Analysing Physiological Data from the Wake-Sleep State Transition with Competing Predictors

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Abstract

We demonstrate that competing neural networks can analyse and predict time series which originate from biological systems with multiple modes of behaviour. Physiological data (eye movements and respiratory signals) measured from wake and sleep phases of humans are studied. With the presented *unsupervised* method each expert network specializes on a different dynamical mode and the time series is segmented into different wake and sleep phases respectively. At the same time the underlying dynamics of the different modes is learned by the respective experts.

I. Introduction

In time series prediction, neural networks have contributed substantial improvements (see e.g. [12]). However, an important prerequisite for their successful application is a certain uniformity of the data: in most cases, stationarity must be assumed. If, on the contrary, a dynamical system operates in multiple modes and *switches* its dynamics, standard approaches like simple multi-layer perceptrons are likely to fail to represent the complex underlying input-output relations. Multimodal time series can originate from many kinds of systems in physics, biology and engineering. Phenomena of this kind are e.g. speech [11], brain data [9], dynamical systems which switch their attractors [3] or physiological data recorded duribg wake-sleep transition in humans, which will be studied in the following sections [19].

Our ansatz uses no explicit information about *whether* the time series contains multiple modes that switch in time or *what* the dynamics of the single operating modes is. We apply a divide-and-conquer learning strategy which forces a set of competing neural network predictors to specialize on sub-sequences of the data. Simultaneously, a segmentation according to the modes is developed. The competition depends only on the relative performance of the predictor networks and *not* on the input. This way of introducing the competition is in contrast to the mixtures of experts (ME) as proposed by Jacobs et al. [2], where an input-dependent gating network is used. The ME algorithm and also an extension, the mixtures of controllers [1], potentially also offer a solution to the problem of switching modes, since they can represent different functions by the respective experts. Recently a similar approach has been proposed bei Weigend et al. in this context, that uses local error bars for every expert [13]. However, there are problems when applying these architectures to the task of identifying alternating dynamics, if the network input does not allow for a unique determination of the current mode [4, 5, 6, 7, 10].

In previous work [4, 5, 10] we applied our framework to analyse non-stationary time series from chaotic signals and to predict non-stationary time series from the Santa Fe competition [12]. As a further application we considered the unsupervised segmentation of speech signals [6, 7]. In the following we present an application of a hard-competition version of our method to physiological data from wake and sleep states recorded from humans.

II. Biological Background

Sleep is a physiological state, which in humans is maintained during approximately one third of their lifetime. Its importance is often underestimated. All sleep disorders affect wakefulness, either directly (primarily disturbed wakefulness) or indirectly (primarily disturbed sleep). The state transition between wakefulness and sleep is crucial. From the neuorpysiological point of view, it brings with it a reorganization of the neuronal network in the reticular formation of the brain stem, which regulates and integrates cardiovascular, respiratory and somatomotor systems and vig-

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ilance [14]. This reorganization can be thought of as "switching to a different mode".

When falling asleep, practically all physiological functions undergo a fundamental modification: the heart slows down, blood pressure, metabolic rate and muscle tone decrease, consciousness becomes blurred, and cortical activity slows. The latter findings, assessed by the electro-encephalogram (EEG), since the pioneering works of Davis and Loomis [15] have been regarded in clinical practice as as identical with the assessment of sleep itself.

This however, is a restricted view: Von Economo was the first to discern between cortical and organic sleep ("kortikaler Schlaf und Organschlaf" cf. [16]). Recently, the old observation of Magnusson [17], that sleep onset and sleep stages can fairly be assessed by analysing merely respiratory patterns, has been extended by Trinder and coworkers [18], who found that respiration is instable during sleep onset. Also, the typical manifestations in the electrooculogram (EOG) and electromyogram (EMG) are well known to clinicians.

At present clinical analysis of sleep stages focuses on time ranges longer than 1 minute. Algorithms have been developed for automatic recognition of sleep stages. These methods mostly rely on EEG recordings. Thus, they are of little value, (1) if time periods shorter than 1 min. are to be analysed, and (2) if artefact-free EEG recording is not possible.

Rather, the pattern recognition of slow signals (e.g. EOG) would have to be performed within a few cycles of the basic oscillatory pattern. If the development of such techniques will be successful, it can also help to elucidate the physiology of the state transition between wakefulness and sleep. Lately, it has been described that during this transition the interaction of different brain stem related oscillatory processes is modified [19]. Methods which would allow for a better time resolution would enlarge our knowledge in this field. Such improvement might be helpful in diagnosis and treatment of sleep disorders in future time.

