Cepstrum Coefficients Based Sleep Stage Classification

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Sleep

- Sleep is the resting state of the body
- External stimuli is weakened
- Activities are reduced

Sleep Disorder

- May cause mental fatigue and stress, even psychiatric or mental illnesses, such as loss of consciousness
- Negative effect on person's professional and social life
- Important to monitor sleep deprivation and disorders

Polysomnography (PSG)

- Current method for the diagnosis and treatment of sleep deprivation and disorders
- Monitors changes during sleep, generally night time
- Simultaneous and continuous recording of neurophysiological, cardiorespiratory, other physiological and physical changes
- Signals obtained by PSG are classified (scored) by an expert for a diagnosis according to some predefined standards

Scoring

- **Sleep staging (scoring) is typically performed manually**
- **Manual of sleep classification by Rechtschaffen and Kales (R&K)**
  - widely used since 1968
  - sleep recordings are divided into 7 discrete stages
  - wakefulness, stage 1 (S1), stage 2 (S2), stage 3 (S3), stage 4 (S4), stage REM and movement time
- **American Academy of Sleep Medicine (AASM)**
  - defined in 2007, scoring rules and terminology of R&K are modified
  - sleep recodings are divided into 5 discerete stages
  - wake (W), NREM1 (N1), NREM2 (N2), NREM3 (N3) and stage REM (R)
  - sleep stages S1 to S4 of R&K are referred to as NREM1 (N1), NREM2 (N2), NREM3 (N3)
  - NREM3 (N3) - slow wave sleep (SWS): reflecting combination of S3 and S4

Scoring / Classification

Scoring is the manual evaluation and labeling of PSG recordings

- An expert for evaluation
- Open to human errors
- Time consuming
- Use various physiological signals as well as multiple sensors
  - Causes the subject to move away from home environment to a hospital
  - Also feels uncomfortable for the use of multiple sensors and wires attached to his or her body during sleep
- Help of a computer using machine learning algorithms
- Automatic classification using single-channel EEG recordings has been widely preferred

