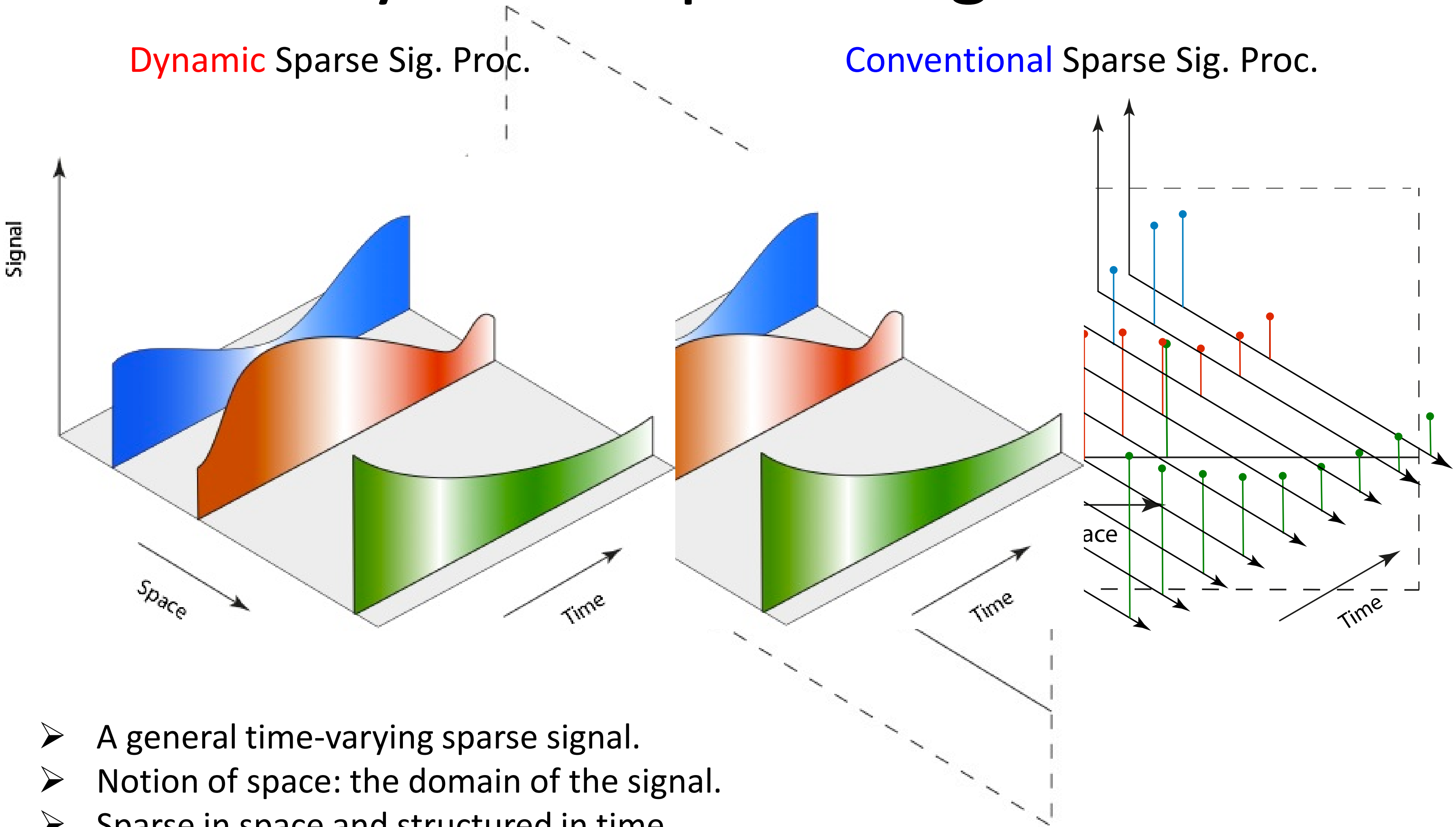
Robust and Scalable Signal Processing for Complex Neural Data

