EEG-Based Estimation of Mental Fatigue: Convergent Evidence for a Three-State Model

Leonard J. Trejo, Ph.D.
Quantum Applied Science and Research
www.quasarusa.com

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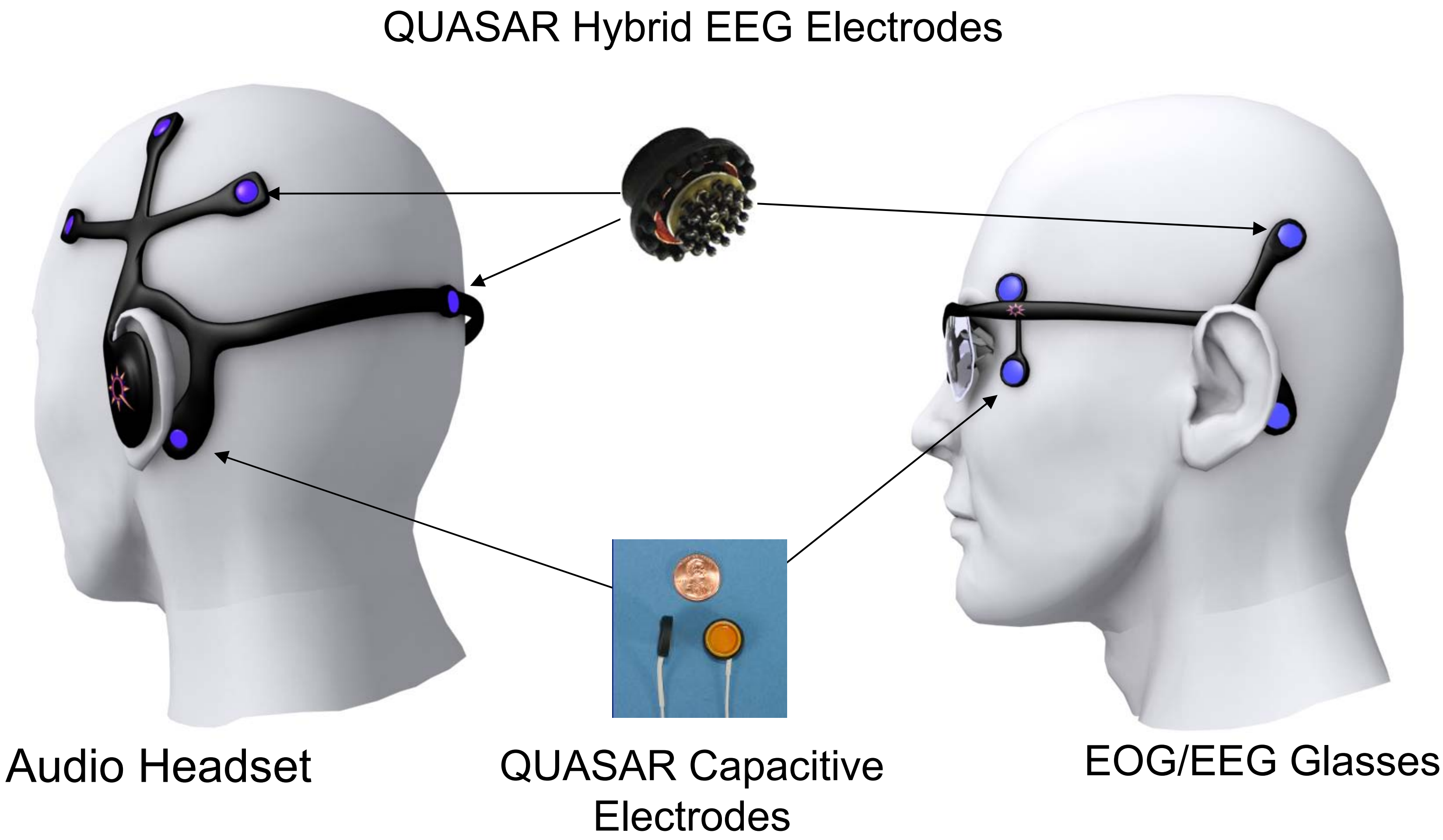
Collaborators

Kevin Knuth
Raquel Prado
Roman Rosipal
Karla Kubitz
Rebekah Kochavi
Bryan Matthews
Zhang Yuzheng

QUASAR HCI/ACI Interests

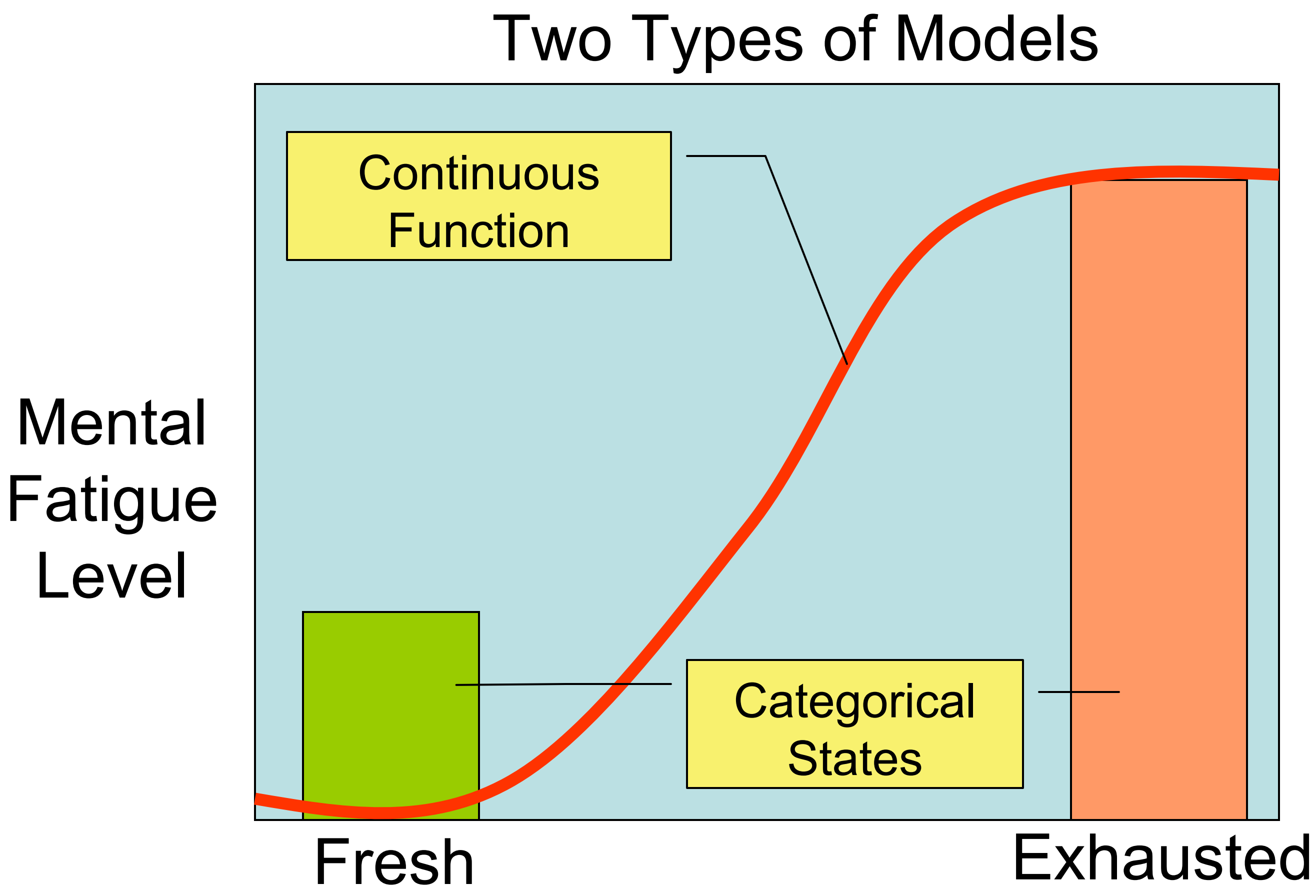
- Truly deployable unobtrusive biosensors
  - Nearly invisible to the user
  - Seamlessly integrated with clothing and appliances
- End-to-end systems for operational bio-sensing
  - Broad application spectrum (e.g., EEG, EOG, ECG and EMG)
  - Low-power, long lasting, wireless electronics
  - Robust algorithms tolerant of noise and sensor dropout
  - Intelligent systems adapt for situational or individual differences

