Real-Time Tracking of Magnetoencephalographic Neuromarkers during a Dynamic Attention-Switching Task

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Background

• Segregating speech streams is one of the most remarkable feature of the brain

• Understanding how the brain segregate multiple sound sources and direct its attention to the intended speaker is an important problem

• Non invasive techniques, such as Electroencephalography (EEG) and Magnetoencephalography (MEG) adopted to investigate neuromarkers modulated by attention
Simple Attention Decoding Experiment: Subject instructed to attend to speaker 1 or 2

Attention Decoding Algorithm:
- **Input:** clean speech data (speech envelopes), MEG channel recordings
- **Output:** the attended speaker at each time

Applications: Brain-Computer Interface (BCI) systems, smart hearing aids
Temporal Response Function (TRF)

- TRF functionally describes how the temporal acoustic features of speech are transformed into cortical responses.
- It can be thought as the “Brain” impulse response to auditory stimuli.
- It has 3 major peaks: M50, M100 and M200
- It appears to be modulated by attention

Ding and Simon (2012) “Emergence of neural encoding of auditory objects while listening to competing speakers”
Major challenge in decoding attention

• Major challenge in using M/EEG attention modulated neuromarkers: poor accuracy of attention decoding algorithms in near real-time settings.

• Current and past attempts to use M/EEG neuromarkers to determine a listener’s attentional focus often use tens of seconds before making decisions.

• This long delay prevents the rapid decisions required in realistic auditory scenes.
Goals of this study

• Expand the near-real time state-space model based on Bayesian filtering approach previously proposed by Miran et al (2018)

• Estimate the performance of our algorithm during a Dynamic Attention-Switching Task
Previous work: State-space model based on Bayesian filtering (Miran et al 2018)

Dynamically extract the attentional modulated neuromarkers (amplitude of M100) for the attended (Speaker 1 = \( m^{(1)} \)) and the unattended (Speaker 2 = \( m^{(2)} \))

\[
\begin{align*}
    m^{(i)}_k &\mid n_k = i \sim \text{Log-Normal} \left( \rho^{(a)}, \mu^{(a)} \right), \quad i = 1, 2 \\
    m^{(i)}_k &\mid n_k \neq i \sim \text{Log-Normal} \left( \rho^{(u)}, \mu^{(u)} \right), \quad i = 1, 2 \\
    \rho^{(a)} &\sim \text{Gamma} \left( \alpha_0^{(a)}, \beta_0^{(a)} \right), \quad \mu^{(a)} \mid \rho^{(a)} \sim \mathcal{N} \left( \mu_0^{(a)}, \rho^{(a)} \right) \\
    \rho^{(u)} &\sim \text{Gamma} \left( \alpha_0^{(u)}, \beta_0^{(u)} \right), \quad \mu^{(u)} \mid \rho^{(u)} \sim \mathcal{N} \left( \mu_0^{(u)}, \rho^{(u)} \right)
\end{align*}
\]

State-Space model

\[
\begin{align*}
p_k &= P \left( n_k = 1 \right) = \frac{1}{1 + \exp(-z_k)} \\
z_k &= c_0 z_{k-1} + w_k \\
w_k &\sim \mathcal{N}(0, \eta_k) \\
\eta_k &\sim \text{Inverse-Gamma} \left( a_0, b_0 \right)
\end{align*}
\]

Parameters \( \Omega = \{ z_1:K_W, \eta_1:K_W, \rho^{(a)}, \mu^{(a)}, \rho^{(u)}, \mu^{(u)} \} \)

Bayesian Inference \( \hat{\Omega} = \underset{\Omega}{\text{arg max}} \ln P(\Omega \mid m^{(1)}, m^{(2)}) = \underset{\Omega}{\text{arg max}} \ln P(m^{(1)}, m^{(2)} \mid \Omega) + \ln P(\Omega) \)

Output \( \hat{p}_k = \frac{1}{1 + \exp(-\tilde{z}_k)} \) Estimated probability of attending to speaker 1
Hidden Markov Model (HMM)

- HMM used to estimate the internal state of the dynamics of the M100 peak based on its first derivative
- Amplitude of neuromarkers boosted or penalized by 1.3% of their peak amplitude based on their positive (P) or negative (N) first derivative, respectively. No changes were made if the derivative was stable (S)

Transition probabilities

\[
P_{ij} = \begin{bmatrix}
0.8 & 0.1 & 0.1 \\
0.15 & 0.8 & 0.05 \\
0.15 & 0.05 & 0.8
\end{bmatrix}
\]

Likelihoods

\[
P(S \mid 1) = 0.7, P(S \mid 2) = 0.15, P(S \mid 3) = 0.15 \\
P(P \mid 1) = 0.25, P(P \mid 2) = 0.7, P(P \mid 3) = 0.05 \\
P(N \mid 1) = 0.25, P(N \mid 2) = 0.05, P(N \mid 3) = 0.7
\]