Behtash Babadi

Department of Electrical and Computer Engineering

A. JAMES CLARK SCHOOL OF ENGINEERING

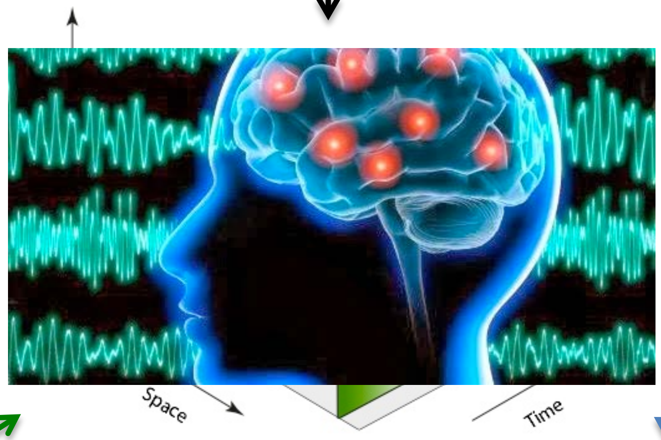
Dynamic Sparse Signals



- A general time-varying sparse signal.
- Notion of space: the domain of the signal.
- Sparse in space and structured in time.
- 'Conventional Compressed Sensing' applies to one cross-section across space.
- Our approach: investigate the 3D object as a whole, rather than its 2D cross sections.

Dynamic Sparse Systems

Sparsity



Dynamicity, Adaptivity, and Stochasticity

Scalability

Robust State-space Models for Dynamic Sparse Data

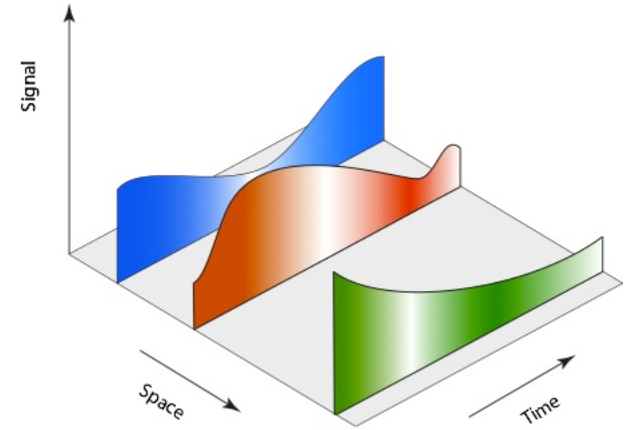
- Markovian stochastic state-space model:

sparse innovations: Laplace(α)

<u>State dynamics:</u> $$\mathbf{x}_k = \mathbf{x}_{k-1} + \mathbf{w}_k$$

<u>Observation model:</u> $$\mathbf{y}_k = \mathbf{A}_k \mathbf{x}_k + \mathbf{n}_k$$

$\mathcal{N}(\mathbf{0}, \mathbf{C})$



- Maximum *a posteriori* (MAP) estimate of the state sequence given observations $\mathbf{y}_1, \mathbf{y}_2, \cdots, \mathbf{y}_T$:

$$\{\widehat{\mathbf{x}}_k\}_{k=1}^T = \arg \min_{\{\mathbf{x}_k\}_{k=1}^T} \sum_{k=1}^T \frac{1}{2} \|\mathbf{y}_k - \mathbf{A}_k \mathbf{x}_k\|_{\mathbf{C}^{-1}}^2 + \alpha \|\mathbf{x}_k - \mathbf{x}_{k-1}\|_1$$

- Total variation denoising.
- General solutions: batch mode.
- Computationally demanding in modern data applications…

Scalable Signal Processing

- This idea can be generalized to MAP estimation:

Hard MAP Estimation Problem

$$\{\widehat{\mathbf{x}}_k^{(\ell)}\}_{k=1}^T = \arg \min_{\{\mathbf{x}_k\}_{k=1}^T} \sum_{k=1}^T \frac{1}{2}\|\mathbf{y}_k - \mathbf{A}_k\mathbf{x}_k\|_{\mathbf{C}^{-1}}^2 + \alpha \sum_{k=1}^T \|\mathbf{x}_k - \mathbf{x}_{k-1}\|_1$$

$$\Big\downarrow \text{EM}$$

Sequence of Easy MAP Estimation Problems

$$\{\widehat{\mathbf{x}}_k^{(\ell)}\}_{k=1}^T = \arg \min_{\{\mathbf{x}_k\}_{k=1}^T} \sum_{k=1}^T \frac{1}{2}\|\mathbf{y}_k - \mathbf{A}_k\mathbf{x}_k\|_{\mathbf{C}^{-1}}^2 + \frac{\alpha}{2} \sum_{k=1}^T \sum_{m=1}^M \frac{(x_{k,m} - x_{k-1,m})^2}{\sqrt{(\widehat{x}_{k,m}^{(\ell-1)} - \widehat{x}_{k-1,m}^{(\ell-1)})^2 + \epsilon^2}}$$

