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

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Background

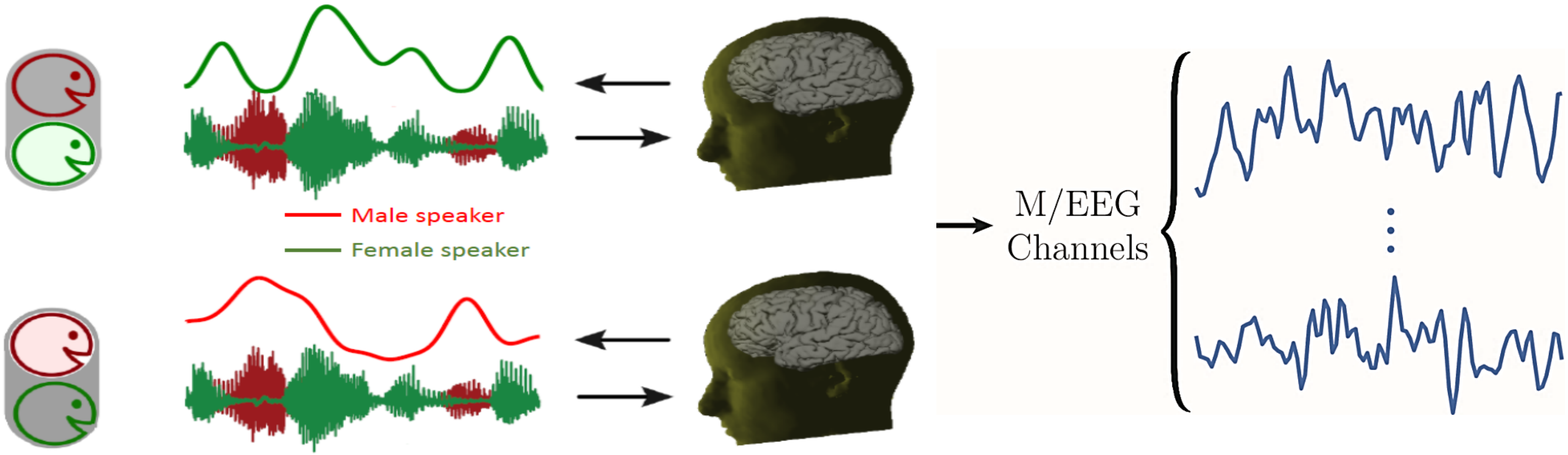
- Segregating speech streams is one of the most remarkable feature of the brain

- 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

Background (con't)

Simple Attention Decoding Experiment: Subject instructed to attend to speaker 1 or 2



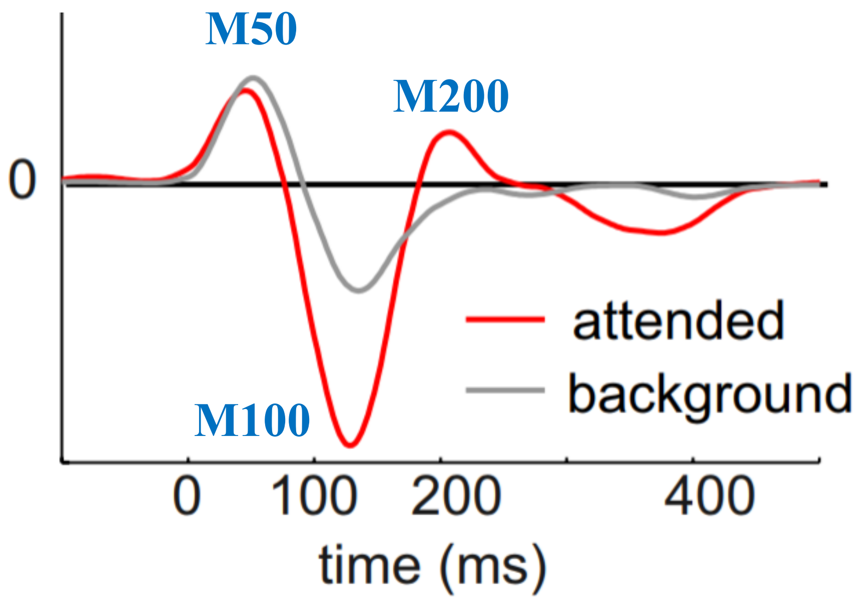
Attention Decoding Algorithm:

- **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

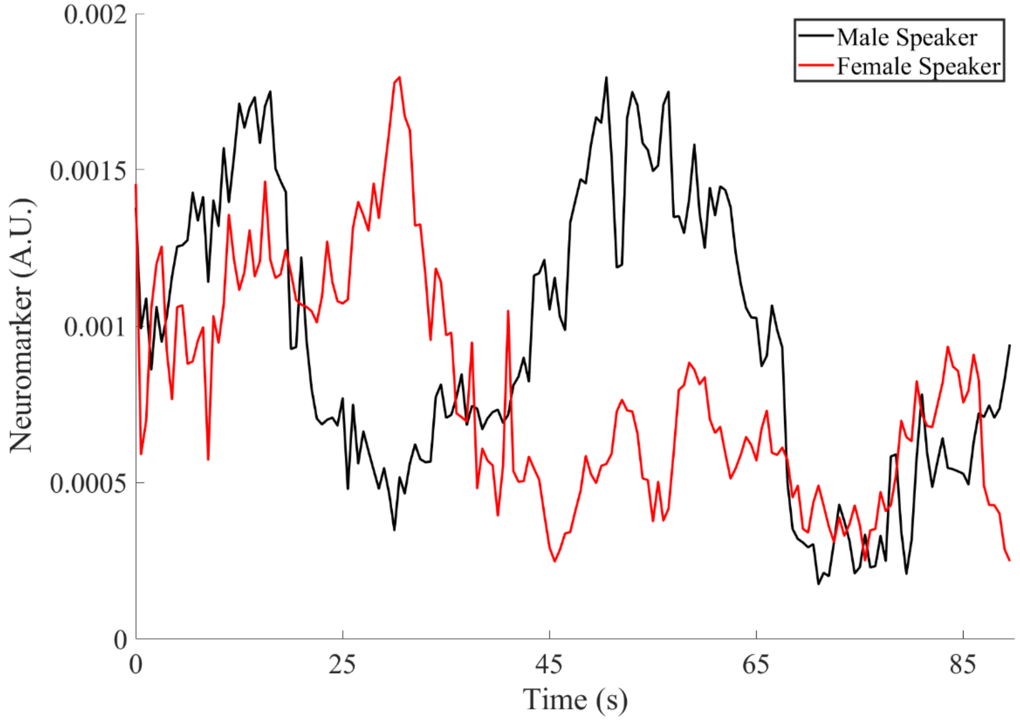
- Expand the near-real time state-space model based on Bayesian filtering approach previously proposed by Miran et al (2018)

- 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 = $\boldsymbol{m}^{(1)}$) and the unattended (Speaker 2 = $\boldsymbol{m}^{(2)}$)

$$\begin{cases} m_k^{(i)} \,\Big|\, n_k = i \sim \text{Log-Normal}\left(\rho^{(a)}, \mu^{(a)}\right), \quad i = 1,2 \\ m_k^{(i)} \,\Big|\, n_k \neq i \sim \text{Log-Normal}\left(\rho^{(u)}, \mu^{(u)}\right), \quad i = 1,2 \\ \rho^{(a)} \sim \text{Gamma}\left(\alpha_0^{(a)}, \beta_0^{(a)}\right), \quad \mu^{(a)} \,\Big|\, \rho^{(a)} \sim \mathcal{N}\left(\mu_0^{(a)}, \rho^{(a)}\right) \\ \rho^{(u)} \sim \text{Gamma}\left(\alpha_0^{(u)}, \beta_0^{(u)}\right), \quad \mu^{(u)} \,\Big|\, \rho^{(u)} \sim \mathcal{N}\left(\mu_0^{(u)}, \rho^{(u)}\right) \end{cases}$$



