Analysis of EEG/MEG Map Topographies and Source Distributions on the Epoch Level using Non-parametric Randomization Tests

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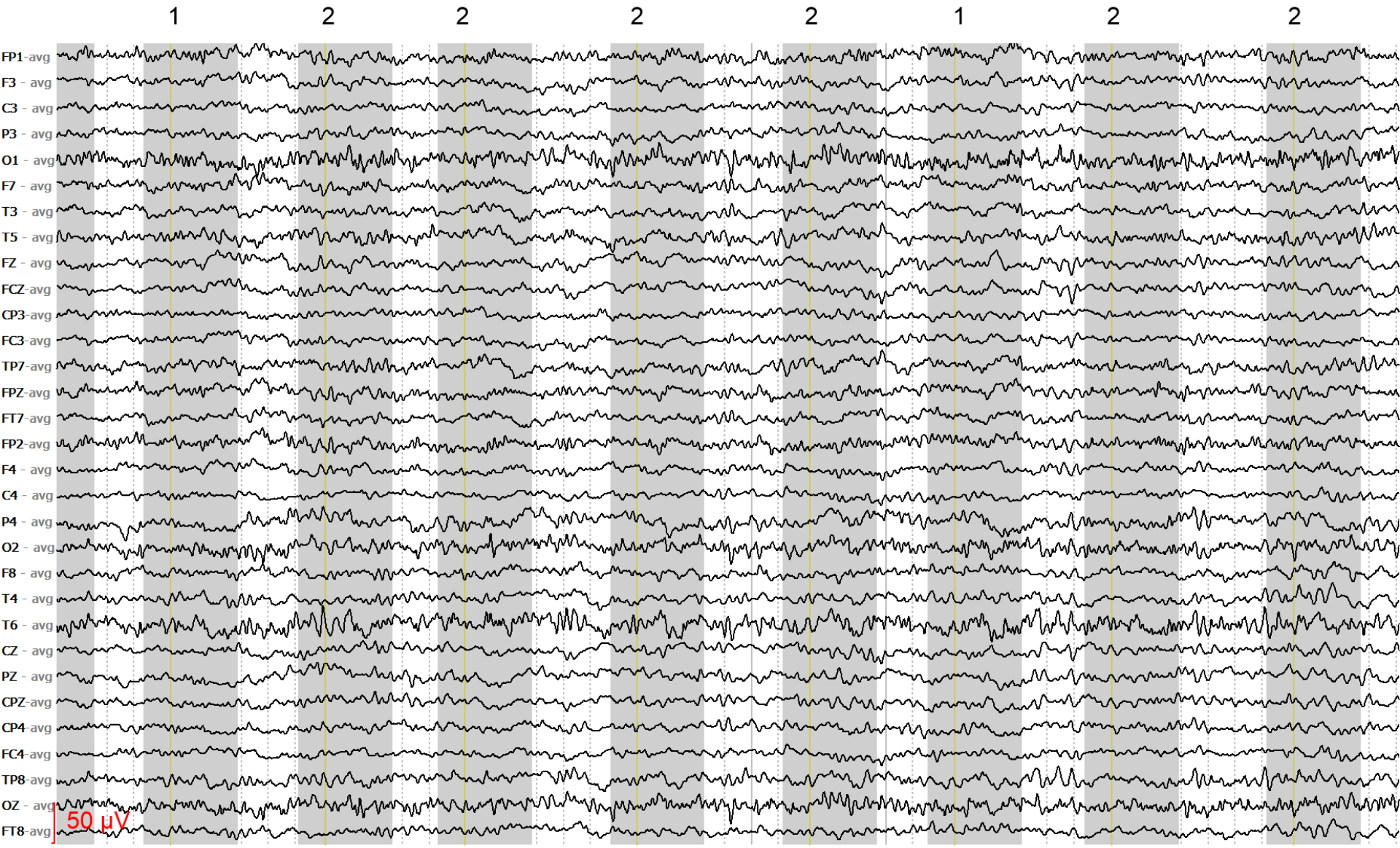
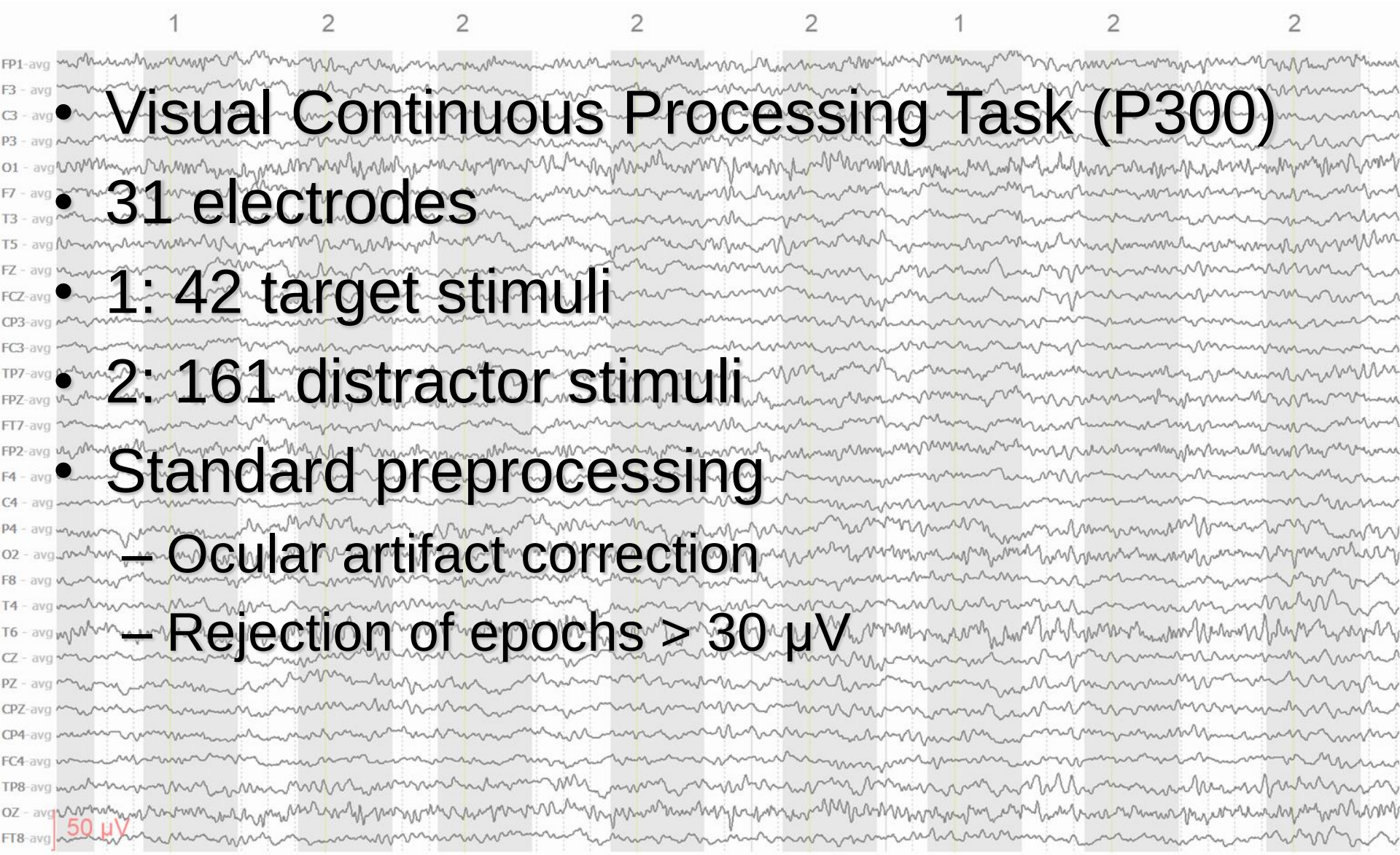
Goals

- For single-subject evoked-response EEG:
- Detect latencies of
  - consistency within epoch type
  - differences between epoch types
- Detect latencies and source locations of
  - differences between epoch types
- Sample-by-sample

