Multi-way Data Analysis for Advanced Physiological Estimation of Cognitive Status

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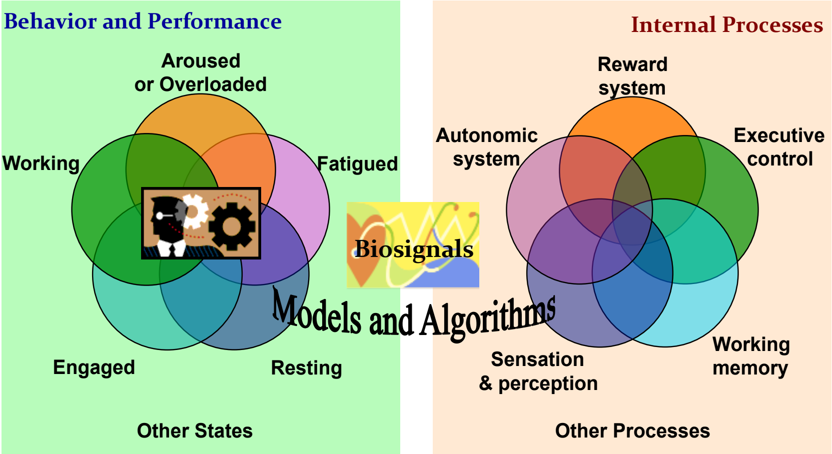
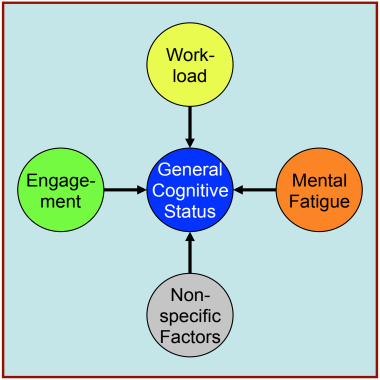
Estimation of Cognitive Status



Useful Definitions



- Engagement: selection of a task as the focus of attention and effort

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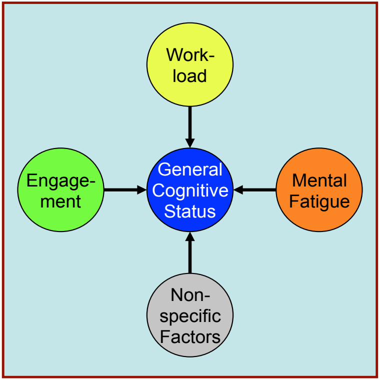

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- Workload: significant commitment of attention and effort to task

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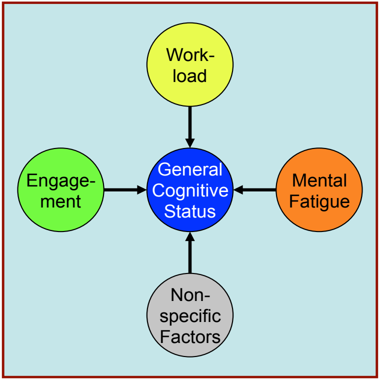

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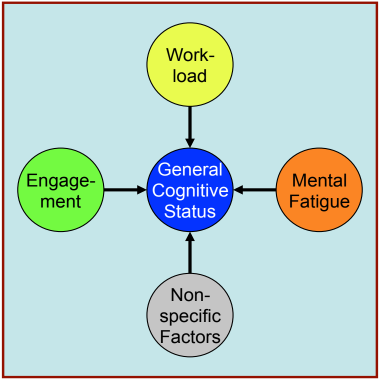
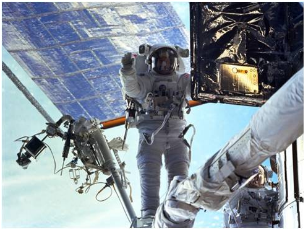


- Engagement: selection of a task as the focus of attention and effort
- Workload: significant commitment of attention and effort to task
- Overload: task demands outstrip performance capacity
- Mental Fatigue: desire to withdraw attention and effort from a task

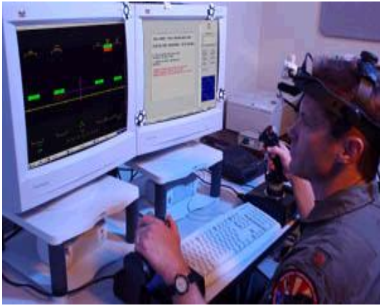
Why to monitor cognitive status?