Current Study

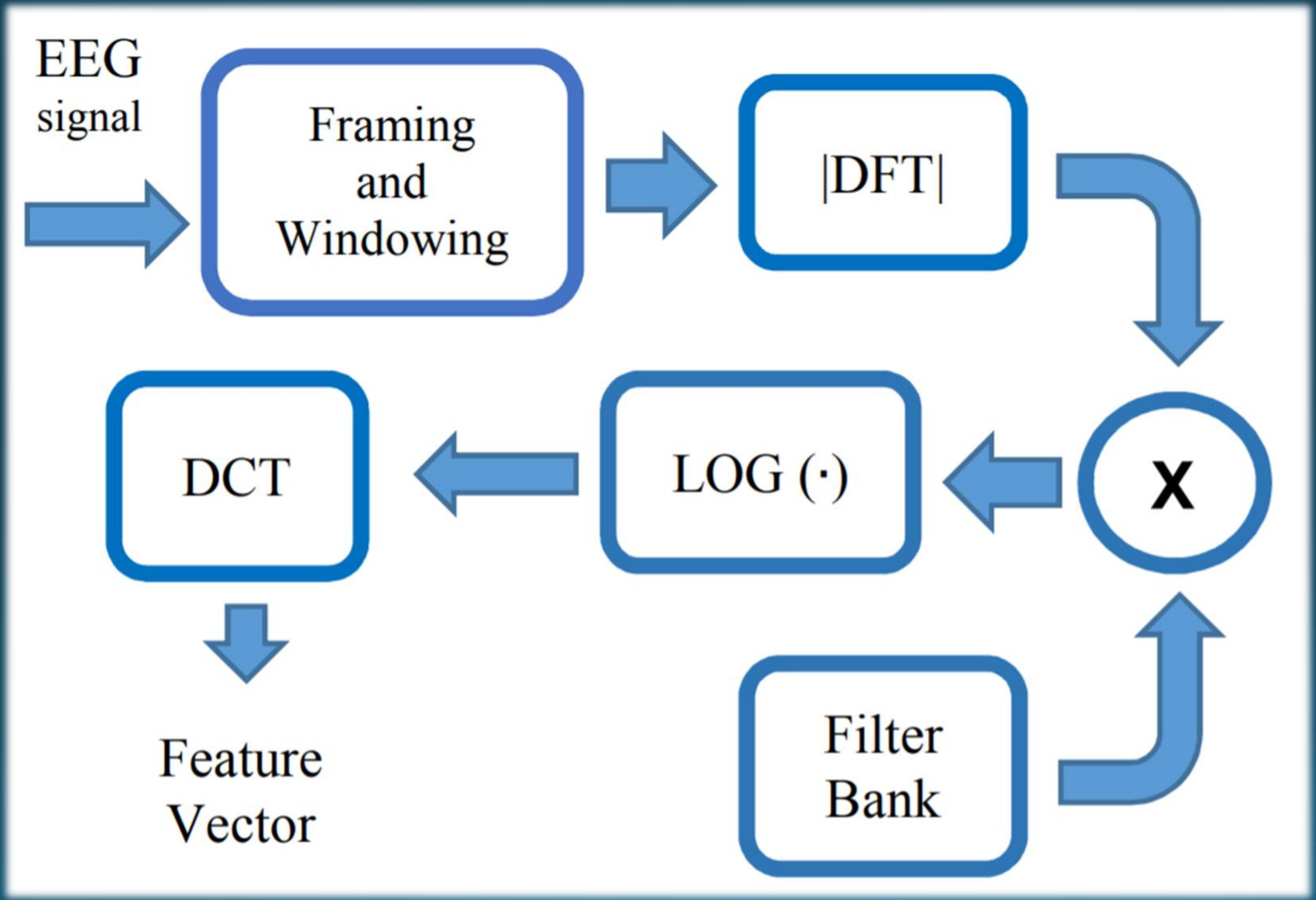
- Classification of sleep stages as wake, REM and NREM
- Single-Channel EEG signals
- Composed of two main steps
  - Feature Extraction
  - Classification
- Cepstrum coefficients are used in feature extraction
- Support Vector Machine (SVM) is used in classification

