Introduction to Magnetoencephalography

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Department of Biology
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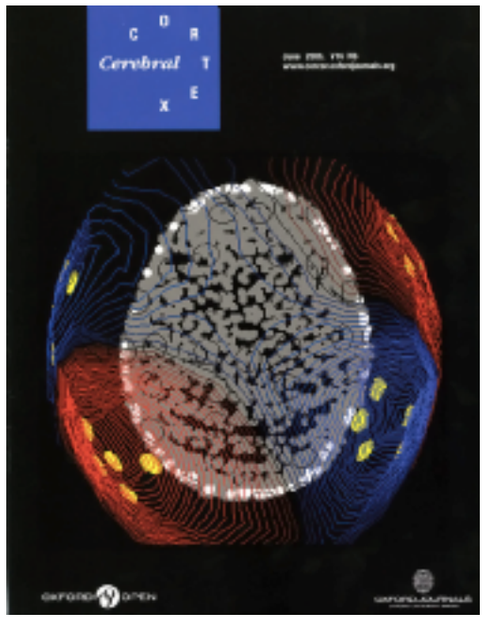
University of Maryland

AFOSR Magneto-Optic Polymers, 12 September 2013

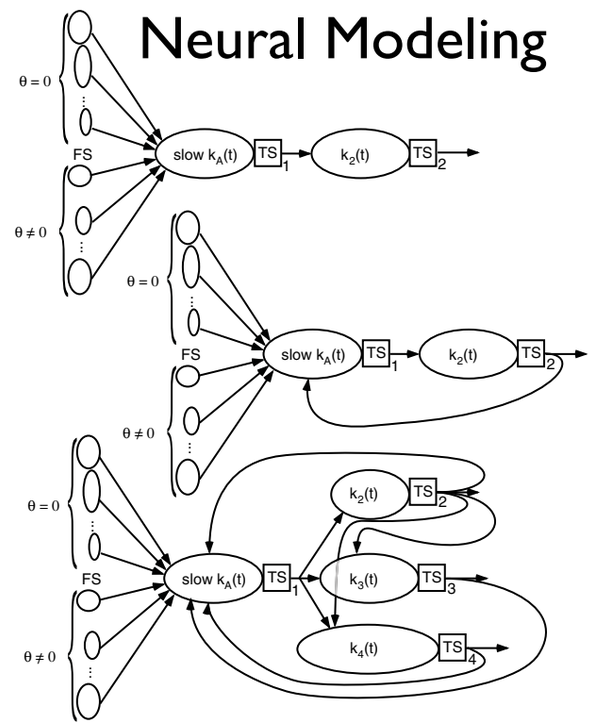
Jonathan Z. Simon

Neural processing of speech and complex auditory streams

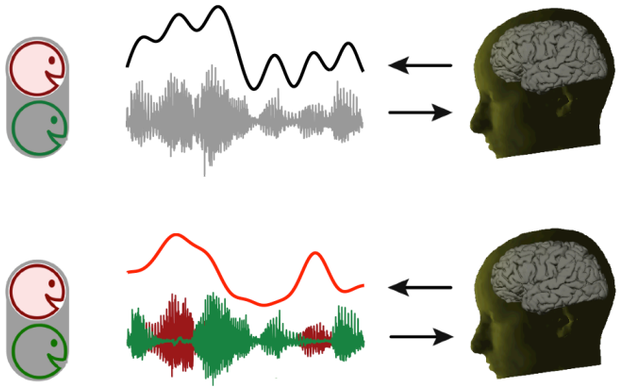
Magnetoencephalography



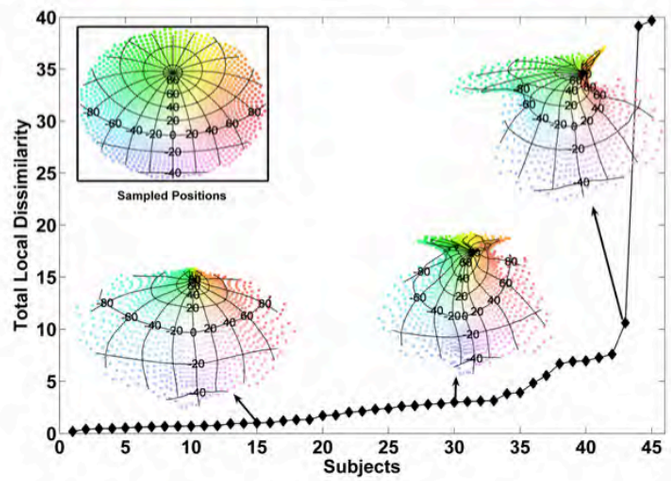
Neural Modeling



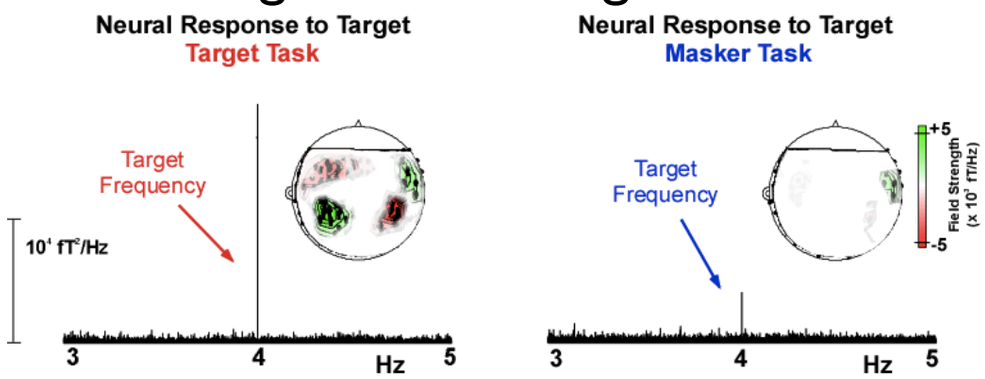
Neural Un-Mixing of Speech



Neurally Inspired Algorithms



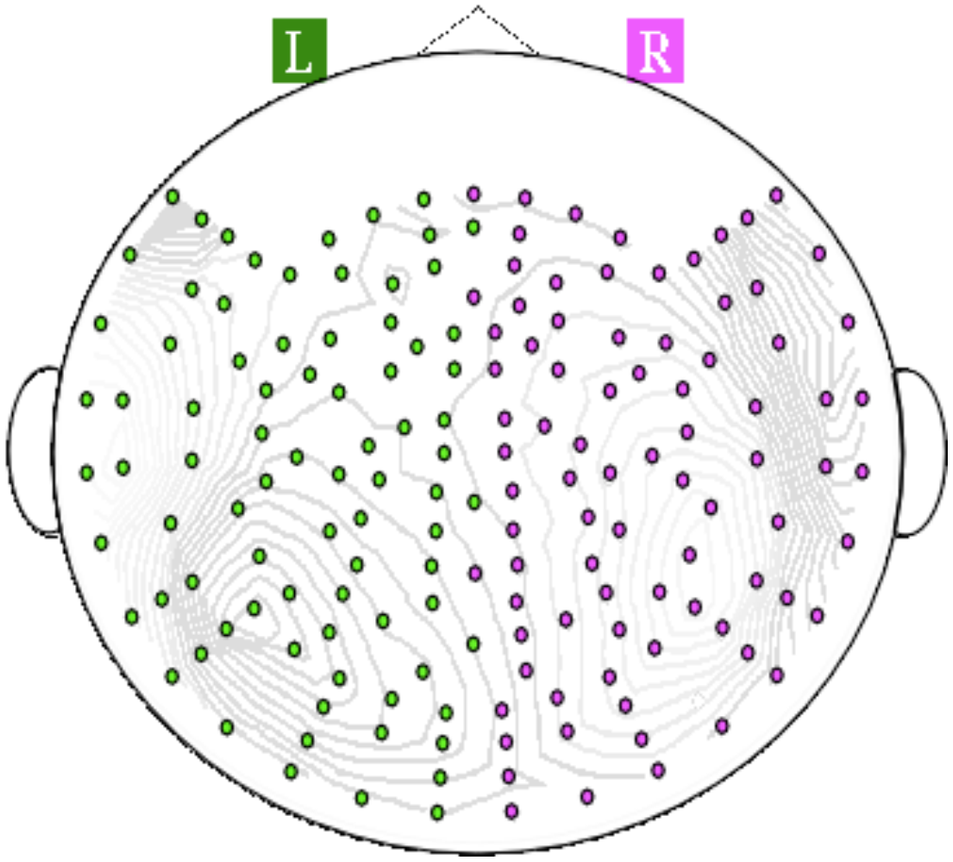
Neural Signal Processing



Advanced Neuroimaging

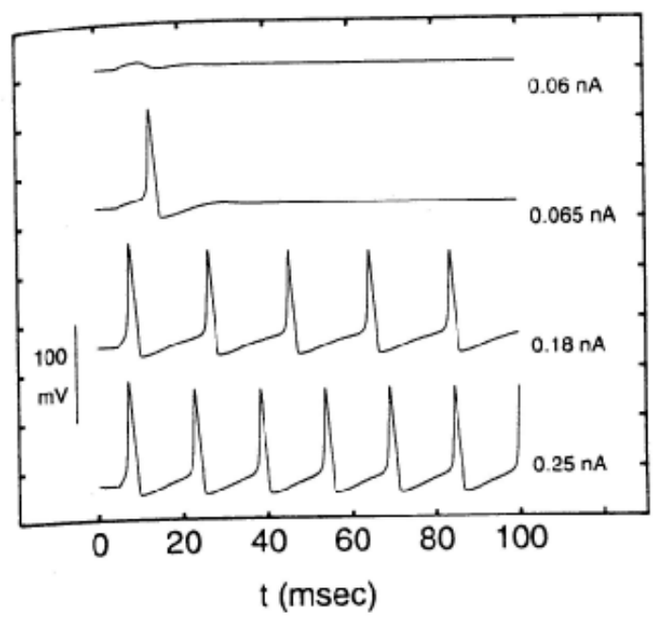
Magnetoencephalography

- Non-invasive, Passive, Silent Neural Recordings
- Simultaneous Whole-Head Recording (~200 sensors)
- Sensitivity
  - high: ~100 fT (10^{-13} Tesla)
  - low: ~10^4 – ~10^6 neurons
- Temporal Resolution: ~1 ms
- Spatial Resolution
  - coarse: ~1 cm
  - ambiguous



Universal Neural Code

- Neural signals
  = spikes in voltage
- Spikes are "all-or-none"
  - Digital in amplitude
  - Asynchronous in time
- Neural Input ≈ current



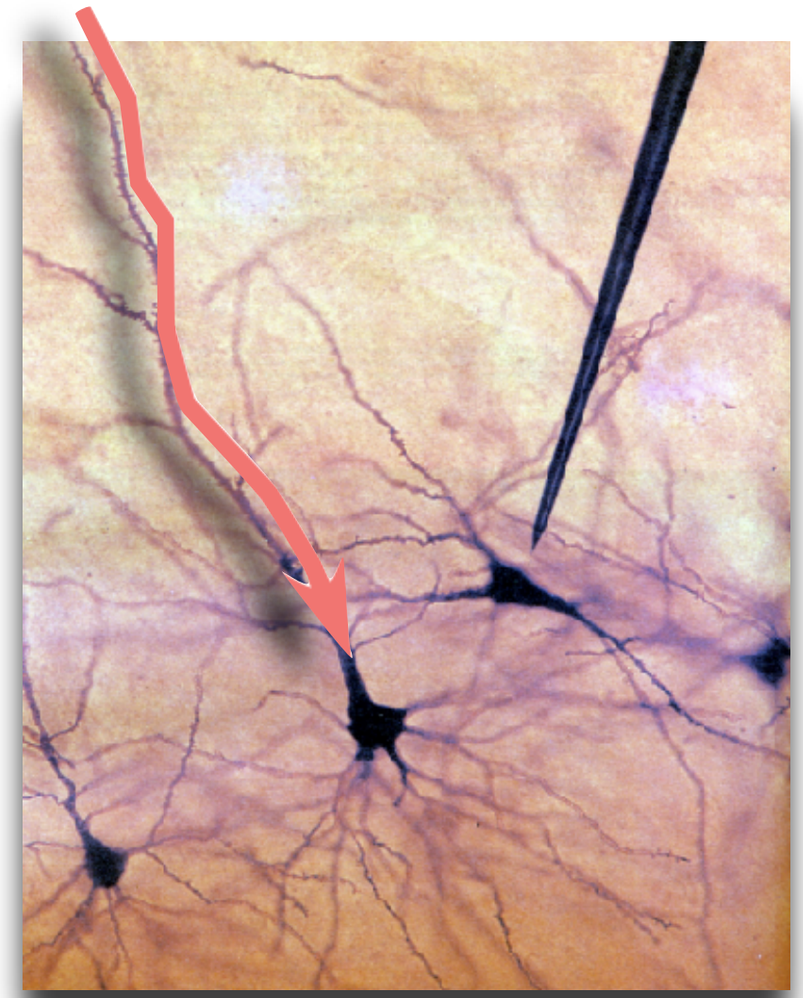


Photo by Fritz Goro

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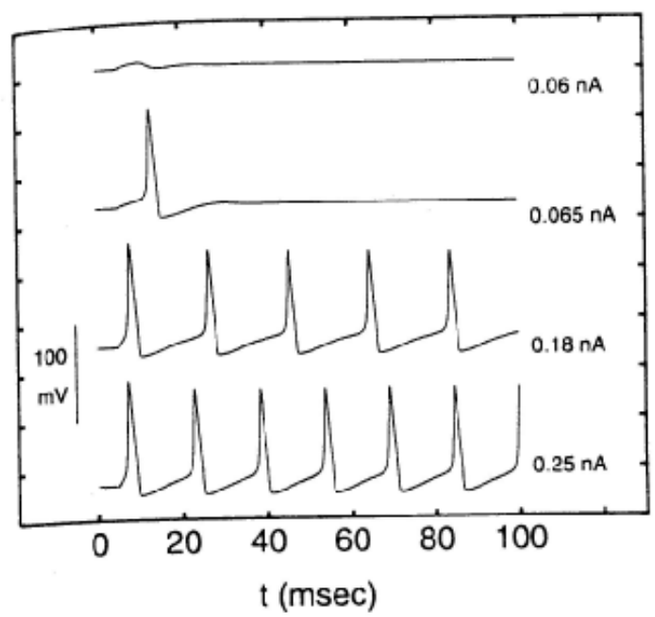