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



Experiments - (A) Cognitive Workload Monitoring

- Uninhabited Air Vehicle (UAV) control



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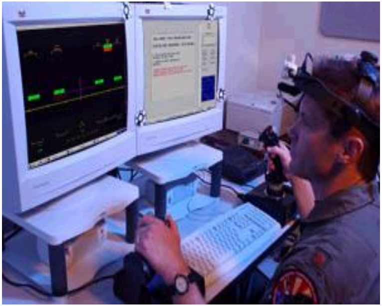

- Trained subjects were monitoring several UAVs as they flew a preplanned mission; processing SAR images (synthetic aperture radar), vehicle health control, etc.

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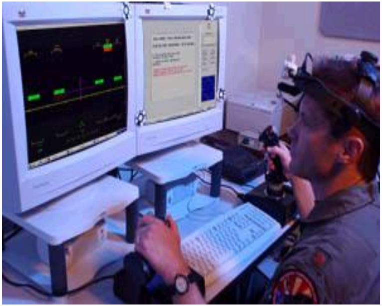
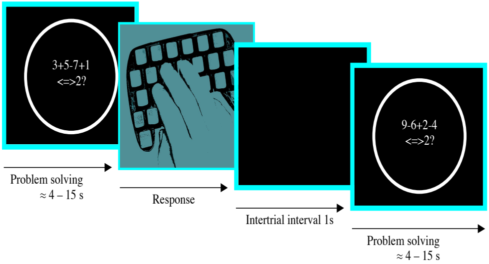
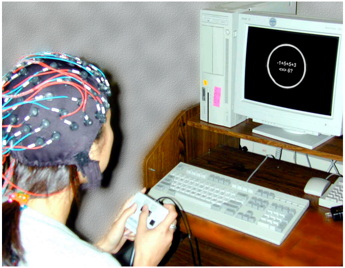


- Trained subjects were monitoring several UAVs as they flew a preplanned mission; processing SAR images (synthetic aperture radar), vehicle health control, etc.
- Different task conditions were used to control cognitive workload levels

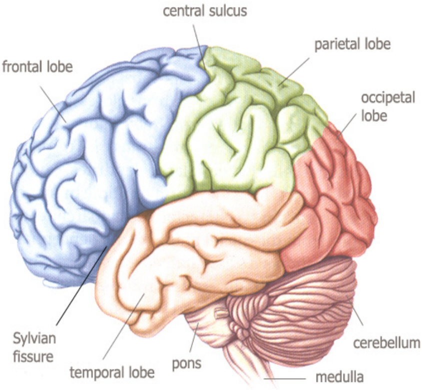
Experiments - (B) Mental Fatigue Monitoring





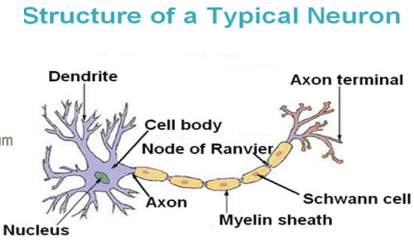
- Continuos performance of mental arithmetic for up to three hours

Data - Electroencephalogram (EEG)

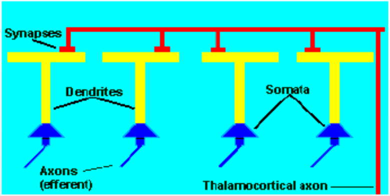


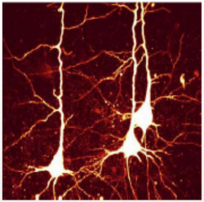
Cerebral Cortex

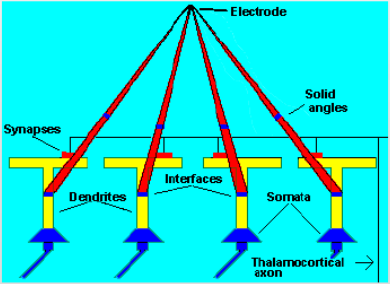
- the outermost layers of brain
- 2-4 mm thick (human)

