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Sparse autoregressive signal modelling and estimation of the l_1-regularization parameter

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Introduction

Autoregressive modelling is of practical importance in signal analysis. An AR model uses observations from previous time points to predict the next signal value. An important task is to estimate the AR coefficients. This can be done by solving the Yule-Walker equations or by least squares fitting. To obtain a good model, the model order must be estimated. This can be achieved by Akaike information criterion (AIC) or Bayesian information criterion (BIC). However, AR coefficient and model order estimation suffers, when the data are short or noisy. This can be cured by l_1-regularization of AR coefficient estimation approach, i.e. sparse autoregression. Here we introduce Gini Index based AIC and BIC estimation of the l_1-regularization parameter λ.

Methods

Yule-Walker equations and least squares fitting AR approach were extended for l_1-regularization. To measure the sparsity of the AR coefficient vector, Gini Index is used. Note, AIC and BIC are related to sample size and total number of model order parameter p. Weighting p with (1-Gini Index) yields an effective model order number. To find the best λ, the minimum of the respective λ-dependent model order criterium is searched. Numerical experiments were done by using Scilab 6.1 for simulated, ECG and EEG signals. For simulated AR signals functional characteristics of standard deviations between true and predicted next signal values are analyzed.

Results

Simulations indicate that the introduced sparse AR coefficient estimation approaches and the approaches to estimate optimal l_1-regularization parameter work. However, BIC_{Gini} performs often better than AIC_{Gini}. The application to ECG and EEG indicate that our approaches can reduce significantly the number of AR parameters to represent these signals with high quality.

Conclusion

The introduced methods can be used for sparse AR modelling of signals. However, the methods are computationally intensive. Future work will focus on their statistical evaluation.

Sleep-stage detection at home: Wearable sleep EEG for automated sleep stage analysis using Mentalab Explore

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Introduction

The wide prevalence of sleep disorders represents a growing societal concern, calling for novel mobile tools for remote and at-home diagnostics. While several such tools exist for the detection of sleep-related breathing disorders, they usually fall short to recognize, if a person is asleep at all, and in which stage of sleep the person is. Mobile systems for the remote detection of sleep stages are needed for the diagnosis and management of highly prevalent, yet underserved sleep conditions, such as insomnia or parasomnia. Such systems, which meansure the amount and depth of sleep, incl. the accurate detection of sleep-stages, in a mobile or home environment require recording of brain activity, usually by EEG. A reliable system for the detection of sleep stages would not only enable wide-spread diagnostics of currently neglected sleep disorders, but at the same time open up new possibilities for scientific investigation of sleep stages in real-world scenarios.

Methods

40 healthy subjects are included in this study. Whole night sleep-EEG data are recorded using a Mentalab Explore 4-channel mobile ExG device (Mentalab, Germany) on the following EEG positions: Fp1, Fp2, Tp9 and Tp10. Simultaneous time-synchronized acquisition of Polysomnography is performed using a standard PSG system (Somnomedics, Germany). PSG data are analysed by two independent sleep specialists according to the AASM manual V 2.6, scoring the states “wake”, “N1”, “N2”, “N3” and “REM”. Any contradictions in scoring are reviewed by a third sleep specialist. A fully convolutional neural network (CNN) with total 13 convolutional and fully connected layers is used to classify each 30 second epoch of EEG data. To take into consideration the temporal dynamics of epoch sequences, 5 minutes of data (the current epoch and its preceding 9 epochs) are fed to the network. This special architecture allows us to utilize the model also for real-time sleep stage classification. Out of the 40 whole night recordings, 25 recordings will be used for training the model, 7 recordings for validation and 8 recordings for testing.

Results

First results of a pilot study using the CNN on over-night sleep-EEG recordings of 6 subjects indicate an accuracy of >80%, and a recall-rate of 0.9 or higher for the correct llabeing of the current sleep stage. We expect these values to be at least equivalent or higher in the detection of sleep stages, as more data should improve the performance of the CNN. Data acquisition is currently ongoing, with final results are expected in July 2020. Recordings show good ExG data quality, with participating subjects reporting no problems.

