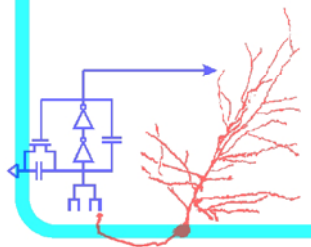


New Methods for Denoising MEG data *and* Attending (at) a Cocktail Party

Jonathan Z. Simon

*Neuroscience and Cognitive Sciences /
Biology / Electrical & Computer Engineering*

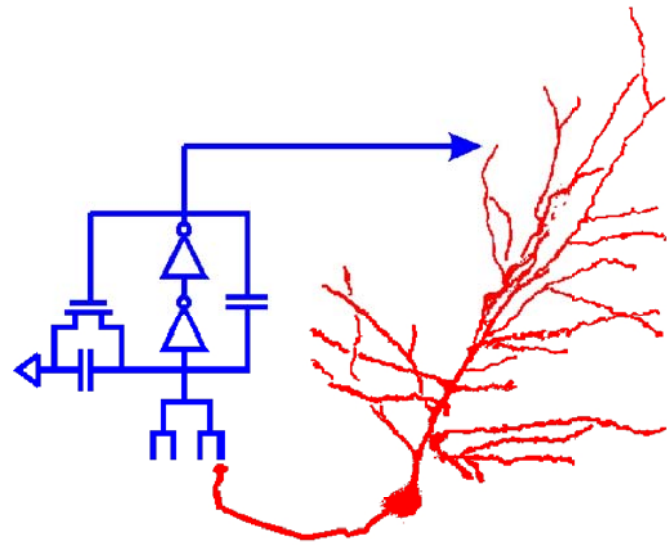
University of Maryland, College Park



N.Y.U. Workshop January 24, 2009

Computational Sensorimotor Systems Laboratory

Computational Sensorimotor Systems Laboratory & Friends



Current & Former Students

Juanjuan Xiang

Nai Ding

Huan Luo

Nayef Ahmar

Jiachen Zhuo

Maria Chait

Ling Ma

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David Poeppel

Alain de Cheveigné

Shihab Shamma

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Yadong Wang

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Jeff Walker

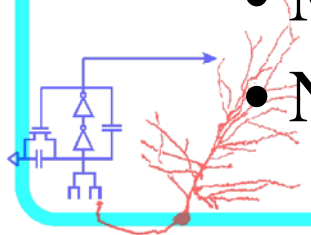
Ray Shantanu

Supported by

NIH: NIDCD, NIBIB, NIA

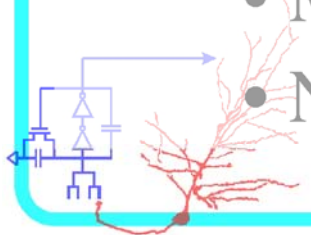
Outline

- Brief Introduction to MEG
- Denoising MEG Data
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 - Sensor Noise Reduction
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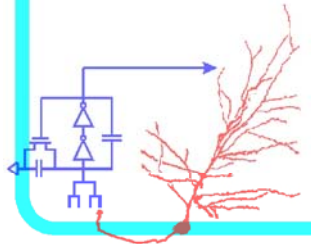
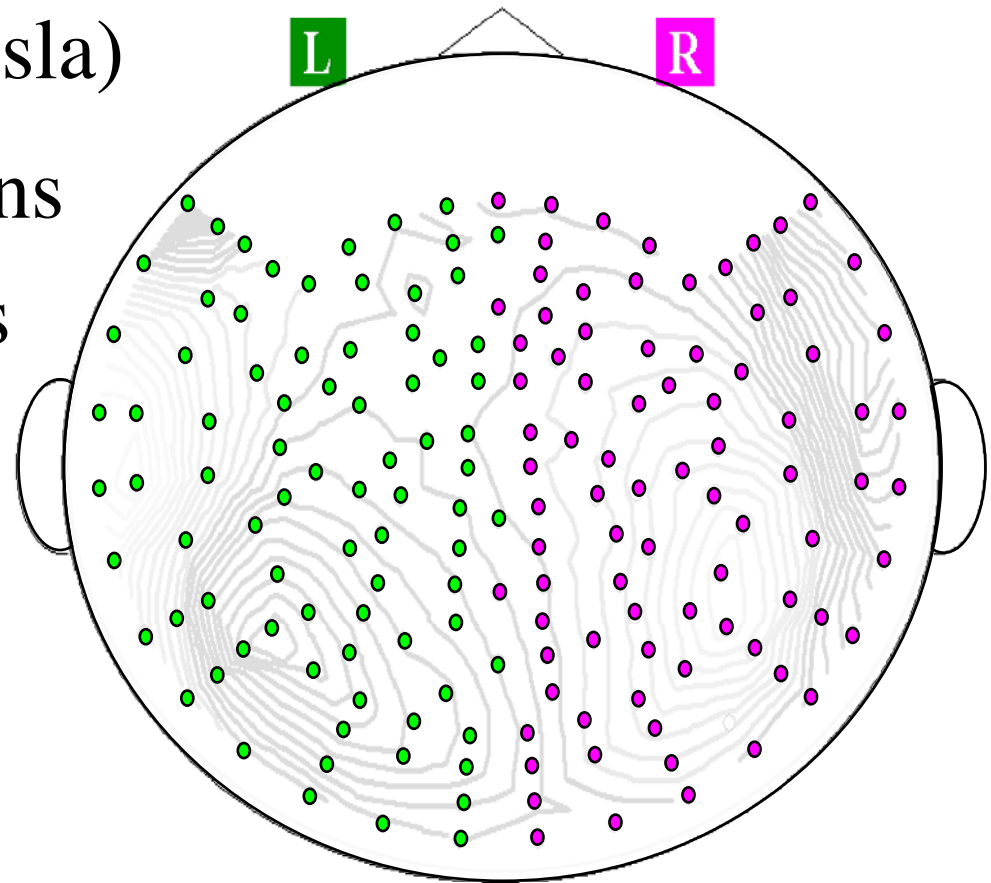
Magnetoencephalography (MEG)

- Non-invasive, Passive, Silent Neural Recordings
- Simultaneous Whole-Head Recording (~200 sensors)
- Sensitivity

high: ~ 100 fT (10^{-13} Tesla)

low: $\sim 10^4 - \sim 10^6$ neurons

- Temporal Resolution: ~ 1 ms
- Spatial Resolution
coarse: ~ 1 cm
ambiguous



Functional Imaging

Non-invasive recording
from human brain
(Functional brain imaging)

Hemodynamic
techniques

Functional magnetic
resonance imaging
fMRI

Excellent *spatial resolution*
($\sim 1\text{-}2\text{ mm}$)
Poor *temporal resolution*
($\sim 1\text{ s}$)

Positron emission
tomography
PET

PET, EEG require
across-subject
averaging

fMRI and MEG can
capture effects in
single subjects

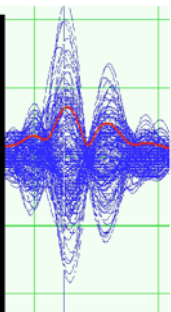
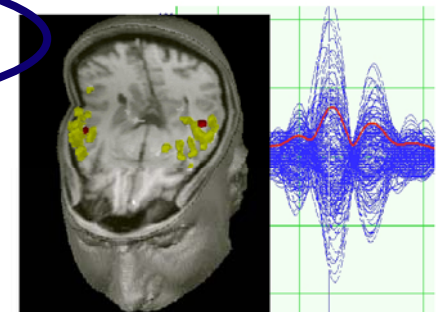
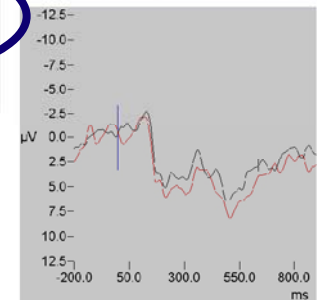
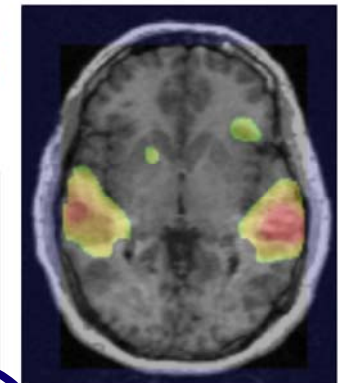
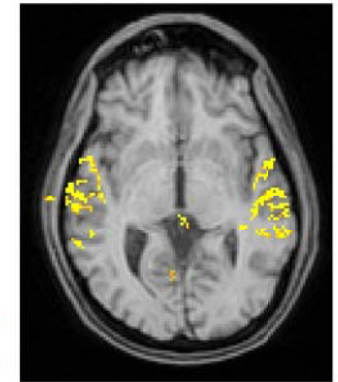
Electroencephalography
EEG

Electromagnetic
techniques

Poor *spatial resolution*
($\sim 1\text{ cm}$)

Excellent *temporal resolution*
($\sim 1\text{ ms}$)

Magnetoencephalography
MEG



Primary Neural Current

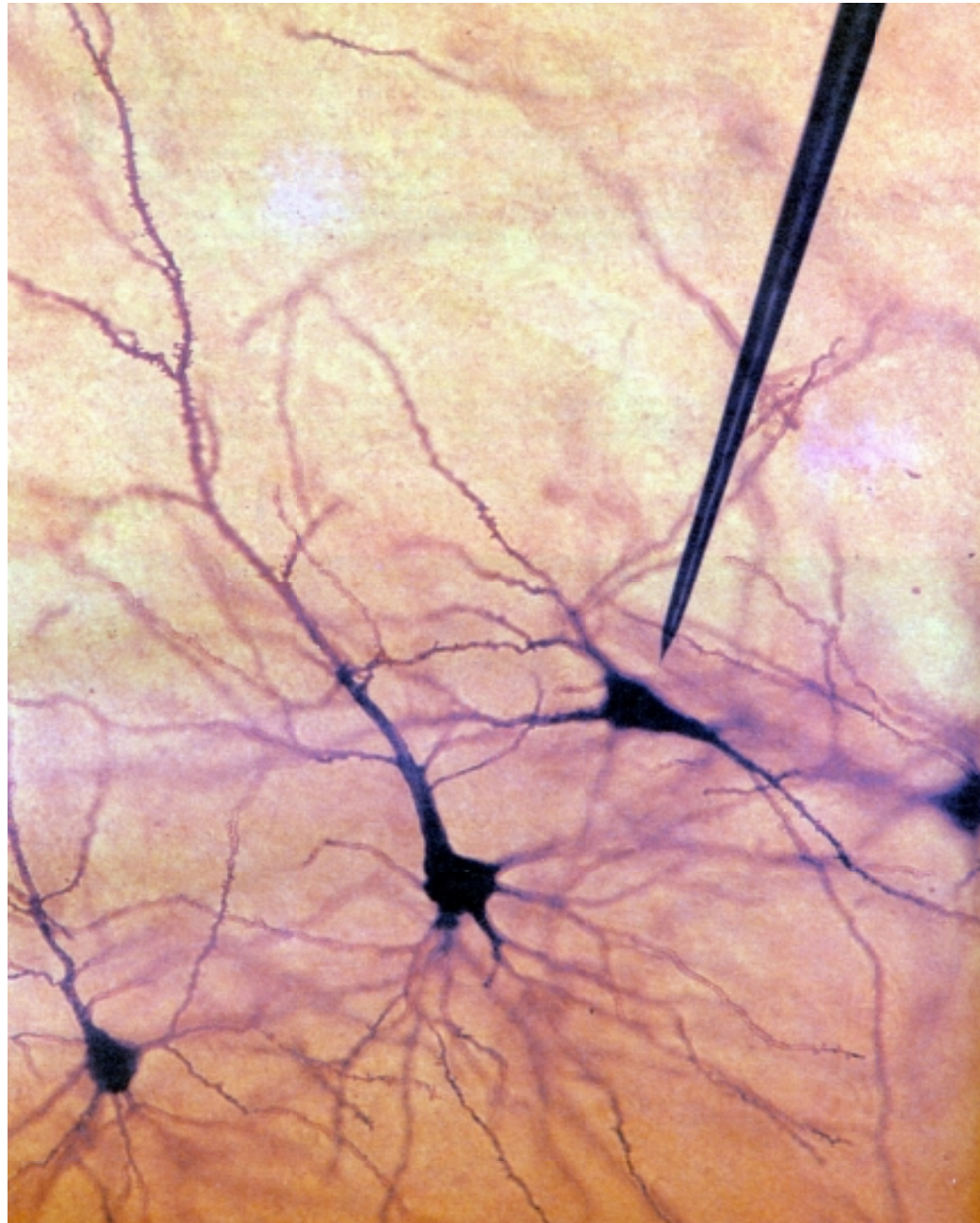
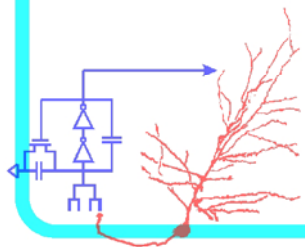