Deployable EEG/EOG Sensor Concepts



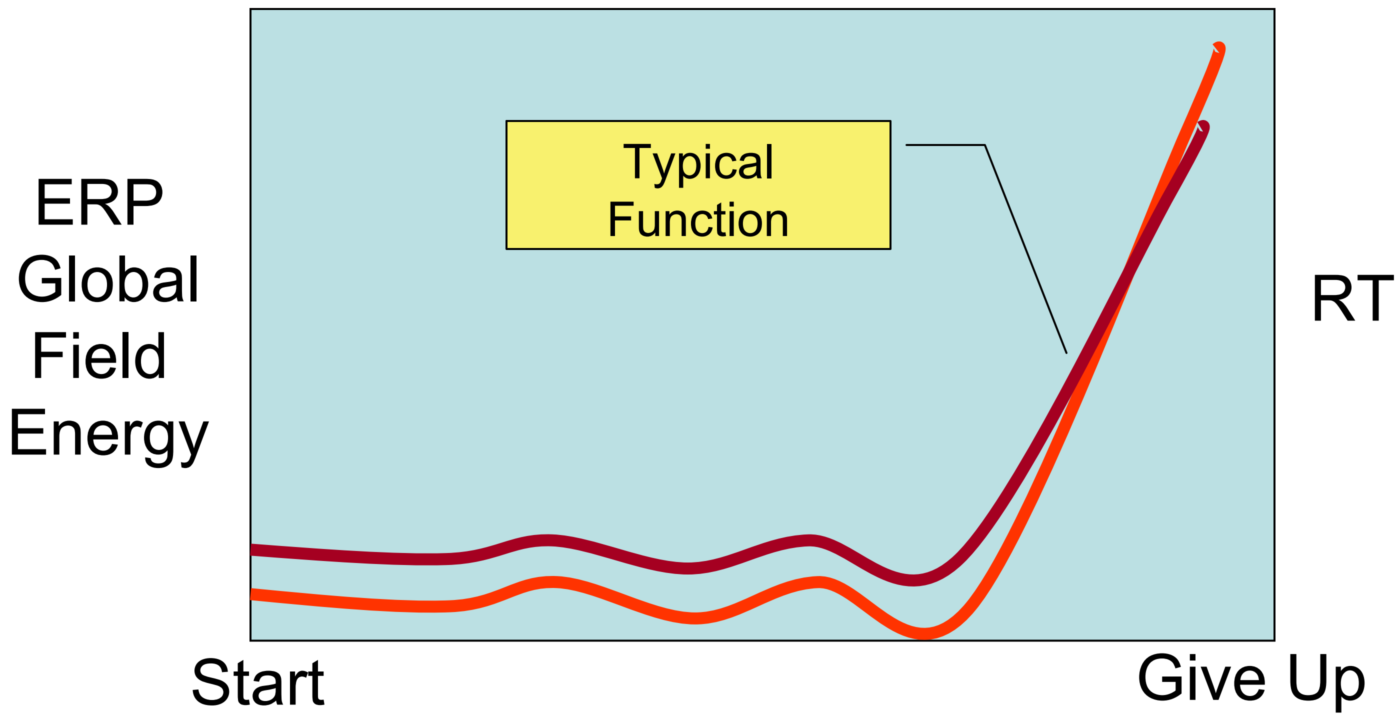
Other Interests

Representing and Estimating Mental Fatigue



Prior Studies

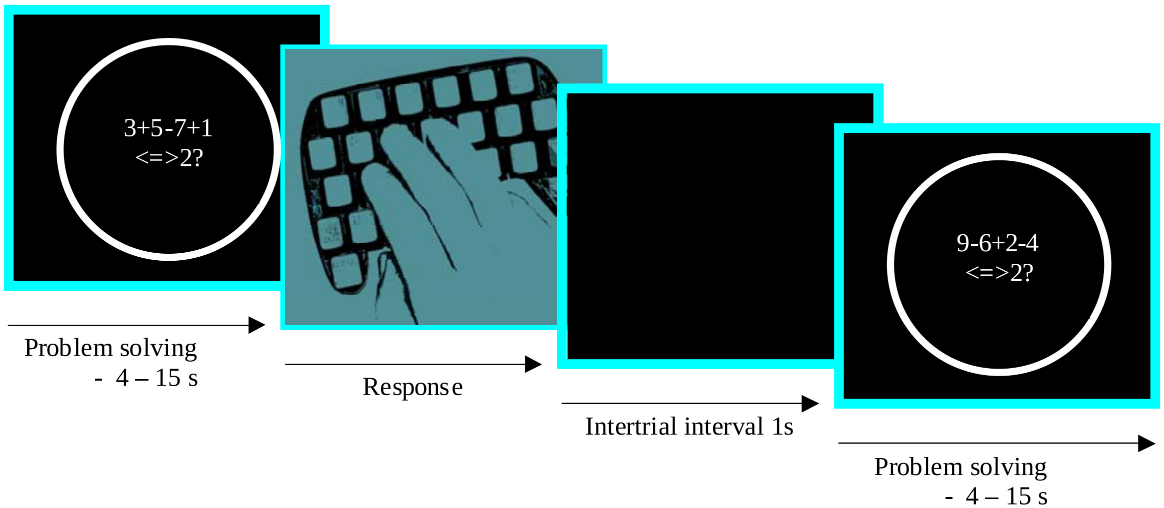
- NASA Space Technology Cognitive Fatigue Program (Montgomery, et al. 2001-2002)
- Up to 3h of Mental Arithmetic
- ERP/behavioral evidence for a two-state model