Conclusion

In this work, we use Mentalab Explore, a new small and mobile EEG sensor system, to record sleep EEG data, which is analysed with a convolutional neural network algorithm to detect sleep stages. We aim to demonstrate that accurate detection of sleep, and proper distinction of sleep stages is feasible via the combination of these two technologies. The goal of the prohect is the feasibility study of an advanced technology system that can help to diagnose highly prevalent, but previously undetected sleep disorders at home.

EEG-Based Classification of the Driver Alertness State

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Introduction

For many questions in professional practice as well as in psychophysiological research, it is important to be able to assess the state of alertness of a person. Here we suggest a way with machine learning by comparing several of these methods with respect to their expected accuracies.

Material and Methods

25 young, healthy volunteers drove in our driving simulation laboratory between 1:00 and 7:40a.m. seven times at 40 minutes each. Vigilance tests were carried out during the breaks, but these are not considered here. The EEG of 6 different 10-20 standard locations (Fp1,Fp2,C3,C4,O1,O2) was sampled at 256Hz. After some pre-processing steps the recordings were split into 6s long, non-overlapping segments and linear trend was eliminated. As features, logarithmically scaled spectral power densities (PSD) were estimated directly with the modified periodogram method and averaged across the interval [0,30]Hz into one Hertz width spectral bands, resulting in 180 PSD features due to 6 channels and 30 bands. They were input data for the following learning methods: 1) Optimised Learning Vector Quantisation, 2) Generalised Relevance Learning Vector Quantisation, 3) Generalised Matrix Learning Vector Quantisation, 4) Light Gradient Boosting Machine, 5) Support-Vector Machine.
Moderate versus severe sleepiness was used as the binary target variable. For this purpose, a subjective assessment on the Karolinska Sleepiness Scale (KSS) was performed every four minutes by the driver and by two observers. Their values were averaged and interpolated between the assessment times. With the threshold values KSS≤7 for class 1 (moderate) and KSS≥8 for class 2 (severe), a balanced learning set with a total of 45214 examples resulted.

Results

Mean classification accuracies of the validation sets within 10-fold cross validation for the different methods were: (1) 90.2±0.3%, (2) 75.1±1.5%, (3) 82.8±0.6%, (4) 91.1±0.3%, (5) 90.9±0.2%.

Conclusion

These results are not satisfactory for an important application, namely the validation of fatigue monitoring devices, for which a laboratory reference standard is needed. In a similar analysis of the EEG of 43 healthy subjects using other methods of feature extraction and Bayesian networks as classifiers, a medium accuracy at a similar level (88.2%) was achieved [Chai et al., 2016]. Probably the sample sizes are still too small to allow accurate and confident learning.

Estimation of transfer function parameters to describe pathological conditions in cardiovascular system models

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Introduction

Cardiovascular diseases are the leading cause of death worldwide. Particularly aortic aneurysms are problematic: they affect 12-14% of the population, early diagnosis is challenging because of the lack of symptoms. The objective of this study is to develop an easy-to-use, non-invasive diagnostic method, based on the classification of transfer function parameters, to generate suspicious facts about the presence of aortic aneurysms at the family physician level.

Methods

We simulate healthy and diseased conditions of cardiovascular blood flow by means of numerical models, using a distributed zero-dimensional lumped approach based on the Windkessel model, in order to regard pressure-pressure transfer functions between two systemic measurement locations. We calculate the phase of the quotient of the FFTs of input and output signal which are artificial zero-mean signals from the arteria brachialis and femoralis in four cases: Besides the control group, the estimations were performed on signals of two aneurysms located in the thoracic (TAA1 and TAA2) and one in the abdominal aorta (AAA). Finally, we quantify the difference between the estimated coefficients in each pathological case, using a distance measure based on the mean and the standard deviation.

Results

There exist coefficients such that one can distinguish between the pathological conditions and the control group. The largest deviation between the pathological conditions and the control group was found for the frequencies 22.7560 Hz (distance control group-pathological cases: 0.7-0.9), 18.9633Hz (distance measure: 0.4-0.6) and 10.1137 Hz (distance measure: 0.1-0.5).

Conclusion

These findings suggest a reasonable situation to distinguish the pathological state of the four underlying pathological cases from the estimated coefficients; therefore, we propose to diagnose the pathological states from the control group using a classification algorithm. This represents an alternative attempt to the previous approach to use ARMA-coefficients instead of Fourier coefficients introduced by the authors.

