Multi-way Data Analysis for Advanced Processing of EEG in Cognitive and Motor-related Tasks

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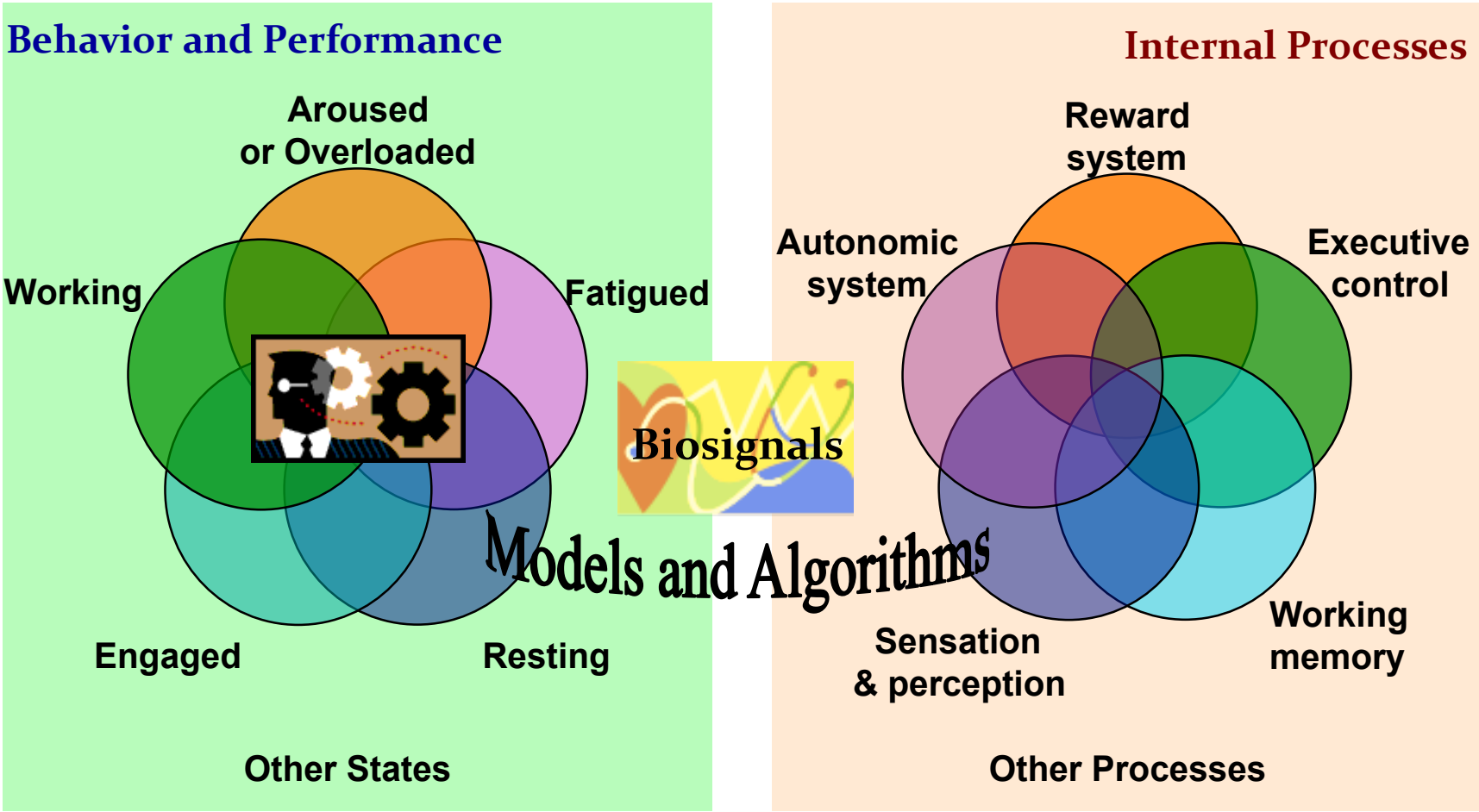
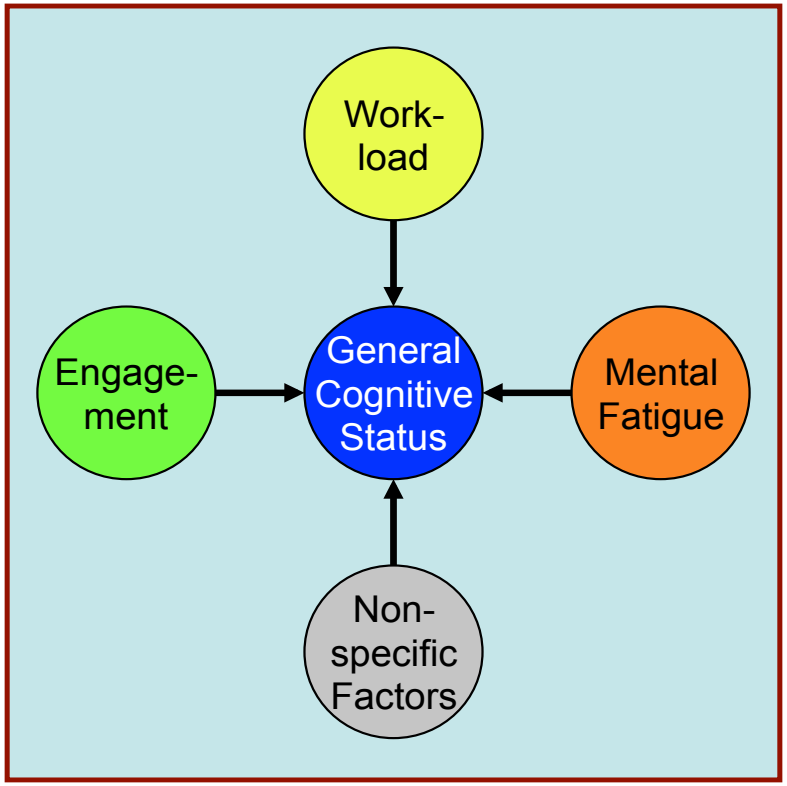
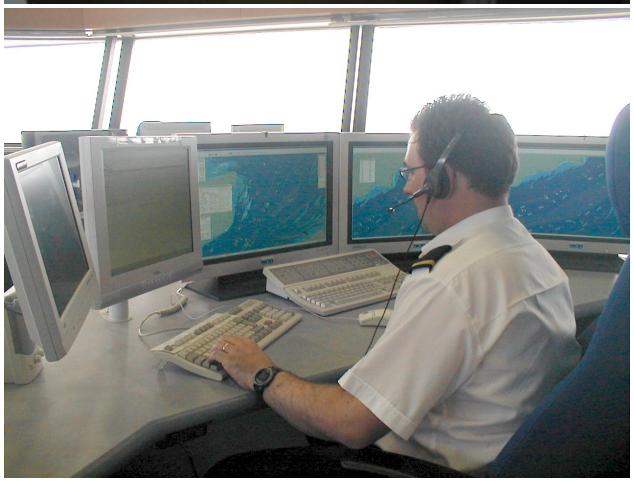
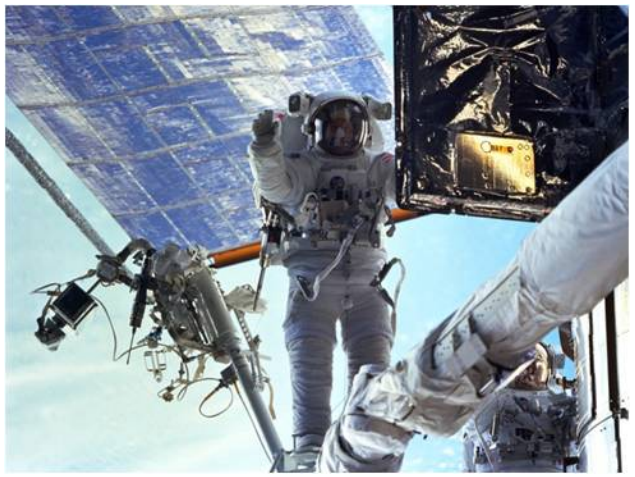

Behavior and Performance
Aroused
or Overloaded
Working
Fatigued
Engaged
Resting
Other States
Biosignals
Models and Algorithms
Internal Processes
Reward
system
Autonomic
system
Executive
control
Sensation
& perception
Working
memory
Other Processes



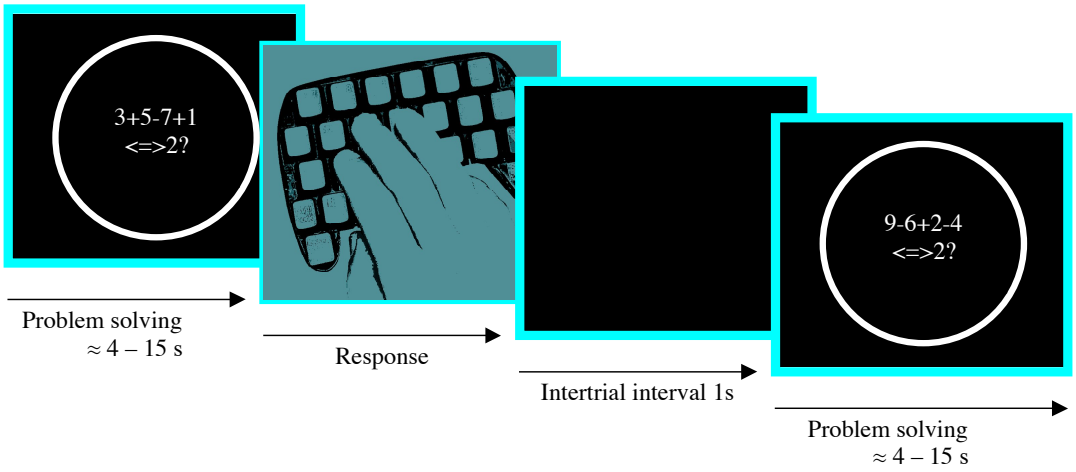
- Engagement: selection of a task as the focus of attention and effort
- Workload: significant commitment of attention and effort to task
- Overload: task demands outstrip performance capacity
- Mental Fatigue: desire to withdraw attention and effort from a task

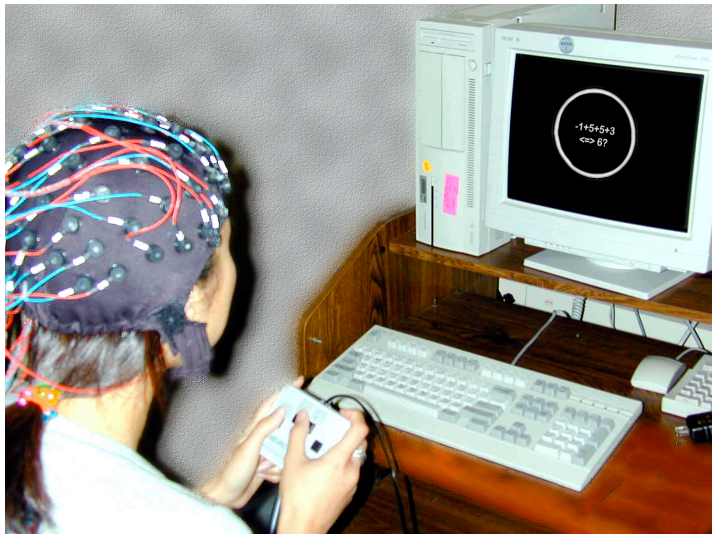
- Critical safety, high workload, stressful, etc., environments





Experiment 1 - Mental Fatigue Monitoring





- Continuos performance of mental arithmetic for up to three hours

Trejo, Rosipal, et al. (2001-2004), NASA Ames

Experiment 2 - Lateralized Attention Network Test (LANT)

- The LANT was developed for measuring selective attention in each hemisphere. It includes:
  - *Conflict Resolution*
  - *Spatial Orienting*
  - *Alerting*
  - *Inhibition of Return*
- The LANT is sensitive to individual differences
  - *In Handedness and in Gender*
  - *In Personality. E.g., anxiety, empathy*
  - *In Social Relations, e.g.,*
    - *Sensitivity to discrimination*
    - *Conditions of teamwork*
- Performance can be optimized by:
  - *Adapting to the complementary diurnal rhythms of the attentional networks in the two hemispheres*
  - *Providing individually emotionally relevant background and spatial cues*
  - *Modulating the attention networks of the two hemispheres, e.g., by using*
    - *meditation / relaxation*
    - *EEG Biofeedback*

