EEG-based drivers' drowsiness monitoring using a hierarchical Gaussian mixture model

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Outline

Introduction

Objectives

- To develop probabilistic modeling 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 behavior (drowsiness, fatigue or vigilance).
- Presented pilot study adapts the methodology for the continuous sleep process modeling developed in the FP7-EU project SENSATION.

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- 45 shift workers, all non-professional drivers - 32 recordings used
- Drove during morning hours directly after a full night-shift with no sleep
- Drove 45 - 90 minutes
- Electrophysiological signals: EOG, EMG and EEG - Fz-A1, Cz-A2, Oz-Pz
- Pre- and post-questionnaires, sleep diary, subjective sleepiness ratings, driving behavior, pupillometry, eye gaze, eye-lid opening, etc.

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Karolinska Drowsiness Score (KDS)

- 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
- Visual data scoring using a single EEG channel (Oz-Pz) and EOG, EMG - artifacts detection
- 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

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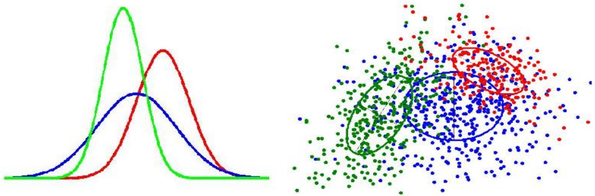
Hierarchical Gaussian Mixture Model - I

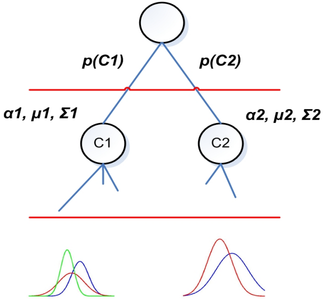


A single GMM

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

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

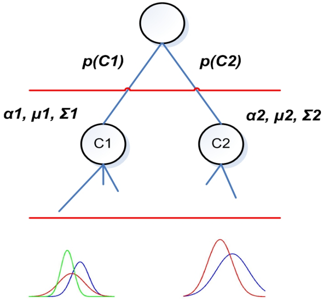
Hierarchical Gaussian Mixture Model - II



Bayes' theorem to estimate class-posteriors:

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

Hierarchical Gaussian Mixture Model - III



Parameters to estimate:

a) class priors; $p(C_1), p(C_2)$
b) # of mix. elements; $|C_1|, |C_2|$
c) mixing proportions; α_i
d) means, covariances; μ_i, Σ_i

Studies A & B

Study A

- Hierarchical GMM trained to discriminate classes/cornerstones: KDS = 0 & KDS $\geq$ 50
- 4-second segments - total 10654 (5433/5221)
- AR representation on each EEG channel: EEG (Fz-A1, Cz-A2, Oz-Pz)
- Spatial variation of electrodes & a number of mixture elements selection: 100 x 20-fold CV

Study B

- 30% of the cornerstones samples used for training the model
- All 4-sec segments applied in the time-course of driving

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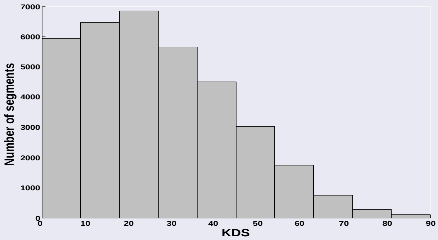
Study A - I

Histogram of the KDS values (35295 4-sec segments)



Study A - II

Electrodes spatial variation

EEG electrodes set	Correct classification rates Mean (standard deviation)	Number of mixture elements Mixture1 / Mixture2
Fz-A1, Cz-A2, Oz-Pz	77.3 (1.7)	4 / 8
Cz-A2, Oz-Pz	72.9 (1.5)	4 / 8
Fz-A1, Oz-Pz	76.3 (1.2)	6 / 12
Fz-A1, Cz-A2	73.5 (1.3)	2 / 6
Oz-Pz	67.2 (1.3)	8 / 16
Cz-A2	67.8 (1.4)	8 / 10
Fz-A1	71.5 (1.3)	4 / 12