Initial probabilities

\[
\Pi_1 = 0.6, \Pi_2 = 0.2, \Pi_3 = 0.2
\]
State-space model based on Bayesian filtering + HMM

Dynamically extract the attentional modulated neuromarkers (amplitude of M100) for the attended (Speaker 1 = \( m^{(1)} \)) and the unattended (Speaker 2 = \( m^{(2)} \))

\[
\begin{align*}
\{ m^{(i)} | n_k = i \} & \sim \text{Log-Normal} \left( \rho^{(a)}(i), \mu^{(a)}(i) \right), \quad i = 1, 2 \\
\{ m^{(i)} | n_k \neq i \} & \sim \text{Log-Normal} \left( \rho^{(u)}(i), \mu^{(u)}(i) \right), \quad i = 1, 2 \\
\rho^{(a)} & \sim \text{Gamma} \left( \alpha_0^{(a)}, \beta_0^{(a)} \right), \quad \mu^{(a)} \sim \mathcal{N} \left( \mu_0^{(a)}, \rho^{(a)} \right) \\
\rho^{(u)} & \sim \text{Gamma} \left( \alpha_0^{(u)}, \beta_0^{(u)} \right), \quad \mu^{(u)} \sim \mathcal{N} \left( \mu_0^{(u)}, \rho^{(u)} \right)
\end{align*}
\]

\[
egin{align*}
\text{Parameters} & \quad \Omega = \{ \hat{z}_{1:K_W}, \eta_{1:K_W}, \rho^{(a)}, \mu^{(a)}, \rho^{(u)}, \mu^{(u)} \} \\
\text{Bayesian Inference} & \quad \hat{\Omega} = \arg \max_{\Omega} \ln P(\Omega | m^{(1)}, m^{(2)}) = \arg \max_{\Omega} \ln P(m^{(1)}, m^{(2)} | \Omega) + \ln P(\Omega) \\
\text{Output} & \quad \hat{p}_k = \frac{1}{1 + \exp(-\hat{z}_k)} \quad \text{Estimated probability of attending to speaker 1}
\end{align*}
\]

Transition probabilities
\[
P_{\theta} = \begin{bmatrix}
0.8 & 0.1 & 0.1 \\
0.15 & 0.8 & 0.05 \\
0.15 & 0.05 & 0.8
\end{bmatrix}
\]

Likelihoods
\[
P(S | 1) = 0.7, P(S | 2) = 0.15, P(S | 3) = 0.15 \\
P(P | 1) = 0.25, P(P | 2) = 0.7, P(P | 3) = 0.05 \\
P(N | 1) = 0.25, P(N | 2) = 0.05, P(N | 3) = 0.7
\]

Initial probabilities
\[
\Pi_1 = 0.6, \Pi_2 = 0.2, \Pi_3 = 0.2
\]

\[
\begin{align*}
p_k &= P(n_k = 1) = \frac{1}{1 + \exp(-z_k)} \\
z_k &= c_0 z_{k-1} + w_k \\
w_k &\sim \mathcal{N}(0, \eta_k) \\
\eta_k &\sim \text{Inverse-Gamma} (a_0, b_0)
\end{align*}
\]
Experimental Set-up

- Participants comprised 5 younger adults (22-33 yr)
- MEG data recorded from 157 sensors
- Participants attended to one of two stories (one narrated by a male speaker, while the other one by a female speaker) presented diotically while ignoring the other one.
- Sound amplitude: ~70 dB sound pressure level
- Duration: 90 seconds
- Signal to-noise ratio of the two speakers: 0 dB
- Participants listened to 3 trials of the same speech mixture
- Participants instructed to switch the focus of their attention at their own will for a minimum of 1 time and a maximum of 3 times.
- Participants given a switching button that they were instructed to press every time they decided to switch attention.
Estimation of TRF, Extraction of Neuromarkers and Estimated probability of attending to speaker 1 or 2

A

Male Speaker TRF

Female Speaker TRF

B

Neuromarker (A.U.)

Reported Att. Speaker

M F M F

Probability
Derivative-based three state HMM proved to be beneficial in tracking the oscillatory patterns of the neuromarkers.
Conclusions

• Our results suggest the feasibility of using a near real-time algorithm pipeline to track the attention state in a dual-speaker setting during a dynamic-attention switching task

• The addition of a derivative-based three state HMM to our algorithm pipeline also proved to be beneficial in tracking the oscillatory patterns of the neuromarkers.

Algorithm development still in progress

• Work is underway to improve the reliability of the estimation of the TRF
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Questions???