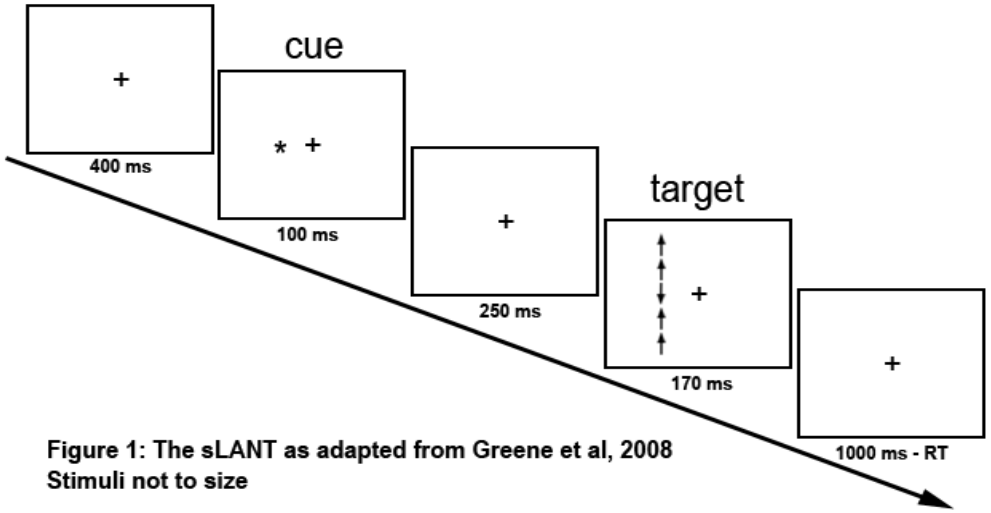
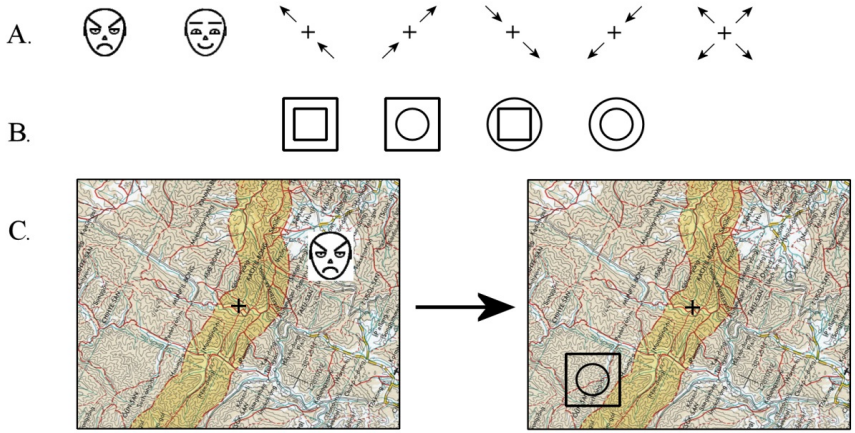


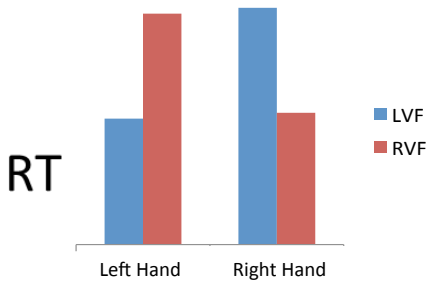
Figure 1: The sLANT as adapted from Greene et al, 2008
Stimuli not to size

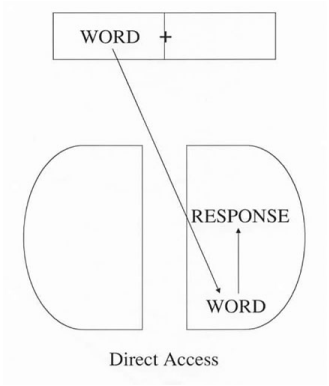


Zaidel, Trejo, Rosipal (2010-2014), PDT, UCLA

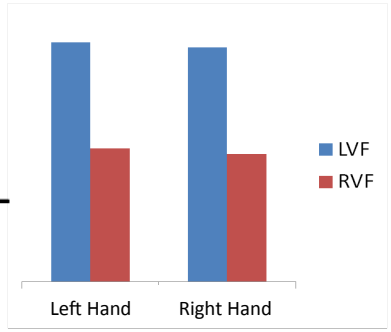
- Left and right brain hemispheres processes task information differently, independently and simultaneously
- Modes of hemispheric interaction
  - There is complementary hemispheric specialization
    - The left hemisphere is linguistic, numerical, analytic, individualistic, non-conventional
    - The right hemisphere is visuo-spatial, synthetic, social, emotional
  - Complex tasks can be optimized by division of labor
  - When resources are limited each hemisphere can monitor errors in the other
  - Conditions of overload and fatigue can be ameliorated by modulating attention in the two hemispheres

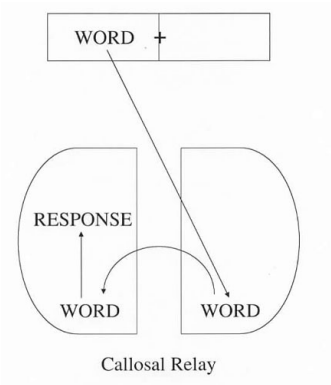
- Direct Access



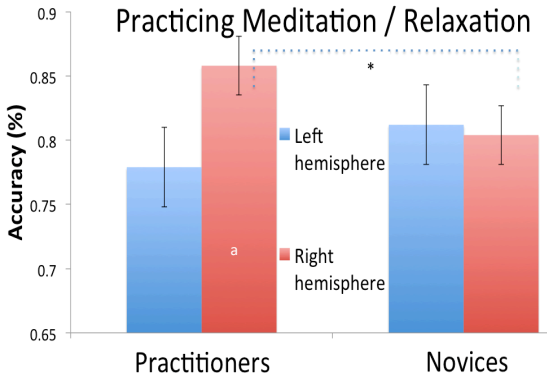


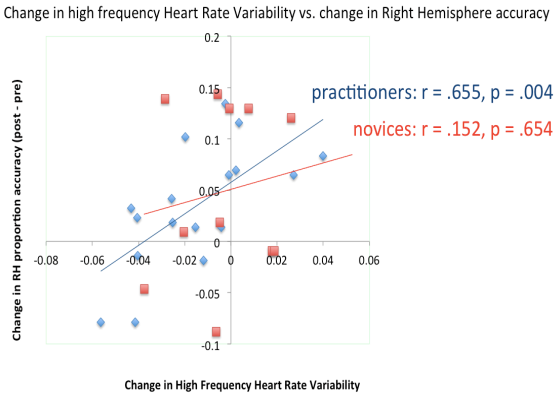
- Callosal Relay





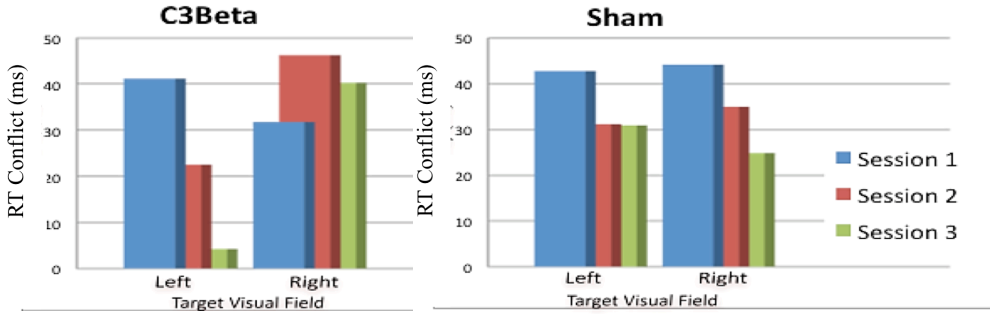
- Meditation / Relaxation



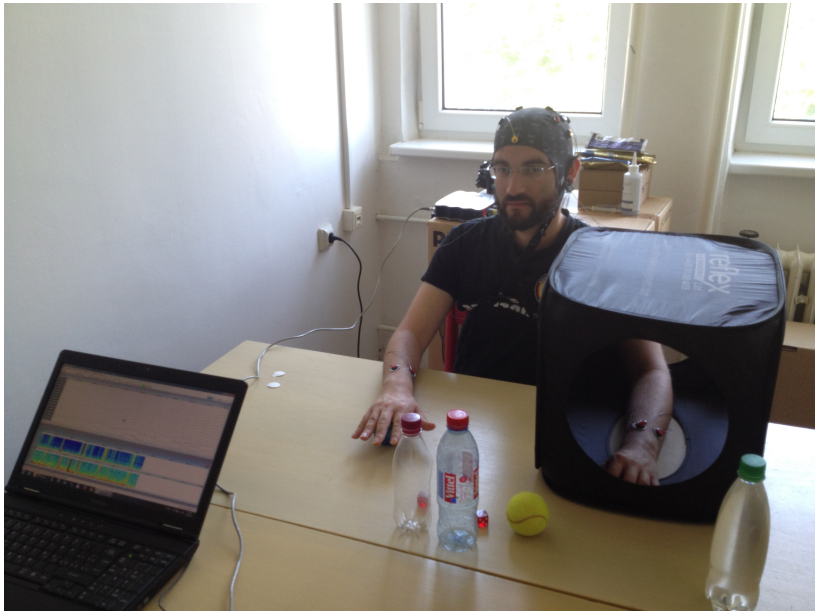


- EEG Biofeedback

Training Beta at C3 Selectively Reduced Conflict in the Right Hemisphere

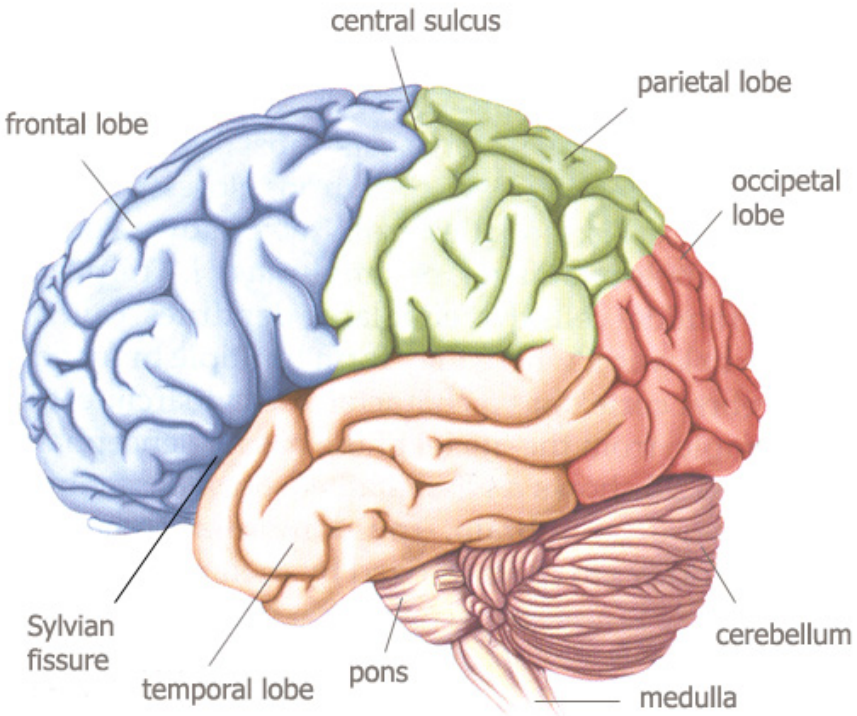


Experiment 3 - Motor Related Mirror-box Training



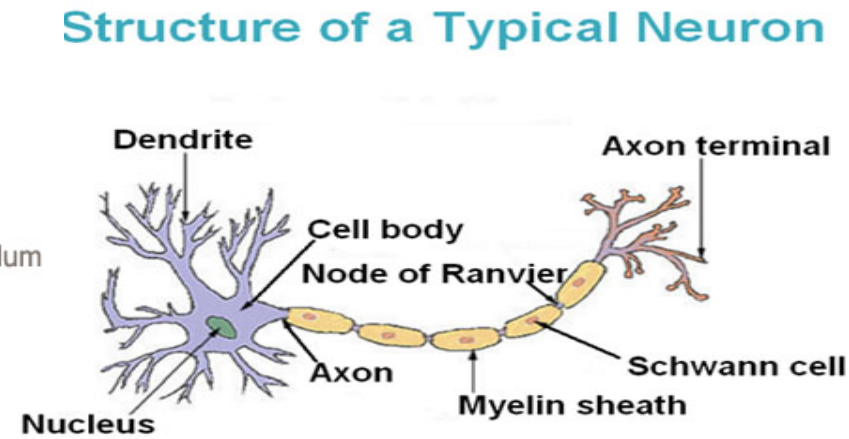
- A block of 10 different upper-arm and hand movements following physical training of subjects after stroke.
- Four blocks including mirror-box, blinded mirror-box, bimanual and single hand movements.
- Control group of healthy volunteers.

