Biomedical Signal Processing and Control 31 (2017) 499–512

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Comparison of *t*-test ranking with PCA and SEPCOR feature selection for wake and stage 1 sleep pattern recognition in multichannel electroencephalograms

T.K. Padma Shri (PhD research student) (Senior Associate Professor)[a,b], N. Sriraam (Professor and Head of the Department of Medical Electronics)[c,*]

[a] *Department of Electronics & Communication, Manipal Institute of Technology, Manipal University, Manipal, Karnataka 576104, India*
[b] *Department of Electronics & Communication, SCSVMV University, Kanchi, Tamil nadu, India*
[c] *M.S. Ramaiah Institute of Technology, An Autonomous Institute, Affiliated to Visvesvaraya Technological University, Bangalore 560054, Karnataka, India*

ARTICLE INFO

Article history:
Received 22 December 2015
Received in revised form
11 September 2016
Accepted 22 September 2016

Keywords:
Electroencephalogram (EEG)
Spectral entropy
t-Test
Principal component analysis (PCA)
Separability & correlation (SEPCOR)
Multilayer perceptron (MLP) neural network
k-Nearest neighbor (k-NN) classifiers

ABSTRACT

Feature selection is critical for effective analysis of data and resource savings. In multi-dimensional datasets, feature selection methods mainly use filter based approach to obtain an optimal feature subspace and wrapper methods to search for an optimal feature subset within this space. In the proposed study, two filter based statistical feature selection methods viz., statistical *t*-test ranking with principal component analysis (PCA) and Separability & Correlation (SEPCOR) analysis are applied to identify patterns with high discrimination between wake and stage 1 sleep of a 8-channel (6 active +2 reference electrodes) electroencephalogram (EEG) sleep dataset. The feature set consists of 6-dimensional Spectral Entropy vectors computed over EEG epochs of one second duration. In the first method, spectral entropy feature ranking is based on a *t*-test statistic that maximizes class separation between wakefulness/stage1 sleep. Prior to classification, PCA is performed on the ranked and non-ranked feature subsets to study the contribution of ranked channels on classifier performance. The second method uses SEPCOR analysis to automatically select an optimal feature subset with low correlation among the chosen features and maximum separation between their class means. A correlation threshold is chosen heuristically in steps of 0.05 from 0.6 to 0.75 in order to select different subsets of features. The optimal feature subsets are evaluated using multi layered perceptron (MLP) network & k-nearest neighbor (k-NN) classifiers with 50% hold out cross validation. For ranked feature subsets N = 3, 4, 5, k-NN classifier outperforms MLP network with an increase in the number of principal components (pcs). Results indicate that the pcs of ranked channels enhance the performance of k-NN classifier whereas MLP network shows only a marginal improvement with ranking for number of channels, $N \leq 4$. As the number of pcs is varied from 2 to 4 in steps of one, there is an improvement of approximately 2% in the classification accuracies of k-NN classifier with ranking as compared to their non-ranked counterparts. The MLP exhibits only 1% improvement with ranking for the same case with number of hidden neurons, N = 50. The k-NN classifier responds with maximum accuracies of 96.43%, 95.7% and 94.10% (pc = 4, 3, 2 for no. of ranked channels, N = 4) as compared to 94.71%, 93.13% and 92% (pc = 4, 3, 2 non-ranked N = 4) respectively. The SEPCOR results show that with correlation threshold increasing from 0.6 to 0.75 in steps of 0.05, it automatically selects feature subsets of 2, 3, 4 and 5 which contribute to detection accuracies of 72.4%, 80%, 91.6% and 92% with k-NN classifier and improved accuracies of 73%, 85%, 95.6% and 95.8% with MLP network (no. of hidden neurons, N = 50) respectively. The SE feature ranking provides better classification results using k-NN classifier than non-ranked cases whereas features obtained using SEPCOR analysis prove to be better discriminators with MLP network for the classification of wake/stage1 sleep data. The computation speed is faster in k-NN classifier and independent of increase in value of k whereas MLP takes much more computation time for training based on the number of hidden neurons.

