A Hierarchical Gaussian Mixture Model for Continuous High-Resolution Sleep Analysis

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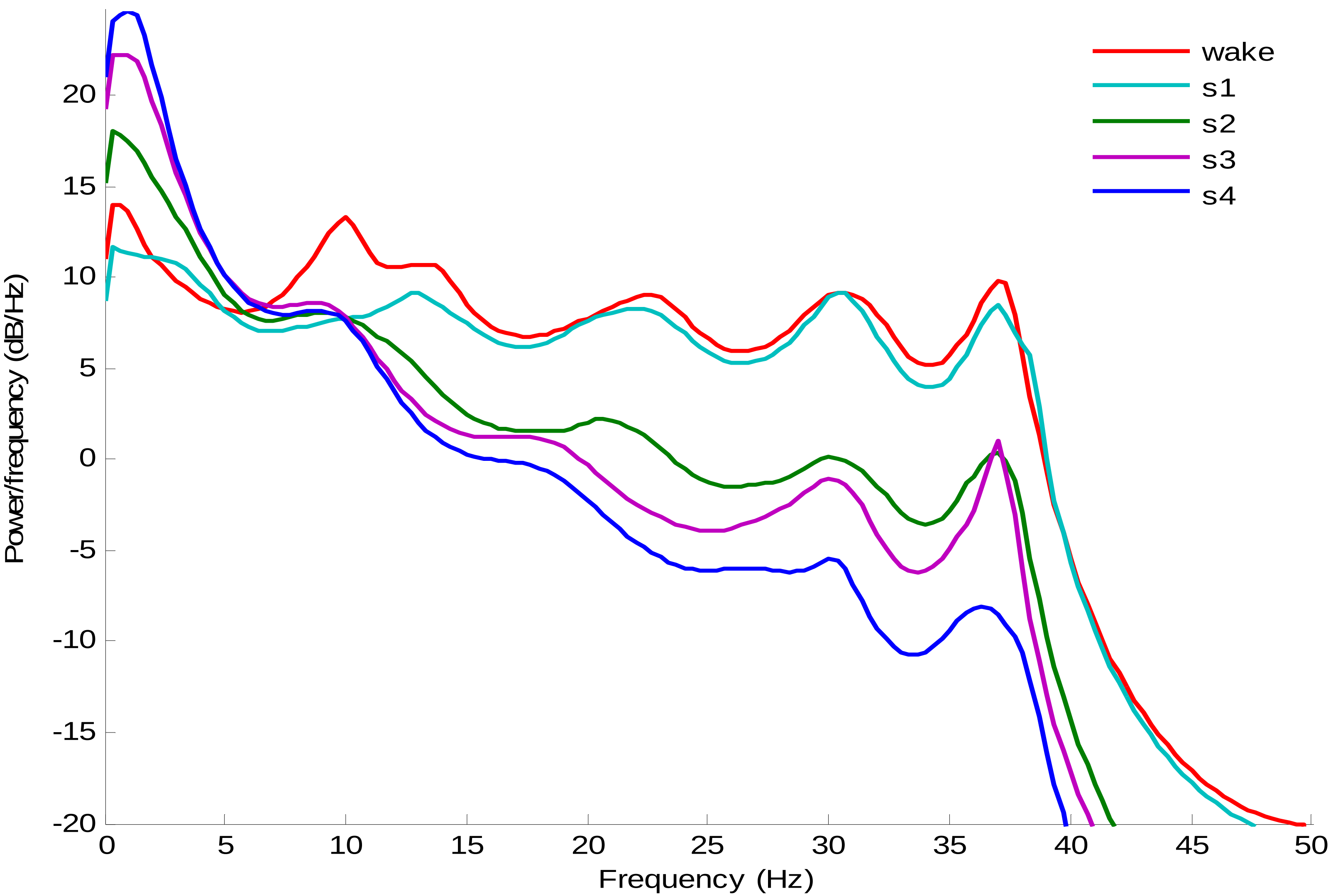
Limits of R&K x Probabilistic Continuous Representation of Sleep

