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Original Article

ORIGINAL ARTICLE

Algorithm for automatic detection of self-similarity and prediction of residual central respiratory events during continuous positive airway pressure

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Abstract

Study Objectives: Sleep-disordered breathing is a significant risk factor for cardiometabolic and neurodegenerative diseases. High loop gain (HLG) is a driving mechanism of central sleep apnea or periodic breathing. This study presents a computational approach that identifies "expressed/manifest" HLG via a cyclical self-similarity feature in effort-based respiration signals.

Methods: Working under the assumption that HLG increases the risk of residual central respiratory events during continuous positive airway pressure (CPAP), the full night similarity, computed during diagnostic non-CPAP polysomnography (PSG), was used to predict residual central events during CPAP (REC), which we defined as central apnea index (CAI) higher than 10. Central apnea labels are obtained both from manual scoring by sleep technologists and from an automated algorithm developed for this study. The Massachusetts General Hospital sleep database was used, including 2466 PSG pairs of diagnostic and CPAP titration PSG recordings.

Results: Diagnostic CAI based on technologist labels predicted REC with an area under the curve (AUC) of 0.82 ± 0.03. Based on automatically generated labels, the combination of full night similarity and automatically generated CAI resulted in an AUC of 0.85 ± 0.02. A subanalysis was performed on a population with technologist-labeled diagnostic CAI higher than 5. Full night similarity predicted REC with an AUC of 0.57 ± 0.07 for manual and 0.65 ± 0.06 for automated labels.

Conclusions: The proposed self-similarity feature, as a surrogate estimate of expressed respiratory HLG and computed from easily accessible effort signals, can detect periodic breathing regardless of admixed obstructive features such as flow limitation and can aid the prediction of REC.

Statement of Significance

This study shows that the proposed self-similarity feature, as a surrogate estimate for respiratory high loop gain and computed from easily accessible effort signals, can detect periodic breathing regardless of admixed obstructive features such as flow limitation and can aid the prediction of residual central respiratory events during continuous positive airway pressure.

Key words: automatic detection; similarity; CPAP

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Introduction

The prevalence of sleep-disordered breathing (SDB) among adults in the United States has increased substantially in recent years, in tandem with the prevalence of obesity. Among adults aged 30–70 years, approximately 13% of men and 6% of women have moderate to severe SDB (more than 15 obstructive events per hour of sleep) [1]. These sleep disorders are significant risk factors for cardiometabolic and neurodegenerative diseases, impaired performance, and decreased quality of life [2–5]. However, tolerance and efficacy of continuous positive airway pressure (CPAP), the primary form of therapy for moderate or greater severities of sleep apnea, are often poor. Among several reasons for CPAP intolerance, one area that stands to benefit from the computational analysis is the precision phenotyping of sleep-breathing patterns.

There is increasing awareness, supported by physiological phenotyping, that different endotypes can give rise to the same clinical apnea–hypopnea index (AHI) [6]. A key endotype–phenotype is high loop gain (HLG) sleep apnea [7–10]. This endotype can remain relatively silent (latent) until provoked by experimental methods or physiological challenges, such as arousals, overventilation with therapy targeting upper airway obstruction, or supine body positioning. The disorder may manifest as classic idiopathic central sleep apnea, periodic breathing, non-rapid eye movement (NREM)-dominant apnea, and treatment-emergent central sleep apnea (acute transient, emergent, or persistent). Current definitions for central apnea and hypopnea are based on PSG data and are scored according to the American Academy of Sleep Medicine (AASM) scoring manual [11]. A central sleep apnea syndrome is defined when five or more central apneas *and/or* central hypopneas are present per hour of sleep with a central AHI (CAHI) comprising more than 50% of all respiratory events [12].

The clinical implications of central sleep apnea with Hunter–Cheyne–Stokes respiration (HCSR) have been debated [13, 14]. Nevertheless, the features of classic HCSR are relatively noncontroversial, with symmetric, self-similar, prolonged (over 60 s) waxing and waning patterns, free of obstructive features (snoring and flow limitation), recognized as the key characteristic. Self-similar breathing oscillations are the norm in idiopathic central sleep apnea [15, 16], periodic breathing with shorter cycle lengths in the absence of cardiac dysfunction [17], high altitude periodic breathing and central sleep apnea [18], and HLG/NREM-dominant obstructive sleep apnea [19]. Moreover, obstructive pathophysiology can coexist in central apnea and at high altitude, thus making manual phenotyping laborious and inaccurate, especially for central hypopneas. In fact, central hypopneas are usually not scored [11].

Currently, the gold standard for assessing loop gain requires the administration of hypoxic or hypercapnic gas during a polysomnography (PSG) measurement [20]. An alternative mathematical method has been proposed from routine PSG [21]; however, this model requires EEG information and does not make use of the cardinal feature of HCSR breathing, namely self-similarity.