State-Space model

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

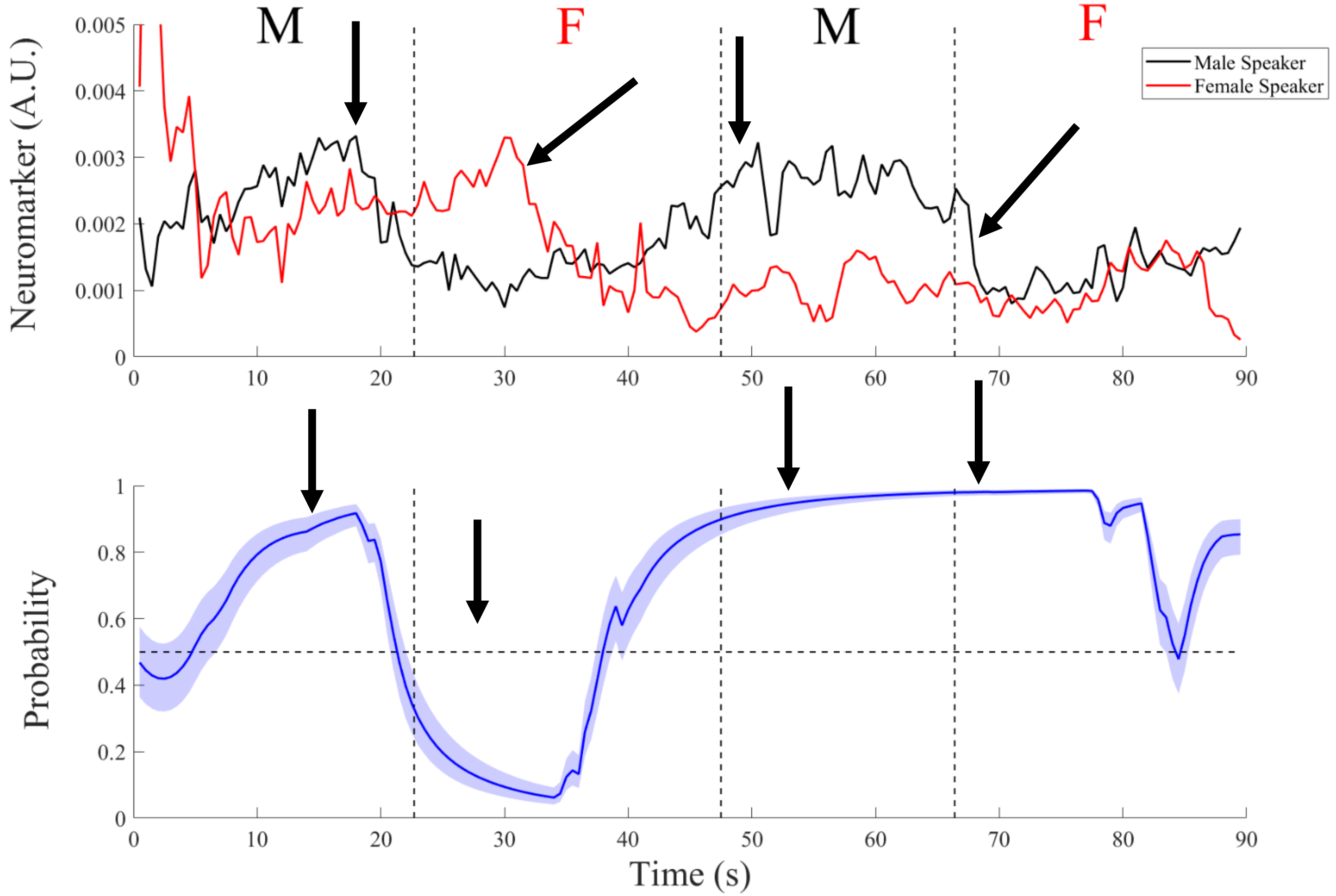
Parameters $\quad \boldsymbol{\Omega} = \left\{ z_{1:K_W}, \eta_{1:K_W}, \rho^{(a)}, \mu^{(a)}, \rho^{(u)}, \mu^{(u)} \right\}$

Bayesian Inference $\quad \widehat{\Omega} = \arg\max_{\Omega} \ln P(\Omega \mid m^{(1)}, m^{(2)}) = \arg\max_{\Omega} \ln P(m^{(1)}, m^{(2)} \mid \Omega) + \ln P(\Omega)$

Output $\quad \widehat{p}_k = \dfrac{1}{1+\exp(-\widehat{z}_k)}$ **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)



HMM

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

$$P(S|1) = 0.7, P(S|2) = 0.15, P(S|3) = 0.15$$
$$P(P|1) = 0.25, P(P|2) = 0.7, P(P|3) = 0.05$$
$$P(N|1) = 0.25, P(N|2) = 0.05, P(N|3) = 0.7$$