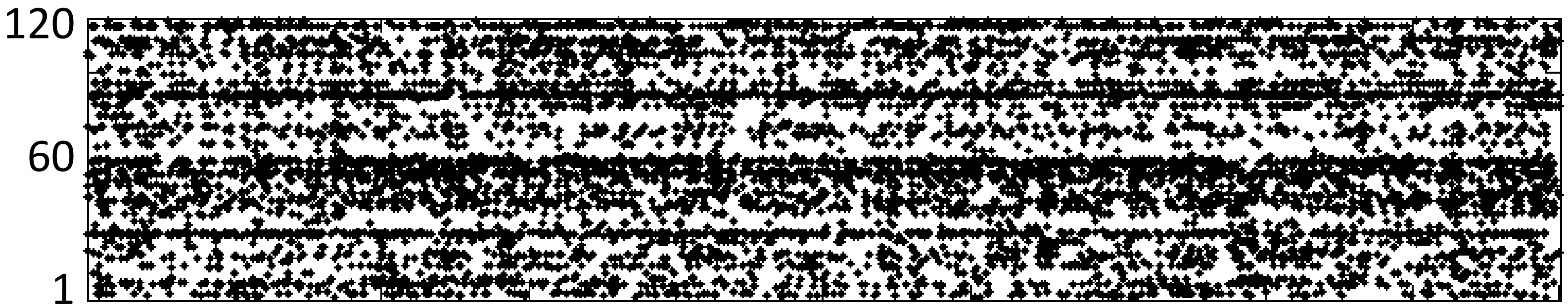
- Iterative solution exists: Fixed Interval Smoother.

- Can be generalized to various other state-space models.

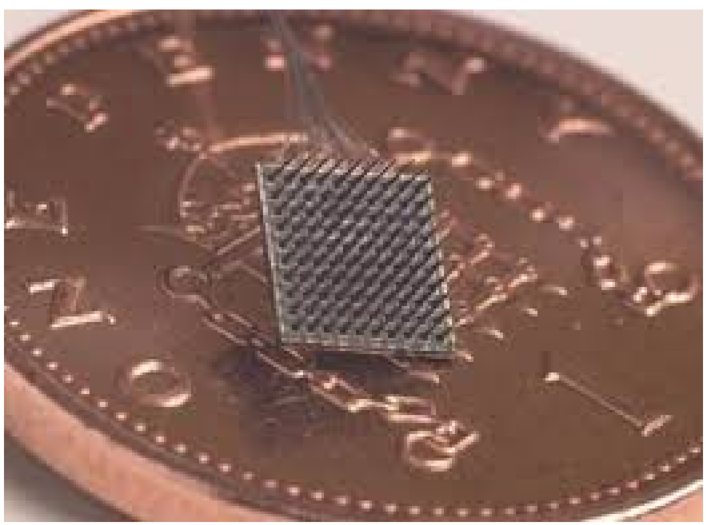
Babadi, Ba, Purdon, and Brown, 2014
Ba, **Babadi**, Purdon, and Brown, preprint, 2014

- Important implications in control theory, image/video processing, machine learning, etc.

