

# PROBABILISTIC FRAMEWORK FOR EEG-BASED DROWSINESS AND VIGILANCE MONITORING

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# Objectives

- To develop probabilistic modelling framework for real-time monitoring of drowsiness, impaired vigilance or fatigue.
- The framework should overcome the main drawback of the existing monitoring systems, which is their limited capability to deal with a wide range of information sources needed to cover many aspects influencing human behaviour (drowsiness, fatigue or vigilance).
- Presented study adapts the methodology for the sleep process modelling developed in the SENSATION project.
- The developed methods are applied to day-time electrophysiological recordings (EEG, EOG, EMG) focused on screening subject's drowsiness (sleepiness) and vigilance.

# Two experiments – 1) driving simulator 2) vigilance test

## ➤ Driving simulator

- the third generation moving base driving simulator
- 45 shift workers
- drove during morning hours directly after a full night-shift with no sleep

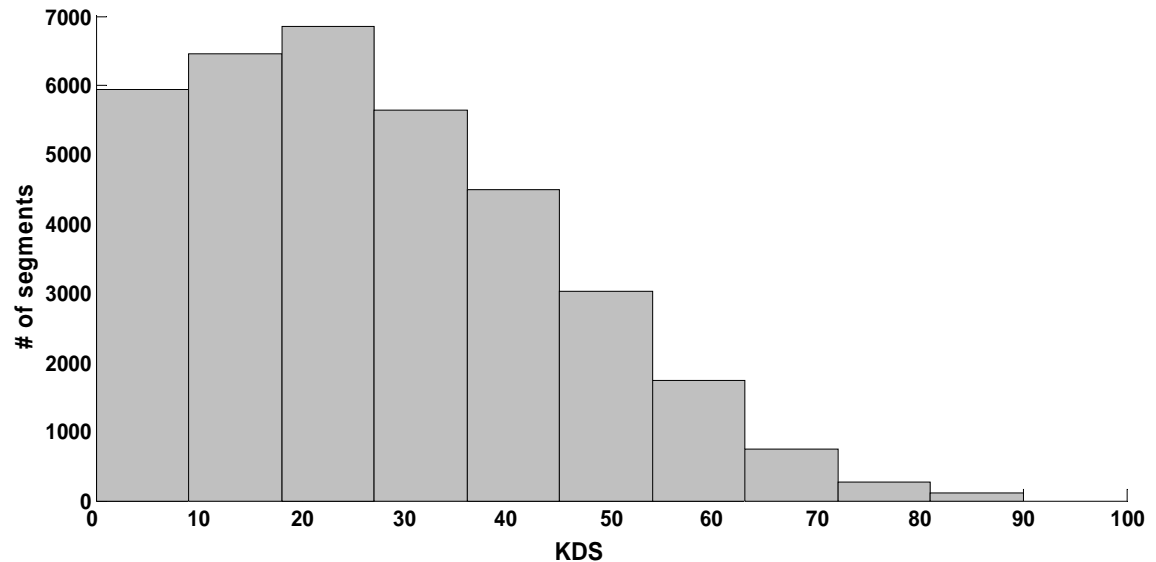


## ➤ Quatember-Maly clocktest

- a computerized version of the Macworth et al (1957) vigilance test
- 15 subjects from a sleep related experiment (two nights in the sleep lab)
- the test was performed during two consecutive day-time periods in
  - i) three 50-min
  - ii) two 25-min long in time separated sessions

# Karolinska Drowsiness Score (KDS)

- Karolinska Drowsiness Score (KDS; Gillberg, Kecklund & Åkerstedt, 1996)
  - visual drowsiness scoring based on a single EEG channel (Oz–Pz), EOG & EMG (artifacts detection)
  - the method was developed to score drowsiness of awake subjects and is based on the Rechtschaffen & Kales sleep scoring rules:
    - slow eye movements, changes in alpha & theta activity
  - 20-sec segments divided into 2-sec bins, each bin visually scored; KDS is the % of scored bins inside a 20-sec window; range 0-100

