Prediction of Immediately Occurring Microsleep Events from Brain Electric Signals -- Getting Wiser or Getting Better?

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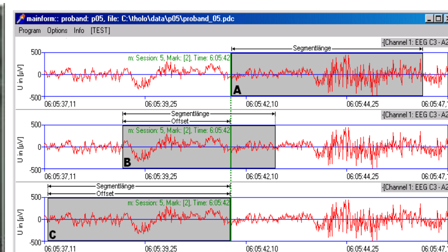

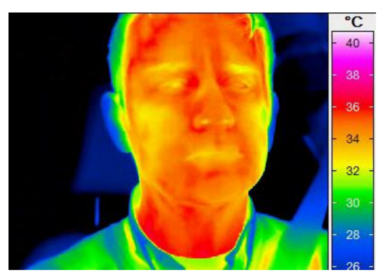

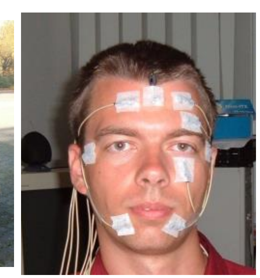

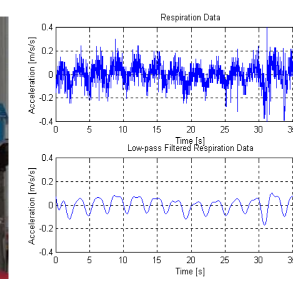

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Agenda

1. Microsleep (MS) Detection and Prediction

1.1 Biosignal Approaches
1.2 (Micro-)Sleep induced EEG Pattern

2. Recording MS Data Corpora

2.1 Sleep Deprivation MS Lab Study I
2.2 Sleep Deprivation MS Test Track Study II

3. Results Detection and Prediction MS

3.1 MS Detection and Prediction: Lab Results
3.2 Future Work: Cross Corpora (From Lab Models to Test Track Study)

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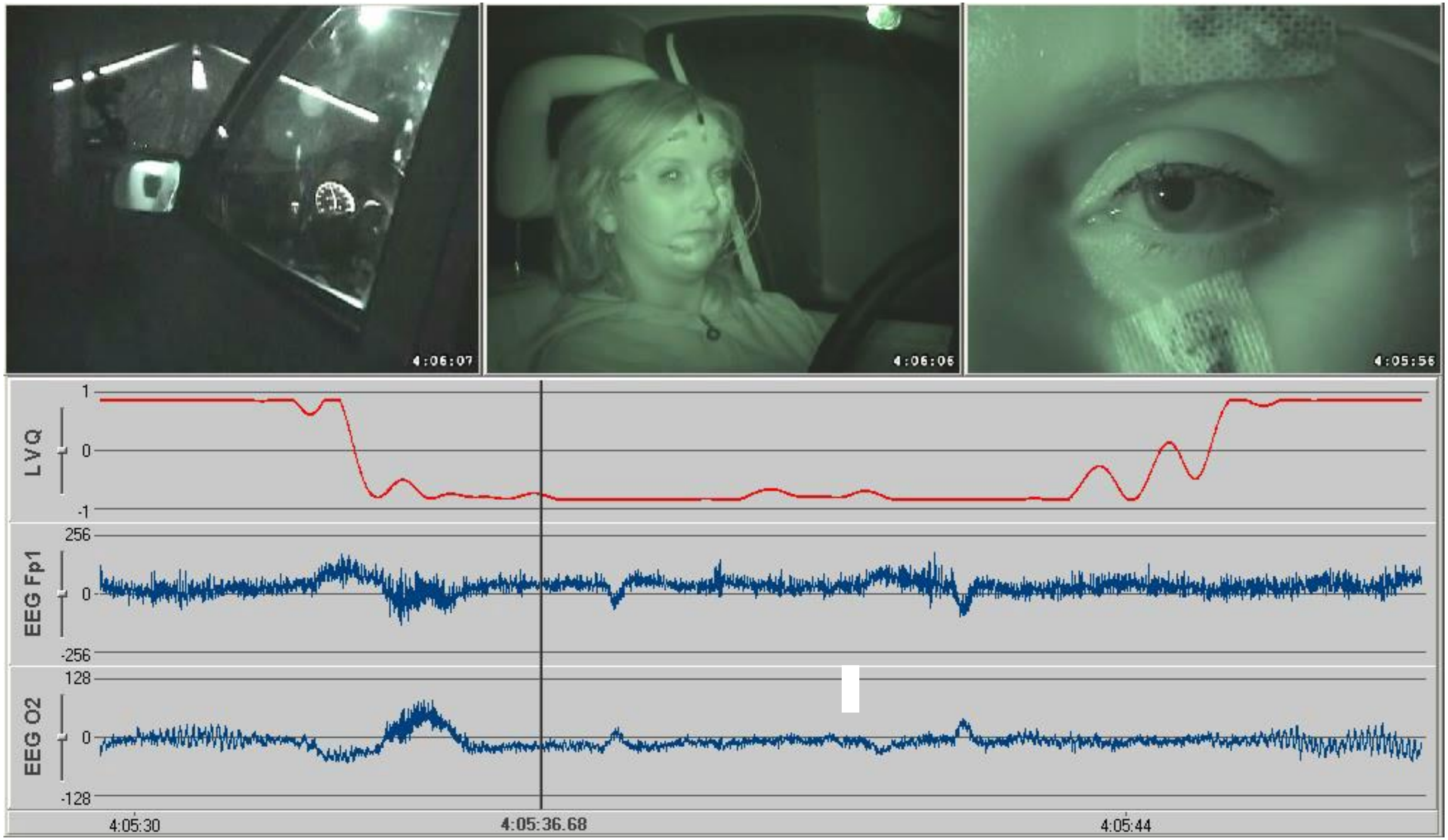
Why Dealing with Microsleep Detection?

Example Microsleep Events



Microsleep events (MS)

Temporary episode of sleep; Short and unintended attention lapses during driving; individual fails to respond to some arbitrary sensory input and becomes unconscious

Behavioral MSs Signs:

Slow Eye Lid Droops. slow eyelid-closure, and head nodding, Duration 300 ms-30 sec;

Related Work: Mostly Fatigue, Nearly None on Microsleep

Krajewski, J., Schnieder, S., Monschau, C., Titt, R., Sommer, D., & Golz, M. (2016). Large Sleepy Reading Corpus (LSRC): Applying read speech for detecting sleepiness. in speech communication; 12. ITG Symposium; Proceedings of (pp. 1-4). VDE.

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Gunsel, B., Cirakman, O., & Krajewski, J. (2015). Speaker emotional state classification by DPM models with annealed SMC samplers. In Signal Processing Conference (EUSIPCO), 2015 23rd European (pp. 120-124). IEEE.

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Schuller, B., Steidl, S., Batliner, A., Schiel, F., Krajewski, J. (2014). Medium-Term Speaker States - A review on intoxication, sleepiness and the first challenge. *Computer Speech and Language, 28,* 346-374. (IF: 1,32)

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Sommer, D., Schenka, A., Krajewski, J., & Golz, M. (2014). Are Smartphones Applicable for Posturography? A Classification Analysis Based on Computational Intelligence. Biomedical Engineering-Biomedizinische Technik, 59, S865-S865

Hönig, F., Batliner, A., Nöth, E., Schnieder, S. & Krajewski, J. (2014). Acoustic-Prosodic Characteristics of Sleepy Speech - Between Performance and Interpretation. *Proceedings Speech Prosody*, 4 Pages, no Pagination.

Hönig, F., Batliner, A., Bocklet, T., Stemmer, G., Nöth, E., Schnieder, S., & Krajewski, J. (2014). Are men more sleepy than women or does it only look like–automatic analysis of sleepy speech. ICASSP.

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Golz, M., Sommer, D., Trutschel, U., Krajewski, J., & Sirois, B. (2013). Driver Drowsiness Immediately before Crashes–A Comparative Investigation of EEG Pattern Recognition. *Proceedings Human Factors in Driver Assessment, Training and Vehicle Design, 7,*516-522

Schnieder, S., Krajewski J., Esch, T., Baluch, B. & Wilhelm, B (2012). Just valid or even accurate: Determine the measurement accuracy of the Pupillographic Sleepiness Test by applying self- and observer ratings. *Somnology, Sleep Research and Sleep Medicine, 1,* 1-15.

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Krajewski, J., Schnupp, T., Heize, C., Schnieder, S., Laufenberg, T., Sommer, D., & Golz, M. (2012). A phonetic approach for detecting sleepiness from speech in simulated Air traffic Controller communication. In D. de Waard, N. Merat, Jamson Y. Barnhard, and O.M.J. Carsten (Eds.) Human Factors of Systems and Technology, (pp. 147-155). Maastricht, the Netherlands: Shaker.

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Golz, M., Sommer, D. Krajewski, J., Trutschel, U. & Edwards, D.I. (2011). Microsleep episodes and related crashes during overnight driving simulations.*Proceedings Human Factors in Driver Assessment, Training and Vehicle Design, 6,* 39-45.