1. Introduction

Sleep onset is a complex physiological process that reflects the health and well-being of a person. It correlates with several

* Corresponding author.
E-mail addresses: padma.shri@manipal.edu (T.K. Padma Shri), sriraam@msrit.edu, natarajan.sriraam@gmail.com (N. Sriraam).

http://dx.doi.org/10.1016/j.bspc.2016.09.016
1746-8094/

physiological and behavioral changes along with changes in Electroencephalogram (EEG) signals [1]. The wake/sleep transition is characterized by an initial drowsiness that progresses to loss of sensory awareness from the surroundings. Sleep is broadly classified into two stages; non rapid eye movement (NREM) and rapid eye movement (REM) stage. NREM sleep is further classified into stages N1, N2 and N3. Sleep onset is defined as the transition from wake state to one of the sleep stages, N1 to N3 or REM sleep. The onset of sleep in healthy adults is always through NREM sleep. In sleep disorders such as insomnia, [2], time duration for wake/sleep transition may be abnormally extended whereas in Narcolepsy, transition occurs within a very short time interval due to which there may be an abnormal entry into sleep through REM sleep [1]. Therefore detection of transition from wakefulness to sleep state is critical for diagnosing sleep disorders, drowsiness detection in drivers and in the development of devices for music induced sleep. Polysomnography (PSG) is a test commonly used to score the sleep process and detect sleep disorders. It requires multiple electrode placements on the human body to record EEG, Electrooculogram (EOG) and Electrocardiogram (ECG) signals, along with respiratory movements and oxygen saturation for the entire duration of night. In PSG recordings, sleep time is divided into short epochs (fixed at 30 s) and classified as a specific stage of sleep according to the guidelines proposed by Allan Rechtschaffen and Anthony Kales [3]

Previous studies show that sleep is essentially a cortical process and hence the brain activity (EEG) has been the primary source of detecting sleep onset. It is very well established [58]that the EEG changes from alpha (8–13 Hz) activity to a low-voltage signal with multiple frequency patterns as a person slips from wakefulness to N1 (stage1) in correlation with slow eye movements. Recent studies from invasive recordings of EEG indicate that the changes in thalamic activity precede the changes in cortical activity, the timing of which varies from person to person [4]. Any biomarkers of sleep must account for the multiple local [5–7] and spatiotemporally-evolving [8–13] factors of the human brain. In addition to EEG signals, EOG and EMG signals too reflect the changes associated with wake/sleep transition.

Numerous studies have reported sleep onset detection using various time and/or frequency, parametric and statistical processing methods on sleep EEG datasets [14–19]. Studies [17,18] on wake-sleep transition use spike rhythmicity as a quantifying feature which is a time domain attribute proved to be statistically significant for recognizing both patterns. Another study by N Sriraam et al. [19] used Hurst exponents as features and claimed 99.96%, 71.8% classification accuracies with k-NN and LDA classifiers respectively for recognizing both patterns. All these studies [17–19] use signals from only two (O1 and O2) locations of the 8-channel EEG dataset of the same PSG recordings as in the proposed study. In a comprehensive study of multimodal correlates of sleep onset, the experimental details of their characterization have been reported in [20]. Various methods have been adopted for an automated scoring of sleep based on single EEG channel data. In a study [21] the arousal states of human were detected using mean frequencies of a single EEG as input to an autoregressive Hidden Markov Model (HMM), resulting in a wake-drowsiness detection rate of 70%. In a similar study [22], a single-channel EEG was modeled by using Kalman filter and HMM that resulted in an accuracy of 60.14%. A Gaussian Observation HMM [23] was proposed to detect sleep stages with a reported accuracy of 86% for wake but only 22% for stage N1. Decrease in the sleep onset power of all frequency bands except delta range was reported in [24] especially in the frontal region. In a study using parametric modeling [25], PSG recordings have been modeled as Time-Varying Autoregressive Moving Average (TV-ARMA) processes with recursive particle filtering for the characterization of sleep onset periods. The findings revealed performance metric achieving maximum accuracy of 93.18%. A multiple feature set consisting of time-based, stochastic, spectral and chaotic features were used in a study [26] for automatic sleep scoring. The achieved mean error rates were reported to be 50% for detection of stage 1 (N1), 10% for slow wave sleep (SWS). Another study with multiple feature extraction consisting of time, frequency and nonlinear features with SVM classifier was reported with an average accuracy of 95:88% using a single EEG channel [27]. Recently, a novel method [28] reported 93.4% accuracy for automatic analysis of sleep macrostructure using full set of PSG signals in a fuzzy reasoning classifier. A similar study [29] reports a fuzzy logic inference engine for early detection of the onset of sleep in people driving a car or a public transportation vehicle using power spectrum density (PSD) of Heart Rate Variability (HRV) signal and Autonomous Nervous System frequency activity reflected by the HRV signal. Sleep onset detection showed the same detection rate as clinically collected data with 90% true detection on a set of 10 analyzed ECG.