Feature Extraction

Filterbank based cepstrum coefficients are used to form feature vector

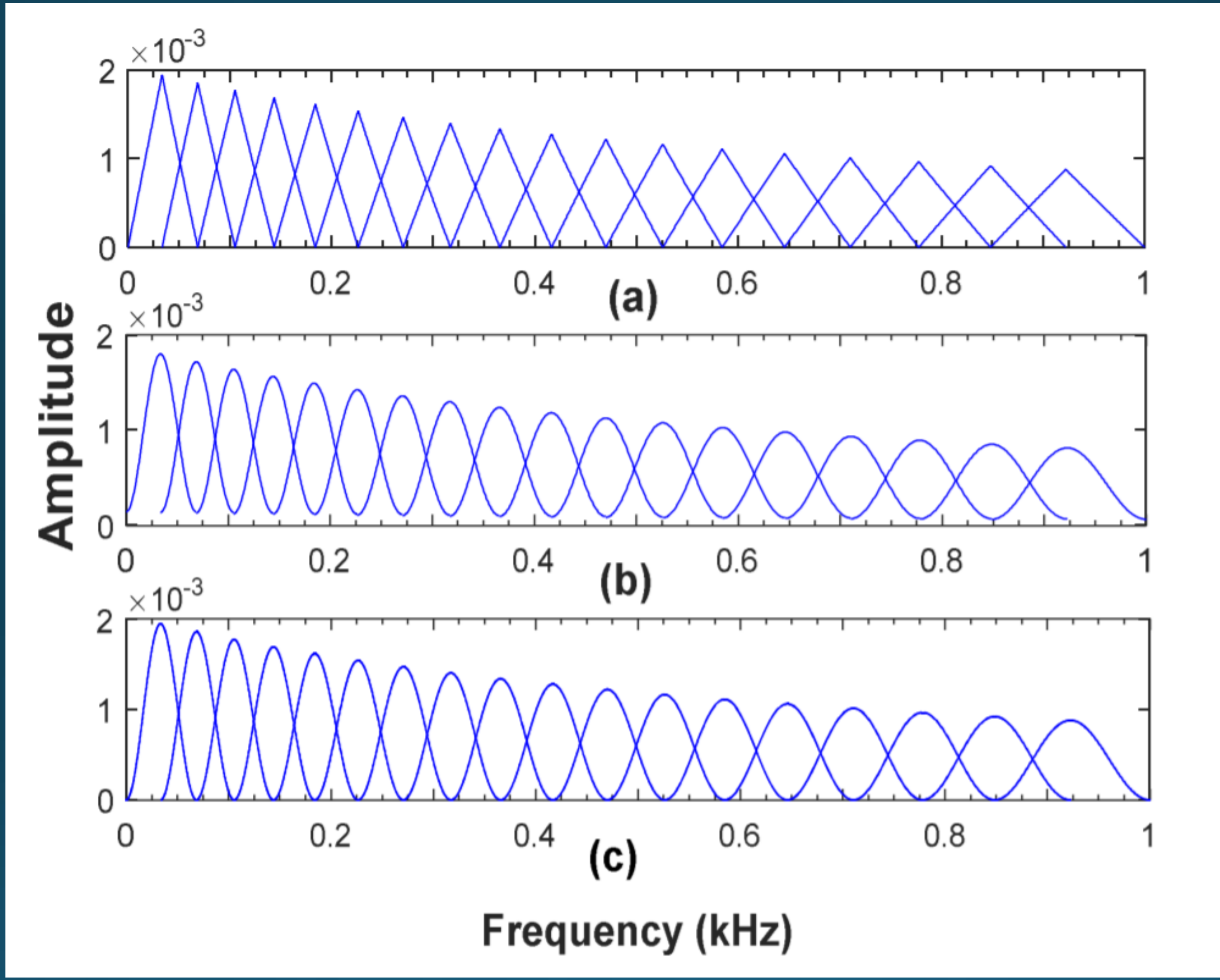
- The EEG signal partitioned into 30s frames
- Each frame is multiplied by a window function to form an epoc
- Discrete Fourier Transform (DFT) of epocs are calculated
- Absolute value DFT is fed to a set of frequency scaled filters (filterbank)
- Each filter output is summed over frequency
- Their log values forms energy quantities of the filter bands
- Discrete Cosine Transform (DCT) of the logarithm spectrum values is calculated to switch back to the time domain
- This gives the cepstrum coefficients to form the feature vector

Feature Extraction Diagram



Filterbank

- Filterbank filters are constructed using three different windowing functions
  - Triangular
  - Hamming
  - Hanning
- Three frequency warping functions are also utilized
  - Linear
  - Mel
  - Bark



Magnitude normalized and linear warping scaled filterbank filters in kHz region

Classification

- Sleep classification is performed with well-known supervised machine learning algorithm SVM
  - Training: SVM binary classifier learns a separating hyperplane between two classes to maximize the margin (distance) between the closest training samples (support vectors) and that hyperplane based on the training data
  - Test: SVM decides the class of each test data point by determining its position relative to that hyperplane
- SVM model can be mapped to a transform space (a higher dimensional space) through the use of a non-linear mapping (kernel function)
- Multiple classification in SVM
  - first converted to binary classification problems, then solved
  - commonly used methods: one-against-one and one-against-all

Database

Single (Pz-Oz) channel EEG of Sleep-EDF database is used in this study(*)

- Obtained in a hospital from eight Caucasian males and females, aged between 21-35, not on medication
- Four of the signals from healthy volunteers, recorded for over 24 hours
- Other four, healthy subjects with slight sleep disorder, collected during night time
- Sampling frequency: 100 Hz
- Sleep stages are scored for 30 second epocs according to R & K standards