Rosipal et al. (2013-2017), SAS

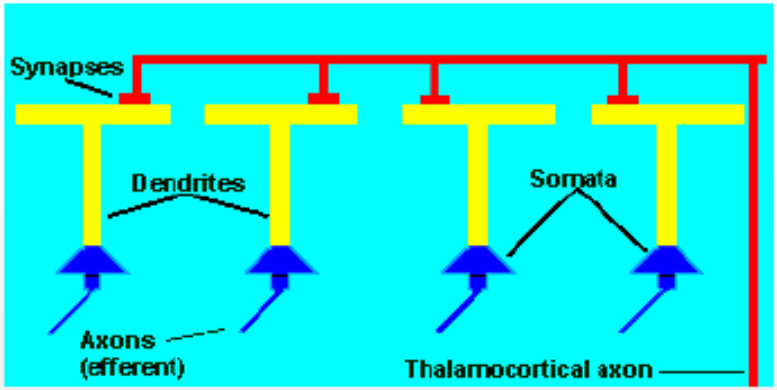


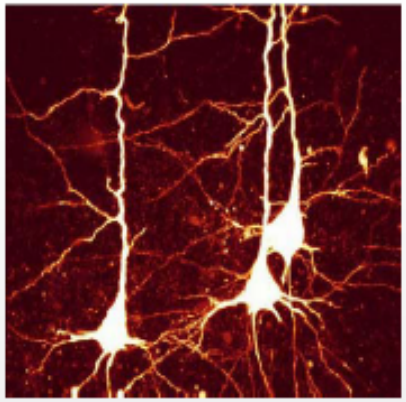
Cerebral Cortex

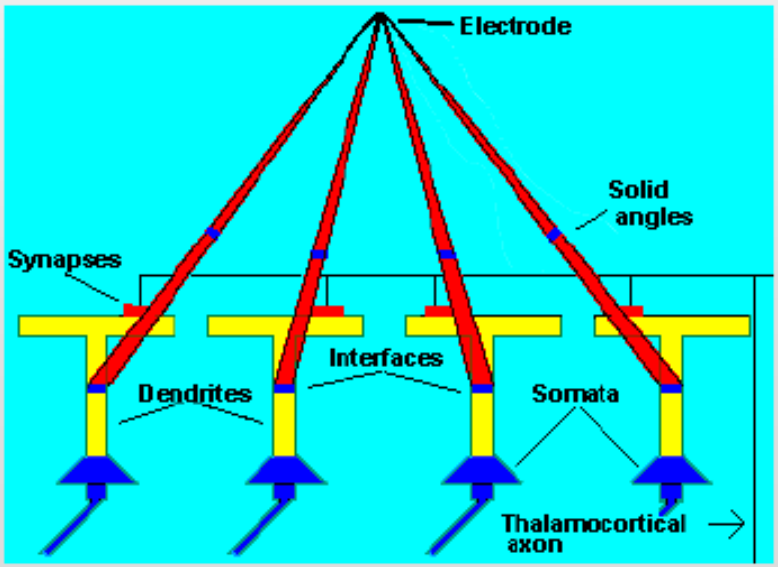
- the outermost layers of brain
- 2-4 mm thick (human)

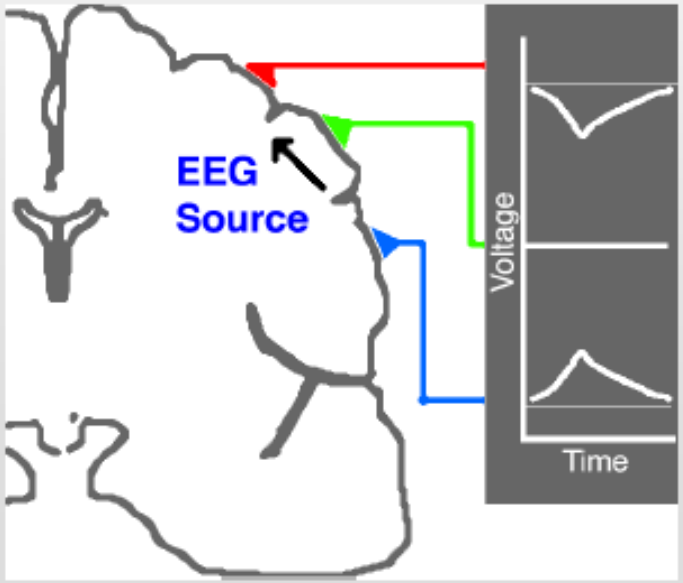


Data - EEG Sources



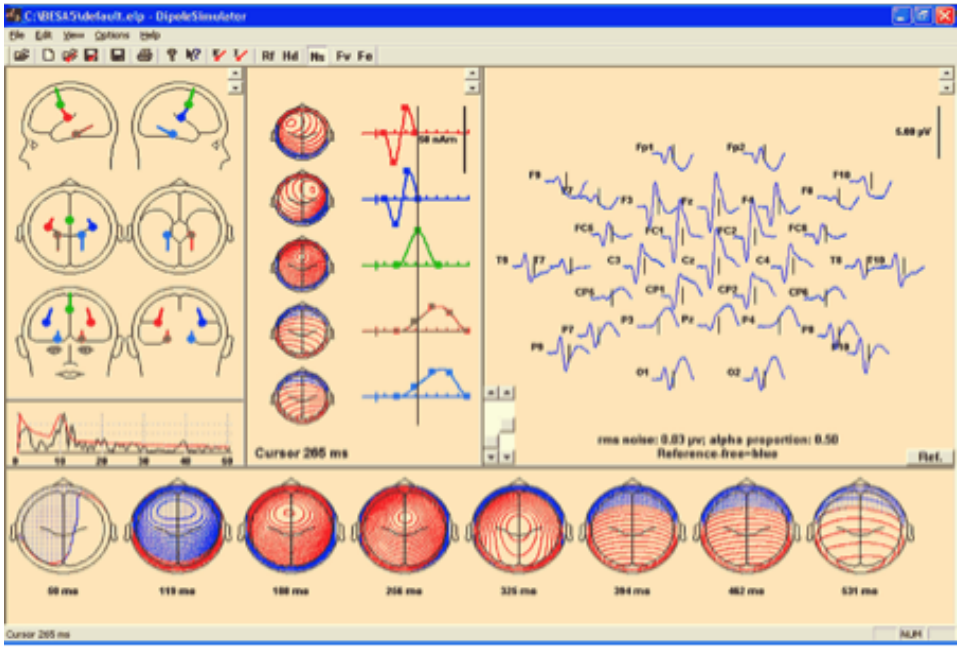


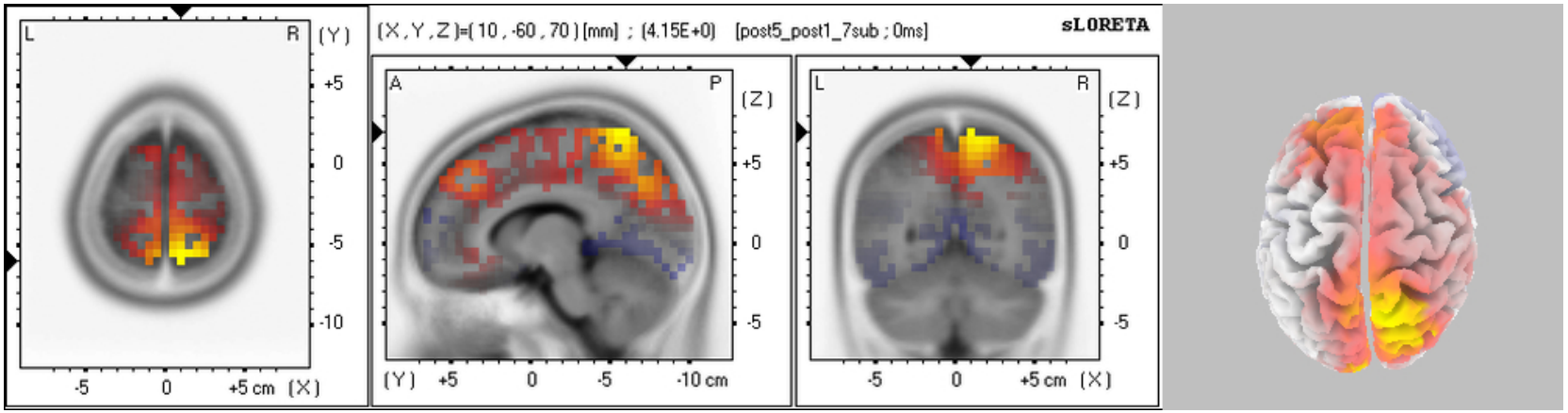




Data - EEG Sample

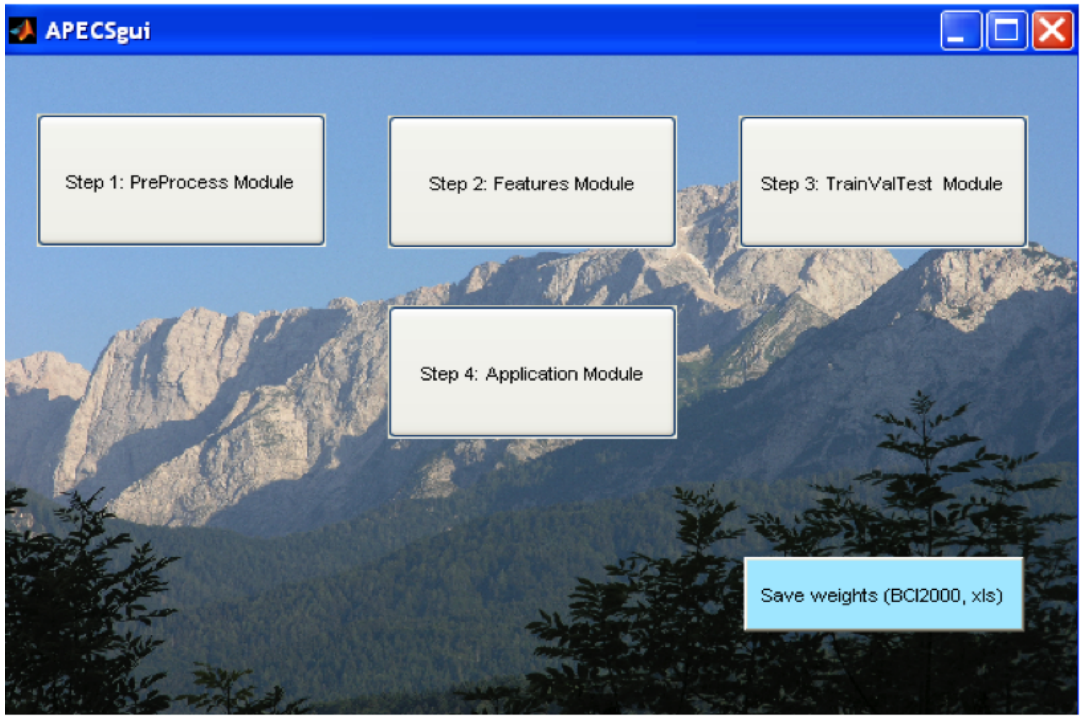
Forward ⇔ Inverse (cortical ⇔ scalp mapping)





