESA



BESA



BESA - C:\Users\Public\Documents\BESA\Examples\Learn-by-Simulations\AC-Coherence\AC_Osc20.foc - StOn, Filters off, -400 ... +1200 ms - Source analysis

Solution: New solution 1

R.V.: 21.168%

Best: 9.900%

RS 1

	x-loc	y-loc	z-loc	x-ori	y-ori	z-ori
Cart./US	-0.57	0.07	0.10	0.2	0.9	0.5

Loc: free

Ori: fixed

Model: 4 shell ellipsoidal

New solution 1 (modified)

Transparency: 100%

450 : 750 ms 22.0-28.0 Hz

SVD-Vals used for image calculation: 26 (signal) 26 (baseline)

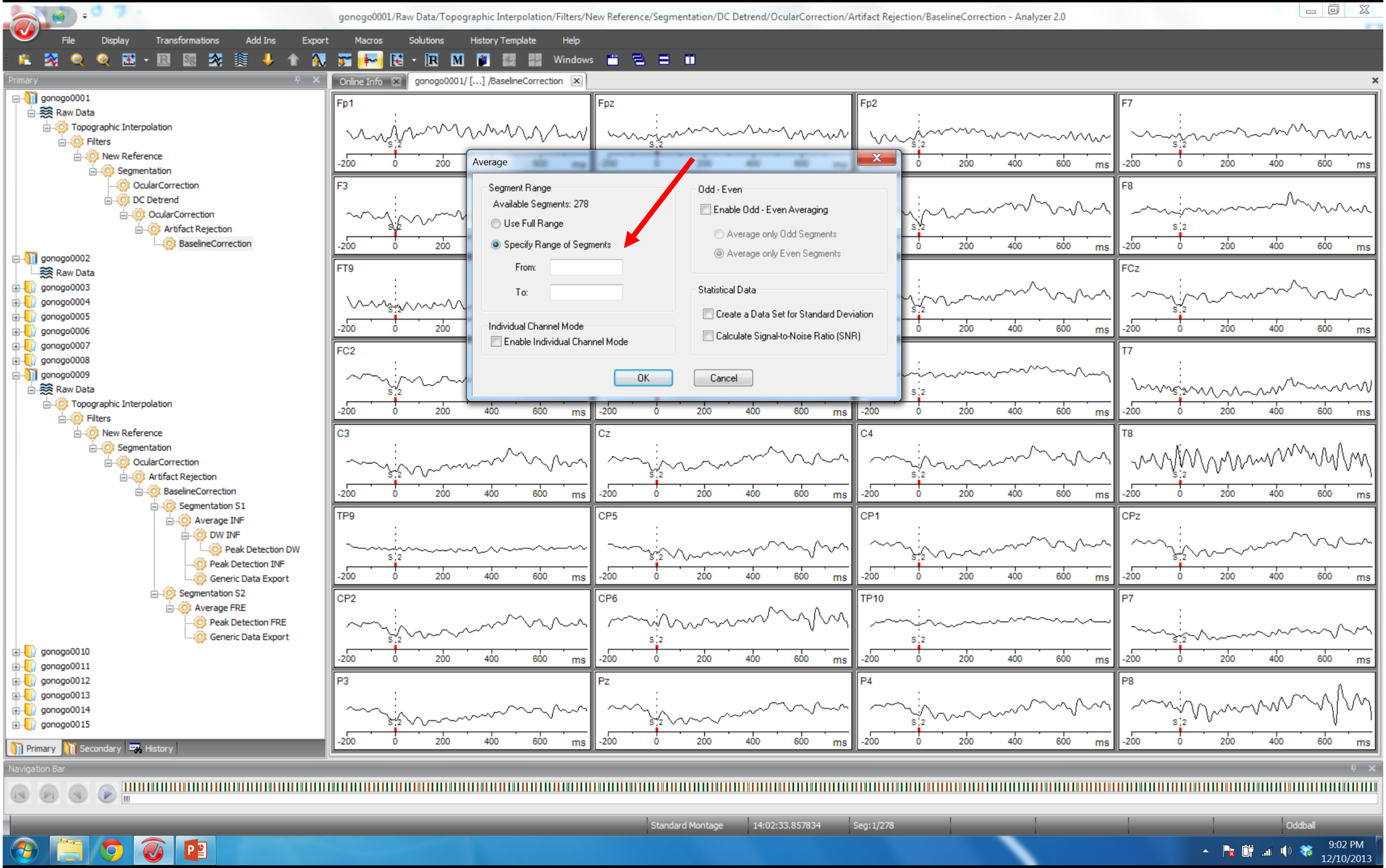
What to do?

Bins and Running Averages

Bins

You do not always have to collapse all of your markers across and entire experiment.

