Importance of the time alignment of the sleep probabilistic curves

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Abstract. *Sleep is a dynamic process which can be described by a finite set of sleep stages. In contrast to the standard discrete Rechtschaffen and Kales sleep model continuous sleep representation provided by the Probabilistic Sleep Model allows to take into account the whole dynamic of the sleep process. However, analysis of the sleep probabilistic curves faces problems when the time misalignment is present. In this article we highlight the necessity of curves synchronisation before further analysis. Original and in time aligned sleep probabilistic curves are transformed into finite dimensional vector space and their ability to predict age or daily measures is computed. We observed that curves alignment significantly improves the prediction of the daily measures especially in the case of the REM sleep stage.*

Keywords: Probabilistic Sleep Model, Time Alignment, Functional Principal Component Analysis

Introduction

Sleep is a continuous process consisting of a finite number of sleep states. Its quality has important influence on our daily–life performance and health.

The Probabilistic Sleep Model (PSM) [1] describes the sleep process with probability values of standard sleep stages *Wake, S1, S2, slow wave sleep SWS* or *REM* [2] (Fig. 1). Considering the probability values as a function of time we obtain a sleep probabilistic curve.

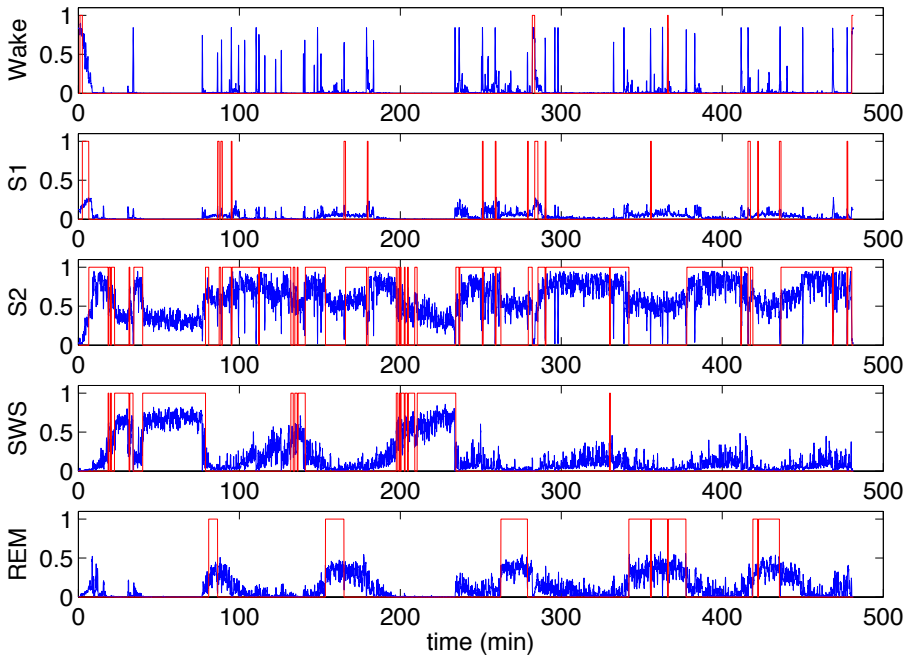

Fig. 1: An example of sleep probabilistic curves for sleep stages *Wake, S1, S2, SWS, REM*. The blue curves represent a whole night profile of a selected 22 years old healthy female. Corresponding Rechtschaffen and Kales scores [2] are depicted in red.

In the analysis of the sleep probabilistic curve we aimed to find typical overnight sleep profiles which significantly correlate with age or daily life performance. Unfortunately, when

the curves with similar shape are misaligned in time (Fig. 2) the relationship with daily life measures is difficult to detect.

The problem of curves time alignment appears frequently in literature. Out of many methods developed for curves alignment we can mention Self–Modeling Time warping [3] or Pairwise Curve Synchronisation [4]. Following our previous practical experience with the presented sleep dataset, we prefer the Elastic Warping method [5].