Photo by Fritz Goro



Primary Neural Current

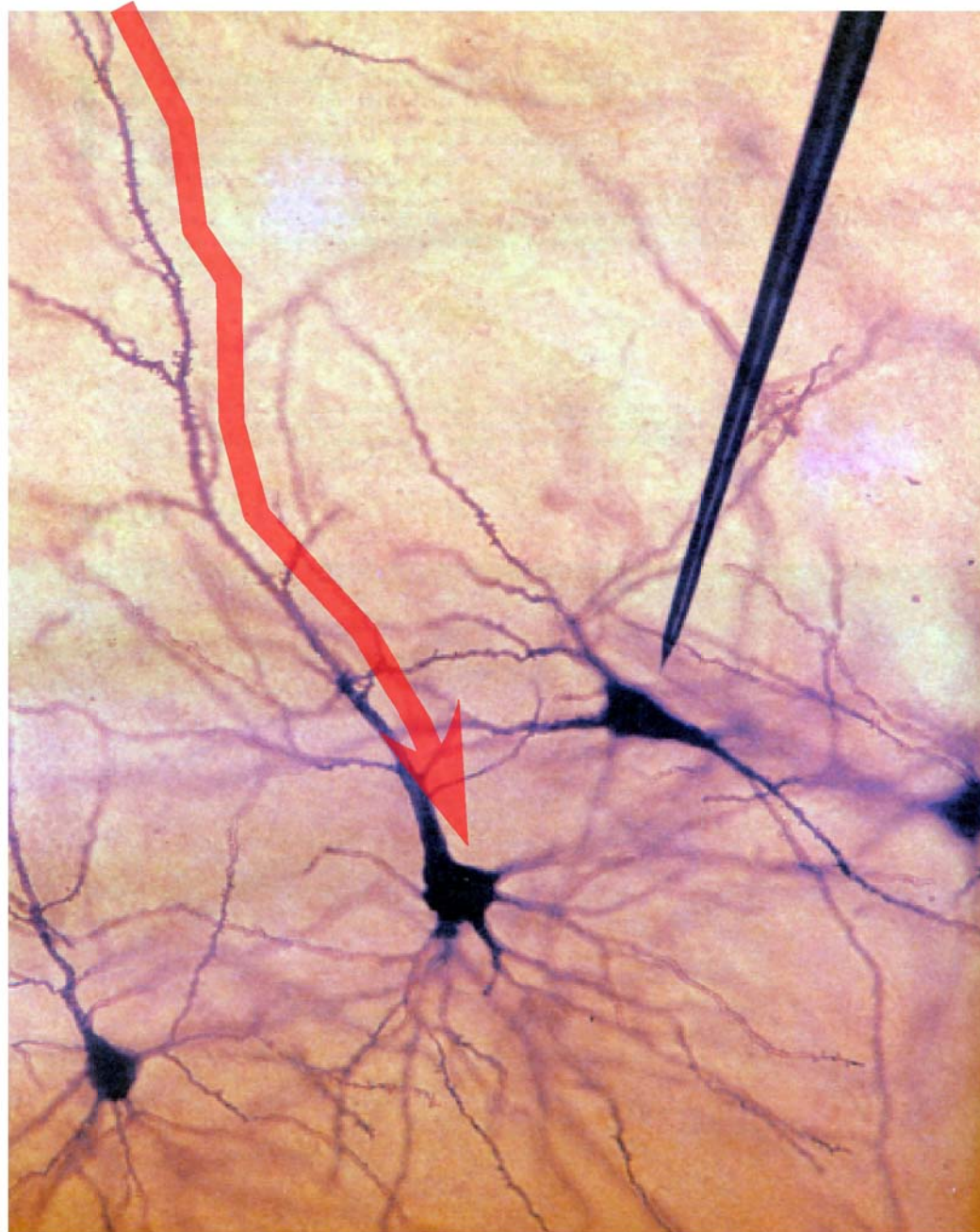
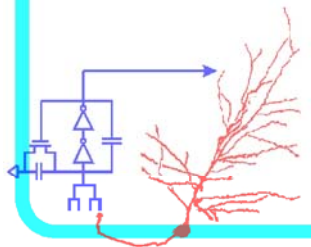
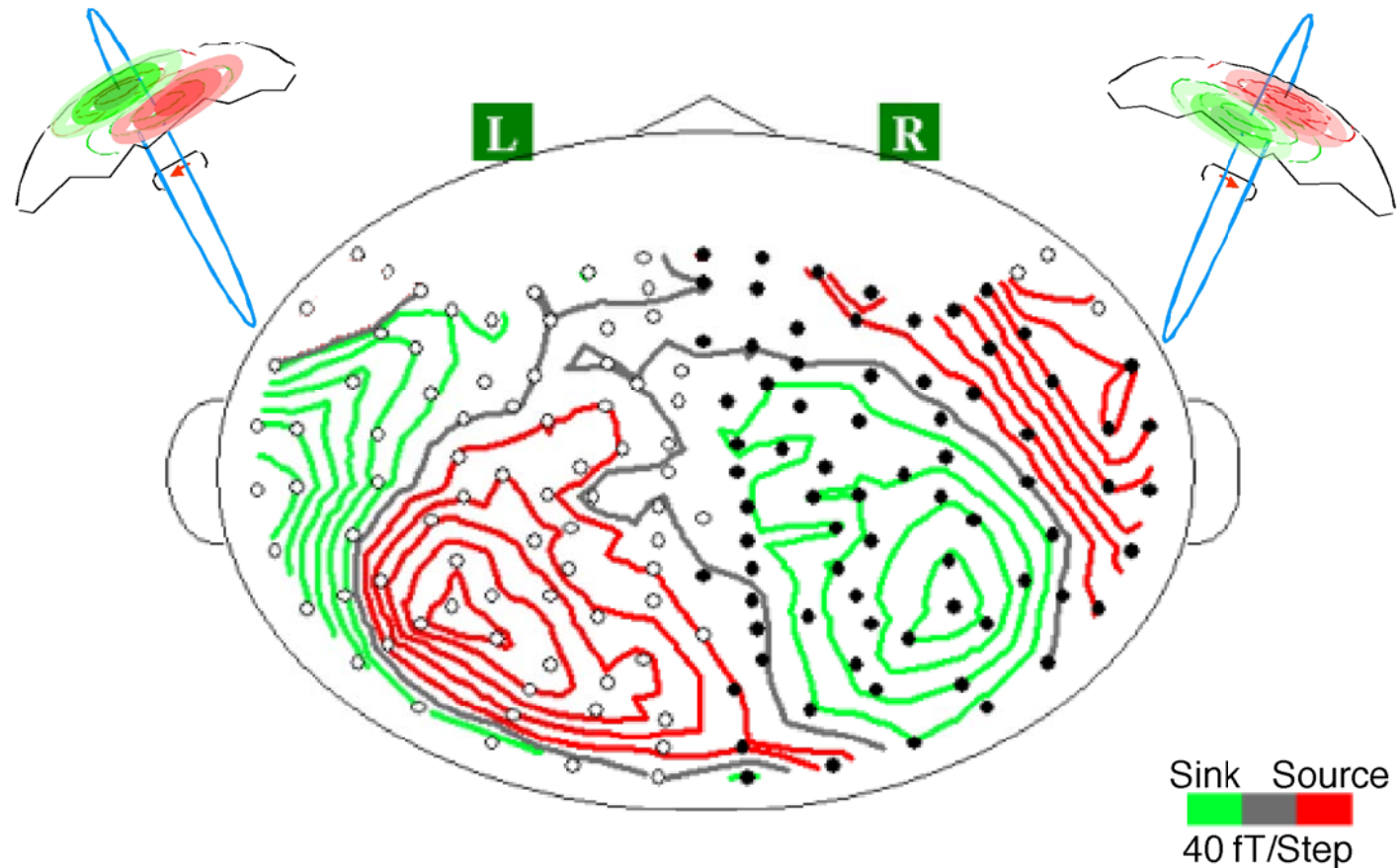
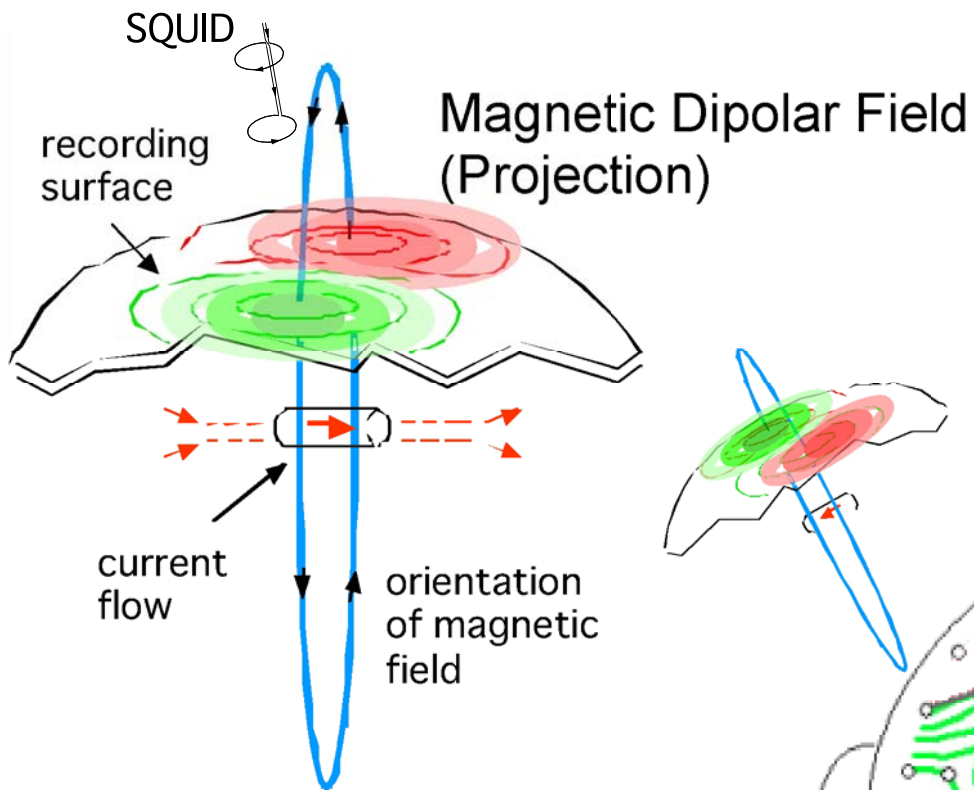


Photo by Fritz Goro



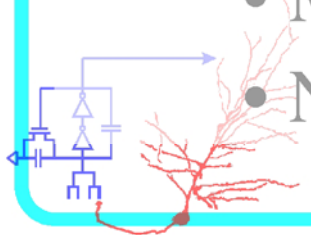
MEG Measures Neural Currents

- Direct electrophysiological measurement
 - not hemodynamic
 - real-time
- No unique solution for distributed source



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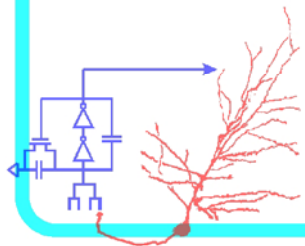
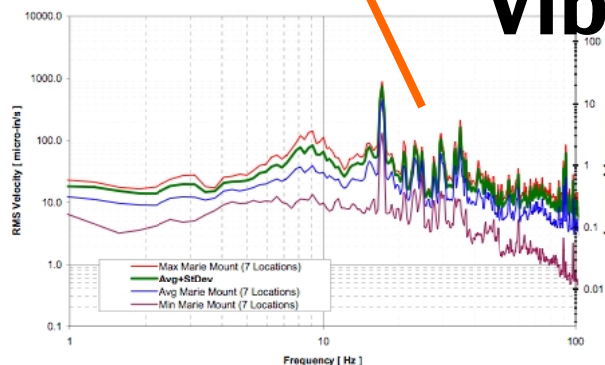


Environmental Noise

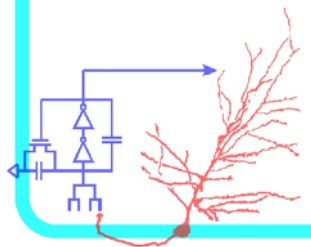
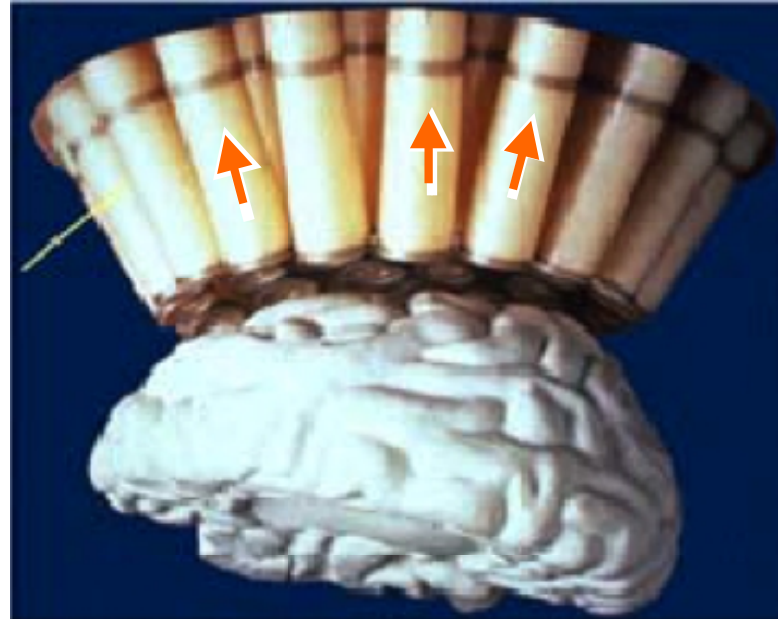
Electromagnetic



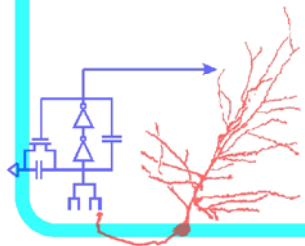
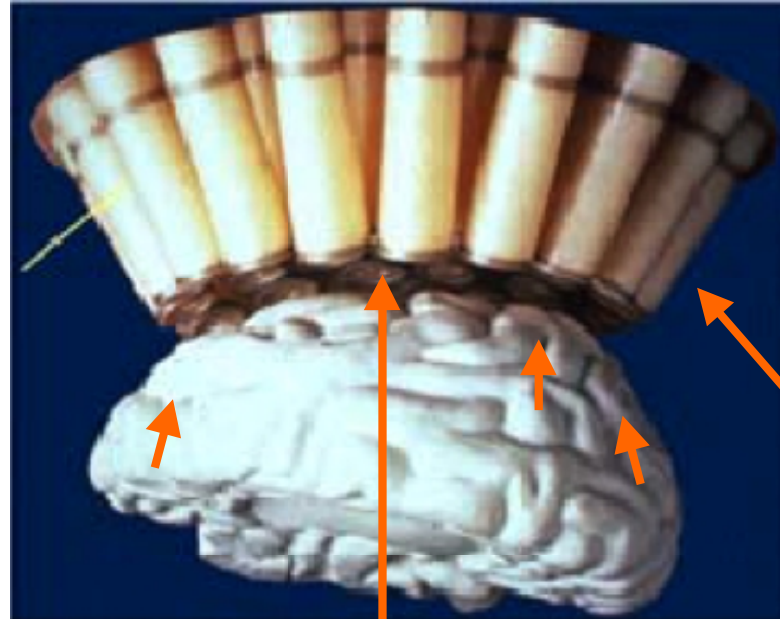
Vibrational



Sensor Noise

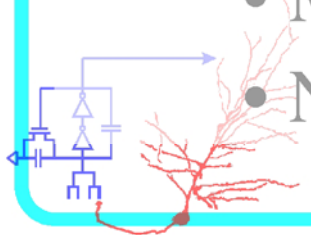


Physiological Noise



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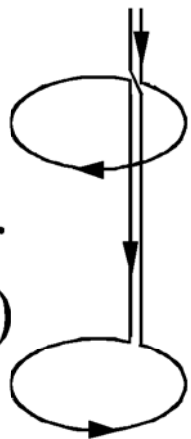
External Noise Reduction Aids



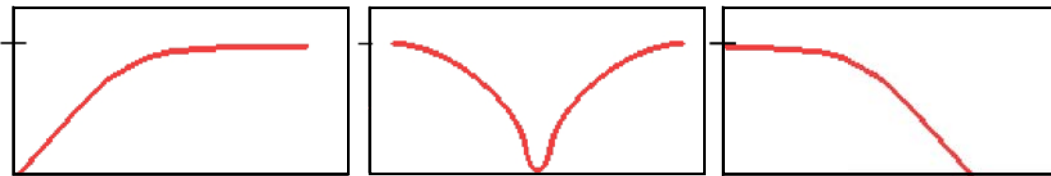
Magnetically shielded room

Magnetic/electromagnetic shielding

Gradiometers (sensitive to near sources)