You may want to look at learning effects for instance.



gonogo0001/Raw Data/Topographic Interpolation/Filters/New Reference/Segmentation/DC Detrend/OcularCorrection/Artifact Rejection/BaselineCorrection - Analyzer 2.0

Average

Segment Range

Available Segments: 278

○ Use Full Range

● Specify Range of Segments

From:

To:

Individual Channel Mode

□ Enable Individual Channel Mode

Odd - Even

□ Enable Odd - Even Averaging

○ Average only Odd Segments

● Average only Even Segments

Statistical Data

□ Create a Data Set for Standard Deviation

□ Calculate Signal-to-Noise Ratio (SNR)

OK Cancel

Standard Montage | 14:02:33.857834 | Seg: 1/278 | Oddball

The Oddball Data

For instance, you have 60 infrequent markers, so:

Bin 1 = Segments 1 to 30, Bin 2 = 31 to 60

In a like manner, for the 240 frequent markers:

Bin 1 = Segments 1 to 120, Bin 2 = 121 to 240

You could then do your peak detection to compare the first half of the experiment.

Obviously, the same logic could be applied to any other break down of the average.

Running Averages

The principle behind a running average is somewhat similar to bins, but somewhat more “smooth”.

As opposed to creating 2 bins (or more bins) you create a series of bins.

If you have 100 segments, you create the following bins:

Average 1 = Segments 1 to 50
Average 2 = Segments 2 to 51
Average 3 = Segments 3 to 52
etc

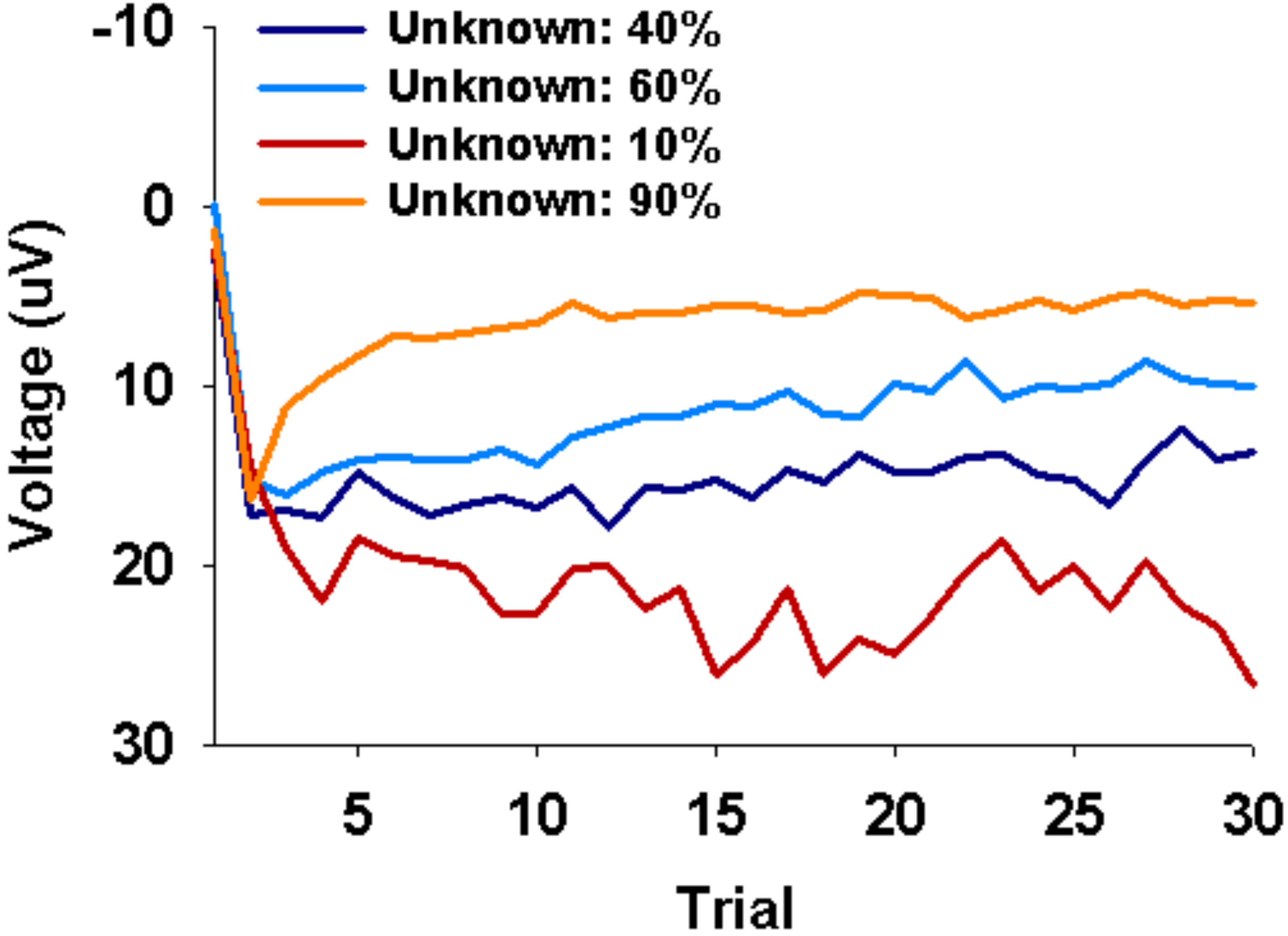
Running Averages

To be able to do this, you need to work with MATLAB.

But, its not as hard as you think.

Analyzer has a MATLAB interface so you can export directly to MATLAB and then bring the data back in.