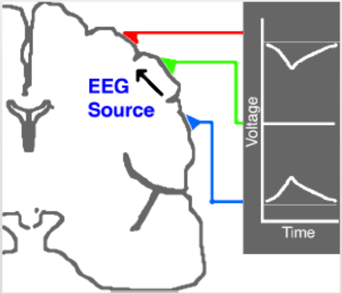


Data - EEG Sources









Data - EEG Sample

Data - Multi-modal Multi-Sensor

- ECG - hear rate, heart rate variability
- EOG and eyes control - hEOG, vEOG movements, blinks, pupil diameter
- EMG
- Skin conductance, SCR, GCR
- Videotaped recordings
- Response time, Correctness of responses
- Subjective responses and questionnaires
- etc.

Spectral EEG Data Representation

- Data were segmented into epochs (usually 2 sec long)

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- Spectral representation: Thompson multitaper 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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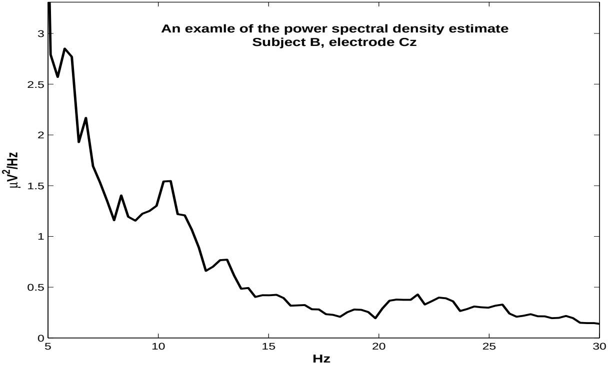
$$P_{xx}(f) = F_x(f)F_x^*(f)$$

where F_x
indicates

- Example:



Coherence EEG Data Representation

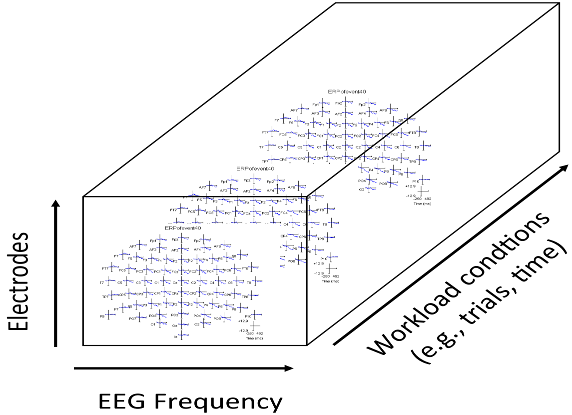
- Coherence representation: Cross power spectra density $P_{xy}(f)$,

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

or magnituted squared (coherence)

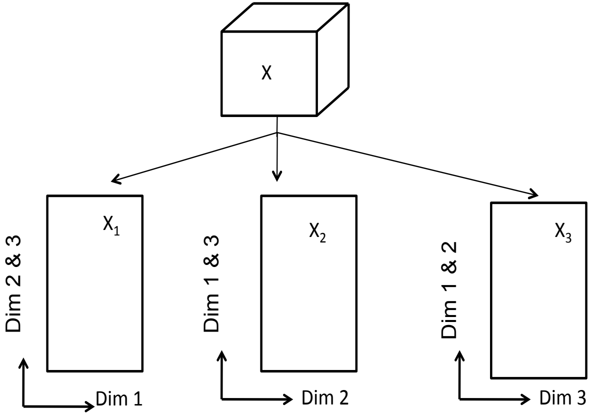
$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)}$$

Data Structure



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

Bilinear Unfolding

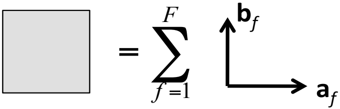


- Representing all experimental factors in one dimension & observations (trials) in second dimension
- Contrast each dimension vs. pair of the other two