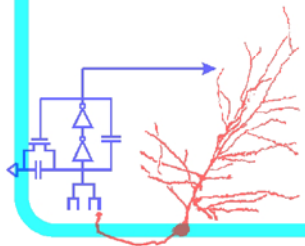


Gradiometer



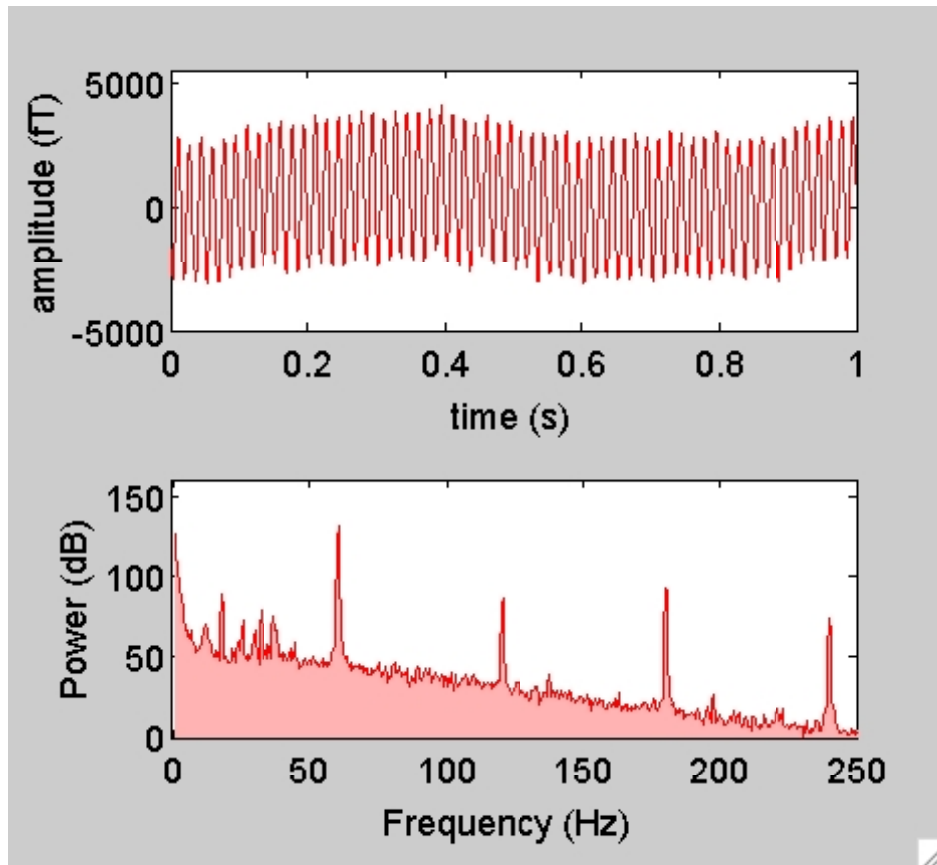
Spectrally Selective Filters

Spectral filtering (high-pass, notch, low-pass)

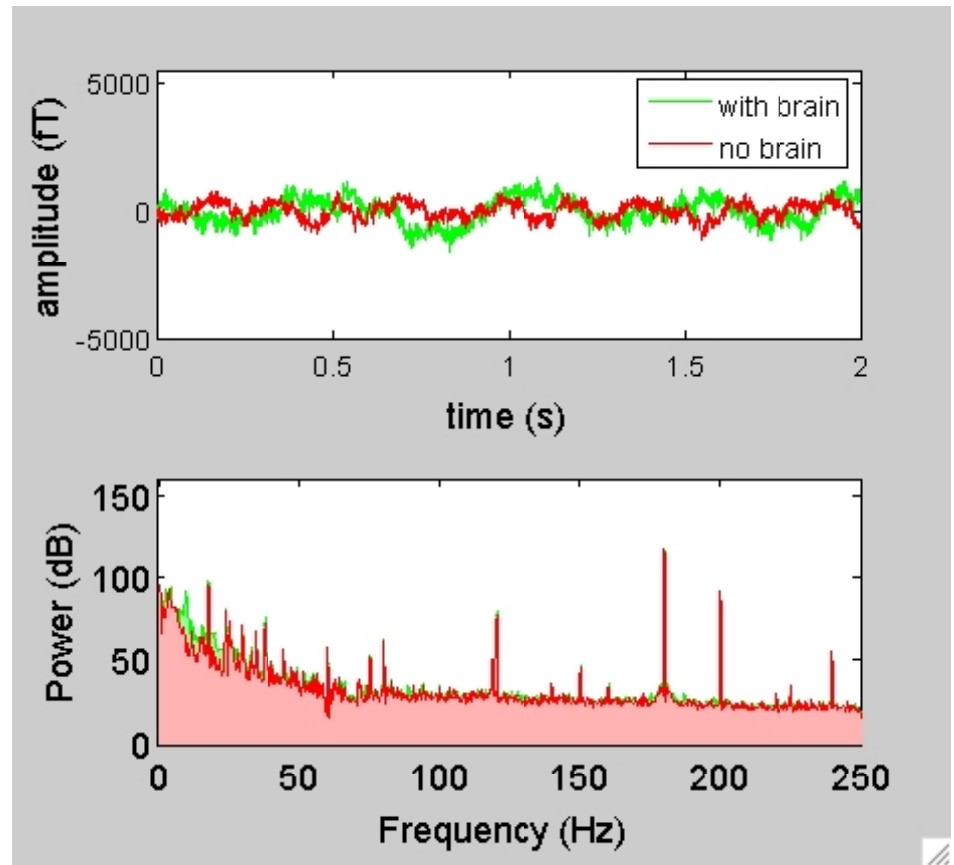


Effects of Filtering

Raw:

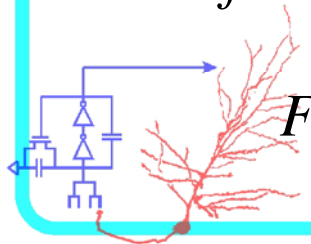


HPF 1 Hz, Notch 60 Hz:



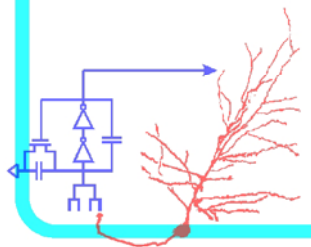
After filtering, typically ~90% of MEG power is still environmental noise.

Filtering also adds distortions (group delay, phase shift, etc.).



TSPCA

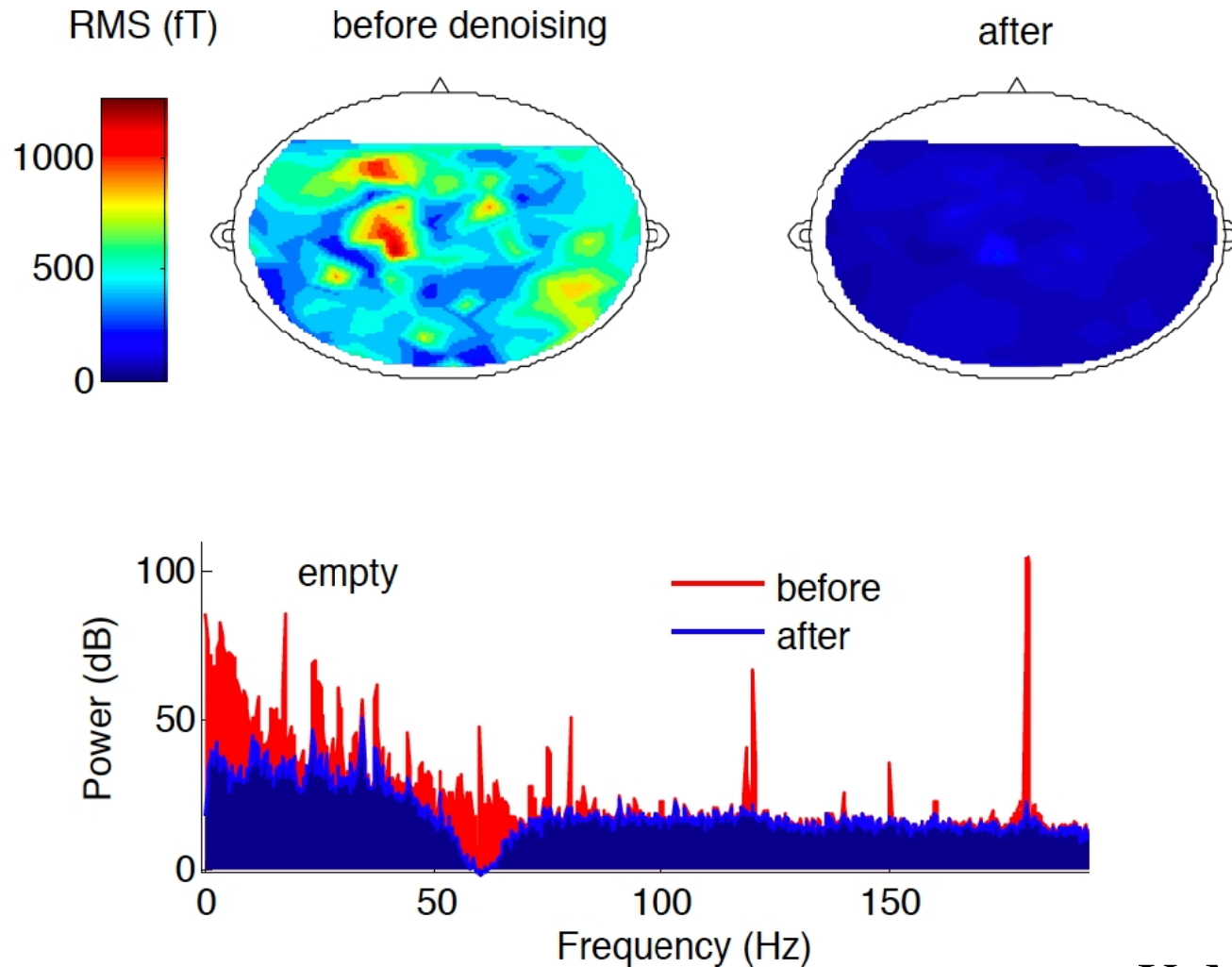
- Time Shifted Principle Component Analysis
- Target: Environmental Noise
- Requirement: Reference channels



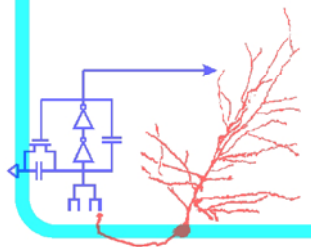
in collaboration with Alain de Cheveigné

TSPCA Example

Empty Chamber

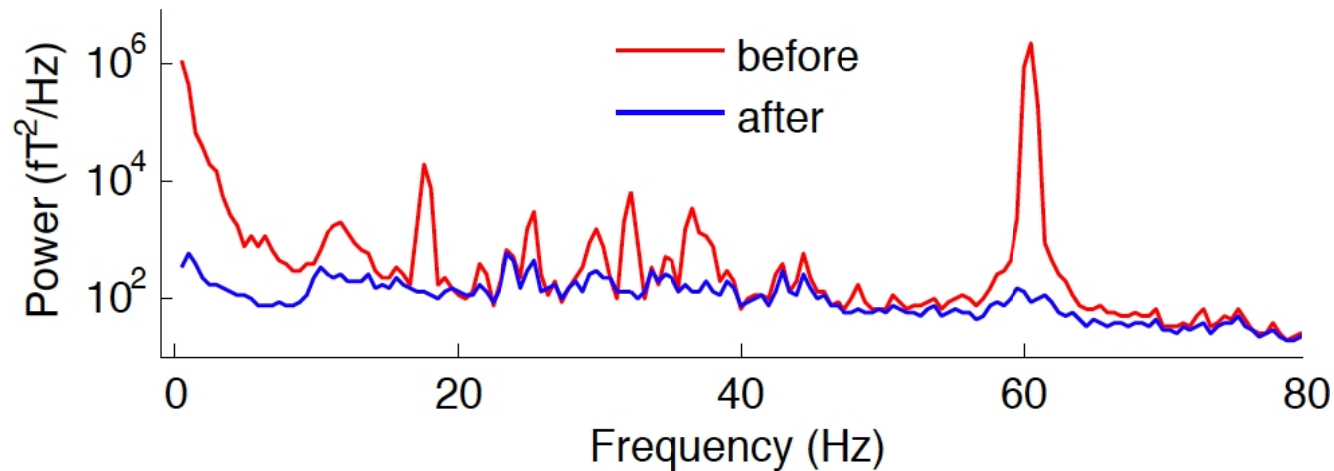
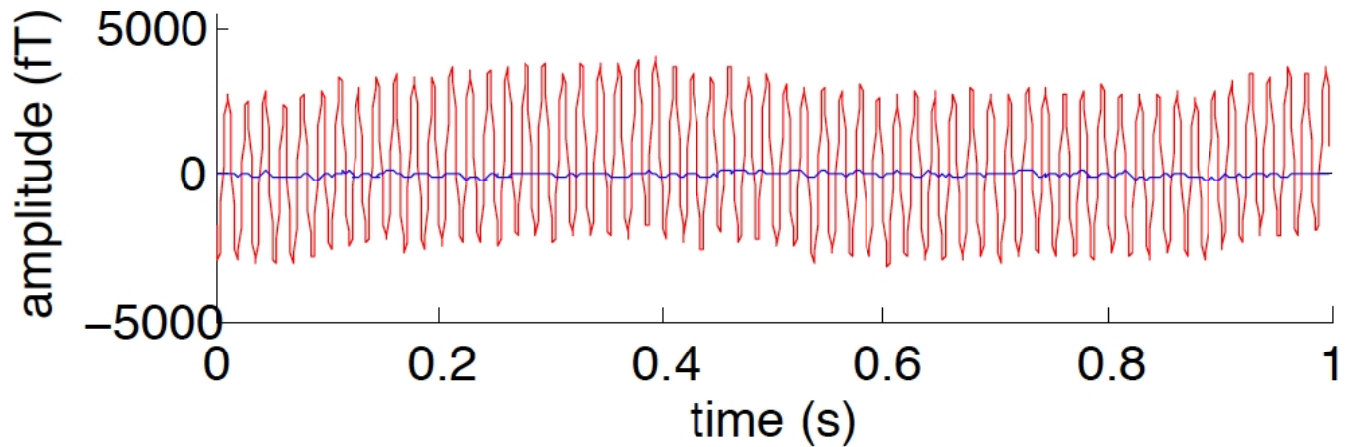


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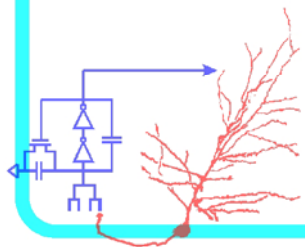


TSPCA Example

Without Notch & HP hardware filters

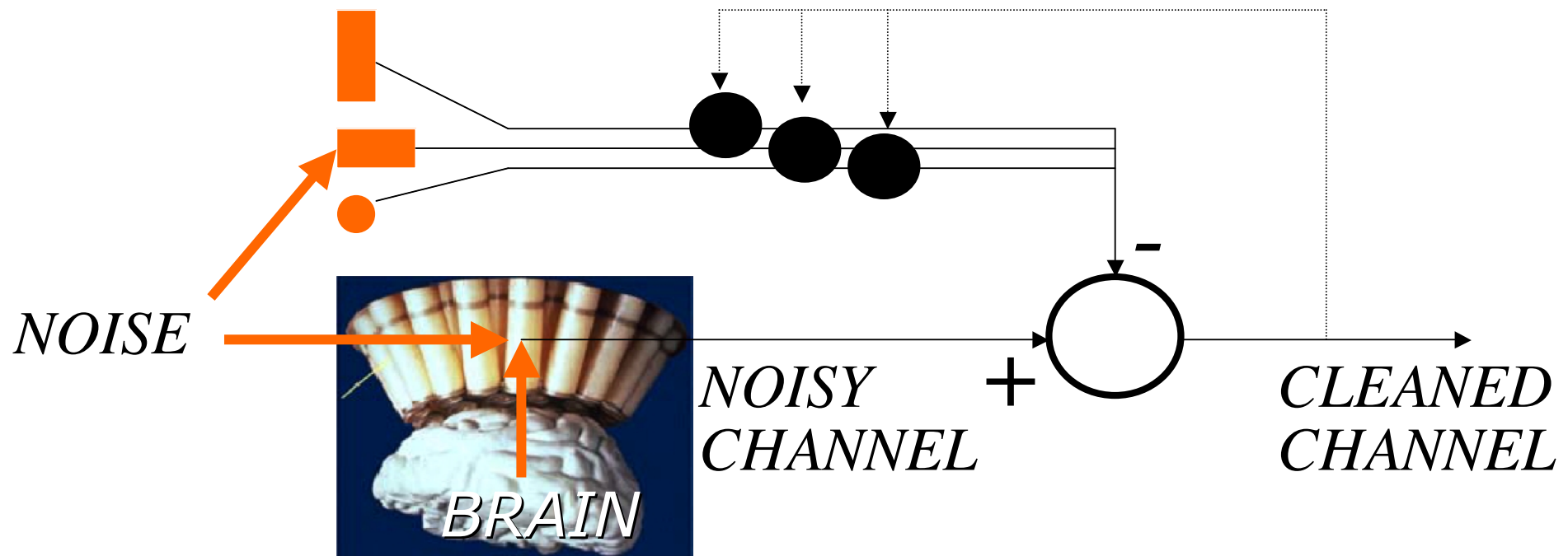


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TSPCA: How it works

First, understand classic Scalar Regression methods
(e.g. CALM)

