

A Sate-Space Model for Decoding Auditory Attentional Modulation from MEG in a Competing-Speaker Environment

Sahar Akram^{1,2}, Jonathan Z. Simon^{1,2,3}, Shihab Shamma^{1,2}, Behtash Babadi^{1,2}

¹Department of Electrical and Computer Engineering, ² Institute for Systems Research,

³ Department of Biology, University of Maryland, College Park, MD

sakram@umd.edu, jzsimon@umd.edu, sas@umd.edu, behtash@umd.edu



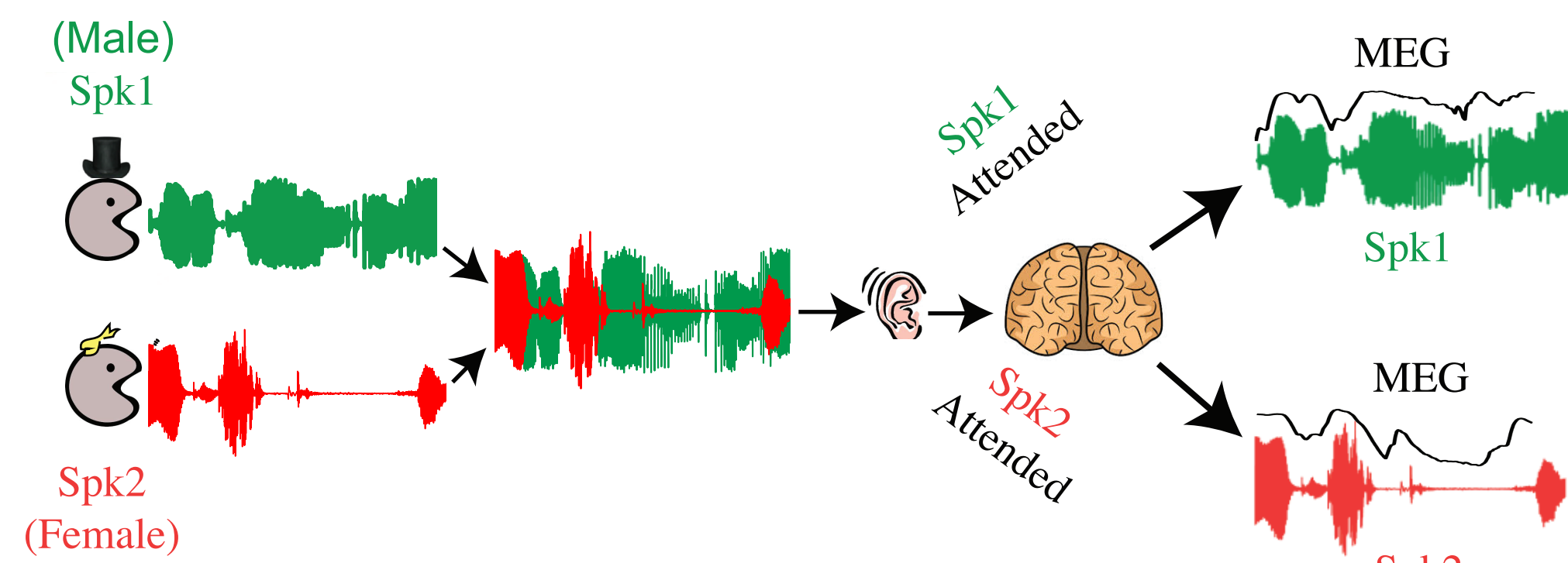
The Cocktail Party Problem

Speech Segregation:

Identifying and tracking a target speaker, corrupted by acoustic interference ①.

Neural Activity at the Cortical level:

Strongly modulated by low-frequency temporal modulations (envelope) of the attended target speaker ②.