Advantages Microsleep Prediction

Advantages:

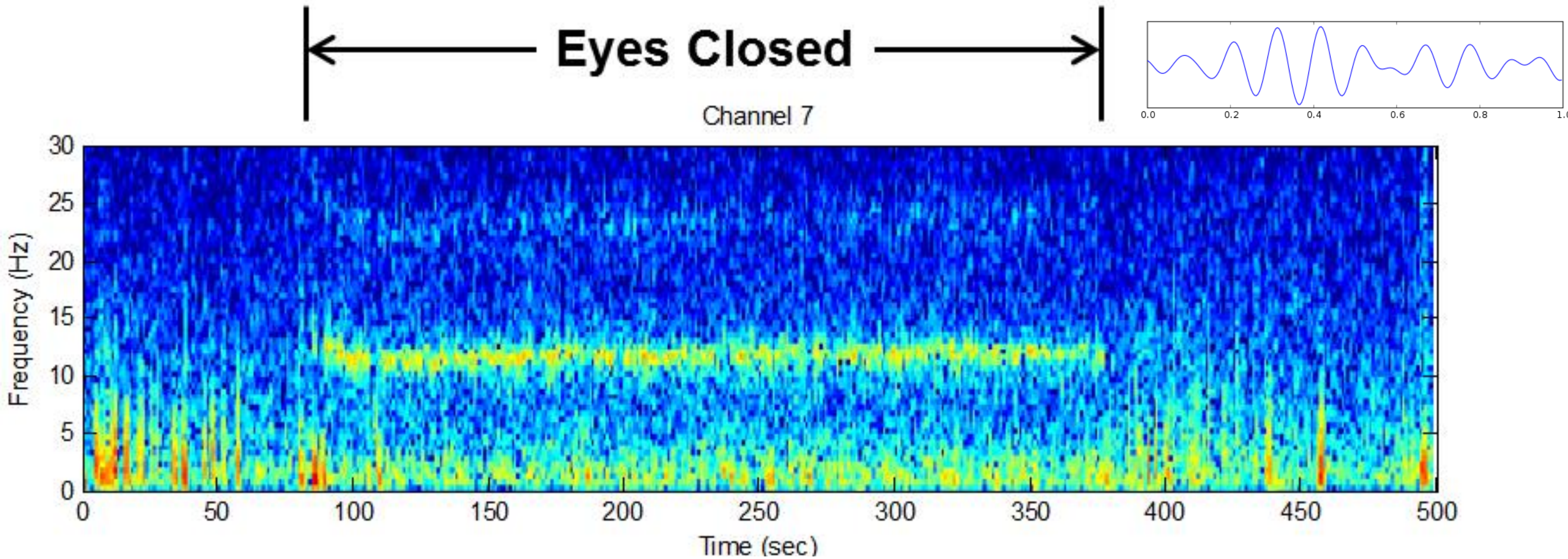
Strong accident relavance

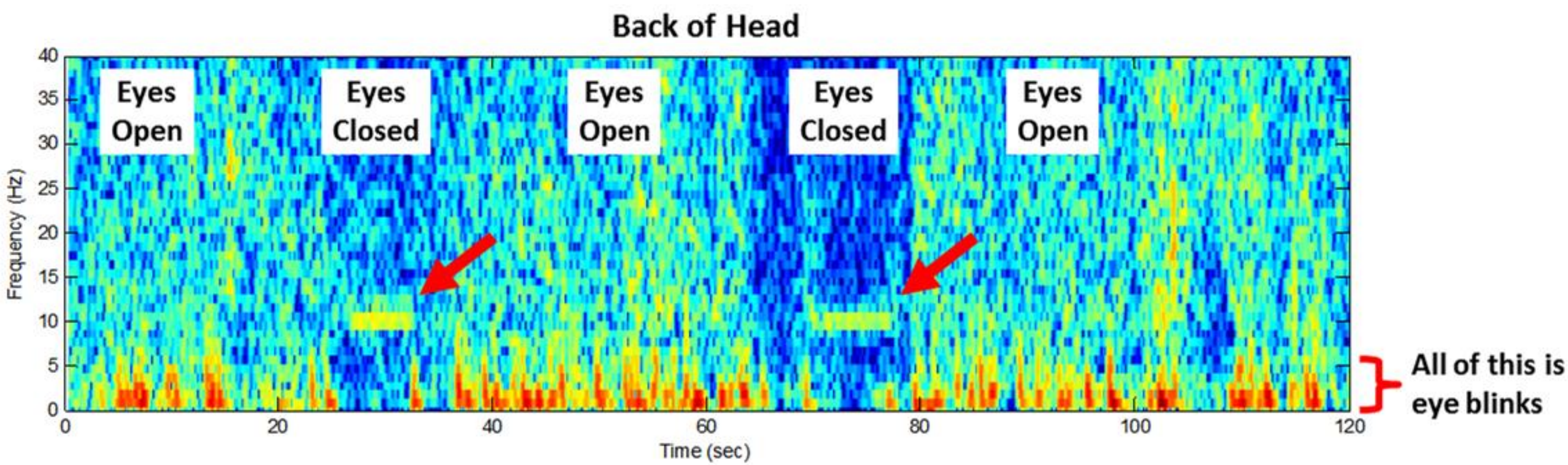
Rather clear behavioral event.

Disadvantages:

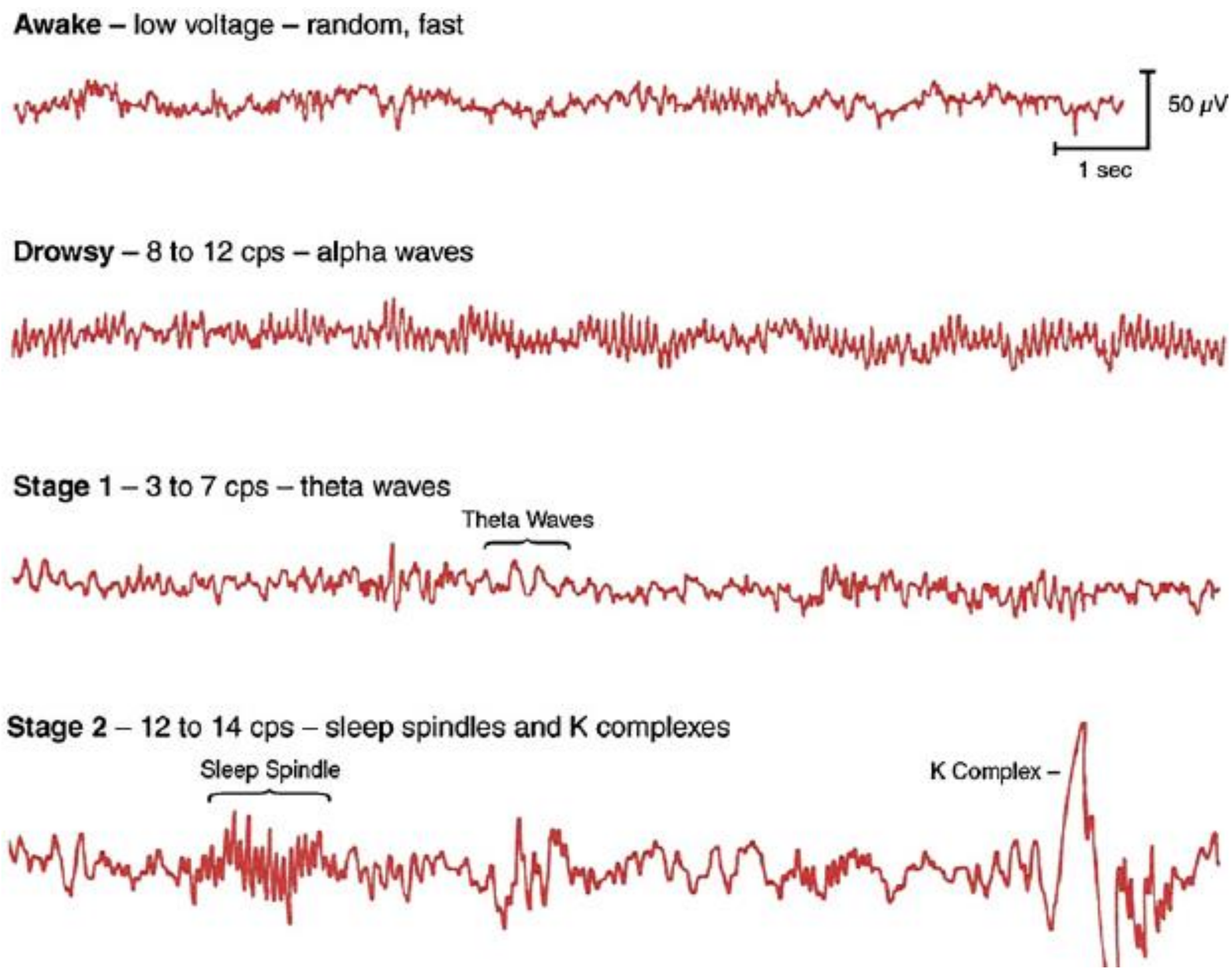
Experimental effort: Long sleep deprivation, monotoneous tasks

Microsleep EEG = Eyes Closed Alpha Bands?