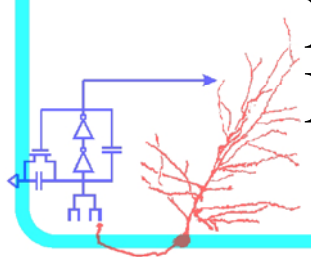


When scalar regression may fail since:

Noise in Reference may be *filtered* w.r.t. Brain channel

Noise in Reference may be *time-shifted* w.r.t. Brain channel

May be *more* independent noise sources than References



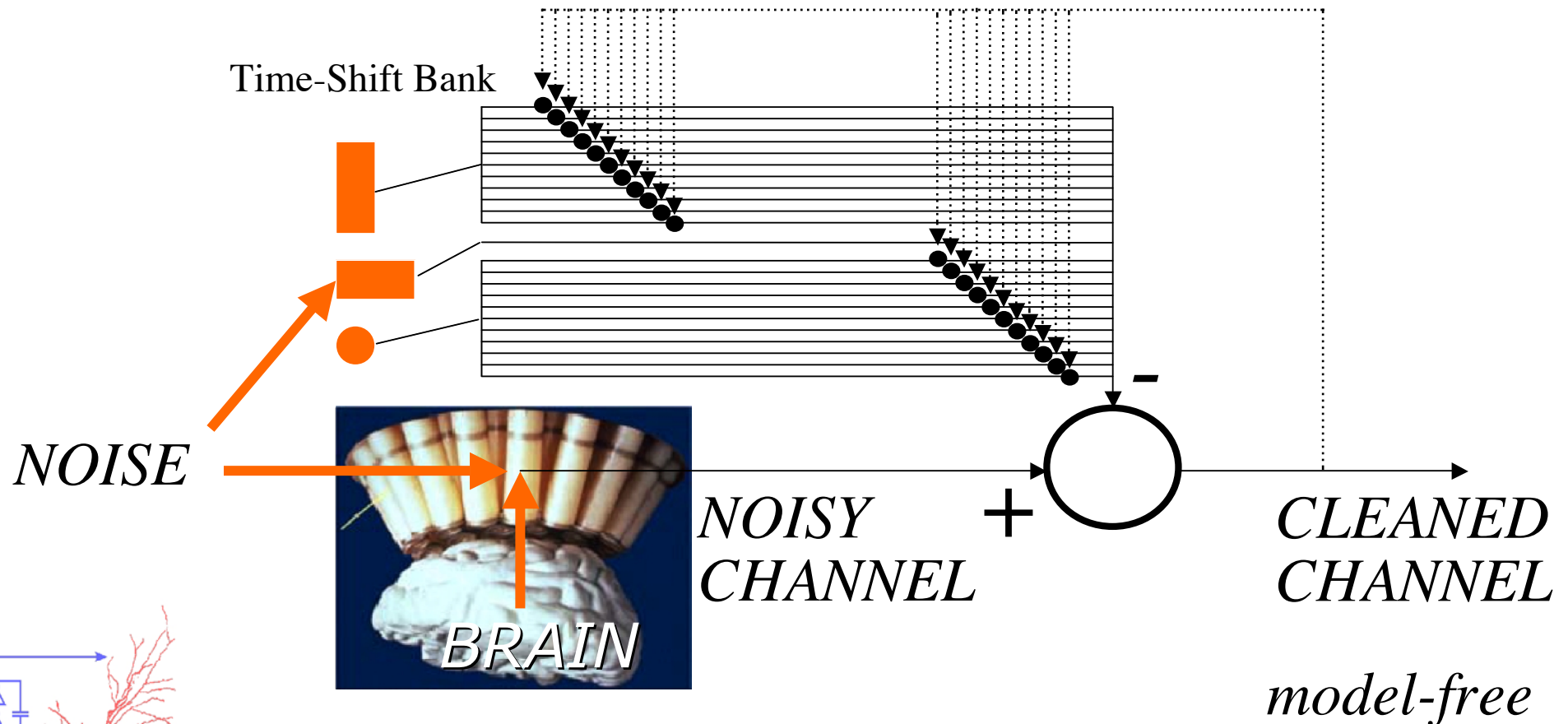
TSPCA: How it works

Generalize Scalar Regression:

Include Multiple Time-Shifted versions of References

Linear combinations of Time-Shifts are Filters

Increases *effective* number of References



TSPCA: How it works

$$\hat{s}_k(t) = s_k(t) - \sum_{j=1}^J \sum_{\tau=1}^N \alpha_{kj\tau} r_j(t + \tau - \frac{N}{2})$$

DELAY (points to τ)

BRAIN CHANNEL (points to $s_k(t)$)

REFERENCE CHANNELS (points to r_j)

Example:

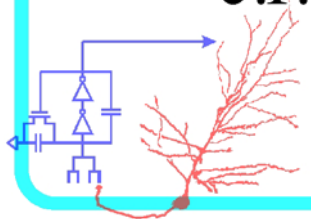
100 Taps (individual time delays)

3 Reference sensors → 300 coefficients/Brain Sensor

157 Brain sensors → 47100 coefficients Total

c.f. Scalar Regression:

$$\hat{s}_k(t) = s_k(t) - \sum_{j=1}^J \alpha_{kj} r_j(t)$$

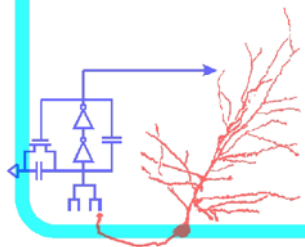


TSPCA: How it works

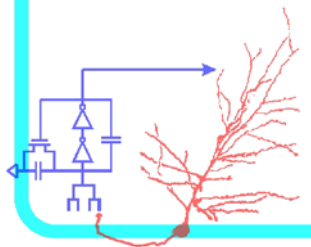
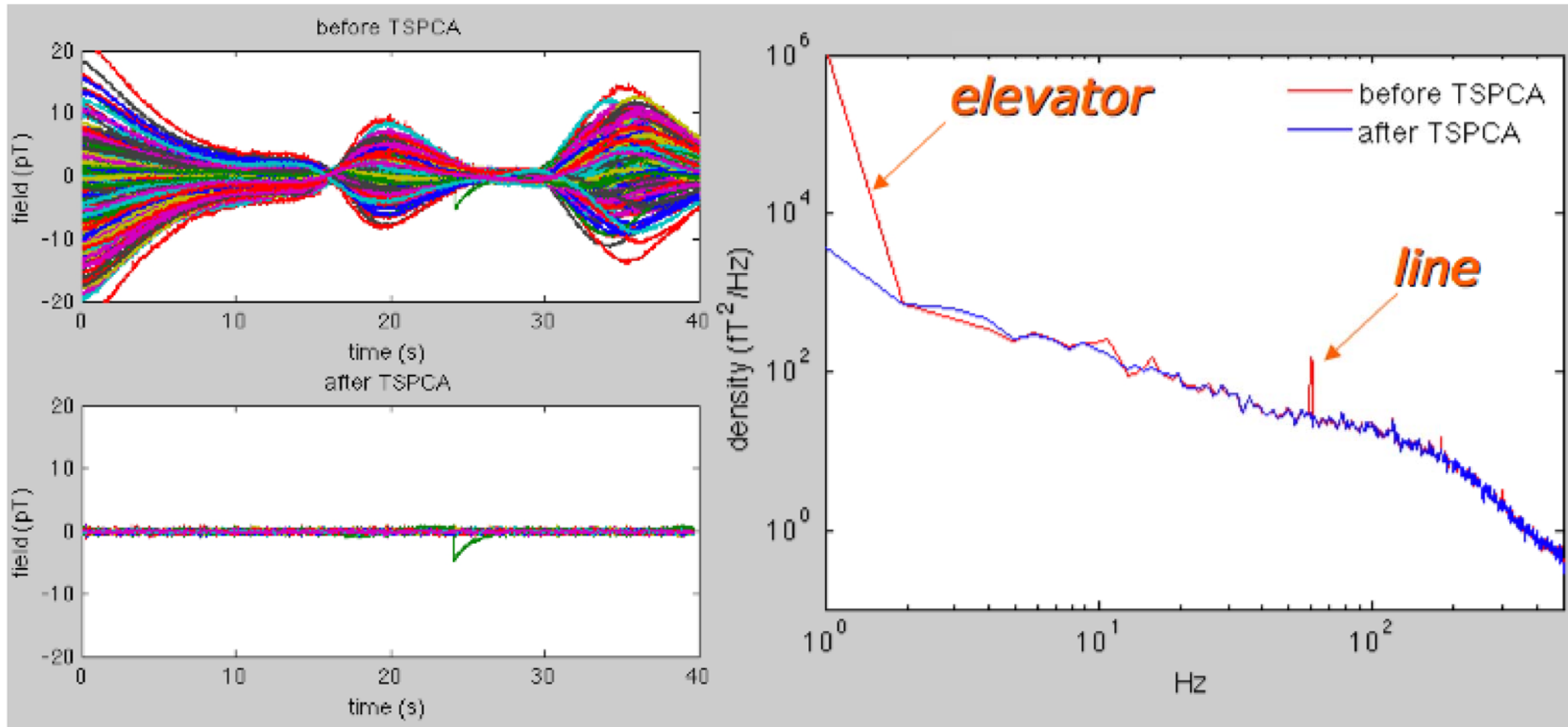
Algorithm:

1. Time-shift 3 reference signals by up to $\pm N/2$ samples ($\rightarrow 3N$ time-shifted signals)
2. Orthogonalize the $3N$ shifted signals to obtain an orthogonal basis (PCA)
3. Project each brain channel on this basis
4. Subtract projection to obtain clean channel...

... et voilà!



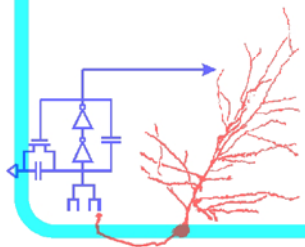
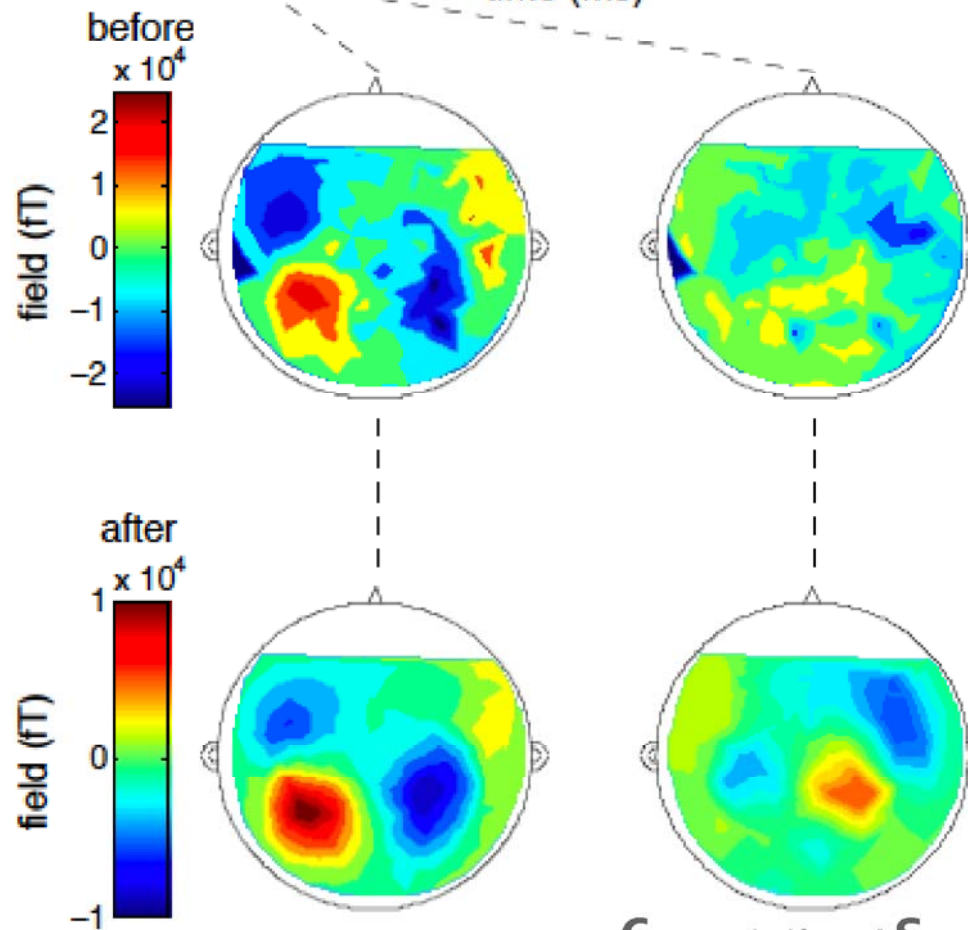
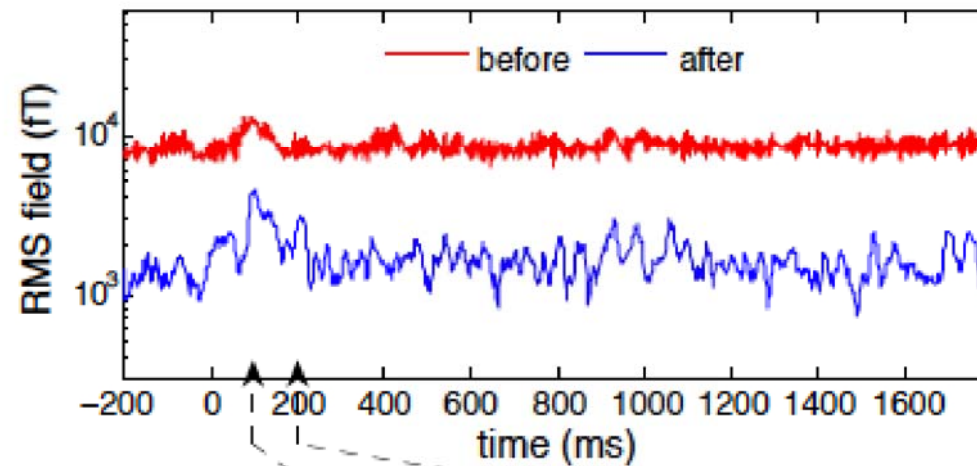
TSPCA Example



ATR MEG
(Advanced Telecommunications Research, Kyoto)