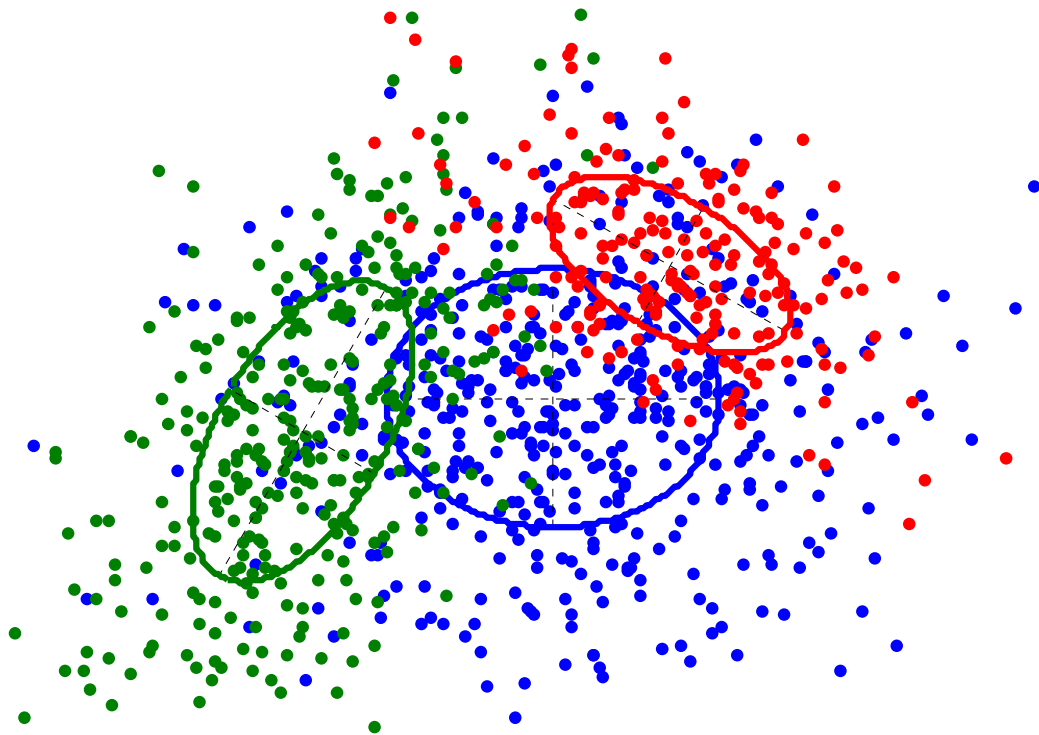
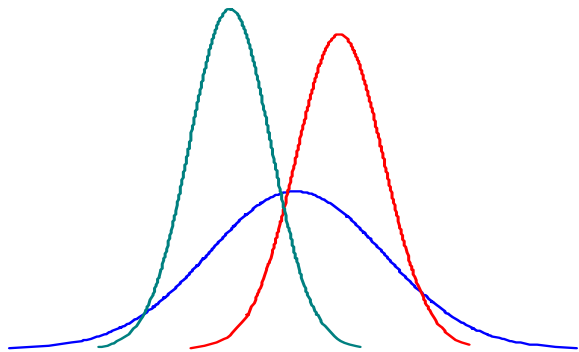


Histogram of the KDS values for the 4-second segments used in the analysis.