Software:

proprietary m-codes developed by PDT, LLC, and subroutines from the N-way toolbox for Matlab (Andersson and Bro, 2000)



Rosipal, Trejo (2010-2014), PDT

- After standard pre-processing, EEG data segmented into epochs (usually 2 to 4 sec long)

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- Spectral representation: FFT, Welch, Thomson multitaper, etc. estimate of the power spectrum density; that is the distribution of power per unit frequency

$$P_{xx}(f) = F_x(f)F_x^*(f)$$

where $F_x(f)$ is the Fourier transform of the signal x and $*$ indicates the complex conjugate

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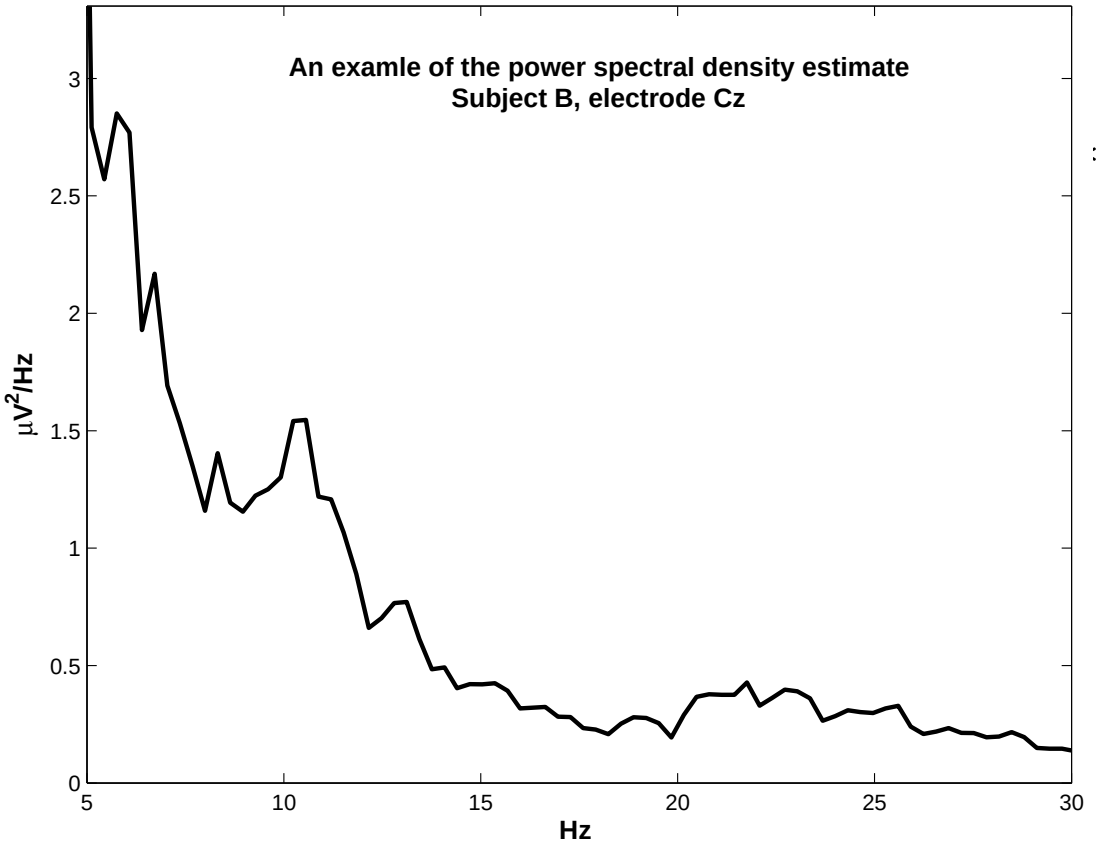
- Spectral representation: FFT, Welch, Thomson multitaper, etc. estimate of the power spectrum density; that is the distribution of power per unit frequency

where $F_x(f$ indicates th

- Example:

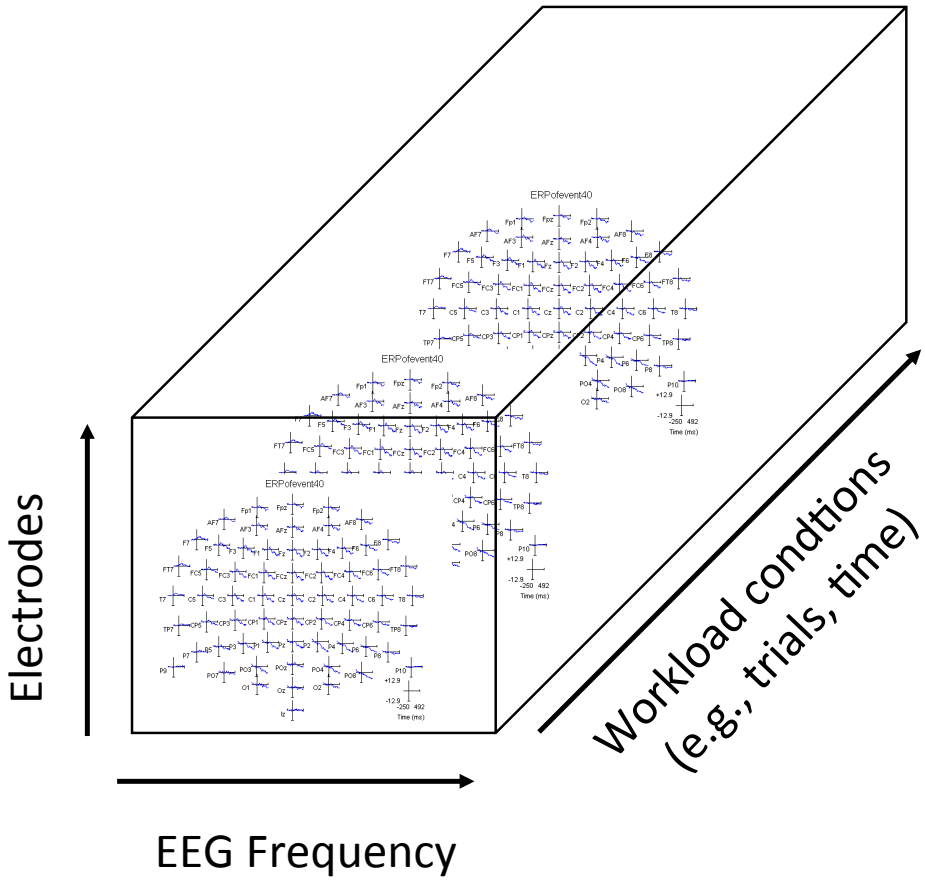


- Coherence representation: Cross power spectra density $P_{xy}(f)$,

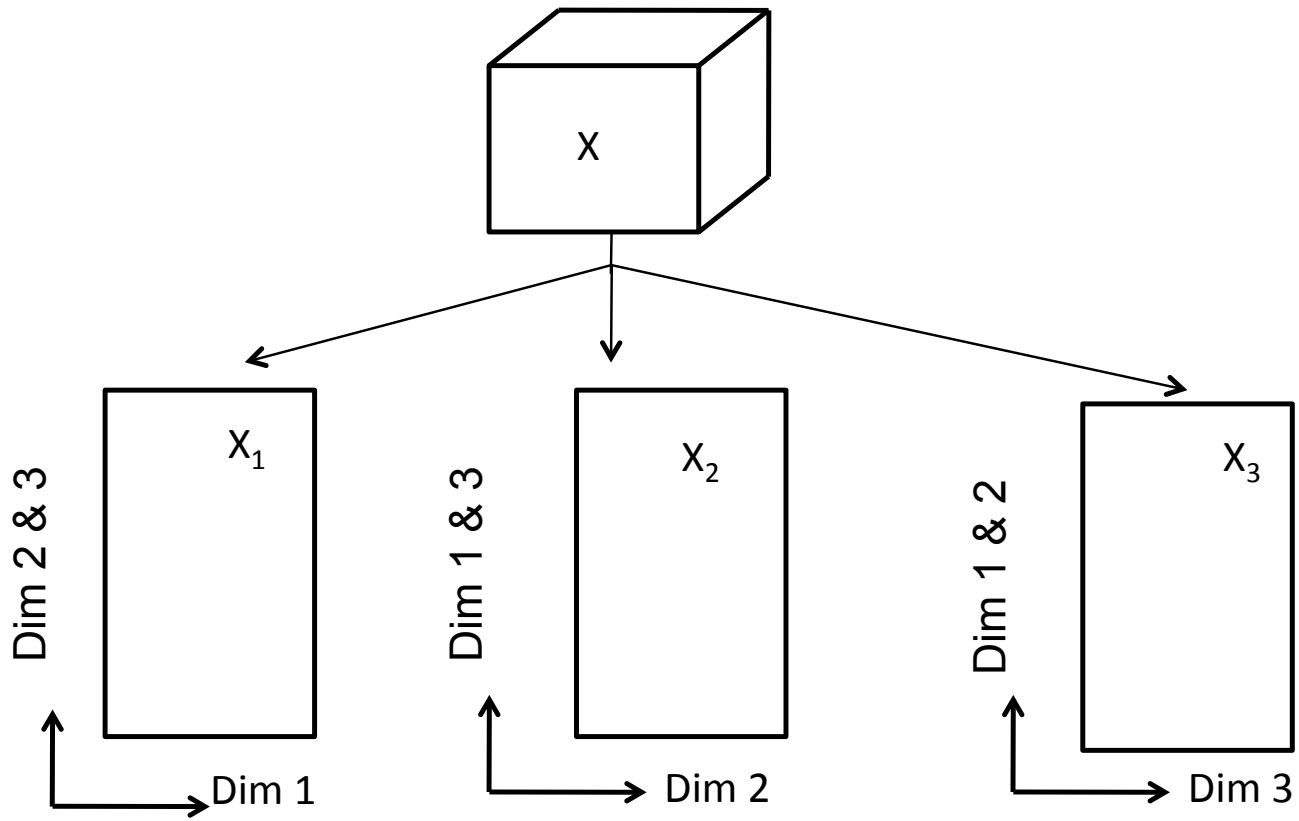
$$P_{xy}(f) = F_x(f)F_y^*(f)$$

or magnituted squared (coherence)

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)}$$



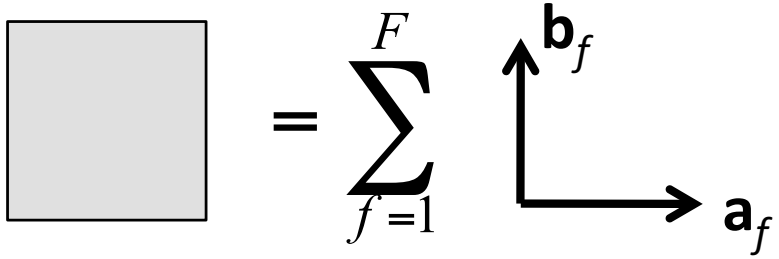
- Data matrix construction: $\mathbf{X}_{(I \times J \times K)}$
  I - time segments
  J - electrodes or electrode pairs
  K - PSD or CSD (coherences)



- Representing all experimental factors in one dimension & observations (trials) in second dimension
- Contrast each dimension vs. pair of the other two

Factor Analysis

$$x_{ij} = \sum_{f=1}^{F} a_{if} b_{jf} + e_{ij}$$



Principal Component Analysis (PCA)

$$e_{ij} = 0$$

Partial Least Squares

- ***Data sets:***

  $\mathbf{X}$ $(n_{objects} \times N_{variables})$

  $\mathbf{Y}$ $(n_{obkjects} \times M_{responses})$

- ***Bilinear decomposition:***

  $\mathbf{X} = \mathbf{T}\mathbf{P}^T + \mathbf{E}$

  $\mathbf{Y} = \mathbf{U}\mathbf{Q}^T + \mathbf{F}$

  where:

  T,U matrices of score vectors (LV, components)