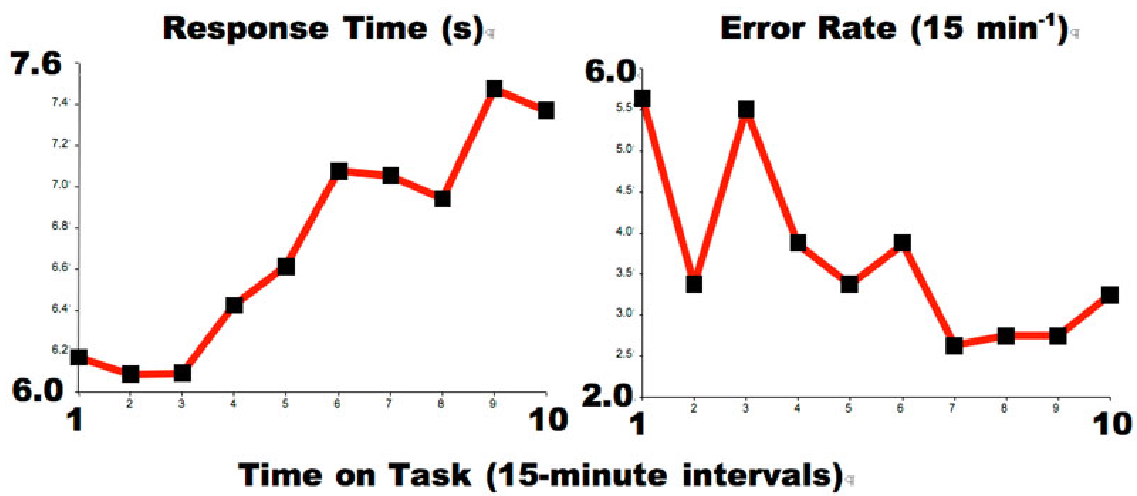


Later Study

- Limitations of Prior Study
  - Small N
  - Unusual ERP Measure (global energy)
  - Lack of controls for EOG, EMG
- New Study: NASA AOS/PPSF Program (2003-2004)
- Same task, more controls, continuous 32ch EEG/EOG
- Video-based monitoring and off-line scoring of behavior
- 16 Participants (27±8y, 4F/12M, normal vision/hearing)
- Public domain database: EEG, EOG, performance