Single Trial Analysis


Unknown: 40%
Unknown: 60%
Unknown: 10%
Unknown: 90%
-10
0
10
20
30
Voltage (uV)
5
10
15
20
25
30
Trial

So how do you do it?

Strategy One

Focus on the P300 – its large and easy to see.

Similar to Running Averages, calculate the a peak voltage - the mean – but do this for every trial and not on the average of a subset of trials.

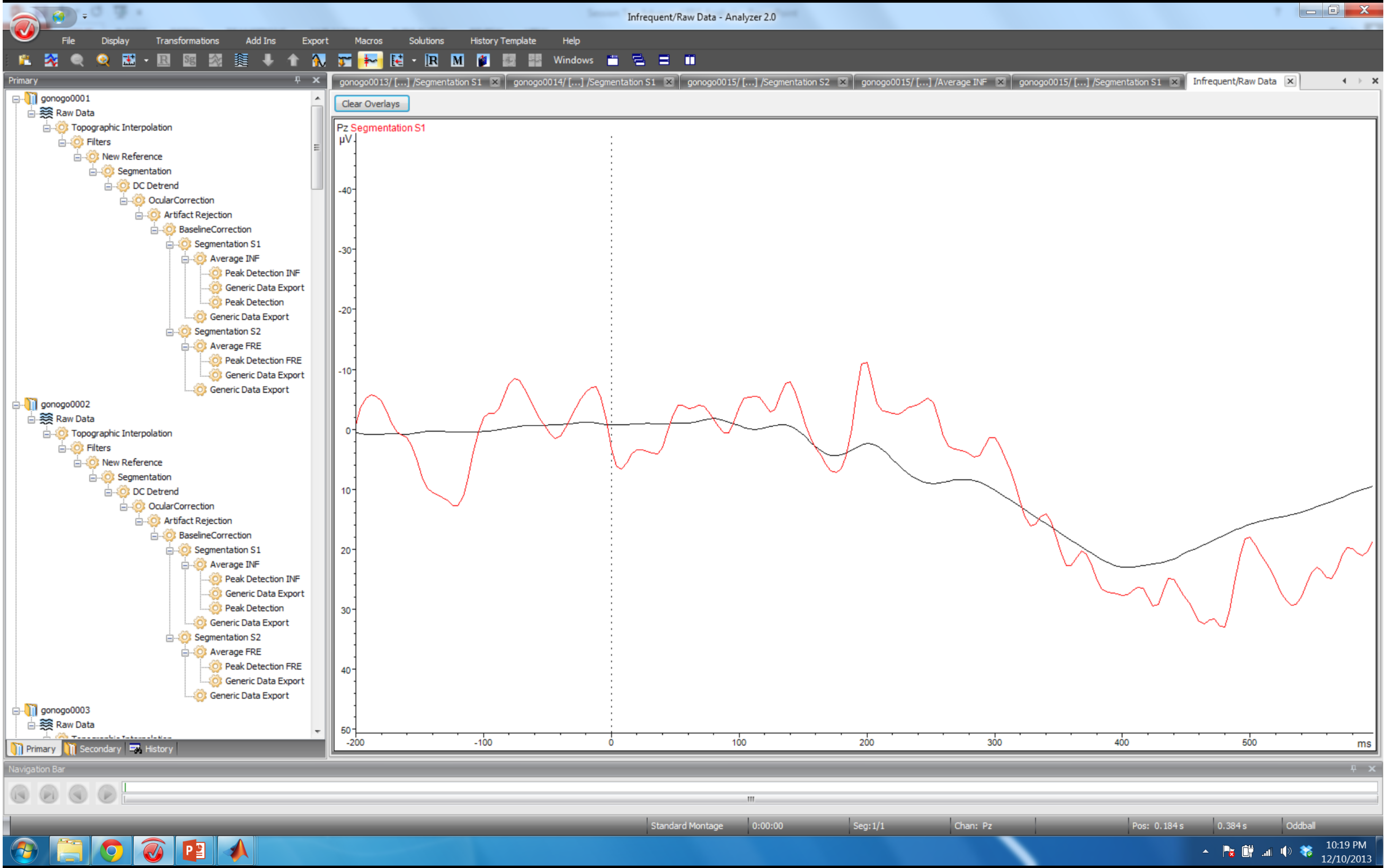
You can then plot this as a function of time.