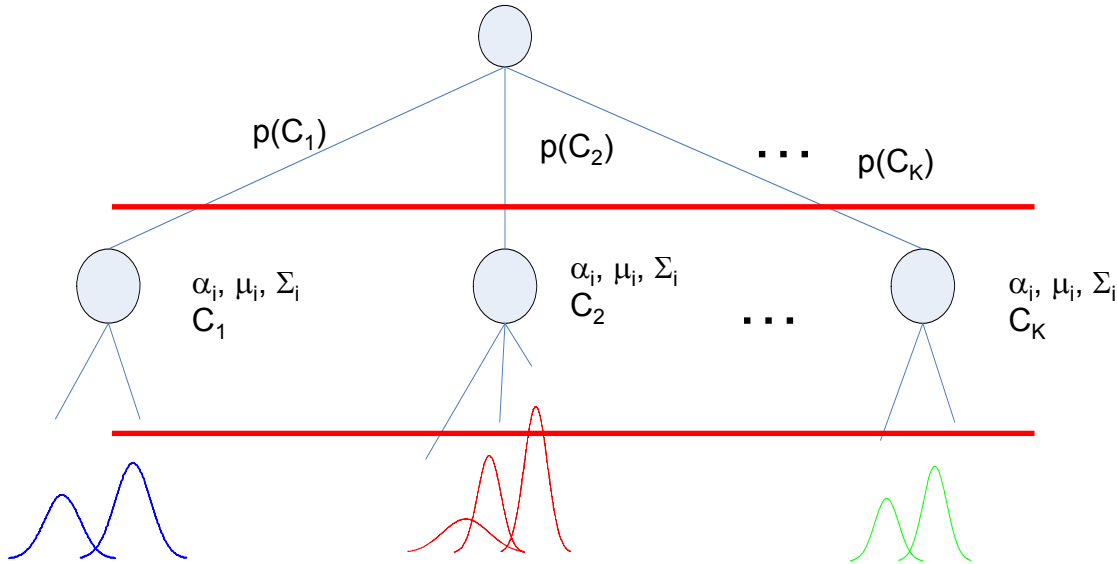
# Gaussian Mixture Model (GMM)

$$p(x | C_i) = \sum_{k \in |C_i|} \alpha_k p(x | \theta_k) \quad \text{where} \quad \sum_{k \in |C_i|} \alpha_k = 1, \quad \alpha_k \geq 0$$

$$p(x | \theta_k) = (2\pi)^{-d/2} |\Sigma_k|^{-1/2} e^{-(x-\mu_k)^T \Sigma_k^{-1} (x-\mu_k)/2}$$



# Structure of a Hierarchical GMM



## Parameters to estimate:

- group priors;  $p(C_1), p(C_2), \dots$
- number of components
- mixing proportions;  $\alpha_i$
- means, covariances;  $\mu_i, \Sigma_i$

## Bayes' theorem to estimate class-posteriors:

$$p(C_i | x) = \frac{p(x | C_i) p(C_i)}{p(x)} \propto p(x | C_i) p(C_i)$$

where  $p(x)$  is the unconditional density:

$$p(x) = \sum_{i=1,2} p(x, C_i) = \sum_{i=1,2} p(x | C_i) p(C_i)$$

# Driver's drowsiness model

➤ First step:

Two classes (cornerstones):  $KDS = 0$  &  $KDS \geq 50$

i) Hierarchical GMM trained to discriminate classes

ii) 4-second segments – total 10654 (5433/5221)

iii) AR representation on each EEG (Fz-A1, Cz-A2, Oz-Pz) channel

iv) 10 x 10-fold cross-validation

Confusion matrix:

0.78	0.22
0.23	0.77

➤ Second step:

30% of the cornerstones samples used for training the model.