Objectives

Existing Techniques:

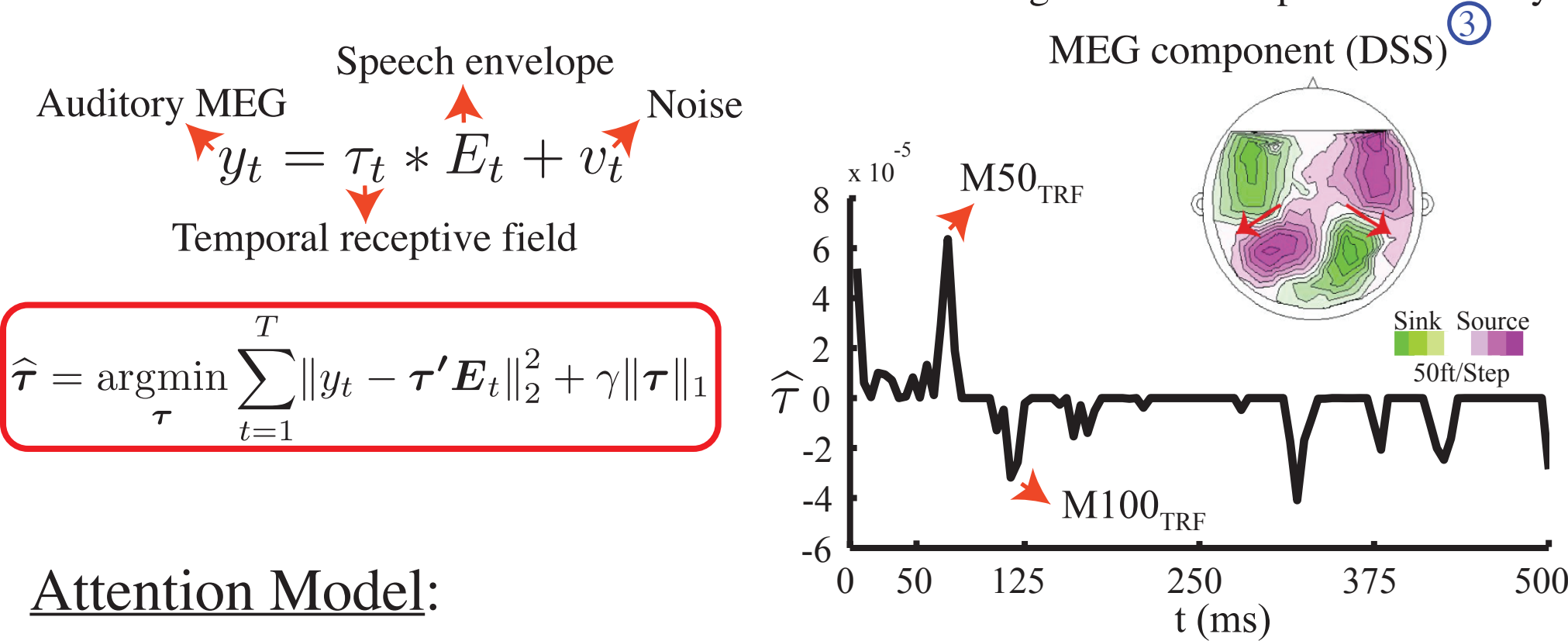
- 1) Full spectrotemporal features as covariates
- 2) Low temporal Resolution
~ Minutes

Our Contribution:

- 1) Parsimonious use of covariates
- 2) High temporal resolution
~ Seconds
- 3) Scalability

The Proposed Model

Forward Model:



Attention Model:

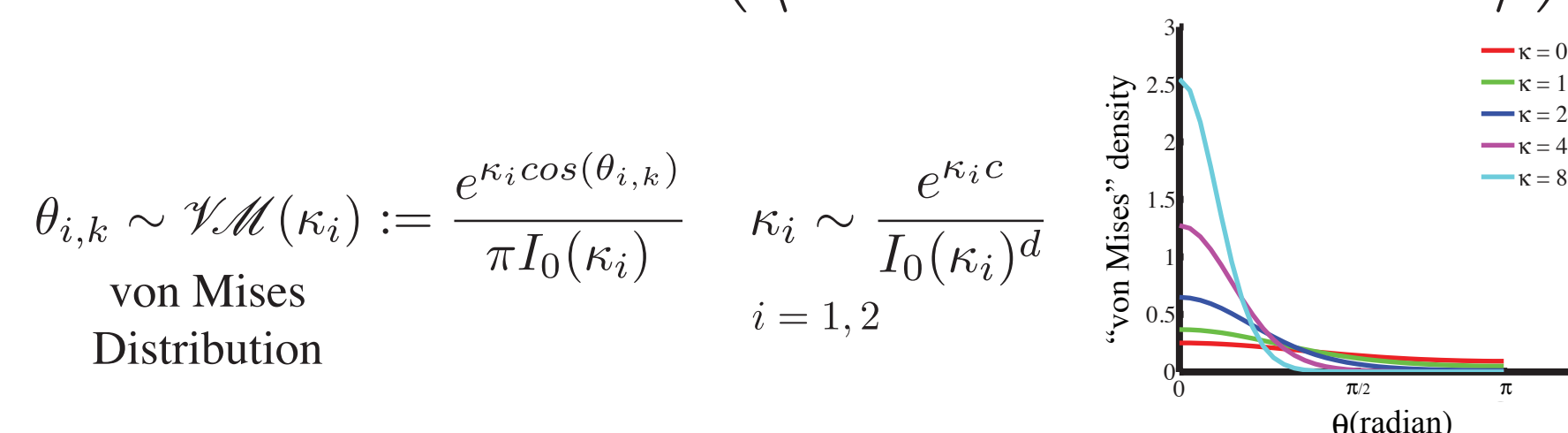
$$n_k = \begin{cases} 0 & \text{attending to Spk2} \\ 1 & \text{attending to Spk1} \end{cases} \quad n_k \sim \text{Bernoulli}(q_k)$$

$$q_k = \text{logit}^{-1}(z_k) := \frac{\exp(z_k)}{1 + \exp(z_k)}$$

$$z_k = z_{k-1} + w_k, \quad w_k \sim \mathcal{N}(0, \eta_k), \quad \eta_k \sim \text{Gamma}(\alpha, \beta)$$

Inverse Model:

$$n_k \begin{cases} 1 \rightarrow \theta_{1,k} := \arccos \left(\left\langle \frac{\mathbf{y}_k}{\|\mathbf{y}_k\|_2}, \frac{\tau^{a'} \mathbf{E}_{1,t} + \tau^{u'} \mathbf{E}_{2,t}}{\|\tau^{a'} \mathbf{E}_{1,t} + \tau^{u'} \mathbf{E}_{2,t}\|_2} \right\rangle \right) \\ 0 \rightarrow \theta_{2,k} := \arccos \left(\left\langle \frac{\mathbf{y}_k}{\|\mathbf{y}_k\|_2}, \frac{\tau^{a'} \mathbf{E}_{2,t} + \tau^{u'} \mathbf{E}_{1,t}}{\|\tau^{a'} \mathbf{E}_{2,t} + \tau^{u'} \mathbf{E}_{1,t}\|_2} \right\rangle \right) \end{cases}$$



The Inverse Solution

The Inverse Problem: Estimating $\Omega := \{\kappa_1, \kappa_2, \{z_k\}_{k=1}^K, \{\eta_k\}_{k=1}^K\}$, given the observed data $\{\theta_{i,k,r}\}_{i,k,r=1}^{2,T,R}$ from R trials.

MAP Estimate: Maximize

$$\log p(\Omega | \{\theta_{i,k,r}\}_{i,k,r=1}^{2,T,R}) = \sum_{r,k=1}^{R,K} \log \left[\frac{q_k}{\pi I_0(\kappa_1)} \exp(\kappa_1 \cos(\theta_{1,k,r})) + \frac{1-q_k}{\pi I_0(\kappa_2)} \exp(\kappa_2 \cos(\theta_{2,k,r})) \right] + [(\kappa_1 + \kappa_2) c_0 d - d(\log I_0(\kappa_1) + \log I_0(\kappa_2))] - \sum_{r,k=1}^{R,K} \left\{ \frac{1}{2\eta_k} (z_k - z_{k-1})^2 + \frac{1}{2} \log \eta_k + (\alpha + 1) \log \eta_k + \frac{\beta}{\eta_k} \right\} + \text{cst.}$$

Convex, but highly **non-linear** and **coupled in time**.