On other hand, there may exist sleep features for which the exact timing is important. Therefore we aimed to detect sleep stages where the time alignment of the sleep probabilistic curves significantly improves correlations between the sleep structure and daily measures and to demonstrate the benefit of the curves alignment in all.

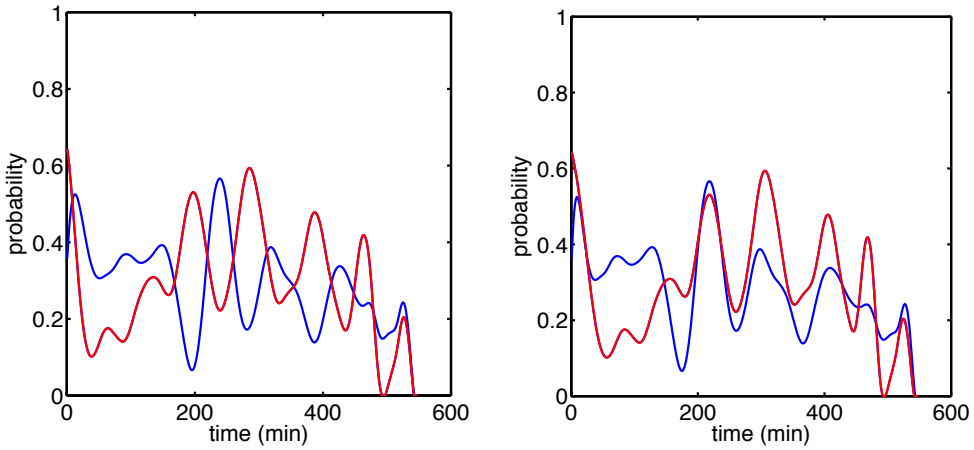

Fig. 2: An example of two smoothed sleep probabilistic curves with similar overnight profile misaligned in time (left) and their aligned versions (right).

Subject and Methods

In this article the polysomnographic (PSG) recordings of 146 healthy subjects spending two consecutive nights in the sleep lab were used. These recordings represent a subset of PSG data collected in the European sleep project SIESTA [6]. After awakening the subjects took part in a battery of neuropsychological tests. They were also asked to subjectively score their sleep quality or level of drive, mood, affectivity and drowsiness [7]. In addition, in the morning and in the evening their pulse rate and blood pressure was measured and results stored. Except of the original daily measures we considered three dominant factors – factor of subjectively scored sleep quality, physiological factor and neuropsychological factor. These factors were obtained by applying the factor analysis method to the set of all available daily measures [7].

First, PSM was applied to the PSG data and sleep probabilistic curves mimicking the standard sleep stages were extracted. Because of high time variation between the beginning of sleep (lights off) and falling asleep among subjects, the beginning of all probabilistic sleep curves was set to the sleep latency which is defined as the three consecutive 30 seconds long periods of the *S1* stage or the first period of the *S2* stage, whichever comes first.

In order to eliminate noise the sleep probabilistic curves were smoothed by applying the Functional Principal Component Analysis (FPCA) method with smoothing covariance surface [8]. Moreover, the FPCA method is able to predict the sleep probabilistic curves profile at the end of the night according to the behaviour of the whole database. Therefore we can define curves of all subjects over the same time interval.

The sleep probabilistic curves are members of a functional half–space of all nonnegative curves. In order to use standard statistical techniques we had to transform them into a finite

dimensional vector space by FPCA [8]. Each smoothed curve can be expressed as a sum of an overall mean curve μ and a linear combination of K functional principal components $\varphi_1, \ldots, \varphi_K$

$$X_i(t) = \mu(t) + \sum_{j=1}^{K} \alpha_{ij}\varphi_j(t), \qquad i = 1, \ldots, N, \quad N = 2 \times 146 = 292.$$

The vector of principal component scores (PCS) $\alpha_i = (\alpha_{i1}, \ldots, \alpha_{iK})^T$ was used in the further analysis as the representative of the i^{th} curve.