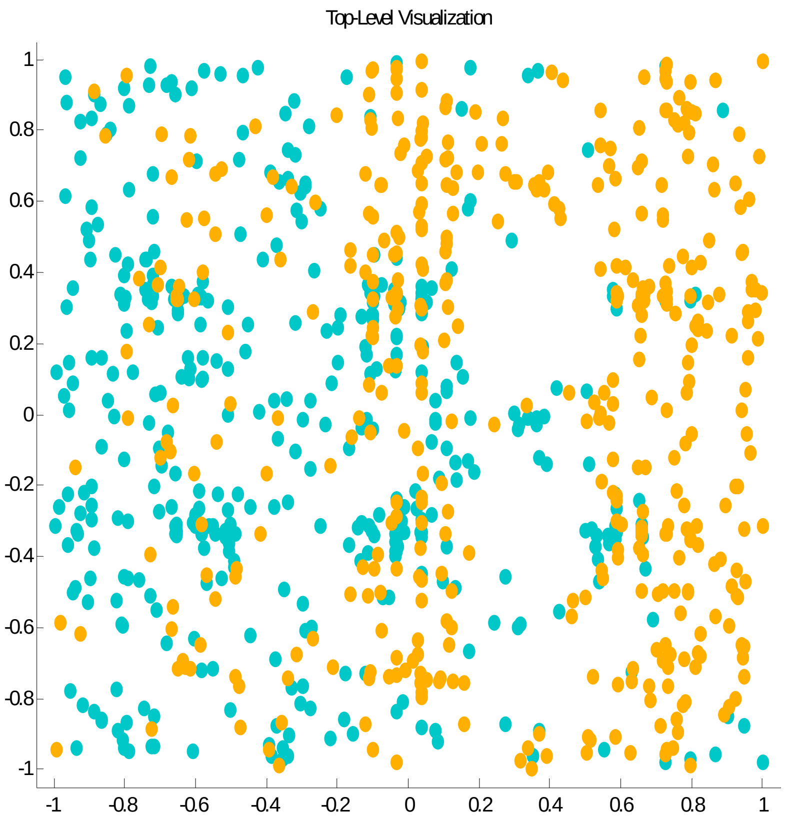
- coarse time resolution (20 or 30 sec) x 3 sec - up to the sampling frequency
- limitation to the central electrodes (C3,C4) x multi-electrodes model
- amplitude dependent delta waves rule for SWS x AR representation of the power spectra
- discrete clustering/classification x continuous probability curves of sleep stages

