AUTOMATIC CLASSIFICATION OF BREATHING SOUNDS DURING SLEEP

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INTRODUCTION

- Hidden Markov model (HMM)-based system to assess sleep-disordered breathing (SDB) severity
- Uses acoustics alone to estimate number of apneic events per hour
- Alternative to clinical polysomnography (PSG): time-consuming, expensive, many attached sensors
- Long-term goal: at-home screening device

SLEEP AUDIO CORPUS

SUBJECTS

- Four adult subjects referred for full-night clinical PSG
- Varying degrees of SDB severity

DATA COLLECTION

- Audio collected in parallel with typical PSG sensor data via ambient microphone
- PSG scored by clinical expert to derive apneic event labels, overall SDB severity
- Audio manually labeled with audibly/visually identifiable respiratory event

MANUAL EVENT LABELING

- Four continuous regions per subject from various times of the night
- Possible labels are: breath in (Bi), breath out (Bo), snore in (Si), snore out (So), rest/no signal (N)

FEATURE EXTRACTION

- 13 cepstral coefficients (CC), Mel-frequency cepstral coefficients (MFCC), or reflection coefficients from linear predictive coding (LPC)
- CC, MFCC features model spectrum smoothly; LPC features focus on modeling spectral peaks

EXPERIMENT

SLEEP BREATHING MODEL

HMM topology with 3 states per respiratory event and 1 state per N. Stars (+) denote the null state at the start of a respiratory cycle. Filled and open circles (●, ○) denote a null state following in/out event.

TRAINING AND TESTING

- Ran subject-dependent (SD), subject-independent (SI) experiment using HMM for classification
- Used k-fold cross-validation scheme to generate training/test sets for each experiment

CLASSIFICATION APPROACH

- Group frame-level feature vectors from training set by state
- For each state, calculate mean, covariance of feature vectors; fit a Gaussian mixture model (GMM) with 3 mixture components, full covariance
- Initialize an HMM using the GMMs

CLASSIFICATION APPROACH

- Train HMM on training set using Baum-Welch EM algorithm with log-likelihood change threshold of 0.01, maximum 10 iterations
- Use trained HMM to decode test set using Viterbi search
- Record predicted state sequence and compare to manually labeled sequence

RESULTS

CLASSIFIER ACCURACY

- Reported 3 levels of granularity: event-, summary-, rest-level
- Event: combined states of the same type into one event
- Summary: combined in and out events of same parent type into one category
- Rest: combined all breath/snores into one generic “respiratory event” category

OVERALL SDB SEVERITY

- Computed apneic index (AI): number of events per hour, related to clinical AHI
- Stratifies into: <5, none; 5–15, mild; 15–30, moderate; >30, severe
- Events must last ≥10 seconds; counted qualifying N events from classifier output
- Also computed snore index: number of snores per hour

CONCLUSIONS

- HMM-based classification system predicts AI and SDB severity with promising results
- LPC features outperformed cepstral features, yielding 86–90% accuracy in the SD experiment and 76–87% accuracy in the SI experiment
- Precise AI differs from clinical PSG results, but correct overall severity may be sufficient
- Future work: explore techniques to reduce confusability between similar event types, such as quiet breathing and rests
- Further analysis of snore index
- Explore hybrid methods using other unobtrusive sensors such as UWB radar or wireless SpO₂ to increase robustness to respiratory cycle tracking errors