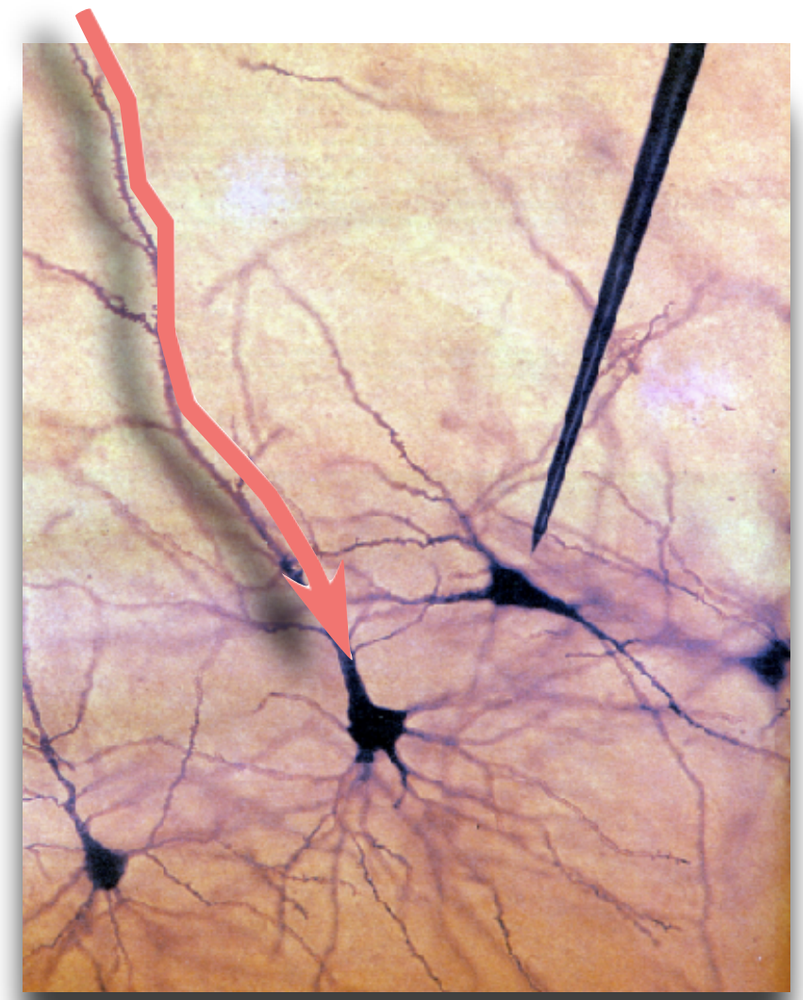


Photo by Fritz Goro

Origin of MEG Neural Signal

Dendritic current
– not axonal currents

Primary current
– not return currents

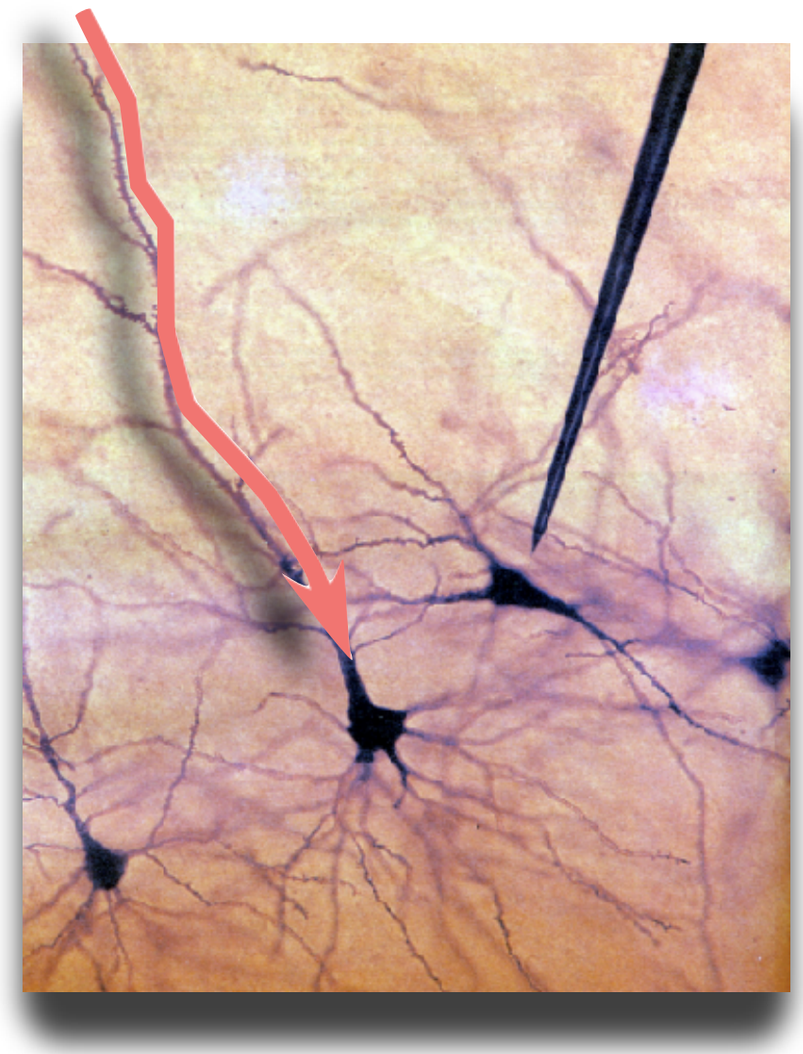


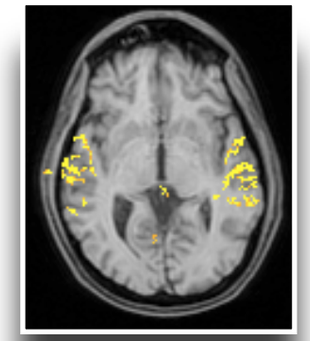
Photo by Fritz Goro

Functional Brain Imaging

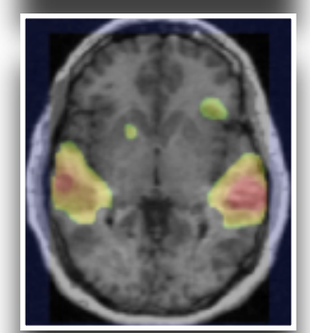
Functional Brain Imaging
= Non-invasive recording from human brain

Hemodynamic techniques

fMRI
functional magnetic resonance imaging



PET
positron emission tomography



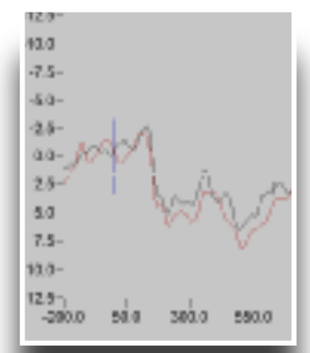
Excellent Spatial Resolution **(~1 mm)**

Poor Temporal Resolution **(~1 s)**

fMRI & MEG can capture effects in single subjects

Electromagnetic techniques

EEG
electroencephalography



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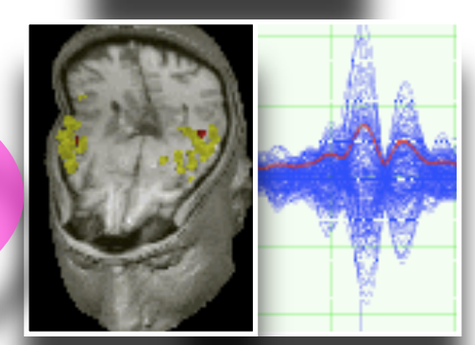

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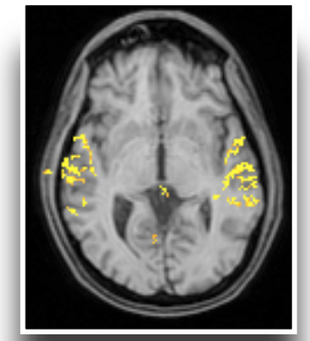

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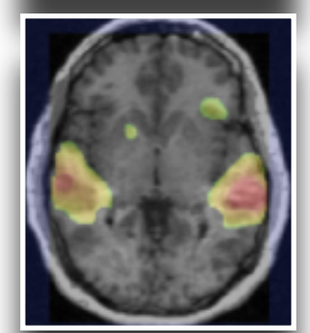

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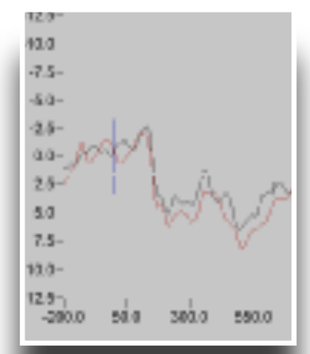

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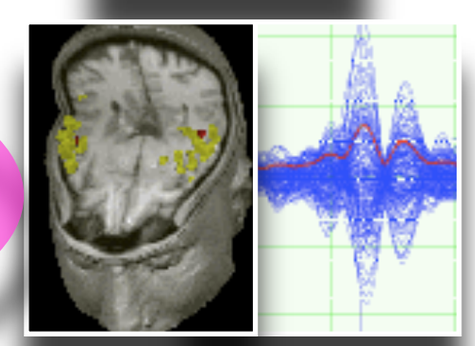

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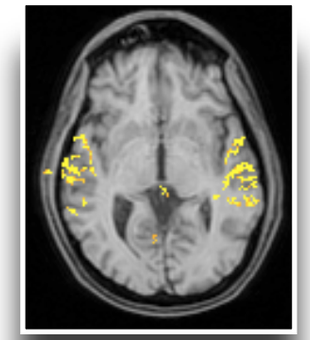

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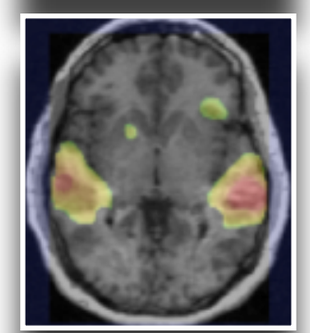

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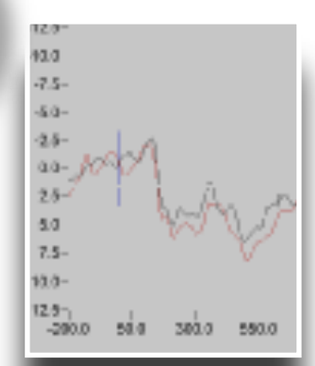

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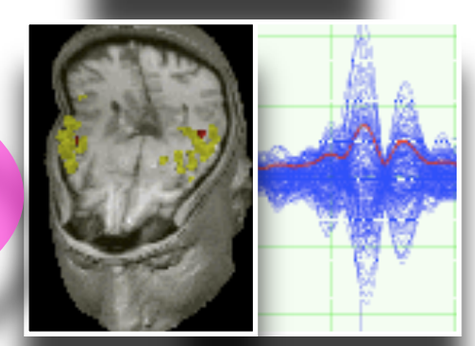
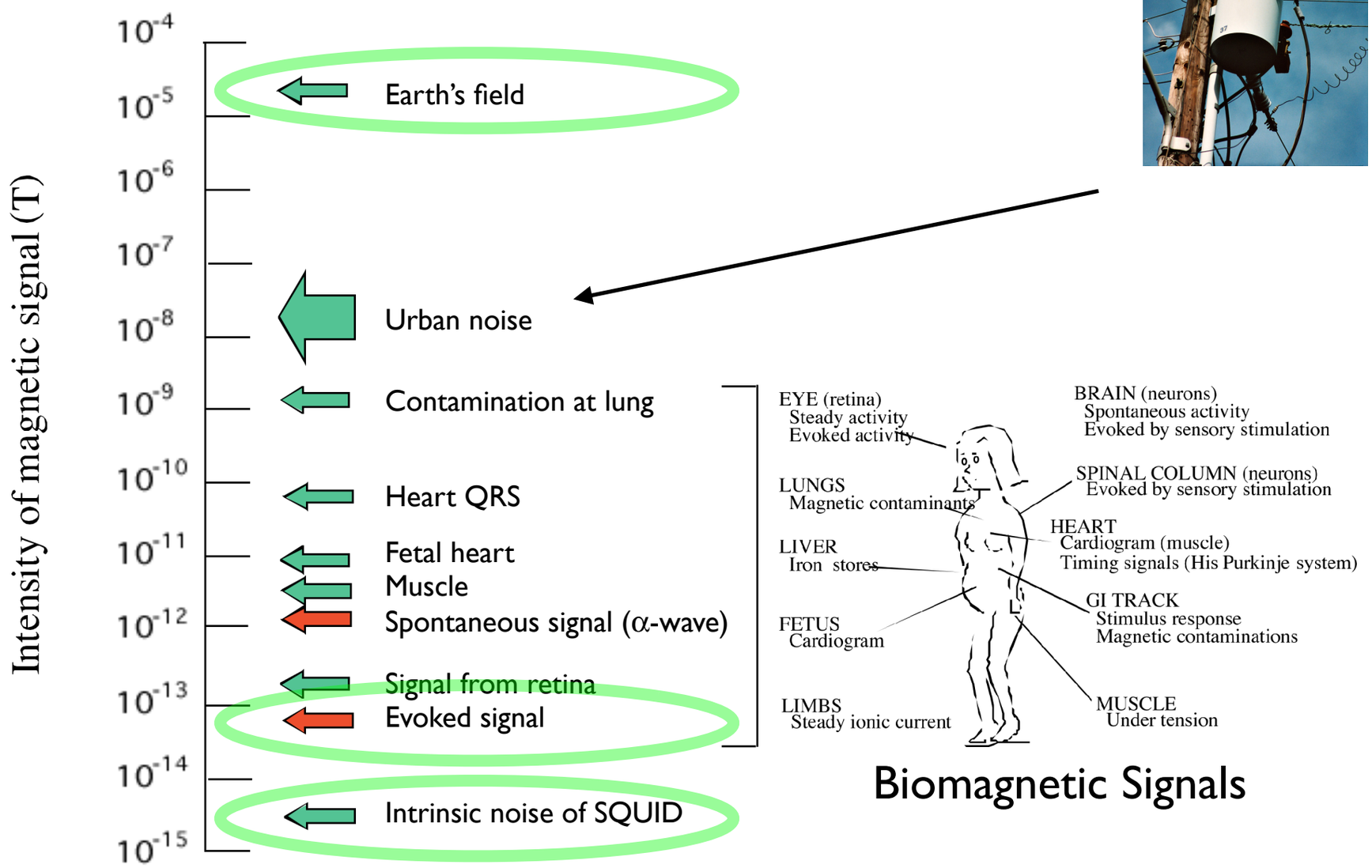