Neural Spiking Data under General Anesthesia



200 second window

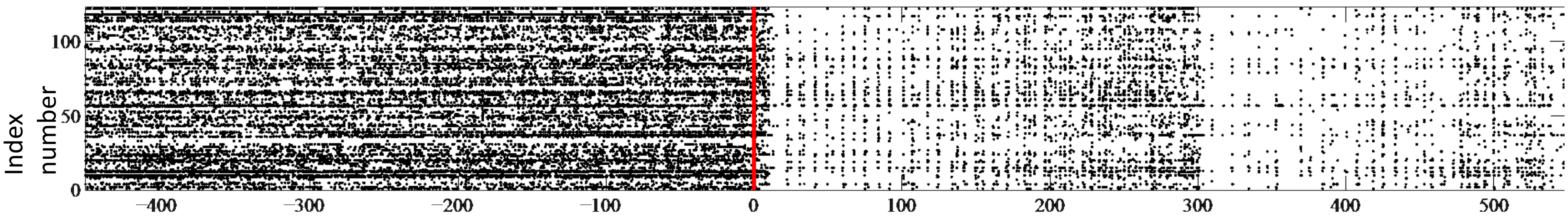


Microelectrode array

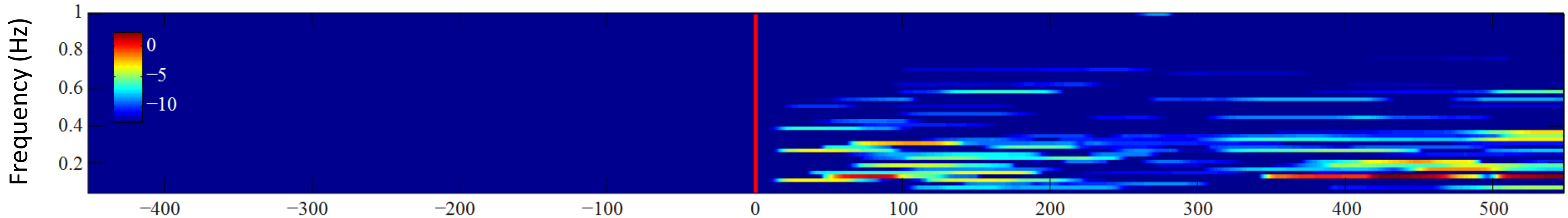
First injection of anesthetic.
Second injection of anesthetic.

Lewis et al., 2012

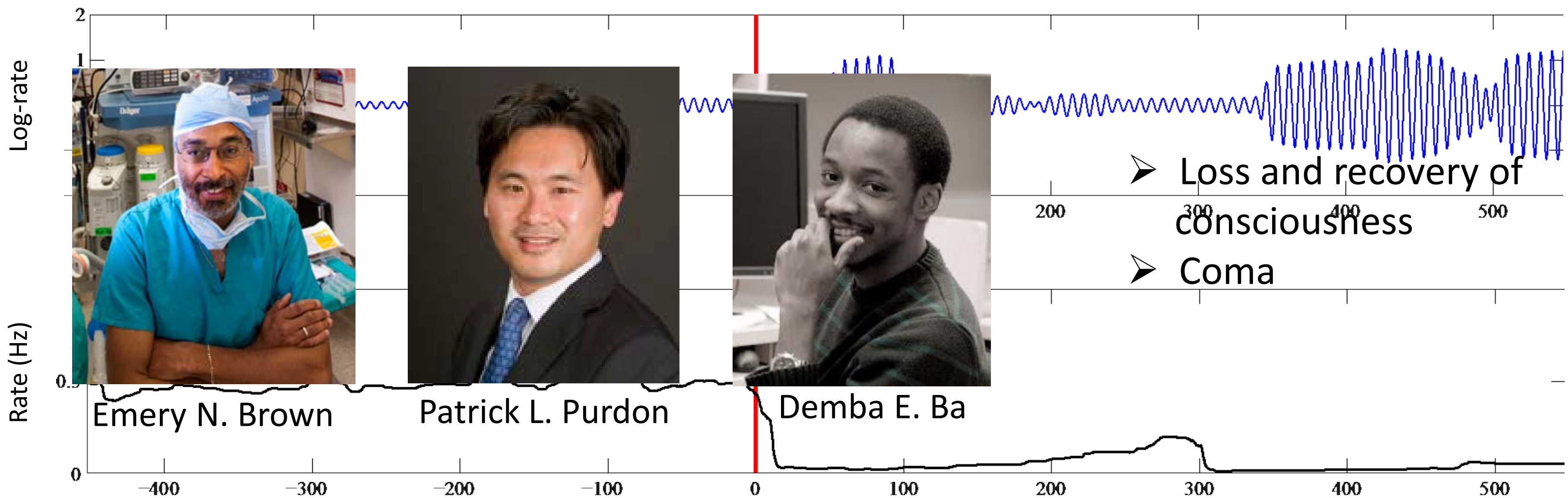
Robust Point Process Harmonic Decomposition



- Robust harmonic decomposition:



- Dominant component of the rate at 0.15 Hz:



Emery N. Brown

Patrick L. Purdon

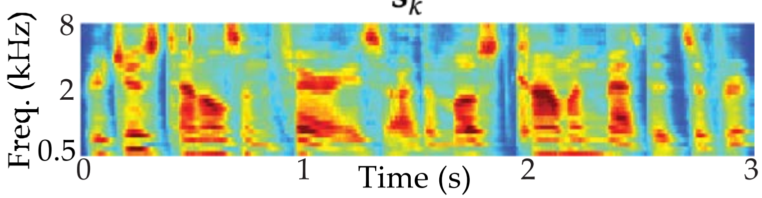
Demba E. Ba

- Loss and recovery of consciousness
- Coma

Real-Time Speech Decoding from Spikes

Neural Encoding

Stimulus:
Speech (Spectrogram)
$\mathbf{s}_k$

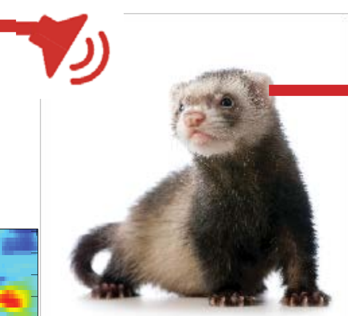


Spectrotemporal Receptive Fields

$$\lambda_k^{(m)}(H_k) = \exp\left(\mu^{(m)} + \textstyle\sum_{i=0}^{I} \langle \boldsymbol{\alpha}_i^{(m)}, \mathbf{s}_{k-i} \rangle\right)$$

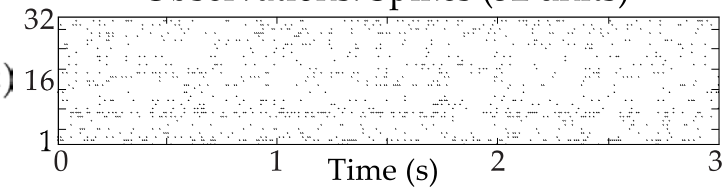
Identification Problem

$$\max_{\alpha_i^{(m)}, \mu^{(m)}} \sum_{k=1}^{K} \left\{ y_k^{(m)} \log \lambda^{(m)}(k|H_k) - \lambda^{(m)}(k|H_k)\Delta \right\} - \sum_{i=1}^{I} \left\{ \gamma_1 \left\| \boldsymbol{\alpha}_i^{(m)} \right\|_1 + \gamma_2 \left\| \boldsymbol{\alpha}_i^{(m)} \right\|_2^2 \right\}$$



$y_k^{(m)}$

Observations: Spikes (32 units)



Recons... m: $\widehat{\mathbf{s}}_k$

Shihab Shamma

Inverse Problem

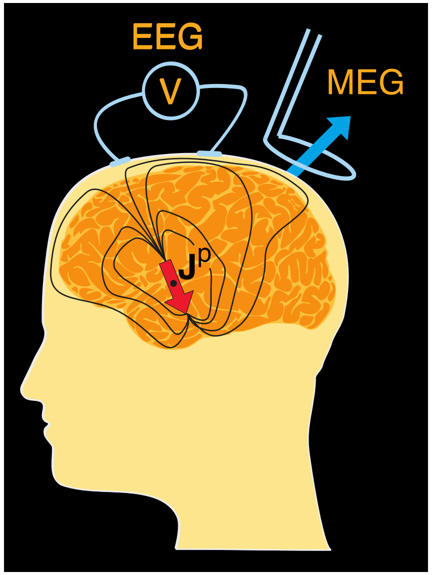
$$\sum_{=1}\sum_{k=1}^{K} \left\{ y_k^{(m)} \log \lambda^{(m)}(k|H_k) - \lambda^{(m)}(k|H_k)\Delta \right\} - \sum_{k=1}^{K} \left\{ \kappa \|\mathbf{s}_k\|_1 + \|\mathbf{s}_k - a\mathbf{s}_{k-1}\|_{\mathbf{Q}^{-1}}^2 \right\}$$

- Understanding auditory processing
- Neural prostheses for speech/hearing disorders

Neural Decoding

Electroencephalography (EEG) and Magnetoencephalography (MEG)

- Popular non-invasive brain imaging techniques.
- Measure the electromagnetic brain activity outside of the scalp.
- Milisecond temporal resolution.

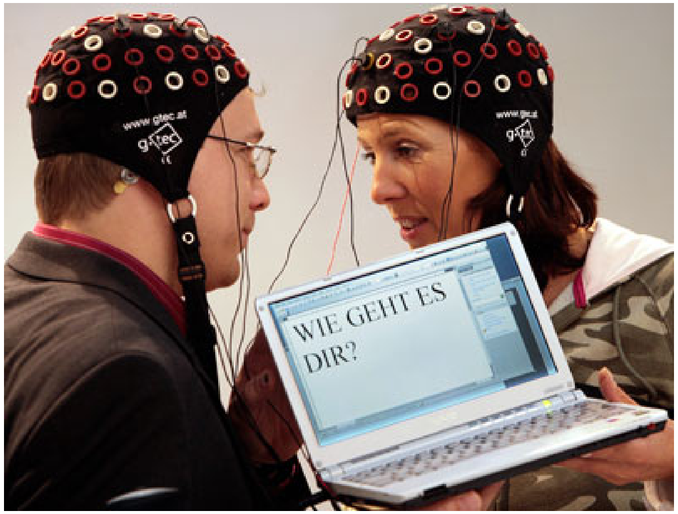


Basic science/technology:

- Cognitive sciences.
- Brain-computer interface.