Computational Sensorimotor Systems Laboratory

TSPCA Example

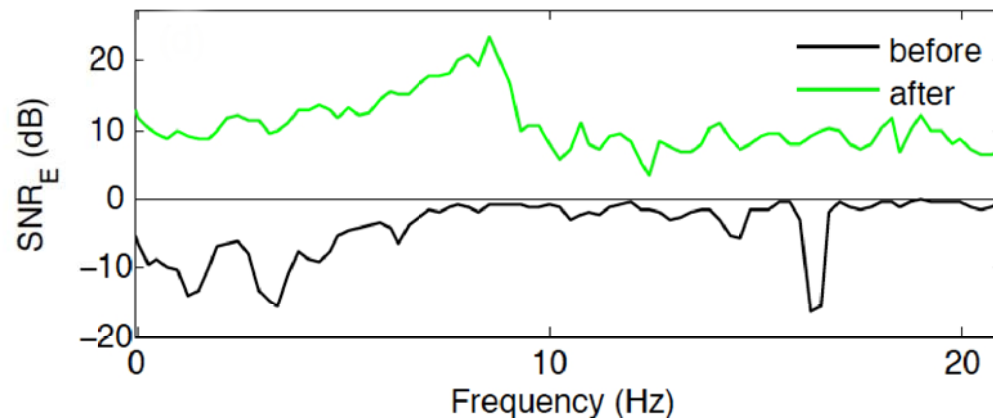


U. Maryland/KIT

Computational Sensorimotor Systems Laboratory

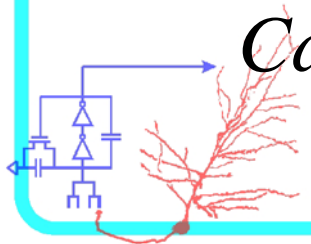
TSPCA Summary

- TSPCA removes $\sim 98\%$ of noise power, SNR increase > 10 dB for low frequencies



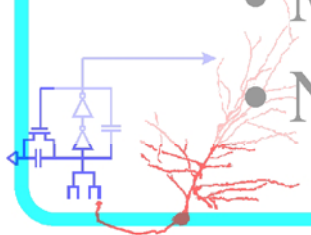
SNR_E : ratio of
Signal other than
Environmental
Noise to
Environmental Noise

- No Target Distortion: only Reference channels filtered;
- Tested on wide range of systems
- Single Parameter to choose: $N = (\# \text{ of taps})$, not sensitive
Caveats: For small durations, N cannot be too large
Large N increases processing time $O(N^2)$
- Can turn off High Pass filter (possibly Notch filter too)
Caveat: If turn off Notch, beware of large amplitudes due to 60 Hz (clipping, finite # of bits)



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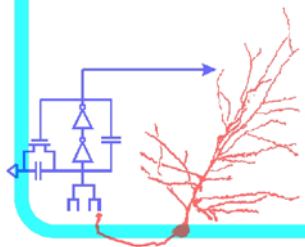
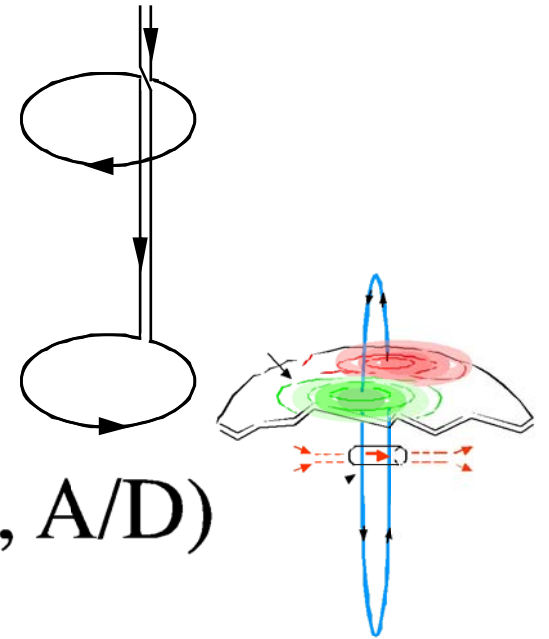


SNS

- Sensor Noise Supression
- Target: Sensor Noise

Transducer Noise (SQUID)

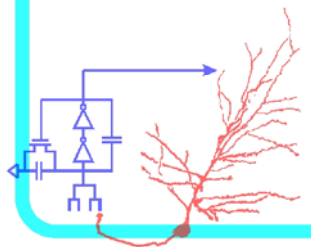
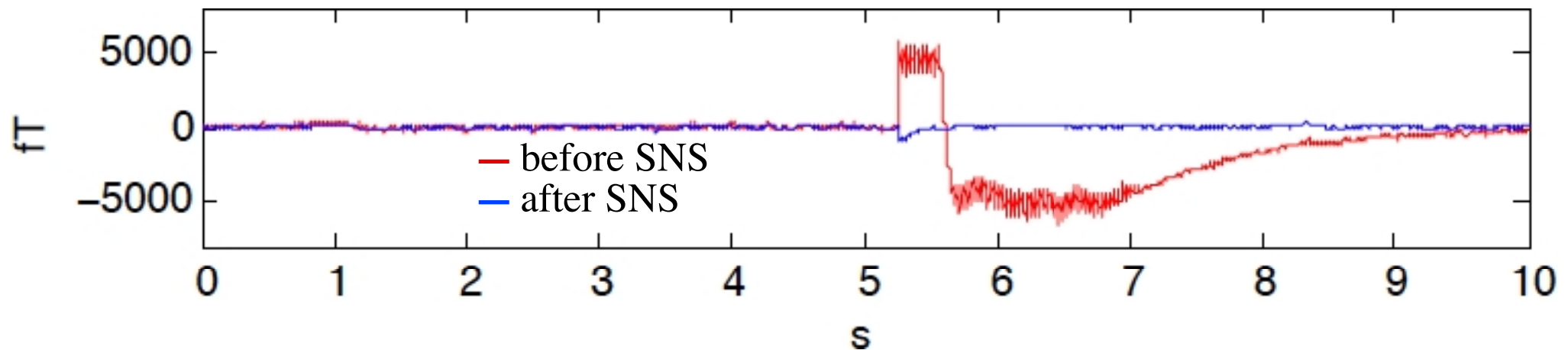
Electronics Noise (FLL, amplifier, A/D)



in collaboration with Alain de Cheveigné

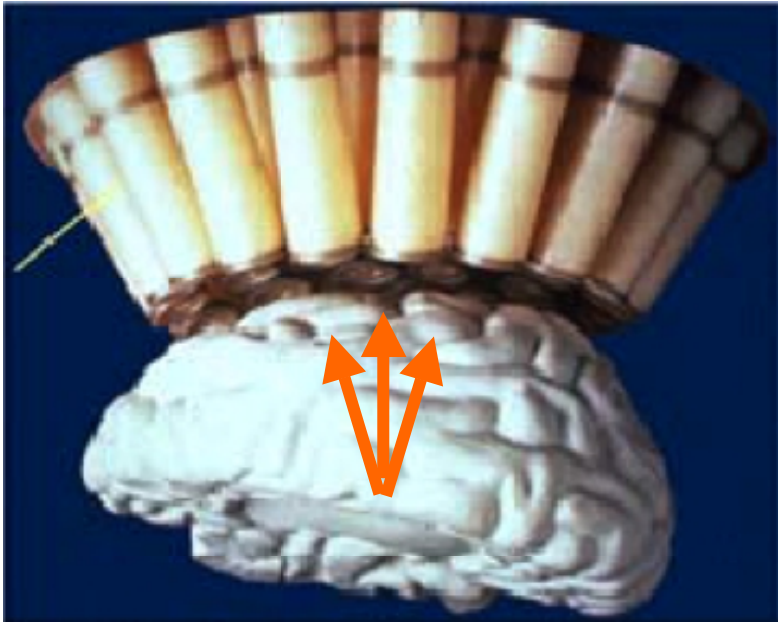
SNS Example

Glitch Removal



U. Maryland/KIT

SNS: How it works

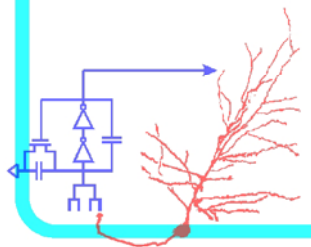


Assumption: Every neural source is picked up by multiple sensors

Consequence: Any component observed on only one sensor is **artifactual**.

Requires spatially dense sensors

Otherwise model-free



SNS: How it works

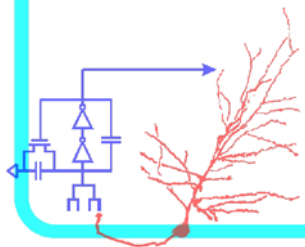
Algorithm:

1. Project each channel on subspace formed by *other* channels.
2. Replace channel by projection.

... et voilà!

$$\hat{S} = AS$$

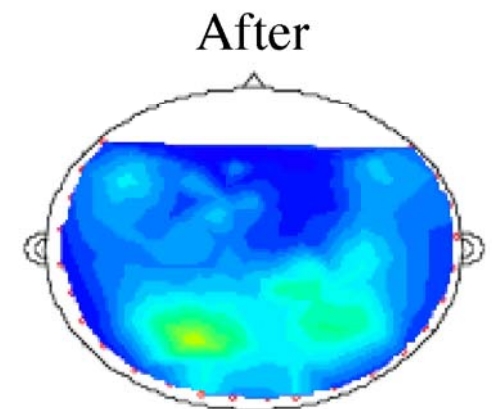
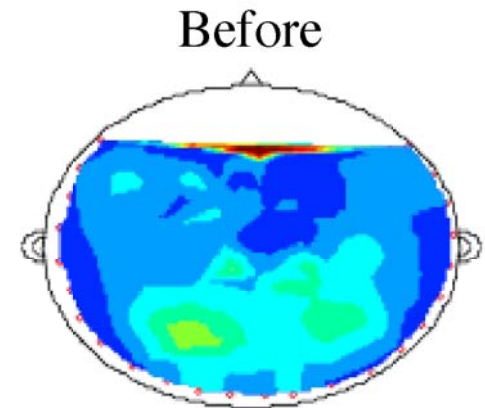
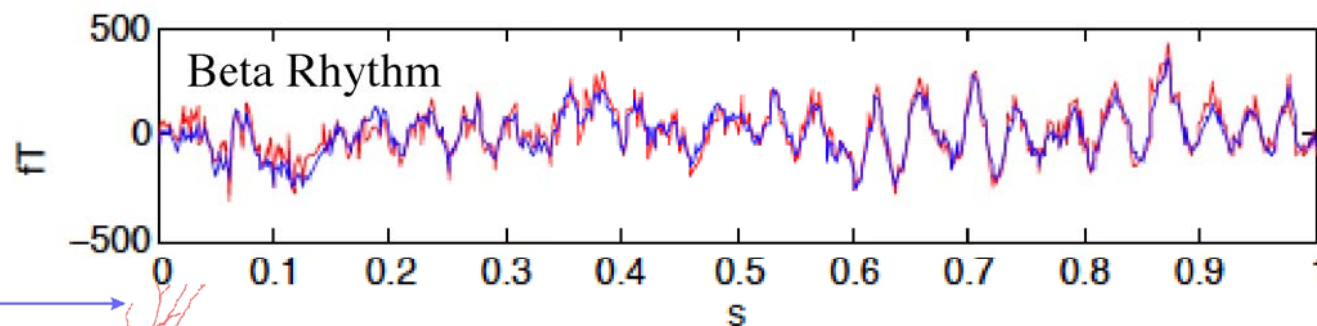
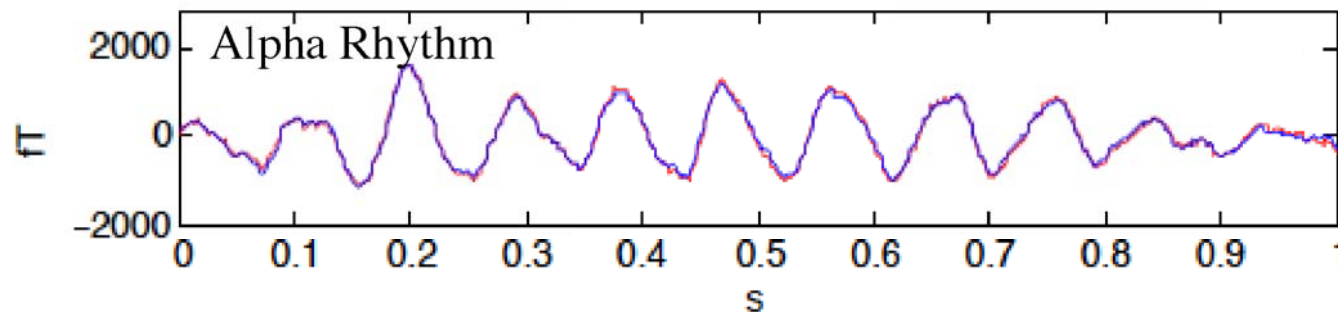
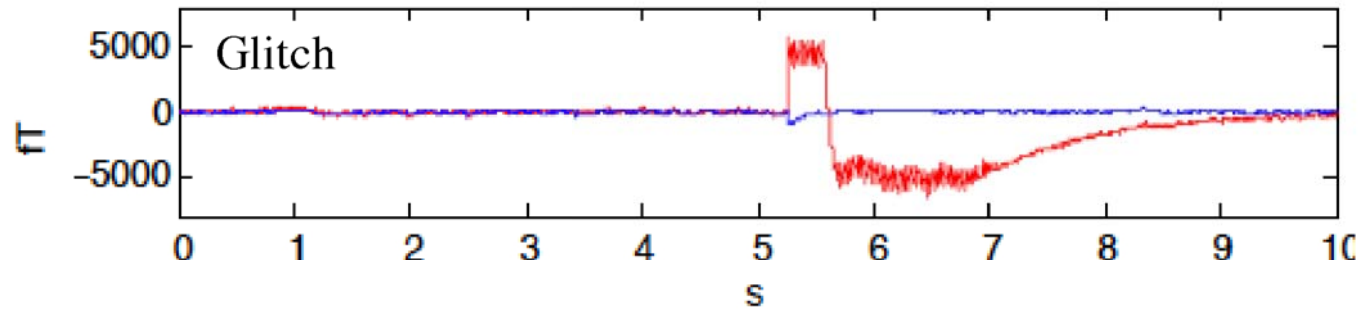
where $\text{diag}(A) = 0$