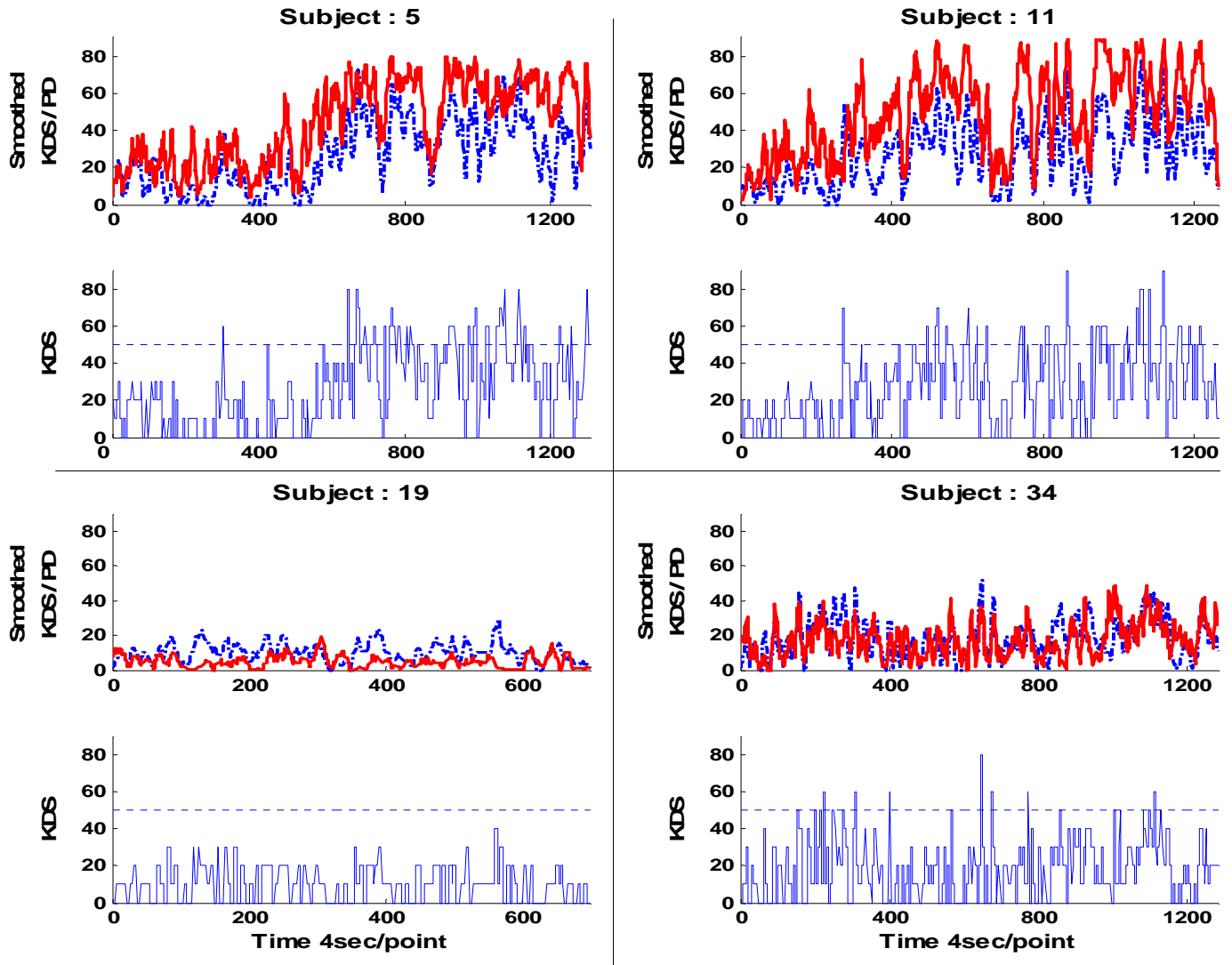
All 4-sec segment data were applied to the trained model.

i) agreement with the KDS scores was visually checked

ii) the nonparametric Spearman's rank correlation coefficient (SC) was computed to compare the smoothed KDS and predicted drowsiness curves.

