Introduction to Magnetoencephalography

Jonathan Z. Simon
Department of Electrical & Computer Engineering
Department of Biology
Institute for Systems Research
University of Maryland
Neural processing of speech and complex auditory streams

Jonathan Z. Simon

Magnetoecephalography

Neural Modeling

Neural Signal Processing

Neurally Inspired Algorithms

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
Universal Neural Code

• Neural signals = spikes in voltage
• Spikes are “all-or-none”
  • Digital in amplitude
  • Asynchronous in time
• Neural Input $\approx$ current
Origin of MEG Neural Signal

Dendritic current
– not axonal currents

Primary current
– not return currents
Functional Brain Imaging

- Non-invasive recording from human brain

**Hemodynamic techniques**

- **fMRI**
  - functional magnetic resonance imaging

- **PET**
  - positron emission tomography

**Electromagnetic techniques**

- **EEG**
  - electroencephalography

- **MEG**
  - magnetoencephalography

**Comparison of Techniques**

- **Excellent Spatial Resolution (~1 mm)**
- **Poor Temporal Resolution (~1 s)**

- **Poor Spatial Resolution (~1 cm)**
- **Excellent Temporal Resolution (~1 ms)**

fMRI & MEG can capture effects in single subjects
Functional Brain Imaging

= Non-invasive recording from human brain

**Hemodynamic techniques**
- **fMRI**
  functional magnetic resonance imaging
- **PET**
  positron emission tomography

**Electromagnetic techniques**
- **EEG**
  electroencephalography
- **MEG**
  magnetoencephalography

**fMRI & MEG can capture effects in single subjects**

Excellent Spatial Resolution (~1 mm)
Poor Temporal Resolution (~1 s)

Poor Spatial Resolution (~1 cm)
Excellent Temporal Resolution (~1 ms)
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)

**Electromagnetic techniques**

- **EEG**
  - electroencephalography
  - Poor Spatial Resolution (~1 cm)
  - Excellent Temporal Resolution (~1 ms)
- **MEG**
  - magnetoencephalography

fMRI & MEG can capture effects in single subjects
Magnetic Field Strengths

- Earth's field
- Urban noise
- Contamination at lung
- Heart QRS
- Fetal heart
- Muscle
- Spontaneous signal (α-wave)
- Signal from retina
- Evoked signal
- Intrinsic noise of SQUID

Biomagnetic Signals
SQUIDs

Superconductivity

→ Magnetic flux quantization

→ Josephson Effect

→ SQUID = Superconducting Quantum Interference Device

\[ \Phi = n \frac{h}{2e} = n\Phi_0 \]

\[ \Phi_0 = \frac{h}{2e} = 2.07 \times 10^{-15} \text{ Wb} \]
MEG SQUIDs

SQUID Magnetometer

Noise reduction from Differential measurement

Planar Gradiometer

5 cm baseline

Axial Gradiometer
Neural Signals & MEG

- 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)

Photo by Fritz Goro
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 Laterialized

- 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

Phasor Isofield Contour Map

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

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
Thank You
TSPCA

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

in collaboration with Alain de Cheveigné
TSPCA Example

ATR MEG
(Advanced Telecommunications Research, Kyoto)
Computational Sensorimotor Systems Laboratory
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

NOISE → NOISY CHANNEL + CLEANED CHANNEL

BRAIN

model-free
**TSPCA: How it works**

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

**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 ±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](image)

- 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 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)
• Sensor Noise Suppression
• 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 Example

Power and PCA Spectra

Power Spectrum

PCA Spectrum

Reduces Dimensionality

Removes spurious sensor-specific dimensions

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 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 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: \( a_{k1}, a_{k2}, \text{etc.} \)
DSS: How it works

“Select best components, discard others”

% of power of summed over all components

- keep
- discard
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

U. Maryland/KIT Computational Sensorimotor Systems Laboratory
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 $\alpha$ (by subject)

Before DSS (20 Best Channels)  First DSS component
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


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