  P,Q matrices of loadings

  E,F matrices of residuals (errors)

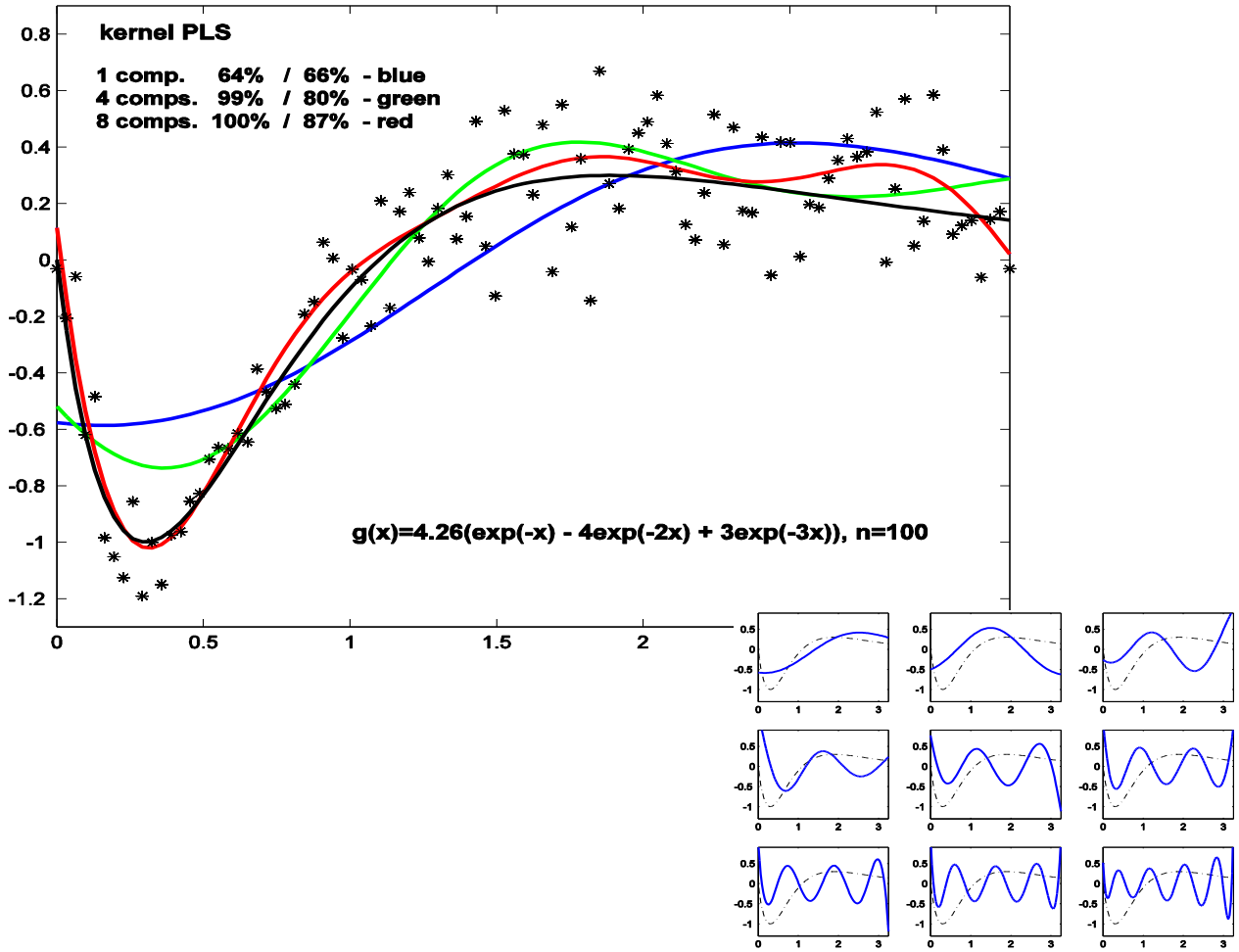
- ***Criterion:***

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

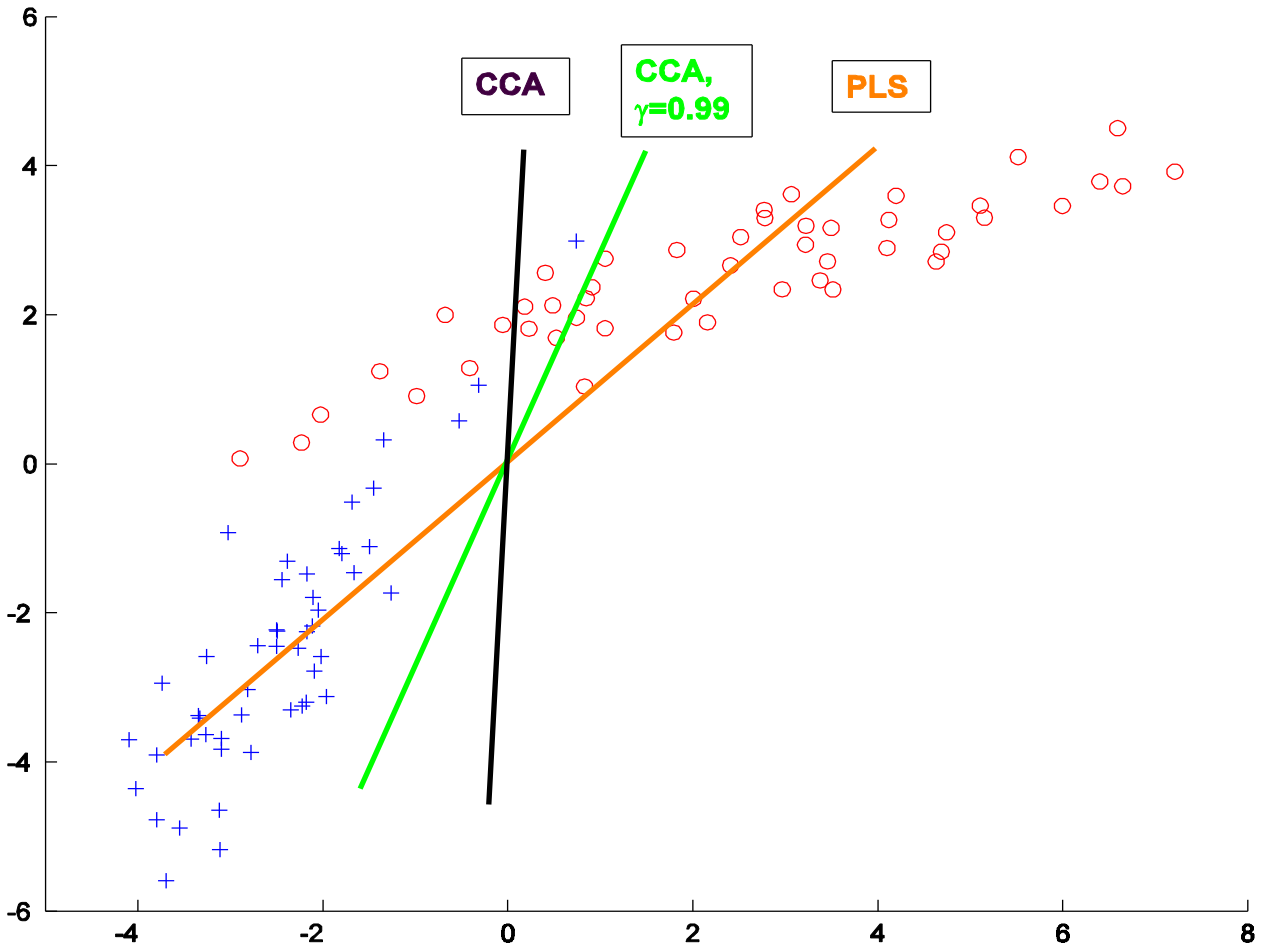
  $= var(\mathbf{Xw})[corr(\mathbf{Xw}, \mathbf{Yc})]^2 var(\mathbf{Yc})$

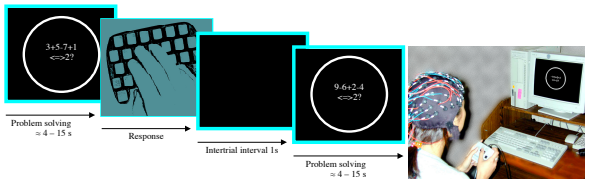
  $= [cov(\mathbf{t},\mathbf{u})]^2$

Bilinear Unfolding - (Kernel) PLS - Regression



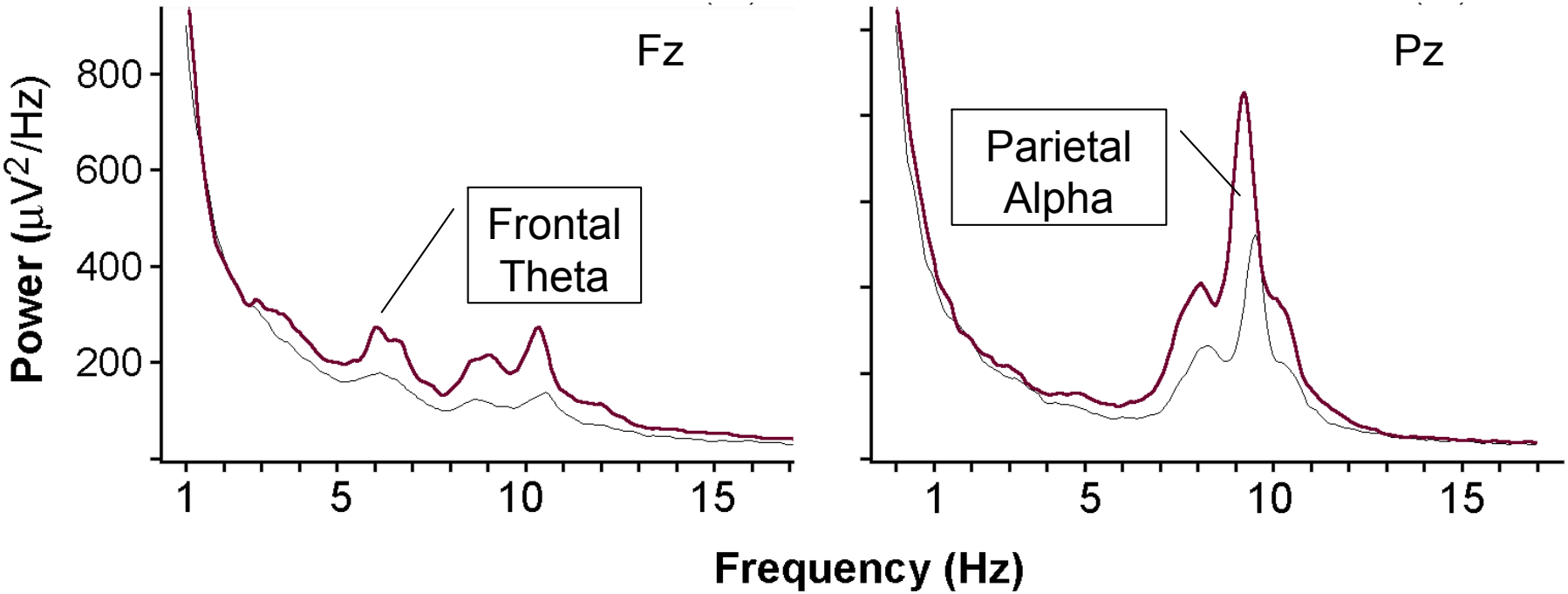
Rosipal,R & Trejo, LJ (2001). Kernel Partial Least Squares Regression in Reproducing Kernel Hilbert Space. Journal of Machine Learning Research, 2(Dec):97-123.