Ongoing EEG

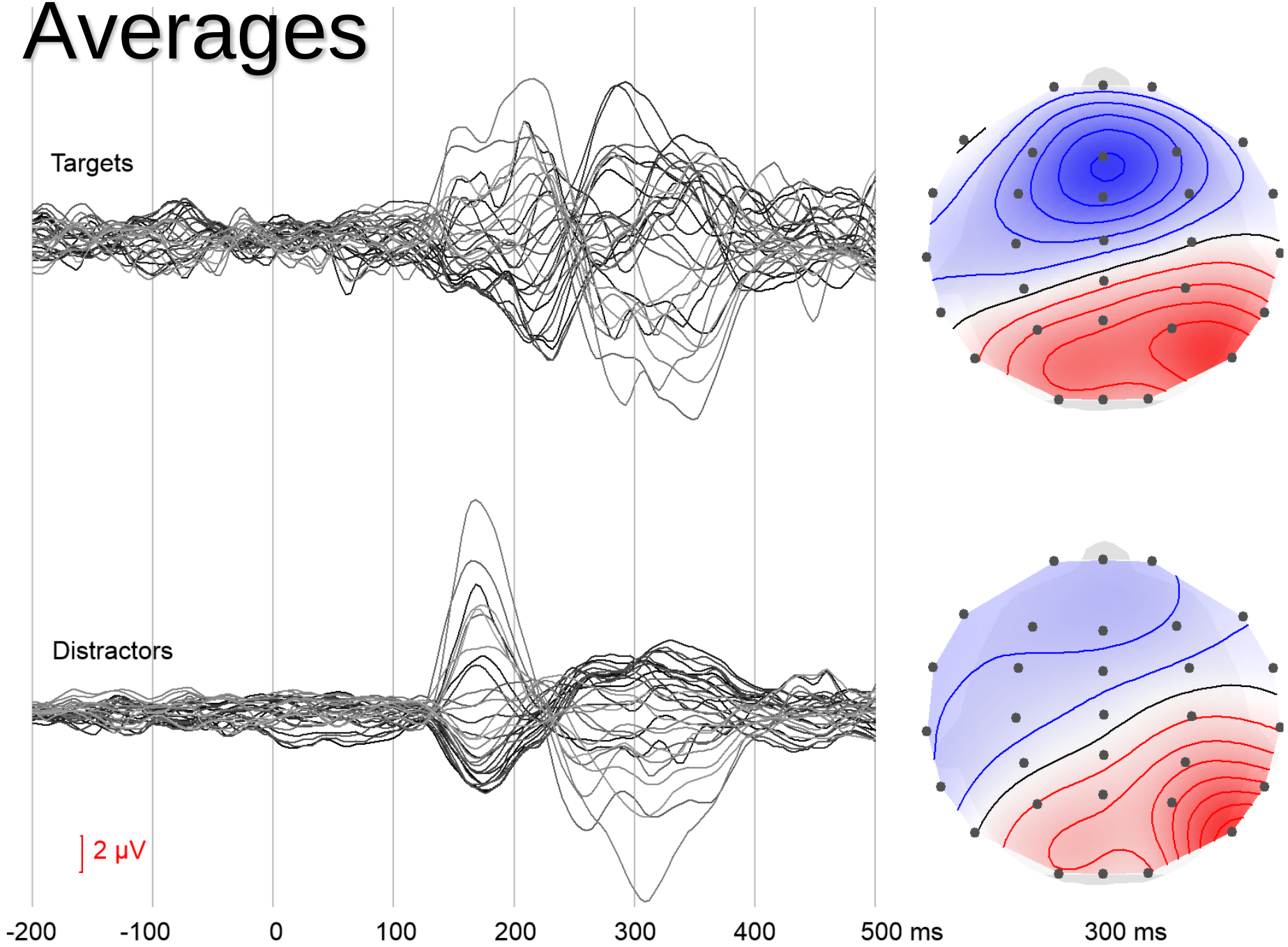

1
2
2
2
2
1
2
2
FP1-avg
F3 - avg
C3 - avg
P3 - avg
O1 - avg
F7 - avg
T3 - avg
T5 - avg
FZ - avg
FCZ-avg
CP3-avg
FC3-avg
TP7-avg
FPZ-avg
FT7-avg
FP2-avg
F4 - avg
C4 - avg
P4 - avg
O2 - avg
F8 - avg
T4 - avg
T6 - avg
CZ - avg
PZ - avg
CPZ-avg
CP4-avg
FC4-avg
TP8-avg
OZ - avg
FT8-avg
50 µV

Ongoing EEG

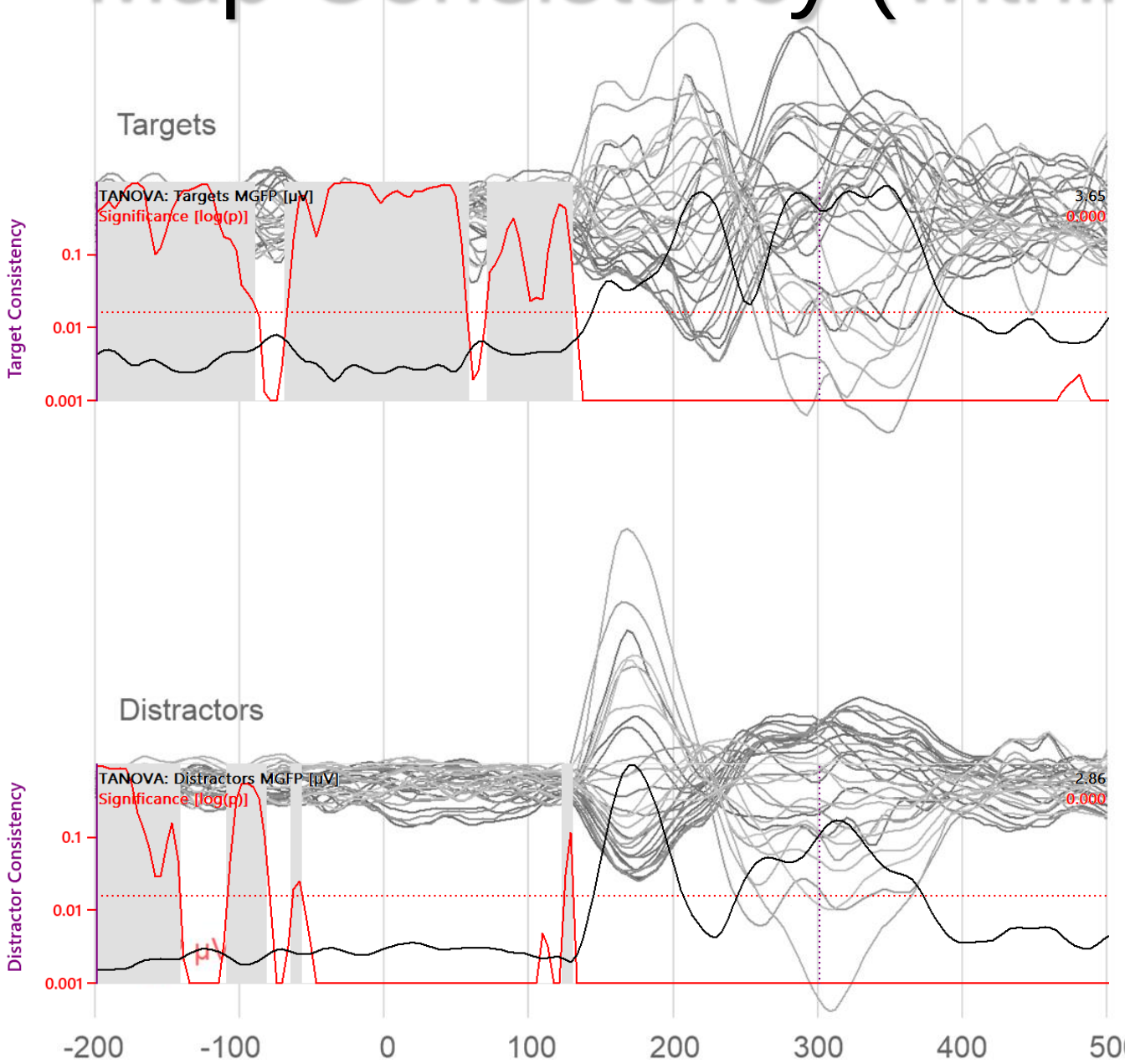


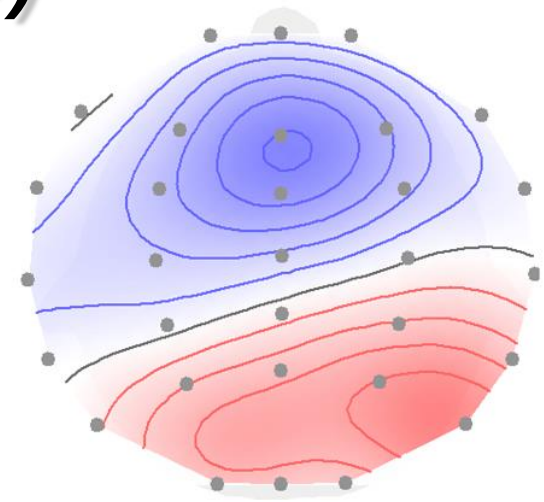
- Visual Continuous Processing Task (P300)
- 31 electrodes
- 1: 42 target stimuli
- 2: 161 distractor stimuli
- Standard preprocessing
  - Ocular artifact correction
  - Rejection of epochs > 30 µV

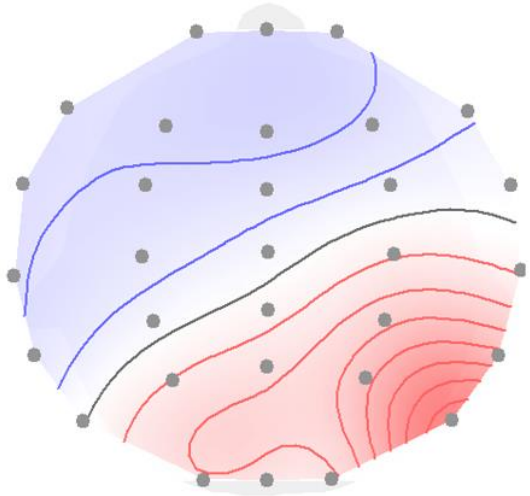
Averages


Targets
Distractors
2 µV
-200
-100
0
100
200
300
400
500 ms
300 ms

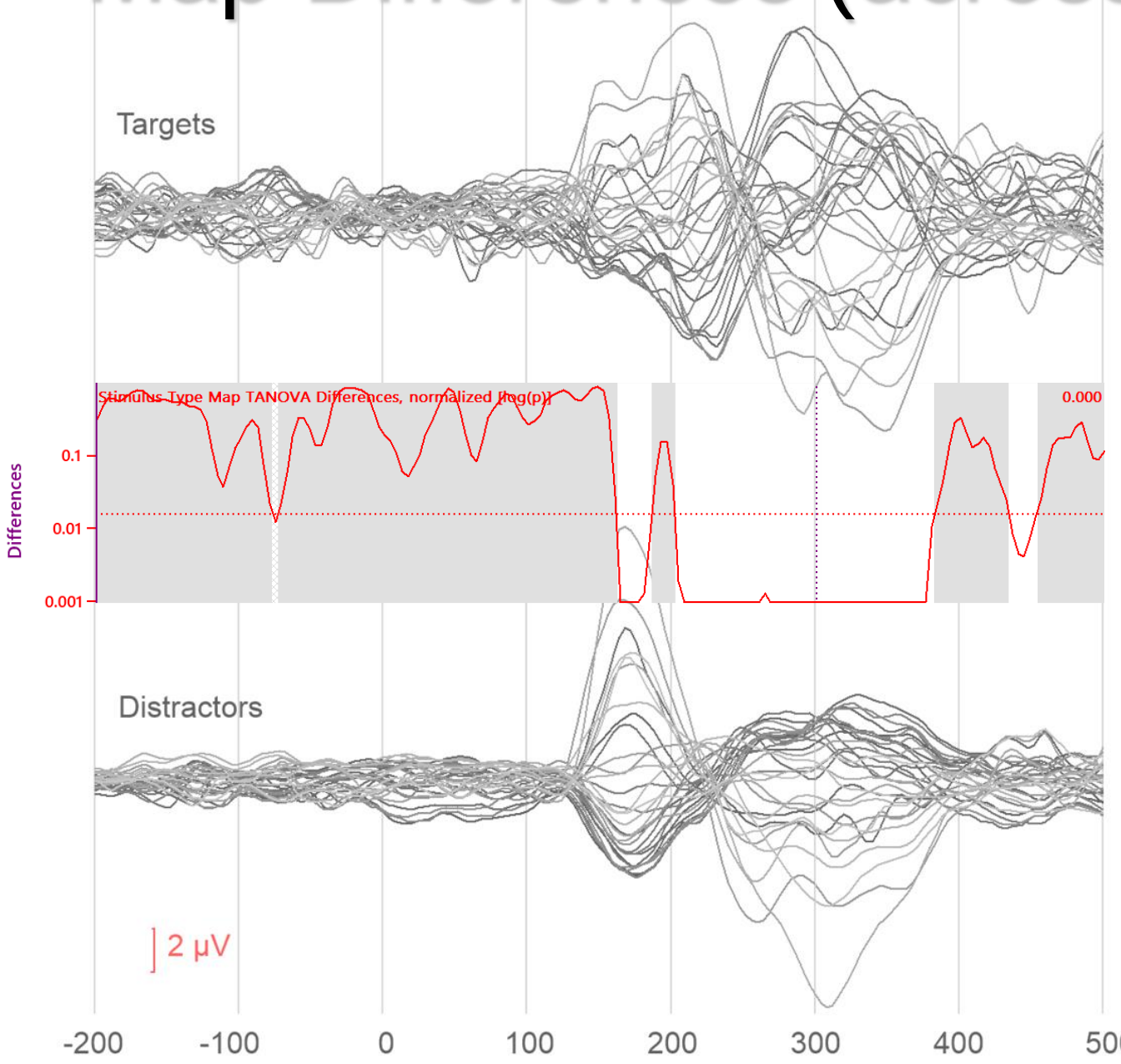
Map Consistency (within)