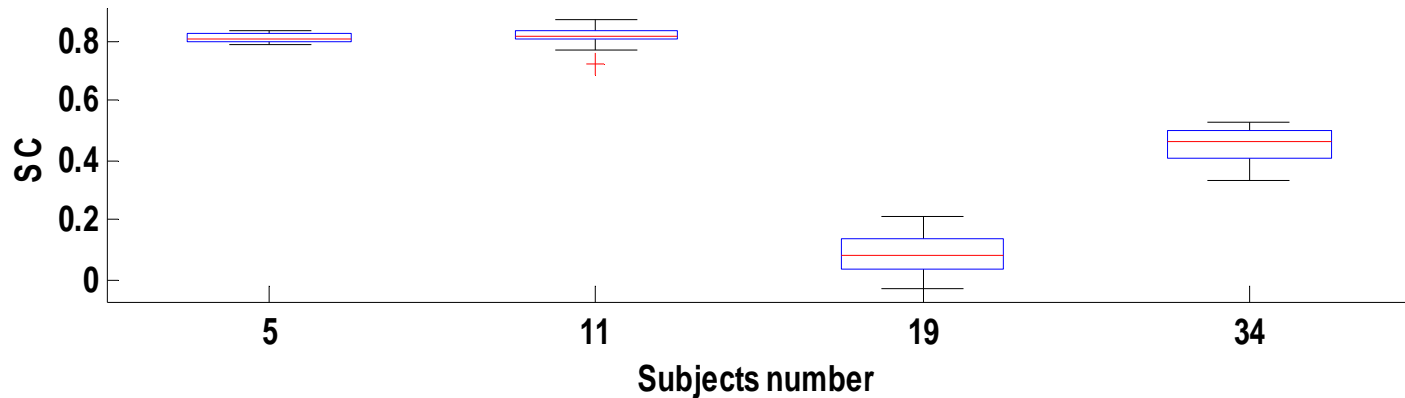
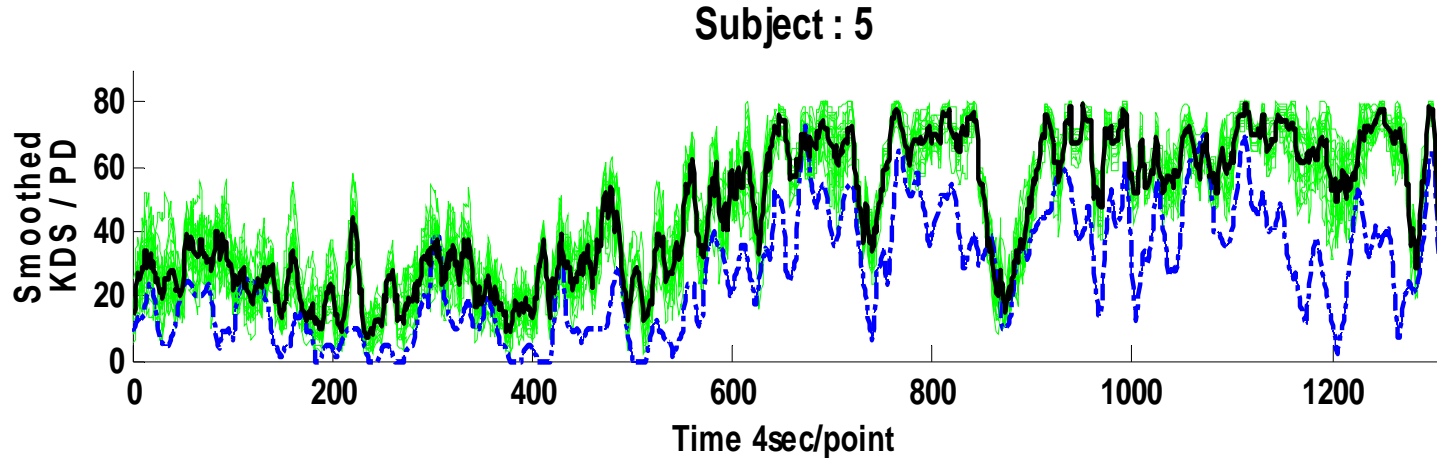
# Results: driver's drowsiness model

In all but three subjects the Spearman's rank correlation  $> 0.2$ ; median 0.53, max. 0.85