Cognitive Fatigue Task

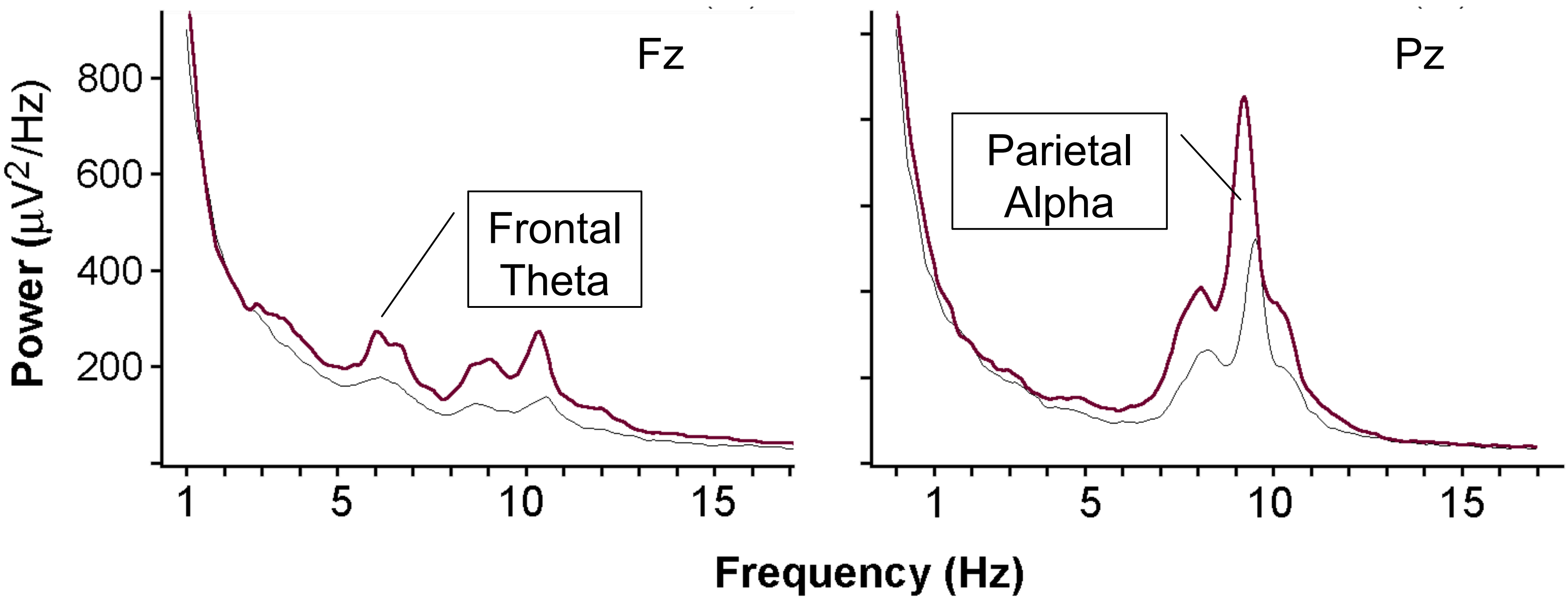




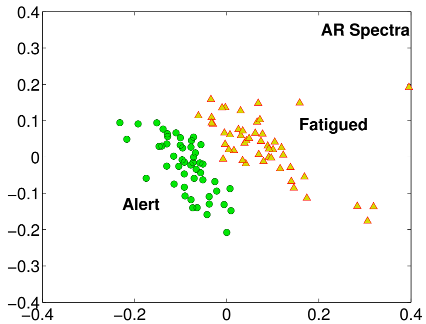
Average EEG Spectrum

Black= First 15 min

Red=Last 15 min

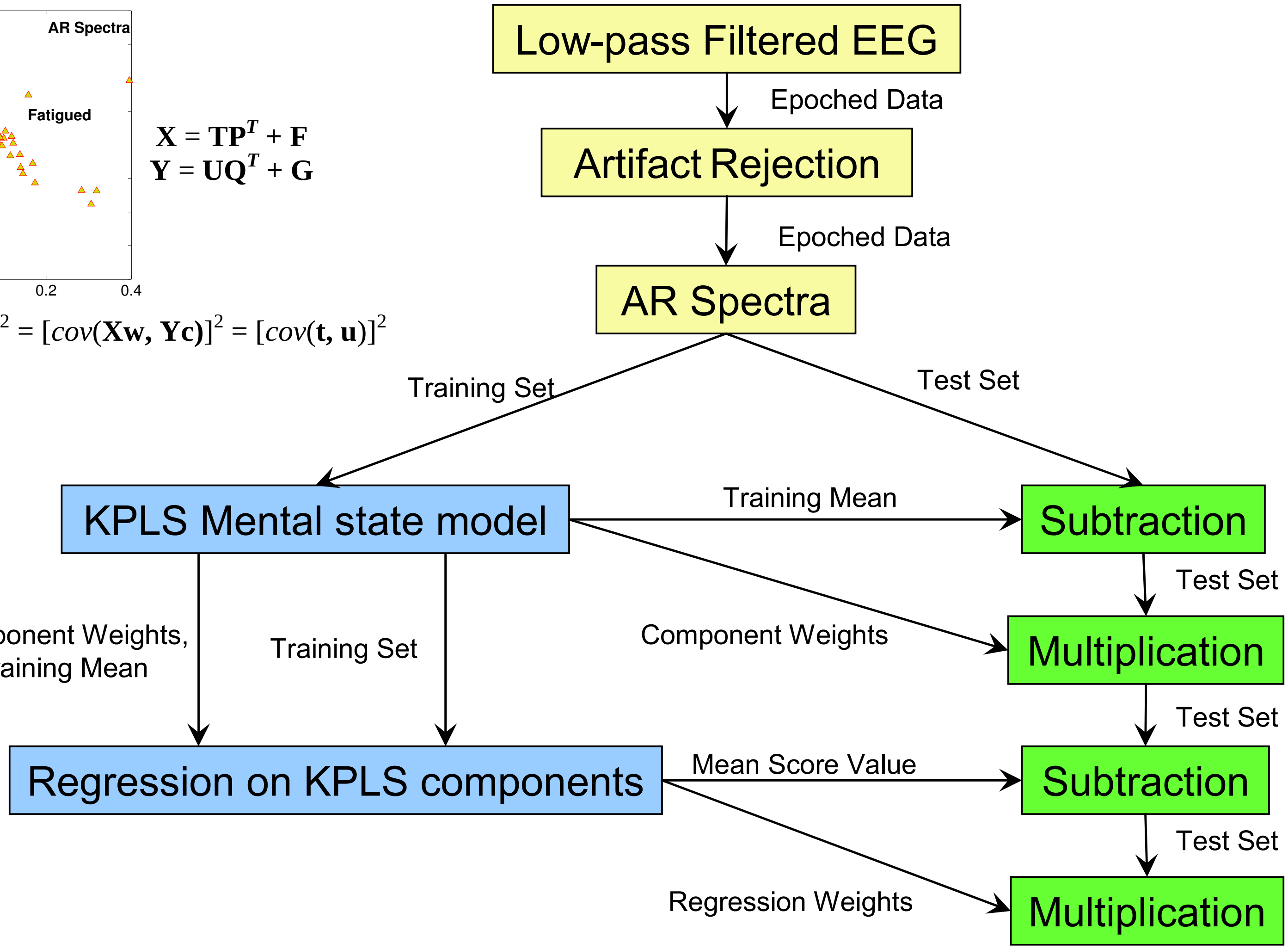


Machine-Learning EEG/Mental State Classifier



$$\mathbf{X} = \mathbf{TP}^T + \mathbf{F}$$
$$\mathbf{Y} = \mathbf{UQ}^T + \mathbf{G}$$

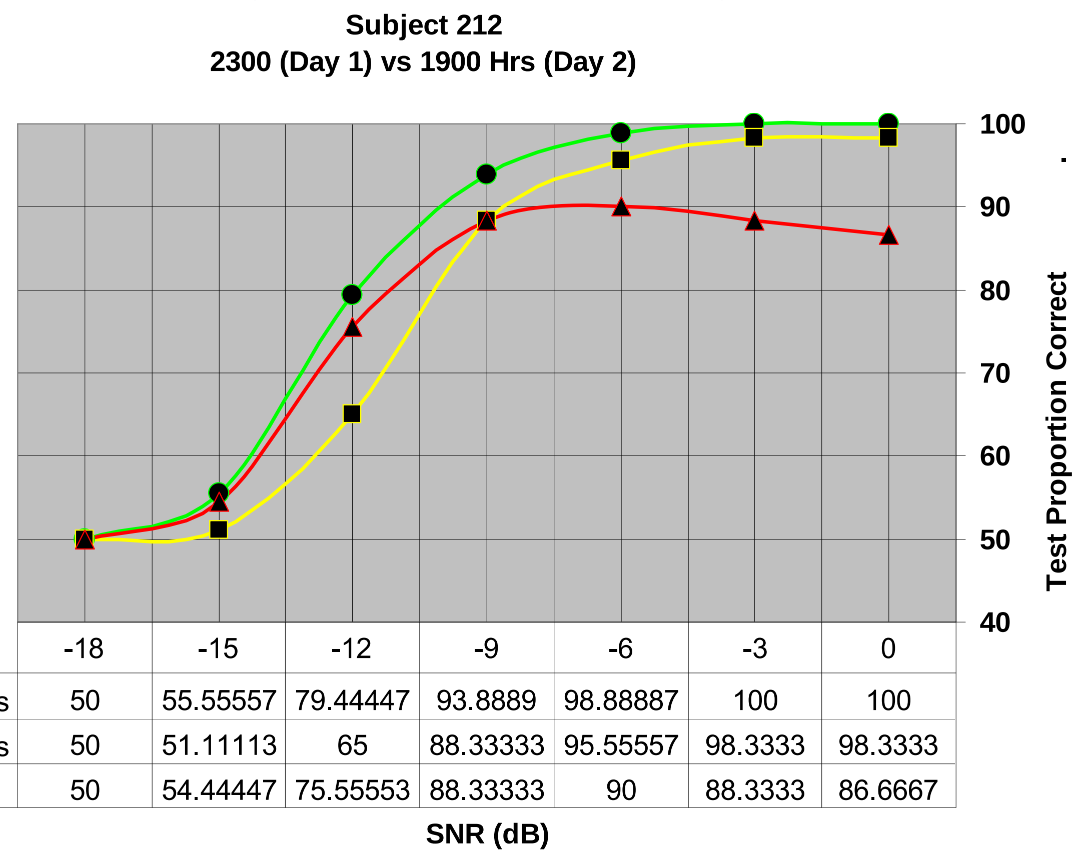
$$max_{|r| = |s| = 1}[cov(\mathbf{Xr}, \mathbf{Ys})]^2 = [cov(\mathbf{Xw}, \mathbf{Yc})]^2 = [cov(\mathbf{t}, \mathbf{u})]^2$$