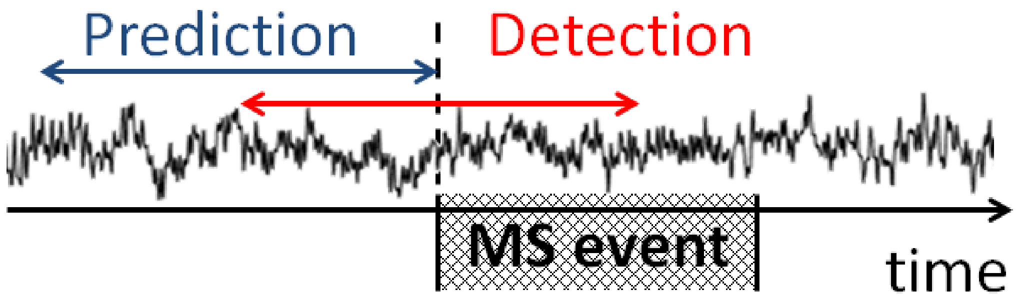


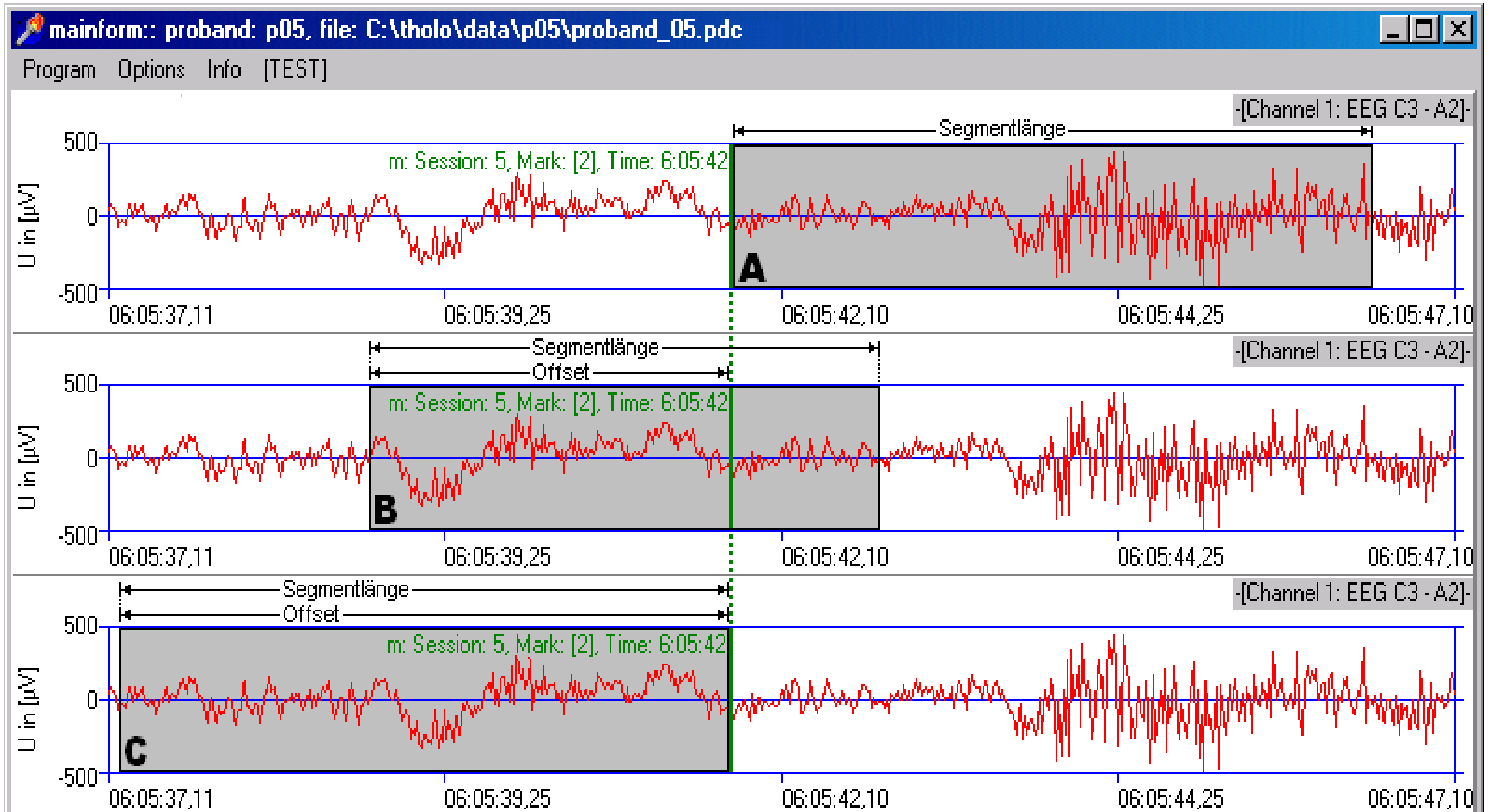
Microsleep EEG = Sleep Stage 1, Theta Waves?



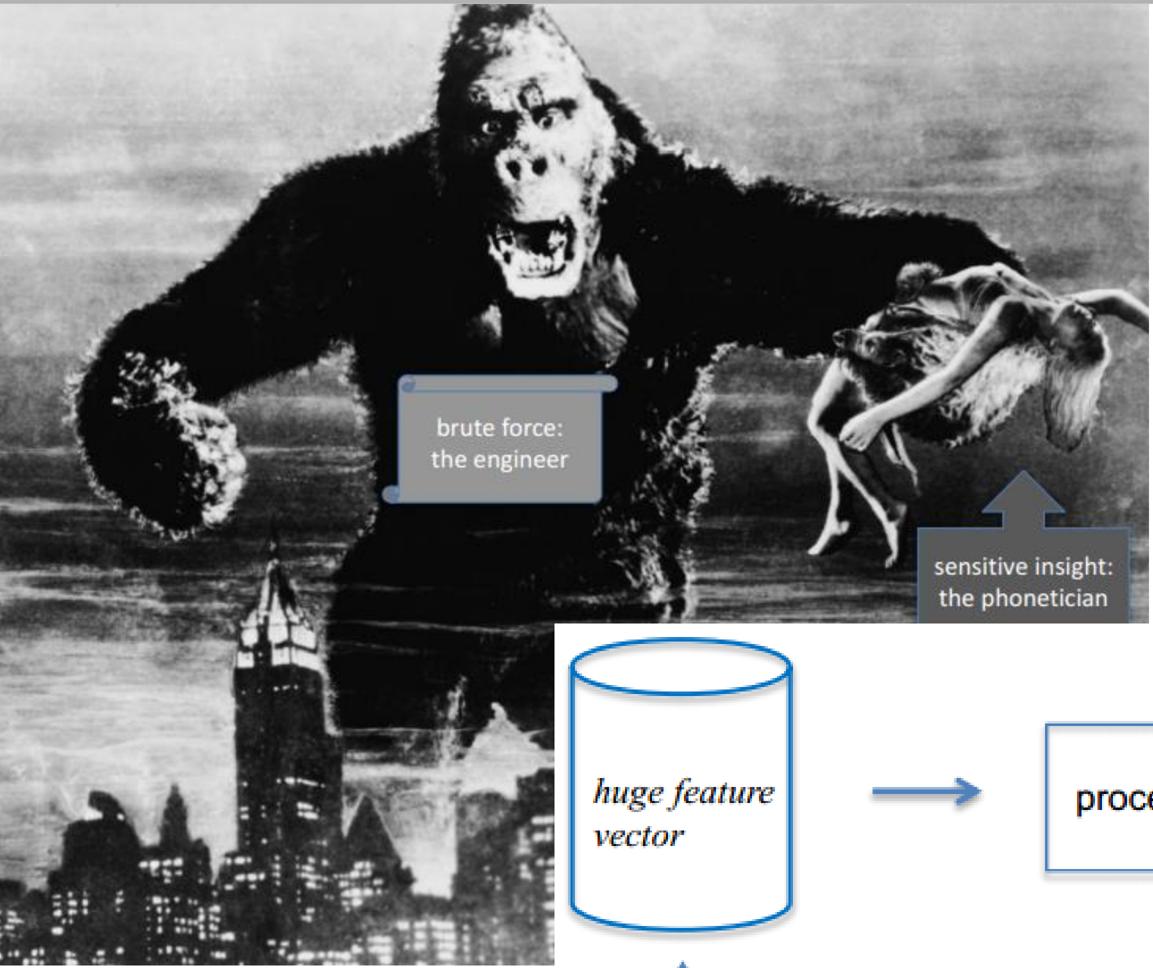
MS are often classified as a shift in (EEG) during which 4–7 Hz Theta Wave activity replaces the waking 8–13 Hz Alpha Wave background rhythm

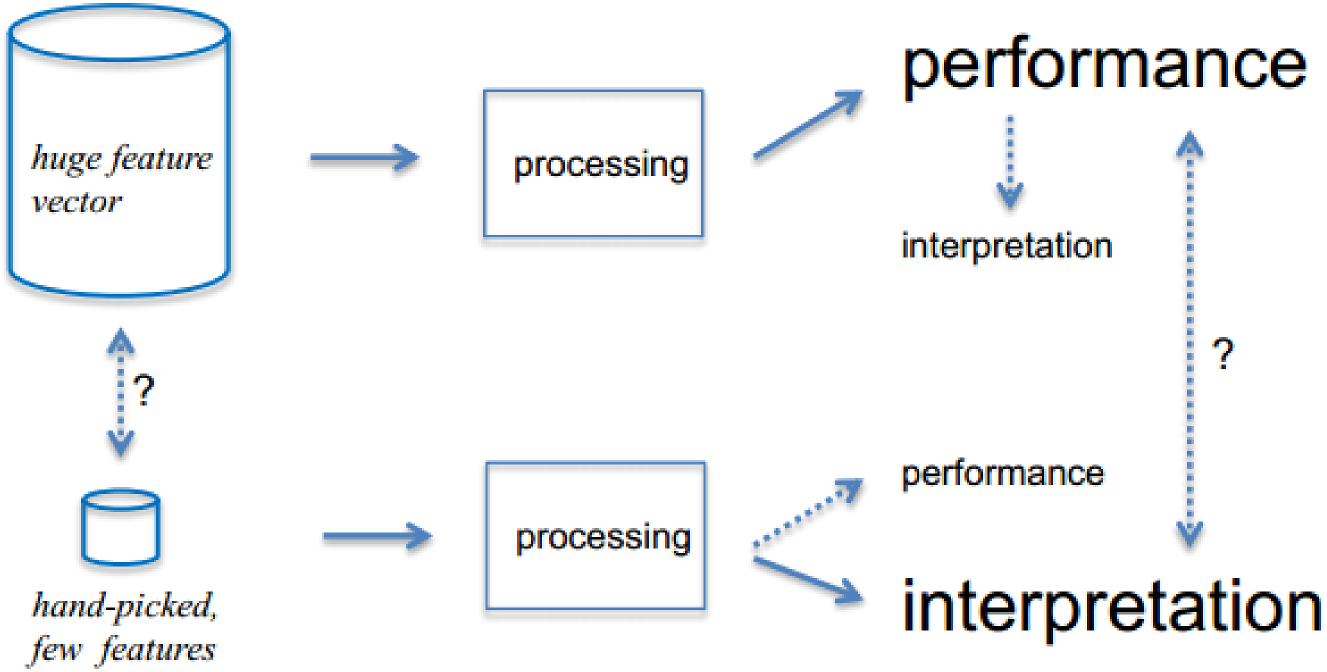
Open Question: MS Detection and Prediction