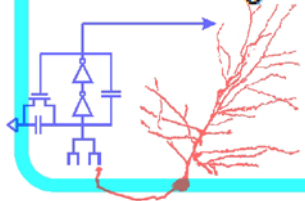
SNS Example

Neural Responses Unaffected

— before SNS
— after SNS



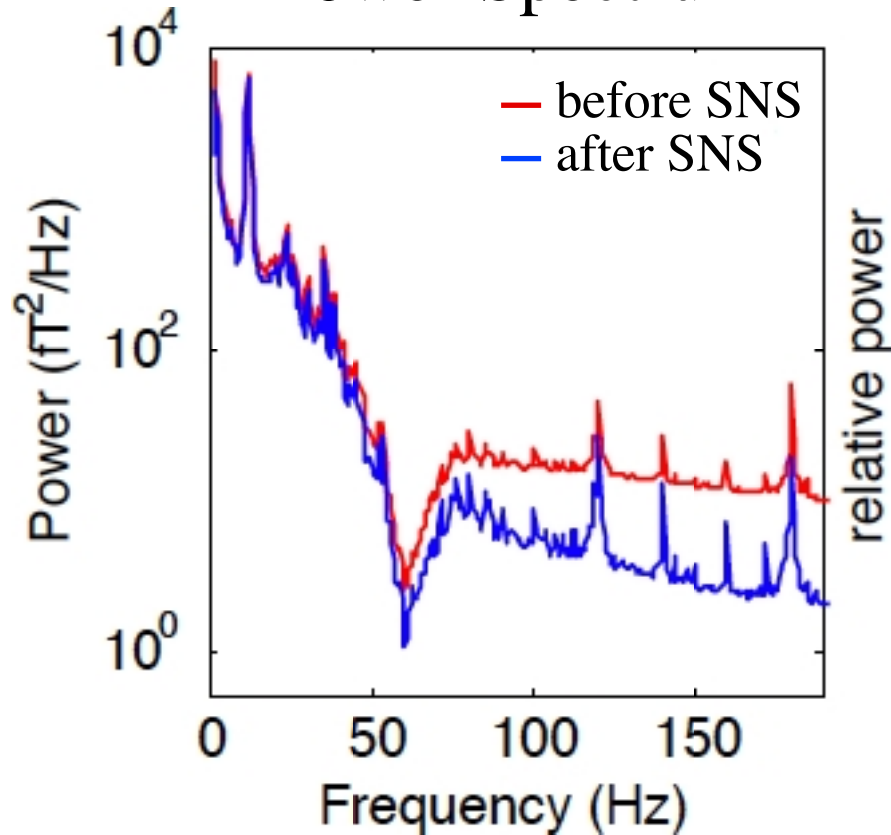
U. Maryland/KIT



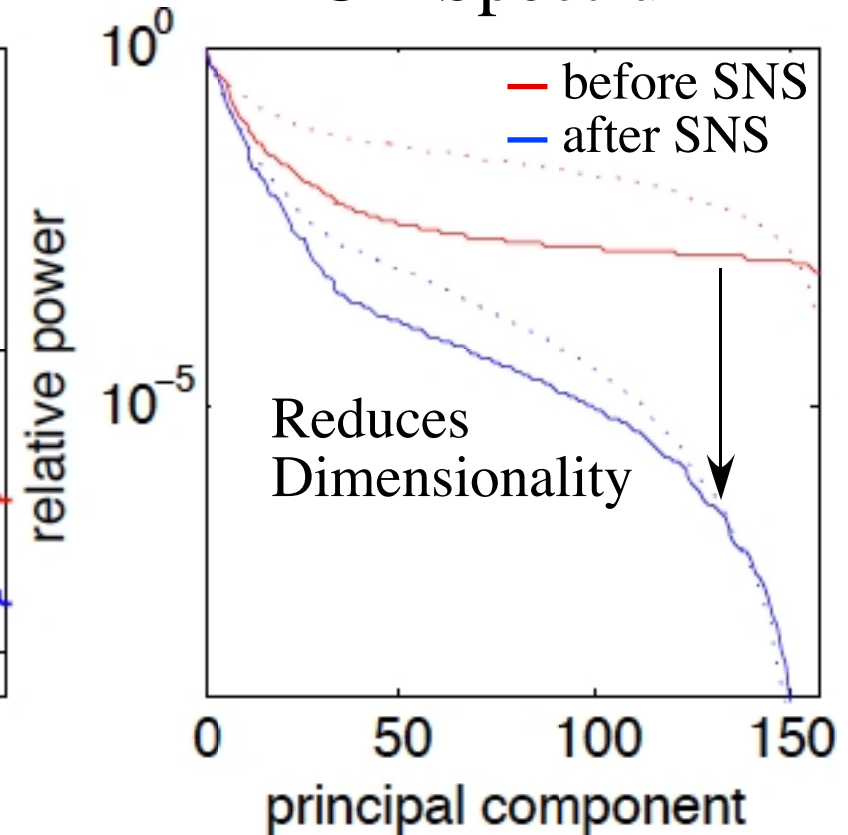
SNS Example

Power and PCA Spectra

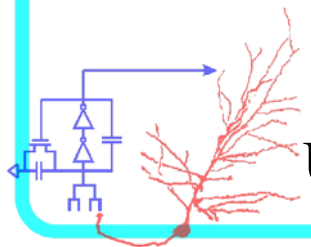
Power Spectrum



PCA Spectrum

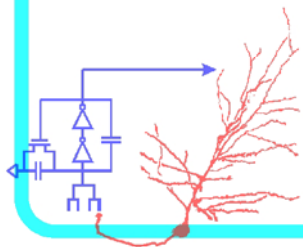
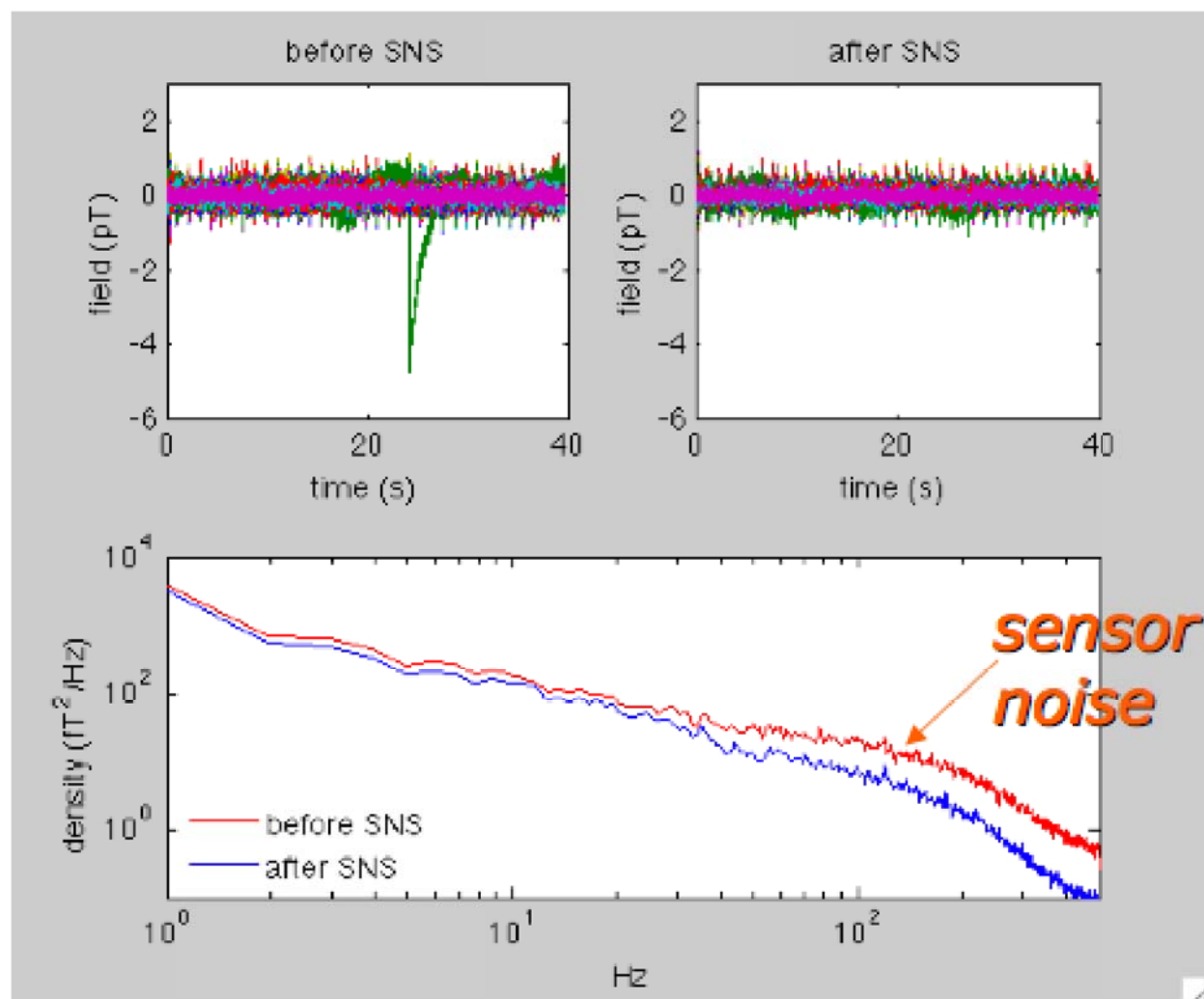


Removes spurious
sensor-specific
dimensions



SNS Example

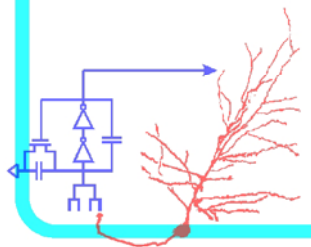
Glitch Removal



ATR MEG

SNS Summary

- Removes Sensor Noise
 - Glitches
 - High frequency noise
- No Target Distortion (unless target loads only 1 sensor)
- Allows:
 - Cleaner Data
 - More usable epochs (no need to discard glitches)
 - Reduction of spurious dimensionality
(e.g. for PCA, ICA)

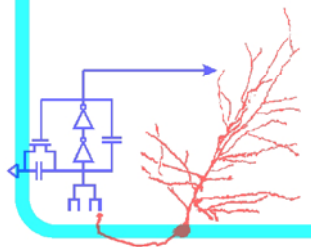


TSPCA + SNS

- Both “user friendly”
 - Can be implemented without parameter fiddling
 - Robust even in poor SNR situations (no false minima)
- Implemented in Matlab for KIT “sqd” files
 - 700MB = 7 minutes on fast desktop computer (2008)
 - Only needs to be run once per file
 - Transparent—output is also sqd file (not Matlab file).

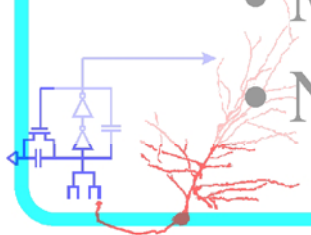
<http://www.isr.umd.edu/Labs/CSSL/simonlab/resources/>

code by Ray Shantanu & Dan Hertz



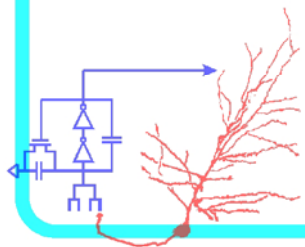
Outline

- Brief Introduction to MEG
- Denoising MEG Data
 - Environmental Noise Reduction
TSPCA = Time Shifted Principle Component Analysis
 - Sensor Noise Reduction
SNS = Sensor Noise Suppression
 - Physiological Noise Reduction
DSS = Denoising Source Separation
- Attention and Auditory Streams
 - MEG in the Frequency Domain
 - Neural & Behavioral Correlates of Auditory Attention



DSS

- Denoising Source Separation
- Target: Physiological Noise
- *Requirements:*
 - Neural sources of signal-of-interest must be *spatially distinct* from noise sources
(overlap is OK)
 - Time courses must be distinguishable
(correlation is OK)
 - A *stimulus-based* criterion exists to say what is signal-of-interest vs. noise



DSS developed by Särelä & Valpola (2005)
Applications in collaboration with Alain de Cheveigné

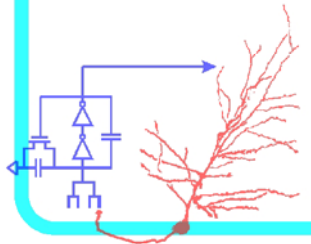
DSS: How it works

DSS produces a *set of spatial filters*

$$\hat{s}_{k'}(t) = \sum_{k=1}^K a_{kk'} s_k(t)$$

such that:

- The DSS components, $\hat{s}_{k'}(t)$, are orthogonal
- Waveforms sum to original waveform
- Powers sum to original power (“partition of power”)
- $\hat{s}_{k'}(t)$ ordered by decreasing quality: $\hat{s}_1(t)$, $\hat{s}_2(t)$
- Spatial filters ordered by decreasing quality: a_{k1} , a_{k2} , etc.

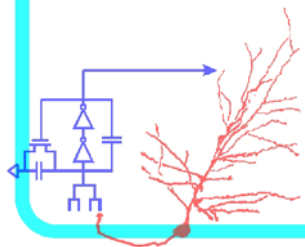


DSS: How it works

Algorithm:

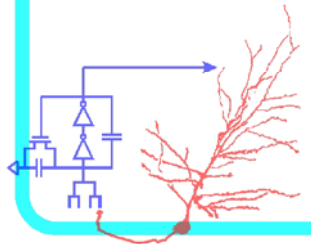
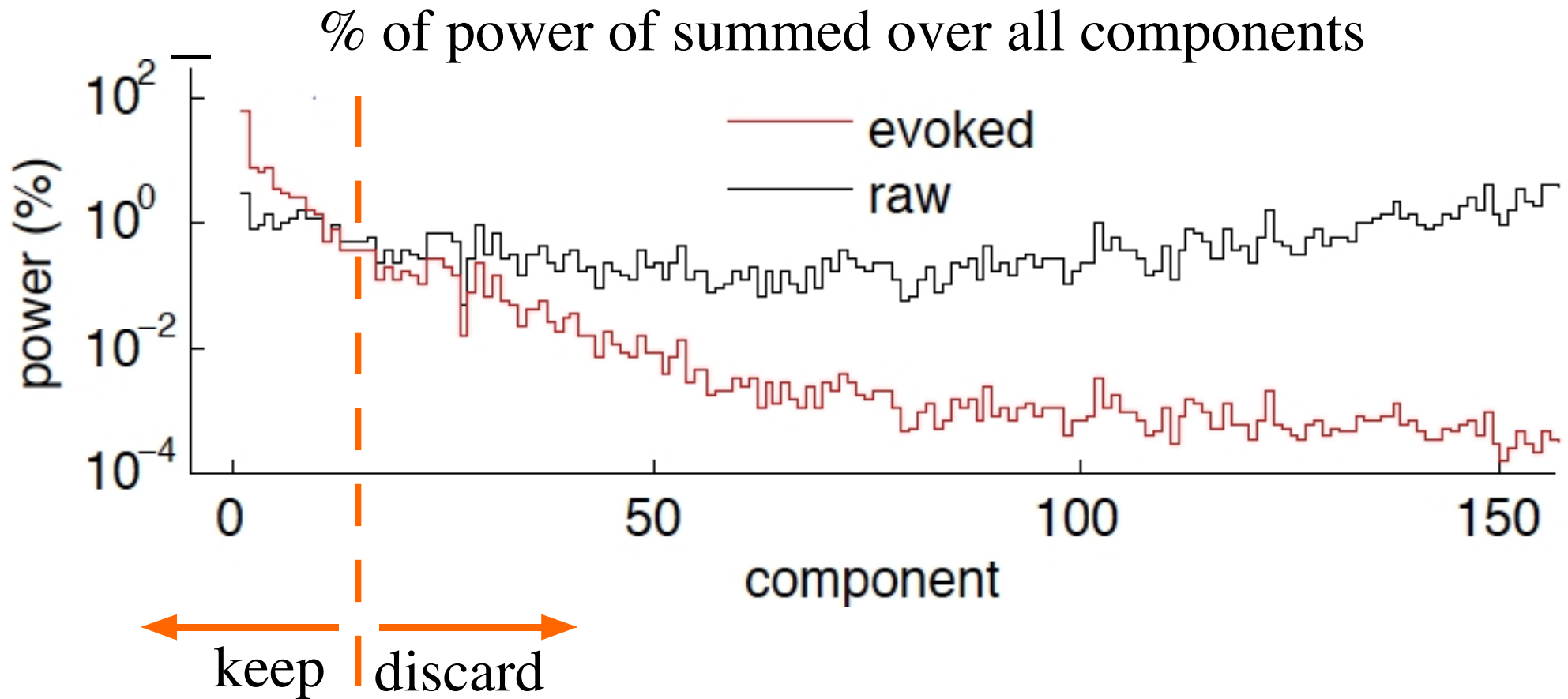
1. Normalize sensor signals & apply PCA to (spatially whiten).
2. Apply Bias (here: *average over trials*)
to enhance good directions.
3. Apply PCA to align/order according to maximum bias.
and retain this transform as a rotation matrix.
4. Apply rotation matrix from previous step to Step 1 data(!).
5. Select best components, discard others (“denoising step”).
6. Project back to sensor space.

... et voilà!



