BCI Project 1 - Mandatory

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Classification of MEG stimulation and control data

Magnetoencephalography (MEG) provides millisecond-scale resolution of neural dynamics, making it ideal for studying sensory-evoked responses such as the auditory M100. Classifying individual trials of stimulus-locked MEG activity versus spontaneous (control) segments is crucial both for basic neuroscience and for brain-computer interface applications. This project implements a complete pipeline—from continuous recording through machine-learning classification—designed to:

- Extract stimulus-locked trials from continuous MEG recordings of left/right auditory cortex.
- Create matched "pseudo-trials" from spontaneous control data.
- Apply consistent signal conditioning to both classes.
- Engineer time-domain, spectral, and wavelet features.
- Train and evaluate a classifier via stratified cross-validation.

0.0.1 Dataset description and Preprocessing

The preprocessing pipeline began by loading continuous magnetoencephalography (MEG) recordings from two auditory cortex channels (left and right hemispheres) for a single subject. Auditory stimulation events were identified using a provided stimulus onset file (stimtimes.mat).

Power Spectral Density (PSD) analysis was performed using Welch's method, verifying the presence of relevant neural activity within the 3–20 Hz frequency range. To isolate trial-specific responses, the continuous MEG signals were segmented into individual trials encompassing a window from 100 samples (160 ms) pre-stimulus to 300 samples (480 ms) post-stimulus.

For comparative analysis, control pseudo-trials were extracted from continuous spontaneous activity recordings, matched precisely in length and number to the stimulus trials.

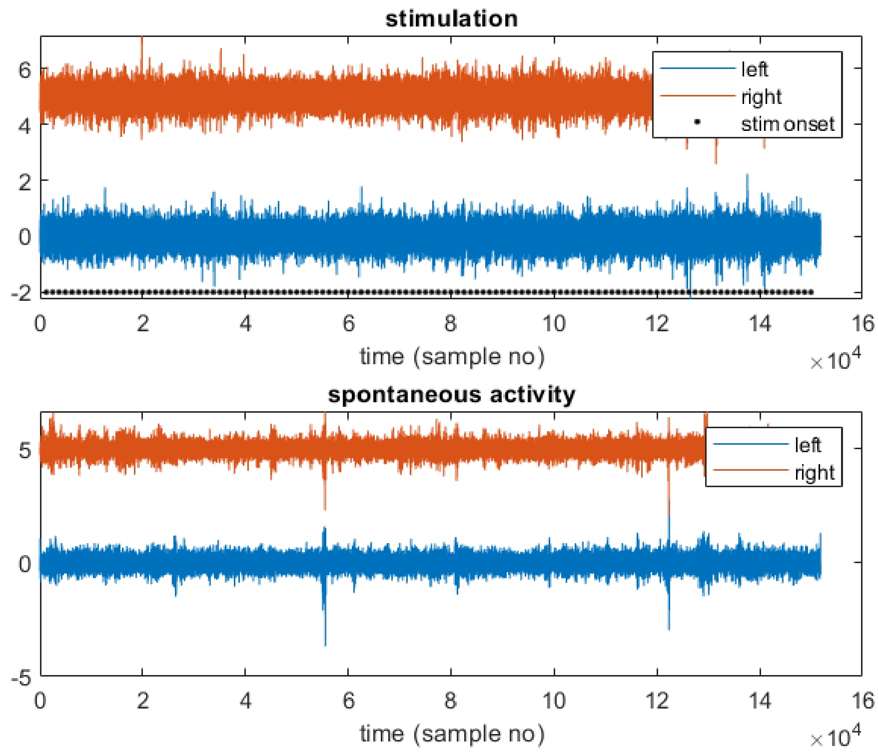

Figure 1: stimulation and spontaneous activity signals

0.0.2 Signal Filtering

After segmentation, every trial—both stimulus-locked and control—was subjected to an identical band-pass filtering stage. The goal was to retain the frequency content that carries the auditory M100 response (roughly 3–20 Hz) while suppressing irrelevant slow drift, sensor offsets and muscle artifacts. A fifth-order Butterworth design was chosen. The lower and upper cut-off frequencies (3 Hz and 20 Hz) were normalized by half of the 625 Hz sampling rate, ensuring the MATLAB butter design routine produced stable coefficients.