Our goal is therefore not only a simple detection of the sleep onset but also a detailed approximation of the dynamics of the signal.

III. Competition of Experts

For a broad discussion of our analysing method we refer to [4, 5, 6, 7, 10]. For the biological time series studies presented here we use hard competition, since it allows a fast interactive analysis of the data: data sets with 14000 data points take typically about 30 seconds on a Sun 20 workstation until a stable segmentation solution is reached. Our ACE algorithm [7, 10] or other ME algorithms using soft-competition are computationally much more expensive [2, 1, 13].

Multimodal dynamics can be unmixed using not one but *several* predictors, which *compete* for the data [7, 10]. In the present application radial basis function (RBF) networks [8] are employed to yield a fast learning algorithm. We assume slow alternation rates, which is a correct assumption for the physiological data studied. Therefore, we can use a simple *moving average* as error function for the predictor i at time t [7, 10]

$$E_i^t = \sum_{\tau=-\Delta}^{\Delta} \epsilon_i^{t-\tau}. \tag{1}$$

The individual errors

$$\epsilon_i^t = \left(y_t - \tilde{f}_i(x_{t-1}, \ldots, x_{t-d})\right)^2, \tag{2}$$

are usual squared errors measuring the quality to predict x_t given the embedding vector $x_{t-1}, \ldots, x_{t-d}$ as input, where $\tilde{f}_i(x_{t-1}, \ldots, x_{t-d})$ is the prediction of the ith network at time t. For the gradient descent we use the cost function

$$E = \sum_t \sum_i \delta_i^t E_i^t \tag{3}$$

with

$$\delta_i^t = \begin{cases} 1 & : \text{ if } \quad E_i^t < E_j^t \quad \forall j \neq i \\ 0 & : \text{ otherwise.} \end{cases} \tag{4}$$

That is, the E_i^t are compared in order to determine the winner for time t and only the winner at time t with lowest error E_i^t is allowed to learn the corresponding data points. The use of a moving average (e.g. Eq.(1)) has proven to be essential for a successful segmentation and prediction of time series from switching dynamics [7, 10].

The practical algorithmic procedure is the following: (1) initialize the set of competing predictors identically. (2) In the first training pass, divide the training set into subsets of equal size, so that each predictor gets a disjoint subset of equal size to learn from. This way we break the symmetry between the predictors and obtain distinctive predictors for the competition. (3) In the second and each following training pass a hard competition is carried out: Only the predictor with the smallest E_i^t is allowed to train on the pattern at time t. As a consequence, unnecessary predictors drop out of the learning process, since they don't win any data after some time. And finally every surviving predictor uniquely specializes on a single mode and the multimodal signal is unambiguously segmented.

IV. Experiments

In the experimental section we only describe results of the analysis and prediction of the respiratory signals and horizontal eye movements (EOG) of one single experimental recording. Further recordings include also

other measurements as blood pressure, pulse, ECG, EEG, which have been studied successfully but details go beyond the scope of this contribution.

In Figs. 1(a) and (b) we see the eye movements and the respiratory signal respectively. Typical Slow Eye Movements (SEM) start at t=5000, indicating a transition from a wake to a sleep phase, which can be observed from the data with some skill. However, it is hard to detect the same transition in the respiratory channel.

A. Segmentation

Both signals from Figs. 1(a) and (b) have been analysed with the hard competition approach using an embedding dimension of $d = 2$, a sampling rate of $r = 5$ and 50 RBF units. The width of the low pass filter is increased during training from $\Delta = 0$ to 400, which corresponds to a timescale of 0 to 40 seconds. The segmentations obtained (cf. Figs. 1(c) and (d)) show similar switching points from wake to sleep[1] and are in good agreement with the diagnosis of a medical expert. Note, that our segmentation was performed completely blind, i.e. only data driven without *any* prior knowledge about the switching points.

B. Prediction

After having obtained a very reasonable segmentation into wake and sleep state, we are now interested in the dynamics that the competing predictors have learned. In other words: How well has the nonlinear dynamics of the signal been captured by the competing predictors, i.e. have we also been able to identify the inherent dynamics of the physiological states?

To find out the prediction performance on the respiratory signal, we take the winning predictors of the wake and sleep phase respectively and iterate them from an arbitrary point in the wake or sleep state respectively. The iteration then yields the long-term prediction of 400 time steps (40 seconds) shown in Figs. 2(a) and (b). Note that although the networks are only trained to predict the next data point, they have captured the underlying dynamics so well, that reliable predictions are possible for at least 50 time steps (5 seconds) in advance within one mode. To measure the complexity or degree of nonlinearity of the signal we also used linear predictors to predict the data. As expected, the linear predictors do not identify the long term behaviour of the dynamics sufficiently.