CCA
CCA,
γ=0.99
PLS
6
4
2
0
-2
-4
-6
-4
-2
0
2
4
6
8

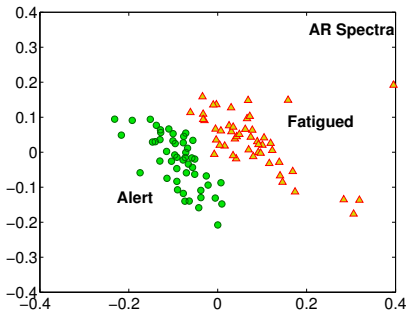


Black= First 15 min

Red=Last 15 min

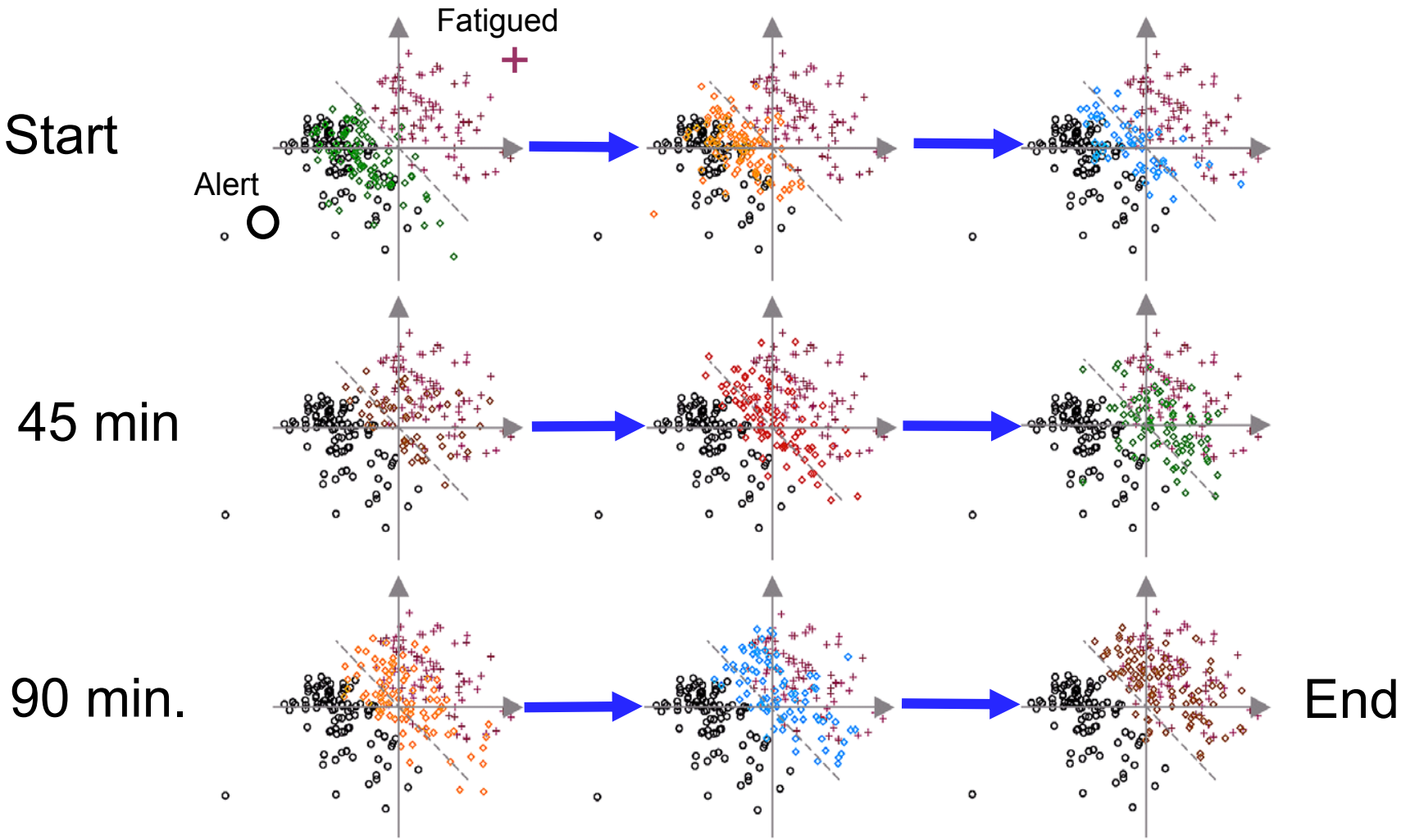


Mental Fatigue - PLS Analysis

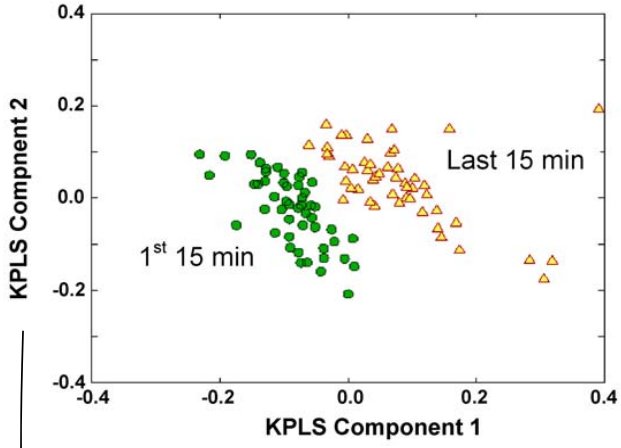


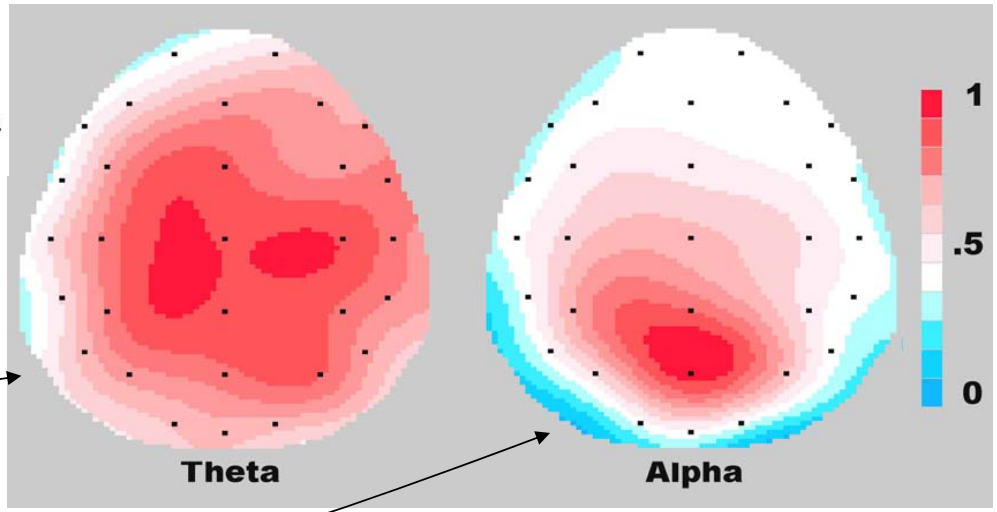
$$\mathbf{X} = \mathbf{TP}^T + \mathbf{F}$$
$$\mathbf{Y} = \mathbf{UQ}^T + \mathbf{G}$$

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


Fatigued
Start
Alert
45 min
90 min.
End

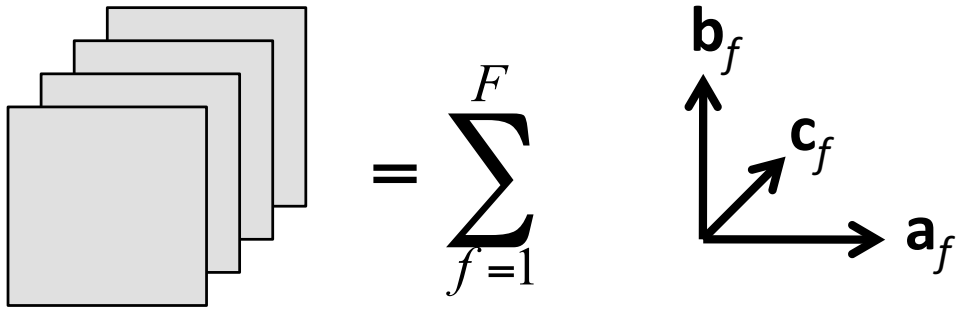
Mental Fatigue - PLS Analysis





PARAFAC

$$x_{ijk} = \sum_{f=1}^{F} a_{if} b_{jf} c_{kf} + e_{ijk}$$



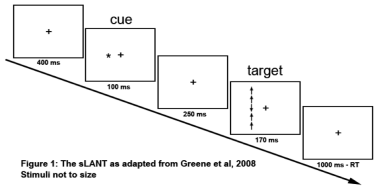
- The PARAFAC model with F factors: decomposition of the data matrix $\mathbf{X}$ using three loading matrices, $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ with elements a_{if}, b_{jf}, and c_{kf}

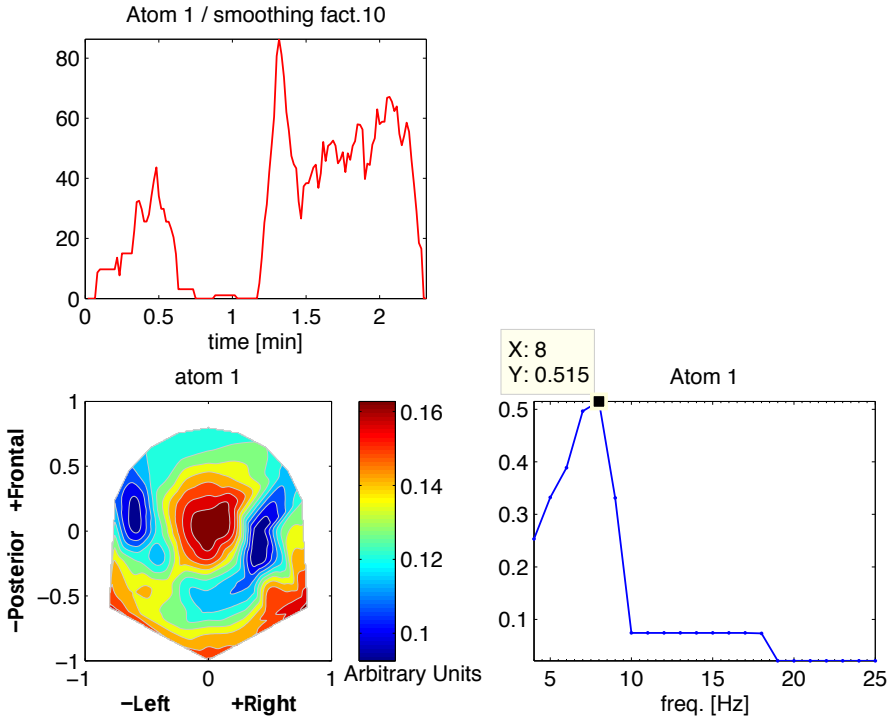
$$x_{ijk} = \sum_{f=1}^{F} a_{if} b_{jf} c_{kf} + \epsilon_{ijk}$$

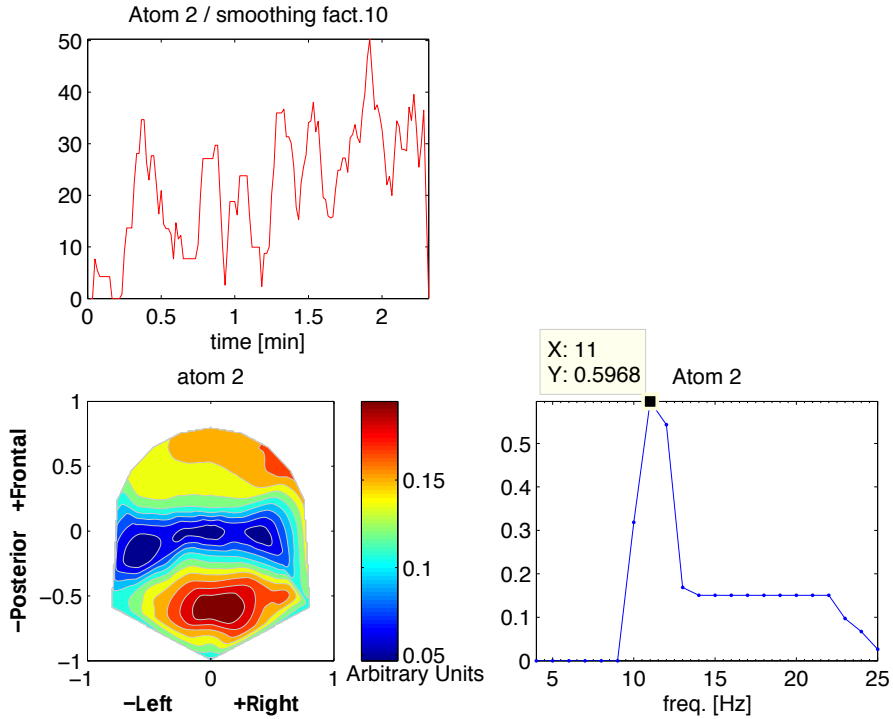
- The criterion:

$$\min_{a_{if}, b_{jf}, c_{kf}} = \| x_{ijk} - \sum_{f=1}^{F} a_{if} b_{jf} c_{kf} \|^2$$

