TRANSIENT MODEL OF EEG USING GINI INDEX-BASED MATCHING PURSUIT

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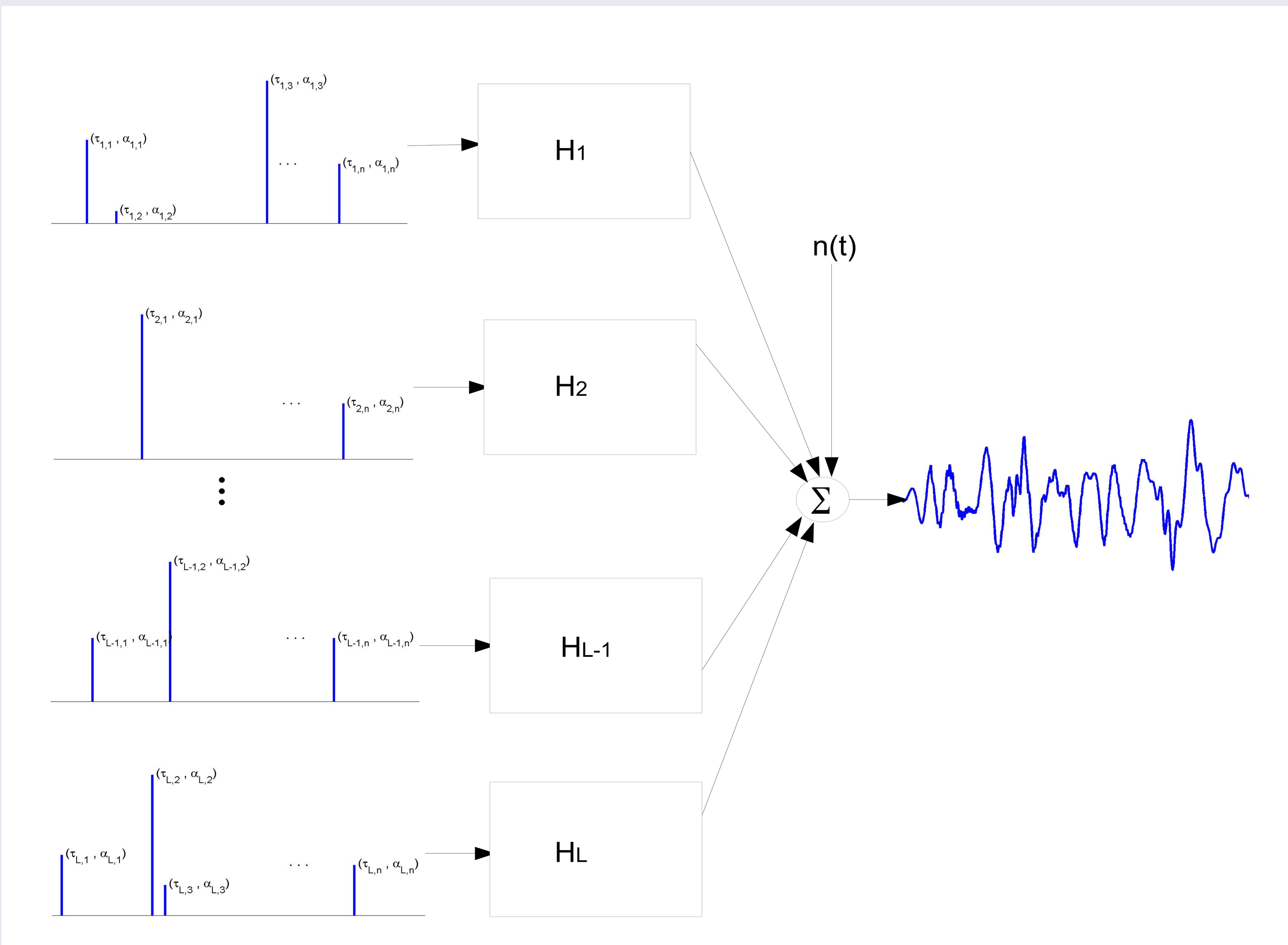
Introduction

- Most of Electroencephalogram (EEG) applications operate under the strong assumption of stationarity.
- However, electrical potentials from the brain are well-known to be non-stationary as a direct consequence of the ongoing reorganization of neuronal assemblies.
- We propose a transient model for single channel EEG traces along with a novel stopping criteria for greedy sparse decomposition algorithms.

Transient Model for EEG

- EEG is posed as the result of transient events over time that encode information concerning a particular physiological state over a noisy background [1].



$$x(t) = n(t) + \hat{x}(t) = n(t) + \sum_{i=1}^{F} y_i(t) \qquad (1)$$

$$y_i(t) = \sum_{j=1}^{n_i} \int_{-\infty}^{\infty} \alpha_{i,j}\delta(t-\tau_{i,j})h_{i,\omega_j}du \qquad (2)$$

- L: number of filter banks, EEG rhythms, or dictionaries.
- Each dictionary contains finite impulse response (FIR) filters with similar spectral characteristics.
- Marked point process samples index the filter banks.
- Amplitude (α) and timing (τ) information is encoded.
- Dictionary-related features are also available, e.g. duration, Q-factor.