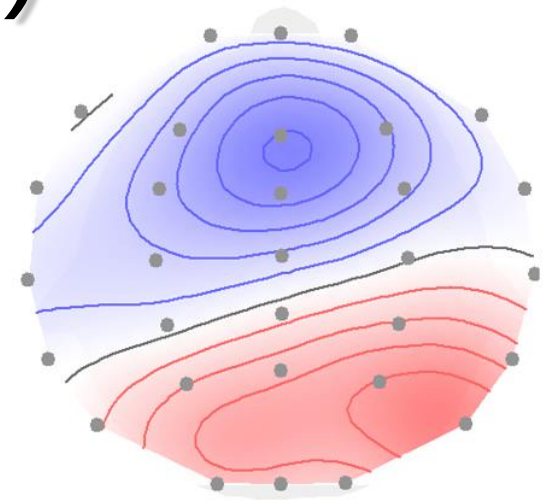


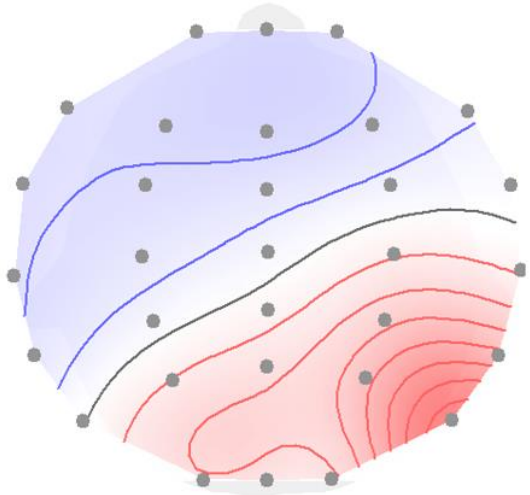




Map Differences (across)