Clinical applications:

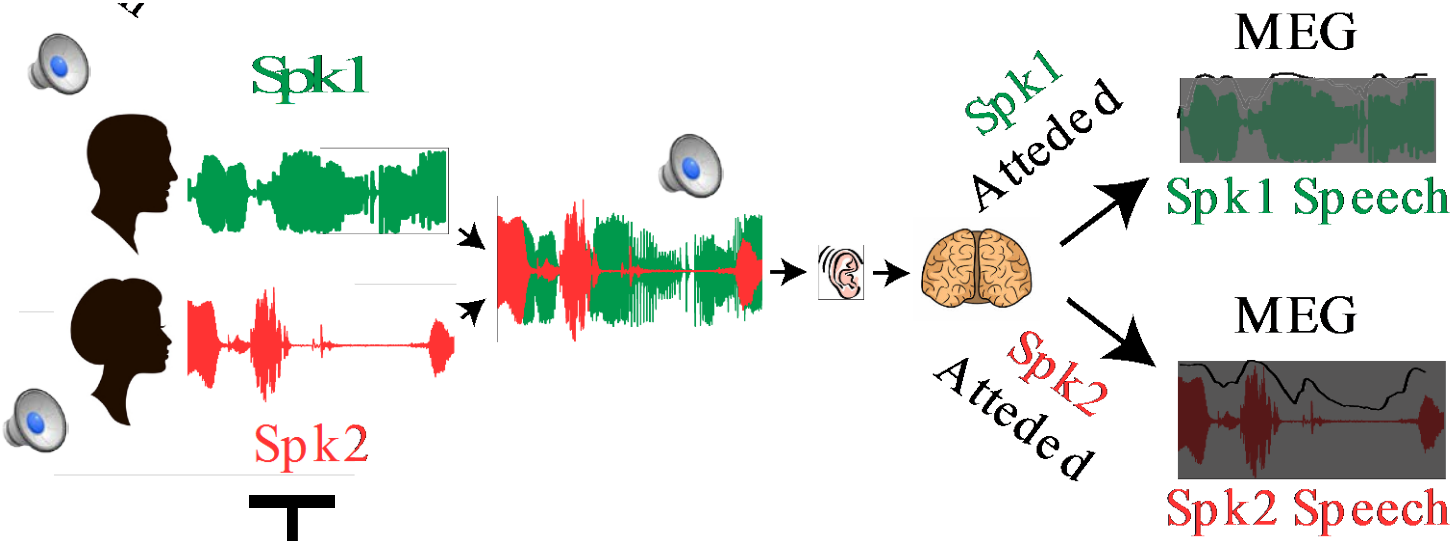
- Cognitive disorders.
- Pre-surgical procedures.