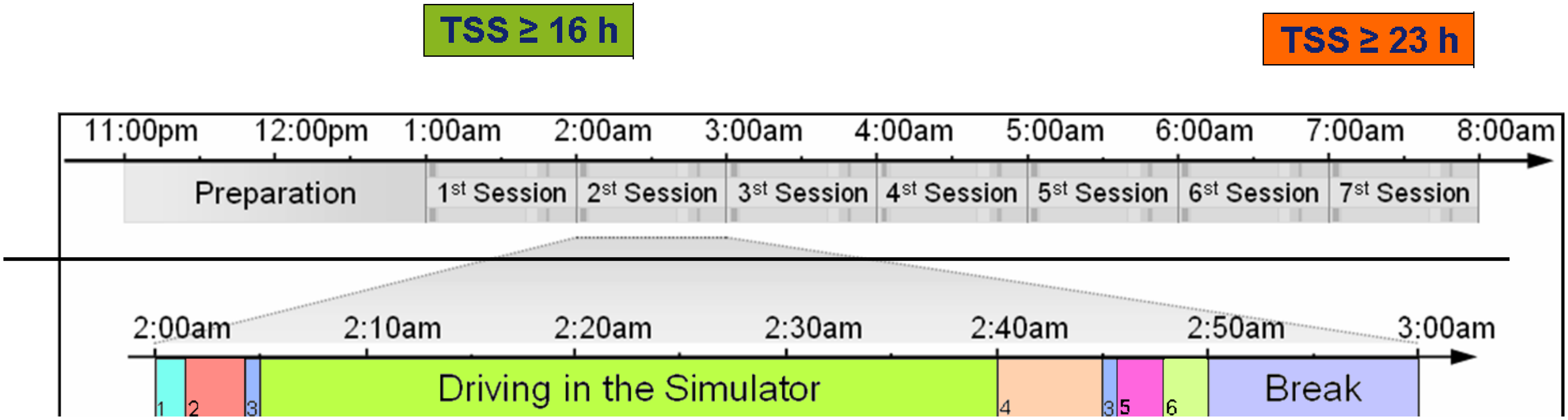
Our Approach: Brute Force (Getting Better, Not Wiser)





Agenda

Sleep Deprivation MS Lab Study I: Experimental Protocol



Protocol Subjects

- 16 subjects (12m+4f); Age: 24.4 ± 3.1; PSQI: 3.8 ± 1.6
- Restrictions: wake-up time: 6:00 – 8:00, time to bed: 22:00 – 1:00, monitored by wrist actimetry, subjects refrained from naps during the day before driving
- Experiments: 22:30 - 7:30 (8 driving sessions of 40 min duration)

MS Events vs. Sustained Attention (SA)

- Periods of time where the driver is indeed drowsy, but still able to keep the car in lane, were used as counterexamples and were labelled as sustained attention (SA)
- 1.484 MS Events
- 1.940 Sustained Attention Events

Ground Truth and Definition of MS

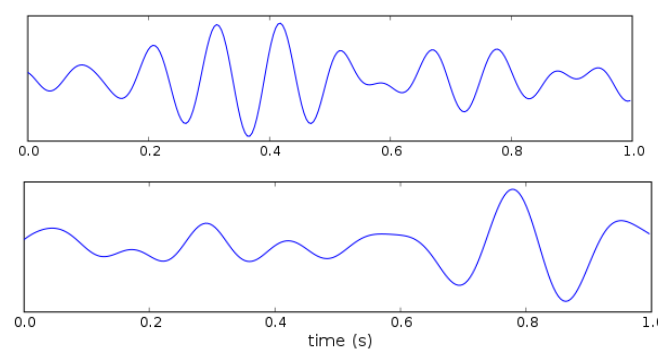
Exclusion and Definition of MS

- Behavioral MS events evaluated by an expert supervisor.
- Evaluations based on visual inspections of video material, of lane deviation time series and of EOG.
- Vague or very short-lasting signs of MS (<0.3 s) excluded.
- The duration of behavioral signs of MS ranged between 0.3 and 6 s.

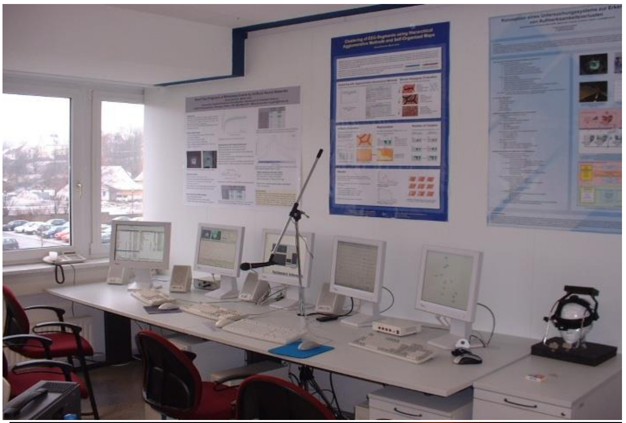
Visual Inspection Criteria

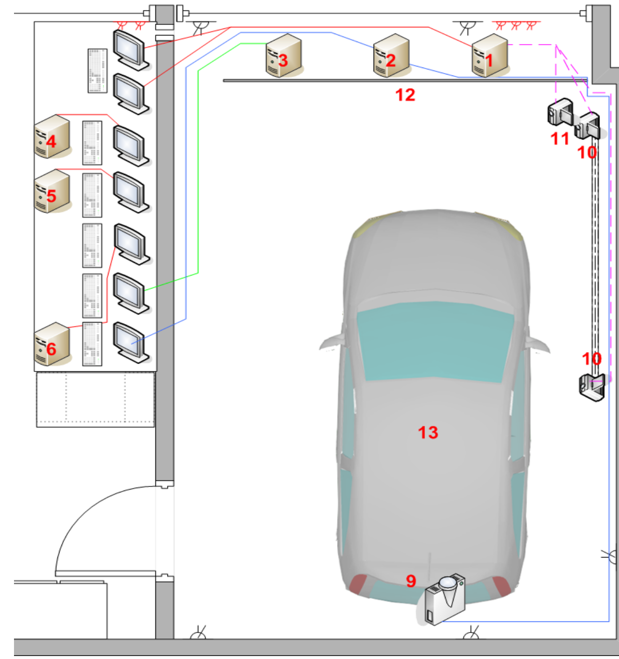
- MSs manifest as droopy eyes, slow eyelid-closure, and head nodding

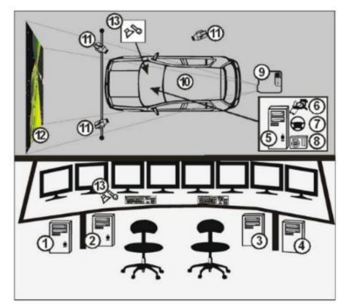
NOT APPLIED: EEG based Definition Alpha to Theta Band



Static Driving Simulator







1. Electropolygraphy (EEG, EOG, ECG, EMG)
2. Eyetracking system (ETS)
3. Equipment control and synchronization
4. Video capture
5. Driving simulation
6. ETS multi camera unit
7. Steering acquisition and force feedback
8. Electropolygraphy head box
9. Video projector
10. Real car (GM Opel "Corsa")
11. Infrared video cameras
12. Projection plane
13. Intercom system

Feature Extraction: Brute Force Fine EEG Spectral Bands

Feature Set 1: PSD (Power Spectral Densities)

Averaging: within small frequency bands
0.1 Hz ... (1 Hz) ... 23.1 Hz (empirically found);
Scaling: logarithmically

161 PSD features

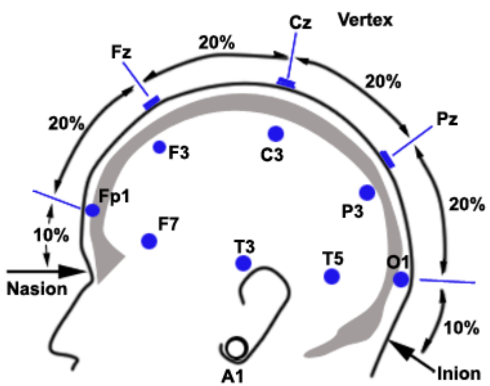
(23 spectral bands x 7 EEG channels (Fp1, Fp2, C3, Cz, C4, O1, O2);

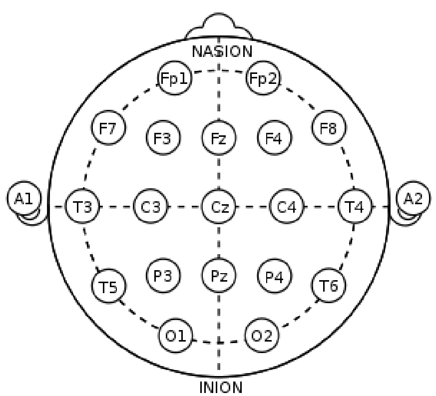
Feature Set 2: Choi-Williams distribution (CWD)