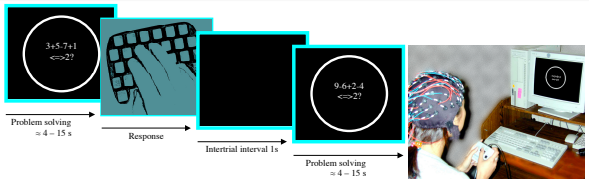
Multi-way Analysis





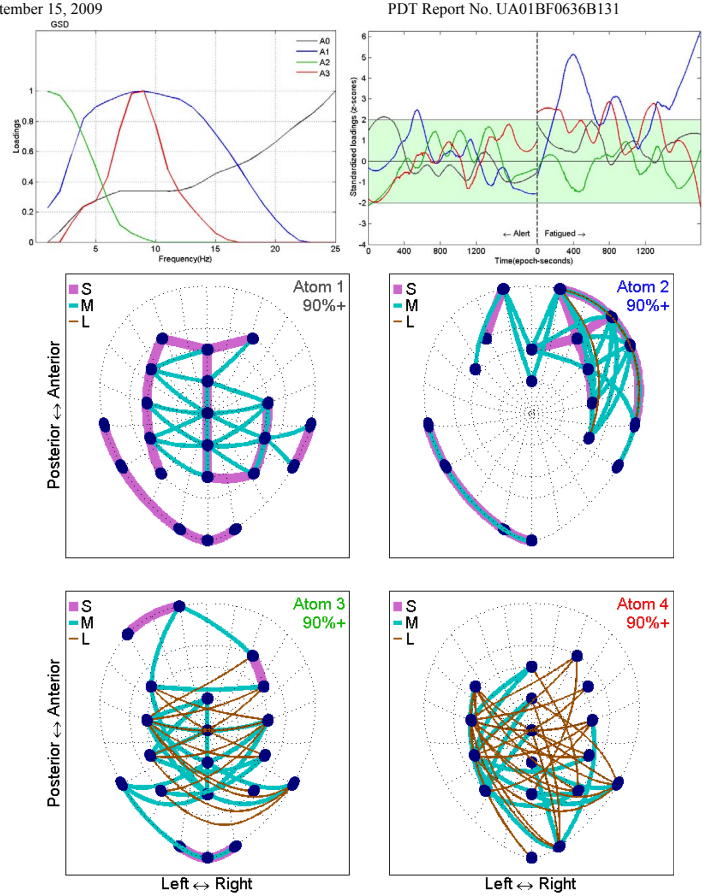


Mental fatigue - PARAFAC coherence analysis

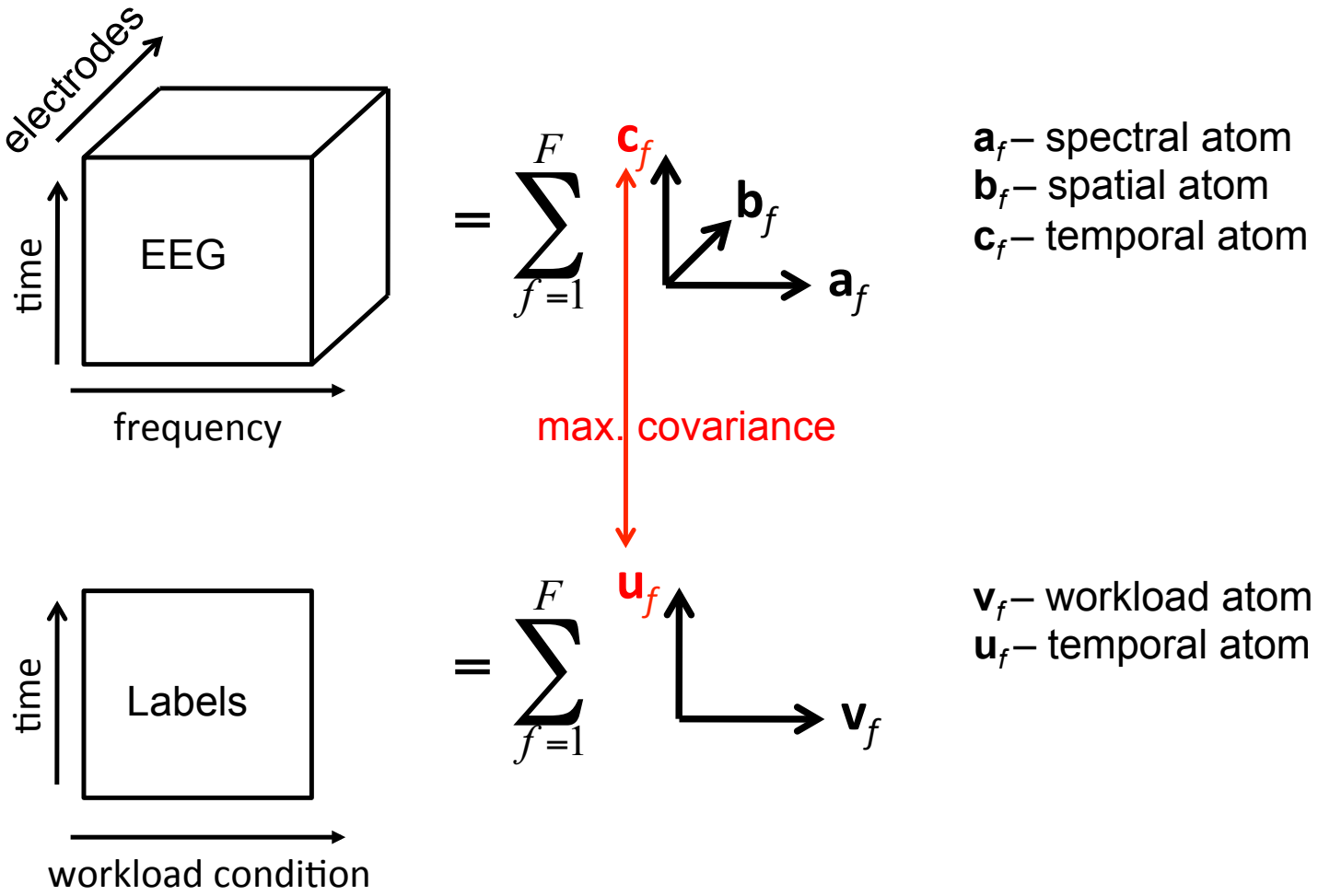


APECS Final Report
September 15, 2009

ARO Contract No. W911NF08CO121
PDT Report No. UA01BF0636B131



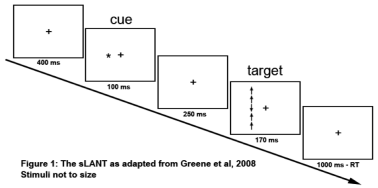
Multi-way PLS (n-PLS)



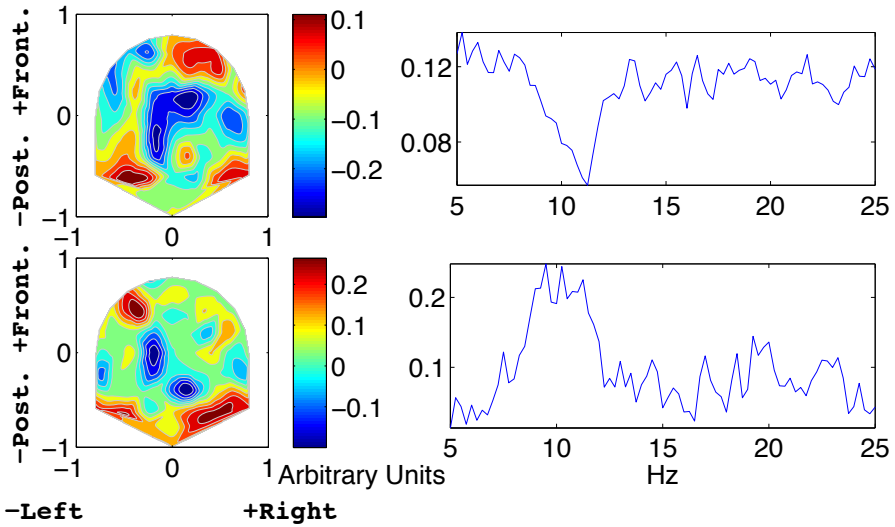
$\mathbf{a}_f$ – spectral atom
$\mathbf{b}_f$ – spatial atom
$\mathbf{c}_f$ – temporal atom

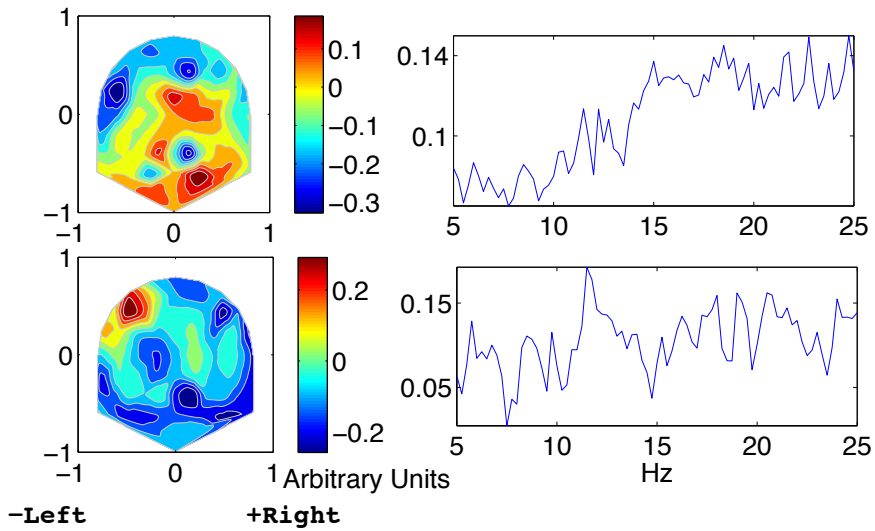
$\mathbf{v}_f$ – workload atom
$\mathbf{u}_f$ – temporal atom