(*): https://physionet.org/physiobank/database/sleep-edf/

Performance Measure

Sensitivity (SN), Specificity (SP) and percent Correct Classification Ratio (CCR) are utilized as the performance measure of the test of any epoc being in a particular class

$$SN = \left(\frac{TP}{TP+FN}\right) \times 100$$

$$SP = \left(\frac{TN}{TN+FN}\right) \times 100$$

$$CCR = \left(\frac{TP+TN}{TP+FN+FP+TN}\right) \times 100$$

All defined in terms of

- True Positive (TP)
- False Negative (FN)
- False Positive (FP)
- True Negative (TN)

test results

Performance Measure

- True Positive (TP): an epoc (labeled in that particular class in database) correctly classified
- False Negative (FN): an epoc (labeled in that particular class in database) incorrectly classified to a different class
- False Positive (FP): an epoc (not labeled in that particular class in database) is incorrectly classified to that class
- True Negative (TN): an epoc (not labeled in that particular class in database) is correctly classified

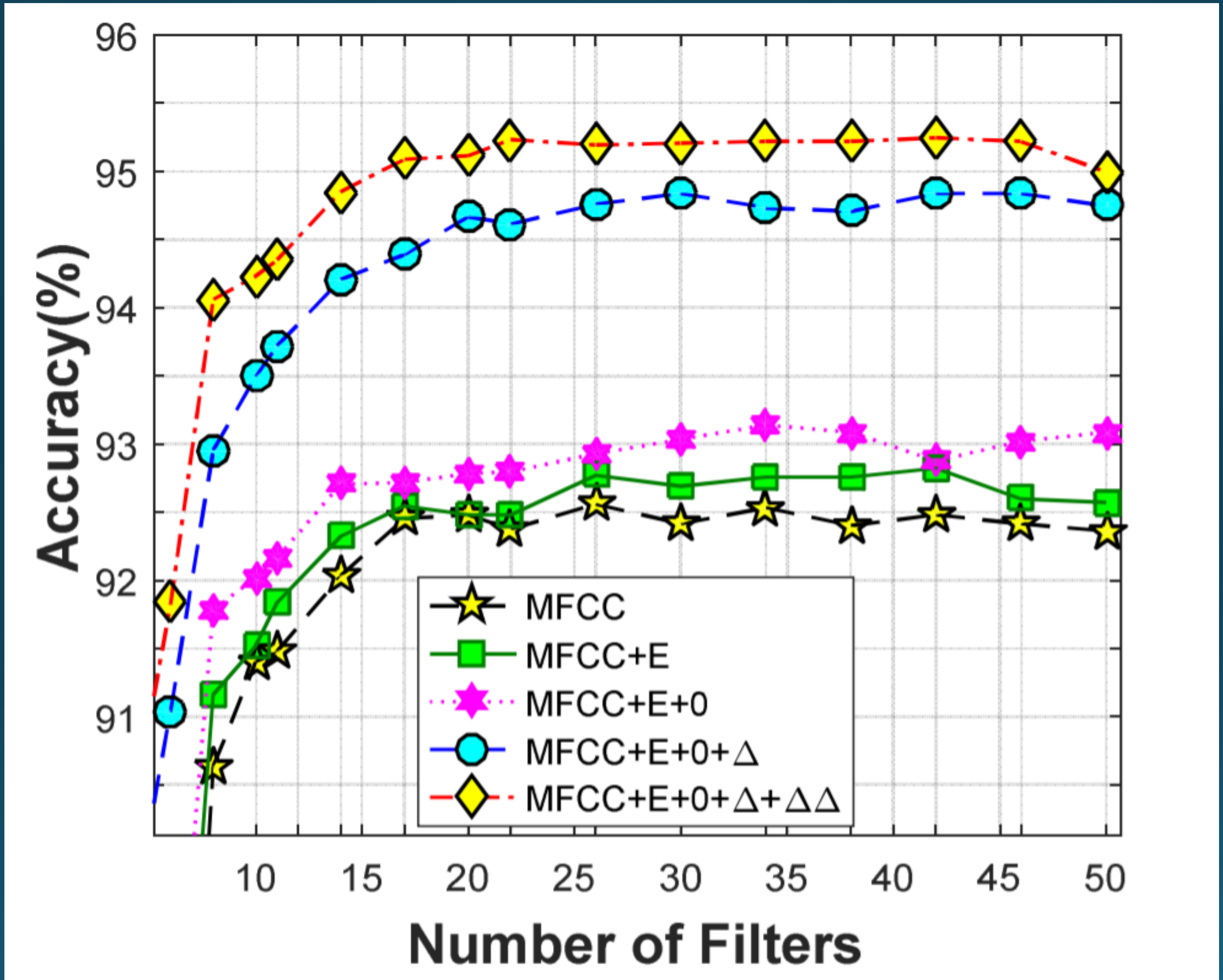
Selection of Training and Test Data

- Validation Set (*) is used to compare the study results with the available published results
- Half of the data is used as the training set
- Other half is used as test set
- Repeated for ten times
- All results are averaged

(*): A.R. Hassan and M.I.H. Bhuiyan, “Computer-aided sleep staging using complete ensemble empirical mode decomposition with adaptive noise and bootstrap aggregating”, Biom. Signal Process Control 24, pp. 1–10, 2016

Results

- Filter set parameters giving the highest CCR ratio is investigated
- Linear, Mel and Bark scales are used for the triangular filter (common filterbank type used in most of the studies in the literature)