Excellent Temporal Resolution **(~1 ms)**

Magnetic Field Strengths

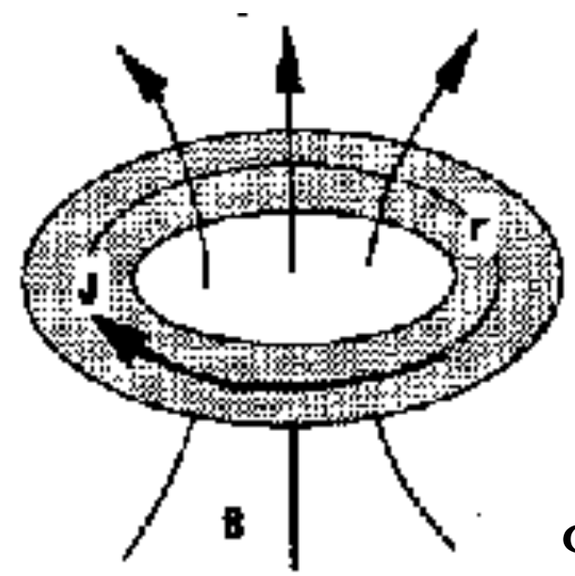


Biomagnetic Signals

SQUIDs

Superconductivity

- ➔ Magnetic flux quantization
- ➔ Josephson Effect
- ➔ SQUID = Superconducting Quantum Interference Device

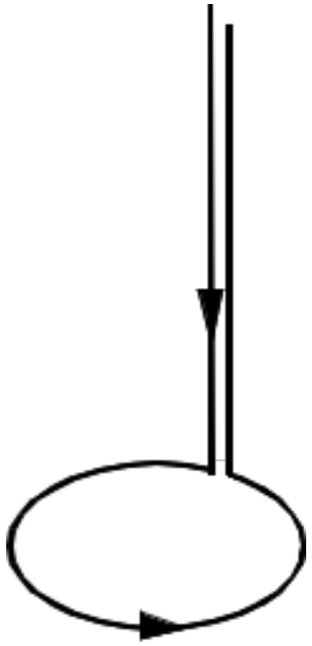


$$\Phi = n\frac{h}{2\mathrm{e}} = n\Phi_0$$

$$\Phi_0 = \frac{h}{2\mathrm{e}} = 2.07\times10^{-15}\ \mathrm{Wb}$$

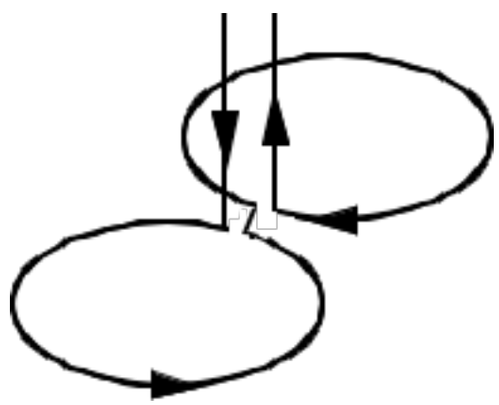
MEG SQUIDs

SQUID Magnetometer

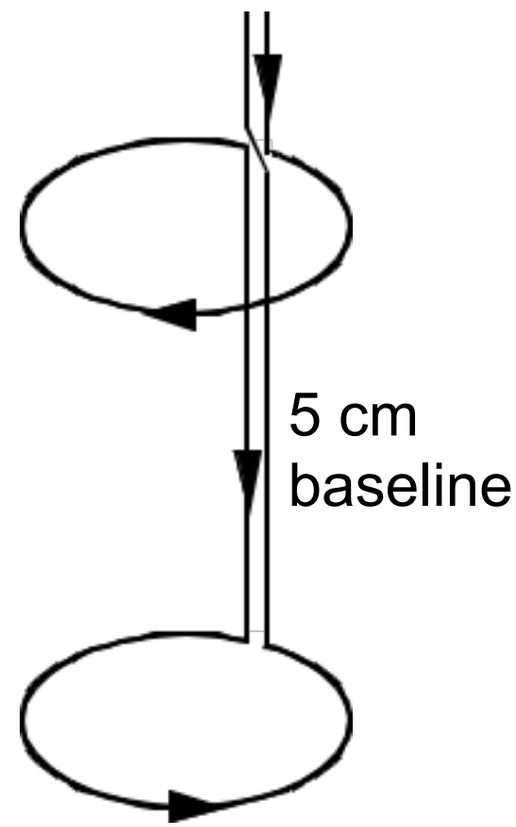


SQUID Gradiometers

Noise reduction from Differential measurement



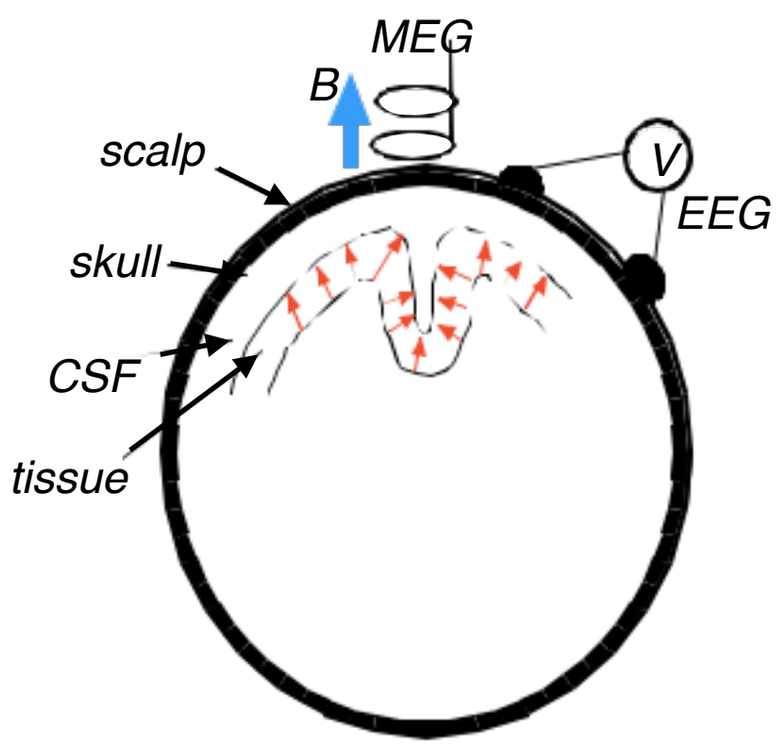
Planar Gradiometer

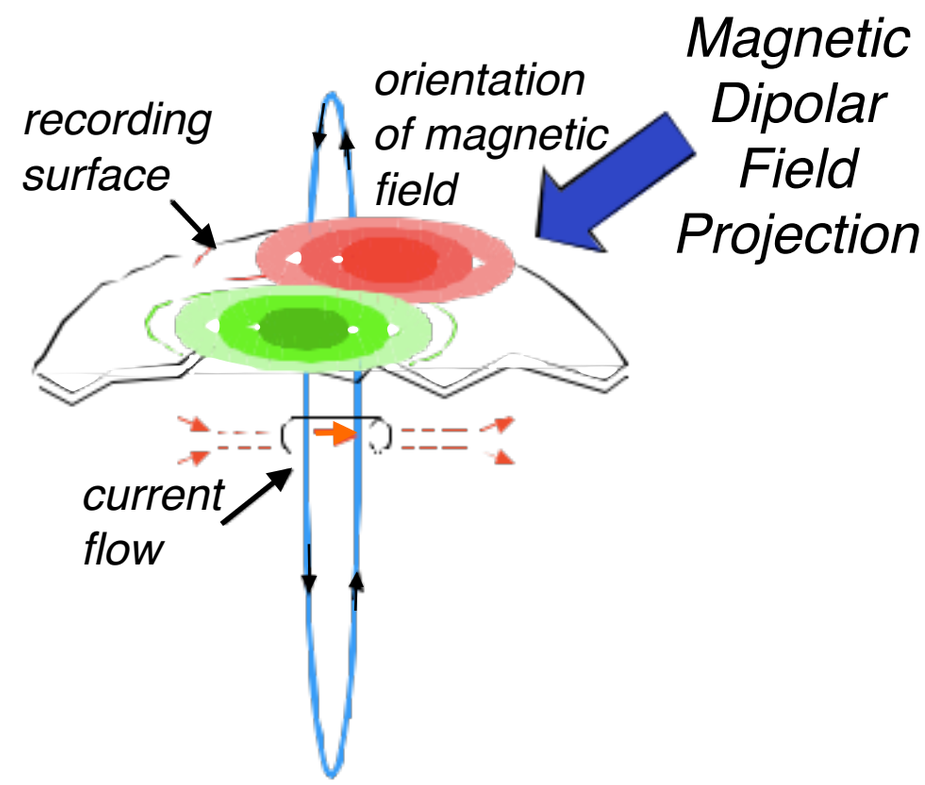


Axial Gradiometer

Neural Signals & MEG

Photo by Fritz Goro



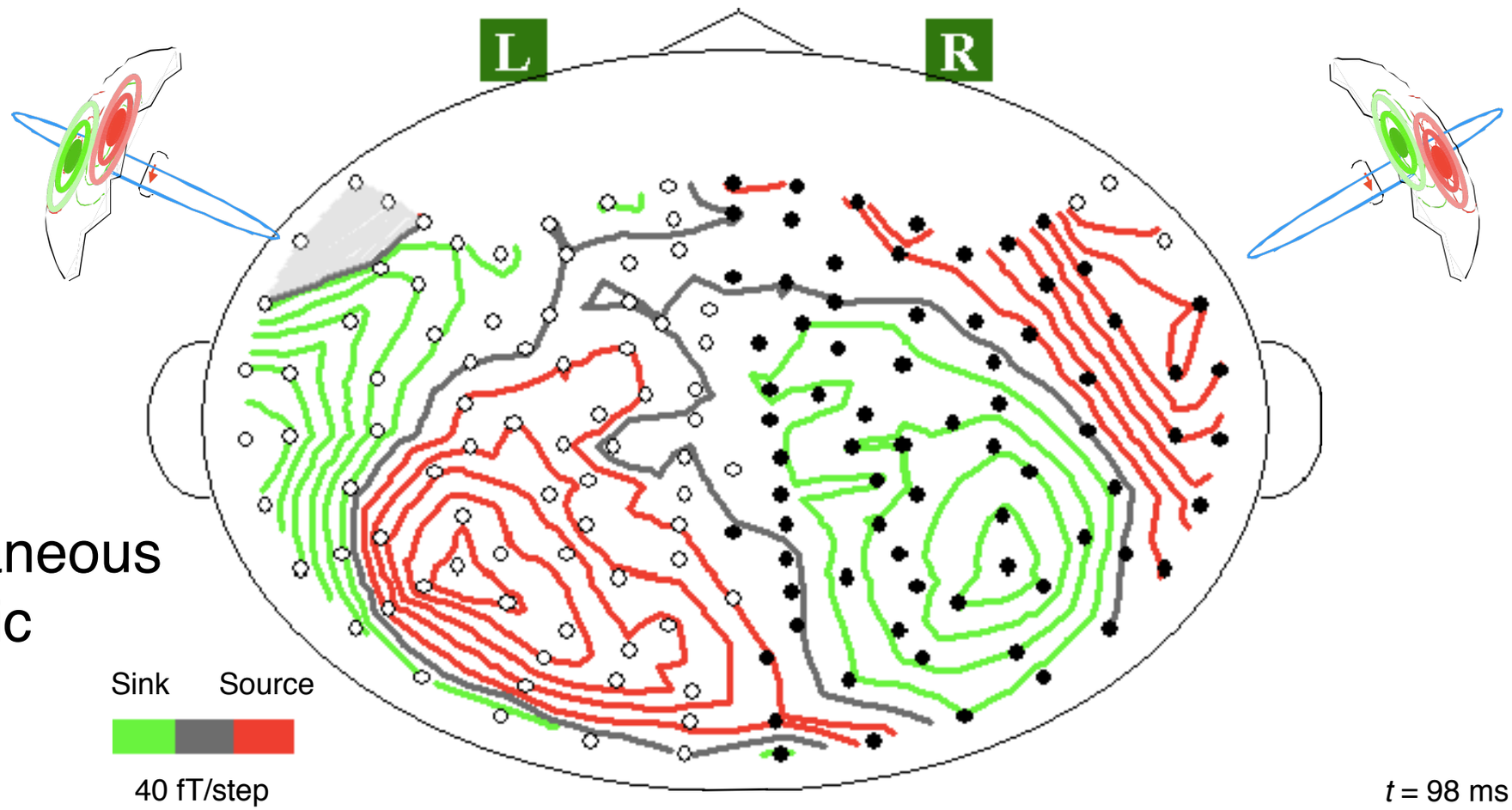


- Direct electrophysiological measurement
  - not hemodynamic
  - real-time
- No unique solution for distributed source

- Measures spatially synchronized cortical activity
- Fine temporal resolution (~ 1 ms)
- Moderate spatial resolution (~ 1 cm)