Bilinear Unfolding - Modelling

Factor Analysis

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



Principal Component Analysis (PCA) $e_{ij} = 0$

Bilinear Unfolding - Regression/Classification

Partial Least Squares

- ***Data sets:***

  X $(n_{objects}\ x\ N_{variables})$
  Y $(n_{obkjects}\ x\ M_{responses})$

- ***Bilinear decomposition:***

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

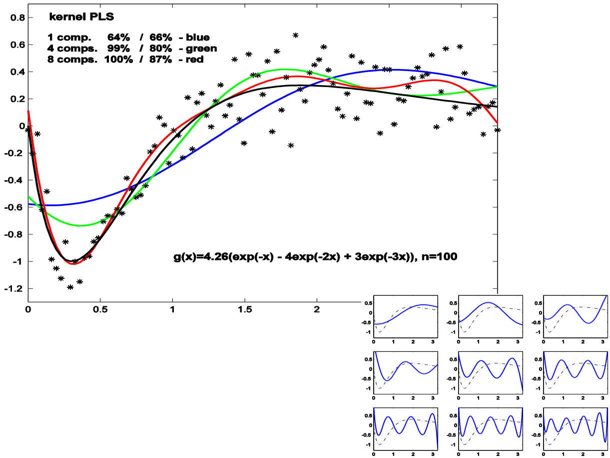
  where:

  T,U matrices of score vectors (LV, components)
  P,Q matrices of loadings
  E,F matrices of residuals (errors)

- ***Criterion:***

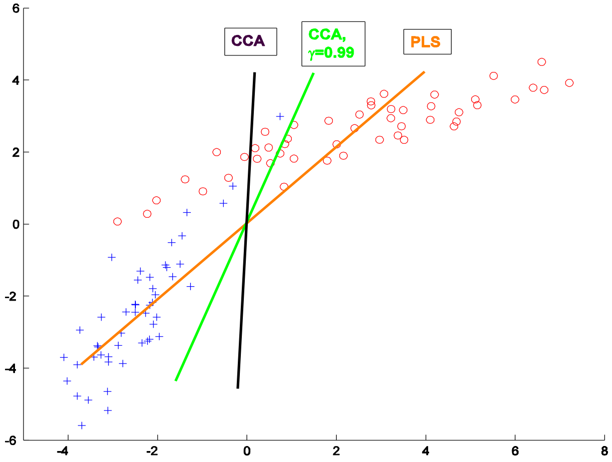
$$\max_{|r|=|s|=1}[cov(\mathbf{Xr}, \mathbf{Ys})]^2 = [cov(\mathbf{Xw}, \mathbf{Yc})]^2$$
$$= var(\mathbf{Xw})[corr(\mathbf{Xw}, \mathbf{Yc})]^2 var(\mathbf{Yc})$$
$$= [cov(\mathbf{t},\mathbf{u})]^2$$

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.

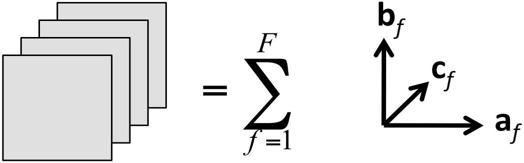
Bilinear Unfolding - (Kernel) PLS - Classification



Multi-way Analysis

PARAFAC

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



PARAFAC model

- 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}

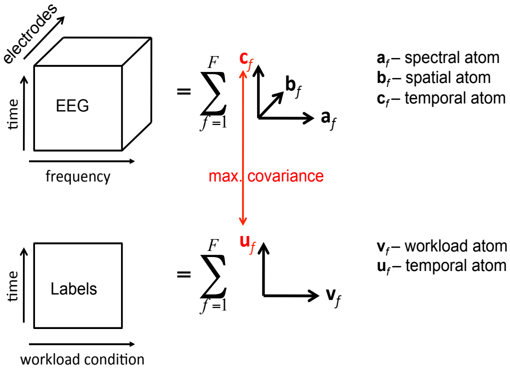
$$x_{ijk} = \sum_{f=1}^{F} a_{if} b_{jf} c_{kf} + \epsilon_{ijk}$$