Filtering was applied with filtfilt, which performs forward and reverse passes. This zero-phase implementation eliminates group-delay distortions that would otherwise shift the latency of the M100 peak. Transposing each trial before and after the call was necessary because filtfilt operates along the first dimension of the input array; reverting the orientation restored the original trial-by-sample layout.

Using identical coefficients on stimulus and control data removed any potential preprocessing asymmetry, a common pitfall that can inflate classification accuracy by letting the model learn filter artifacts rather than neurophysiology. Edge effects were minimized by padding inherent to filtfilt, and the 100-sample pre-stimulus baseline ensured that boundary-related transients did not contaminate the neurologically relevant post-stimulus window.

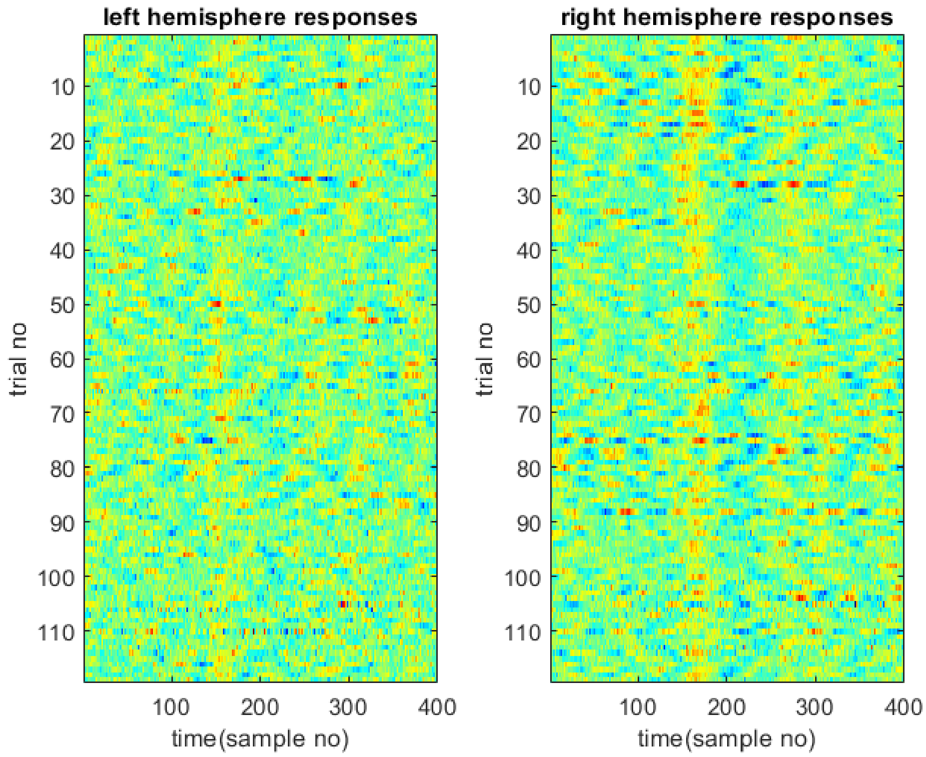

Figure 2: time frequency plots for stimulation signals

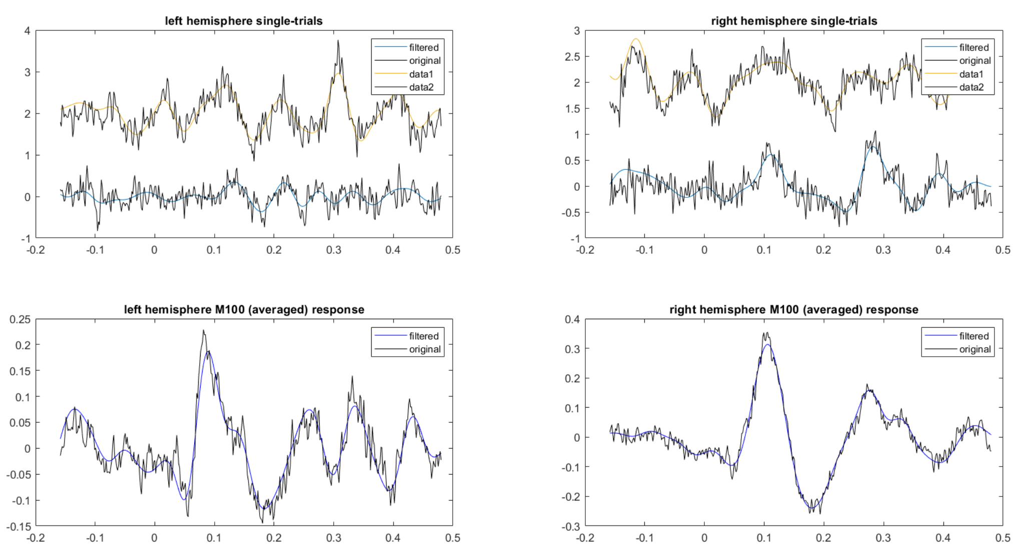

Figure 3: stimulation signals and averaged response

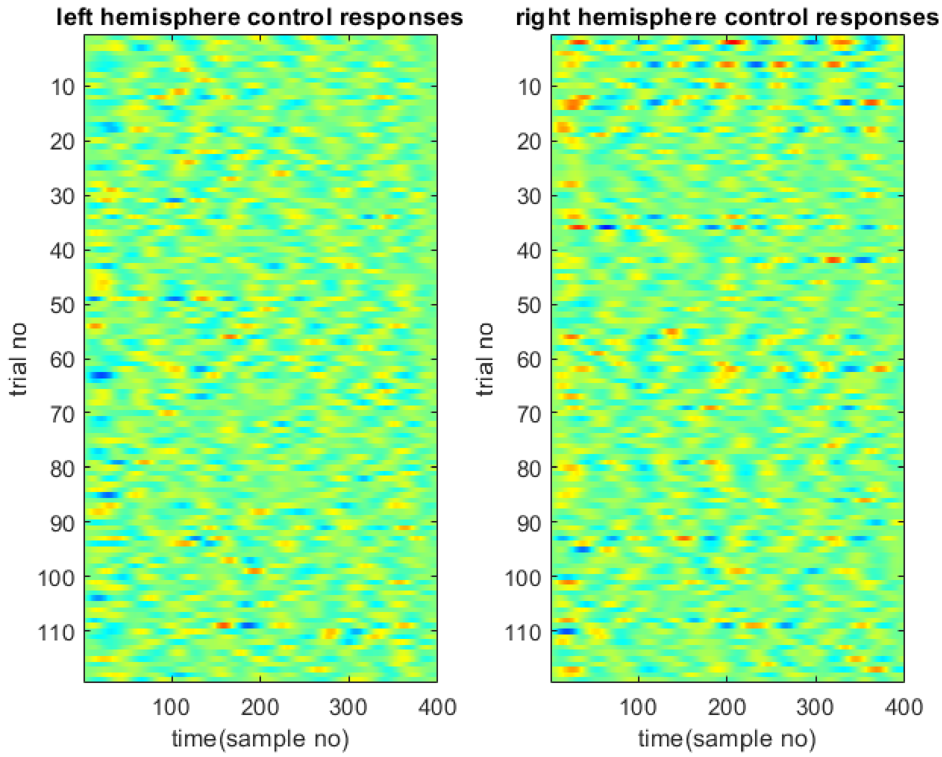

Figure 4: time frequency plots for control signals

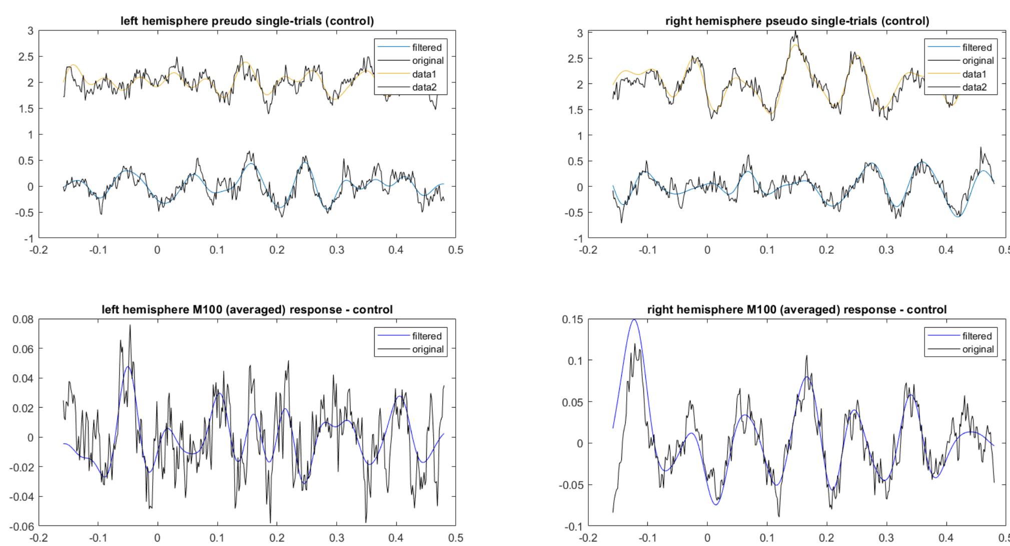

Figure 5: control signals and averaged response

0.0.3 Feature Extraction

Feature engineering translates raw trial waveforms into numerical descriptors that a classifier can exploit. In this pipeline three complementary families—time-domain morphology, stationary spectral power, and time–frequency wavelet energy—were computed separately for each hemisphere and then concatenated.All features were extracted after baseline correction (mean of -100 to 0 ms) to eliminate slow drift bias. MEG