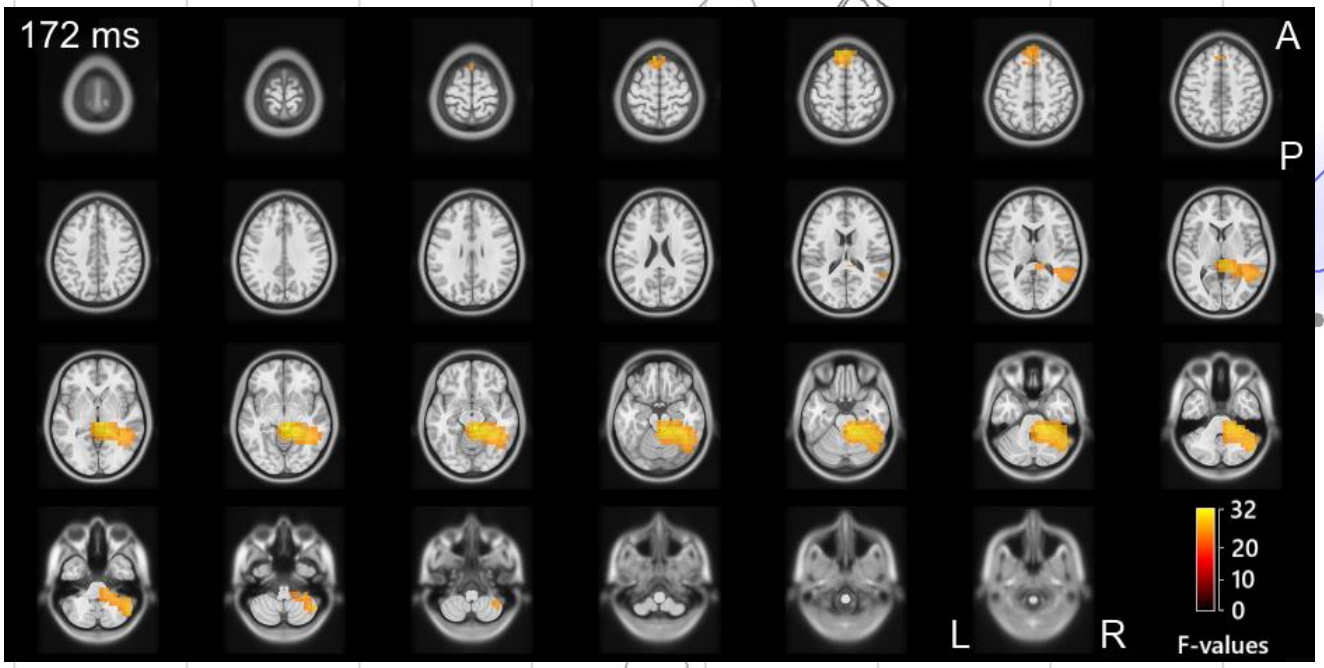


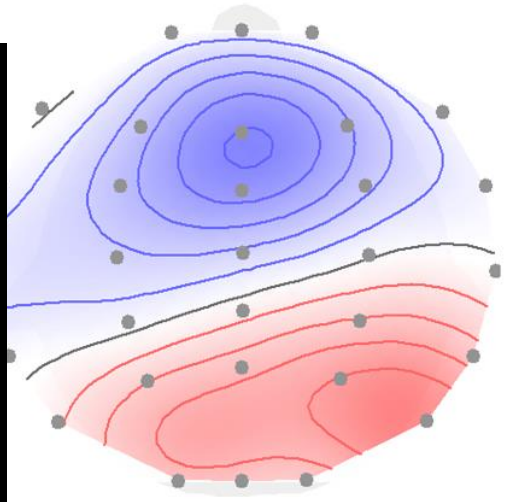


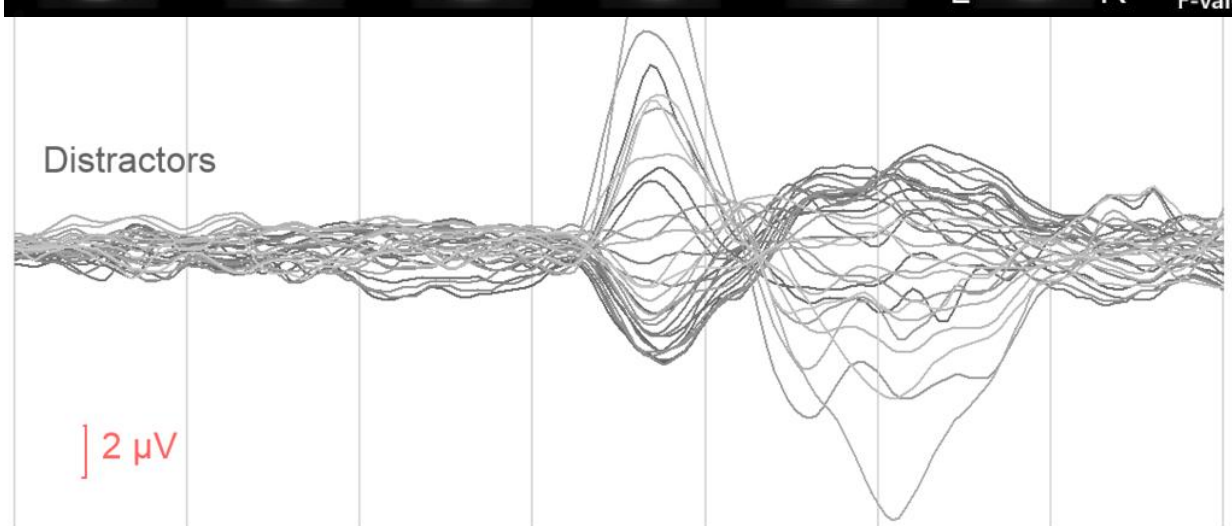


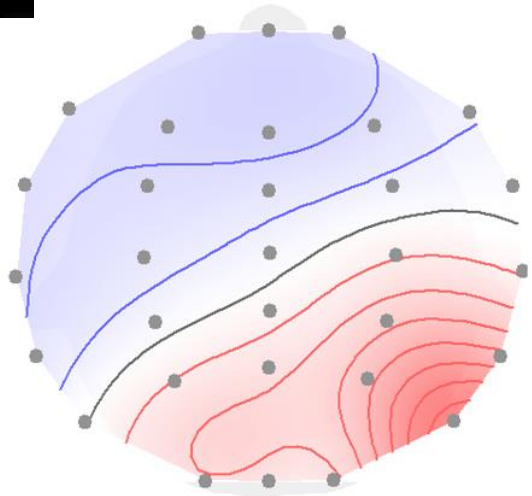
300 ms

Source Differences



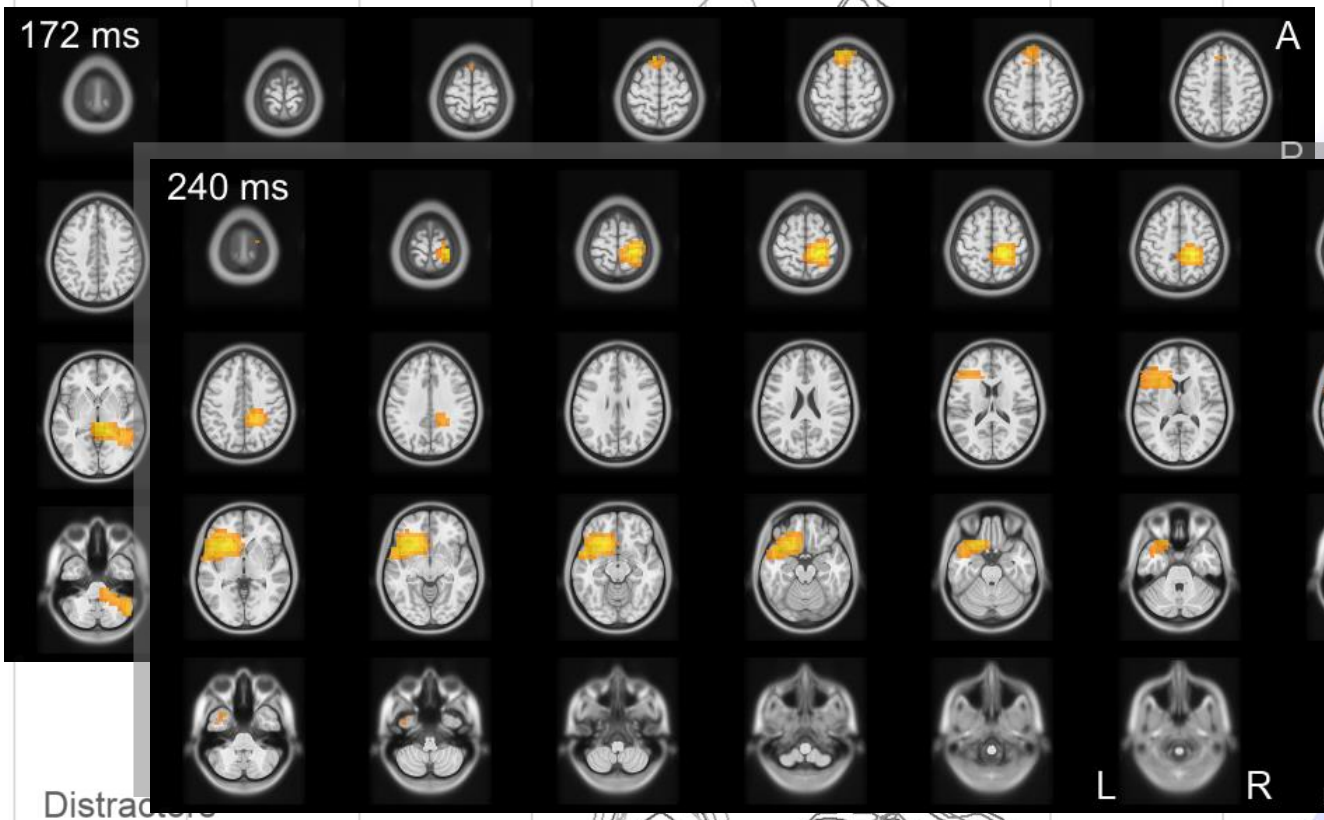


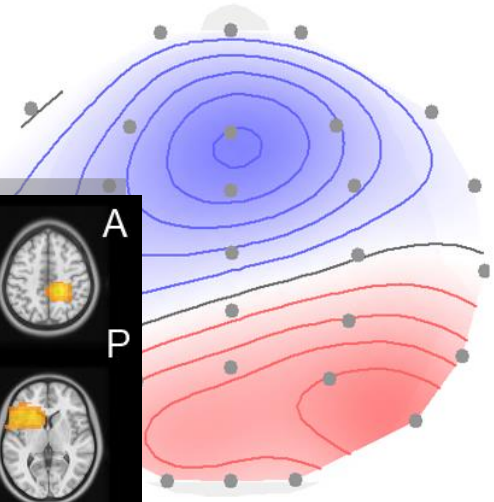


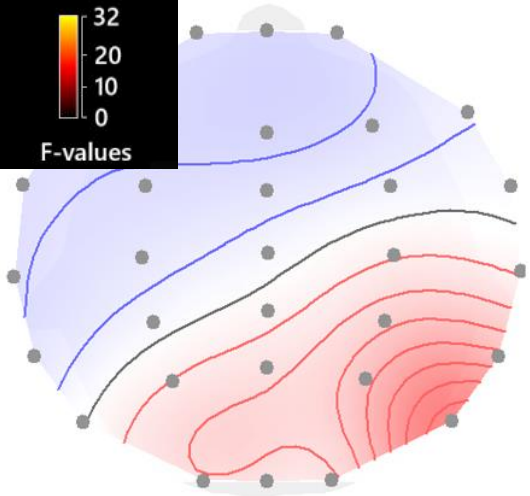


-200 -100 0 100 200 300 400 500 ms 300 ms

Source Differences







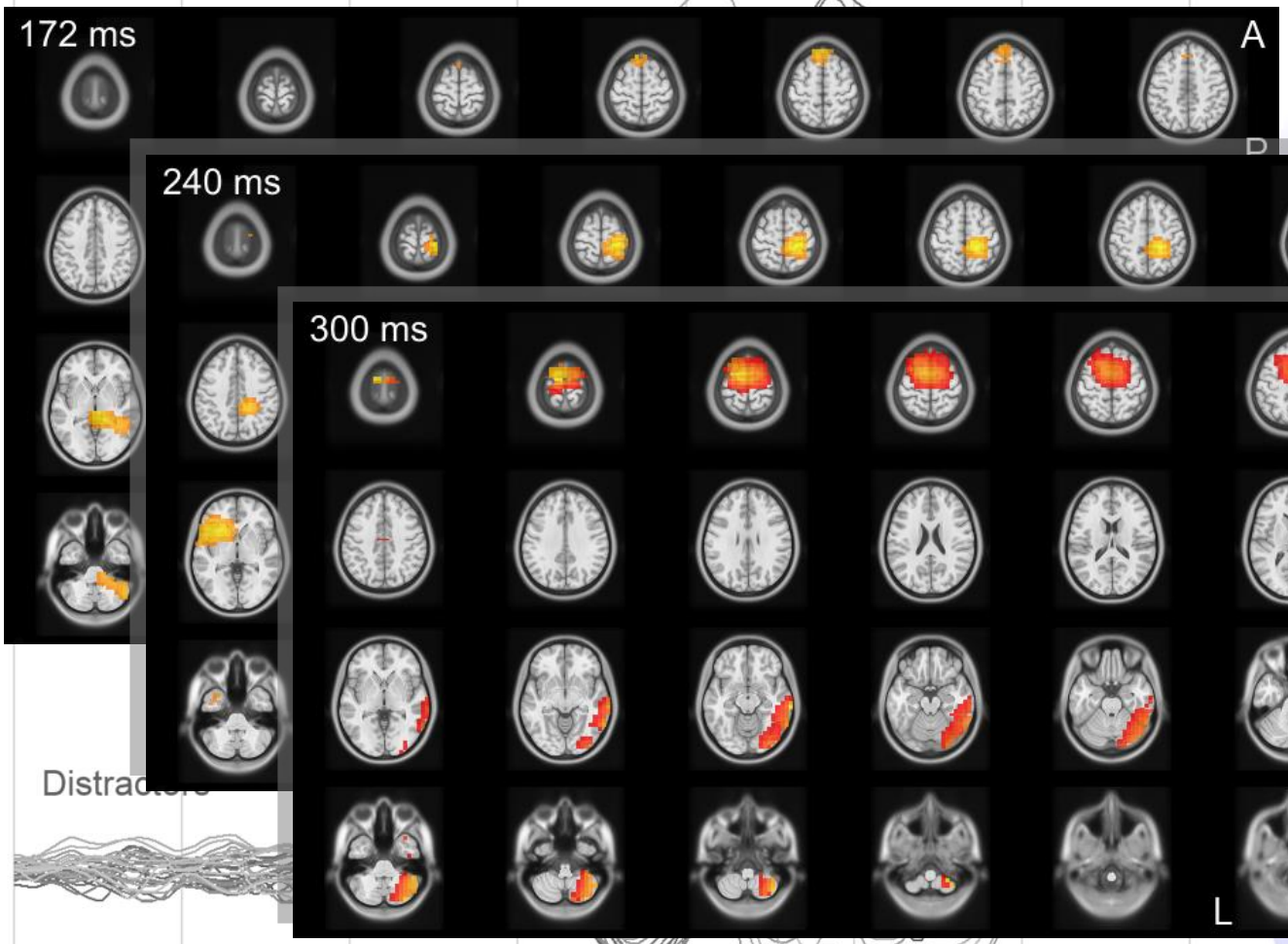
Distract

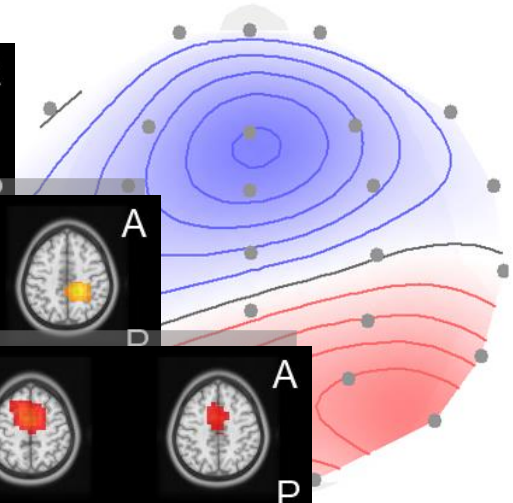
2 µV

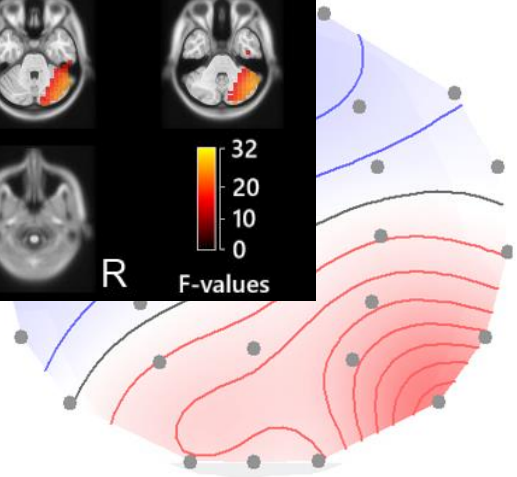
-200 -100 0 100 200 300 400 500 ms

300 ms

Source Differences



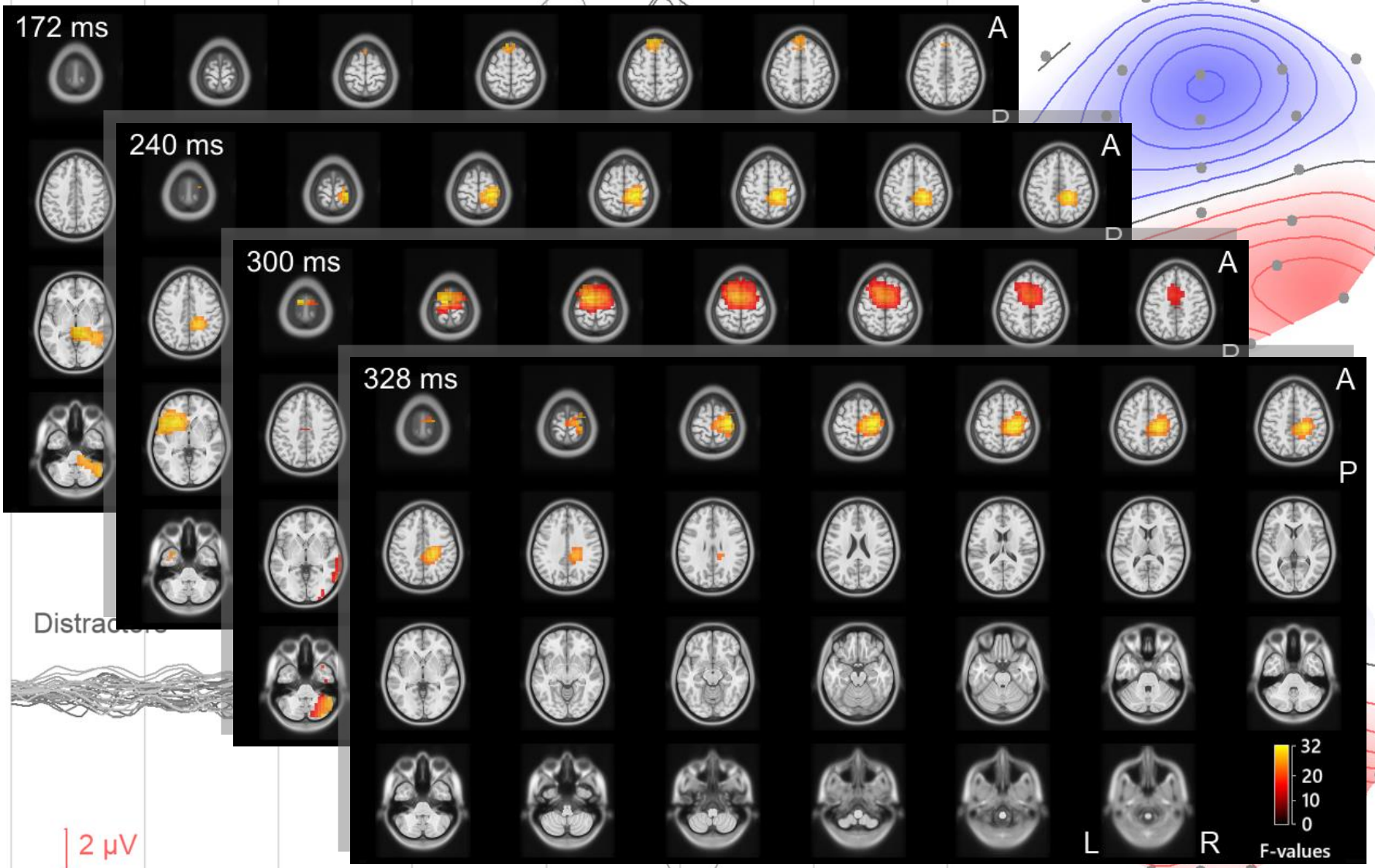




2 µV

-200 -100 0 100 200 300 400 500 ms 300 ms

Source Differences

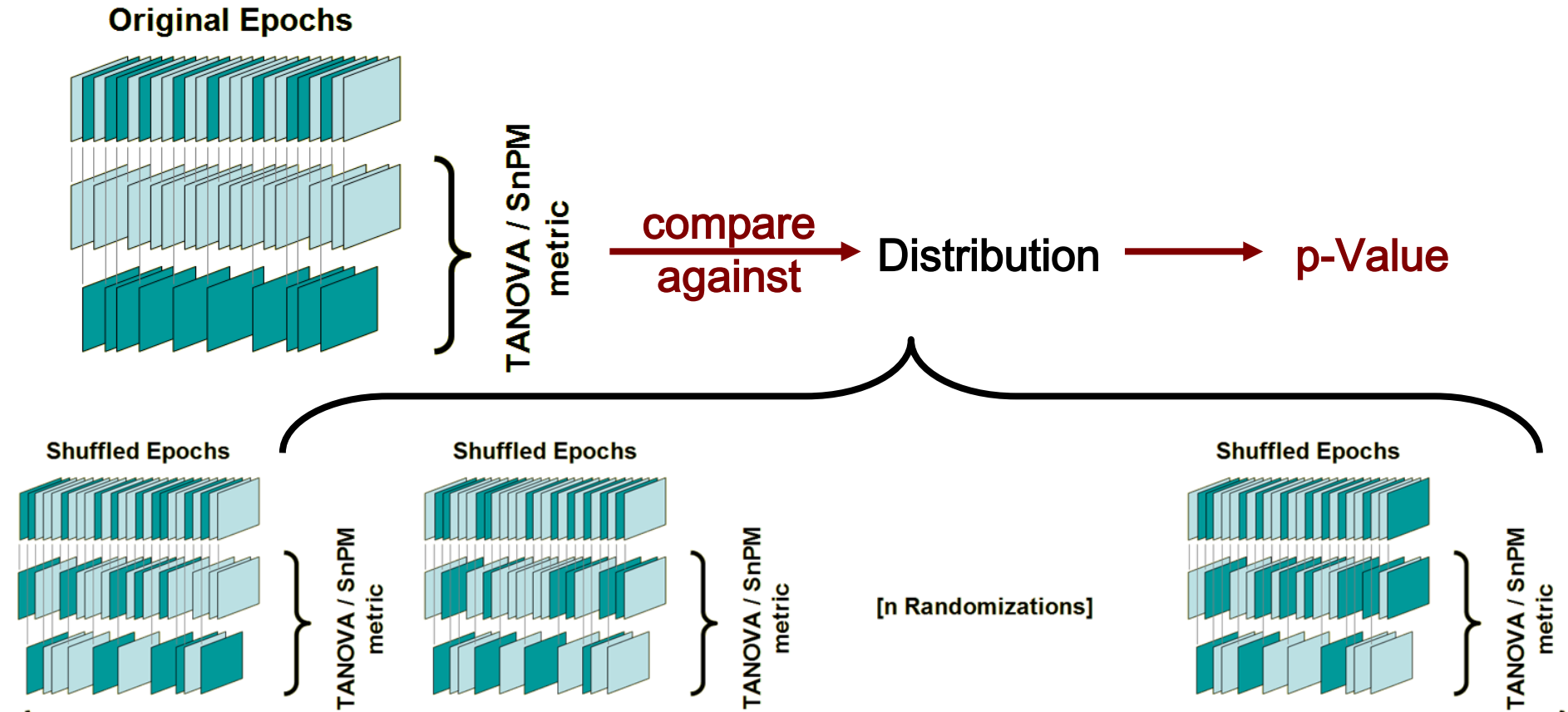


How is this Done?

- Existing work:
  - TANOVA (Koenig et al 2010): map analysis (used for EEG group studies)
  - SnPM (Nichols & Holmes 2002): image analysis (for medical imaging modalities)
- What's new:
  - Framework for epoch-by-epoch analysis
    - Single-subject data and group data
  - Apply SnPM to EEG source analysis
  - Temporal multiple comparison correction

Non-Parametric Statistics

- Compare actual and re-labeled (shuffled) data
  - re-labeling: “forget” epoch type (repeatedly)
  - significance: if actual data stands out



Non-Parametric Statistics

- Compare actual and re-labeled data
  - re-labeling: “forget” epoch type (many times)
  - significance: if actual data stands out
- Assumption-free
  - with respect to properties of underlying distribution
- Permutation-based / randomization-based