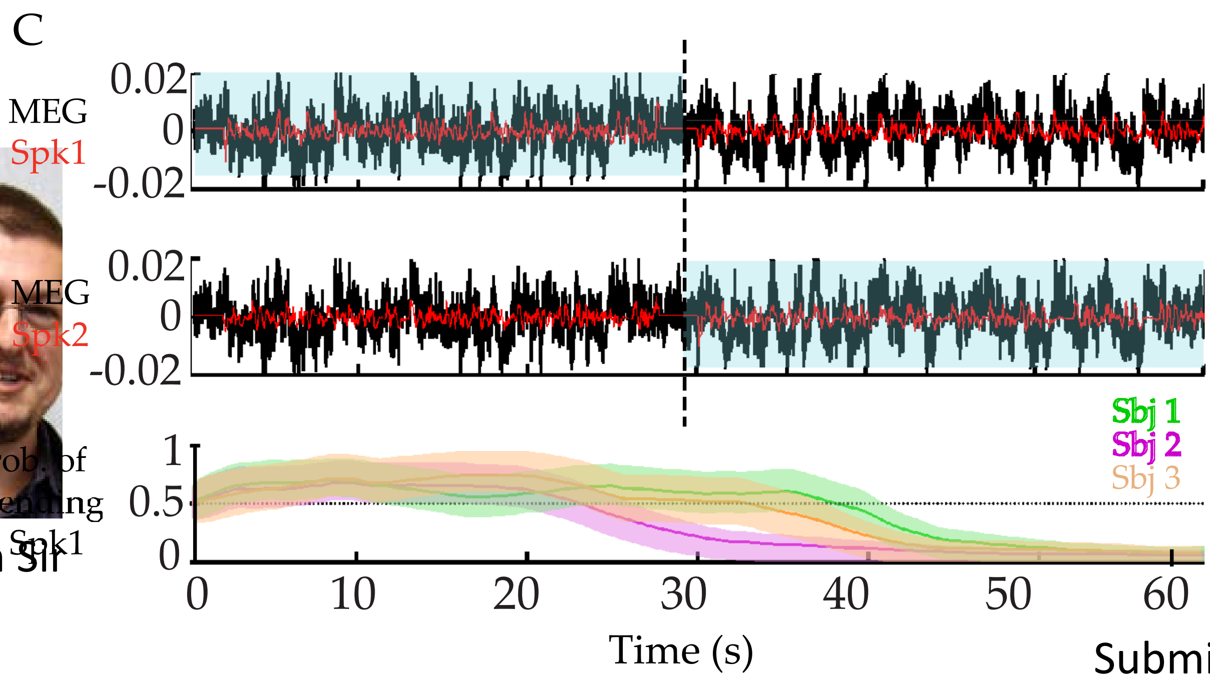


EEG

MEG

Decoding Attentional Modulation from MEG



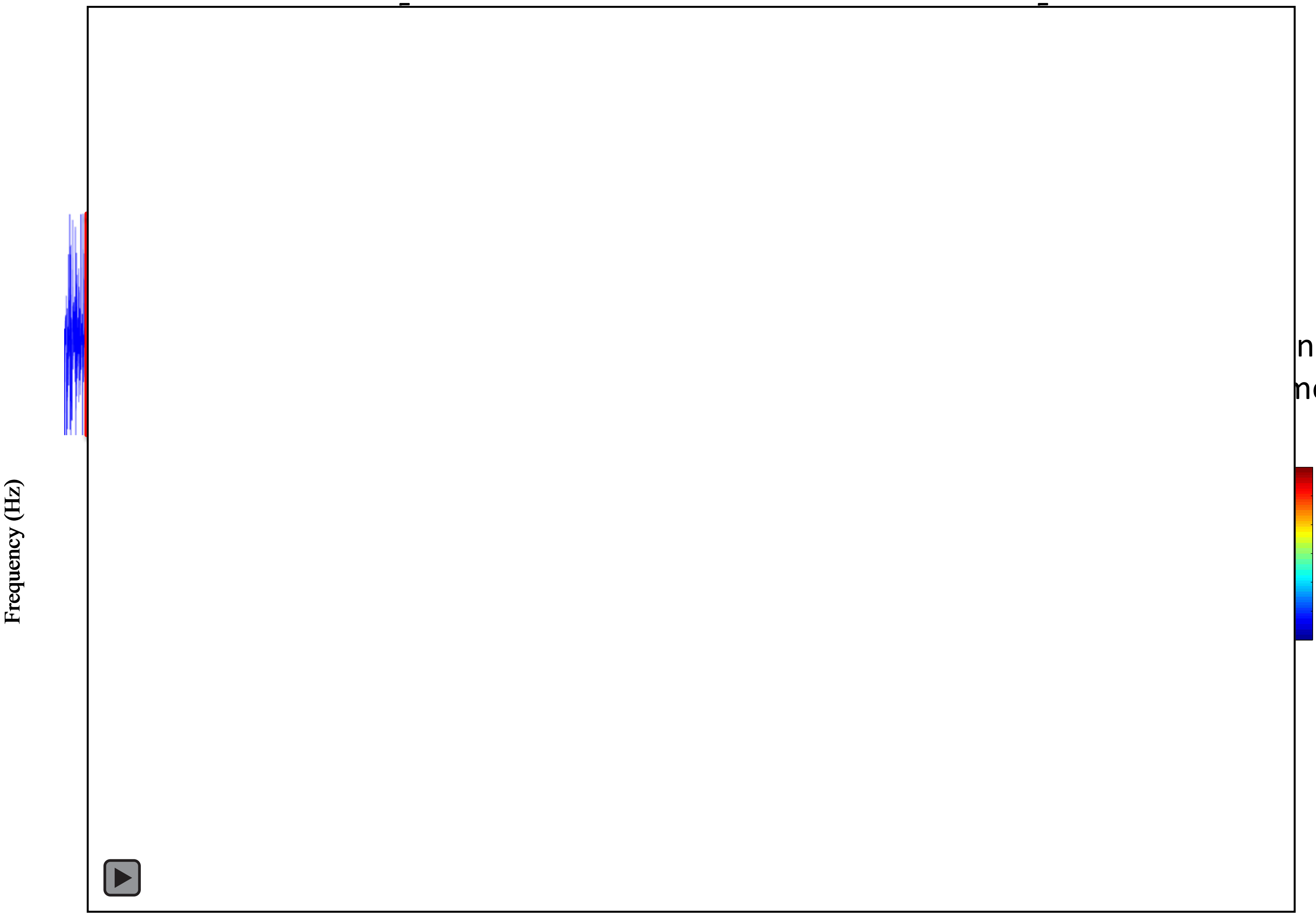


Jonathan Sir

devices

Submitted to NIPS 2014

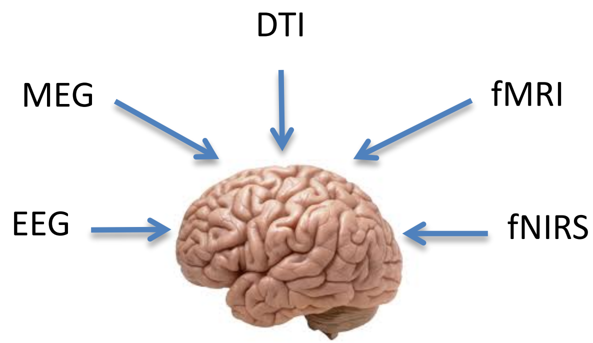
Human EEG During General Anesthesia



Cimenser et al., 2011

Future Research Direction

Multi-Modal Neural Sig. Proc.



Modeling
Multi-scale Data Fusion

Dynamic Calcium Imaging

Ahrens and Keller, 2013

From image to video processing
Nonlinear signal processing

Luiz Pessoa
Dept. of Psychology

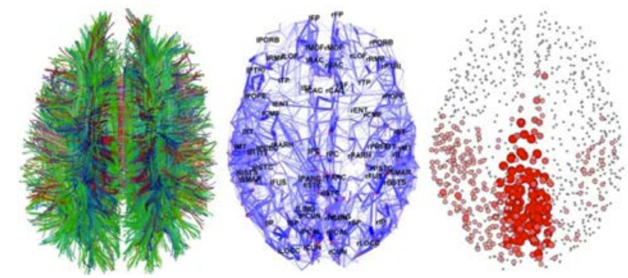
Cynthia Moss
Dept. of Psychology

high-dimensional
structured
dynamic
networks

Patrick Kanold
Dept. of Biology

Shihab Shamma
Jonathan Simon
ECE/ISR