To relate PCS of the sleep probabilistic curves with daily measures a linear regression model was considered. For a chosen sleep stage the dataset was divided into a training and a testing part. A daily measure was modelled as a linear combination of PCS of the training dataset and we tested whether the formed model is significantly better than a constant model. After that values of the daily measure for the testing dataset were predicted by the estimated linear model and Spearman's correlation coefficient was computed between real and predicted values.

To avoid misinterpretation of results caused by random splitting into training and testing dataset the 10–fold cross–validation was considered.

In the next step sleep probabilistic curves were aligned in time by Elastic Warping method [5] right after smoothing. Transformation of aligned curves into PCS and modelling of daily measures was done in the exactly same way as in the previous case. Finally, the Wilcoxon test was performed to detect whether the difference between correlation coefficients obtained from original and aligned curves is significant.

Different division of the data into 10 folds may lead to slightly different results. Therefore the whole procedure was repeated 100 times and the differences in correlations based on misaligned or aligned curves were considered as significant if the Wilcoxon test rejected the null hypothesis about no difference between correlation coefficients in more than 40 trials.

Results and Disscussion

The alignment of the sleep probabilistic curves caused changes in correlations between real and predicted results of daily measures especially for the *REM* stage (Table 1). Improvement was observed in the case of the physiological factor, age or the results of the numerical memory test. In the last case, the insignificant correlation between daily measures and misaligned curves changed to statistically significant after alignment. Moreover, the percentage of linear models which were significantly better than a constant model increased from 0.1% for misaligned curves to 84.8% for aligned curves.

In the case of the level of mood or affectivity the average correlations between real and predicted values were significantly lower for aligned curves for the *REM* stage. However, neither for aligned nor misaligned curves any estimated linear model was better than a constant model. We hypothesize, that the relationship between the *REM* stage and the level of mood or affectivity simply does not exist or we are not able to detect it either with original or in time aligned curves.

For the *Wake* stage the only significant change was observed in decreased correlation with the level of drive for the aligned curves. More than a half of linear models were significantly better than a constant model when using PCS of the misaligned curves. This indicates the existence of a relationship between the *Wake* stage profile and the level of drive. However, after alignment this relationship disappeared (the percentage was exactly 0).

We hypothesize that for the *Wake* stage the exact timing of sleep features is important. Therefore it is appropriate in this case to analyse both original and aligned sleep probabilistic curves and to carefully interpret obtained results.

Regarding to the sleep stages *S1, S2* or *SWS*, the correlations between real and predicted values of daily measures were higher for aligned curves in several cases, but not significantly.

Table 1: Average correlation coefficients for daily measures and sleep stages. Only results where significant difference between original and aligned curves was detected by Wilcoxon test are presented. The percentage of linear models which were significantly better than a constant model is depicted in brackets.

Daily measure	Sleep stage	p–value	$\bar{\rho}$, misaligned curves	$\bar{\rho}$, aligned curves
physiological factor	REM	0.021	0.23 (83.2%)	**0.42** (100%)
age	REM	0.026	0.40 (100%)	**0.58** (100%)
numerical memory test	REM	0.014	−0.03 (0.1%)	**0.13** (84.8%)
drive	Wake	0.021	**0.14** (60%)	−0.05 (0%)
mood	REM	0.006	**0.02** (0%)	−0.23 (0%)
affectivity	REM	0.003	**0.01** (0%)	−0.22 (0%)
	S2	0.021	0.03 (8%)	**0.24** (13%)

Conclusion

In this article we demonstrated the benefit of time alignment of the sleep probabilistic curves when detecting relationship between sleep structure and daily measures. The improvement was visible especially in the REM stage where new or improved correlations with daily measures were observed. On the other hand, the exact timing of the wake–related sleep features is important in detecting relationship with subjectively scored sleep quality.

Acknowledgements

This research was supported by the Slovak Research and Development Agency (grant number APVV–0668–12) and by the VEGA 2/0011/16 grant.

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