MEG Auditory Field

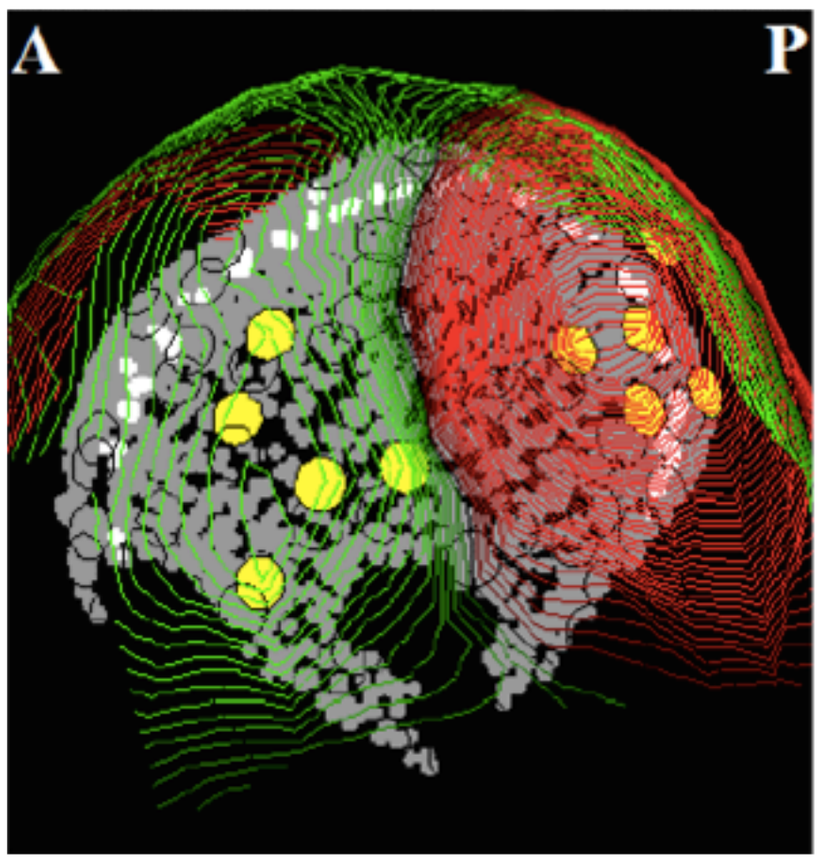
Flattened Isofield Contour Map



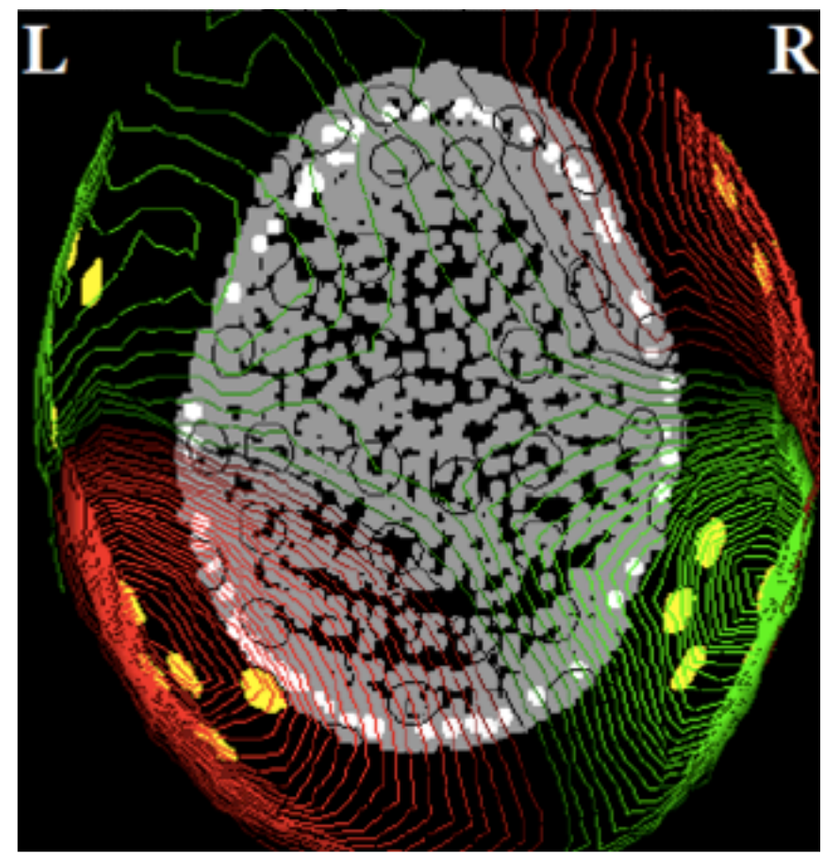
Instantaneous Magnetic Field

MEG Auditory Field

3-D Isofield Contour Map



Sagittal View



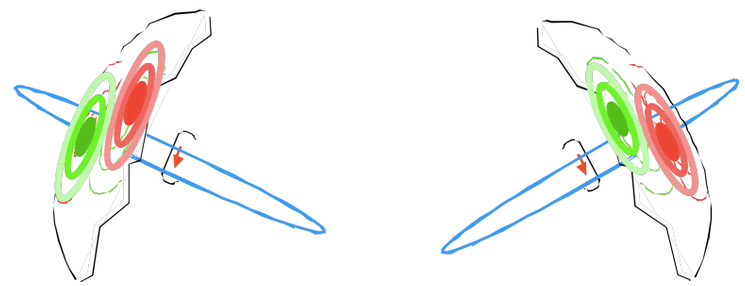
Axial View

Chait, Poeppel and Simon, Cerebral Cortex (2006)

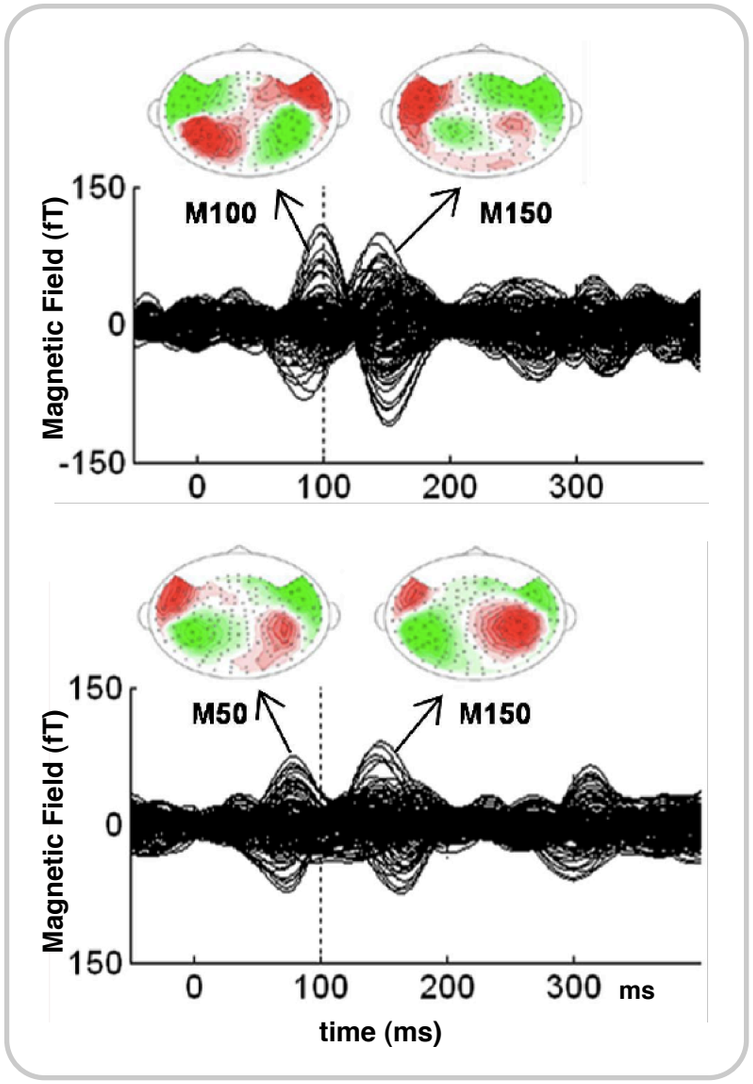
Time Course of MEG

Auditory Evoked Responses

- MEG Response Patterns Time-Locked to Stimulus Events
- Robust
- Strongly Lateralized



Pure Tone

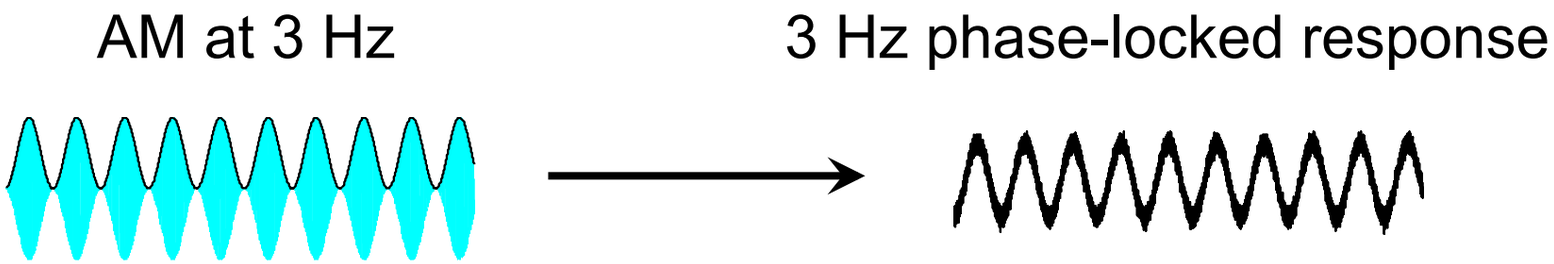


Broadband Noise

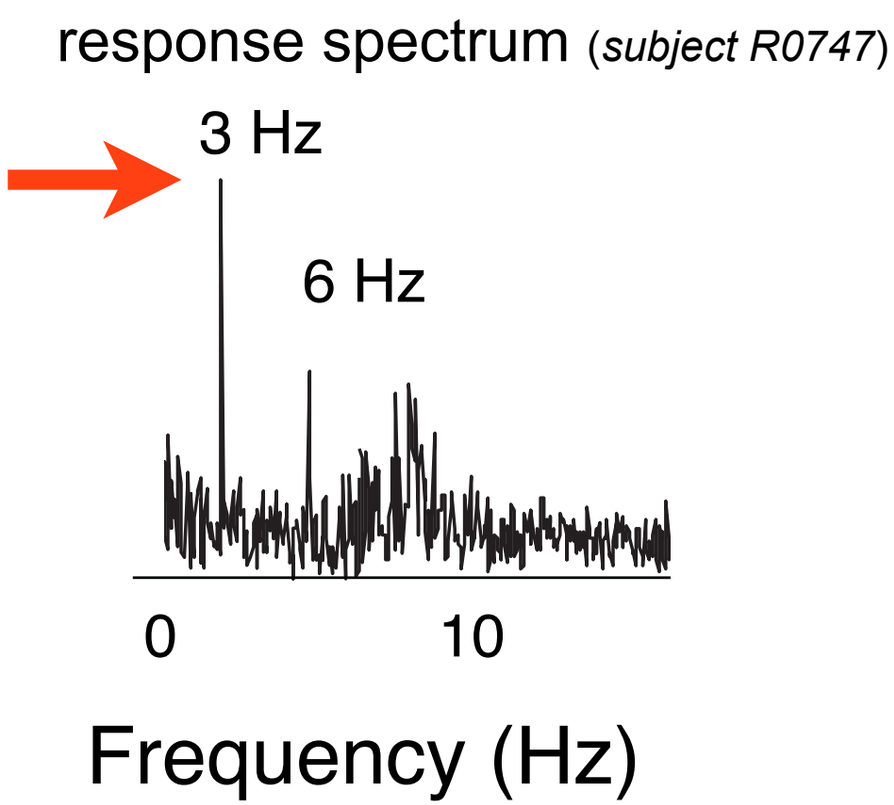
- **Auditory Induced Responses**

- MEG Response Patterns not Time-Locked to Stimulus Events
- Can be larger than Evoked Responses but cannot be averaged directly

Phase-Locking in MEG to Slow Acoustic Modulations



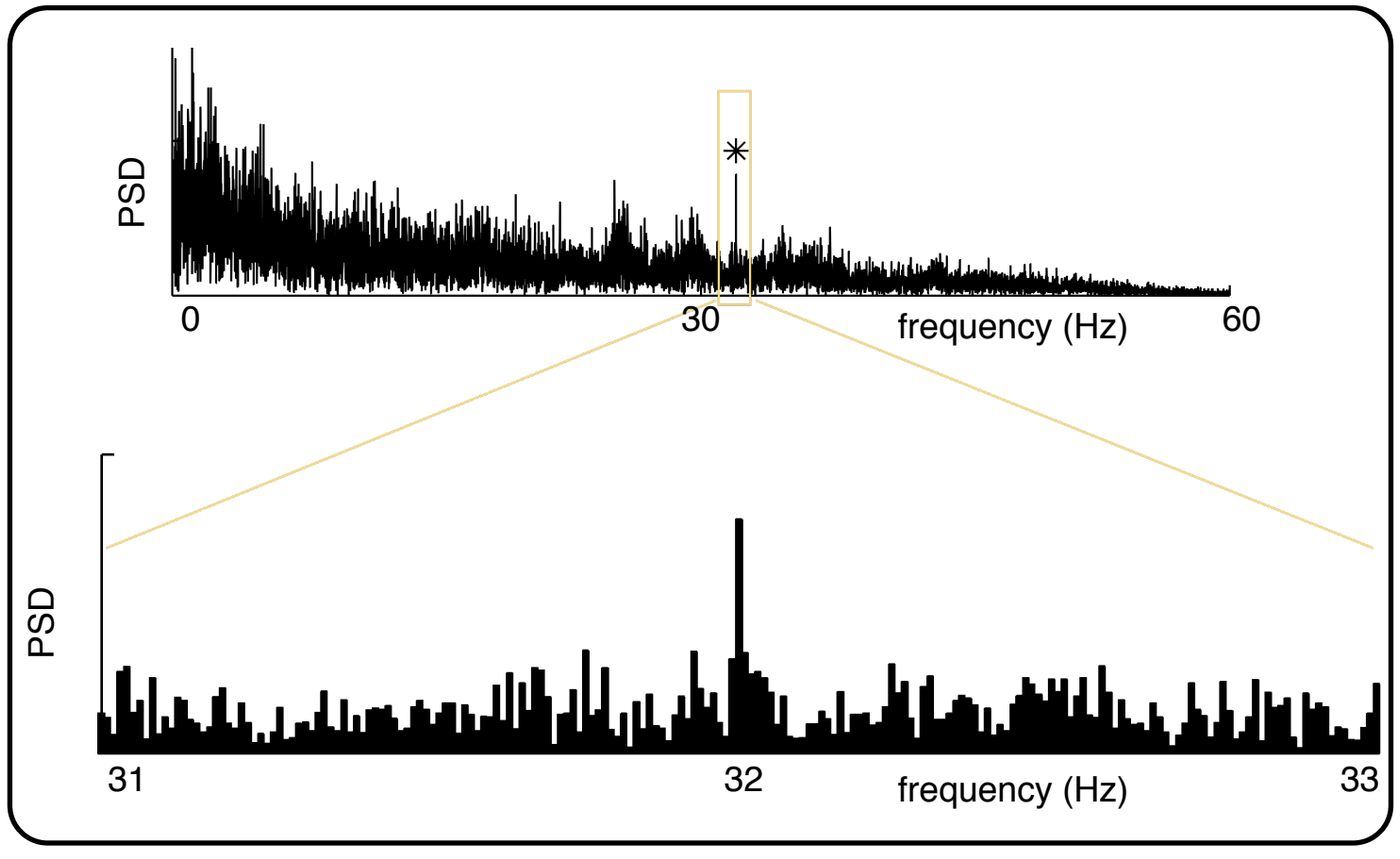
MEG activity is precisely phase-locked to temporal modulations of sound



Ding & Simon, J Neurophysiol (2009)
Wang et al., J Neurophysiol (2012)