EEG-based Classification with Low-density Arrays or Low-SNR Signals

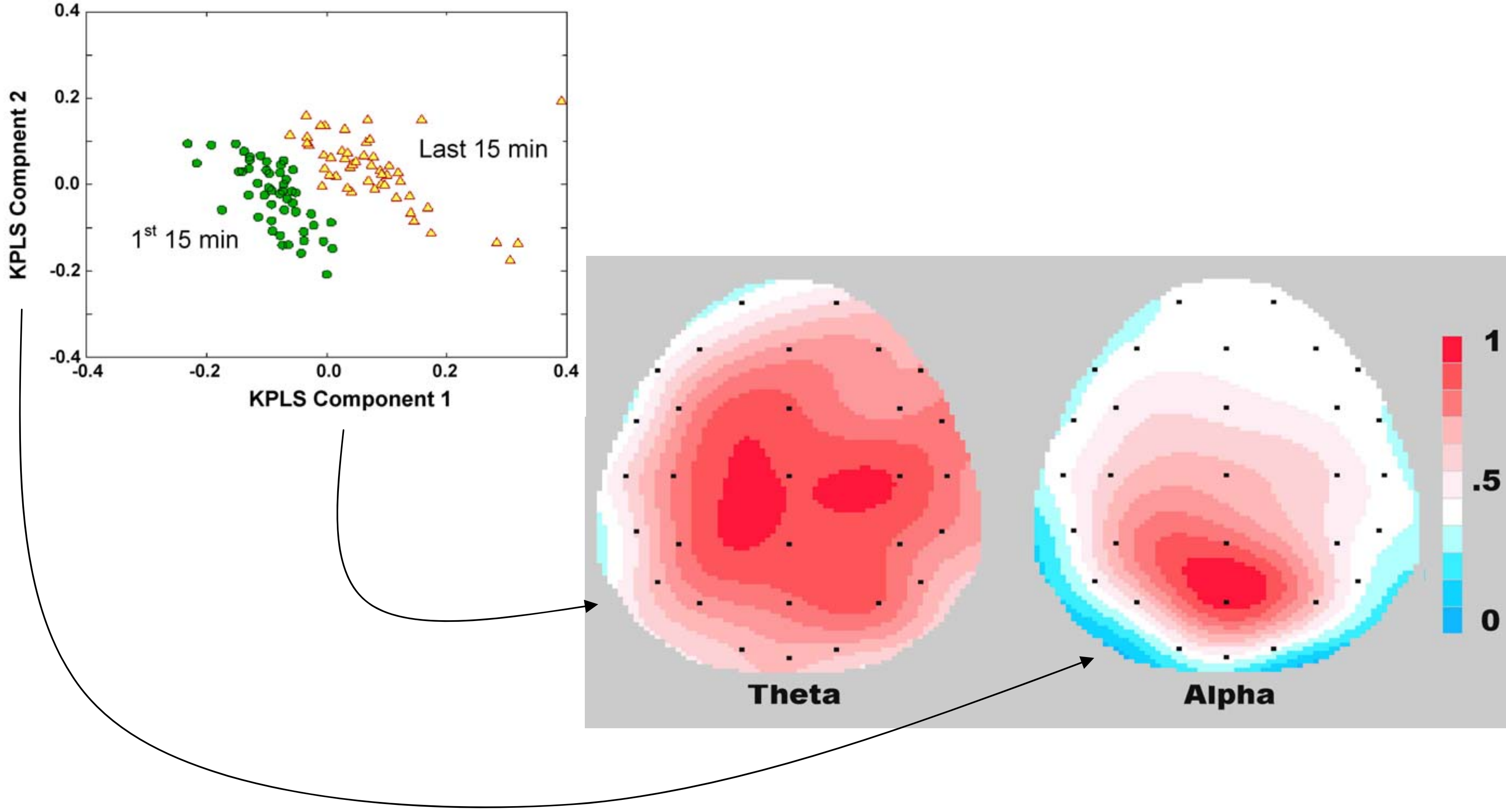
Description of the method (Wallerius, Trejo & Matthews 2005)

- Robust algorithm applied to mental fatigue classification using multichannel EEG spectra
- Trained KPLS classifier in Air Force pilots EEG using 19 channels
- Corrupted signal from SNR of 0 dB to -18 dB
- Reduced density from 19 to 4 electrodes
- Preserved >80% accuracy with -9 dB SNR and four electrodes

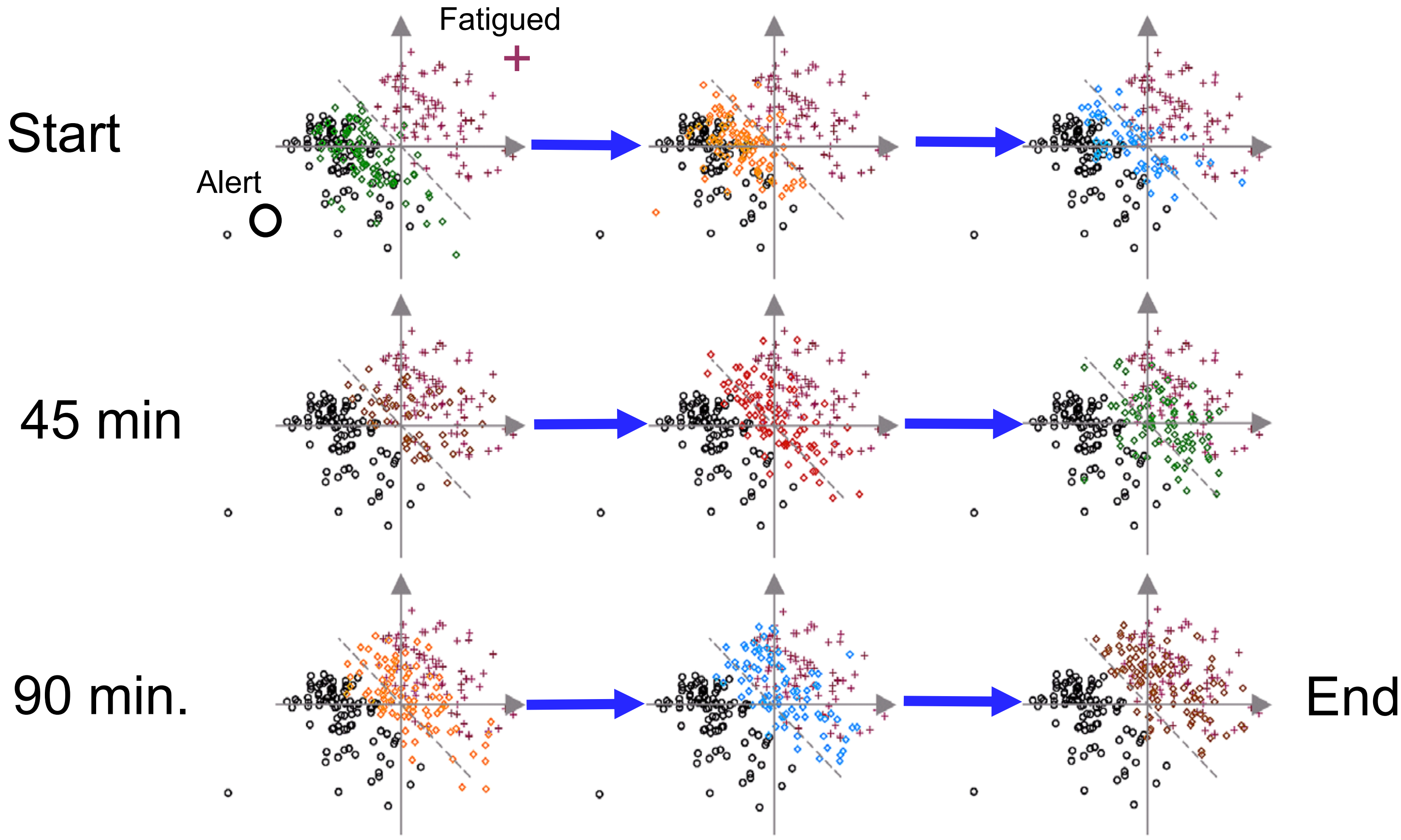


	-18	-15	-12	-9	-6	-3	0
21 Electrodes	50	55.55557	79.44447	93.8889	98.88887	100	100
12 Electrodes	50	51.11113	65	88.33333	95.55557	98.3333	98.3333
4 Electrodes	50	54.44447	75.55553	88.33333	90	88.3333	86.6667