Transient Analysis of EEG

- Goal: Given a set of dictionaries and a single EEG trace, estimate all marked point process features.
- Sparse approximation framework [2]:

$$\min_{\Lambda\subset\Omega}\min_{\mathbf{b}\in C^{\Lambda}}\left|\left|\mathbf{x}-\sum_{\lambda\in\Lambda}\mathbf{b}_{\lambda}\varphi_{\lambda}\right|\right|_2 \quad \text{such that } |\Lambda| \leqslant L \qquad (3)$$

- m determines the sparsity of the decomposition.
- Non-convex, combinatorial, NP hard problem.
- Alternative: Greedy algorithms such as Matching Pursuit (MP) [3].

Gini Index-based Matching Pursuit

- For MP, if m is set too low, only low-frequency components will be selected.
- If m is too high, overpopulated marked point process. Sparsity assumption becomes meaningless.
- Gini Index provides a sparsity measure suitable for automatic MP stopping criteria:

$$\text{Gini}(\vec{c}) = 1 - 2\sum_{k=1}^{N}\frac{c(k)}{||\vec{c}||_1}\left(\frac{N-k+0.5}{N}\right) \qquad (4)$$

$r(t) \leftarrow x(t)$
$G(0) = 0$
$i \leftarrow 1$
$G(i) = 0$
while $G(i-1) <= G(i)$ do
  $b_q(t) = \text{xcorr}(\varphi_q(t), r(t)) \quad q = 1,\ldots,P$
  $p_i \leftarrow \text{argmax}_q \max_t |b_q(t)|$
  $\tau_i \leftarrow \text{argmax}_t |b_{p_i}(t)|$
  $\alpha_i \leftarrow b_{p_i}(\tau_i)$
  $r(t) \leftarrow r(t) - \int_{-\infty}^{\infty}\alpha_i\delta(t-\tau_i-u)\varphi_{p_i}(u)du$
  $G(i) = Gini(\|r(t)\| / \|x(t)\|)$
  $i \leftarrow i+1$
end while

- Keep track of normalized reconstructed signal power.
- Stop when Gini Index maximum is achieved.