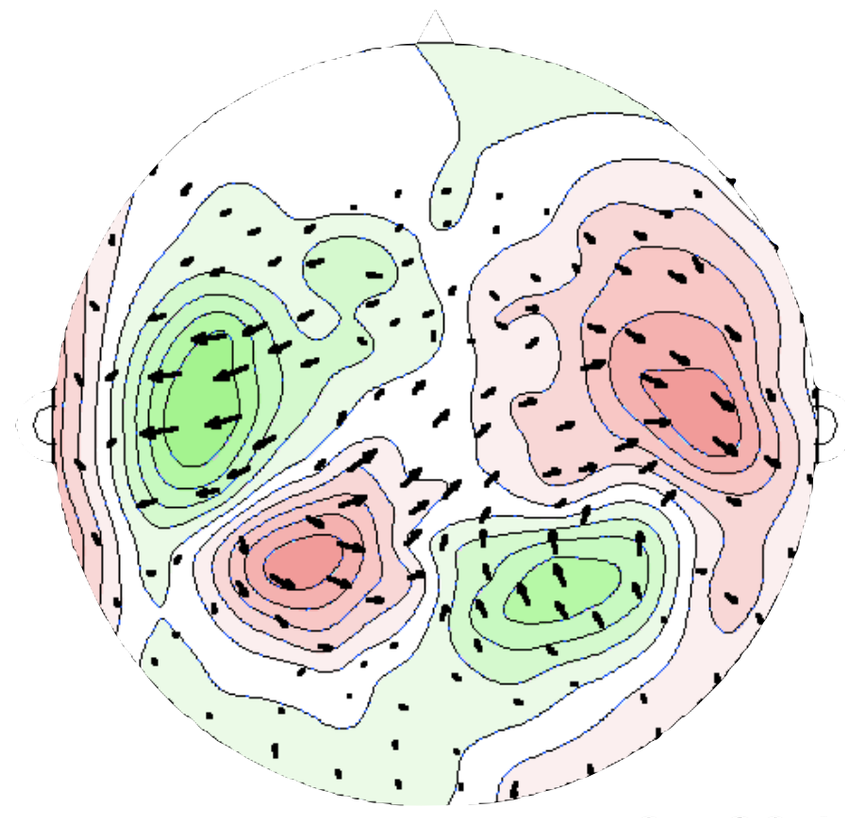
MEG Fourier Phase Analysis

Frequency Response to 32 Hz Amplitude Modulation



400 Hz tone carrier
100 trials @ 1 s
(concatenated)

Phasor Isofield Contour Map



f = 32 Hz

Simon and Wang, J. Neurosci. Methods (2005)

Neural Source Localization

- No Unique Solution from Magnetic Field Configuration to Neural Current Distribution ("Inverse Problem")
- Several Widely Used Methods
    - Equivalent-Current Dipoles
    - Minimum Norm Estimation & variants
    - Beamforming & variants
    - Others

Neural Source Troubles

- Equivalent-Current Dipoles
  - How Many?
  - Non-intuitive side effects
- Minimum Norm vs. Beamforming
  - Each “side” can easily produce datasets that show misleading results from using other method
- Recommended Tutorial
  - Lütkenhöner & Mosher in “Auditory Evoked Potentials” by Burkard et al.

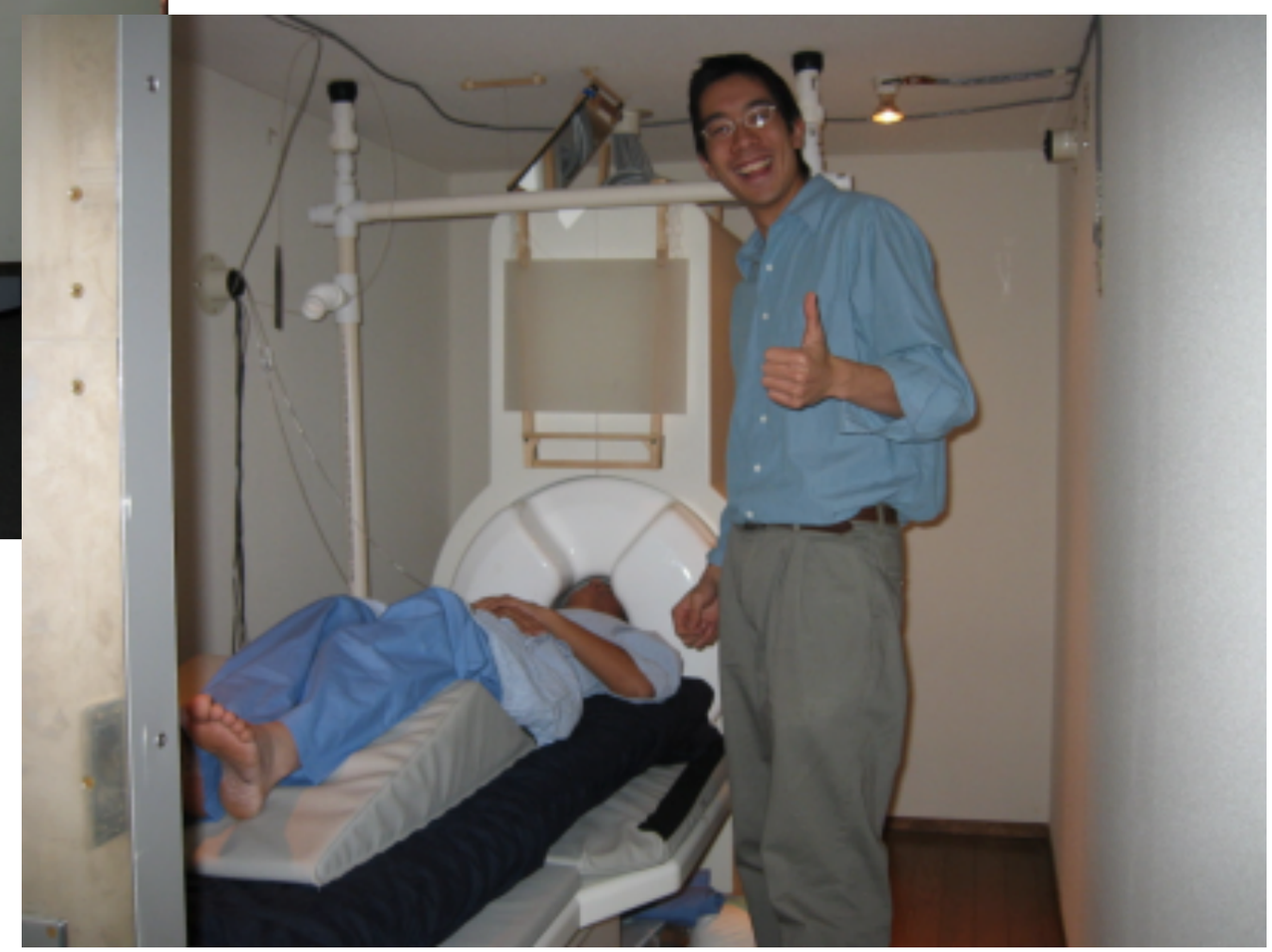
Neural Source Solutions?

- All of the major methods are good
  - Can give physiologically plausible result
  - Can give “correct/true” result
- Any might also get you into trouble
  - Each has weaknesses & blind spots

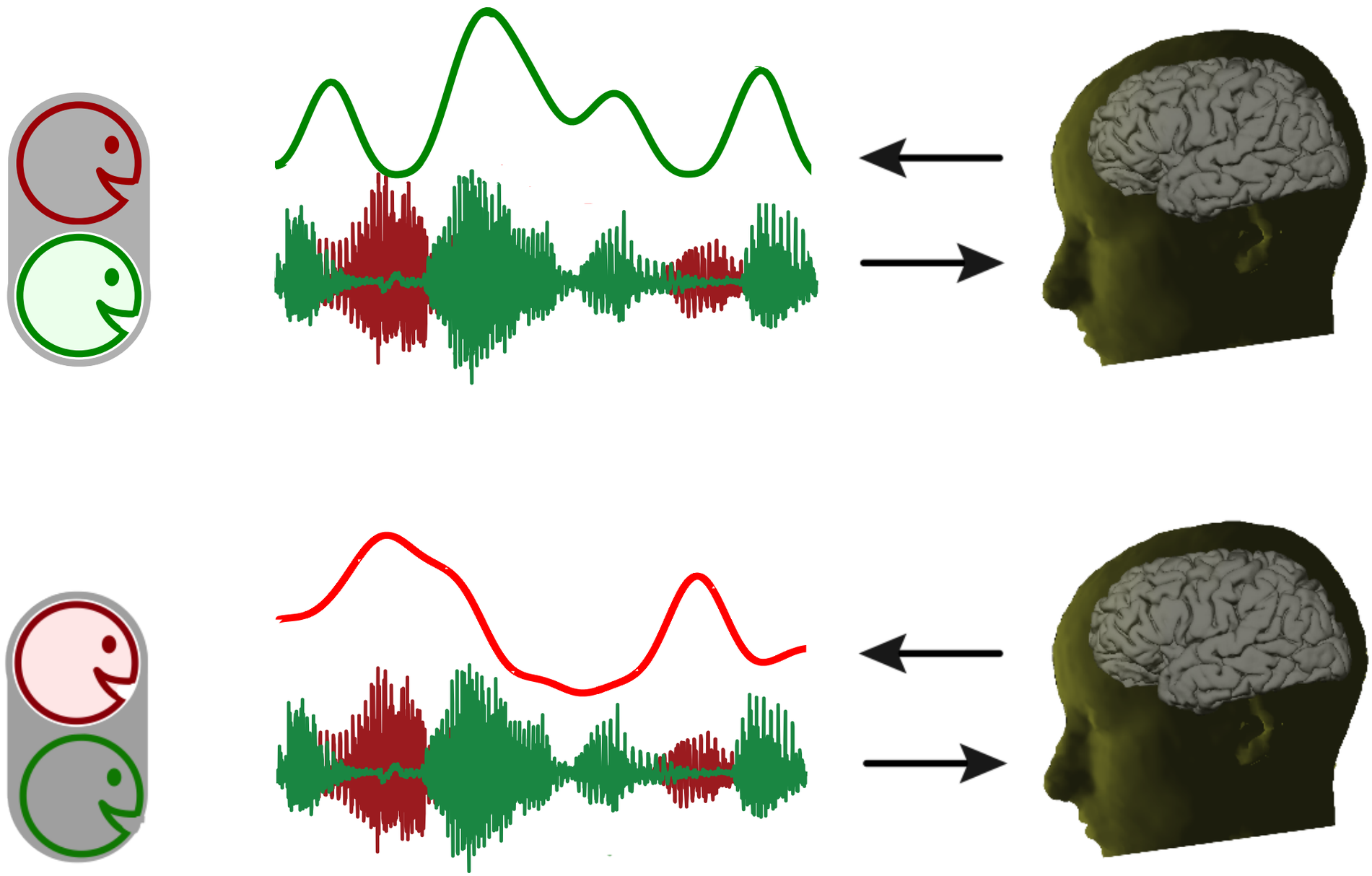
EEG

- High temporal resolution
- Room temperature
- Inexpensive
- Slow, careful set-up
- Electric fields strongly distorted
  - Brain = inhomogeneous anisotropic dielectric
  - Poor spatial neural reconstruction unless distortions carefully modeled
  - Inverse problem: worse? better?
- Complementary with MEG

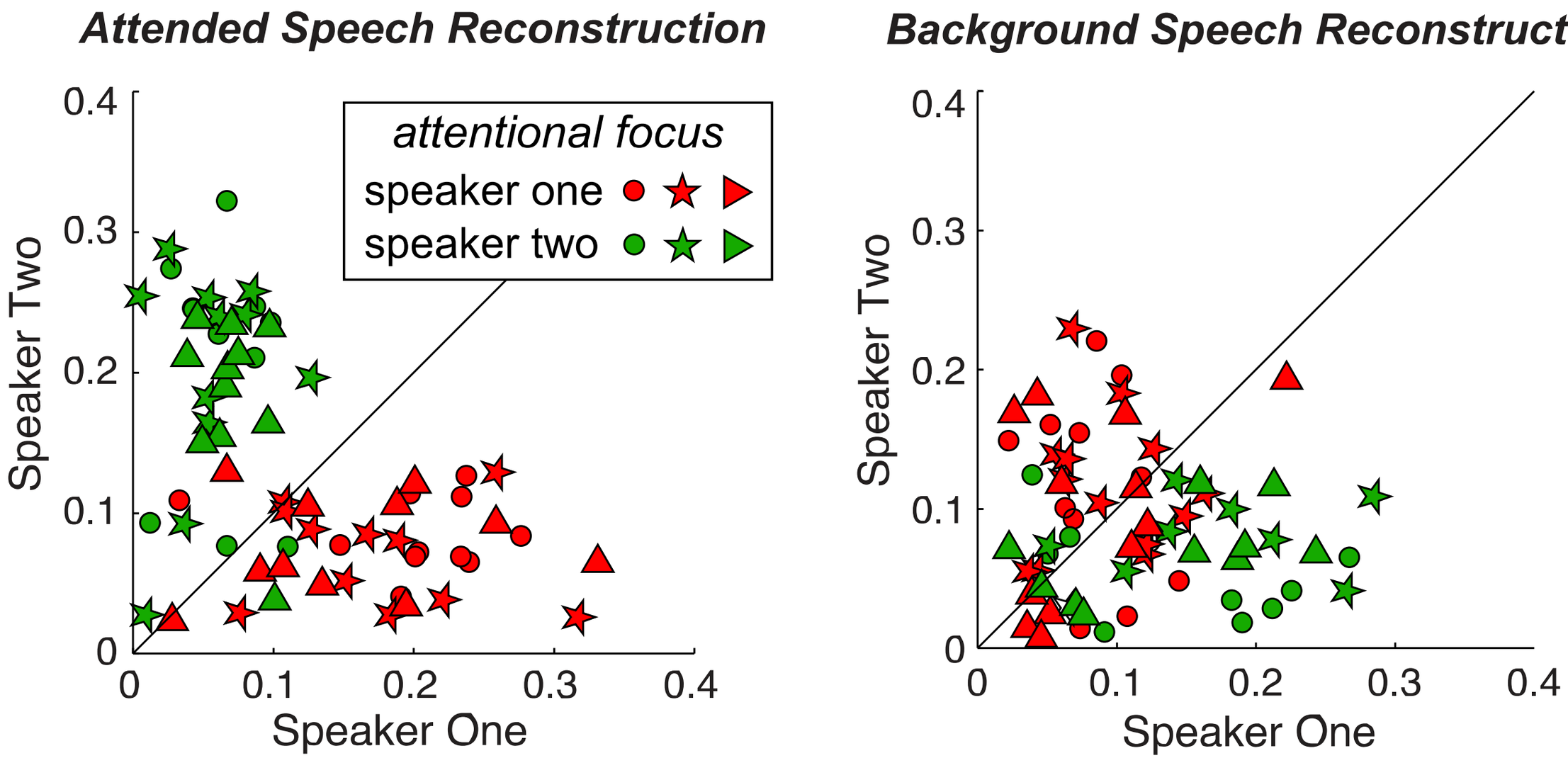
MEG Usage Examples



Selective Neural Encoding



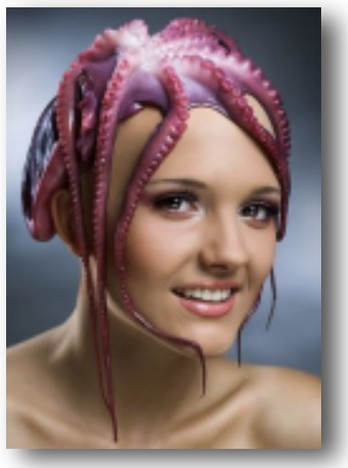
Single Trial Speech Reconstruction



Ding & Simon, PNAS (2012)