Example 1: mean AR(10)-based power spectrum

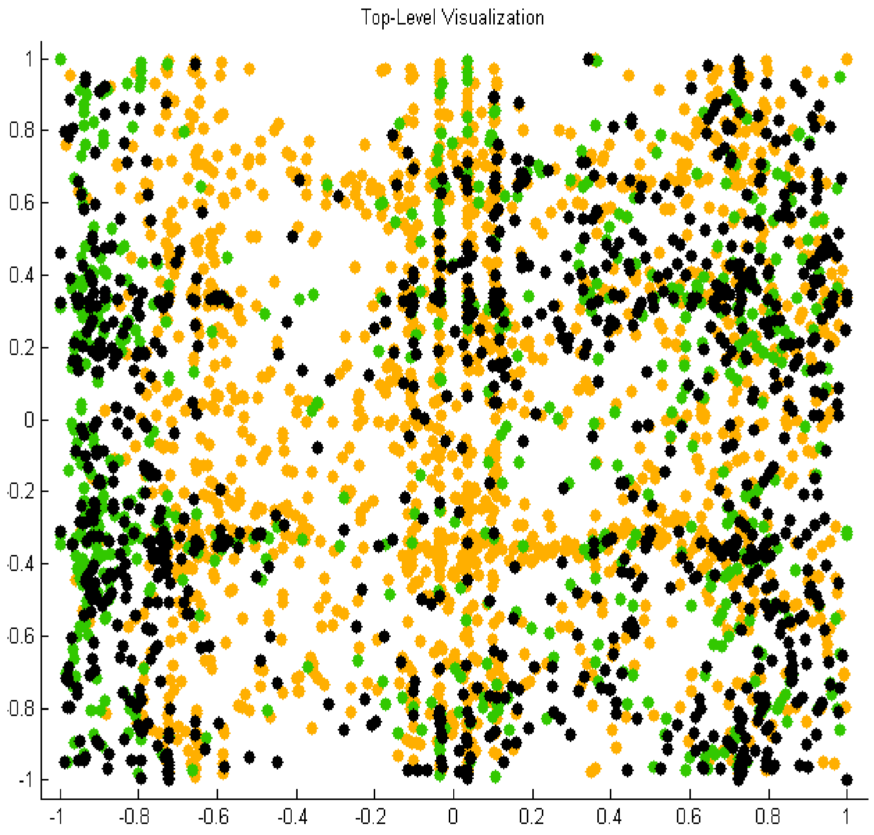


Example 2: 2-D projection of AR(10) coefficients - GTM

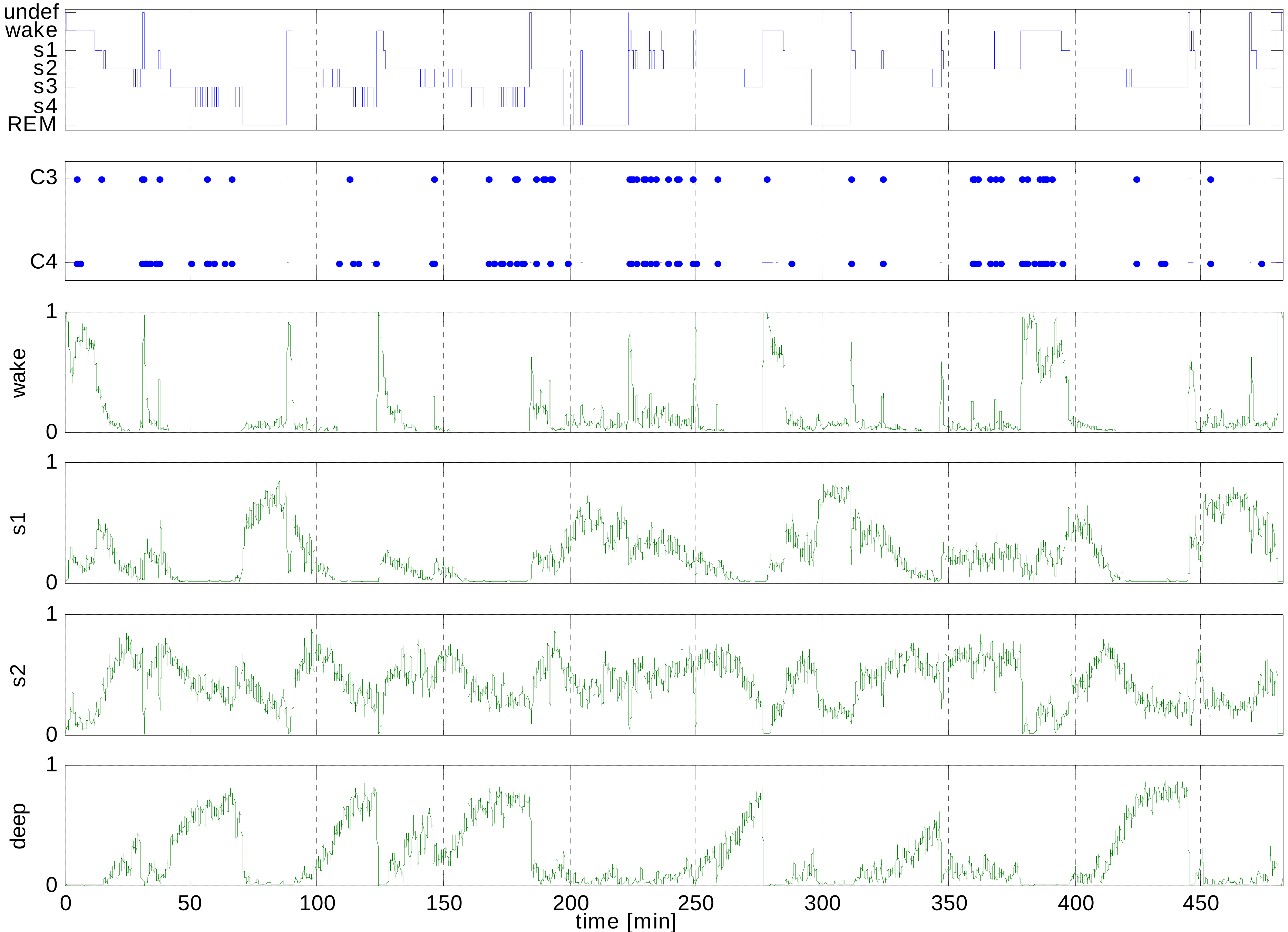
S1 vs S2



S2 vs deep (S3+S4)