Initial probabilities

$$\Pi_1 = 0.6, \Pi_2 = 0.2, \Pi_3 = 0.2$$

State-space model based on Bayesian filtering + HMM

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

$$\begin{cases} m_k^{(i)} \,\Big|\, n_k = i \sim \text{Log-Normal}\left(\rho^{(a)}, \mu^{(a)}\right), \quad i = 1,2 \\ m_k^{(i)} \,\Big|\, n_k \neq i \sim \text{Log-Normal}\left(\rho^{(u)}, \mu^{(u)}\right), \quad i = 1,2 \\ \rho^{(a)} \sim \text{Gamma}\left(\alpha_0^{(a)}, \beta_0^{(a)}\right), \quad \mu^{(a)} \,\Big|\, \rho^{(a)} \sim \mathcal{N}\left(\mu_0^{(a)}, \rho^{(a)}\right) \\ \rho^{(u)} \sim \text{Gamma}\left(\alpha_0^{(u)}, \beta_0^{(u)}\right), \quad \mu^{(u)} \,\Big|\, \rho^{(u)} \sim \mathcal{N}\left(\mu_0^{(u)}, \rho^{(u)}\right) \end{cases}$$

$\boldsymbol{m^{(1)}}$, $\boldsymbol{m^{(2)}}$)

HMM

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Likelihoods

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$$P(N\,|\,1) = 0.25, P(N\,|\,2) = 0.05, P(N\,|\,3) = 0.7$$

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State-Space model

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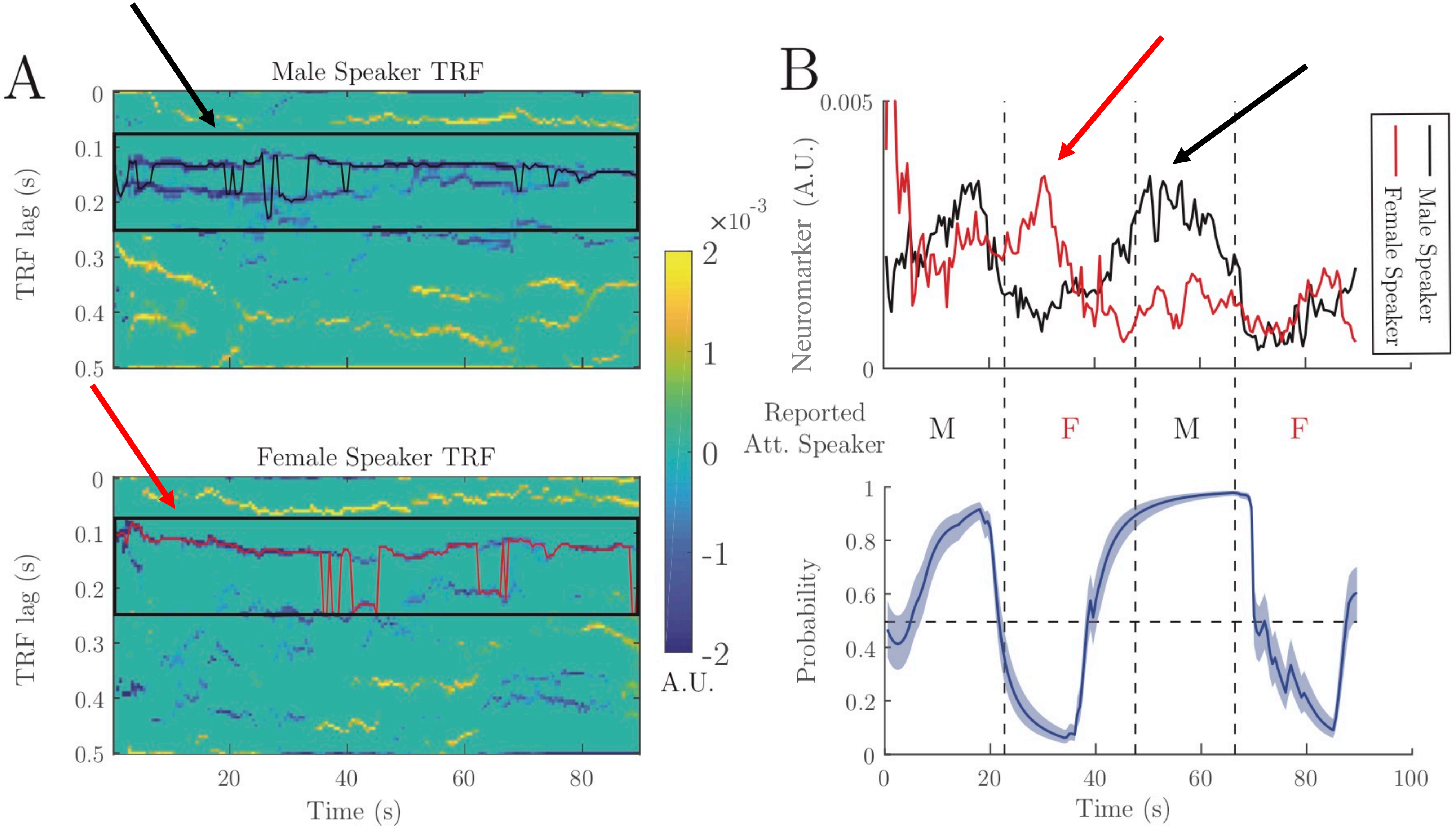
Output $\quad \widehat{p}_k = \dfrac{1}{1+\exp(-\widehat{z}_k)}$ **Estimated probability of attending to speaker 1**