Thank You

At the monthly meeting of
Squidheads Anonymous

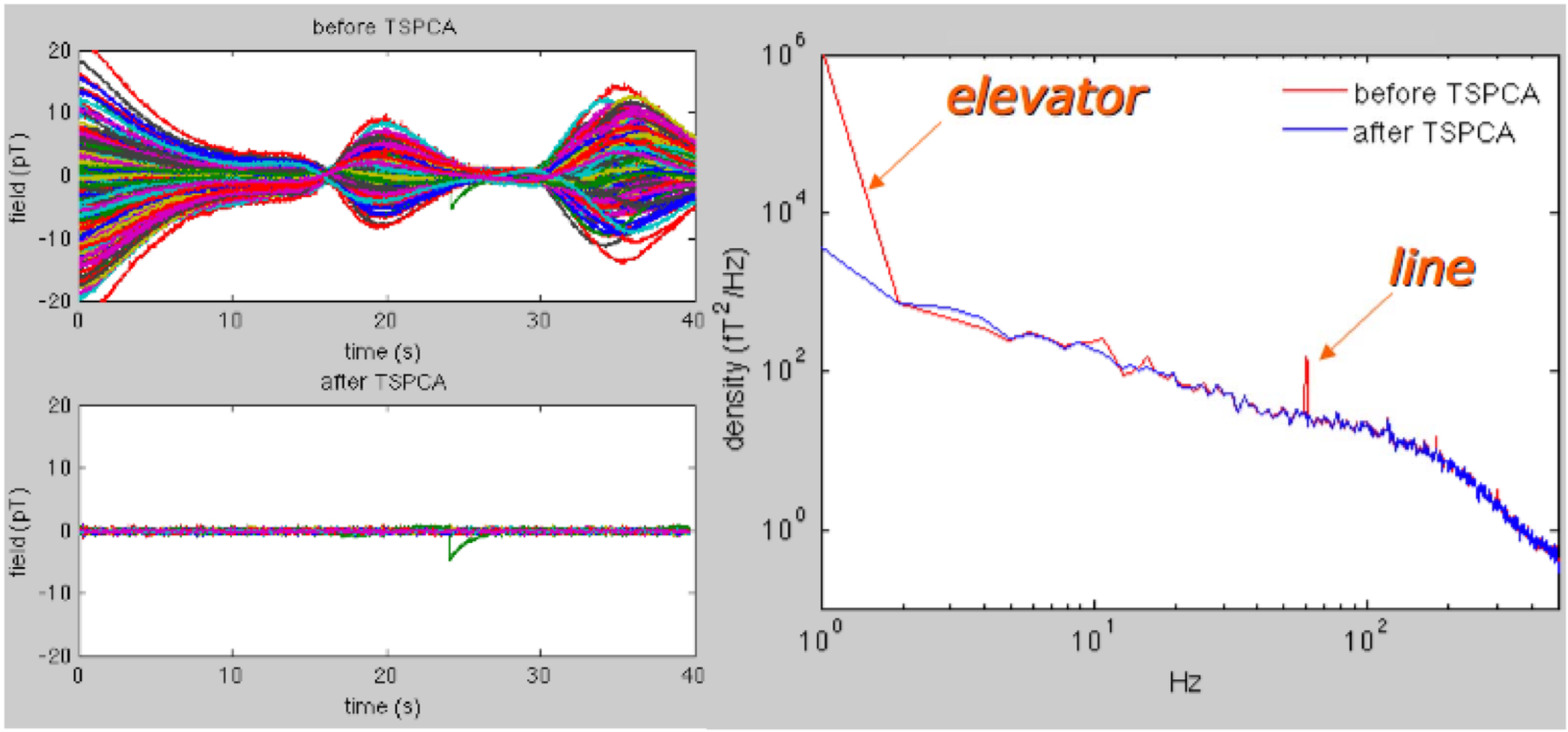


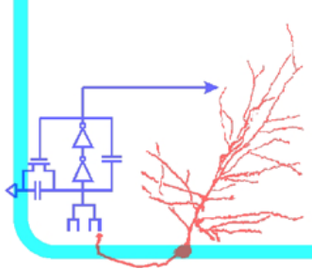
TSPCA

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

in colloboration with Alain de Cheveigné

TSPCA Example

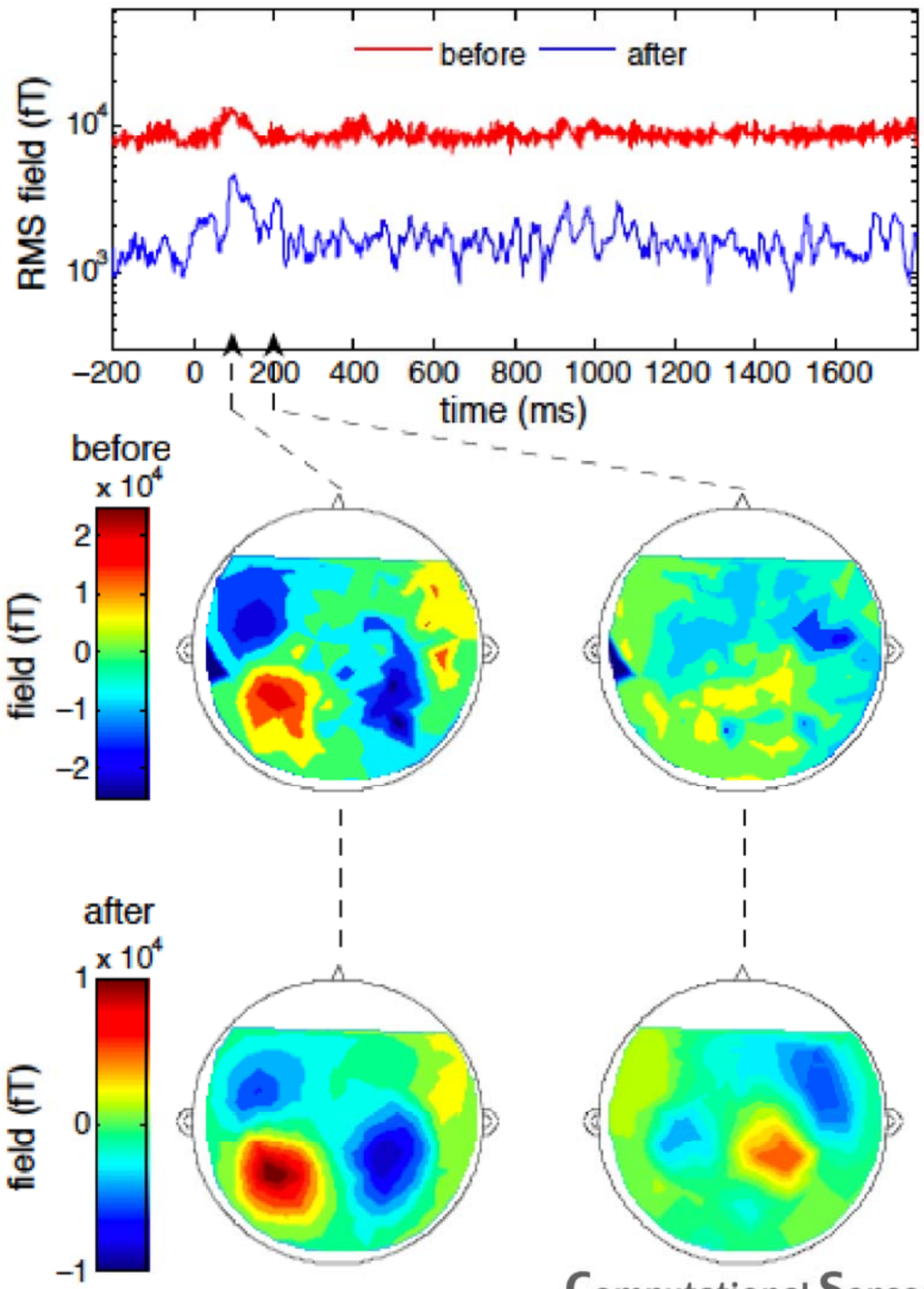


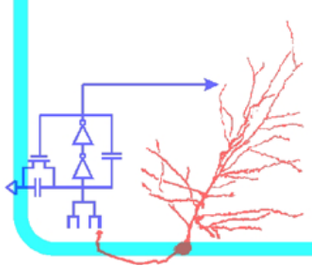


ATR MEG
(Advanced Telecommunications Research, Kyoto)

Computational Sensorimotor Systems Laboratory

TSPCA Example





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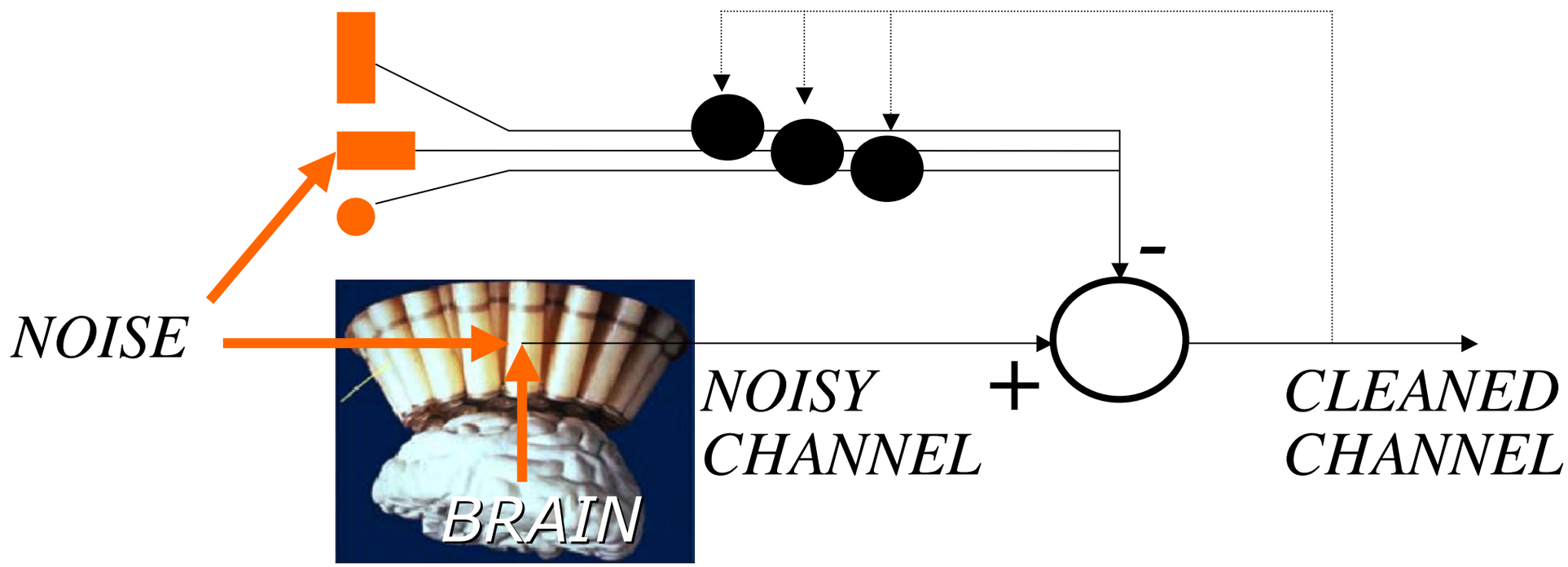
TSPCA: How it works

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



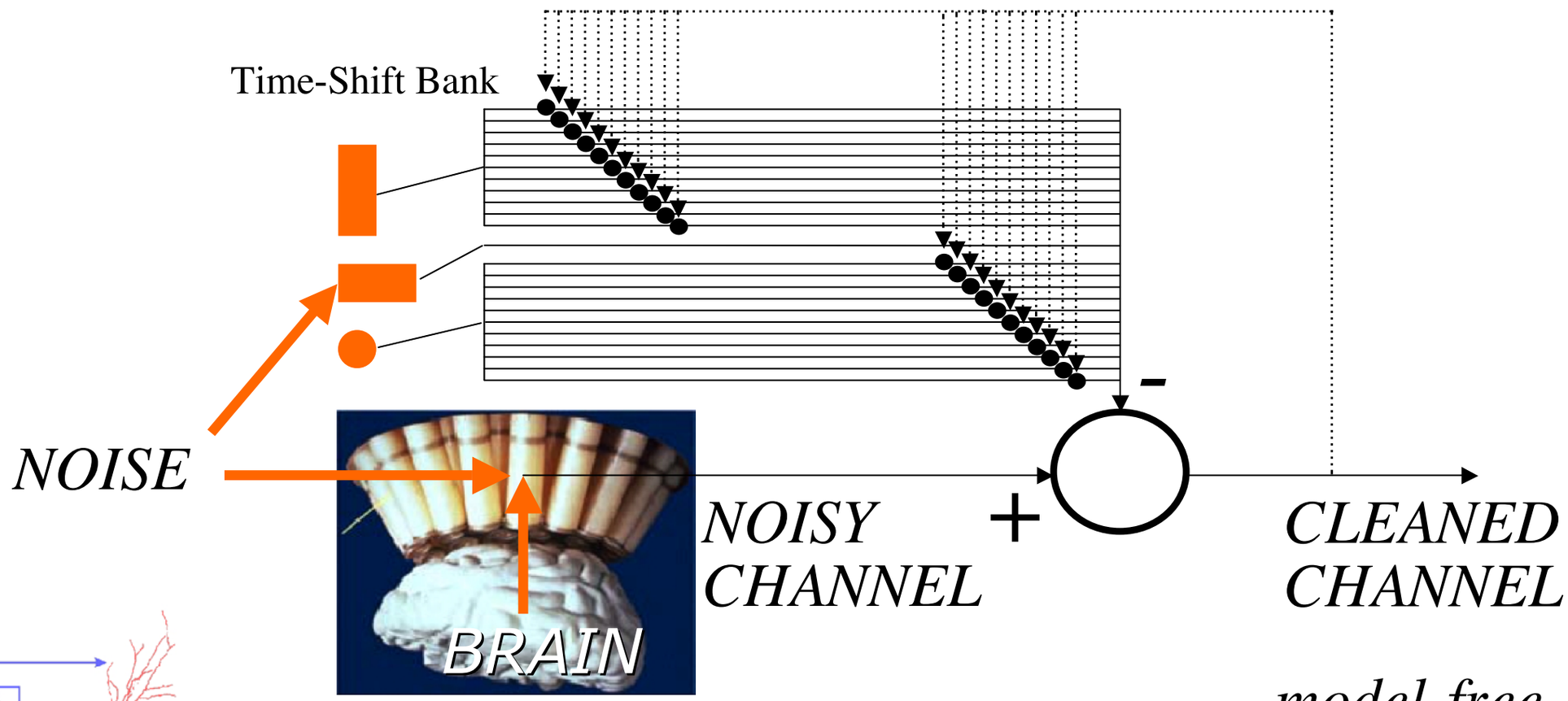
When scalar regression may fail since:

- 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



model-free

TSPCA: How it works

DELAY

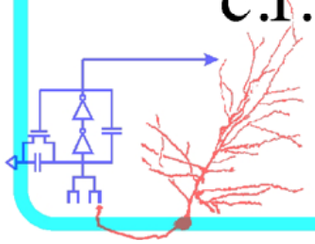
$$\hat{s}_k(t) = s_k(t) - \sum_{j=1}^{J}\sum_{\tau=1}^{N} \alpha_{kj\tau} r_j(t+\tau-\frac{N}{2})$$

BRAIN CHANNEL

REFERENCE CHANNELS

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

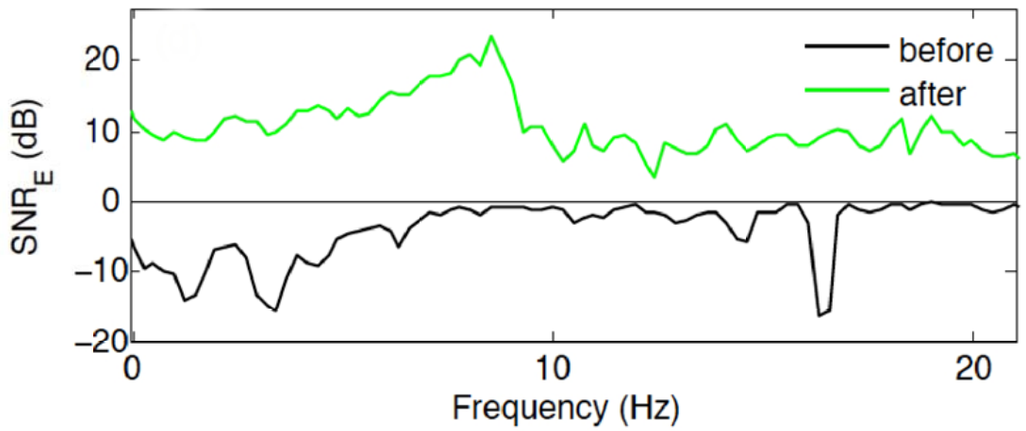
Algorithm:

1. Time-shift 3 reference signals by up to $\pm N/2$ samples (➔ $3N$ 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!

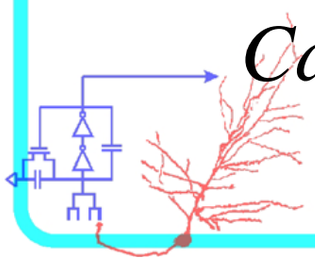
TSPCA Summary

- TSPCA removes ~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 = (# of taps), not sensitive
  Caveats: For small durations, N cannot be too large
  Large N increases processsing 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)

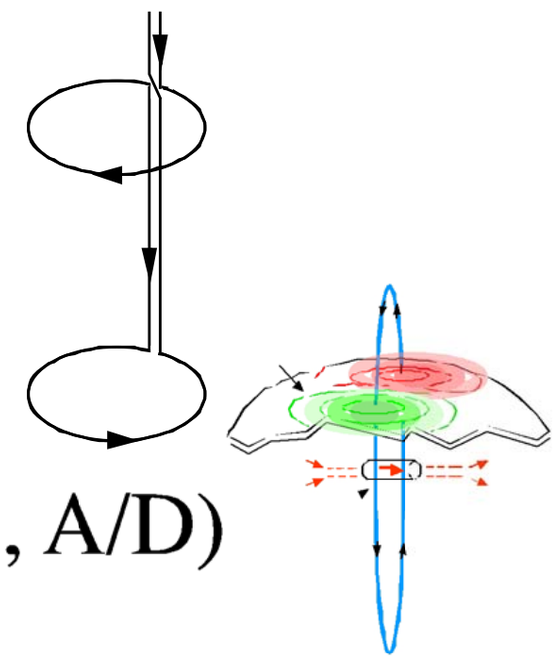


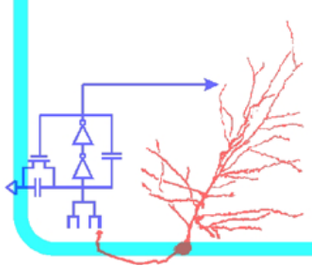
SNS

- Sensor Noise Supression
- Target: Sensor Noise

  Transducer Noise (SQUID)

  Electronics Noise (FLL, amplifier, A/D)

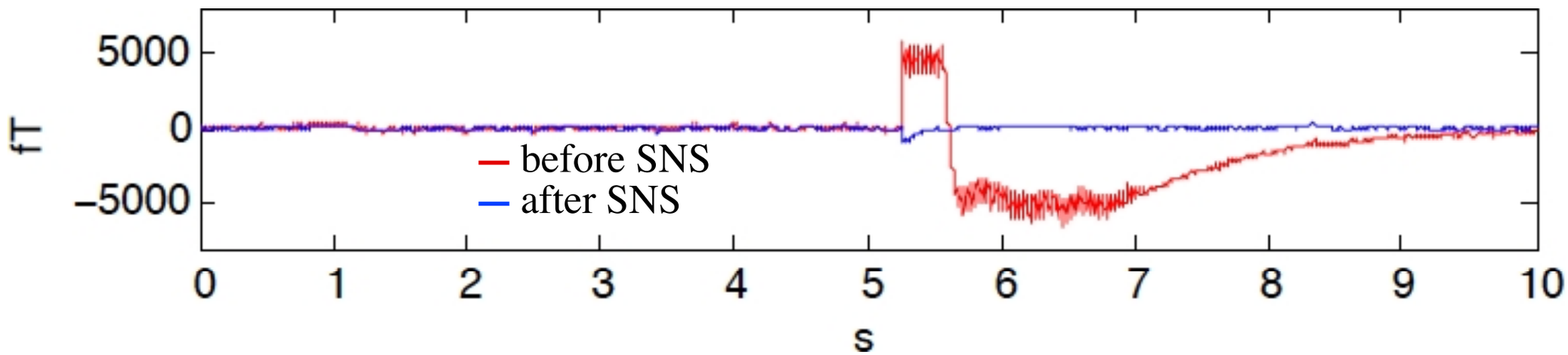




in colloboration with Alain de Cheveigné

SNS Example

Glitch Removal



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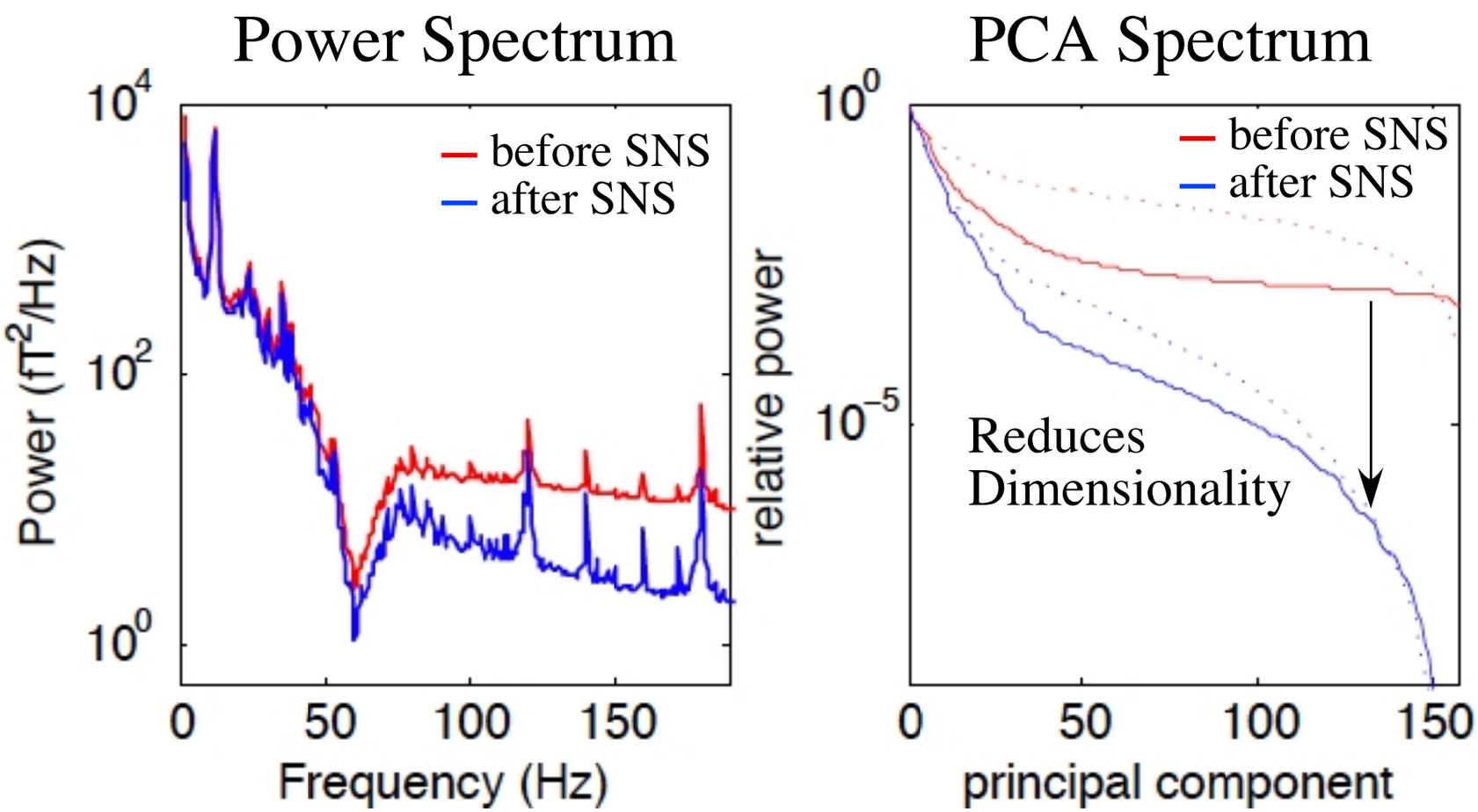
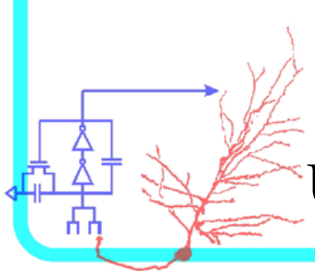
SNS Example

Power and PCA Spectra



Removes spurious sensor-specific dimensions



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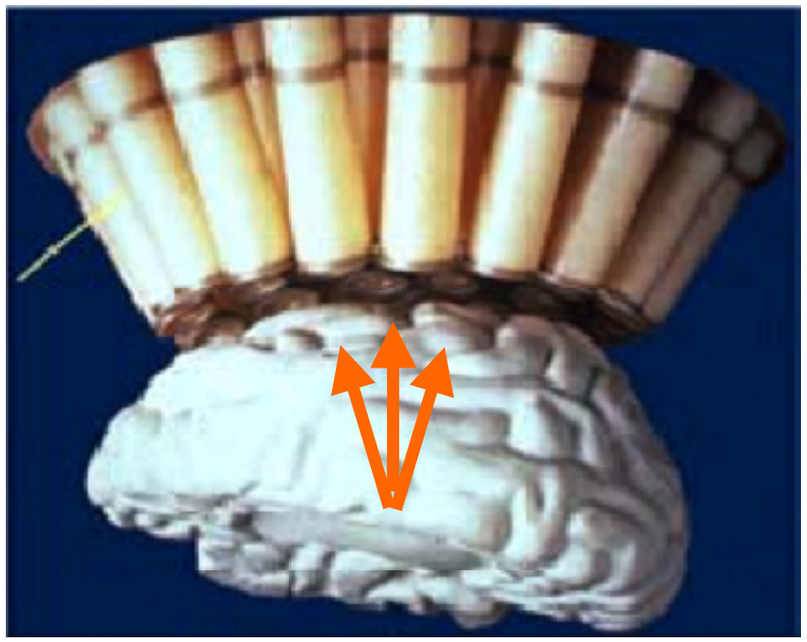
SNS: How it works



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!

$$\hat{S} = AS$$

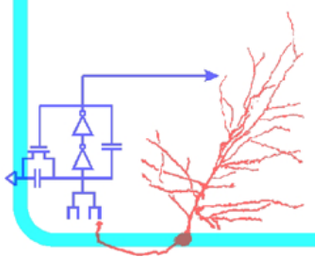
where $diag(A) = 0$

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

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 colloboration with Alain de Cheveigné

DSS: How it works

DSS produces a *set of spatial filters*

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

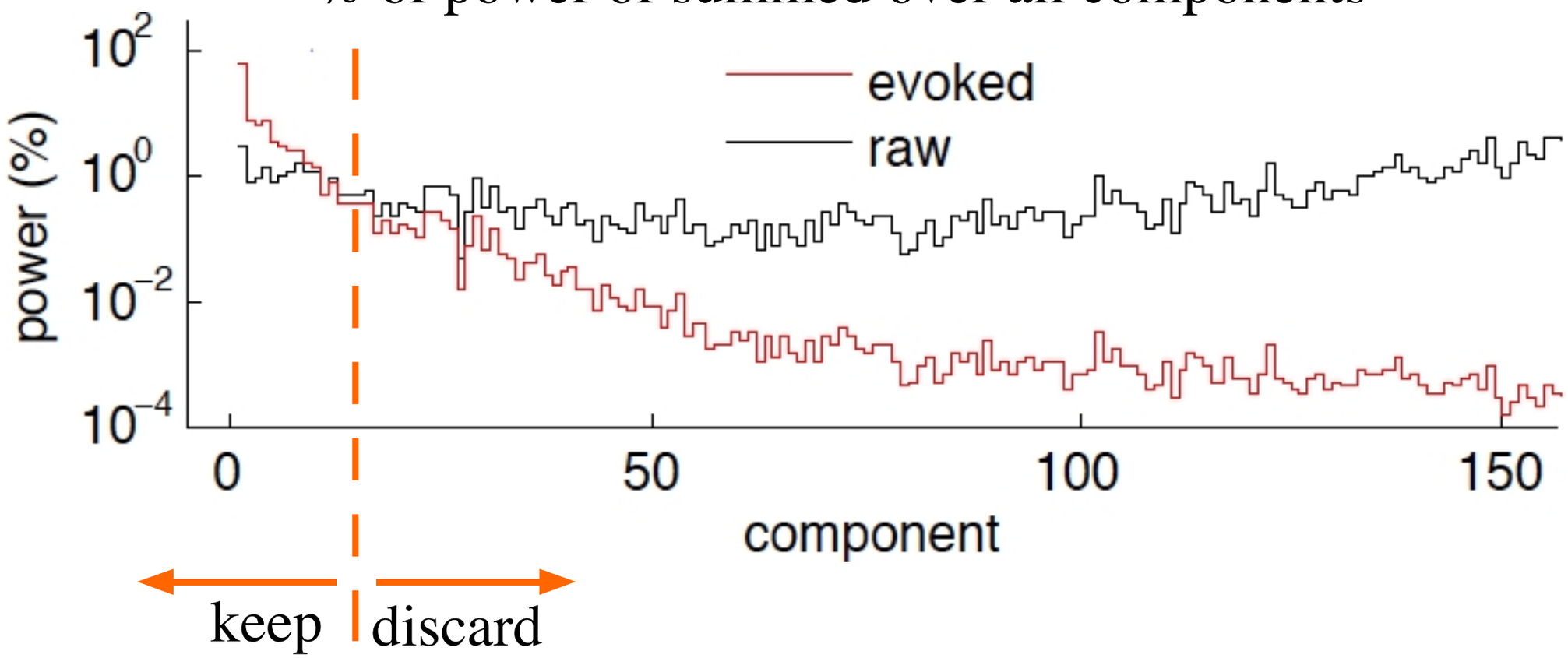
such that:

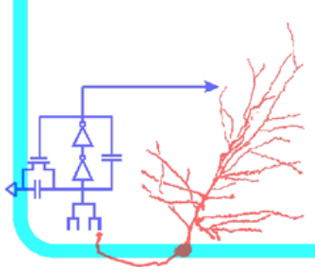
- The DSS components, $\hat{s}_{k'}(t)$, are orthogonal
- Waveforms sum to original waveform
- Powers sum to original power ("partition of power")
- $\hat{s}_k'(t)$ ordered by decreasing quality: $\hat{s}_1(t)$, $\hat{s}_2(t)$
- Spatial filters ordered by decreasing quality: a_{k1}, a_{k2}, etc.

