6/21/2016

Today's Goal: Total Paper Review

Neural Network Model: Applications to Automatic Sleep Analysis of Human Sleep

Feature extraction from 3 different channels (EEG, EMG, EOG) 30 sec epochs, with a 17 component feature vector. EEG/EMG/EOG channels were transformed to Power Scale through FFT. Then, features were extracted (see 6/20/16)

They used a Neural Net to classify, a multilayer perceptron network. Optimized size of the hidden layer for accuracy (too large=memorization of certain input patterns, too small=requiring more iterations and less accuracy).

To validate the Neural Net, they also used KNN and Bayes Classification with Gaussian assumptions for comparison.

Automated sleep scoring in rats and mice using the naive Bayes classifier.

The program takes the raw EEG and EMG signals as input together with the manually scored states of the selected training epochs, and returns the automatic scoring result as an output.

The raw EEG and EMG signals of each epoch were preprocessed in MATLAB before classification. The program calculates the power spectral densities of the EEG and EMG signals using a FFT. The resulting EEG spectrogram is traditionally divided into delta (0.5–4 Hz), theta (4–10 Hz), sigma (10–15 Hz), beta (15–30) and gamma (30–100 Hz) bands that are used as the basis of automatic classification.

The feature vector consists of the total signal powers of the EEG frequency bands and the power of the EMG signal. A band-pass filter from 10 to 40 Hz for the EMG signal is used to eliminate artefacts. The logarithms of the EEG and EMG signal powers are calculated to normalize the statistical distribution of the features. The resulting feature vectors consist of 17–21 elements, or 6 elements for the traditional EEG frequency bands.

The performance of the naive Bayes classifier was validated against the *k*-nearest neighbor (*k* = 3) algorithm with both principal component analysis (PCA) and linear discriminant analysis (LDA) for mapping the data.

A more finely grained, logarithmic distribution of frequency bands improves scoring accuracy.

5 traditional vs 20 logarithmically distributed EEG frequency bands

Compared NB with kNN+PCA/LDA mapping. NB turned out to be better.

Unsupervised Online Classifier in Sleep Scoring for Sleep Deprivation Studies

4 EEG parameters and 1 EMG parameter are extracted from each 5-s epoch: the standard deviation of the rectified EEG (SD-EEG), the number of sign inversions of the filtered EEG (Zero-crossings), theta (5–9 Hz) to delta (0.5–4.5 Hz) power ratio (hereafter named EEG Ratio 1), and the 0.5–20 Hz/0.5–55 Hz power ratio (EEG Ratio 2).

The values of the spectral power in selected bands result from a fast Fourier transform (FFT) of the filtered EEG with 0.5 Hz resolution.

The EMG signal is subjected to a simple rectification and its median amplitude calculated.

Used Bayes Classifier (with Gaussian assumption)

FASTER: an unsupervised fully automated sleep staging method for mice

Overview of steps in their method:
1. Power spectrum of each epoch is calculated by Fast Fourier Transform.
2. EEG/EMG power spectra are transformed into Principal Components via PCA. Top 4 are used.
3. Components are clustered through non-parametric density estimation clustering method. Estimates probability density of dataset and defines a cluster has a high density area connected with Delaunay triangulation.
4. Clusters are annotated based on avg EEG/EMG powers.

Parameter optimization:
1. Character Extraction- Optimized number of principal components for high performance and low computation time.
2. Clustering- Bandwidth of density estimation kernel (smoothing factor) and number of grids for dataset size.
3. Annotations- Optimize the threshold values determined manually.

They used the entire EEG/EMG power instead of certain bands. This was intended to account for individual variability.

Does not take into account the transitions.

Automatic Sleep Stages Classification Using EEG Entropy Features and Unsupervised Pattern Analysis Techniques

The aim of the feature extraction stage was to compare the performance of different entropy estimators when applied to the experimental set, and find out if some metrics are more sensitive to EEG patterns. Below were the features used:

Fractal Dimension-statistically quantifies how well a fractal matches the input data at different scale.

Detrended Fluctuation Analysis- allows the detection of long-range power-law correlations in a time series

Shannon Entropy- Measure of data spread, where p(xi)=xi^2

Approximate Entropy- Regularity of a time series

Sample Entropy- evolution of ApEn devised to solve the bias of ApEn due to counting self-matches.