648 CWD features per EEG segment.

TABLE I
EEG BANDS AND FREQUENCY DIVISIONS

EEG Band	Frequency
Delta (δ)	1.0 – 4.5 Hz
Theta (θ)	4.5 – 8.0 Hz
Alpha 1 (α_1)	8.0 – 10.5 Hz
Alpha 2 (α_2)	10.5 – 12.5 Hz
Alpha (α)	8.0 – 12.5 Hz
Beta 1 (β_1)	12.5 – 15.0 Hz
Beta 1 (β_2)	15.0 – 25.0 Hz
Beta (β)	12.5 – 25.0 Hz
Gamma 1 (γ_1)	25.0 – 35.0 Hz
Gamma 2 (γ_2)	35.0 – 45.0 Hz
Gamma (γ)	25.0 – 45.0 Hz
High	> 45.0 Hz





I. PSD (power spectral densities)

- Assumption: EEG is quasi-stationary within the segment
- Methods: periodogram modified by data tapering
- Scaling: logarithmically
- Averaging: within small frequency bands
  0.1 Hz ... (1 Hz) ... 23.1 Hz (empirically found)
- In total: 161 PSD features
  (23 spectral bands x 7 EEG channels
  (Fp1, Fp2, C3, Cz, C4, O1, O2)
- Alternatives:
  - WOSA (weighted overlapped segment analysis)
  - MTM (multi-taper method, Thomson's method)

  → Slightly less accuracy in subsequent machine learning

II. CWD (Choi-Williams distribution)

- Assumption: EEG is non-stationary within the segment
- Methods of Cohen class might be considered [Santamaria et al., 2015]
- CWD satisfies a number of properties
  - Signals with quasi-constant instantaneous frequency
    → potentially better time-frequency concentration than e.g. smoothed pseudo Wigner-Ville distribution
  - Depends on the signal's time-frequency structure
    → performs potentially poor if signal components overlap in time and frequency

II. CWD (Choi-Williams distribution) (continued)

– Cross-CWD between two signals $x(t)$ and $y(t)$ [Choi & Williams, 1989]

$$T_{xy}(t,f) = 2 \iint_{-\infty}^{\infty} \frac{\sqrt{\sigma}}{4\sqrt{\pi}|\tau|} e^{-\nu^2\sigma/(16\tau^2)} x\left(t+\nu+\frac{\tau}{2}\right) y^*\left(t+\nu-\frac{\tau}{2}\right) e^{-j2\pi f\tau} \, d\nu \, d\tau$$

– CWD features:

(1) Instantaneous power function (IP)

$$S_{xy,i}(t) = \frac{\int_{f_{i1}}^{f_{i2}} |T_{xy}| \, df}{\int_{f_{TB1}}^{f_{TB2}} |T_{xy}| \, df}$$

– f_{i1}, f_{i2} : lower / upper limit of the i-th spctral band,

– f_{TB1}, f_{TB2} : lower / upper limit of the total band (0.1 Hz / 45 Hz) [Santamaria et al., 2015]

II. CWD (Choi-Williams distribution) (continued)

(2) Instantaneous frequency (IF)

$$f_{IF}(t) = \frac{\int_{f_{TB1}}^{f_{TB2}} f\,T_{xy}(t,f)\,df}{\int_{f_{TB1}}^{f_{TB2}} T_{xy}(t,f)\,df}$$

– First moment of the CWD with respect to frequency

(3) Instantaneous spectral entropies (ISE)

$$\boldsymbol{H_i(t) = -\int_{f_{i1}}^{f_{i2}} T_{xy}(t,f) log_2\left(T_{xy}(t,f)\right) df}$$

- Based on Shannon entropy
- Complexity of the CWD within each band
- Indications
  - High ISE values → broad-band spectral characteristics (uniform, flat spectrum)
  - Low ISE values → line spectrum characteristics (power concentrated into a few frequency bins)

II. CWD (Choi-Williams distribution) (continued)

mean, median, min, max

delta, theta, alpha, beta

- 36 features per channel
  - 16 IP features (4 statistical parameters x 4 EEG spectral bands)
  - 4 IF features (4 statistical parameters)
  - 16 ISE features (4 statistical parameters x 4 EEG spectral bands)
- 18 channels [Santamaria et al., 2015]
  - 7 channels: Fp1, Fp2, C3, Cz, C4, O1, O2
  - 6 ipsilateral pairs: Fp1-C3, Fp2-C4, Fp1-O1, Fp2-O2, C3-O1, C4-O2
  - 5 contralateral pairs: Fp1-Fp2, C3-C4, O1-O2, C3-O2, C4-O1
- In total: 648 PSD features
  (36 features x 18 channels)

I. OLVQ1 (optimized learning vector quantization)

- Artificial neural network
- Performs stochastic learning
- Aims at approximating the probability density function in the feature space
- Converges very rapidly in most applications.

II. SVM (support-vector machine)

- Search of an optimal linear separation functions
- Under 3 basic concepts
  1) Large margin
  2) Soft margin
  3) Kernel trick
- Computationally expensive optimization problem

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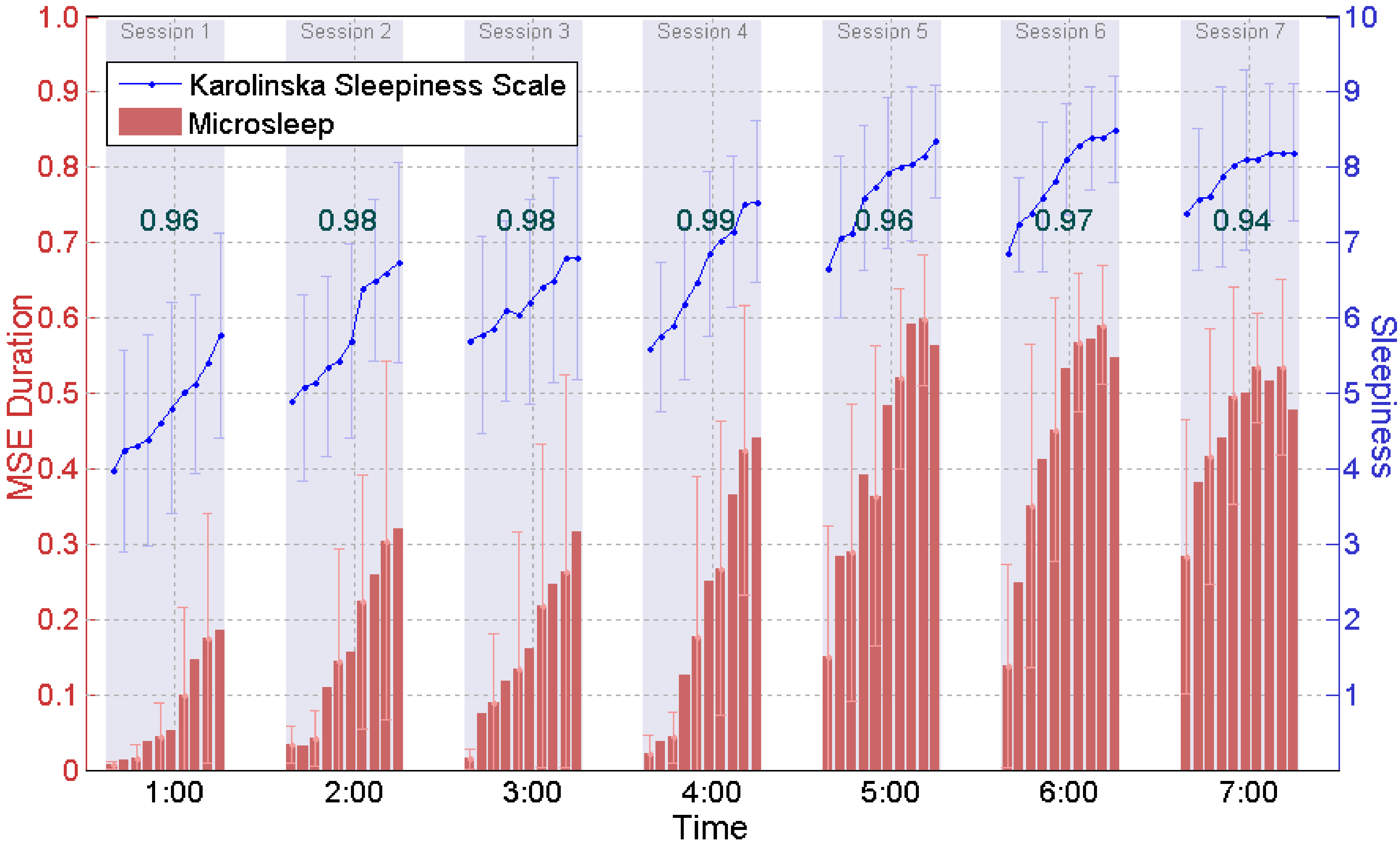
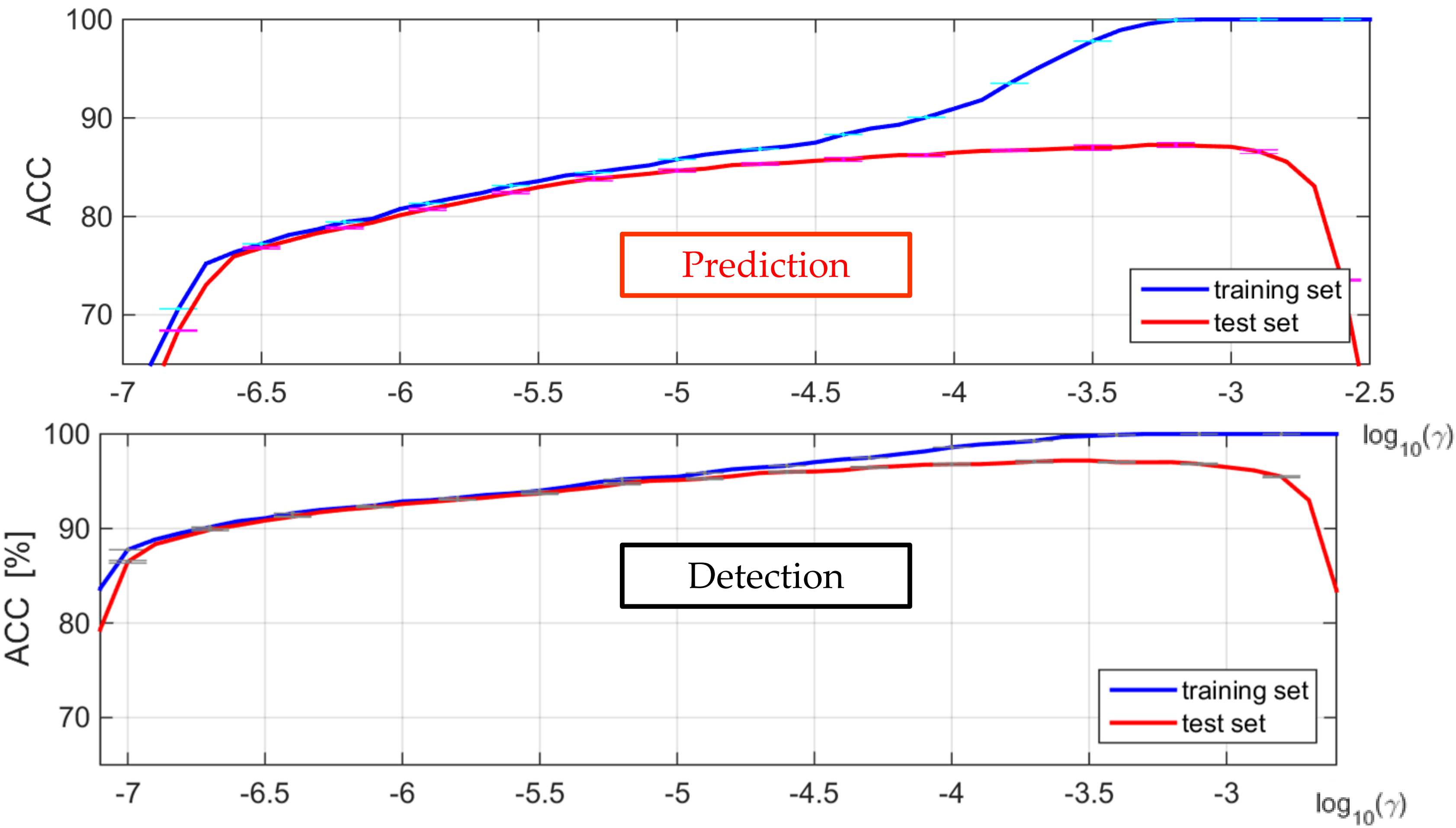
MS: Time-on-Task, Time-of-Day Effects