- The criterion:

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

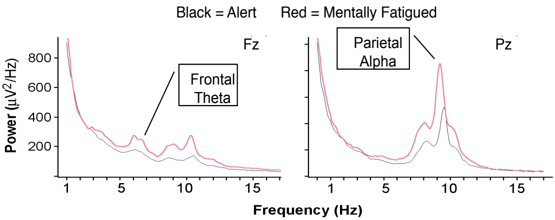
Multi-way PLS

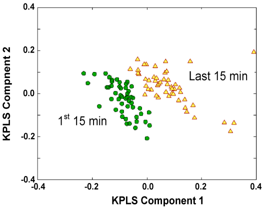
Multi-way PLS (n-PLS)

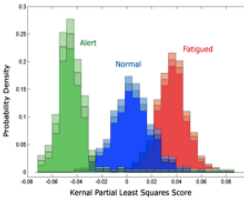


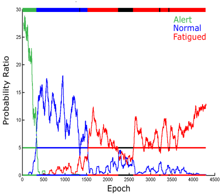
Software: proprietary m-codes developed by PDT, LLC, and subroutines from the N-way toolbox for Matlab (Andersson and Bro, 2000)

Mental Fatigue - PLS analysis









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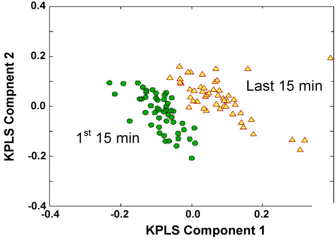
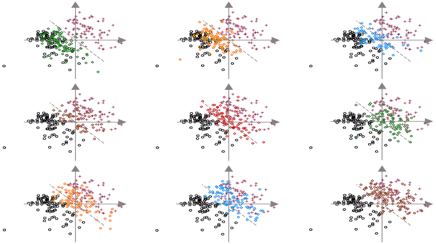
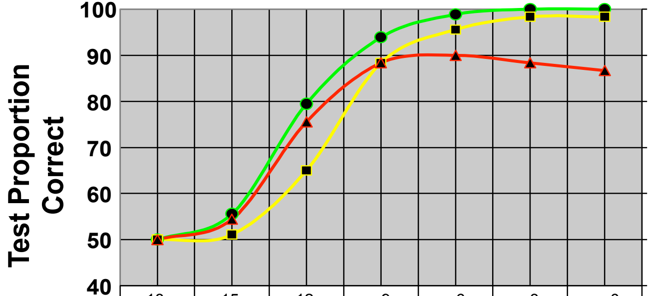




Mental Fatigue - PLS analysis

Robust EEG-Based Classification of Mental Fatigue

2300 (Day 1) vs. 1900 Hrs (Day 2)



	-18	-15	-12	-9	-6	-3	0
21 Channels	50	56	79	94	99	100	100
12 Channels	50	51	65	88	96	98	98
4 Channels	50	54	76	88	90	88	87

Signal-to-noise Ratio (dB)

Mental Fatigue - Spectrum Analysis - PARAFAC

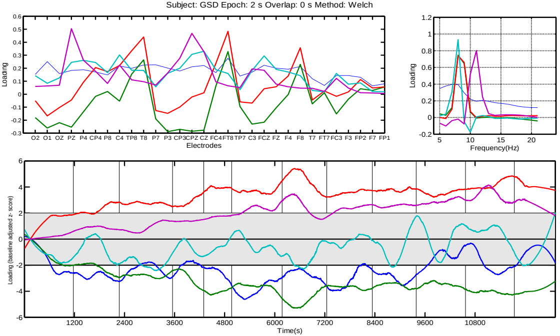


Figure 33. Atomic decomposition of EEG from participant GSD of the NASA-C study. EEG recordings from 30 channels were processed using PARAFAC decomposition to yield a model consisting of four atoms, each have dimensions of space (electrodes), frequency (power spectral density) and time (time on task). *Graphical conventions are the same as in Figure 32.* This participant performed the task for three hours, or 12 15-minute blocks. The time axis measures seconds as multiples of 2-second long EEG epochs which were not all contiguous, due to rejection of EEG segments containing movement or other artifacts. Some blocks have fewer epochs than others because the incidence of EEG artifacts increased during those blocks.