Stability assessment of bipolar coronary sinus sequences during atypical atrial flutter

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Introduction

Atrial flutter is commonly treated by catheter ablation during an electrophysiological study. To determine the optimal ablation lesion, the electrophysiologist sequentially records an electroanatomical map to characterize the excitation spread. During sequential mapping, it is crucial to accept only those beats which represent the target arrhythmia. Usually, a linear multi-electrode catheter positioned spatially stable in the coronary sinus (CS) is used as reference catheter. The stability of the CS sequence serves as criterion for beat acceptance or rejection. However, different stability measures may yield different results. This study assesses different methods to define stability of bipolar CS sequences.

Methods

For bipolar CS sequences of 25 full-chamber maps of distinct atypical atrial flutter cases recorded with the Rhythmia HDx (Boston Scientific) electroanatomical mapping system, active segments were computed with the non-linear energy operator. Any active segment of any bipolar CS lead with an overlap of less than 25% with a QRS complex was further processed. The active segments of all leads were grouped into beats according to the flutter cycle length calculated from the best bipolar CS lead. Time delays between neighboring leads as well as the correlation coefficient of active segments of the same lead were considered as possible criteria to assess stability.

Results

In the presence of several good quality bipolar CS leads with little QRS overlap, the consideration of multiple time delays as well as the similarity of electrogram morphology increased the robustness of stability compared to considering a single delta reference only. CS leads with low presence and prominence of clear atrial activations did not add value and were ignored.

Conclusion

Considering time delays of several electrode pairs and the similarity in morphology of active segments in the reference catheter enhances robustness in the determination of stability during repetitive arrhythmias and thus yields maps of higher quality.

Using Level Set Functions and Gaussian Mixture Models for Skin Segmentation in Imaging Photoplethysmography

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Introduction

Current research focuses on non-contact methods to record physiological signals. Imaging PPG (iPPG) is one approach. iPPG captures changes in blood volume through video recordings. Remote heart rate estimation is the most widespread application. Whereas heart rate estimation works well under stationary conditions, currently available methods often fail in case of movements and lighting variations. To overcome the existing limitations, the optimized segmentation of a region of interest is fundamental. This contribution presents initial investigations on the combination of Gaussian mixture models and level set methods to segment skin from non-skin and derive a pulse signal.

Methods

Level sets are commonly used in image segmentation. They describe a contour implicitly, segmenting foreground from background by applying a threshold to the level set function. The function itself is estimated through an iterative procedure, taking into account length of the contour, smoothness constraints and a data penalty originating from the skin and non-skin models.
We model the classes for skin and non-skin by Gaussian mixture models. The probability distribution of RGB values for the skin and non-skin class are estimated by the combination of two (skin) and four (non-skin) three-dimensional Gaussians in RGB space. Both models are learned on the first frame of a video by initializing the colour distributions based on the bounding box acquired by a common face detection algorithm (OpenCV Viola & Jones face detection). After the first frame, the level set function incorporating the information from the Gaussian mixture model is updated for every new frame and used to segment the skin area.

Results

To test the algorithm's performance in context of remote heart rate estimation under difficult recoding conditions, a video set of persons moving their head for 30 seconds was evaluated. To determine the heart rate, the pulse signal is filtered and transformed to the frequency domain. As competing method, the bounding box from the face detector was tracked using the Kanade-Lucas-Tomasi tracker and the skin segmented with a Bayesian skin classifier. For both methods, a pulse signal was generated by averaging over green channel and using the CHROM algorithm (a well-known method that combines RGB channels to yield a pulse signal).
Using the green channel, the presented method achieved a correct heart rate classification accuracy of 47.6 % compared to 33.3 % using the tracked bounding box. When combining the presented algorithm with CHROM, the heart rate was classified correctly in 61,9% (bounding box) and 85.7% (level set approach).

Conclusion

The proposed method has a strong positive effect on the heart rate detection, both using the green channel and the CHROM algorithm. Additionally, our method has further potential for improvements by incorporating other constraints to the level set function. However, future works have to extend the evaluation in order to optimize the algorithmic parameters and yield generalizable results.