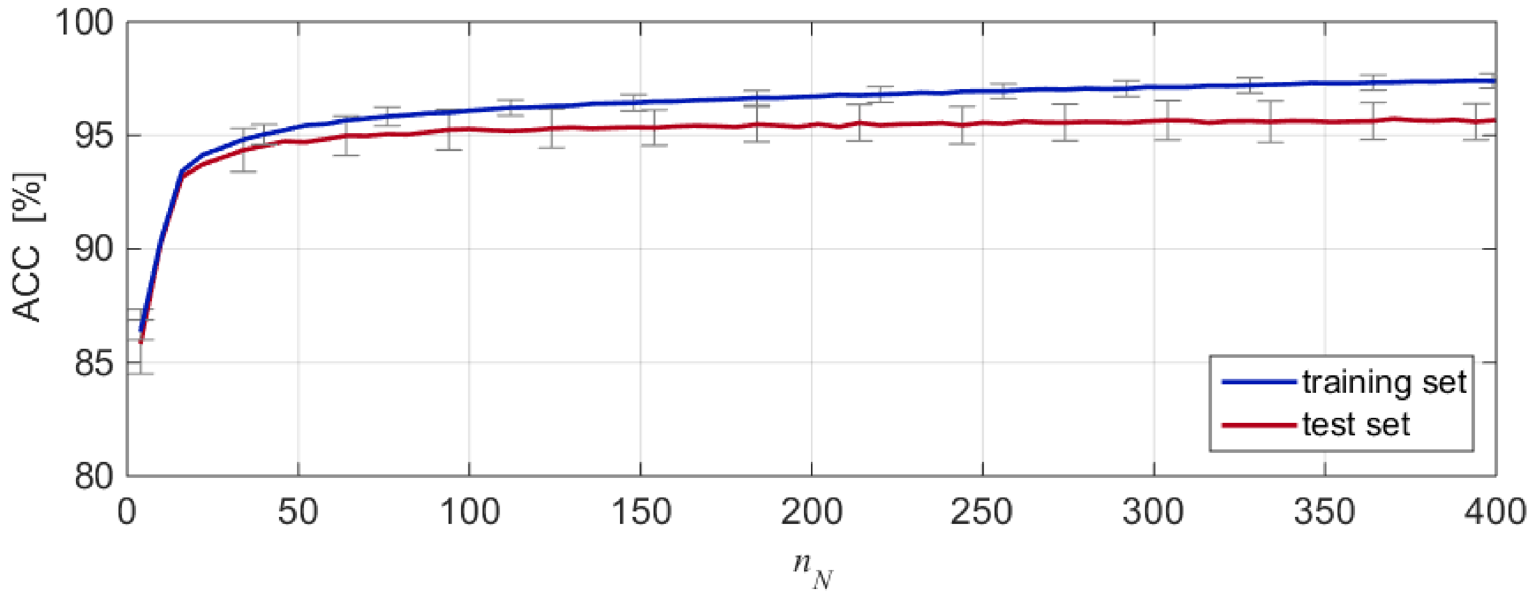


Prediction vs Detection Results: SVM Classification



Classification Accuracy

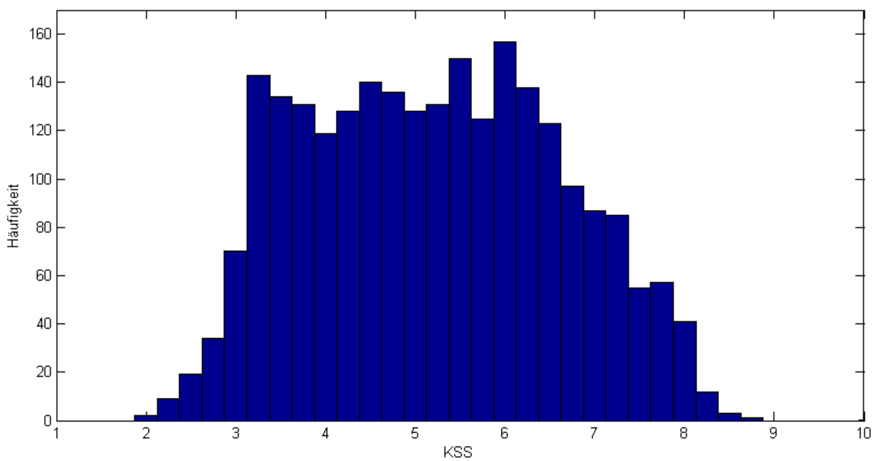
Classifier Feature set	OLVQ1 CWD	OLVQ1 PSD	SVM CWD	SVM PSD
Prediction	81.6 ± 1.5 %	82.9 ± 1.5 %	82.7 ± 0.1 %	87.5 ± 0.1 %
Detection	91.1 ± 1.3 %	95.5 ± 0.7 %	91.2 ± 0.1 %	97.3 ± 0.1 %



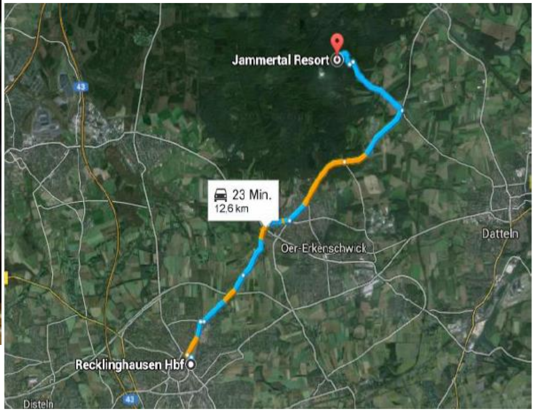
Sleep Deprivation MS Test Track Study II