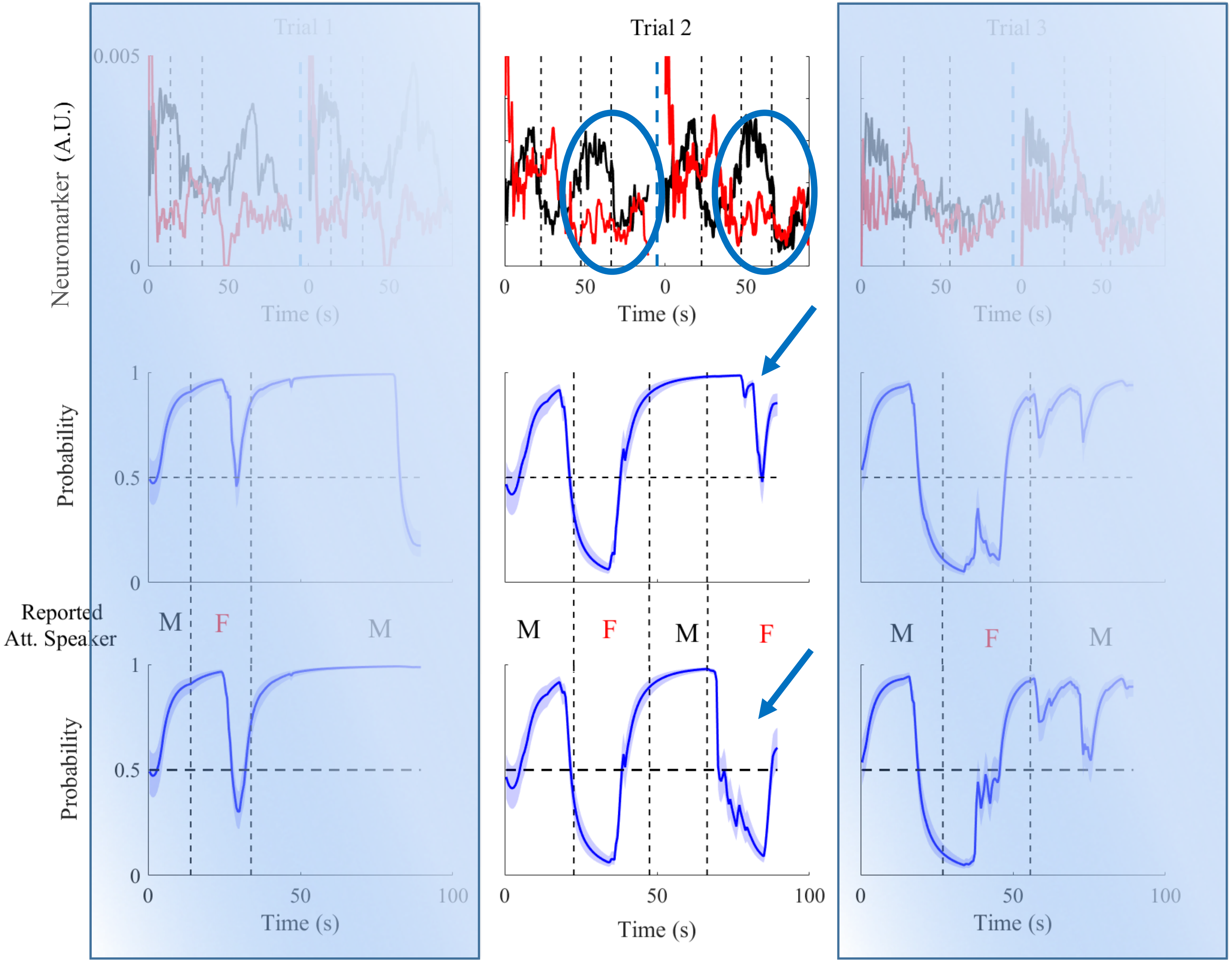
Experimental Set-up

- 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



HMM performance



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???