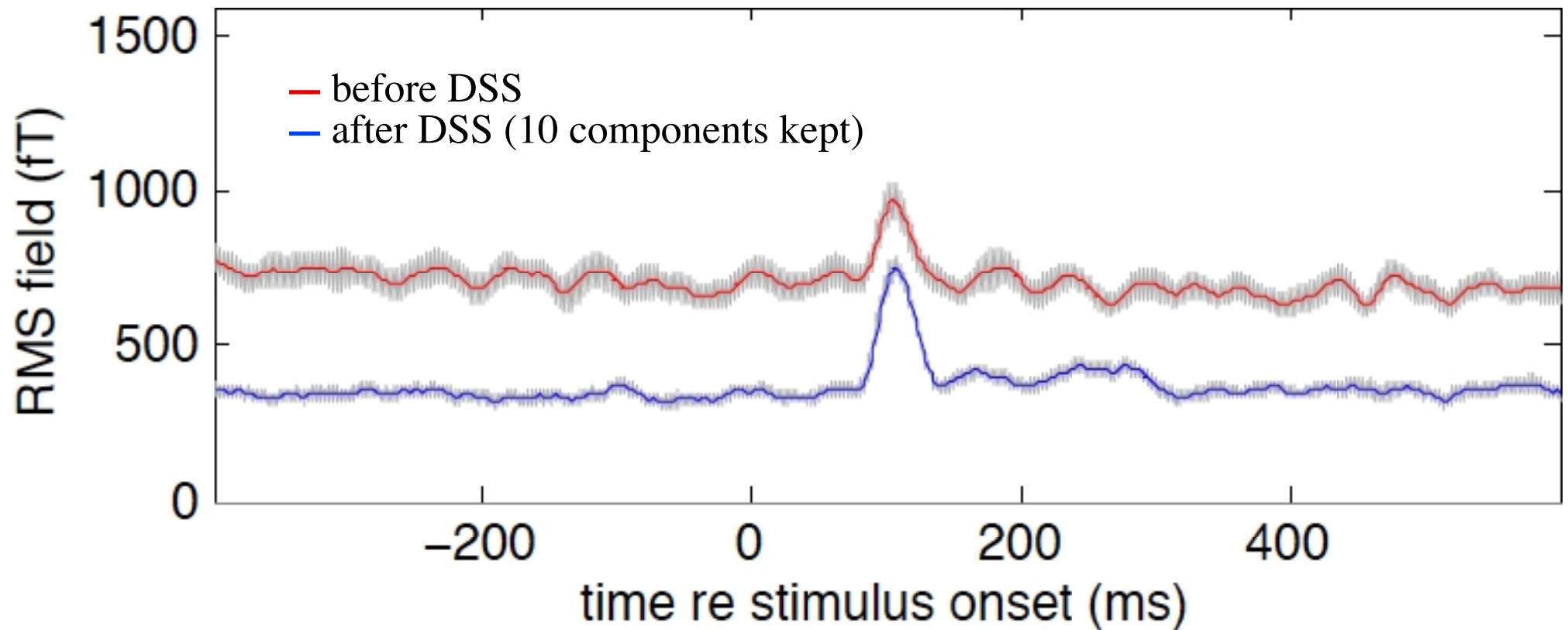
DSS: How it works

“Select best components, discard others”

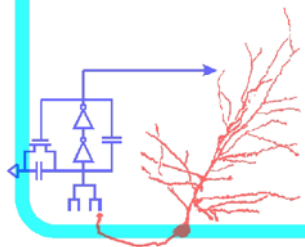


DSS Example

RMS (over all channels) of response to auditory stimulus



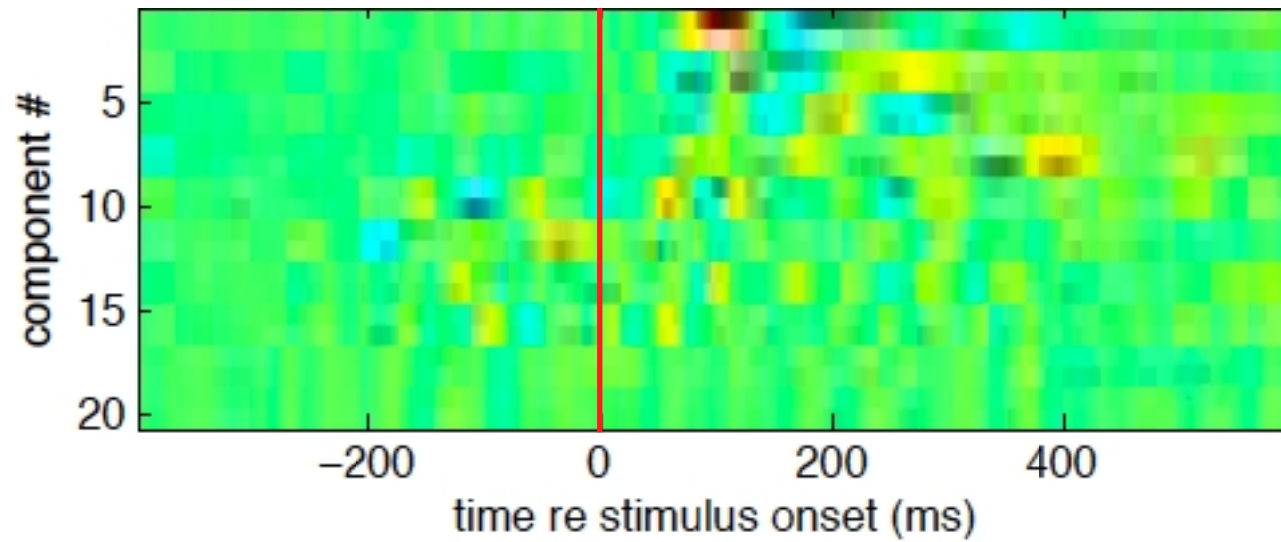
gray band = ± 2 SD (via bootstrap)



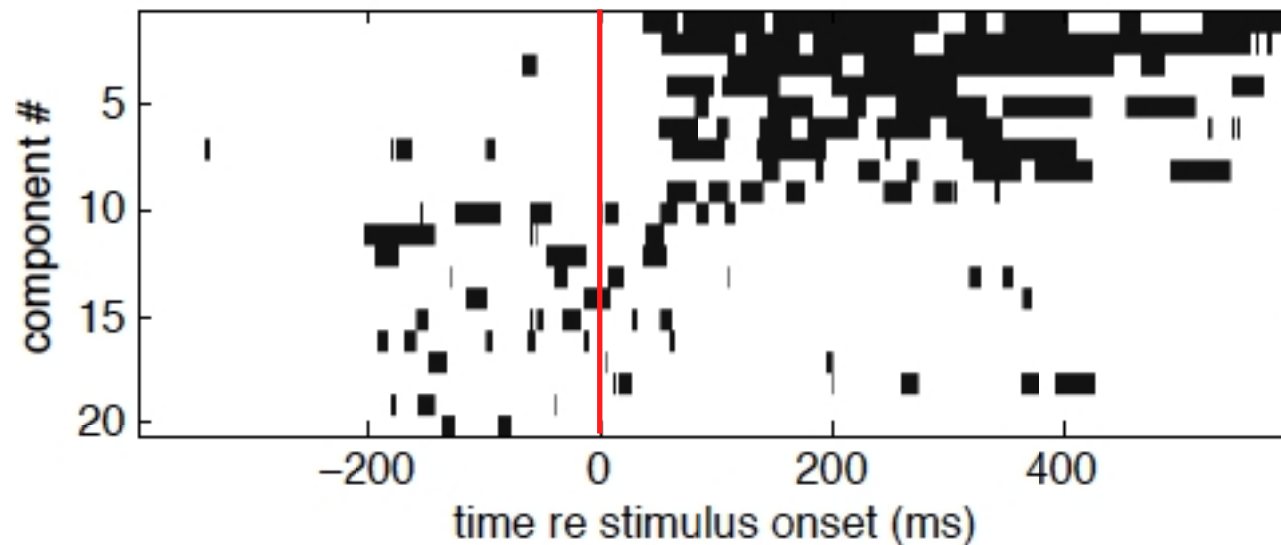
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Computational Sensorimotor Systems Laboratory

DSS Example

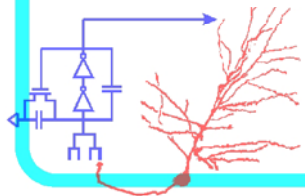


20 first (best) DSS components



Reliability map
(4 SD threshold)

auditory stimulus, 100 repetitions

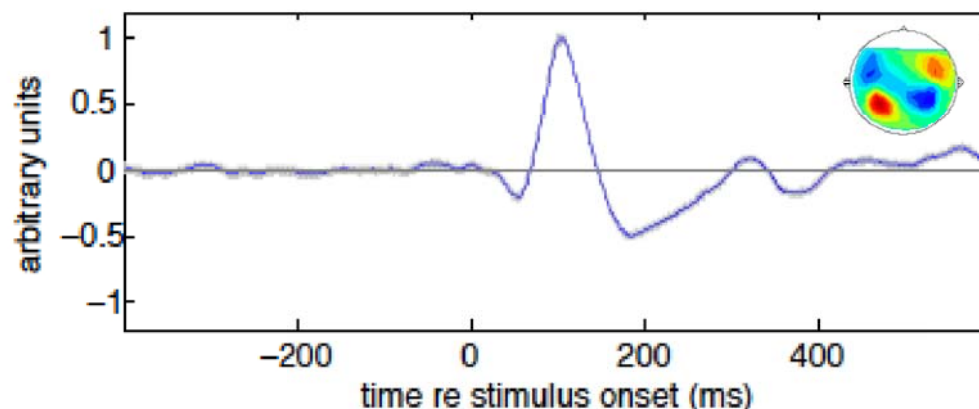


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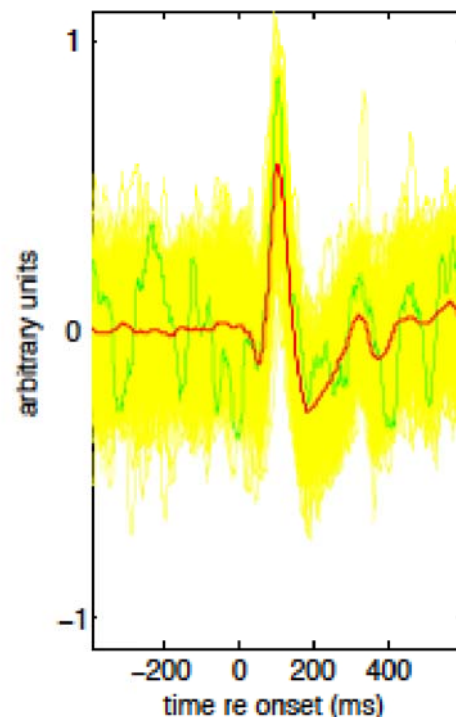
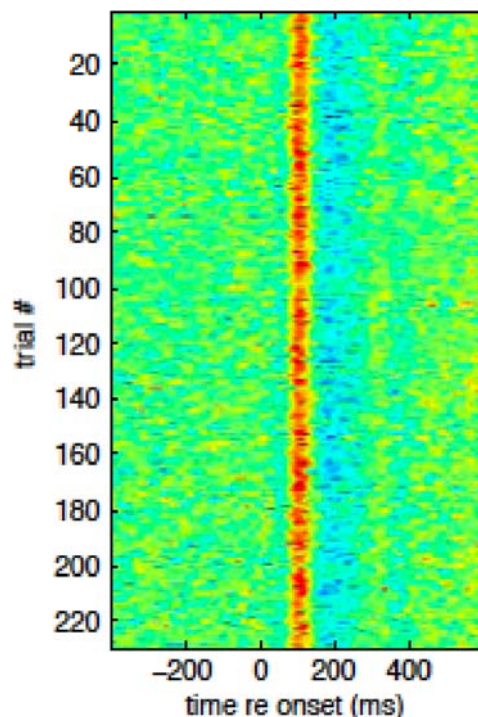
DSS Example

Best Component:



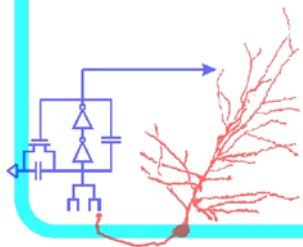
= output of Spatial Filter with the most reproducible linear combination of sensors

Single trials passed through spatial filter of best component



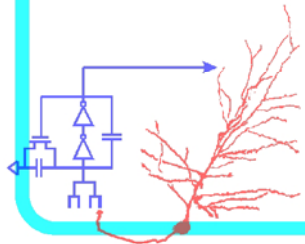
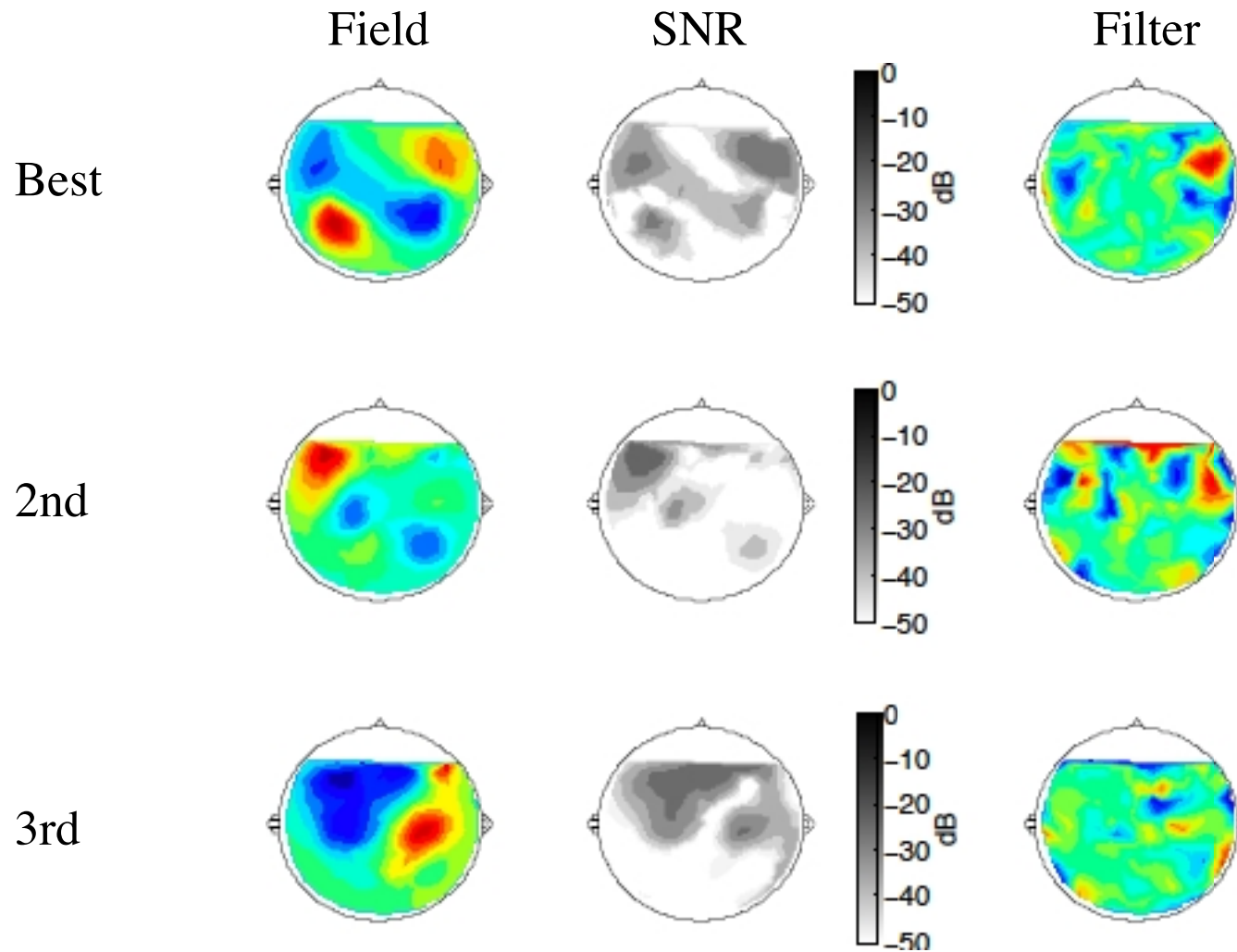
red:
average