sensors accumulate millivolt-level shifts from environmental magnetism, head movement, or subtle changes in SQUID bias. These slow trends add a constant (or slowly varying) offset to each trial. Without correction, amplitude-based features (e.g., RMS, theta-band power) capture that offset in addition to the neural response, inflating variance and obscuring genuine differences between classes.

Time-domain features:

- Area-Under-Curve 0–200 ms (per hemisphere): Integral of the waveform from stimulus onset to 200 ms. Accumulates total negative deflection, smoothing out jitter and single-sample noise that hamper peak measures.

- RMS 0–300 ms (per hemisphere): Root-mean-square amplitude over the entire post-stimulus window. Provides an energy-like metric insensitive to polarity and isolated spikes, rising whenever a coherent evoked pattern is present.

- Hjorth Mobility: Lower in evoked data because the response is dominated by a narrow-band 10 Hz component, reducing the relative amount of rapid slope changes.

- Hjorth Complexity: Measures how "non-sinusoidal" the waveform is—spontaneous activity, being irregular, yields higher complexity values.

Spectral features:

- Theta-band Power 4–7 Hz (per hemisphere): Absolute power in the theta range. Often increases during the M100 burst, acting as a frequency-specific indicator of evoked processing.

- Alpha-Band Power 8–12 Hz (per hemisphere): Power around the dominant 10 Hz rhythm of the auditory response. Contributes to discriminability when theta alone is insufficient

- Spectral Centroid 3–20 Hz (per hemisphere): Power-weighted mean frequency from Welch's PSD. Shifts downward in evoked trials where alpha dominates, upward in broadband spontaneous segments.