  - within- / between-subject tests straightforward
- Computationally demanding
  - typically used for group studies only
  - high-performance implementation (multi-core)

Randomization vs. Permutation

- How many tests need to be done?
  - depends on p (typical value: p = 0.05)
  - at least: 1 / p = 20
  - better: 50 / p = 1000
- Permutation: all possible re-labelings
  - 8+8 epochs: (8+8)!/(8! 8!) = 12870
  - 41+161 epochs: (41+161)!/(41! 61!) > 10^{44}
- Randomization: randomized re-labelings
  - for real-life epoch counts

Epoch-by-Epoch Analysis

- For single-subject data
  - normalize (unless effect size is relevant)
- For group data (all epochs of all subjects)
  - shuffle within or between subjects
  - normalize (optional within, mandatory between subjects)

TANOVA (topography maps)

- For two epoch types (conditions)
  - calculate average map per epoch type
  - effect size: GFP of difference map
- No multiple comparisons across sensors
- Also possible for
  - more epoch types
  - factorial designs
  - consistency test within epoch type (by re-labeling / shuffling sensors)

CDR SnPM (source images)

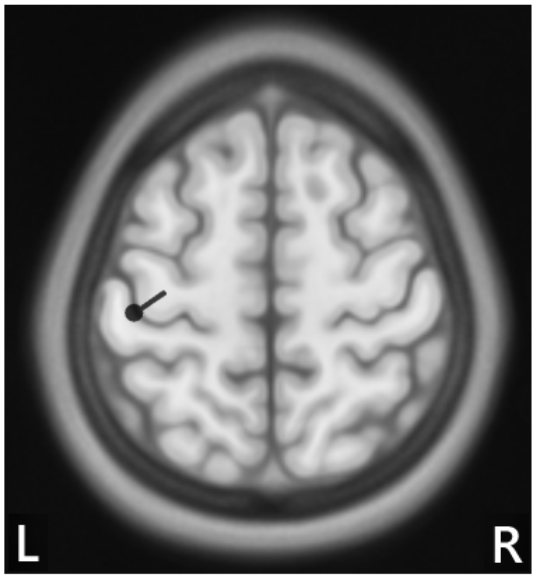
- For two epoch types (conditions)
  - calculate source activity images for all epochs and samples (e.g. using sLORETA)
  - F-test (per location, across epochs)
  - effect size: maximum F-value across locations
- No multiple comparisons across locations
- Also possible for
  - more epoch types
  - factorial designs
  - consistency test within epoch type (by re-labeling / shuffling locations)