Efficient solution: two nested EM algorithms

» Outer EM iteration ℓ :

E-Step: Compute $\mathbb{E}^{(\ell)}\{n_{k,r}\} := \mathbb{E}\{n_{k,r} | \{\theta_{i,k,r}\}_{i,k,r=1}^{2,T,R}, \Omega^{(\ell)}\}$ *

M-Step: Update $\kappa_1^{(\ell+1)}$ and $\kappa_2^{(\ell+1)}$ **

» Inner EM iteration m :

E-Step: Compute $\bar{z}_{k|K}^{(\ell+1,m)} := \mathbb{E}\{z_k | \mathbb{E}^{(\ell)}\{n_{k,r}\}_{k,r=1}^{K,R}\}$ ***

M-Step: Update $\eta_k^{(\ell+1,m+1)}$ ****

» end

» end

Decoupled in time with tractable non-linear operations

$$\mathbb{E}^{(\ell)}\{n_{k,r}\} = \frac{\frac{q_k^{(\ell)}}{\pi I_0(\kappa_1^{(\ell)})} \exp(\kappa_1^{(\ell)} \cos(\theta_{1,k,r}))}{\frac{q_k^{(\ell)}}{\pi I_0(\kappa_1^{(\ell)})} \exp(\kappa_1^{(\ell)} \cos(\theta_{1,k,r})) + \frac{1-q_k^{(\ell)}}{\pi I_0(\kappa_2^{(\ell)})} \exp(\kappa_2^{(\ell)} \cos(\theta_{2,k,r}))}$$

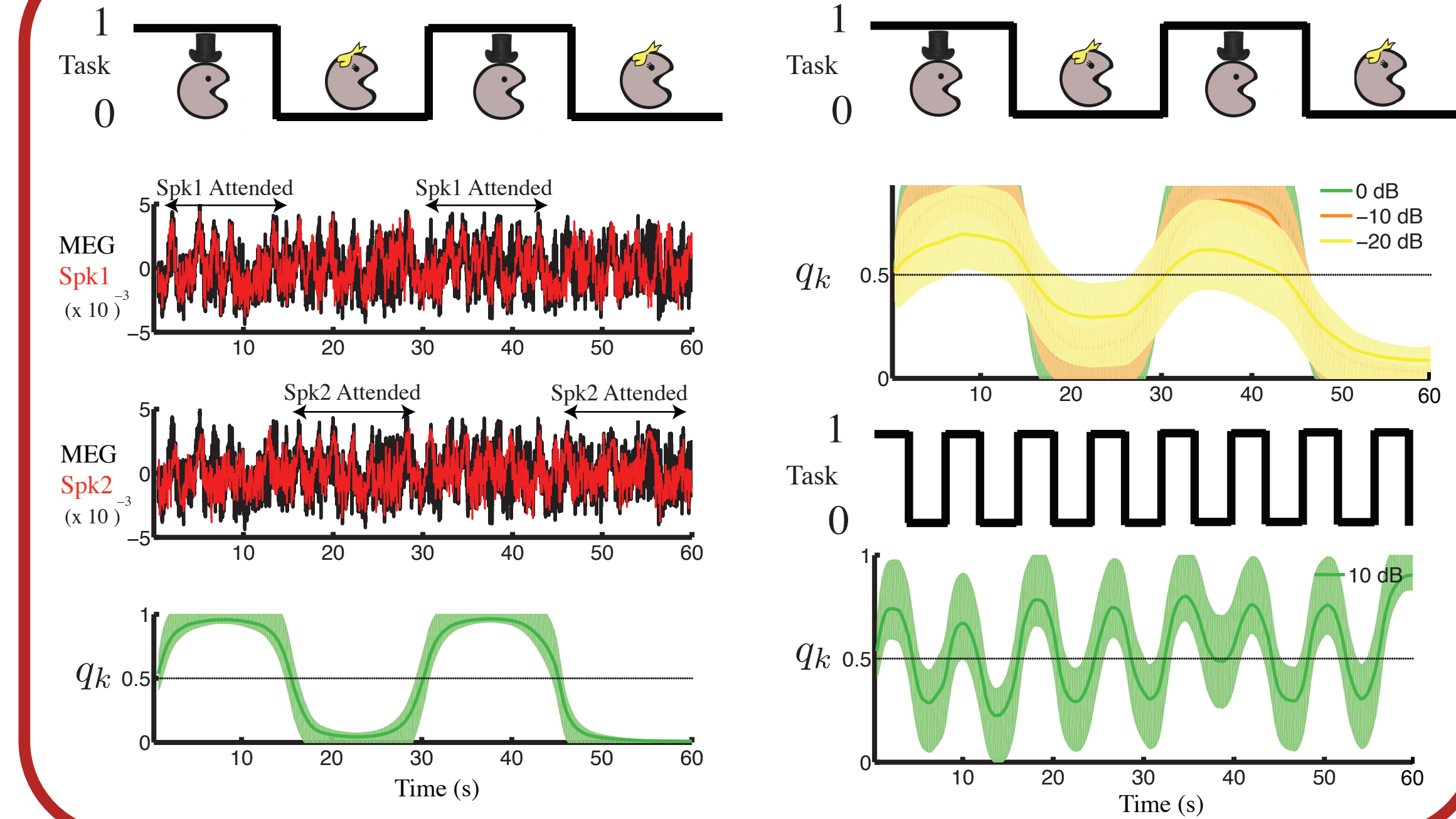
$$\kappa_i^{(\ell+1)} = A^{-1} \left(\frac{c_0 d + \sum_{r,k=1}^{R,K} \varepsilon_{i,k,r}^{(\ell)} \cos(\theta_{i,k,r})}{d + \sum_{r,k=1}^{R,K} \varepsilon_{i,k,r}^{(\ell)}} \right), \quad \varepsilon_{i,k,r}^{(\ell)} = \begin{cases} \mathbb{E}^{(\ell)}\{n_{k,r}\} & i=1 \\ 1 - \mathbb{E}^{(\ell)}\{n_{k,r}\} & i=2 \end{cases}, \quad A(x) := I_1(x)/I_0(x)$$