Mental Fatigue - Coherence Analysis - PARAFAC

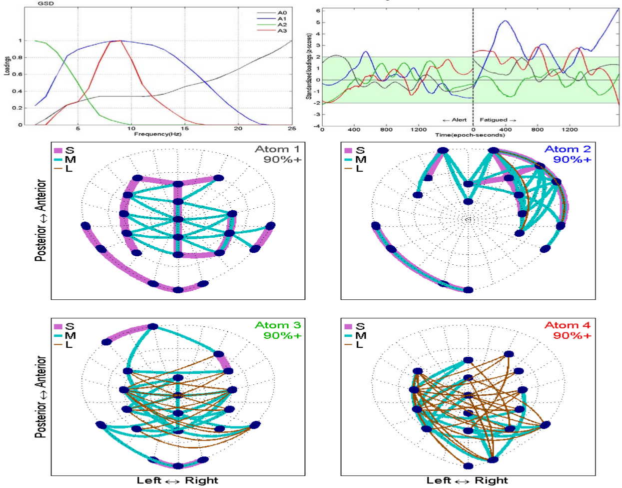
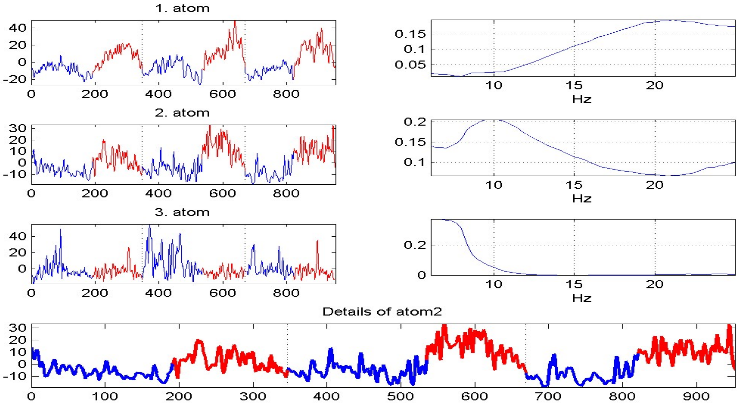


Figure 45. Coherence analyses for participant GSD. Graphing conventions are explained in Figure 44.

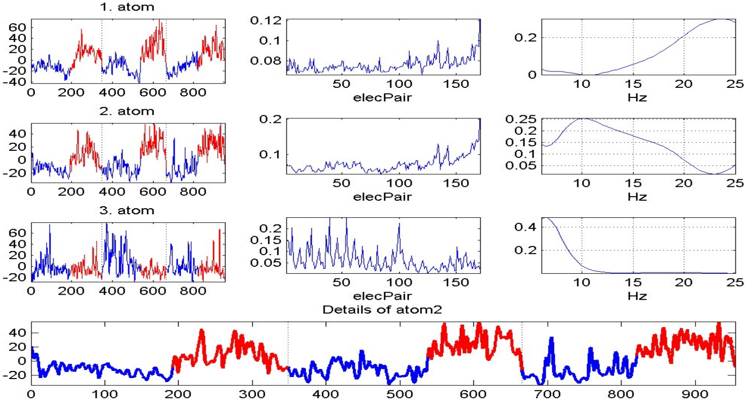
Workload - UAV - PARAFAC

- Subjects E,G,I, K (plotted subject E)