Visualizing PLS components



PLS Components & Development of Fatigue

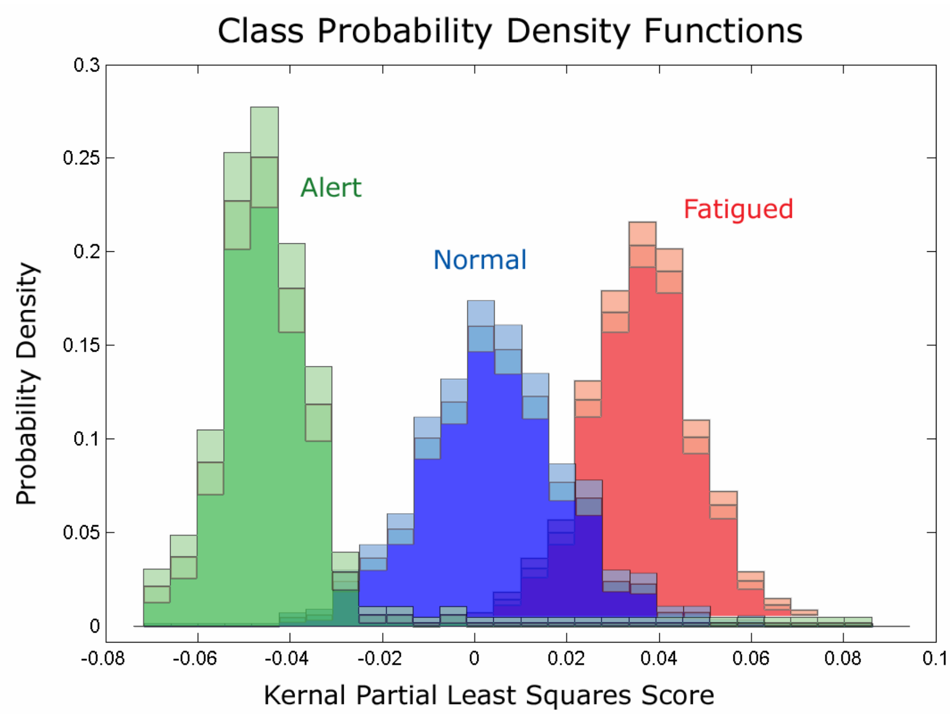


Optimal Binning of PLS Component Scores
(Bayesian Likelihood Estimator)

Approach

- Experimental epochs were chosen to be representative of the Alert, Normal, and Fatigued states
- Scores generated by the Kernel Partial Least Squares (KPLS) classifier during these epochs were used to define histogram-based probability density functions describing the likelihood that given a particular state one could observe a resulting score.
- Without prior information, the probability of being in a state A, N, or F given the score is proportional to the likelihood:

$$p(F \mid score) \propto p(score \mid F)$$



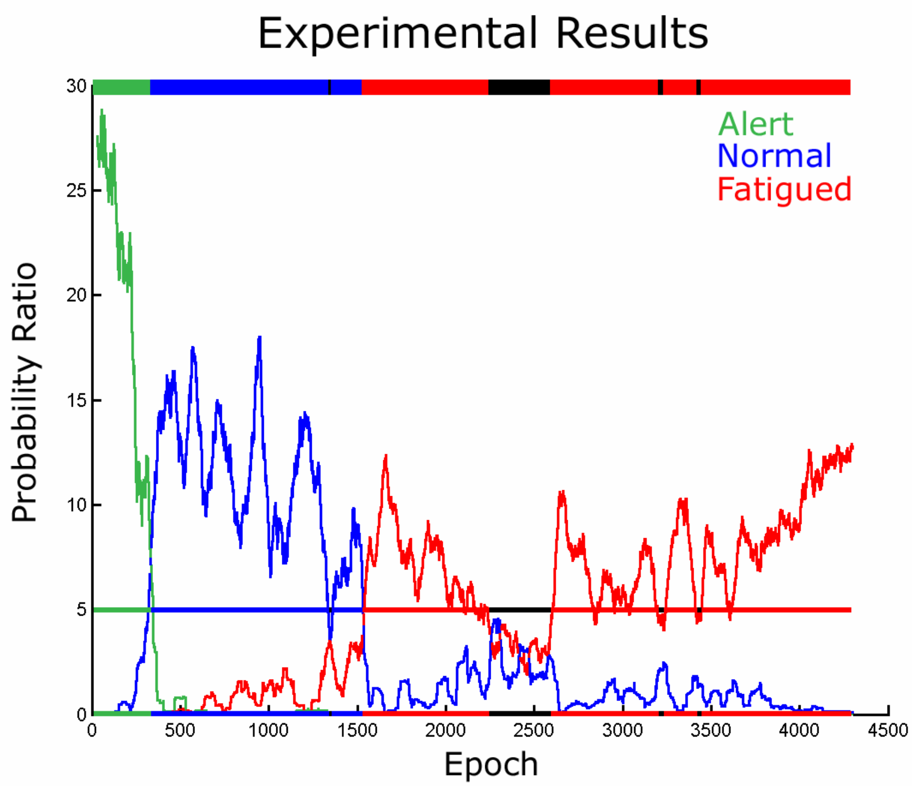
Optimal Binning of PLS Component Scores
(Bayesian Likelihood Estimator)

Sample Results

- The likelihood ratios were computed to indicate the relative probabilities of the subject's state. The red curve indicates

$$\frac{p(F \mid score)}{P(A \mid score) + P(N \mid score)}$$

- If a state was more than 5 times more probable than the sum of the others, we assigned that state to the subject (see color bar). Green regions indicate high alertness, blues indicates normal alertness, and red indicates fatigue in this 3 hour experiment. Black regions are indeterminate.

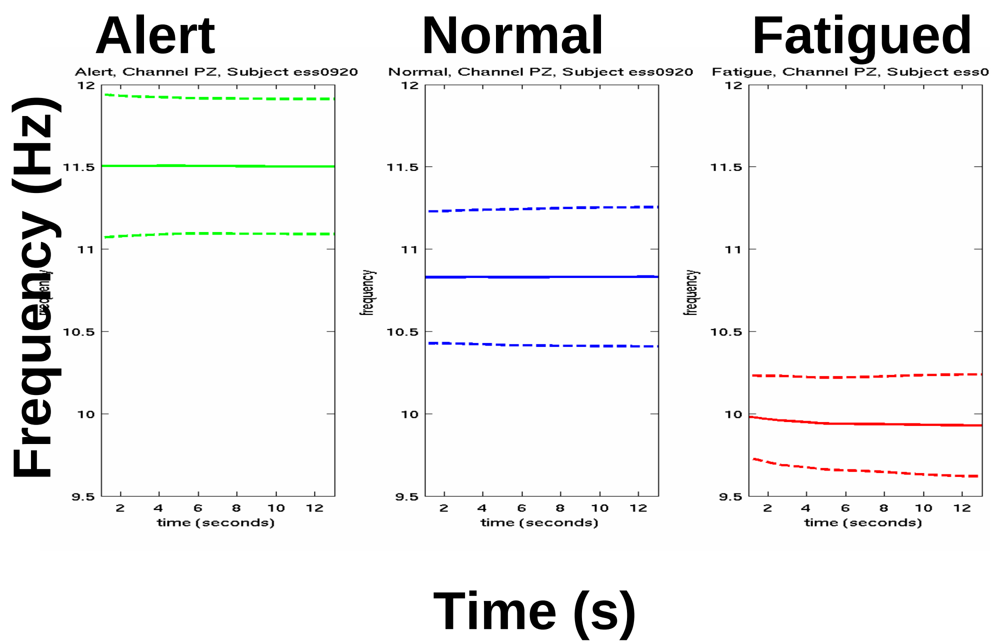


Autoregressive Probabilistic State Model
(Bayesian Likelihood Estimator)