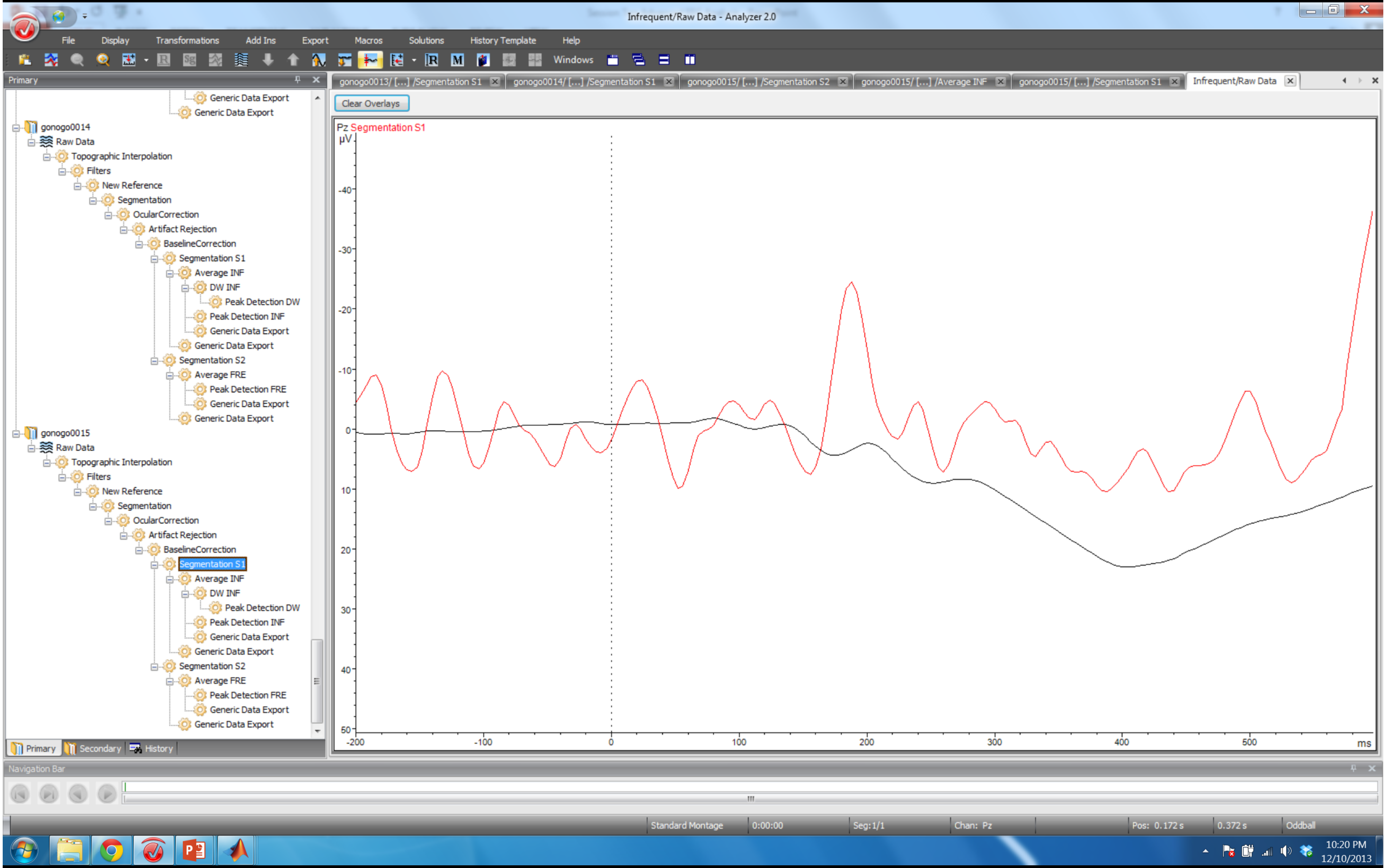
So how do you do it?

Strategy Two

Fit a function to the component of interest on the grand average.

Estimate the quality of fit for each individual trial.


Infrequent/Raw Data - Analyzer 2.0
File
Display
Transformations
Add Ins
Export
Macros
Solutions
History Template
Help
Windows
Primary
gonogo0001
Raw Data
Topographic Interpolation
Filters
New Reference
Segmentation
DC Detrend
OcularCorrection
Artifact Rejection
BaselineCorrection
Segmentation S1
Average INF
Peak Detection INF
Generic Data Export
Peak Detection
Generic Data Export
Segmentation S2
Average FRE
Peak Detection FRE
Generic Data Export
Generic Data Export
gonogo0002
Raw Data
Topographic Interpolation
Filters
New Reference
Segmentation
DC Detrend
OcularCorrection
Artifact Rejection
BaselineCorrection
Segmentation S1
Average INF
Peak Detection INF
Generic Data Export
Peak Detection
Generic Data Export
Segmentation S2
Average FRE
Peak Detection FRE
Generic Data Export
Generic Data Export
gonogo0003
Raw Data
Primary
Secondary
History
gonogo0013/ [...] /Segmentation S1
gonogo0014/ [...] /Segmentation S1
gonogo0015/ [...] /Segmentation S2
gonogo0015/ [...] /Average INF
gonogo0015/ [...] /Segmentation S1
Infrequent/Raw Data
Clear Overlays
Pz Segmentation S1
µV
-40
-30
-20
-10
0
10
20
30
40
50
-200
-100
0
100
200
300
400
500
ms
Navigation Bar
Standard Montage
0:00:00
Seg: 1/1
Chan: Pz
Pos: 0.184 s
0.384 s
Oddball
10:19 PM
12/10/2013