DSS: How it works

"Select best components, discard others"

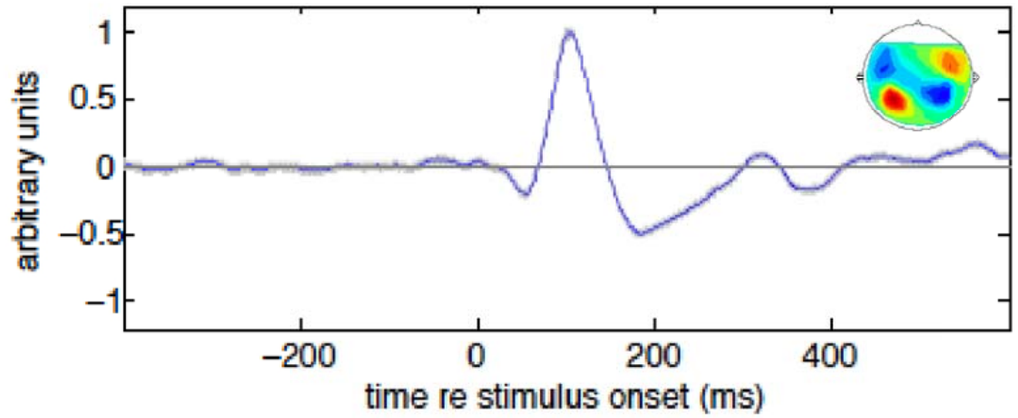
% of power of summed over all components





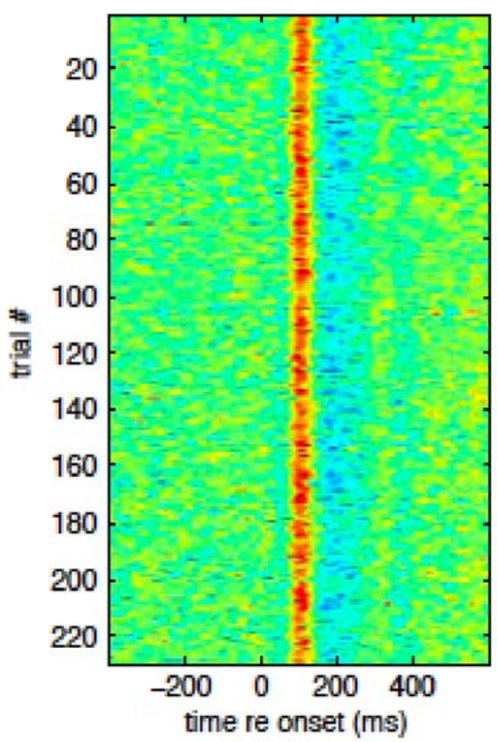
DSS Example

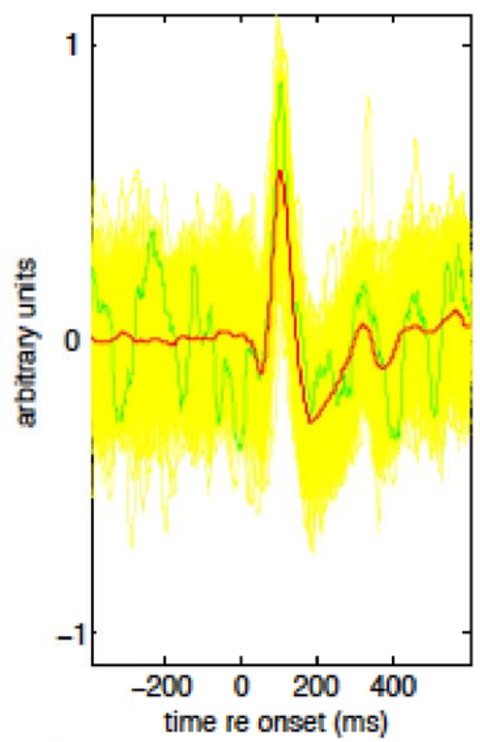
Best Component:



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

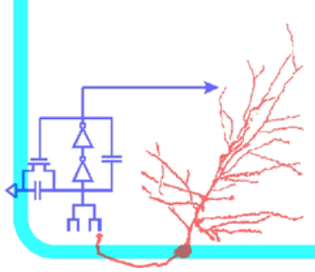
Single trials passed through spatial filter of best component





red: average

yellow & green: individual trials



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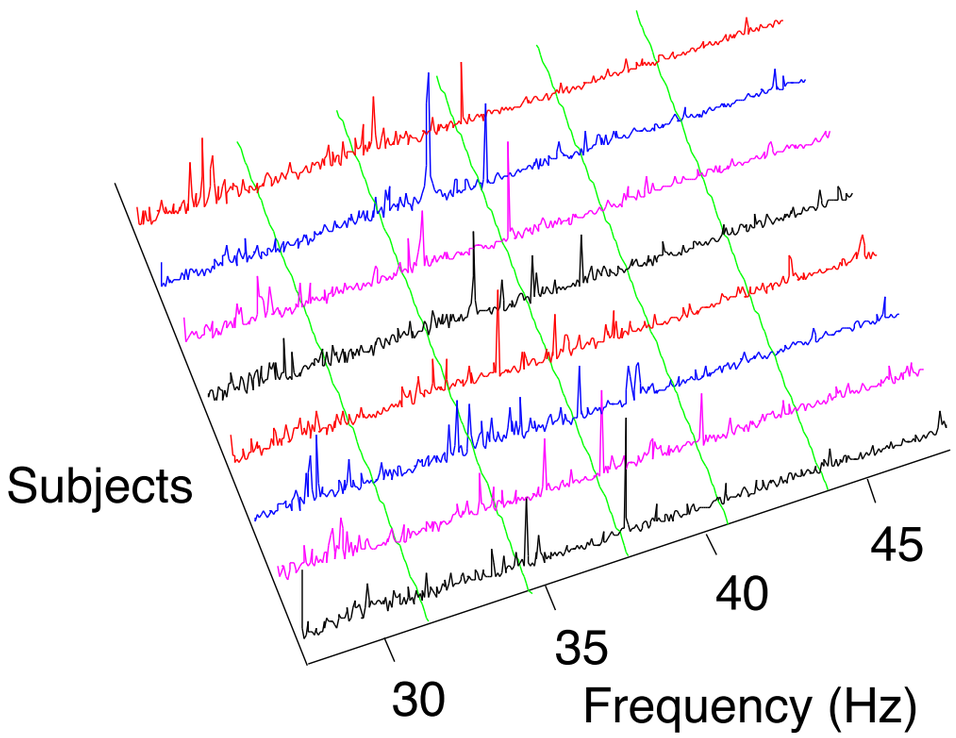
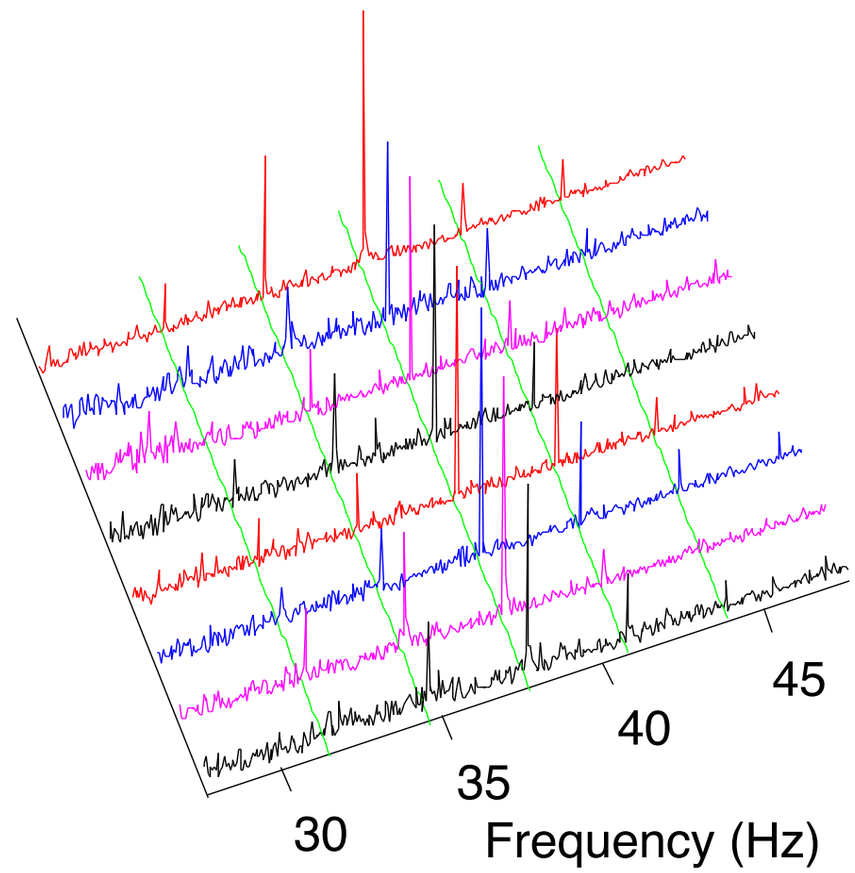
DSS Example

Spectra of MEG Steady State Response (to dual modulation)

Before DSS (20 Best Channels)



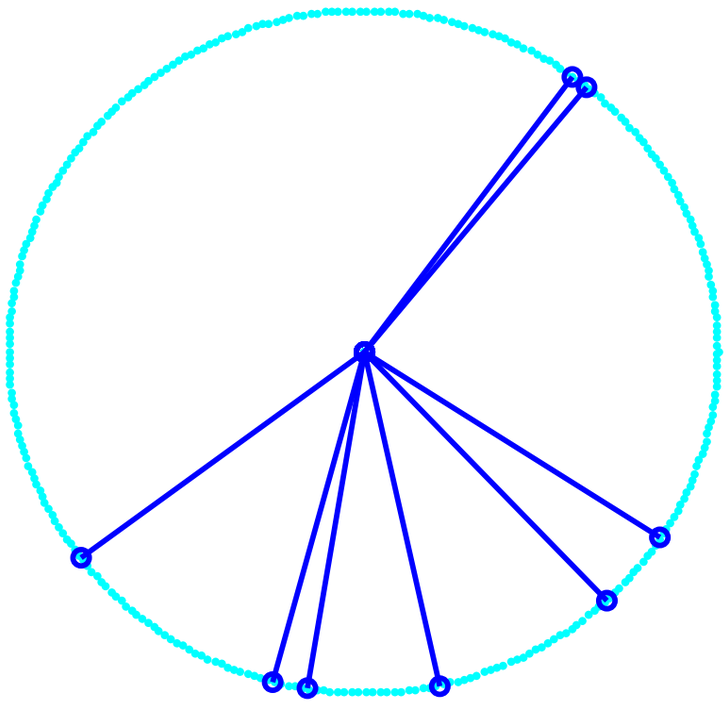
First DSS component



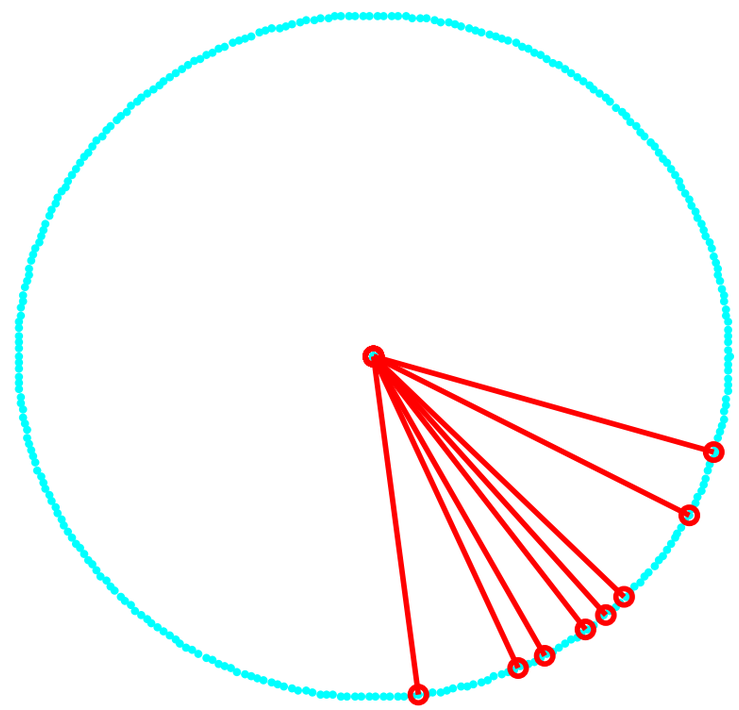
U. Maryland/KIT, courtesy of Nai Ding

DSS Example

Phase coding parameter α (by subject)



Before DSS (20 Best Channels)



First DSS component

U. Maryland/KIT, courtesy of Nai Ding

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!

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?

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/