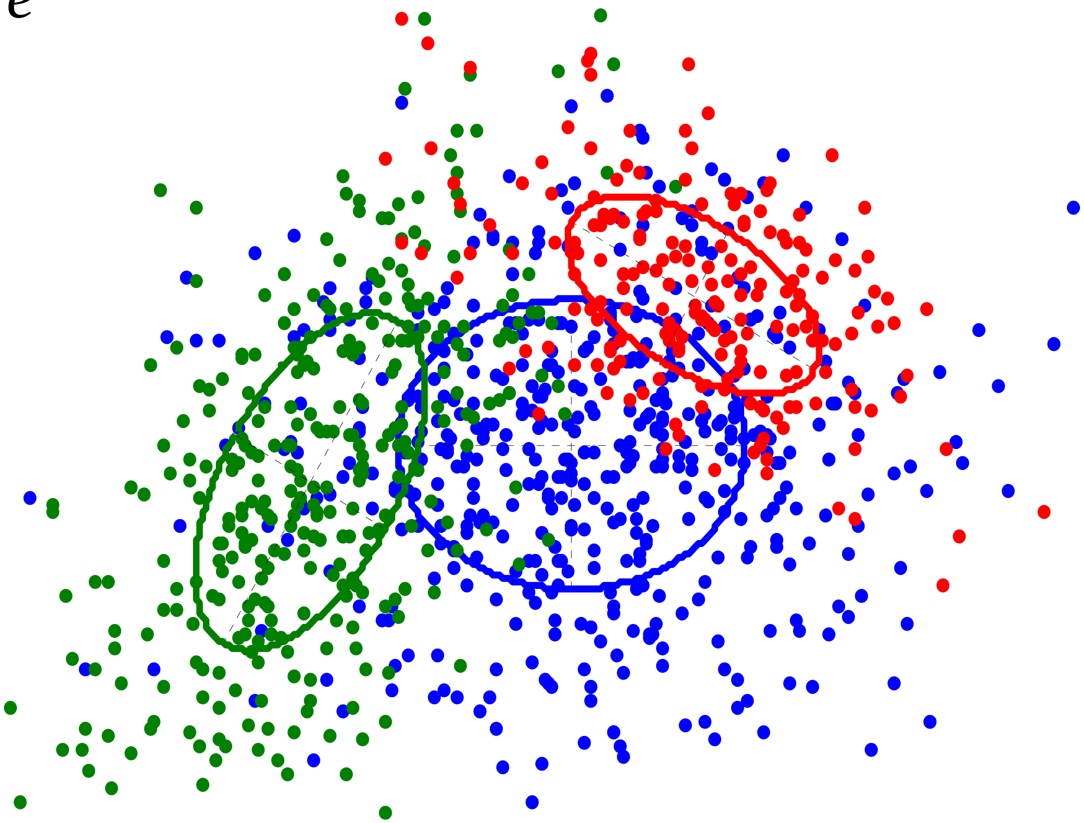
subject b0042, 2nd night, age 74, female, healthy control, filter 15 time points



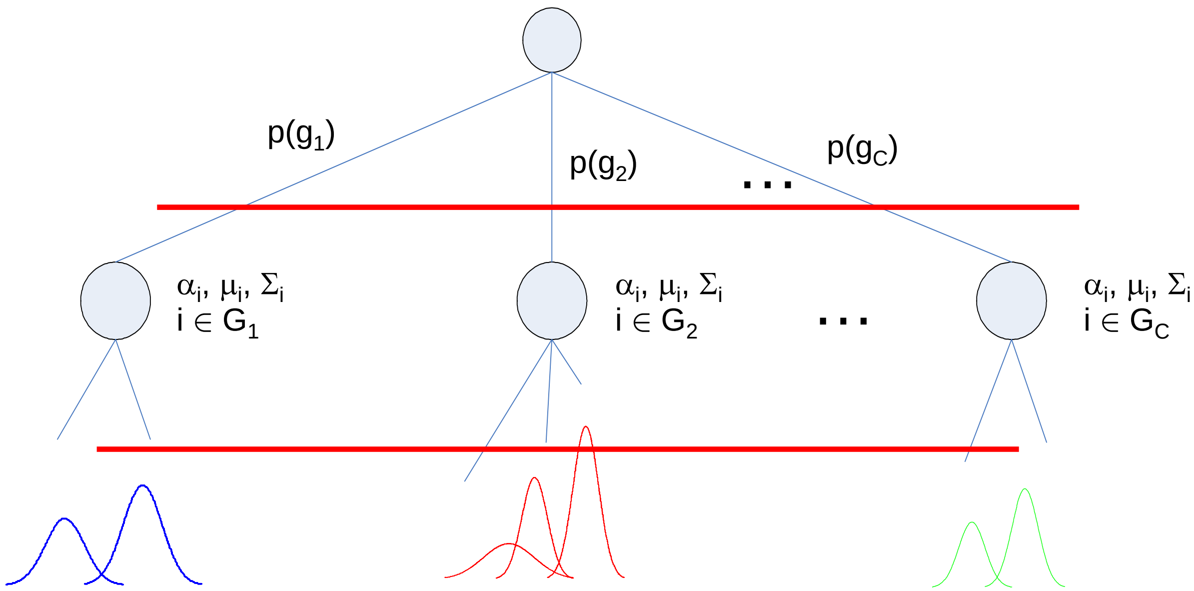
Gaussian Mixture Model (GMM)