Infrequent/Raw Data - Analyzer 2.0
File
Display
Transformations
Add Ins
Export
Macros
Solutions
History Template
Help
Windows
Primary
gonogo0013/ [...] /Segmentation S1
gonogo0014/ [...] /Segmentation S1
gonogo0015/ [...] /Segmentation S2
gonogo0015/ [...] /Average INF
gonogo0015/ [...] /Segmentation S1
Infrequent/Raw Data
Clear Overlays
Generic Data Export
Generic Data Export
gonogo0014
Raw Data
Topographic Interpolation
Filters
New Reference
Segmentation
OcularCorrection
Artifact Rejection
BaselineCorrection
Segmentation S1
Average INF
DW INF
Peak Detection DW
Peak Detection INF
Generic Data Export
Generic Data Export
Segmentation S2
Average FRE
Peak Detection FRE
Generic Data Export
Generic Data Export
gonogo0015
Raw Data
Topographic Interpolation
Filters
New Reference
Segmentation
OcularCorrection
Artifact Rejection
BaselineCorrection
Segmentation S1
Average INF
DW INF
Peak Detection DW
Peak Detection INF
Generic Data Export
Generic Data Export
Segmentation S2
Average FRE
Peak Detection FRE
Generic Data Export
Generic Data Export
Primary
Secondary
History
Pz Segmentation S1
µV
-40
-30
-20
-10
0
10
20
30
40
50
-200
-100
0
100
200
300
400
500
ms
Navigation Bar
Standard Montage
0:00:00
Seg: 1/1
Chan: Pz
Pos: 0.172 s
0.372 s
Oddball
10:20 PM
12/10/2013

Component Latency and Onset Analysis

Component Latency

It is relatively easy to do a component latency analysis.

All you need to do is use a maxima / minima peak detection approach and get a latency value for the peak for each subject for each condition.

Following that, traditional null hypothesis testing can be used.

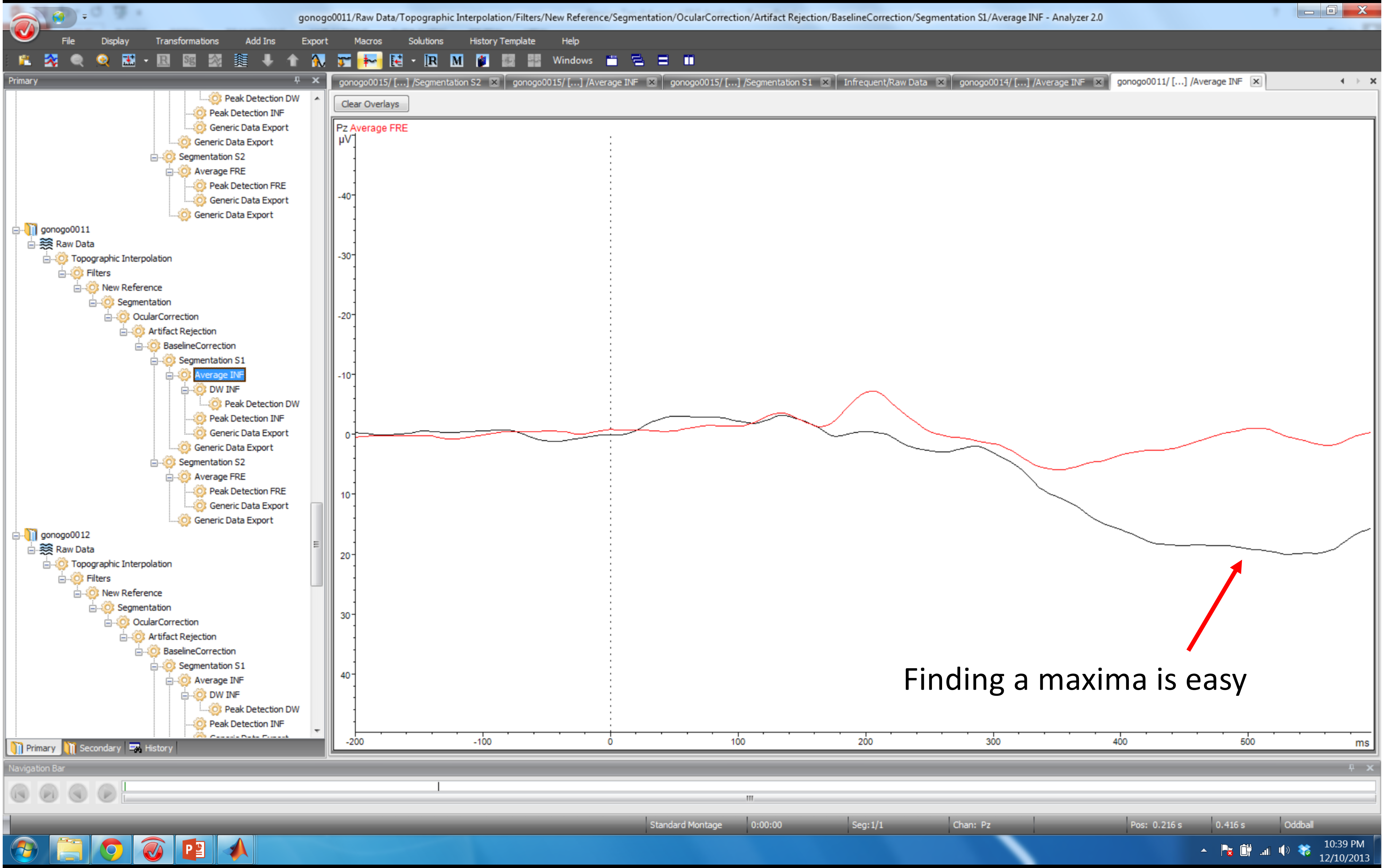
Condition A			Condition B	
12.4 uV	324 ms		11.3 uV	378 ms
9.8 uV	333 ms		10.4 uV	402 ms
10.3 uV	356 ms		8.8 uV	444 ms
4.2 uV	401 ms		7.6 uV	424ms
7.8 uV	367 ms		6.4 uV	401 ms