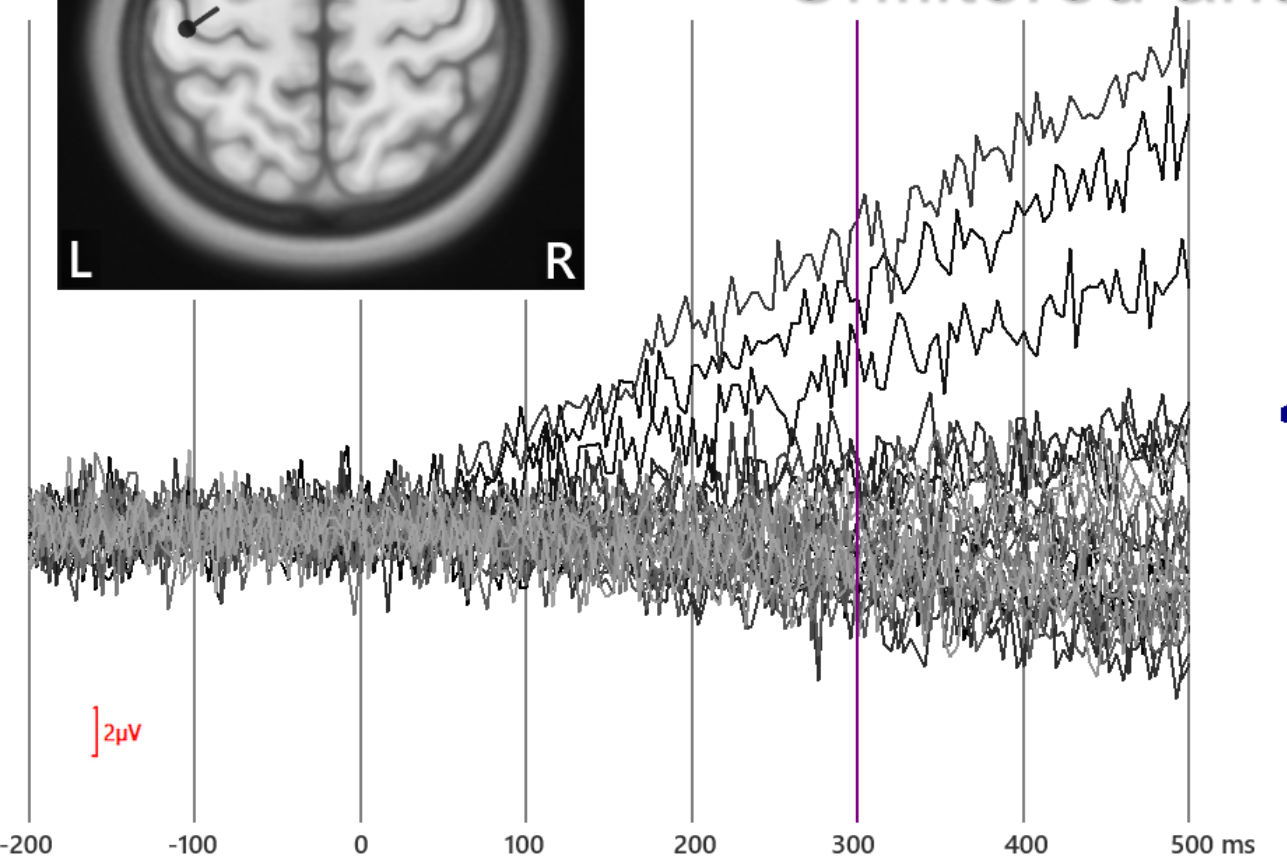
Multiple Comparison Correction

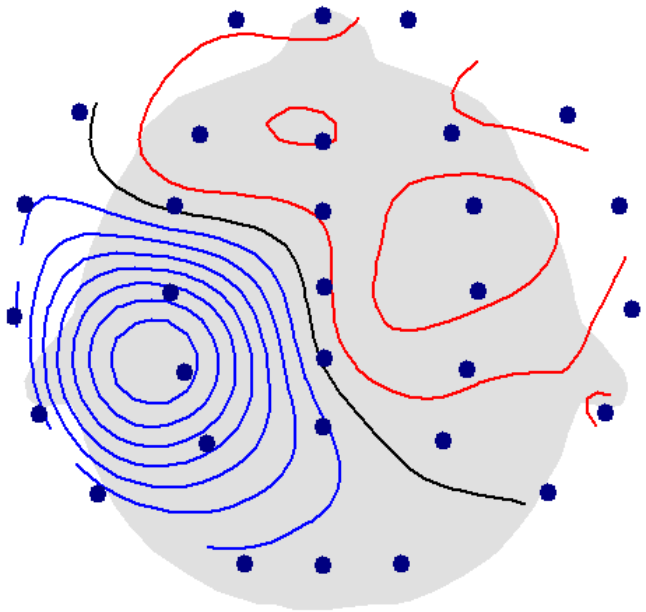
- Analysis performed sample-by-sample
  - high temporal resolution
- Typical ERP setup
  - 1000 Hz sampling rate, 40 Hz low-pass filter
  - neighboring samples are similar (how many?)
- Nyquist-Shannon sampling theorem
  - after filtering, resample at 2x filter frequency
  - n = 1000 / (2 x 40) = 12.5 ways to do this
- Temporal multiple comparison correction
  - adjusted significance level based on n

A Simulation Study

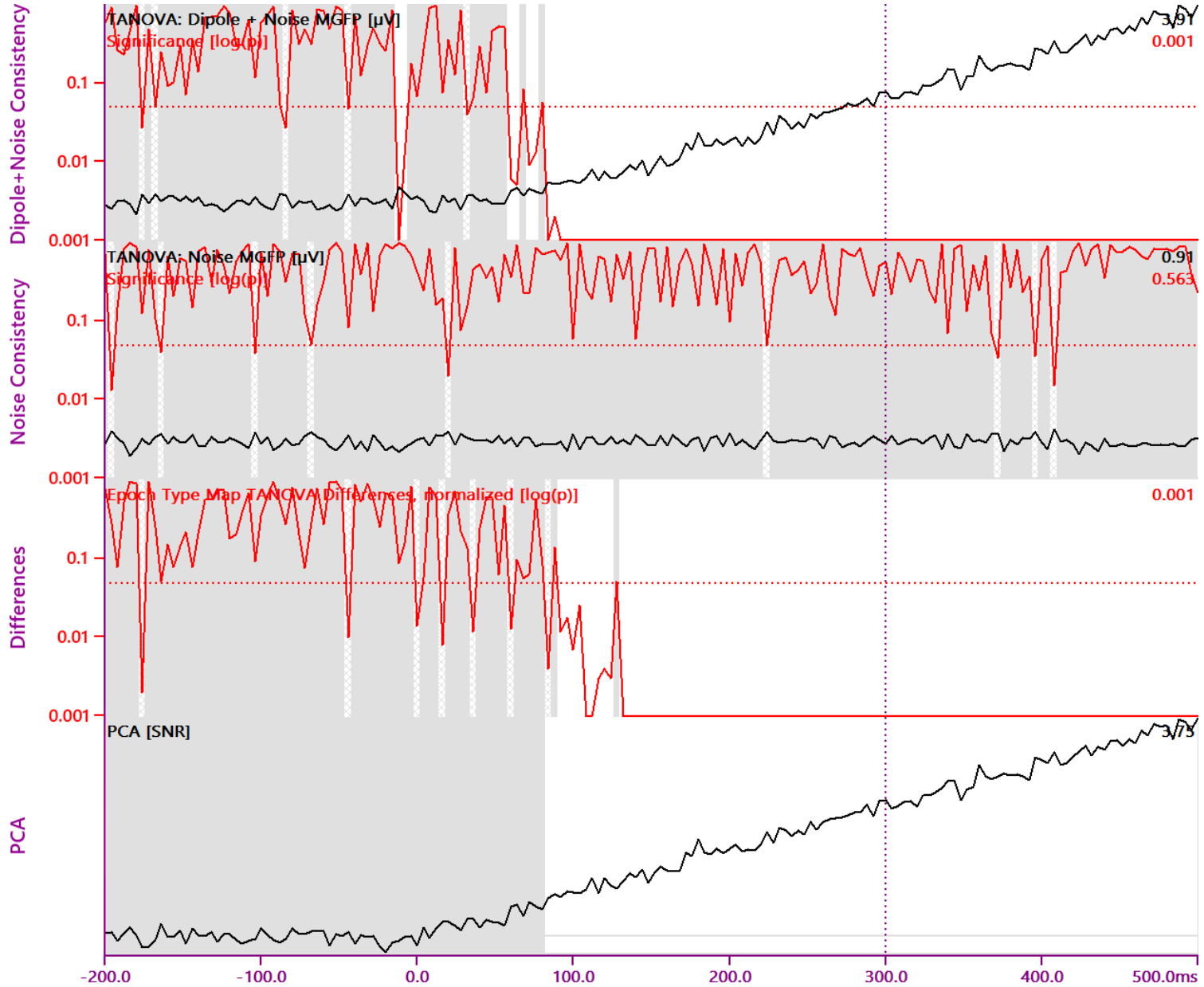
- 100 epochs dipole+noise
- 100 epochs noise only
- Unfiltered and 10Hz low-pass