Wavelet features:

- Wavelet Detail-3 Energy around 10 Hz (per hemisphere): Sum of squared coefficients at level 3 of the db4 wavelet. Captures the transient 10 Hz burst tightly in time–frequency space.
- Wavelet Detail-2 Energy around 20 Hz (per hemisphere): Energy at the next finer scale. Useful for detecting residual beta-range transients that occasionally accompany the M100.
- Wavelet Approximation-3 Energy (low-theta, per hemisphere): Energy in the coarse approximation after three level. Reflects sustained low-frequency shifts.

0.0.4 Classification and Validation

A stratified 5-fold cross-validation was selected to estimate out-of-sample performance while preserving the 50-50 class ratio inside every fold. 5 folds provide a reasonable bias–variance trade-off for the modest dataset without excessive computation. Stratification is essential because an imbalanced fold could yield misleading accuracy if, for instance, a test fold contained mostly stimulus trials.
Inside each iteration, the training subset is z-scored standardized and the same standardization is applied to the corresponding test subset.
An SVM with a linear kernel was chosen.
This way, training completes in milliseconds per fold, facilitating rapid iteration.
Accuracy for each fold is computed as the proportion of correctly classified trials. Reporting the mean across folds conveys expected variability if the model were retrained on different subsets.

Fold 1 Acc.: 0.765957446808511
Fold 2 Acc.: 0.770833333333333
Fold 3 Acc.: 0.833333333333333
Fold 4 Acc.: 0.958333333333333
Fold 5 Acc.: 0.893617021276596

Mean Acc.: 0.8444