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

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



Structure of a Hierarchical GMM



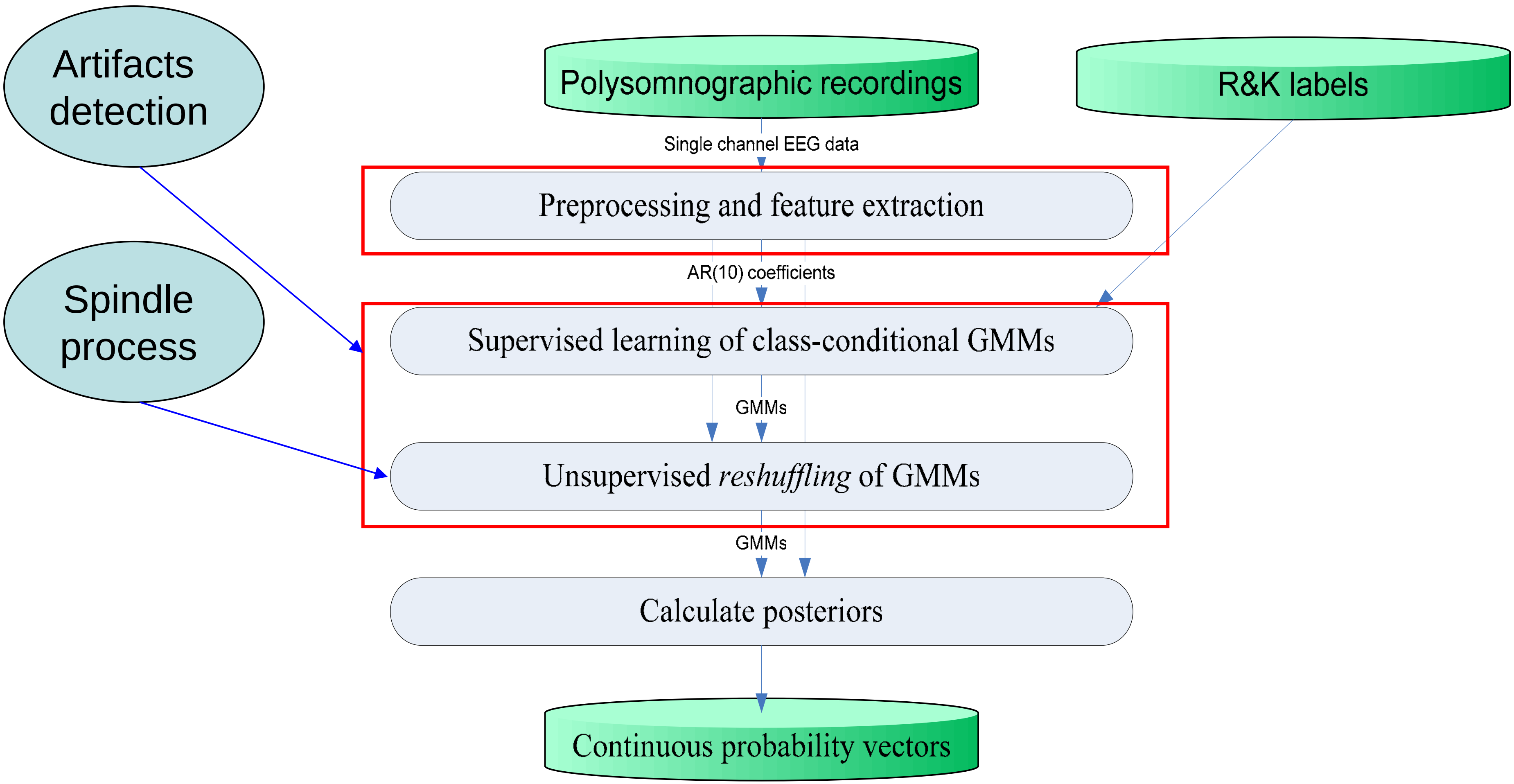