Performance of the full EEG (Fz-A1, Cz-A2, Oz-Pz) setting vs. different sets of mixture elements

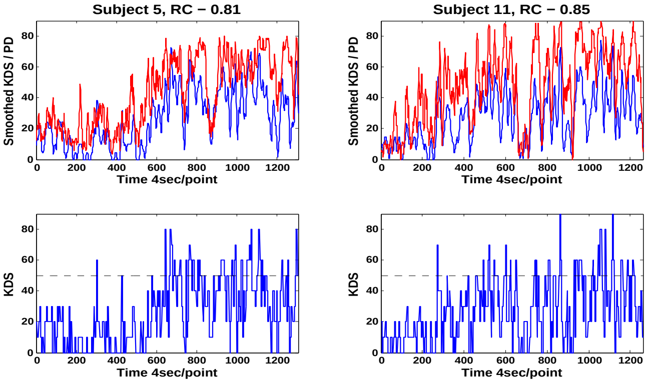
Mixture1 / Mixture2 4 / 8		Mixture1 / Mixture2 **8 / 8**		Mixture1 / Mixture2 **10 / 10**	
76.1	23.9	78.0	22.0	77.5	22.5
21.6	78.4	23.0	77.0	22.7	77.3

Study B - I

Spearman's rank correlation coefficient

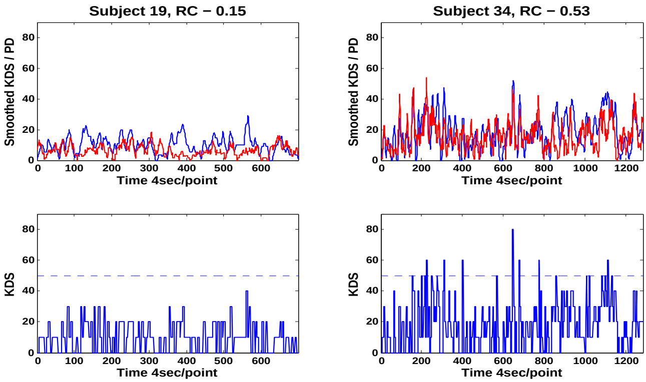
- The nonparametric Spearman's rank correlation coefficient was computed to compare the smoothed KDS and predicted drowsiness curves.
- The RC values were $>$ 0.2 in all but three subjects
- Tha maximum RC value was 0.85
- The median RC value was 0.53

Study B - II



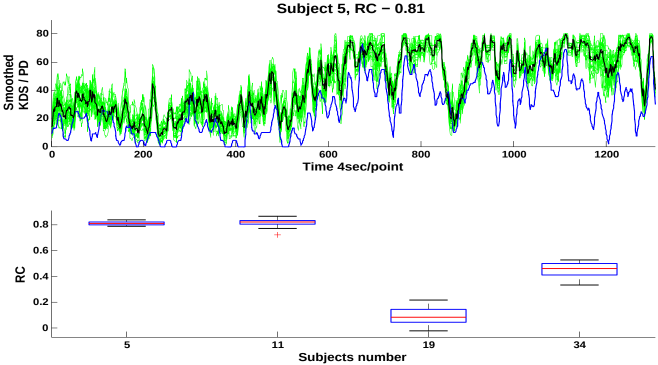
Subjects with the highest rank correlation coefficients between the predicted drowsiness and KDS curves

Study B - III



Subjects with the lowest and median rank correlation coefficients between the predicted drowsiness and KDS curves

Study B - IV



The sensitivity of the hGMM to a training set selection and to the EM method convergence

Summary

- 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 KDS, a broadband spectral representation of multi-electrode EEG signals was considered.
- The computations associated with the presented approach are fast enough to build up a practical real-time system.

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- Applying developed model to vigilance or fatigue data
- Fusion of multi-modal sensor and contextual information

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