[1] The switching points in both channels are not expected to be identical since physiologically the breathing and the saccadic data change their modes with a slight time lag with respect to each other.

V. Summary

Complex dynamics from multimodal physiological data on the wake-sleep transition recorded from humans was analysed and predicted within our framework. The results clearly show that our method can be used for the unsupervised segmentation of the signals.

At the same time, little is known in the medical field about the dynamical properties of the Slow Eye Movements themselves. So future work will try to make use of the successful identification (long-term prediction) of the signal within each mode for a further understanding of the physiological processes.[2]

Our future interest is also dedicated to estimate the dynamics of switchings in order to predict not only the inter-switch dynamics but also the dynamical changes themselves – a question of interesting practical applicability.

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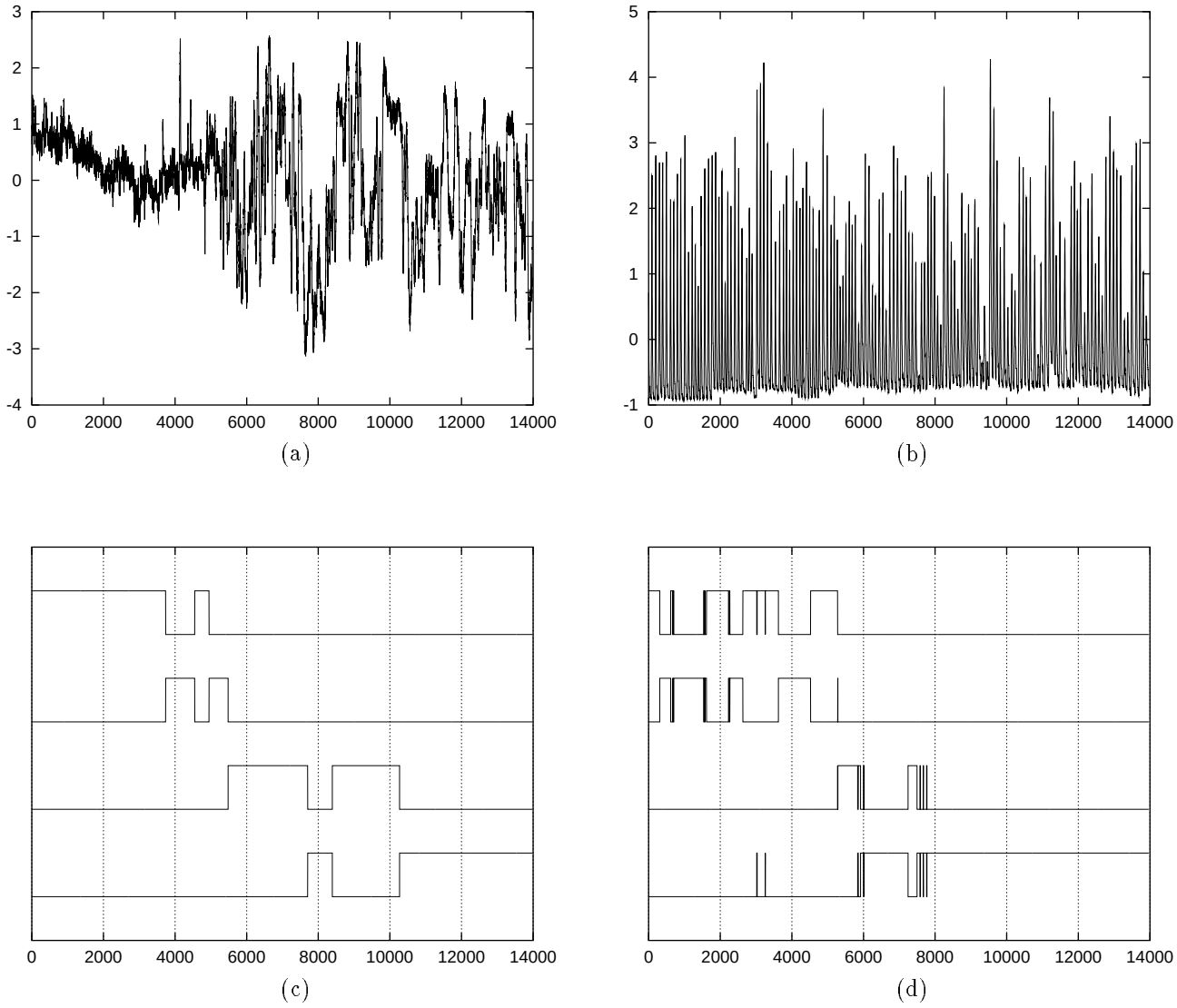
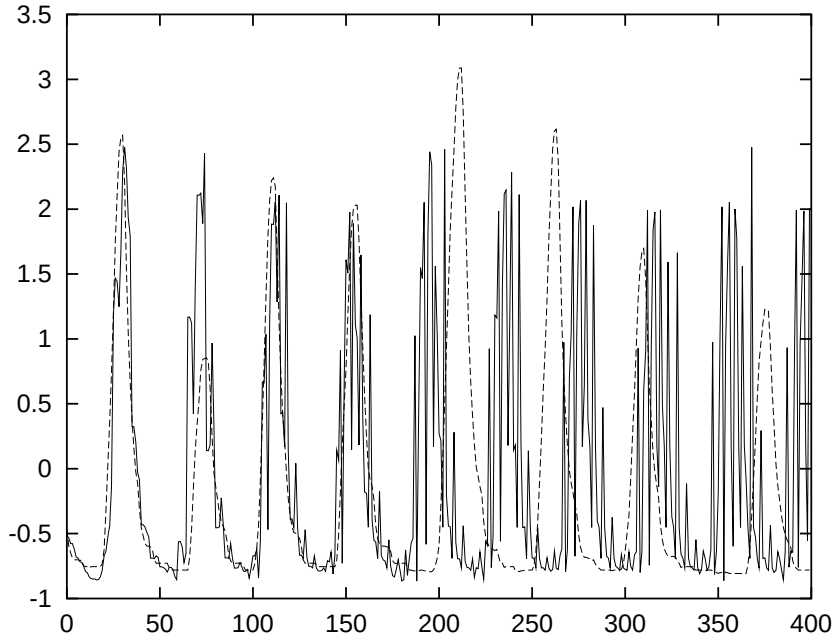
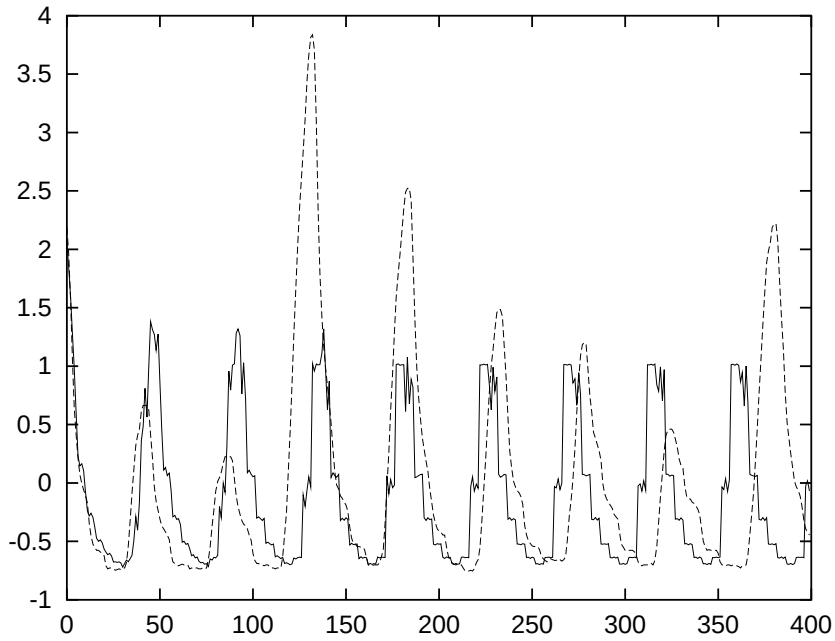


Figure 1: *The segmentation of (a) the eye movement signal and (b) the respiratory signal using 4 competing experts is shown in (c) and (d), respectively. In both cases, two experts share the task of identifying the wake resp. the sleep phase. The transition between wake and sleep after approx. 5000 time steps is properly detected not only in these two signals, but also in other physiological data (not shown here).*



(a)



(b)

Figure 2: *Iterating the predictors responsible for (a) the wake phase and (b) the sleep phase 400 time steps into the future (solid lines) shows a good accordance with the true continuation (dashed lines) of the respiratory signal for at least 50 time steps.*