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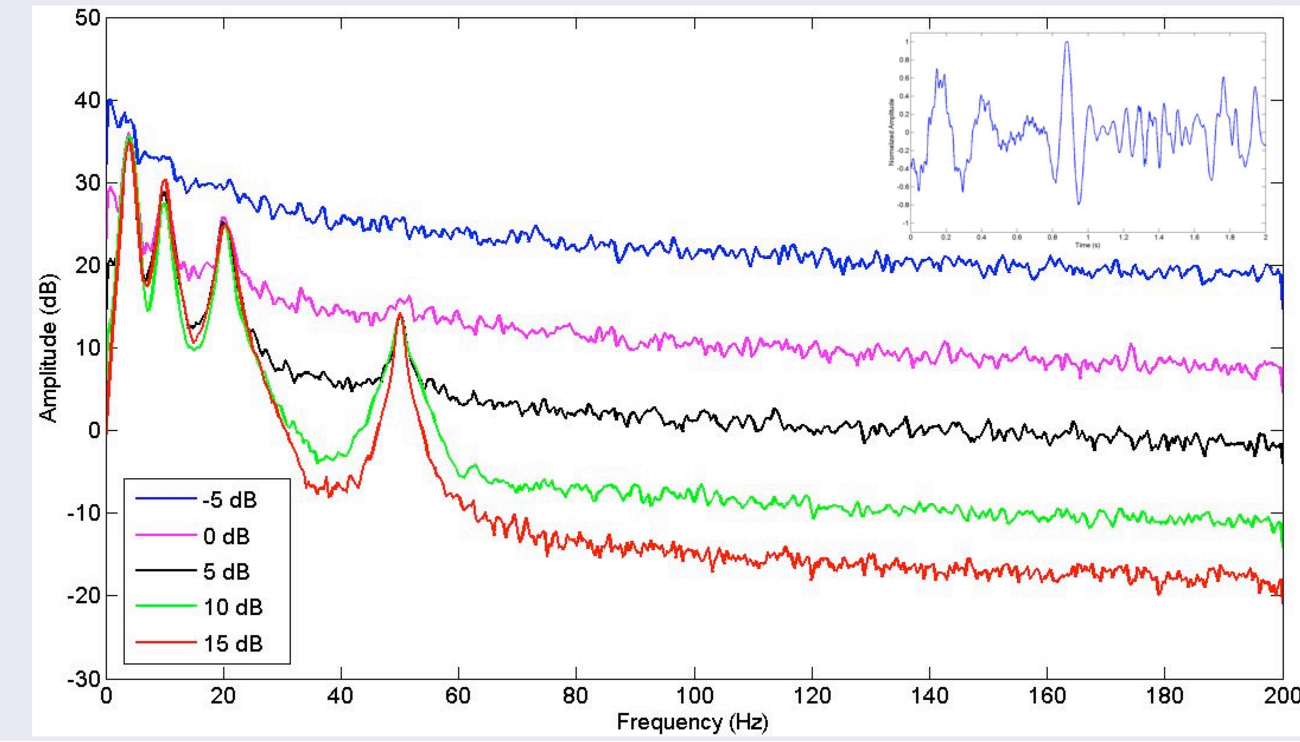
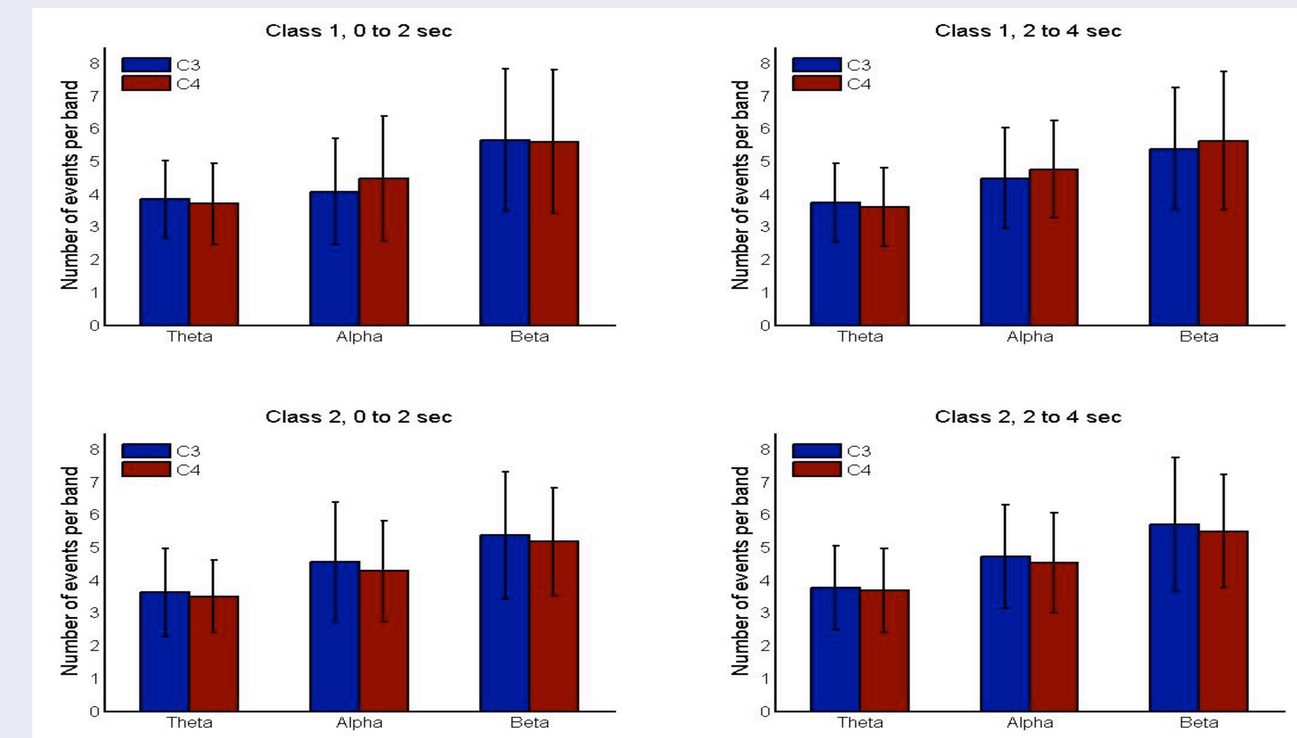
Results: Synthetic EEG-like traces

- Model α as samples from exponential pdf.
- Model τ as samples from uniform pdf.
- Use temporal Gabor filters as filter bank elements.
- Simulate theta, alpha, beta, and gamma rhythms.
- Add pink noise.



Results: BCI Competition Data

- Motor imagery experiment: 2 tasks and 2 bipolar electrodes over C3 and C4.
- Utilize Gabor filter dictionaries
- Apply Gini Index-based MP:



- Amplitude discriminability is preserved with exceptional temporal resolution.
- Additional features beyond power-based measures.

References

[1] Tatum IV, William O. Handbook of EEG interpretation. Demos Medical Publishing, 2014.
[2] Tropp, J. "Greed is good: Algorithmic results for sparse approximation." Information Theory, IEEE Transactions on 50.10 (2004): 2231-2242.
[3] Mallat, Stphane G., and Zhifeng Zhang. "Matching pursuits with time-frequency dictionaries." Signal Processing, IEEE Transactions on 41.12 (1993): 3397-3415.