Component Onset

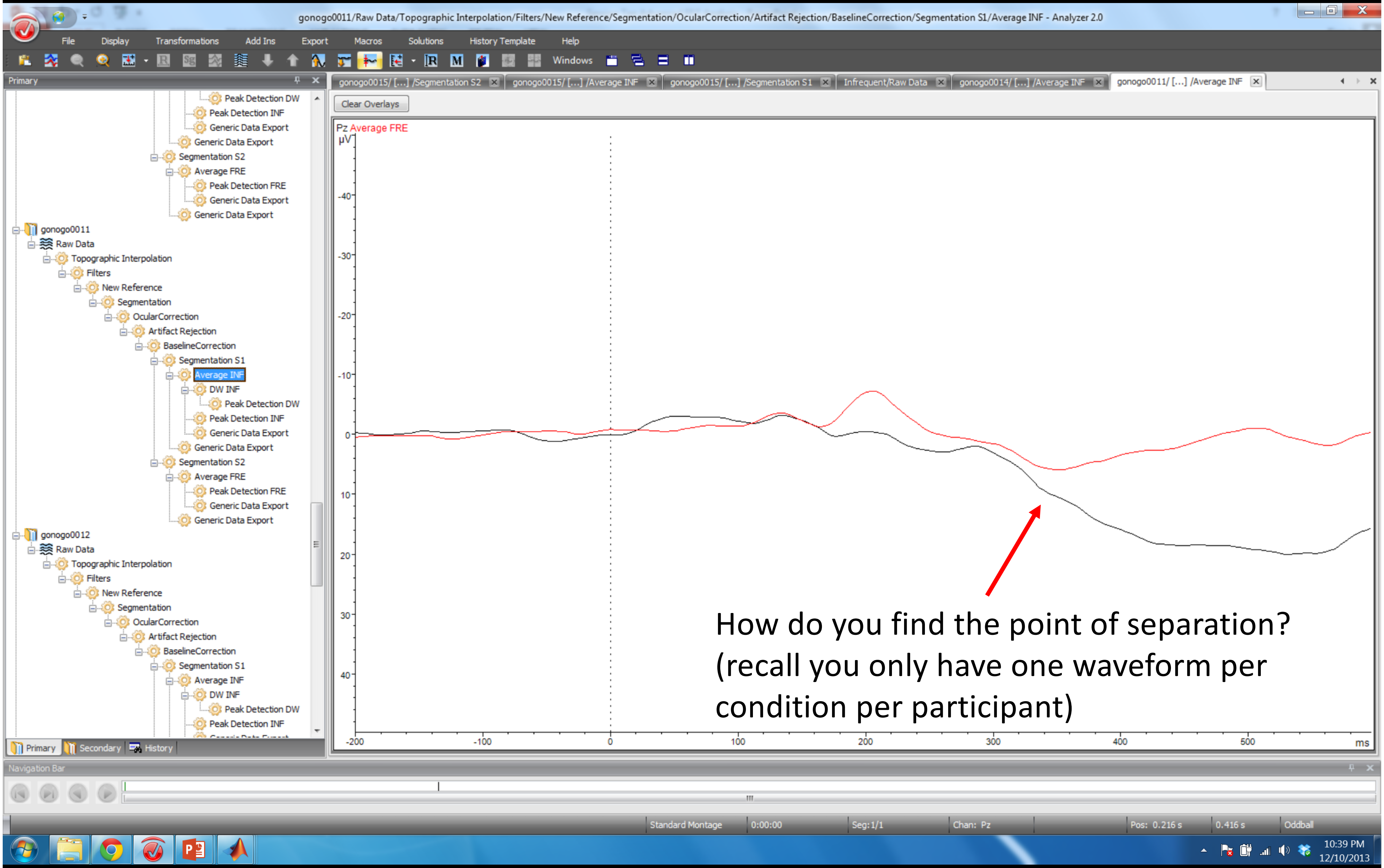
Component onset is a bit trickier.

Why?

Because we cannot do single trial analysis very effectively, we cannot get an onset value for each subject based on their own data. Why is that?