$$\begin{cases} \bar{z}_{k|k-1}^{(\ell+1,m)} = \bar{z}_{k-1|k-1}^{(\ell+1,m)} \\ \sigma_{k|k-1}^{(\ell+1,m)} = \sigma_{k-1|k-1}^{(\ell+1,m)} + \frac{\eta_k^{(\ell+1,m)}}{R} \\ \bar{z}_{k|k}^{(\ell+1,m)} = \bar{z}_{k|k-1}^{(\ell+1,m)} + \sigma_{k|k-1}^{(\ell+1,m)} \left[\sum_{r=1}^R \mathbb{E}^{(\ell)}\{n_{k,r}\} - R \frac{\exp(\bar{z}_{k|k}^{(\ell+1,m)})}{1 + \exp(\bar{z}_{k|k}^{(\ell+1,m)})} \right] \\ \sigma_{k|k}^{(\ell+1,m)} = \left[\frac{1}{\sigma_{k|k-1}^{(\ell+1,m)}} + R \frac{\exp(\bar{z}_{k|k}^{(\ell+1,m)})}{(1 + \exp(\bar{z}_{k|k}^{(\ell+1,m)}))^2} \right]^{-1} \end{cases}$$

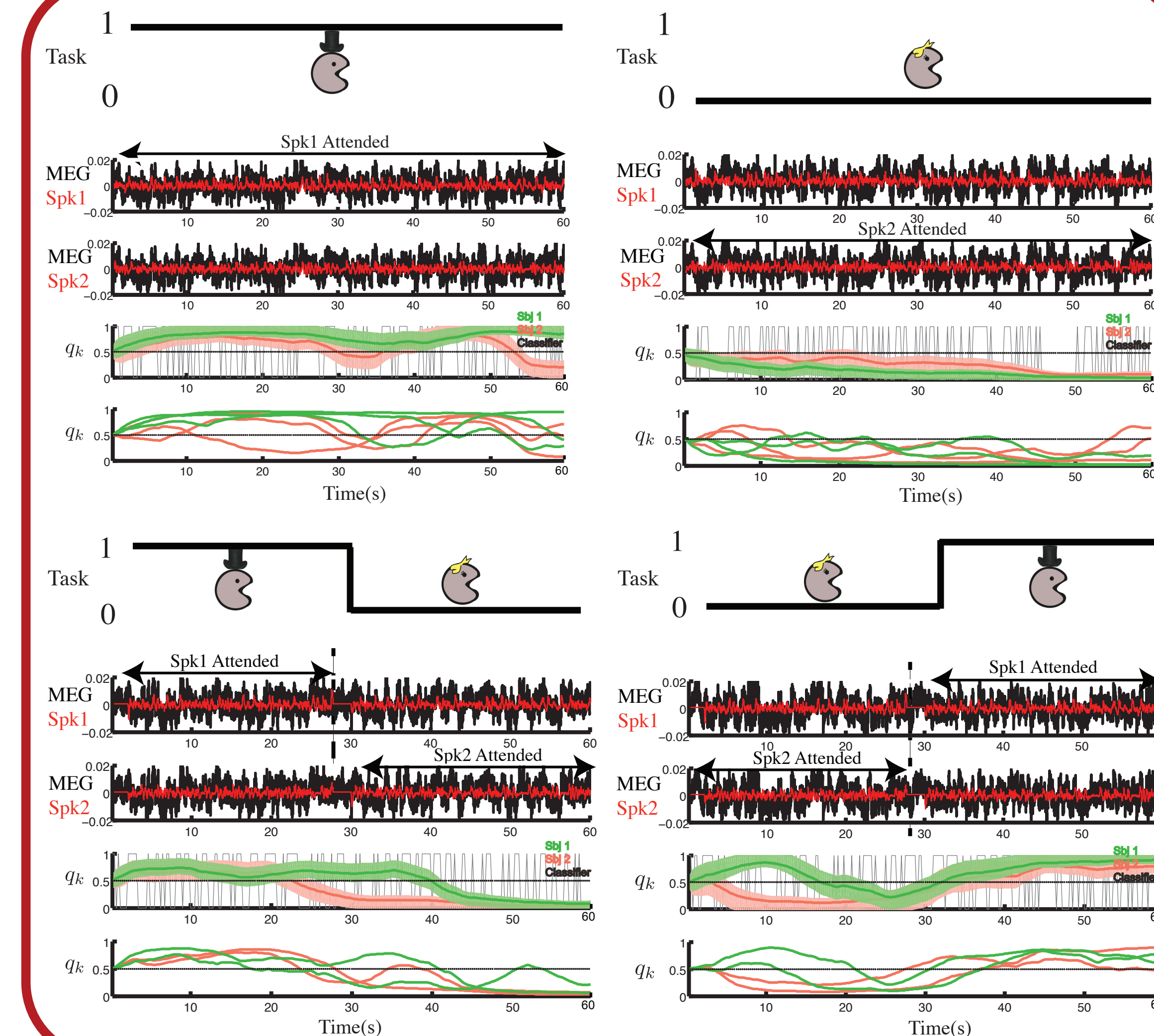
$$\begin{cases} s_k^{(\ell+1,m)} = \sigma_{k|k}^{(\ell+1,m)} / \sigma_{k+1|k}^{(\ell+1,m)} \\ \bar{z}_{k+1|k}^{(\ell+1,m)} = \bar{z}_{k|k}^{(\ell+1,m)} + s_k^{(\ell+1,m)} (\bar{z}_{k+1|k}^{(\ell+1,m)} - \bar{z}_{k|k}^{(\ell+1,m)}) \\ \sigma_{k+1|k}^{(\ell+1,m)} = \sigma_{k|k}^{(\ell+1,m)} + s_k^{(\ell+1,m)} (\sigma_{k+1|k}^{(\ell+1,m)} - \sigma_{k|k}^{(\ell+1,m)}) s_k^{(\ell+1,m)} \end{cases}$$

$$\eta_k^{(\ell+1,m+1)} = \frac{(\bar{z}_{k|K}^{(\ell+1,m)} - \bar{z}_{k-1|K}^{(\ell+1,m)})^2 + \sigma_{k|K}^{(\ell+1,m)} + \sigma_{k-1|K}^{(\ell+1,m)} - 2\sigma_{k|K}^{(\ell+1,m)} s_{k-1}^{(\ell+1,m)} + 2\beta}{1 + 2(\alpha + 1)}$$

Simulation Results



Application to Real Data



References

- ① Cherry, E. C. (1953). Some experiments on the recognition of speech, with one and with two ears. The Journal of the acoustical society of America, 25(5), 975-979.
- ② Ding, N., & Simon, J. Z. (2012). Emergence of neural encoding of auditory objects while listening to competing speakers. Proceedings of the National Academy of Sciences, 109(29), 11854-11859.
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