group priors, i = 1 ...C

number of components
mixing proportions
means, covariances

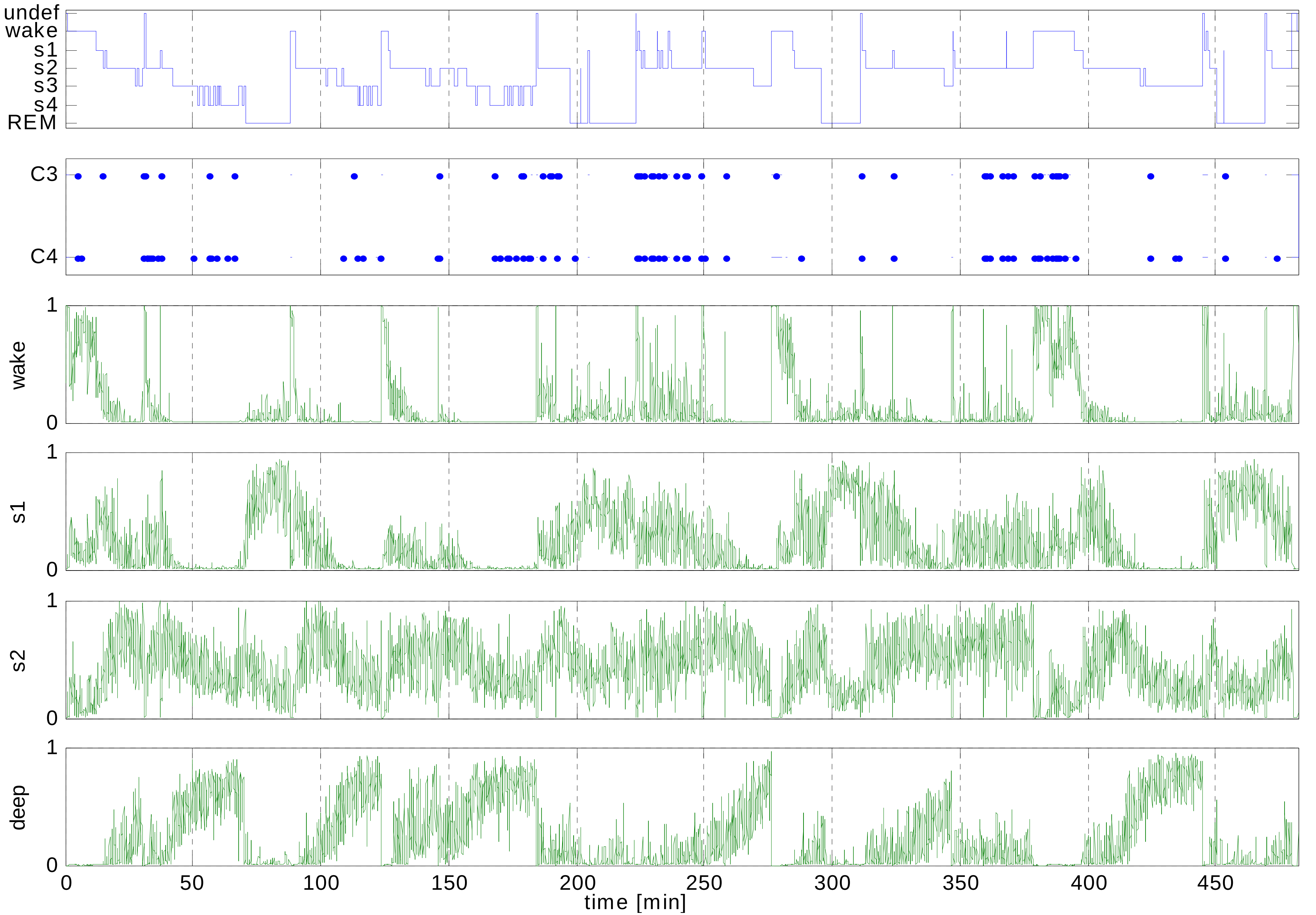
Step1: train mixtures of individual classes, set group priors