# Results: drowsiness model robustness analysis

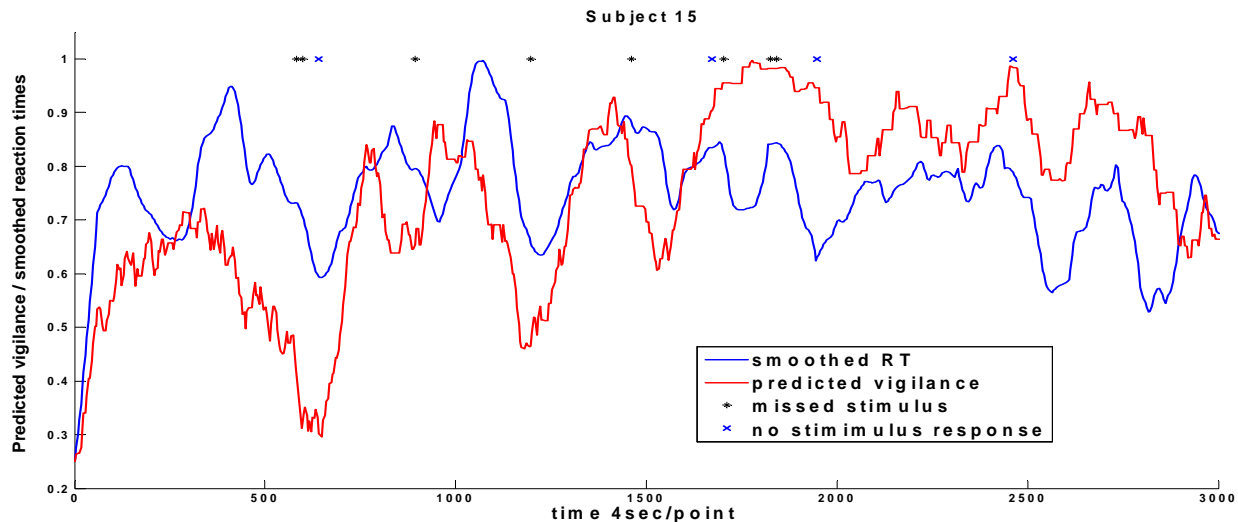


*Top:* The KDS (dash-dotted) and twenty predicted drowsiness (PD) (solid lines) curves. The thicker line represents the mean value of the PD curves.

*Bottom:* The boxplot of the Spearman rank coefficients (SC) for subjects 5,11,19 and 34.

