A continuous probabilistic approach to sleep and daytime sleepiness modeling

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Introduction: We propose and validate a continuous, entirely probabilistic model of the all night sleep and daytime sleepiness processes. The model is implemented as a hierarchical Gaussian Mixture Model (hGMM). We use features extracted from recordings following a polysomnographic (PSG) setting. In the study we focus on describing sleep and transitions to sleep as a continuous process. The output of a GMM is a set of curves representing probability of each sleep or wakefulness state at a given time point. Results are based on data recorded in the SIESTA and SENSATION projects.

Methods: We use data from C3-M2 and C4-M2 EEG channels for the sleep process modeling task. To unify laboratory differences we downsample data to 100 Hz and bandpass filter data with a Butterworth filter of order 8 and the frequencies range from 0.4 to 40 Hz. We cut data into segments of three seconds and we compute a compact spectral representation of the individual segments using autoregressive (AR) model coefficients. Next, we use hierarchical mixtures to model the distribution of the AR coefficients (Figure 1).

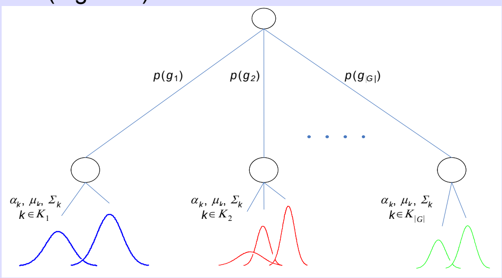
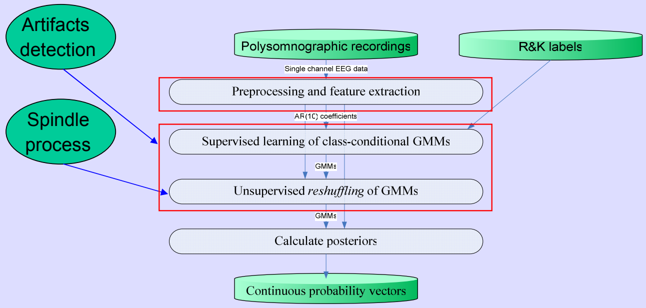


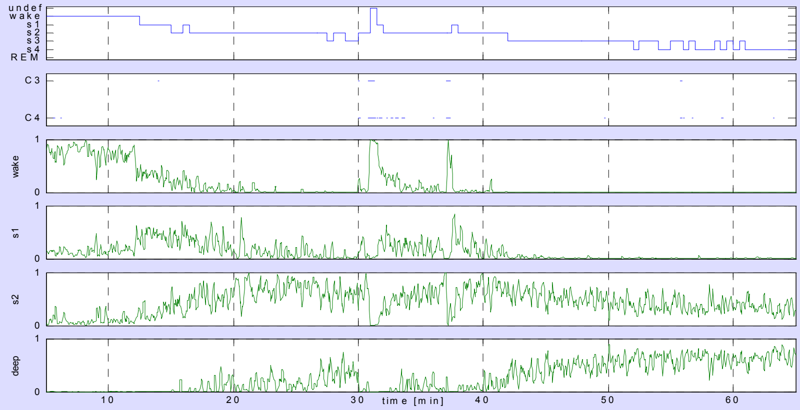
Figure 1: *A hierarchical GMM structure.*

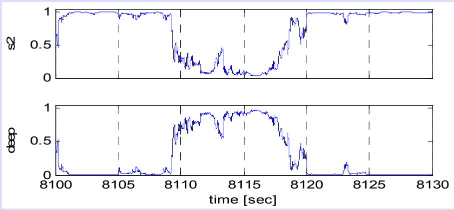
GMMs are used in the lower part of the hierarchy. Inference about the model parameters is done in a semi-supervised manner, where information from the R&K sleep profiles is used for model selection and parameters initialization. In the second step, unlabeled data is used to allow the models to adapt more freely to the data (Figure 2). Finally, Bayes' theorem is applied to compute the probabilities of group membership for unseen data.



We validate the new sleep representation through a comparison with the R&K sleep profiles. We correlate the features extracted from both the discrete R&K and continuous GMM sleep profiles with 26 external criteria of sleep−psychometric variables.
PSG recordings of 176 healthy subjects (83 males and 93 females) age between 20 and 95 were used. Two nights PSG recordings were available and R&K scored for each subject.
Using EEG (Fz, Cz, Oz) from a driving simulator experiment we discriminate between epochs with the high (>50) and low (0) values of the Karolinska Drowsiness Scores (KDS) computed per 20 sec.

Results:.





Top: R&K and hGMM continuous traces for 74 year old healthy control female; filter 3 time points.
Left: Continuous sleep traces for S2 and deep sleep, 42 years old healthy control female. In the epoch scored as stage S2 according to R&K, a 10 sec period of deep sleep is identifiable

Statistically significant rank correlations were observed with 12 psychometric variables (p-values < 0.01).

c_eff	-0.538	rk_eff	-0.542
c_wake_tsp	0.527	rk_wake_tsp	0.517
c_rAUC_wake	*0.529*		
c_s1_tst	0.328	rk_s1_tst	0.332
c_rAUC1_s1	*0.336*		
c_s2	-0.303	rk_s2	-0.325
c_rAUC_s2	*-0.311*		
		rk_s4	-0.245
c_rAUC2_deep	*-0.401*		
c_rAUC1_deep	*-0.396*		
c_rAUC_deep	*-0.289*		
c_fw	0.300	rk_fw	0.213

c_wake_tsp	-0.307	rk_wake_tsp	-0.296
c_AUC1_tsp__wake	*-0.381*		
		rk_s1_tst	-0.211
c_AUC1_s1	*-0.340*		
c_AUC_s2	*-0.250*		
		rk_s4	0.299
c_fw	-0.354	rk_fw	-0.277
c_eff	0.297	rk_eff	0.281

c_eff	0.291	rk_eff	0.223
c_wake_tsp	-0.387	rk_wake_tsp	-0.312
c_AUC1_tsp_wake	*-0.458*		
c_AUC2_tsp_wake	*-0.458*		
c_fw	-0.457	rk_fw	-0.307
c_fs	-0.423	rk_fs	-0.280
c_AUC1_s2	*-0.374*		
c_AUC_s1	*-0.337*		

Correltaions of the selected R&K and hGMM based sleep features with:

Top left: Sleep Quality Index (Saletu et al. 1987)

Top right: Fine motor activity test (Grunberger 1977)

Left: Alphabetical cross-out test (Grunberger 1977)

The confusion matrix of classifying the 4 sec long segments of low drowsiness (KDS=0) versus the segments of high drowsiness (KDS>=50) representing "sleep onset". 29 subjects, 10654 (5433/5221) segments, 10 x 10-fold CV.

0.80	0.2
0.22	0.78

Conclusions: The continues sleep model has shown the same or a higher level of information about the sleep process in the investigated correlation tasks. The continuous sleep model can successfully complement the R&K standard for a comprehensive description of sleep. Promising preliminary results were obtained when discriminating low and high drowsiness states of subjects driving on a simulator.

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