Participants

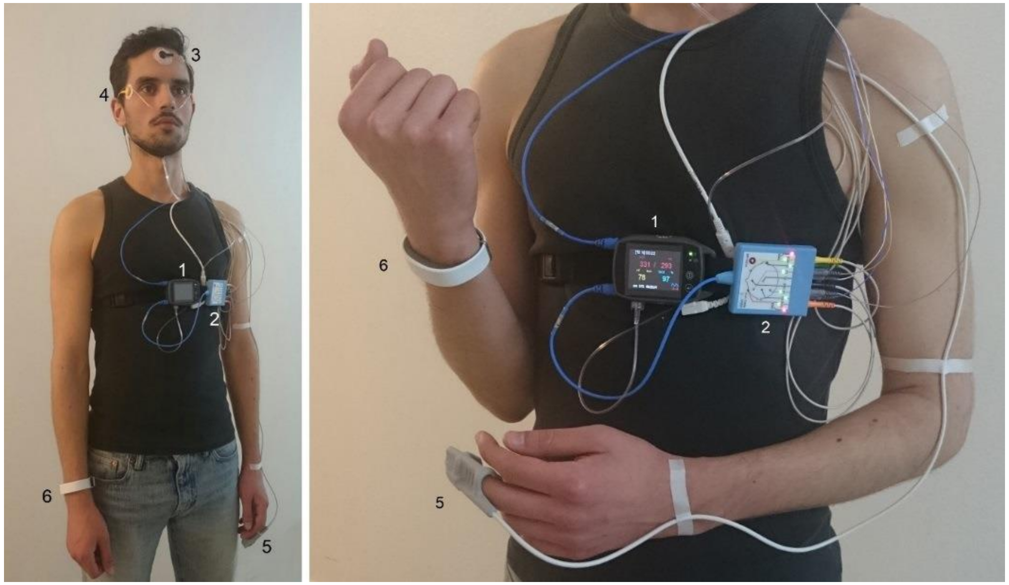
We conducted a sleep deprivation study with 151 male participants. The subjects under sleep deprived conditions slept less than 2 hours prior the recording session. 4 h Driving on test track

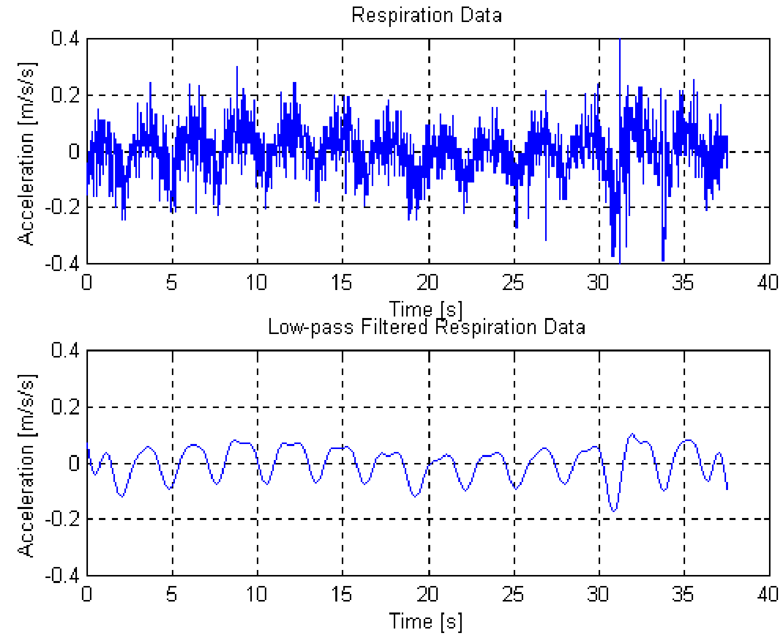


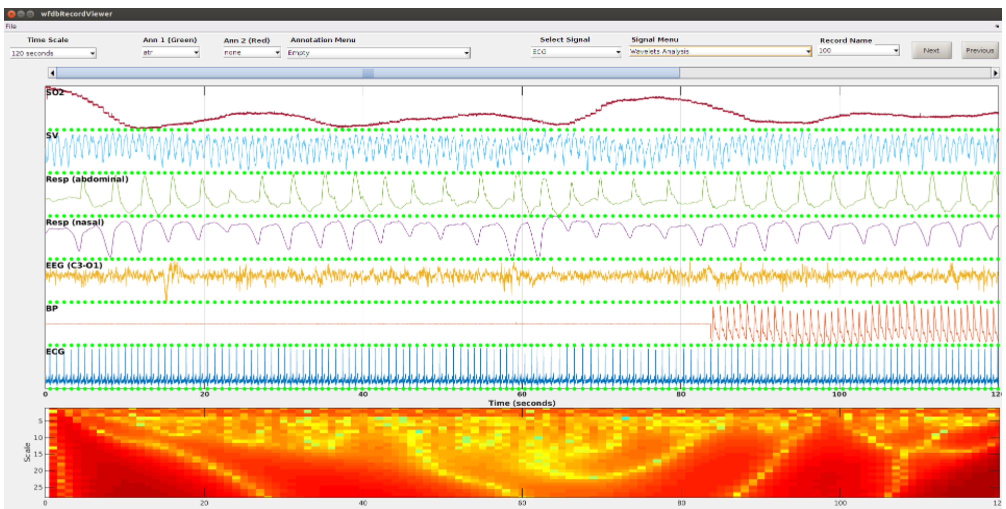
CamCar and High Security Test Track Facilities



Candidates for MS Detection: Breathing Pattern, BP, ECG

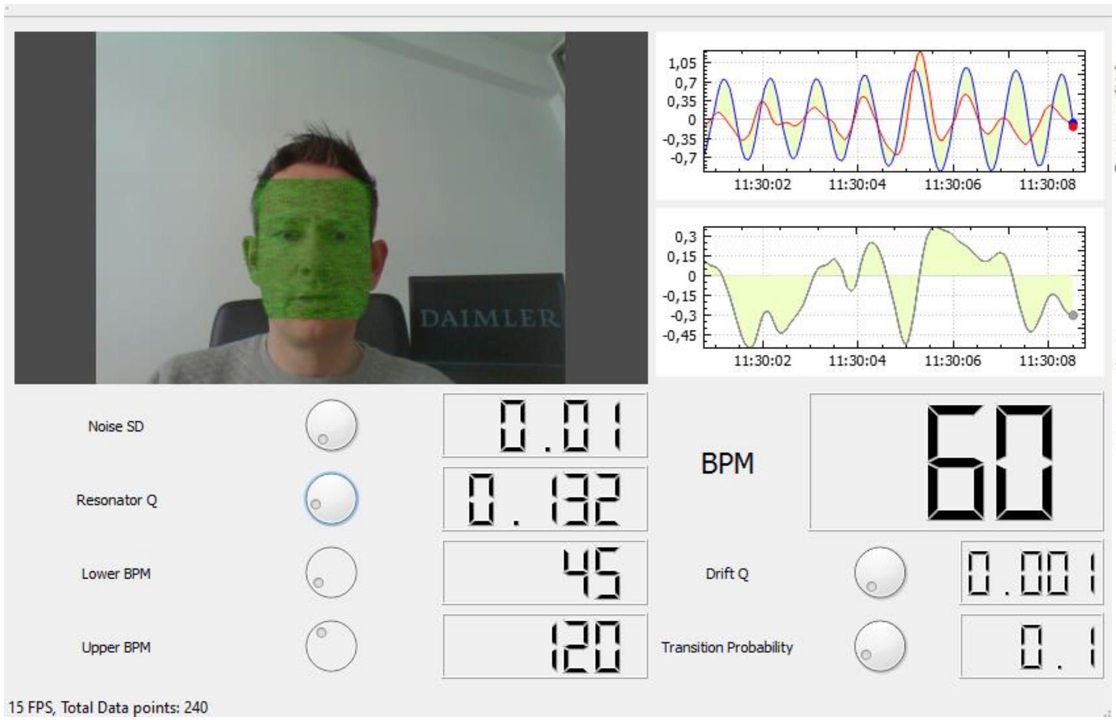


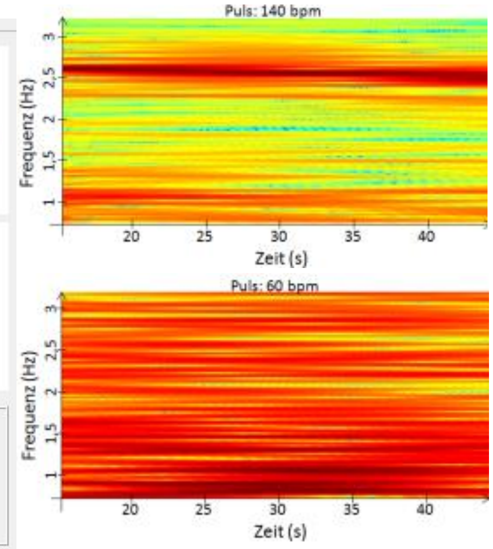


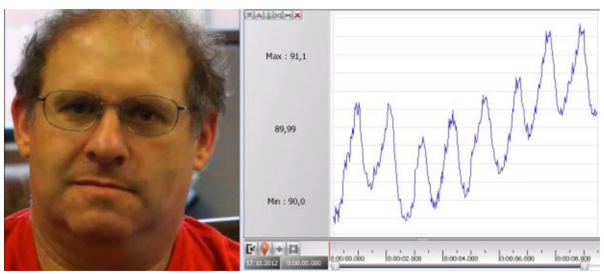


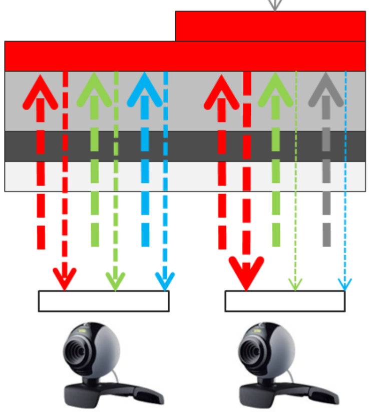
Heinze, C., Trutschel, U., Schnupp, T., Sommer, D., Schenka, A., Krajewski, J. & Golz, M. (2009). Operator fatigue estimation using heart rate measures. *World Congress on Medical Physics and Biomedical Engineering, IFMBE Proceedings*, 25 (9), 930-934.