Step2: unsupervised (semi-supervised) *reshuffling*, keep structure

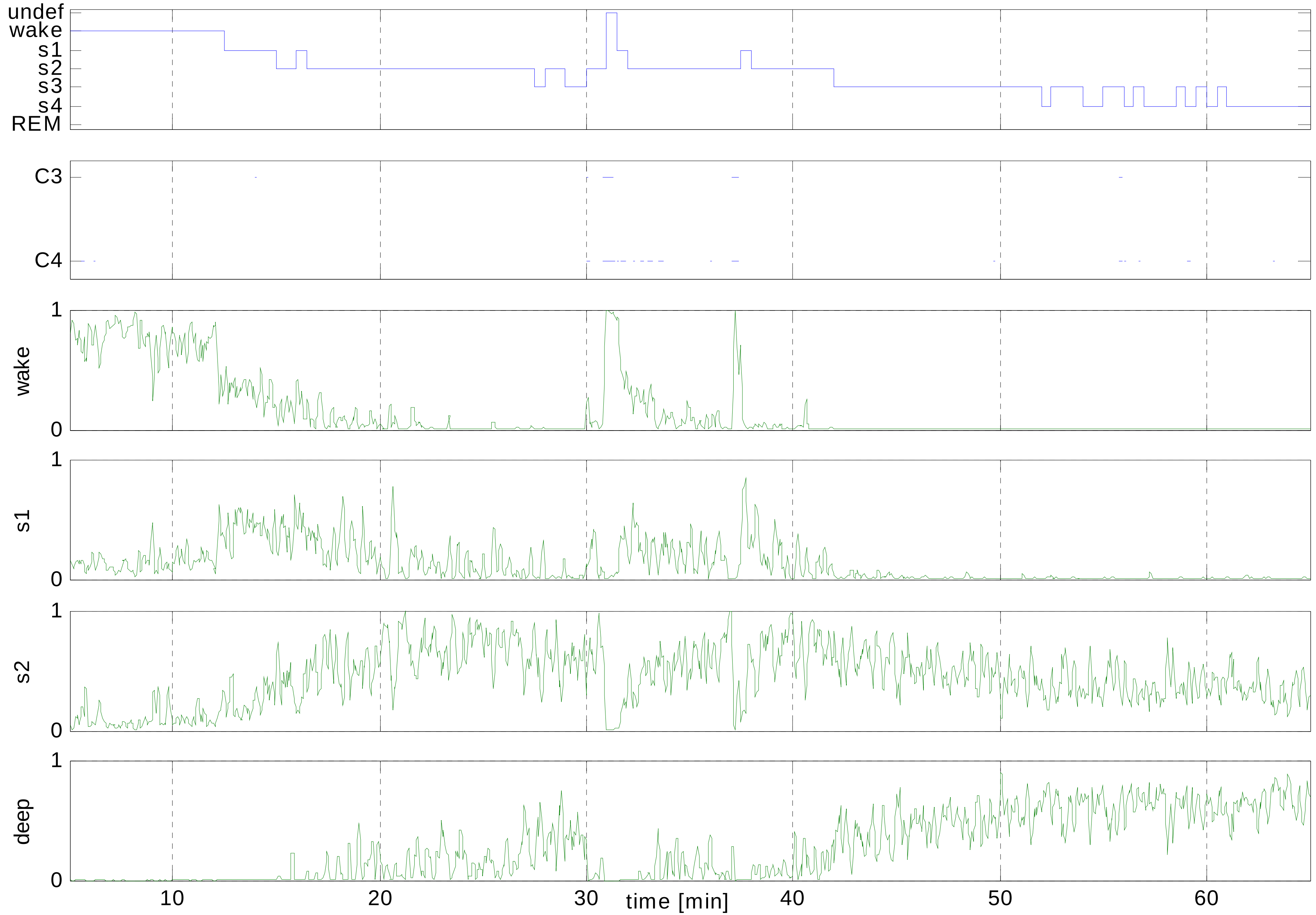
Data flow of the model building process



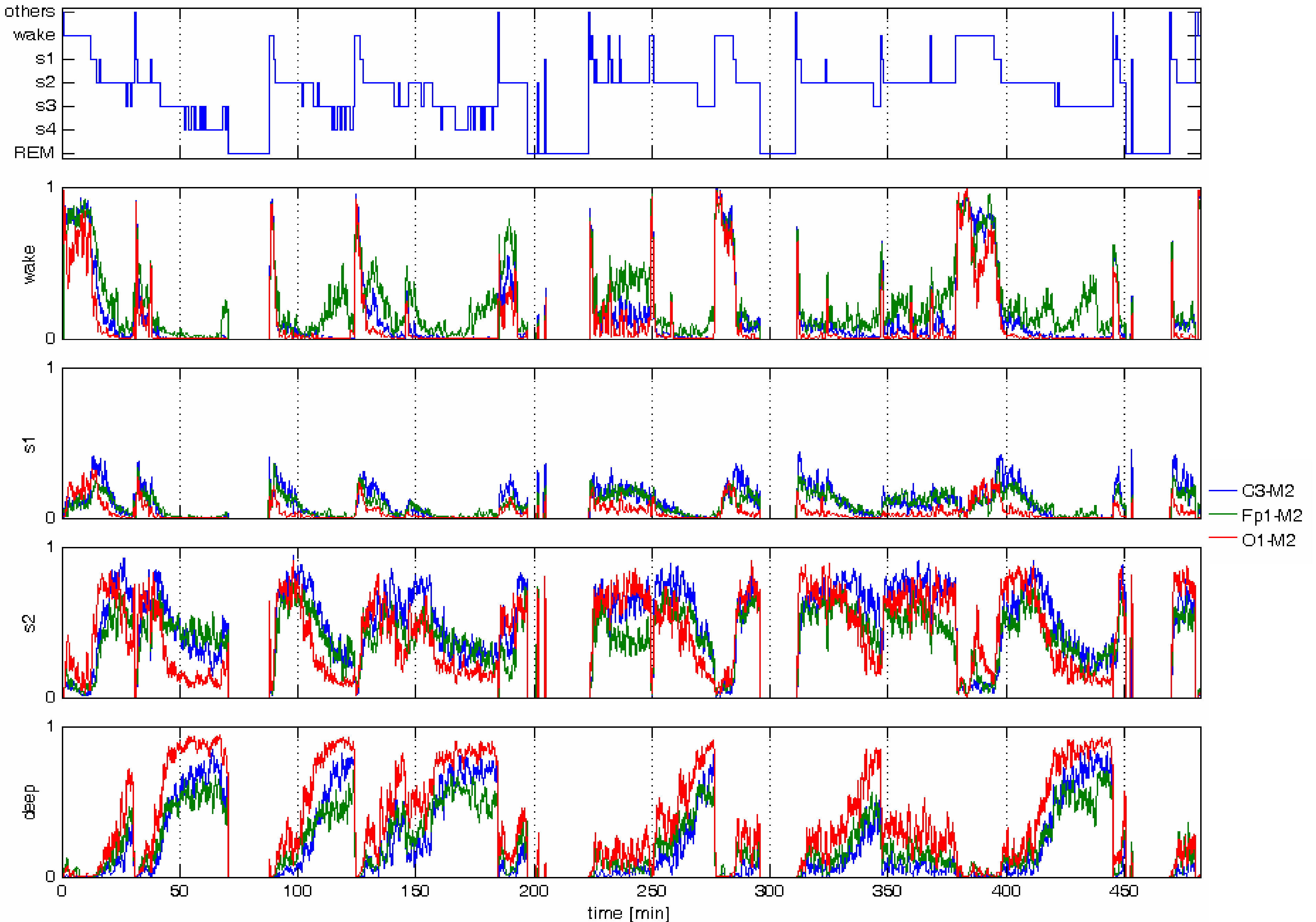
subject b0042, 2nd night, age 74, female, healthy control, filter 3 time points



subject b0042, 2nd night, age 74, female, healthy control, filter 3 time points



subject b0042, 2nd night, age 74, female, healthy control, filter 15 time points



Results

Normal Healthy Subjects (PSQI $\leq$ 5)

- 176 healthy subjects (83 males and 93 females) aged between 20 and 95 years.

A) Night differences (p-values < 0.01)

Sleep Quality Index (SSA-1) (Saletu et al. 1987)

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

Mood (VAS score)

c_s2	0.244	rk_s2	0.258
c_s2_tst	0.201	rk_s2_tst	0.201
c_rAUC_s2	*0.250*		

Drowsiness (VAS score)

c_eff	-0.201	rk_eff	-0.229
c_wake_tsp	0.196	rk_wake_tsp	0.219
c_AUC_wake	*0.205*		
c_AUC1_deep	*-0.197*		

B) Individual Nights (p-values < 0.01)

Fine motor activity test
(Grunberger 1977)

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*		

Alphabetical cross-out test
(Grunberger 1977)

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

Conclusions

- Continuous probabilistic sleep modeling shows higher flexibility to model several characteristics of sleep (sleep arousals, sleep stages transitions, delta process)
- The continues sleep model has shown the same or a higher level of information about the sleep process in the investigated correlation and discrimination (not presented here) tasks
- The continuous sleep model can successfully complement the R&K standard for a more comprehensive description of sleep
- The probabilistic approach allows principled sensor and different processes fusion (spindle process, EOG or EMG modeling) and a new sleep process interpretation