Dynamic Functional Connectivity



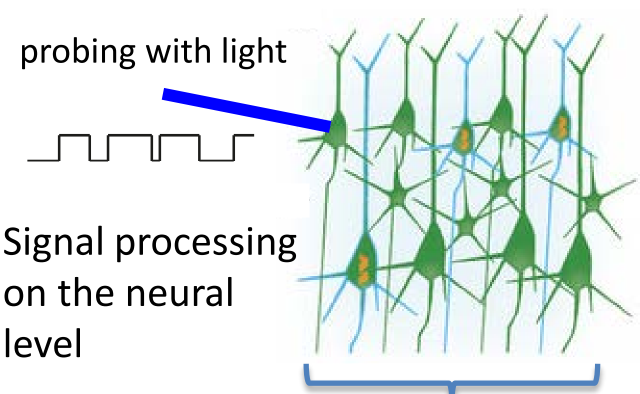
Existing results are static.

Hagmann et al., 2008

Modeling
Sampling theory
Harnessing the dimensionality

Compressed Dynamic Optogenetics

probing with light



Signal processing on the neural level

measuring with calcium imaging

Future Educational Direction

- **'Brain in Action':**
  High school level hands-on workshops
  on Computational Neuroscience

  Signal Processing + Neuroscience

Non-Invasive Commercial
Wireless EEG Headset

- **Capstone Design Project:**
  EEG-based Brain-Computer Interfacing

- The **GEMSTONE** at UMD

- Inter-disciplinary **undergraduate and graduate course curricula**
  NACS program
  Mathematical Foundations of Neural Data Analysis