Finding a maxima is easy



How do you find the point of separation? (recall you only have one waveform per condition per participant)

One Solution

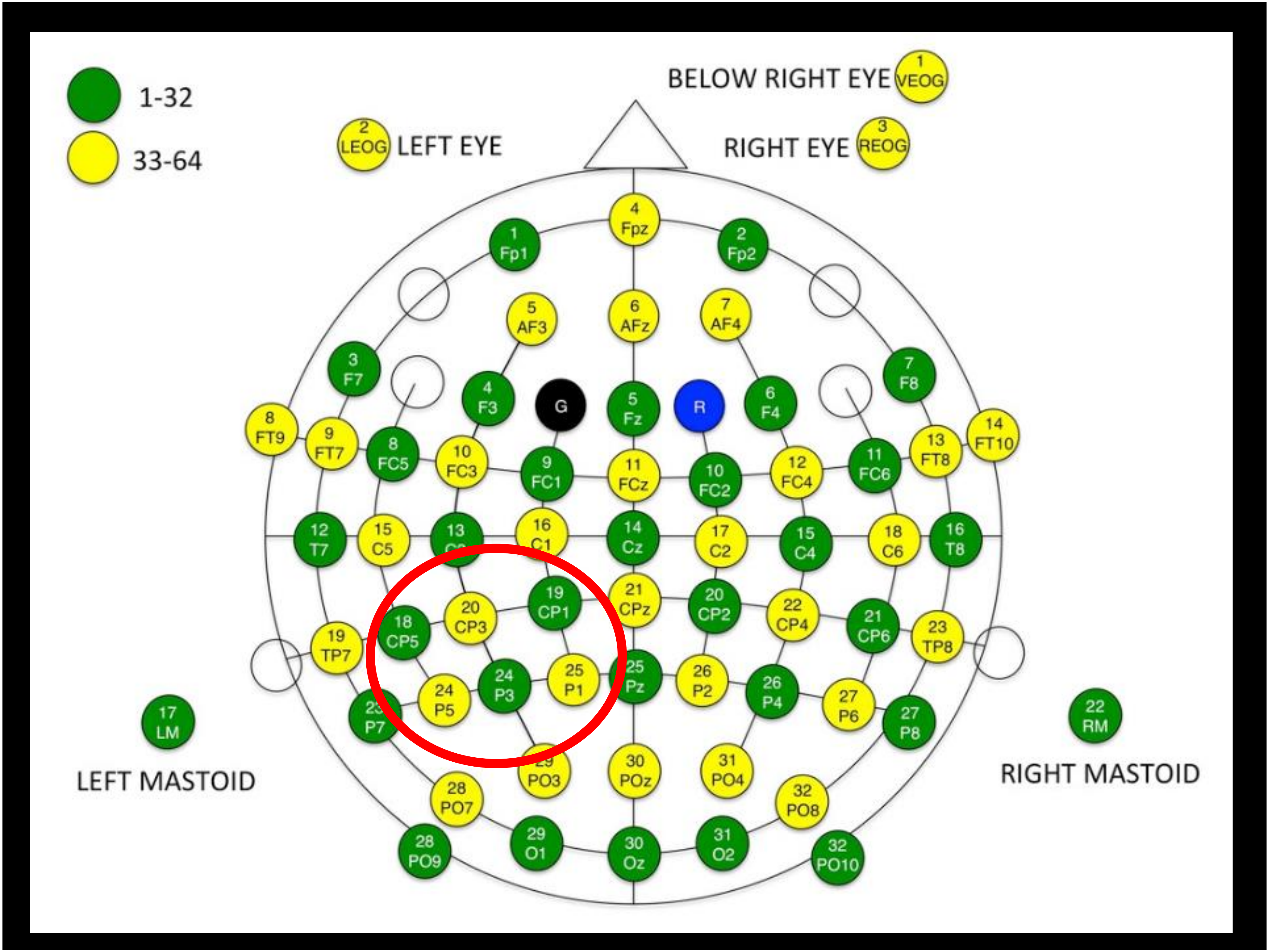
Rodrigues – Fornells

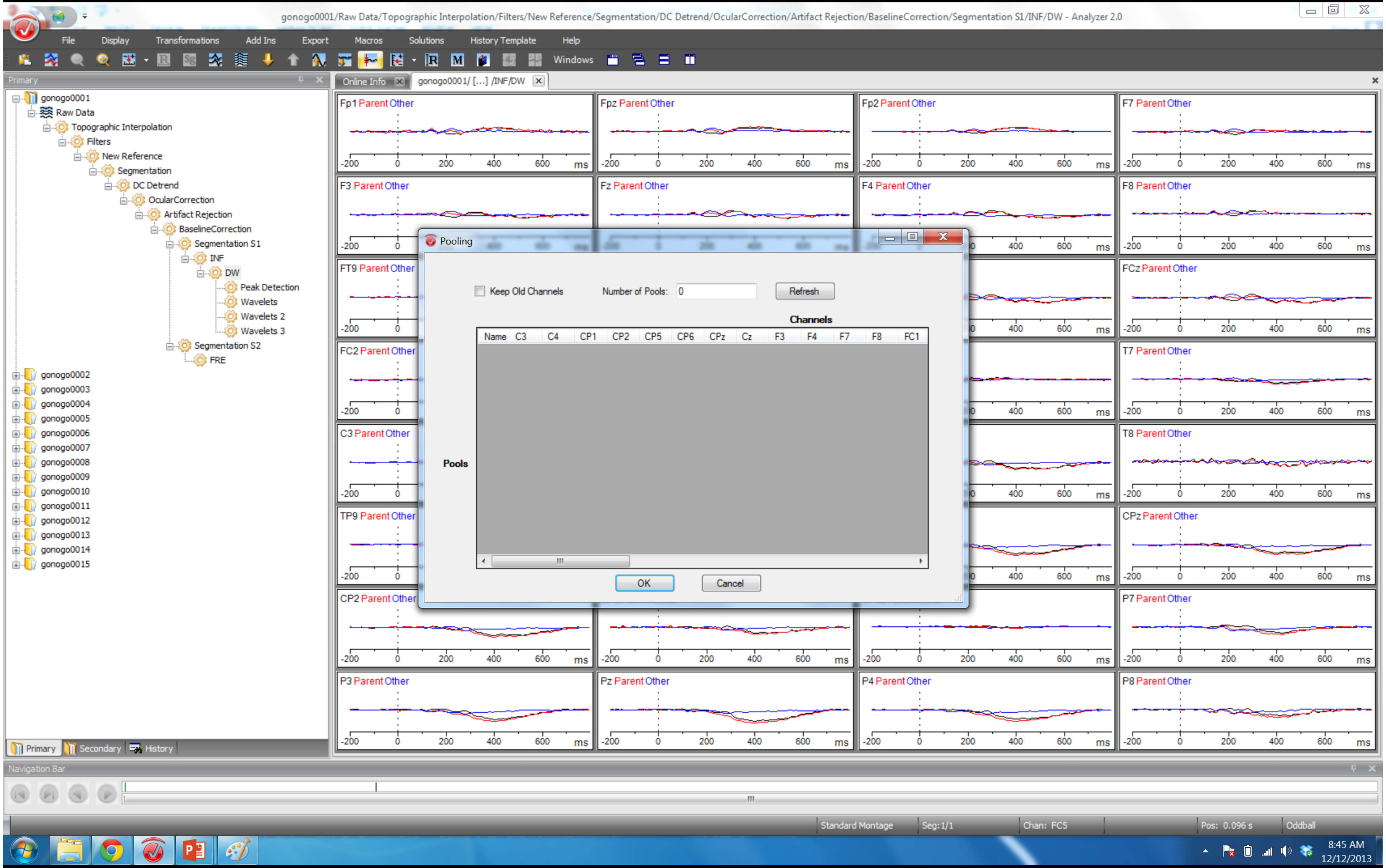
1. Get the average waveform for each participant for the channel of interest for each condition.
2. Use a running average to smooth these, say +/- 5 time points on either side.
3. Sequentially t-test every point of the smoothed waveforms till there is a significant difference using a stricter alpha (0.001)

The Problem

This approach will tell you when two conditions diverge, it does not allow you to compare the difference of onset between A and B with the difference in onset between C and D.

Pooling Electrodes


1-32
33-64
BELOW RIGHT EYE
1 VEOG
2 LEOG
LEFT EYE
RIGHT EYE
3 REOG
4 Fpz
1 Fp1
2 Fp2
5 AF3
6 AFz
7 AF4
3 F7
4 F3
G
5 Fz
R
6 F4
7 F8
8 FT9
9 FT7
8 FC5
10 FC3
9 FC1
11 FCz
10 FC2
12 FC4
11 FC6
13 FT8
14 FT10
12 T7
15 C5
13 C3
16 C1
14 Cz
17 C2
15 C4
18 C6
16 T8
18 CP5
20 CP3
19 CP1
21 CPz
20 CP2
22 CP4
21 CP6
23 TP8
19 TP7
23 P7
24 P5
24 P3
25 P1
25 Pz
26 P2
26 P4
27 P6
27 P8
17 LM
22 RM
LEFT MASTOID
RIGHT MASTOID
28 PO7