yellow & green:
individual trials



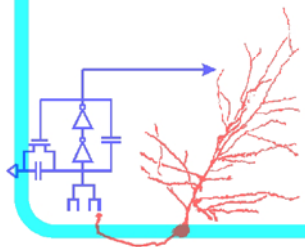
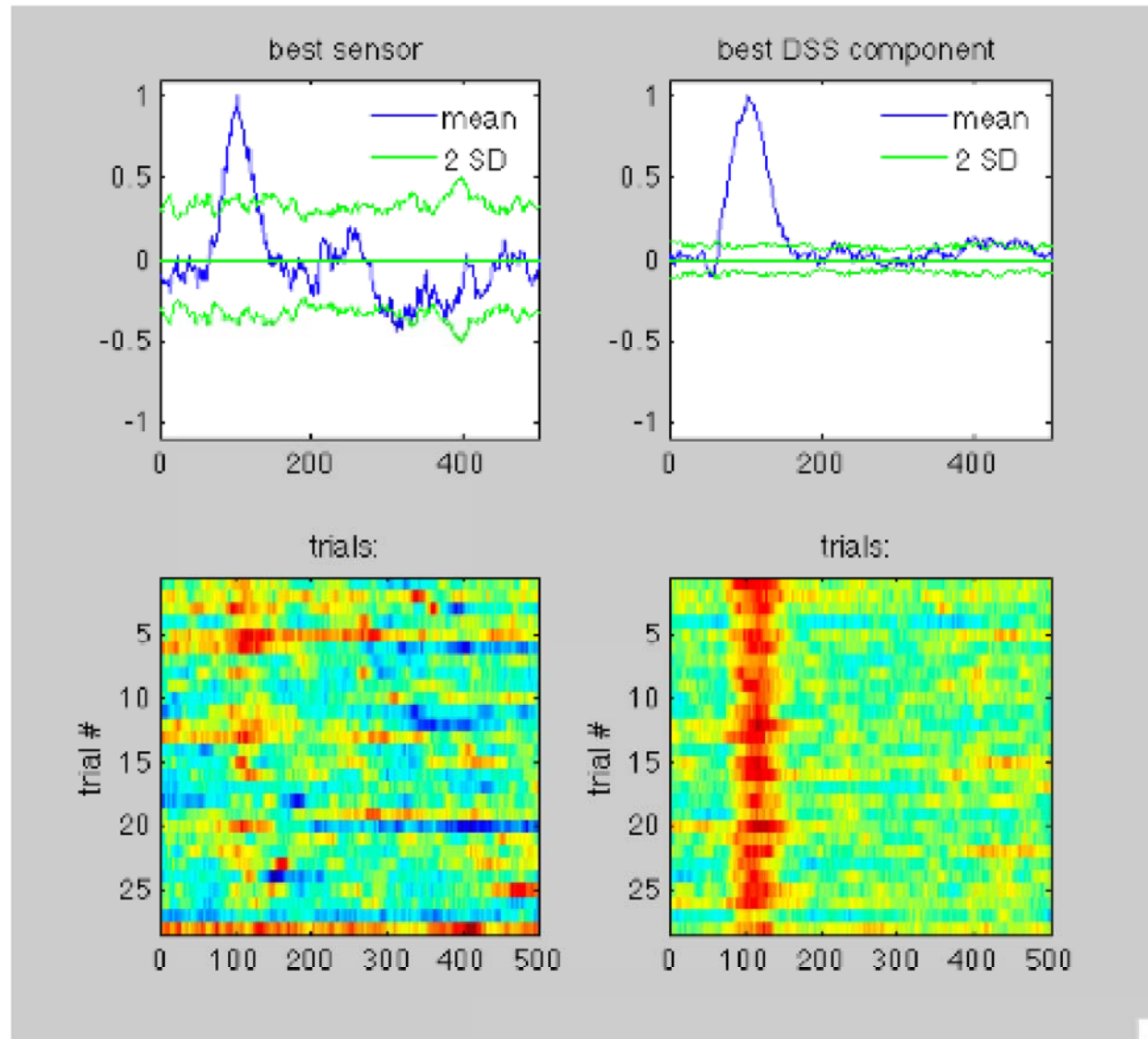
DSS Example 4

Spatial Properties of top 3 DSS filters



DSS Example

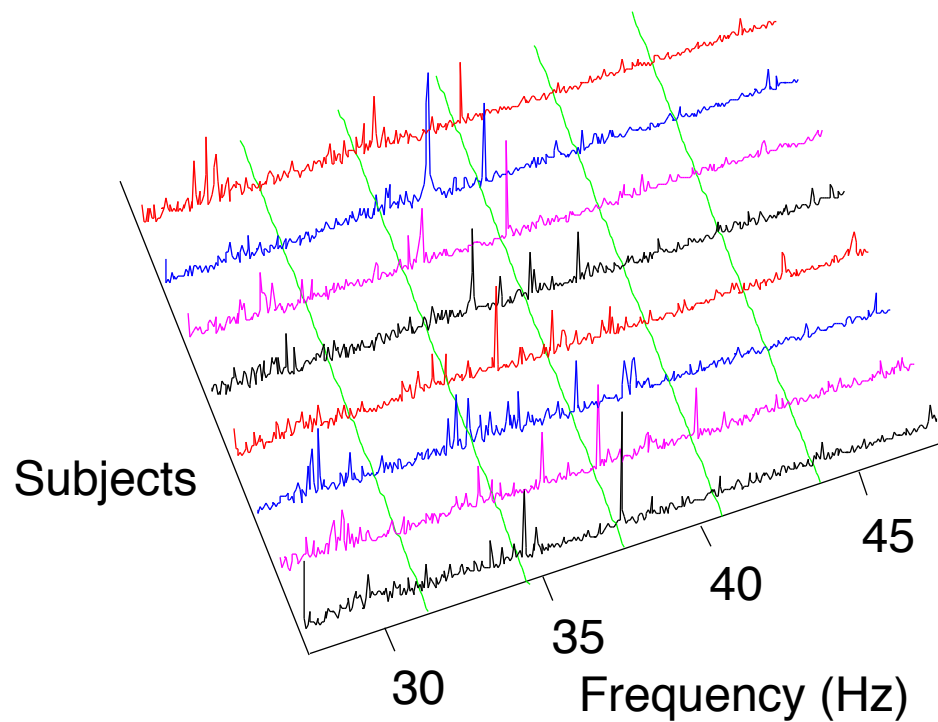
DSS as replacement for “best sensor” or “best 20” (etc.) sensors



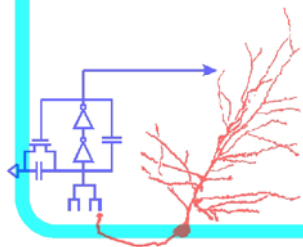
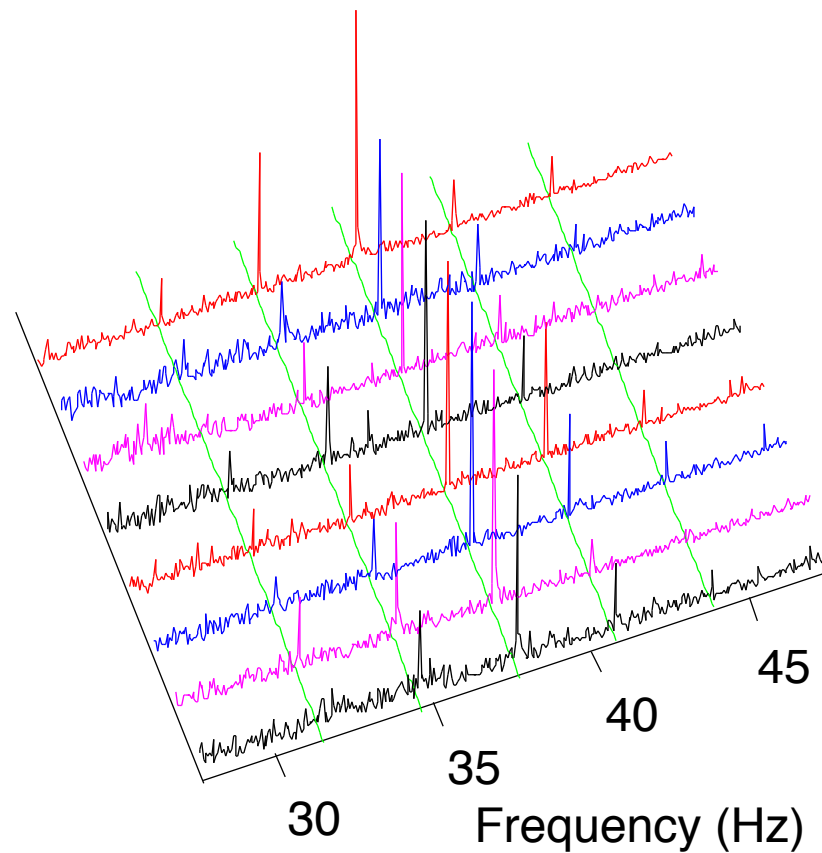
DSS Example

Spectra of MEG Steady State Response (to dual modulation)

Before DSS (20 Best Channels)



First DSS component

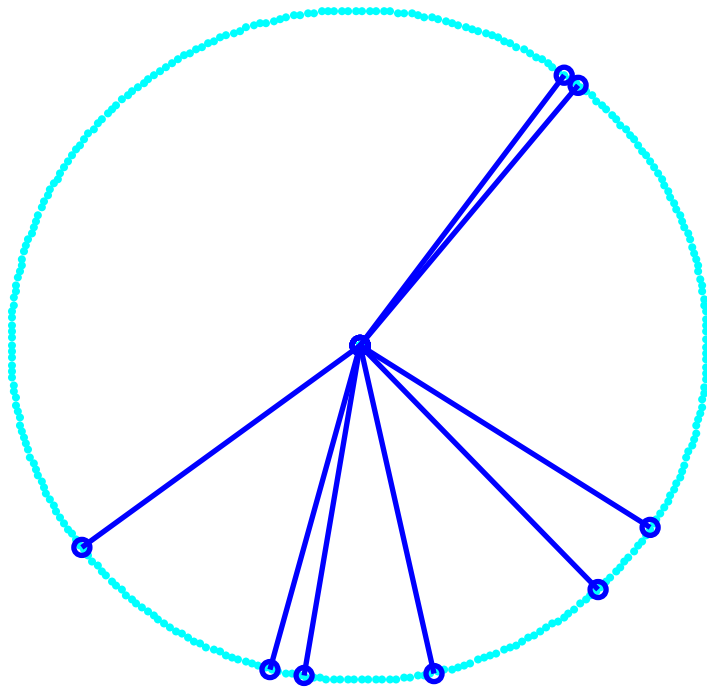


U. Maryland/KIT, courtesy of Nai Ding

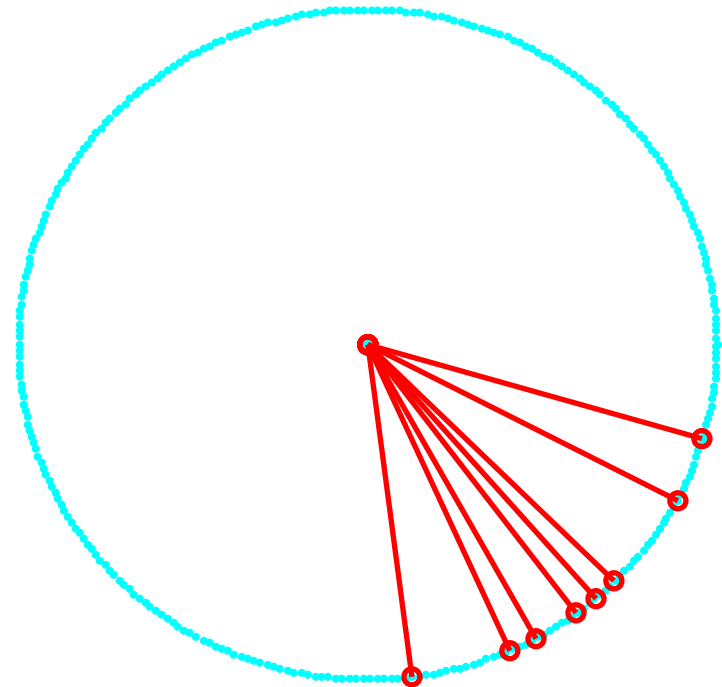
Computational Sensorimotor Systems Laboratory

DSS Example

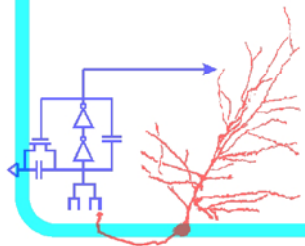
Phase coding parameter α (by subject)



Before DSS (20 Best Channels)

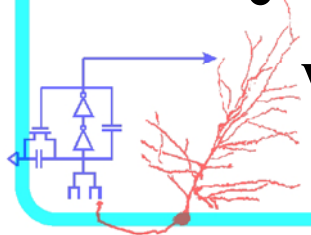


First DSS component



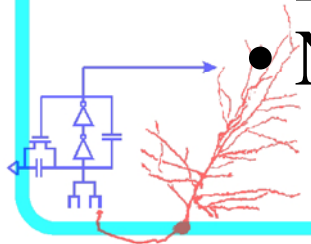
DSS Summary

- Removes Physiological Noise
- Complementary with:
 - Other denoising algorithms (TSPCA, SNS)
 - Standard analysis tools (beamforming, dipole source analysis, etc.)
- Flexible, other bias criteria can be used:
 - Bandpassed evoked response (e.g. theta, gamma)
 - Induced response(?)
 - Any stimulus-dependent representation of response
- Caveats:
 - Bias should be robust, so remove outliers temporarily (e.g. ~20% of trials), but fine to use in end
 - When SNR is poor (weak evoked response), may fail to work, or give component-of-interest as 2nd component.



Denoising Summary

- Denoising tools presented here are:
 - Effective: reduce noise & preserve signals of interest
 - Complementary with existing analysis tools
 - Available in Matlab
- For users:
 - Increase your MEG signal quality
 - Relax hardware filtering & loss of neural signal
 - retain slow changes
 - retain frequencies near 60 Hz
 - no filter-based distortion
- Additional applications:
 - BMI/BCI?
 - Non-shielded (portable) MEG?



Thank You



References & Links

de Cheveigné, A. and Simon, J. Z. (2007). “*Denoising based on Time-Shift PCA.*” *Journal of Neuroscience Methods* 165: 297-305.

de Cheveigné, A. and Simon, J. Z. (2008). “*Sensor Noise Suppression.*” *Journal of Neuroscience Methods* 168: 195-202.

de Cheveigné, A. and Simon, J. Z. (2008). “*Denoising based on spatial filtering.*” *Journal of Neuroscience Methods* 171: 331-339.

<http://www.isr.umd.edu/Labs/CSSL/simonlab/resources/>