NPLS Fatigue Prediction



Sub 107 / Day 1 + Day 2/ NPLS 4





NPLS Fatigue Prediction

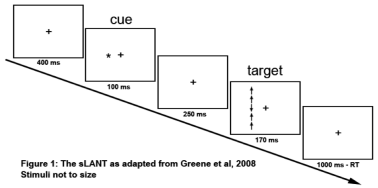
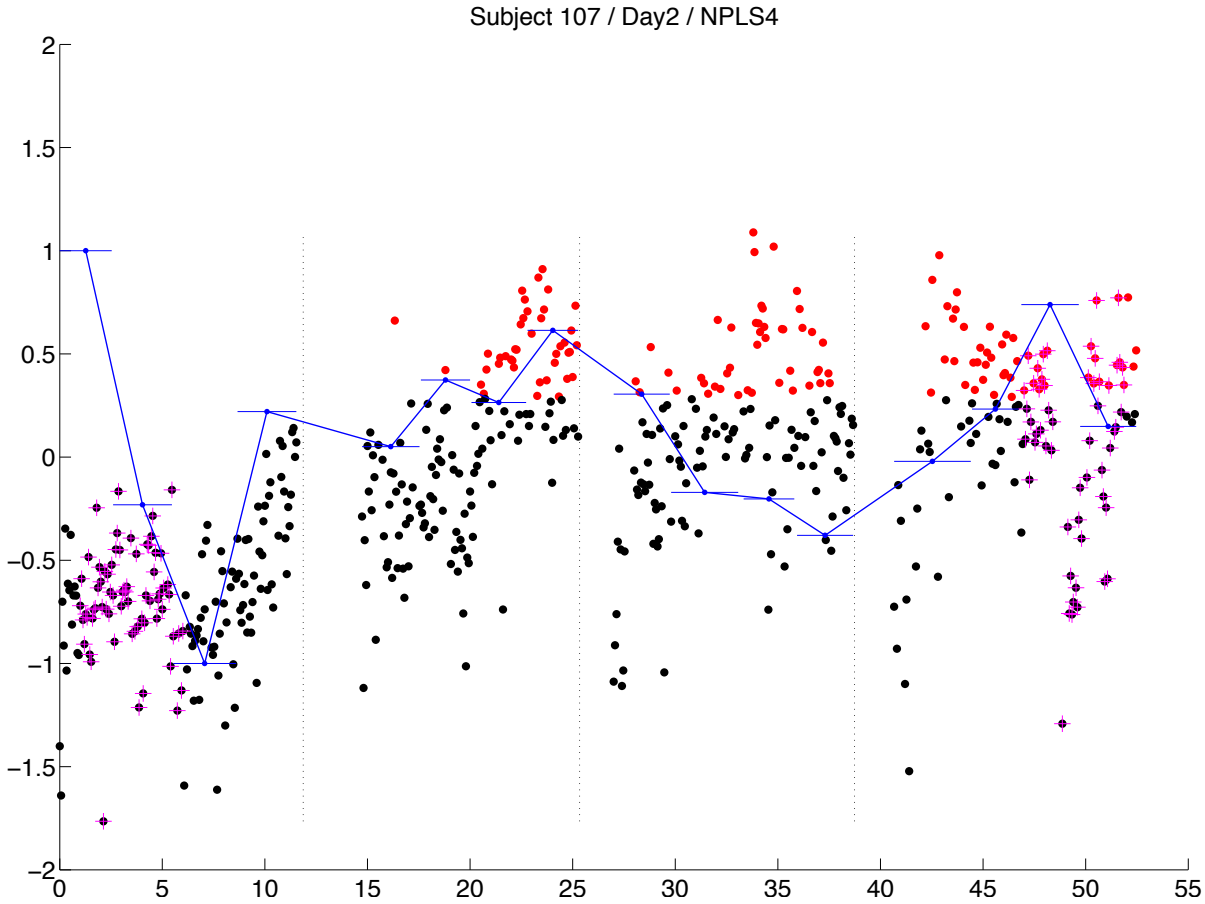
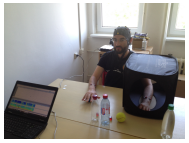
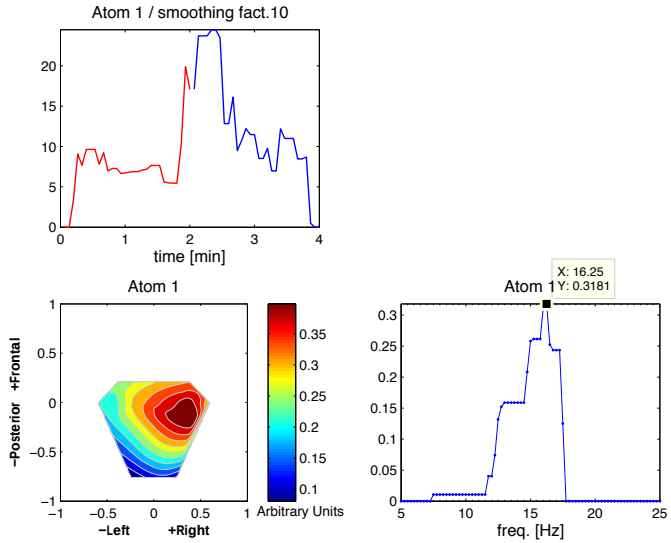


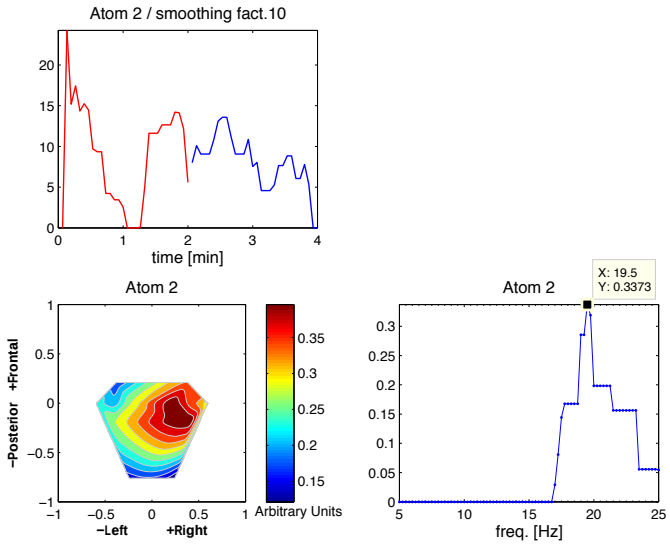
Figure 1: The sLANT as adapted from Greene et al, 2008
Stimuli not to size

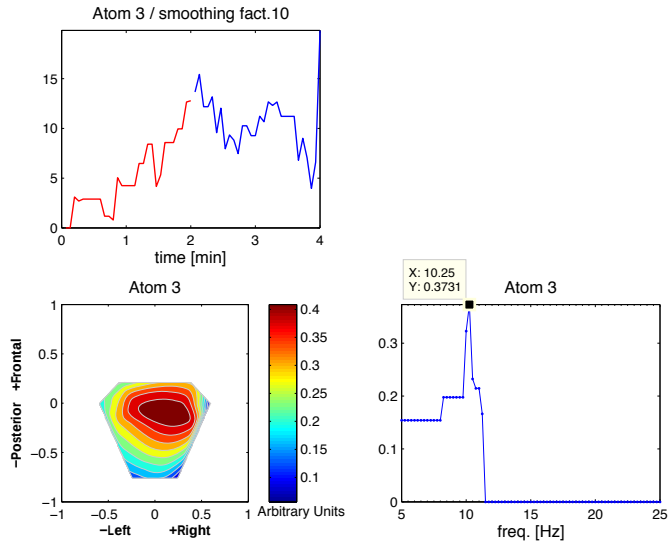




- Atomic PARAFAC decomposition of eyes-open two minutes rest blocks prior and after mirror-box training.







Multi-way Analysis and Inverse Cortical Mapping - A Way to Stabilize and Train BCI?

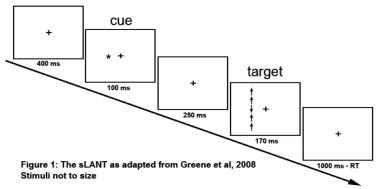
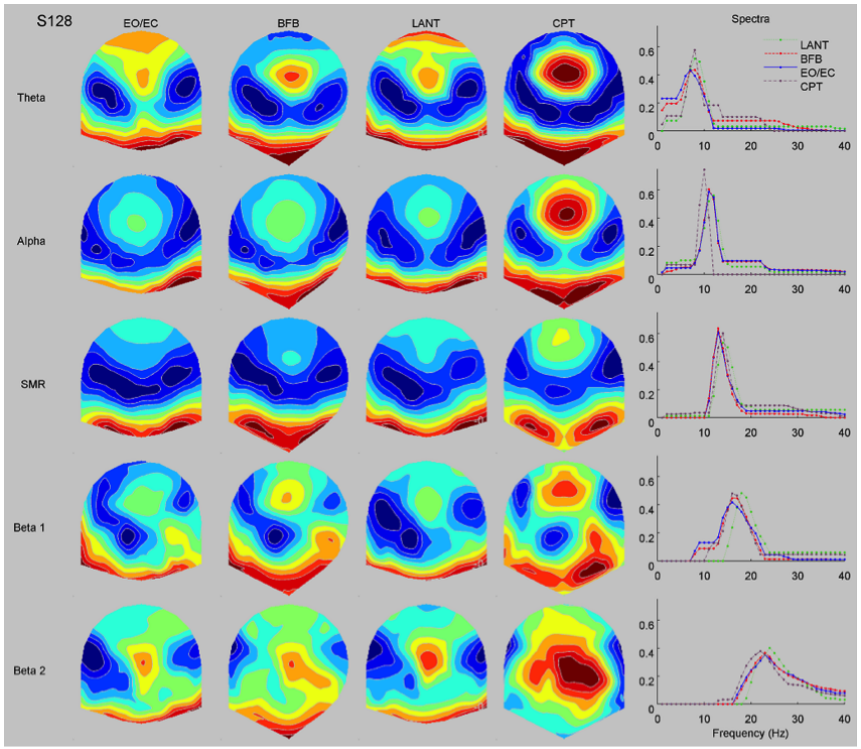
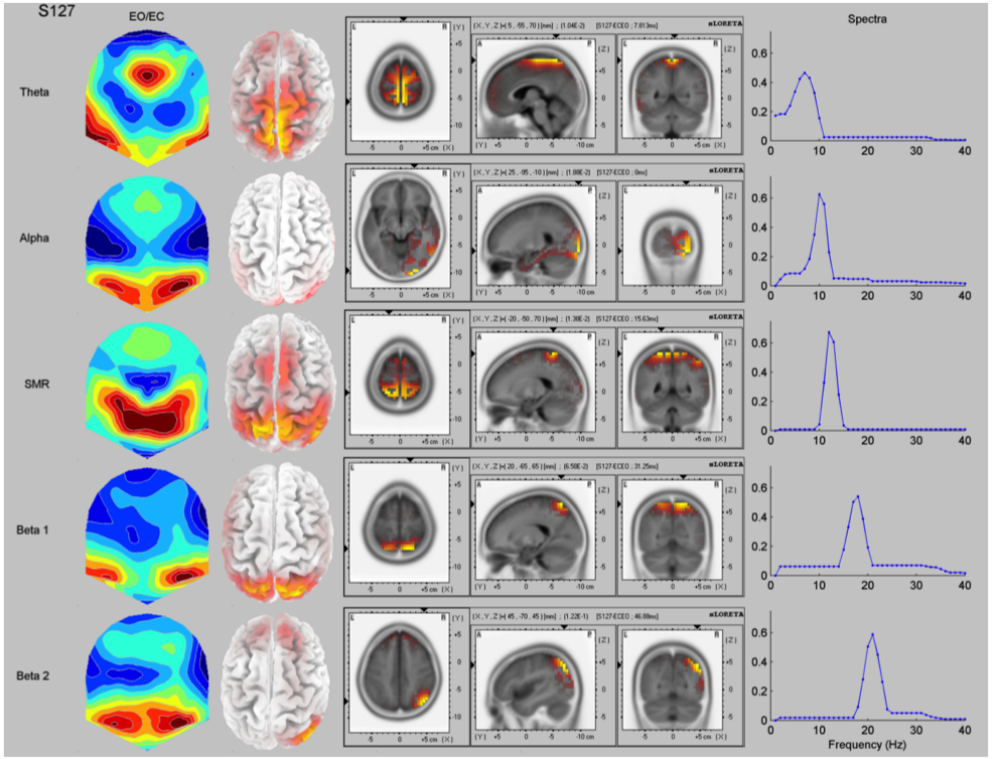


Figure 1: The sLANT as adapted from Greene et al, 2008
Stimuli not to size





- Results show that mental fatigue (workload, engagement - not presented here) can be tracked by EEG components isolated using PARAFAC or NPLS atoms.
- The mental fatigue related atoms were found to be remarkably stable.
- We observed similarly promising and remarkable results on several different data sets monitoring cognitive. status
- The concept of multi-way analysis will be implemented in BCI-robot-assisted system design for neurorehabilitation of patients after stroke.

- `http://aiolos.um.savba.sk/~roman/`

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  - Rosipal, R., Trejo, L. J., Nunez, P. L. (2009). Application of Multi-way EEG Decomposition for Cognitive Workload Monitoring. In Proceedings of the 6th International Conference on Partial Least Squares and Related Methods, Vinzi V.E, Tenenhaus M., Guan R. (eds.), Beijing, China, pp. 145-149, 2009.
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