29 PO3
30 POz
31 PO4
32 PO8
28 PO9
29 O1
30 Oz
31 O2
32 PO10



gonogo0001/Raw Data/Topographic Interpolation/Filters/New Reference/Segmentation/DC Detrend/OcularCorrection/Artifact Rejection/BaselineCorrection/Segmentation S1/INF/DW - Analyzer 2.0

- gonogo0001
  - Raw Data
    - Topographic Interpolation
      - Filters
        - New Reference
          - Segmentation
            - DC Detrend
              - OcularCorrection
                - Artifact Rejection
                  - BaselineCorrection
                    - Segmentation S1
                      - INF
                        - DW
                          - Peak Detection
                          - Wavelets
                          - Wavelets 2
                          - Wavelets 3
                    - Segmentation S2
                      - FRE
- gonogo0002
- gonogo0003
- gonogo0004
- gonogo0005
- gonogo0006
- gonogo0007
- gonogo0008
- gonogo0009
- gonogo0010
- gonogo0011
- gonogo0012
- gonogo0013
- gonogo0014
- gonogo0015

Pooling

□ Keep Old Channels

Number of Pools: 0

Channels

Name	C3	C4	CP1	CP2	CP5	CP6	CPz	Cz	F3	F4	F7	F8	FC1

Standard Montage | Seg: 1/1 | Chan: FC5 | Pos: 0.096 s | Oddball

8:45 AM
12/12/2013