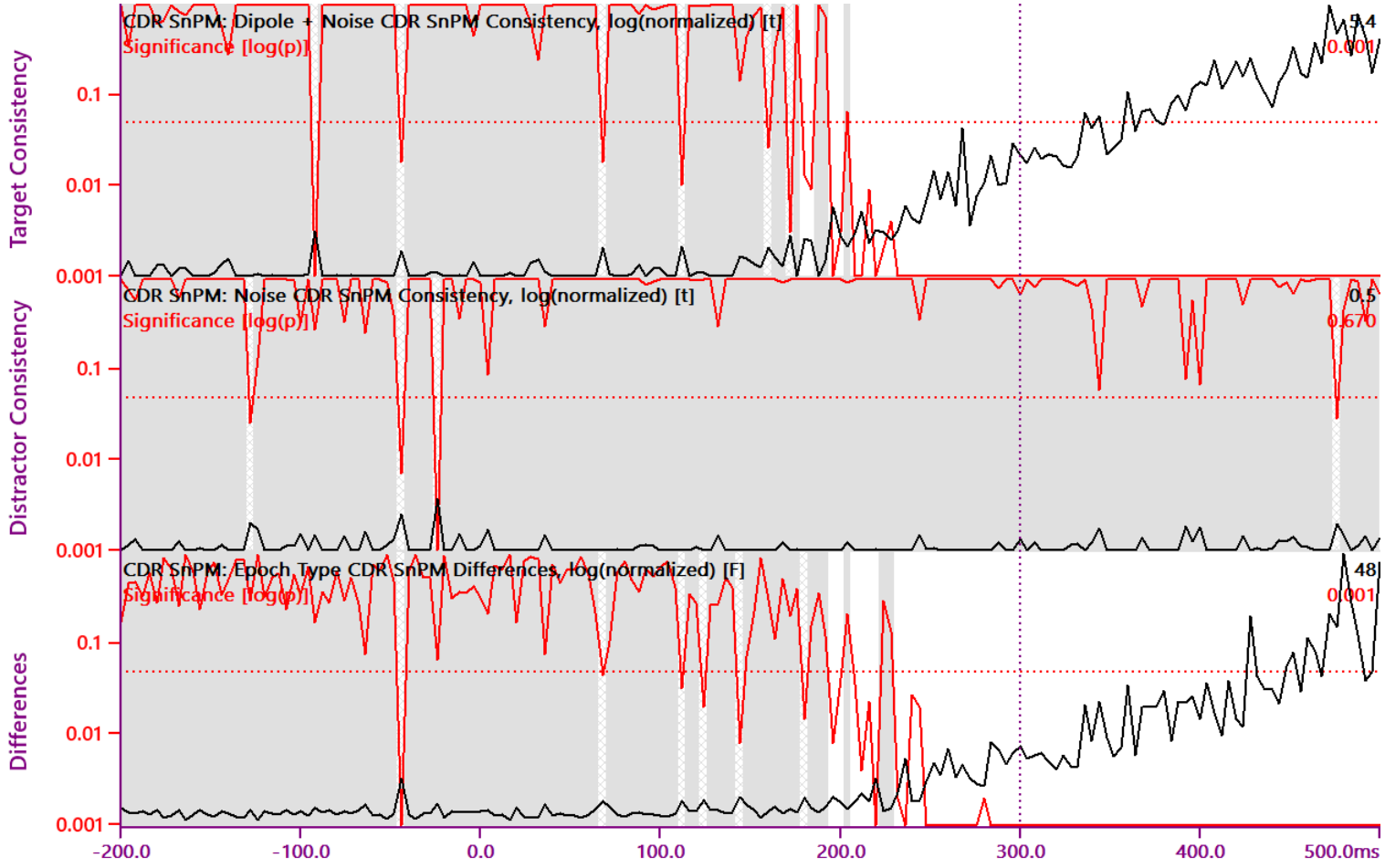




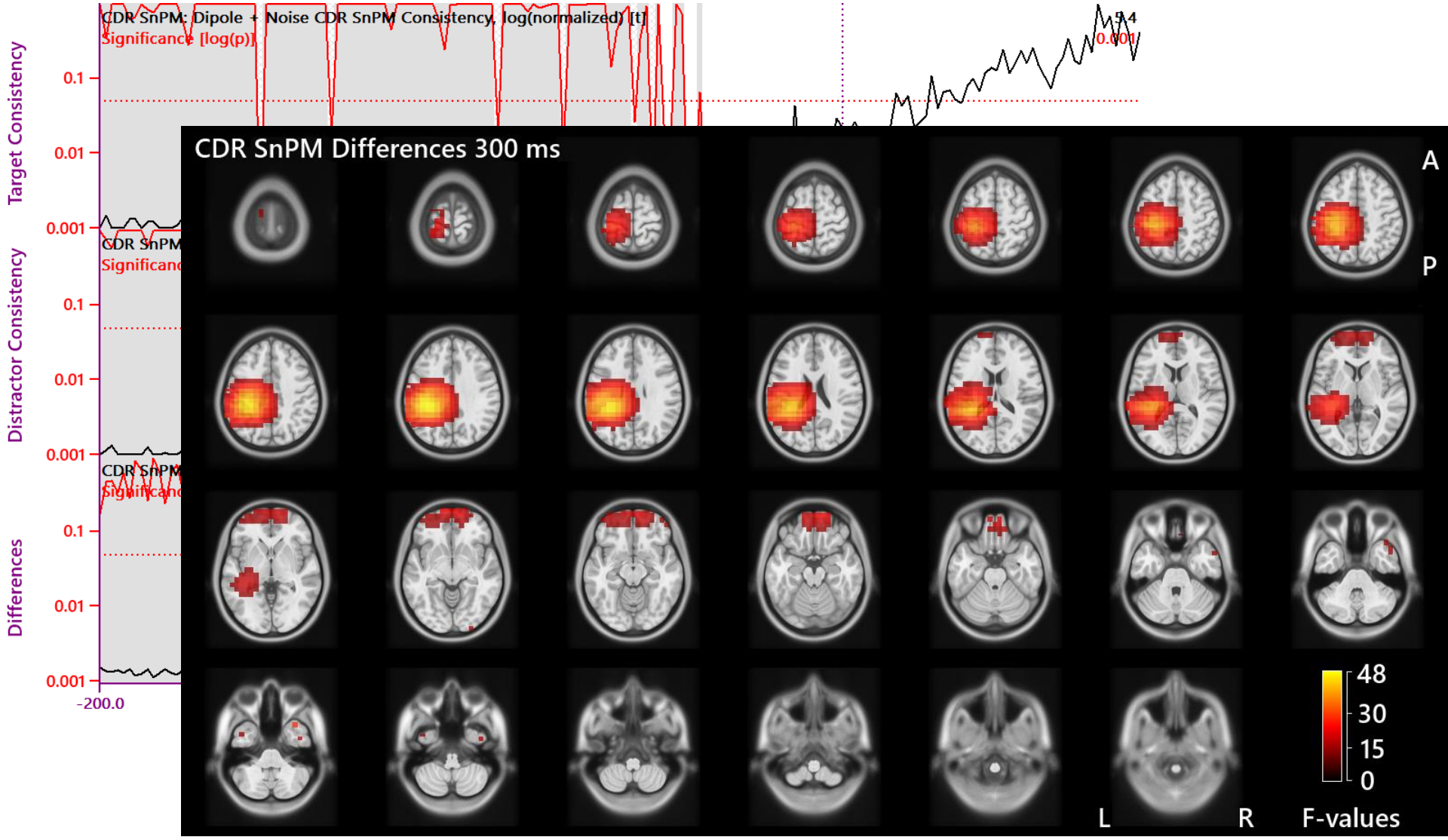
A Simulation Study: TANOVA



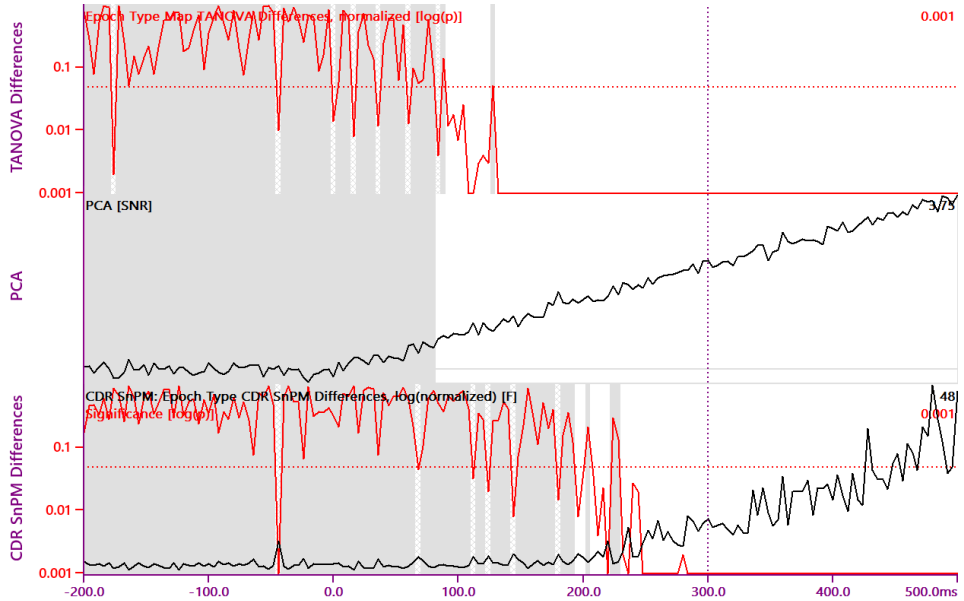
A Simulation Study: CDR SnPM



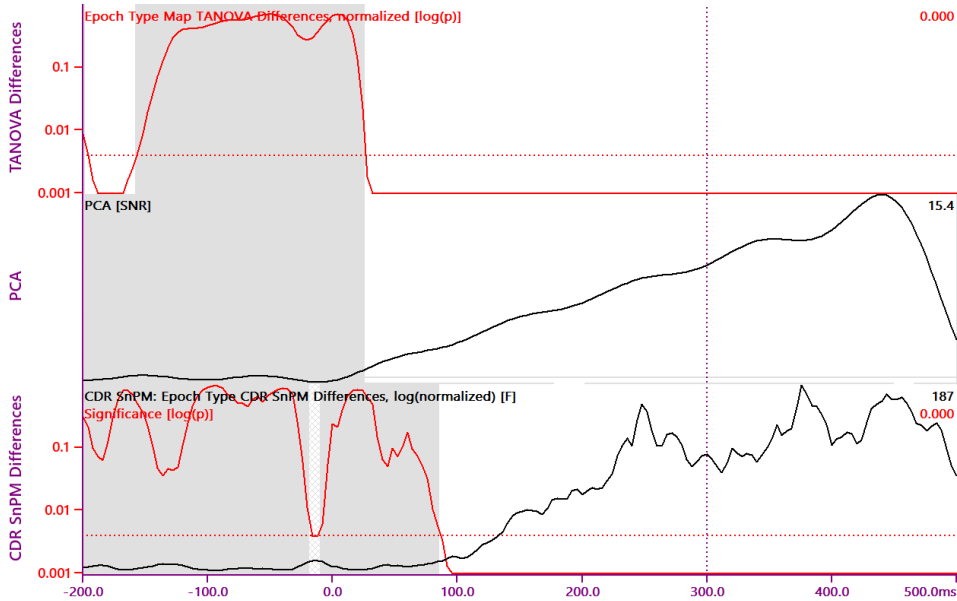
A Simulation Study: CDR SnPM



A Simulation Study



unfiltered

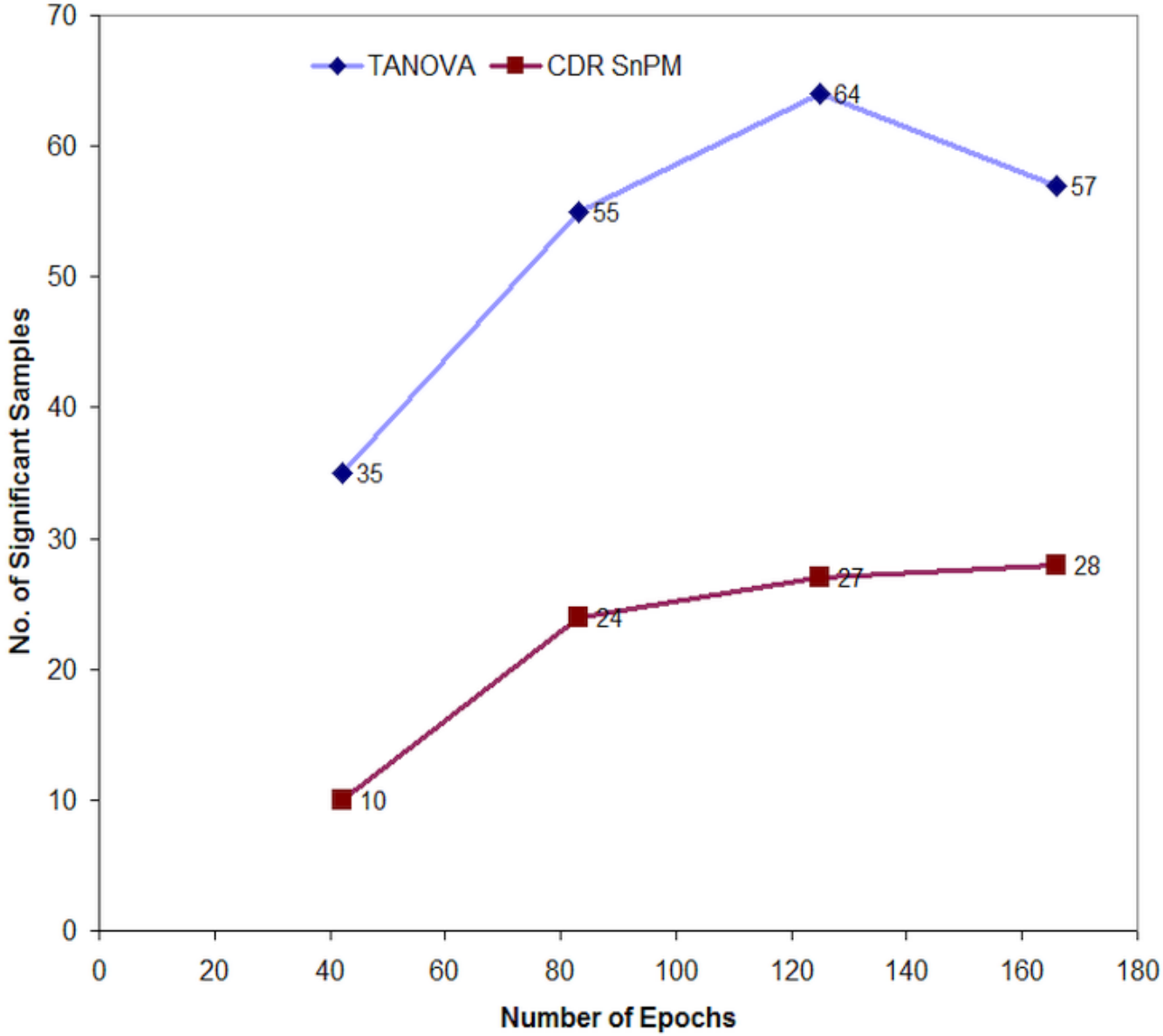


low-pass filtered

- Temporal multiple comparison correction: lower significance level for filtered data
- Less samples with CDR SnPM differences

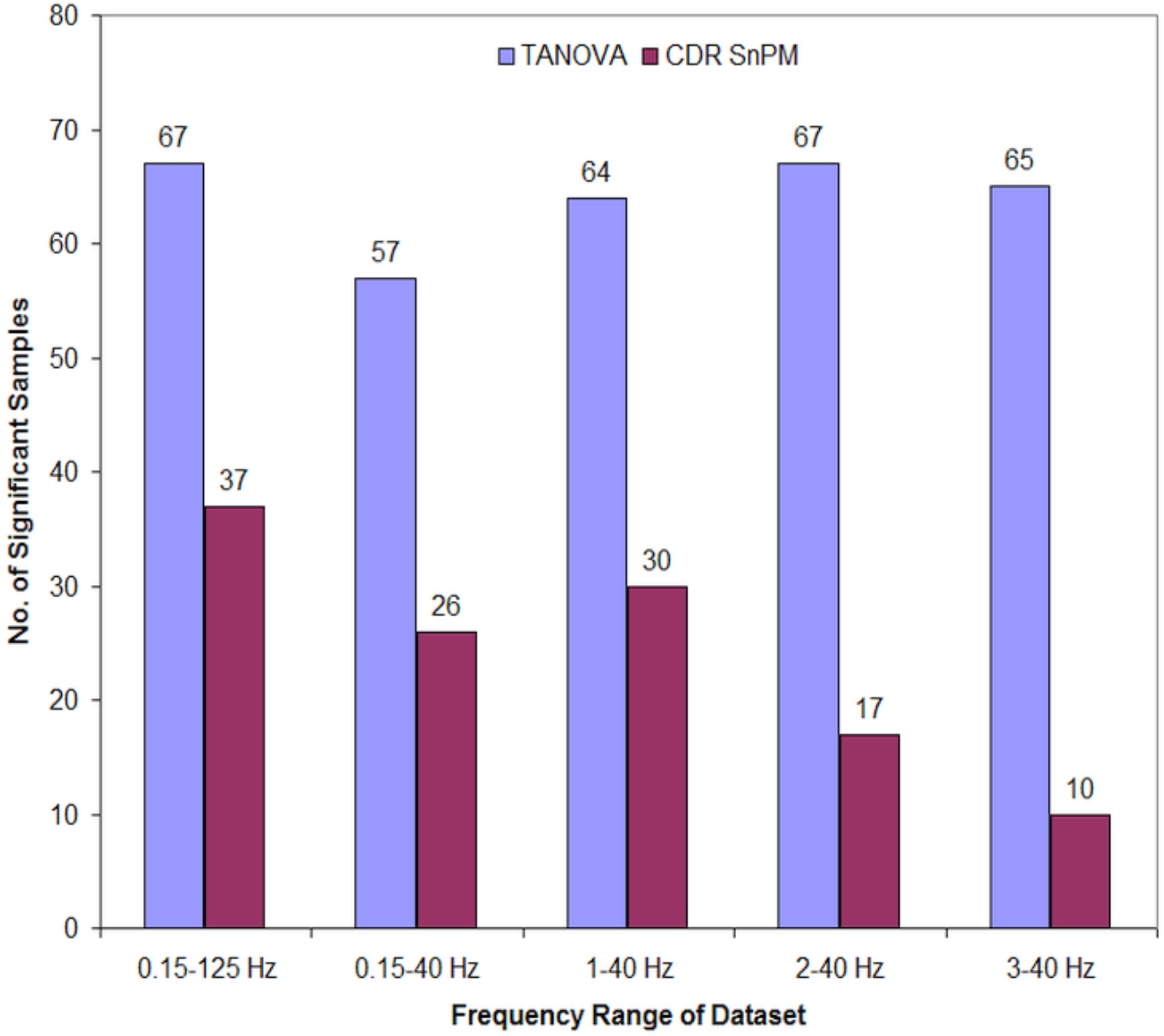
How Many Epochs?

- Different subsets of epochs
- 41+161 CPT data
- No. of samples with significant differences



Different Filter Bands?

- Different high-pass, low-pass
- 41+161 CPT data
- No. of samples with significant differences



Conclusion

- For single-subject (and group) ERPs:
- Detect latencies of
  - consistency within epoch type
  - differences between epoch types
- Detect latencies and source locations of
  - differences between epoch types
- Sample-by-sample
  - with temporal multiple comparison correction

Paper & Book Chapter

M. Wagner, C. Ponton, R. Tech, M. Fuchs, & J. Kastner

— **Non-Parametric Statistical Analysis of EEG/MEG Map Topographies and Source Distributions on the Epoch Level**

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In an Event-Related Potential (ERP) or Event-Related Field (ERF) experiment, an Electroencephalography (EEG) or Magnetoencephalography (MEG) device records the brain response related to a sensory, cognitive, or motor event. Depending on the experimental design, events (stimuli or responses) may be of the same or of different types. Data segments with distortions such as ocular, cardiac, or muscle artifacts are later detected and artifacts are either reduced or excluded from further processing. After splitting the data into epochs time-locked to events, many repetitions per event type are available and usually averaged and compared. After averaging, though, it is no longer possible to establish whether and for which latencies the averaged waveforms differ significantly between event types, nor whether the trials (epochs) of a given type yield significant averages in the