Workload - UAV - PARAFAC

- Subjects E - coherence



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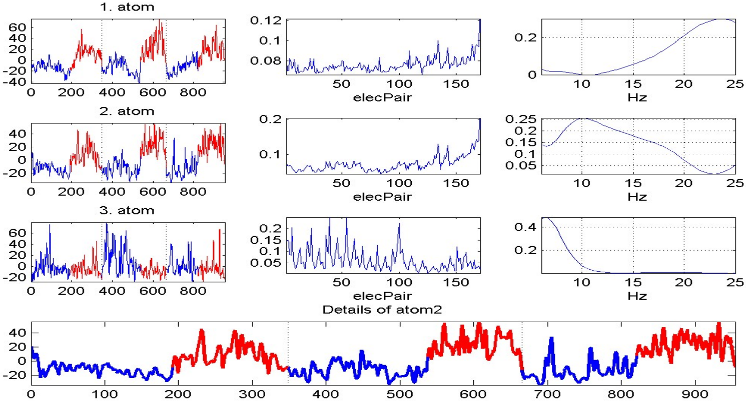
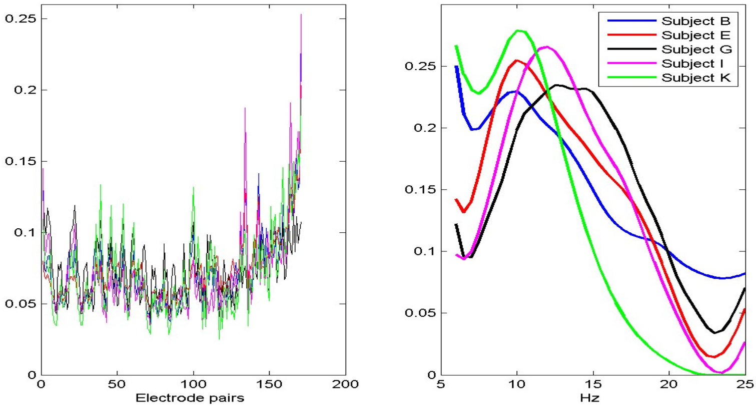


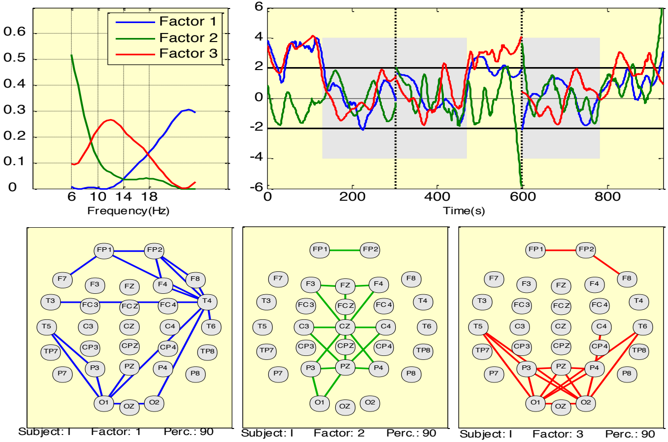
- We found the similar decomposition for subjects B, G, I, K

Workload - UAV - PARAFAC

- Subjects B,E,G,I, K - coherence



Workload - UAV - Coherence Analysis



Conclusions

- Results show that mental workload may be tracked by EEG components isolated using PARAFAC
- On UAV data set, the workload related atoms was remarkably stable in 5 out of the 6 subjects
- The short-and long range coherence related atoms are more stable across the subjects, provide higher discrimination of the low and high workload levels and seem to be less susceptible to the movement related artifacts
- We observed similarly promising and remarkable results on additional two data sets monitoring cognitive status

Detailed Results

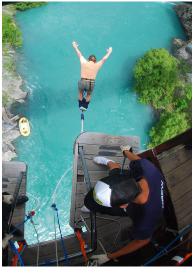
- http://www.um.savba.sk

- References:

  - Trejo L.J., Rosipal R., Nunez P.L. Advanced Physiological Estimation of Cognitive Status (APECS). Final project report, U.S. Army Research Offfice, Research Triangle Park, NC, September 2009.
  - Trejo L.J., Rosipal R., Nunez P.L. Advanced Physiological Estimation of Cognitive Status. The 27th Army Science Conference, Orlando, Florida, November 29 - December 2, 2010.
  - 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.
  - Trejo L.J., Knuth K., Prado R., Rosipal R., et al. (2007). EEG-based Estimation of Mental Fatigue: Convergent Evidence for a Three-State Model. In Proceedings HCII 2007, Beijing, China, Springer, pp. 201-211.

Work carried out with:

- Leonard J Trejo & Paul Nunez



Thank you !!!