- Also included test result obtained with the use of expanded features
  - energy of epoc (E)
  - zero order coefficient (0)
  - cepstrum coefficients first order derivatives (Δ)
  - cepstrum coefficients second order derivatives (ΔΔ)
- Each new term included in the feature vector increased the test performance



96
95
94
93
92
91
Accuracy(%)
10
15
20
25
30
35
40
45
50
Number of Filters
MFCC
MFCC+E
MFCC+E+0
MFCC+E+0+Δ
MFCC+E+0+Δ+ΔΔ

Results

- Highest CCR result is obtained for the number of filters is about 32 (linear scaling) and 43 (Mel scaling)
- No significant difference between the performances of the scaling types
- The best CCR results obtained in this work for LFCC + 0 + E + Δ + ΔΔ and MFCC + 0 + E + Δ + ΔΔ are 95.39 and 95.28, respectively
- Confusion matrix with Sensitivity, Specificity and CCR results are also presented

	AWAKE	*NREM*	*REM*	*% SN*	*% SP*
AWAKE	4000	20	8	99.30	96.45
NREM	96	2584	80	93.62	97.33
REM	24	108	674	83.62	98.68
% ACC	95.58				

Confusion Matrix, Sensitivity, Specificity and CCR for LFCC + 0 + E + Δ + ΔΔ feature set

- Hamming and Hanning window based filterbank performance also studied

Type of filterbank	*CCR (%)*
LFCC + 0 + E + Δ + ΔΔ + Triangular	95,39
LFCC + 0 + E + Δ + ΔΔ + Hamming	95,52
LFCC + 0 + E + Δ + ΔΔ + Hanning	95,40
LFCC + 0 + E + Δ + ΔΔ + Triangular + Normalize	95,47
LFCC + 0 + E + Δ + ΔΔ + Hamming + Normalize	95,58
LFCC + 0 + E + Δ + ΔΔ + Hanning + Normalize	95,48

- LFCC + 0 + E + Δ + ΔΔ feature set for 32 filters in the filterbank results
- The average percent CCR result 95.58

Comparison

CCR (%)
88,30
88,97
89,77
94,80
92,60
93,55
94,10
95,58

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- CURRENT STUDY

Thanks for listening