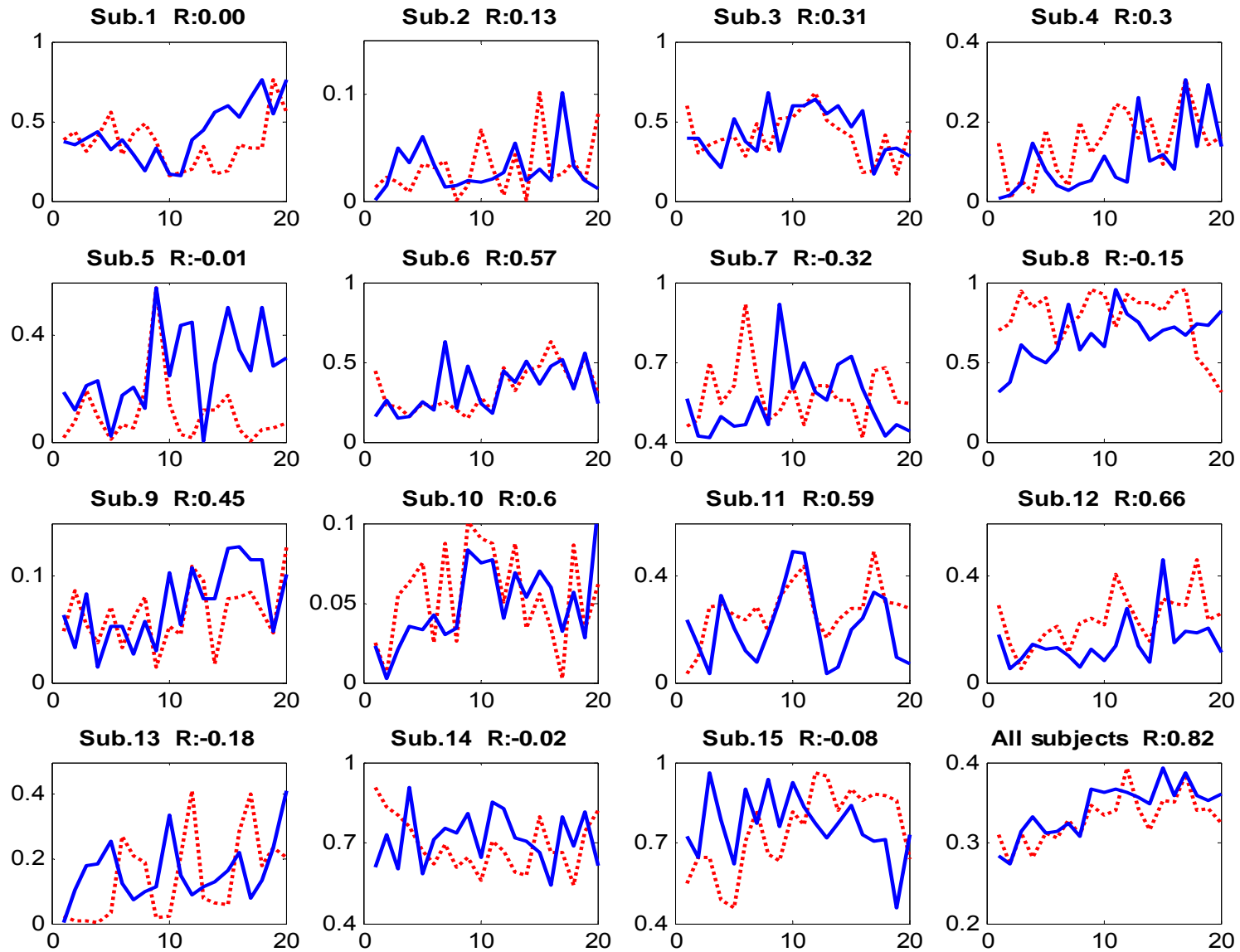
# Vigilance model

- 15 subjects used; each subject: 2 morning & 1 afternoon 50-min sessions
- Pre-trained driving simulator drowsiness model was used:  
**EEG (Fz-A1, Cz-A2, Oz-Pz)**
- The model was applied to all data and periods of low & high posteriors were selected ( $<0.2$  /  $>0.8$ )
- The model was then re-trained using the selected segments from the first and last third time periods
- Reaction time (response) values were 'smoothed' using the cubic spline method



- Analysis was done on 2.5-min segments where the mean of the predicted impaired vigilance and response times was computed ( $\approx 20$  values).

# Results: vigilance model



Mean predicted vigilance (red, dotted) and extrapolated reaction time values. Afternoon session

# Conclusions

- **A reasonably high level of correlation was observed between predicted drowsiness levels and the KDS values.** This was despite the fact that the hGMM was applied to shorter data segments, no EOG information was used and, in contrast to the Karolinska scoring protocol, broadband spectral information from multi-electrode EEG setting was considered.
- **On vigilance task data the results were not so conclusive. High correlations were found on data recorded during the afternoon session only.** However, it needs to be stressed that the presented analysis relates the continuously predicted vigilance and extrapolated reaction time values. This is new and in contrast to the approaches where global statistics computed from whole vigilance test experiments are analysed.
- **The computations associated with the presented approach are fast enough to build up a practical real-time drowsiness or vigilance monitoring system.**