Multi scale Entropy- Estimator of the complexity of the time series

Q-a took these metrics and found the most important ones.

J means algorithm:

(1) Initialization: A standard k-means clustering is used to set an initial partition of the feature vectors and the centroids. This reduces the temporal cost of the partition calculation.
(2) Search: Given a tolerance threshold (4 standard deviations of the intra-cluster distance), find the unoccupied points (feature vectors that do not belong to any cluster).
(3) Update: Add a new cluster centroid at some unoccupied location and find the index of the best centroid to delete. Update the partition according to the new centroids.
(4) Finalize: If a local minimum is found in the previous iteration, stop. For each resulting cluster, a sleep stage can be assigned as the most frequent class (using a k-Neighbors method), which in clinical practice could be done by a whole cluster manual scoring. Otherwise return to step 2.

Control of REM sleep by ventral medulla GABAergic neurons

They wrote a “custom-written” Matlab program to do automatic classification of their behavior states (REM/NREM). First, they calculated the power spectrum of the EEG/EMG data using a 5 second window shifted by 2.5 second intervals. They took a sum of the EEG power for frequencies 1-4 Hz and 6-12 Hz, which gave a delta and theta power value. They took the ratio (delta/theta). They also computed total EMG power for 20-300 Hz frequencies. Following was their classification threshold algorithm:

if delta power<avg_delta power && emg power<avg_emg power+1SD—>NREM
if delta power<avg_delta power && |theta/delta|>1SD && emg power<avg_emg power+1SD—>REM
else—>Wake
so wake was characterized by high EMG (active) or low delta without elevated EMG and delta/theta ratio (quiet)

SegWay: A simple framework for unsupervised sleep segmentation in experimental EEG recordings

Does transitions between states.

Hidden Markov Model for classification

Three features were extracted in each recording: 1. The r.m.s. power of the EMG after bandpass-filtering from 80 to 100Hz, which expresses muscle tone and differentiates sleep from F. Yaghouby, S. Sunderam / MethodsX 3 (2016) 144–155 145 wakefulness; 2. The ratio of the mean-squared signal power of the frontal EEG after bandpass-filtering in the delta (0.5–4Hz) and theta (6–9Hz) bdands, respectively, which helps differentiate REM from NREM; and 3. The ratio of mean-squared frontal EEG power in high frequency (9–45Hz) and low frequency (0.5–9Hz) bands, respectively, which further distinguishes REM.

Used k-means for initial clustering. Then used HMM w/ Viterbi to model transition and make the clusters better.

Automated sleep staging systems in rats

Compares multiple automated systems.

While most procedures extracted information from the frequency domain of the EEG, some groups chose to work in the time domain. Both methods have advantages and shortcomings. Though frequency analysis relies on a well-established basis (Papoulis, 1984) and provides independent measures for frequency bands, the prerequisite stationnarity of the EEG signal of the epoch under consideration is not generally fulfilled.

The intuitive grasp of parameters is a strong argument in favour of time domain feature extraction. Regarding EEG frequency analysis, two frequency bands predominate: the delta band (0–5 Hz) widely used to detect slow wave sleep and the theta band (5–10 Hz) with high activity during REM sleep (Timolara et al., 1970; Monmaur, 1981). An important discrepancy consists in the choice of the band limits (the theta band is 5–10 Hz for Winson (1976), 6–9 Hz for Benington et al. (1994) and 5.5–8.5 Hz for Gottesmann et al. (1977)).

With regard to the time domain feature extraction procedures, one notices that the amplitude or a derived measure such as the standard amplitude (EEG standard deviation) of the EEG was the most frequently computed parameter (Neuhaus and Borbely, 1978; Van Luijtelaar and Coenen, 1984; Bergmann et al., 1987; Clark and Radulovacki, 1988; Itowi et al., 1990; Karasinski et al., 1994)

Classification: Used to be simple logic rules. Now its machine learning.

Sleep Stage Classification Using Unsupervised Feature Learning

Uses deep learning (Deep Belief Neural Nets) to pick which features/combinations learns the best, then trains an HMM to classify. 28 Features total.

For tomorrow,
Comb through papers, choose a bunch of features, and choose a bunch of classifiers to get started.