Magnetoencephalography: From Signals to Dynamic Cortical Networks
Supek, Selma, Aine, Cheryl J. (Eds.)
In Print
Springer, June 20, 2014
ISBN 978-3-642-33044-5

Non-Parametric Statistical Analysis of Map Topographies on the Epoch Level

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Keywords: Magnetoencephalography, Electroencephalography, Event-Related Fields, Event-Related Potentials, Mismatch Negativity, Mandarin Language, Statistical Analysis, Randomization Statistics, Non-Parametrical Statistics, Topographical Analysis of Variance

1. Introduction

In Event-Related Field (ERF) experiments, stimuli - often of several different types - are presented repeatedly, and the subject's brain response is recorded using MEG. After removing artifacts and epoching the data, many repetitions per stimulus type are available, which are later usually averaged and compared. At this stage, though, it is no longer possible to establish whether and for which latencies the averaged waveforms are significantly different between stimulus types, nor whether the trials (epochs) for a given stimulus type are consistent enough to warrant averaging them in the first place. A statistical analysis of all individual epochs can provide exactly this information.

Traditional statistical measures in channel space such as the t-test make disputable assumptions regarding repeatability and independence (Murray et al. 2008, Koenig and Melie-Garcia 2009). Therefore, a new non-parametric family of methods has recently attracted attention as it became computationally feasible for the analysis of Event-Related Potential (ERP) group studies (Murray et al. 2004). Although - misleadingly - referred to as Topographic Analysis of Variance (TANOVA), no analysis of variance is being conducted, but rather a non-parametric randomization test.

In this contribution, a framework is proposed that allows the application of TANOVA not only to individual averages in the context of an ERP group study but to the un-averaged individual epochs themselves, as obtained in a Mismatch Negativity (MMN) MEG experiment.