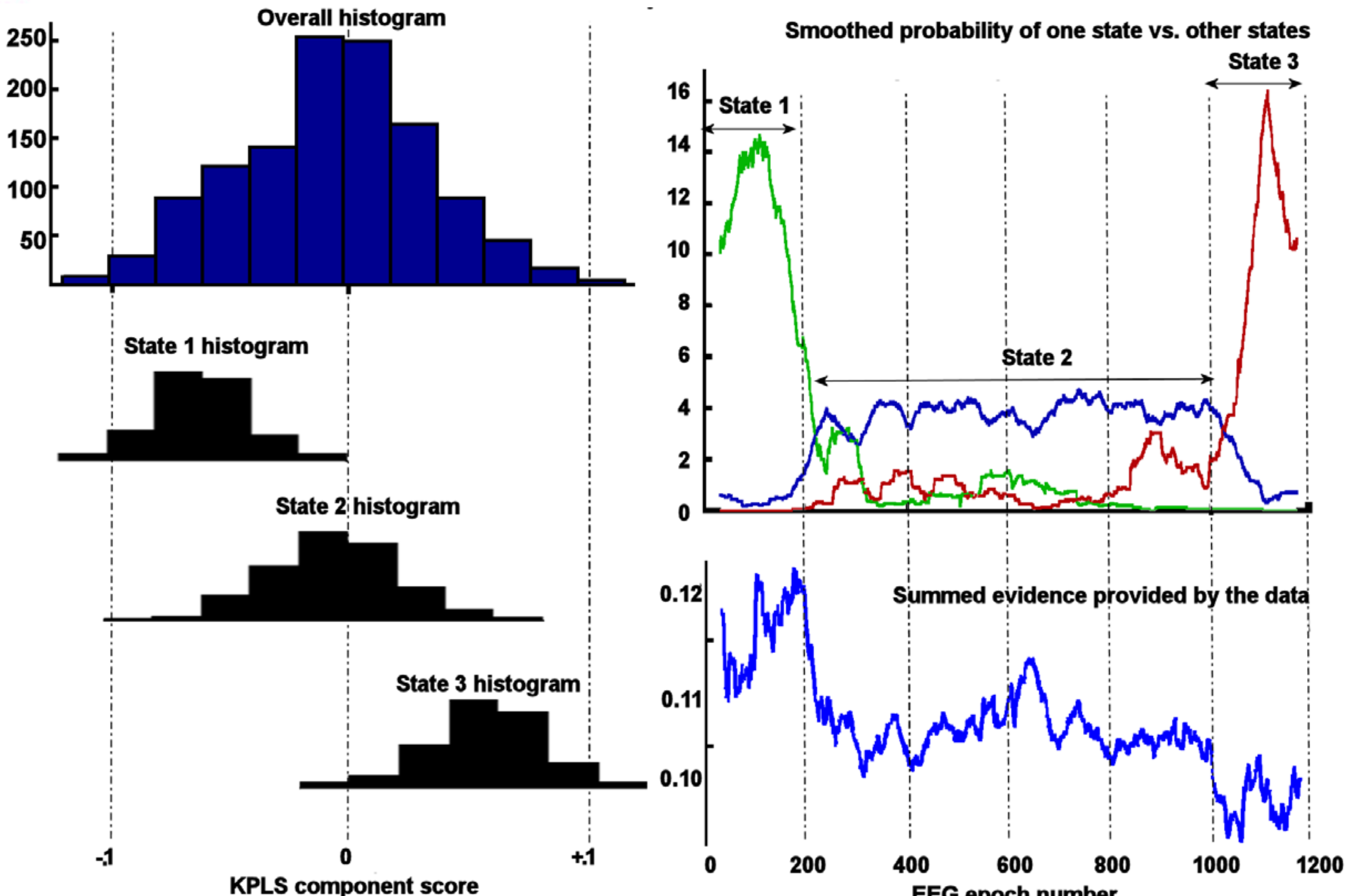
Approach

- Experimental 13-s epochs were chosen to be representative of the Alert, Normal and Fatigue states for each S and for each EEG channel.
- Autoregressive models of order 8 were fitted to each epoch for each channel
- Estimated frequencies in the Alpha band obtained from the models were isolated for each epoch.
- The frequency traces in the Alpha band for each epoch were used to define probability density functions describing the likelihood that given a particular state one could observe a resulting trace.