Candidates for MS Detection: Video-based PPG Heart Rate



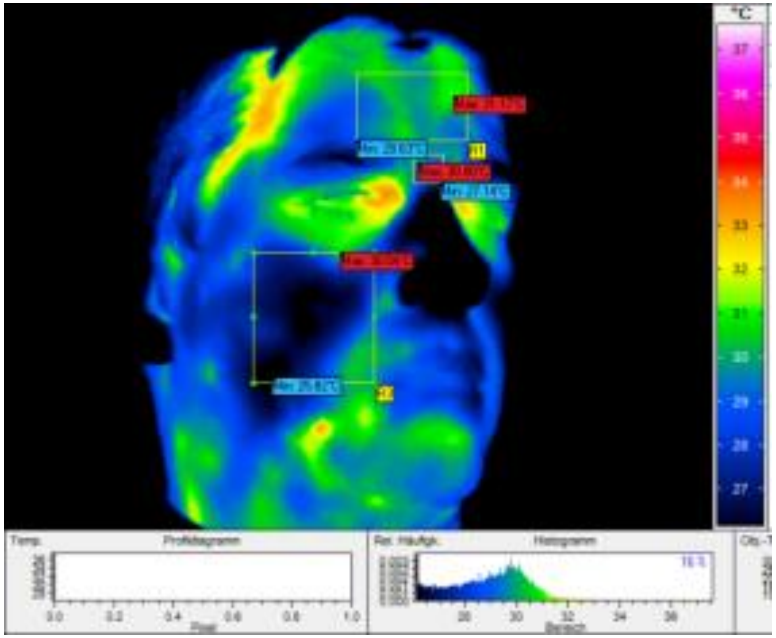


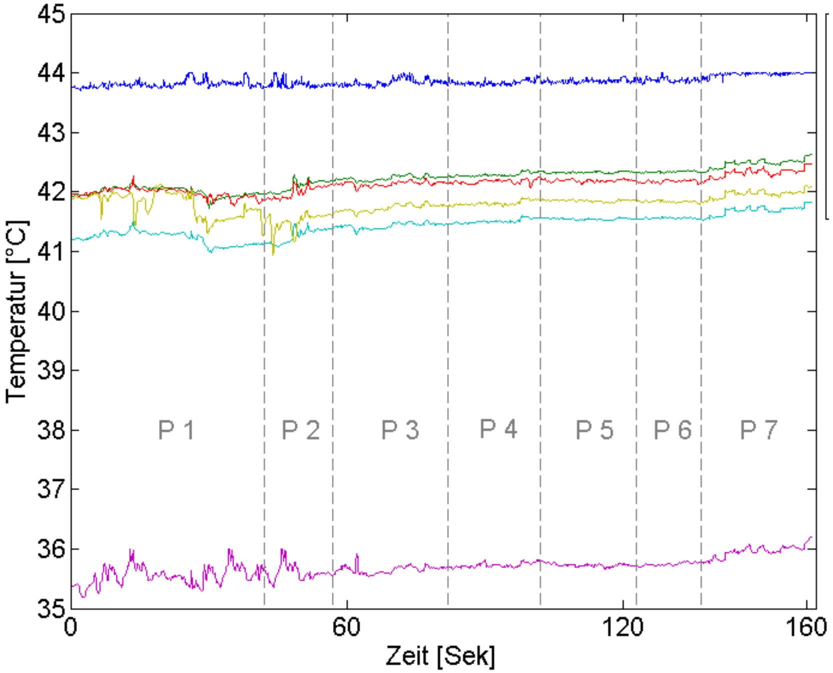


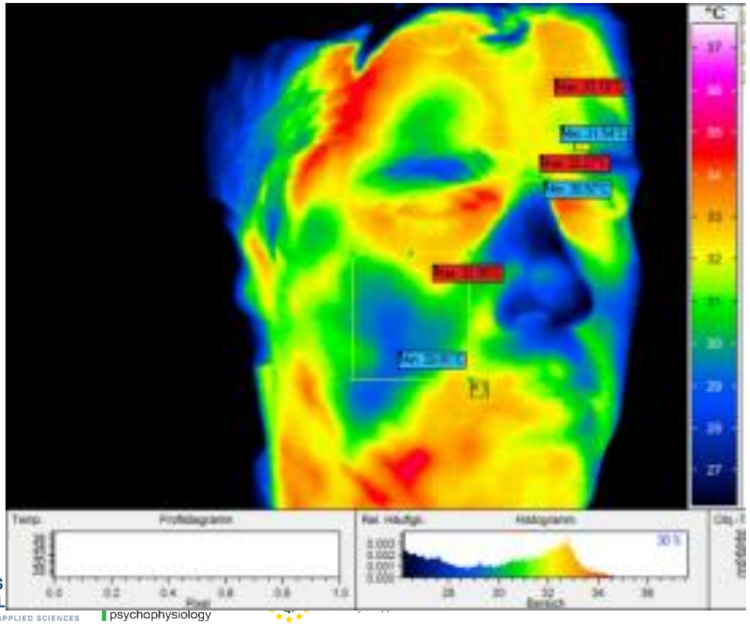


Pursche, T., Krajewski, J., & Möller, R. (2012). Video-based heart rate measurement from human faces. IEEE International Conference on Consumer Electronics, 29, 544 – 545.

Candidates for MS Detection: Facial Thermal Imaging

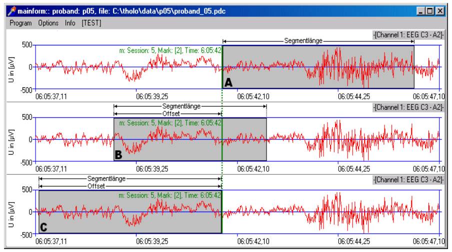




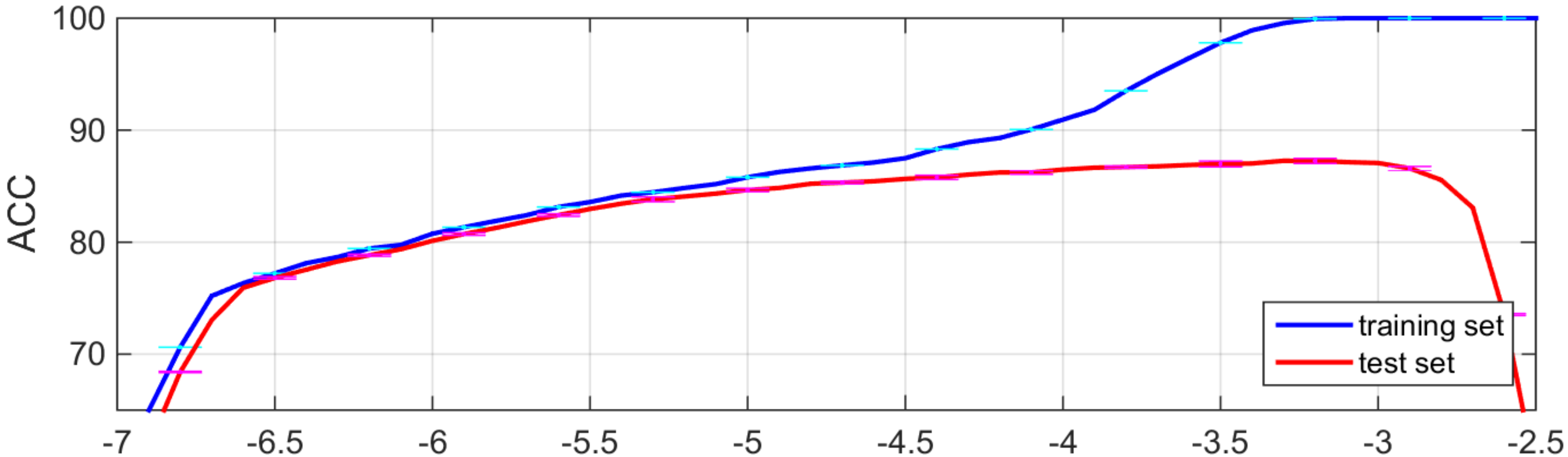


Puri, C., Olson, L., Pavlidis, I., Levine, J., & Starren, J. (2005). StressCam: non-contact measurement of users' emotional states through thermal imaging. In *CHI'05 extended abstracts on Human factors in computing systems* (pp. 1725-1728). ACM.

Summary



brute force:
the engineer
sensitive insight:
the phonetician



ACC
100
90
80
70
-7
-6.5
-6
-5.5
-5
-4.5
-4
-3.5
-3
-2.5
training set
test set

Prediction of Immediately Occurring Microsleep Events from Brain Electric Signals -- Getting Wiser or Getting Better?

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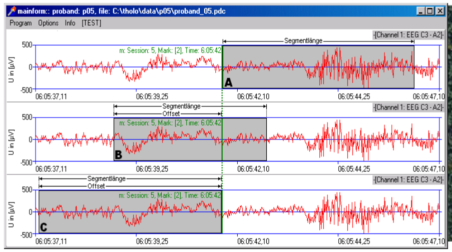




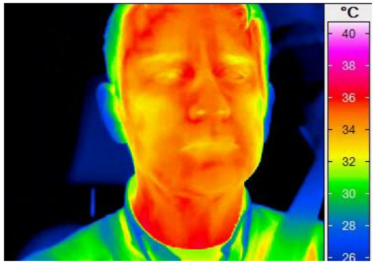



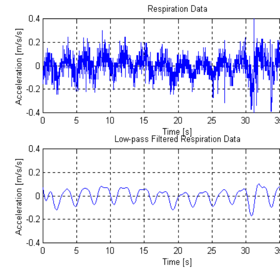

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