Multivariate techniques have been adopted to determine the mutual dependence of different cortical regions in sleep process. Studies on EEG signals using spectral coherence measures and other nonlinear interdependence measures have reported that there is a higher coherence between cortical regions of normal young subjects during deep sleep [30–32]. Previous reports also suggest that the spectral coherence of different cortical regions during sleep is an age-dependent factor [33–36]. In order to automate the sleep scoring process, it is required to build a robust classifier with minimum number of optimal channels at the input. This can be realized by applying feature selection methods on multichannel PSG records so as to discriminate wake and sleep states. Though several methods have attempted to process PSG signals, few studies have reported feature selection for achieving significant sleep/wake stage classification [37–43]. In a study on neonate EEG sleep state classification [44], filtering method with a complete search strategy

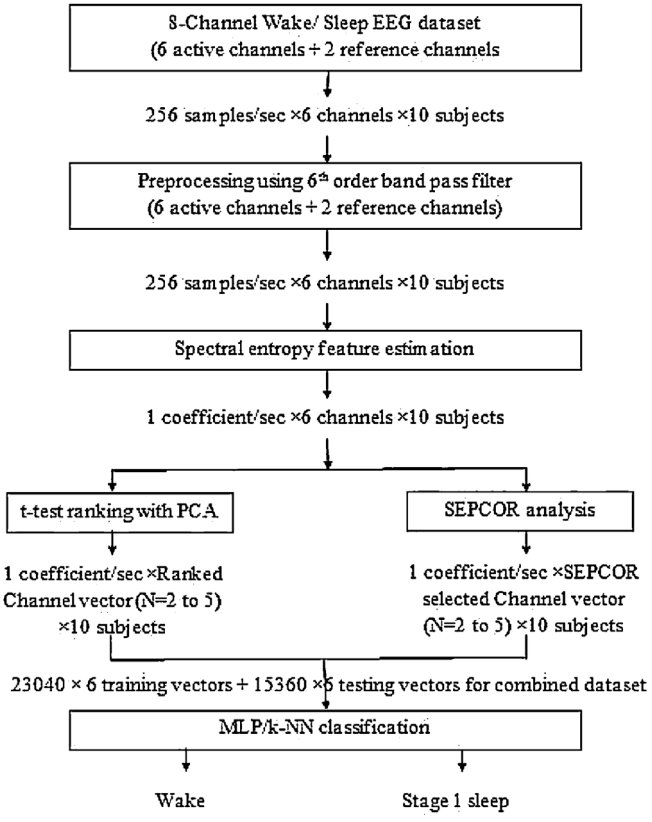

Fig. 1. Schematic of the Proposed Method.