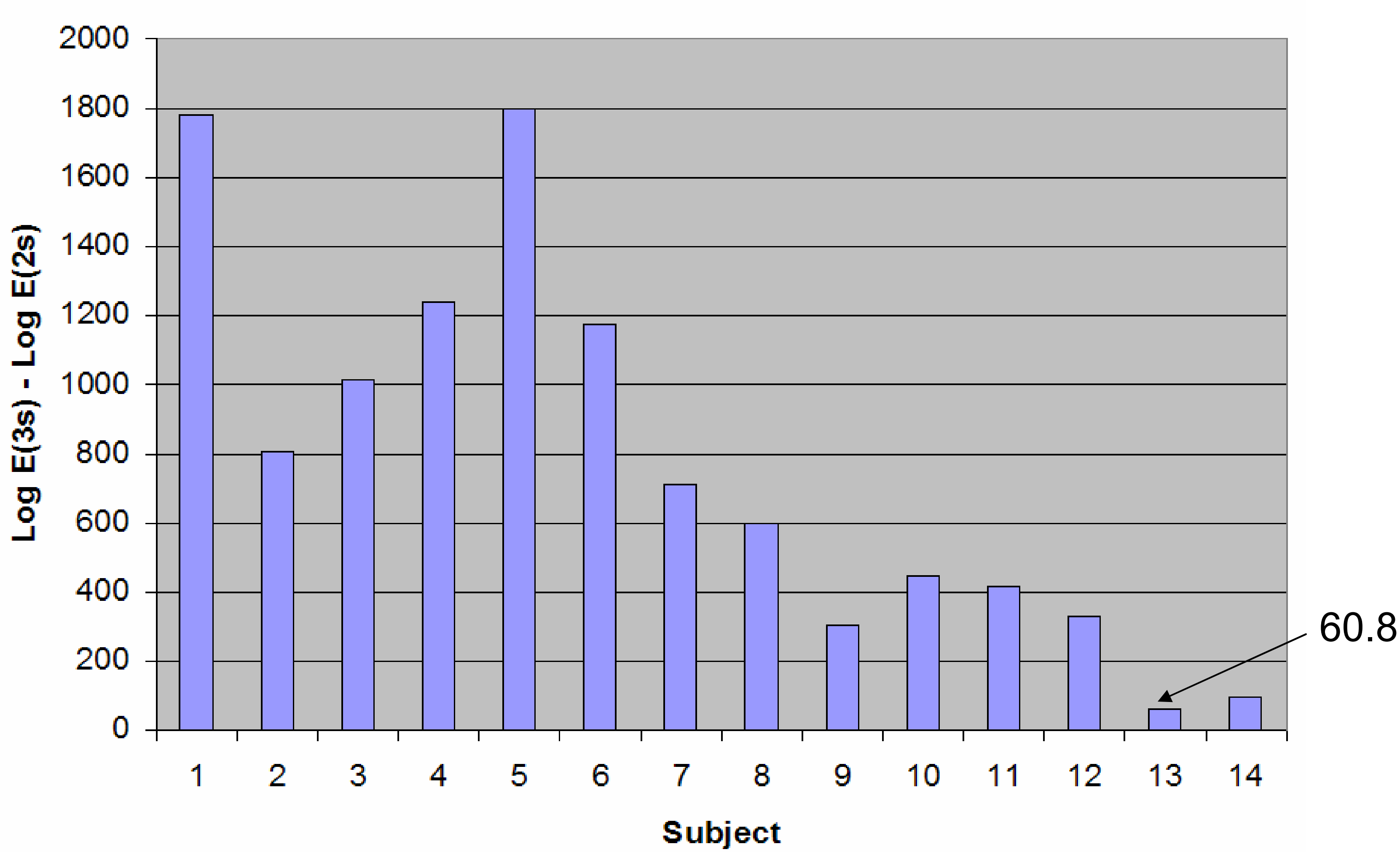
Subject 0920, Pz



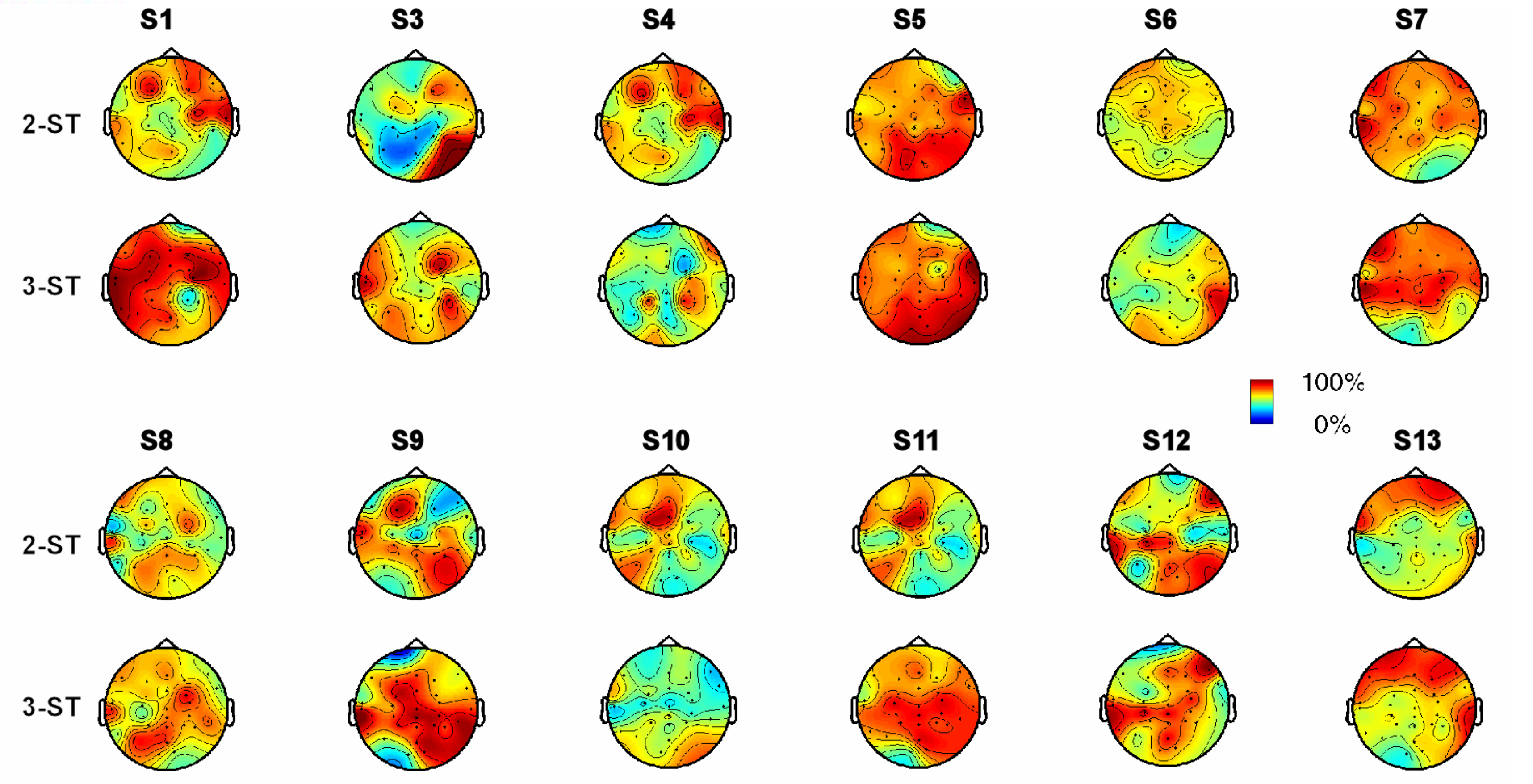
Results with Optimal Binning Algorithm



Results with Optimal Binning Model



Results with Autoregressive Model



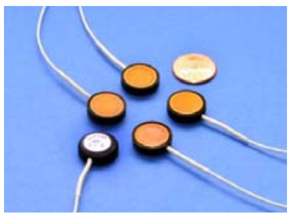
Each topo plot shows the accuracy of classification as a function of electrode location.

Summary and Conclusions

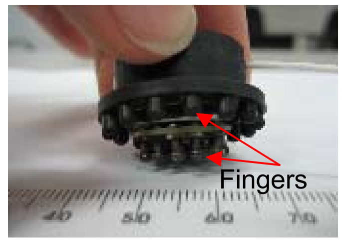
- EEG spectral features accurately reflect the development of mental fatigue
- A KPLS model extracts robust features that can serve to explore the temporal structure of fatigue
- Evidence from two studies supports state-like transitions from alertness to fatigue over time (cf. Billings)
- An optimal binning method provided strong evidence for at least three states: high alertness, normal alertness, and fatigue
- An autoregressive method provided additional evidence for a three- vs. two-state model of mental fatigue
- This has implications for on-line monitoring of fatigue, for example, an on-line fatigue detector for system operators
- I hope this talk has left you in one of the alert states!

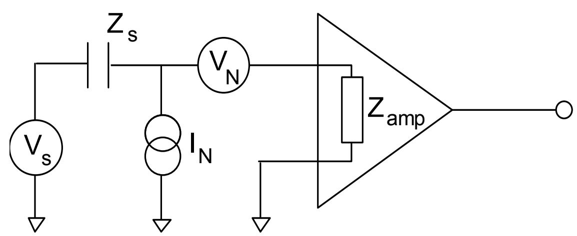
QUASAR EEG Sensor Technologies

QUASAR Capacitive sensors (on skin EEG, EOG, ECG)

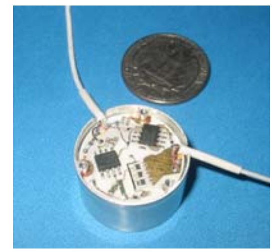


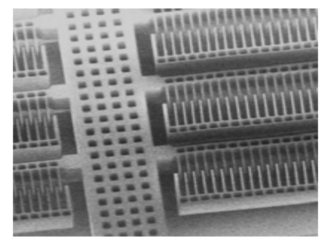
QUASAR Hybrid sensors (through hair)





QUASAR Next Gen sensors (standoff detection)





Validation Studies Completed

2004 2006 2008-2009

Development of an Integrated Neurocognitive Sensor Array