The current study aimed to develop a computational approach to detect HLG based on self-similarity in respiratory oscillations during sleep solely using breathing patterns, as measured via respiratory inductance plethysmography (RIP). RIP measures the expansion of the thorax and abdomen using two sinusoid wire coils. A system based on RIP tracings could be useful for automated phenotyping during routine PSG recordings and complementary to any manual approach to phenotyping. We developed a simple algorithm for detecting apneas as periods with reduced breathing effort, manifested in the RIP signal as low signal amplitude. Subsequently, our algorithm calculates self-similarity in breathing patterns between consecutive periods of apnea or hypopnea. The degree of self-similarity present over the entire night is summarized as the percentage of total sleep time during which high similarity was present. To quantify the potential clinical utility of this "full night similarity" metric, we developed an algorithm to predict, based on the diagnostic PSG, substantial (CAI higher than 10) residual central respiratory events during the subsequent CPAP (REC) titration PSG.

Methods

Dataset

The dataset used in this study is from the Massachusetts General Hospital (MGH) sleep laboratory. The MGH Institutional Review Board approved retrospective analysis of clinically acquired PSG data without requiring additional consent. The dataset consists of in-lab PSG recordings that include electroencephalogram (EEG), respiratory signals (RIP), and electromyogram signals (EMG) and was scored as part of routine clinical practice by certified sleep technologists using the AASM guidelines. Each PSG is scored by one technologist. There are seven technologists in total. The dataset consists of a mixture of diagnostic, split night, and CPAP titration protocols.

Data selection

A pair of diagnostic and CPAP PSG was only included in the study set when events were labeled and sleep was staged by the sleep technologists, and when both baseline and CPAP period were available. In cases with split-night PSG, sleep time before and after the split was required, and cases with multiple splits within one night were excluded. Full-night diagnostic PSGs were included when there was a CPAP titration PSG available for the same patient within 2 years following the initial diagnostic PSG.

Data analysis

Data were analyzed using the MATLAB R2019a programming environment (The Mathworks, Natick, MA). Based on annotations from the PSG technologists, CAI and AHI in the diagnostic PSGs (both split night and full night) were calculated, as well as in the CPAP titration part of the PSG (split night and full night).

Scoring apneas and hypopneas

We used two complementary methods to label apnea and hypopnea events and to compute their total impact, measured by the central apnea index (CAI). The first method was standard manual/visual scoring by sleep technologists. Because inspection of the manually labeled data raised concerns about possible "label noise" (inaccuracies in routine clinical annotations of apnea and hypopnea events), we also used an automated method to label events and compared the results with those based on visual event scoring. Both methods are described below.

Manual/visual event scoring. Standard AASM scoring rules were followed by the sleep technologists. Apneas were scored when the flow was equal to or lower than 10% of baseline regardless of oxygen desaturation, and hypopneas when the flow was equal to or lower than 70% of baseline (a 30% reduction) with a 3% oxygen desaturation or an arousal. Central apneas were scored when effort and flow were equal to or lower than 10% of baseline regardless of oxygen desaturation.

Although the AASM scoring rules state that central hypopneas are defined as a concordant reduction of flow and effort by at least 30% in the absence of snoring and flow limitation, these were not manually scored in the current dataset.

Automated labeling of central apneas and hypopneas. For automatic labeling, the envelope of the abdominal RIP band tracing (Figure 1A) was calculated automatically using the Matlab function "envelope" (Figure 1B; for code, see GitHub link at bottom of the paper). The envelope function returns the upper and lower envelopes of the signal, as the magnitude of its analytic signal (using its discrete Fourier transform). The difference between the upper and lower envelope was used to detect central events. When the difference between the upper and lower envelope fell to 20% or lower of the upper 90th percentile of amplitudes from the preceding 3 minutes, a central apnea was detected. A central hypopnea or hypoventilation event was defined as a period with RIP signal amplitude below 70% of the upper 90th percentile from the preceding 3 minutes. Subsequently, the same analysis was done for the RIP chest band. Only events detected in both chest and abdominal RIP signals were included for further analysis. According to AASM guidelines, a central apnea or hypopnea is defined only when an event lasts at least 10 seconds. As the envelope causes some signal smoothing, the algorithm used a minimum of 9 seconds to define central events.

Definition of residual central respiratory events during CPAP (REC)

Residual central respiratory events during CPAP (REC) were defined as substantial in the case of a CAI during CPAP titration higher than 10/hour of sleep. CPAP success was defined as a CAI during CPAP titration lower than 5/hour of sleep. REC were analyzed in two ways, based on technologist labels and on our automatically generated labels as the basis for calculating CAI.

Automated computation of self-similarity

Within 2 minutes before and after the detected central events, the similarity was calculated using the following procedure: Peaks in the envelope signal were detected, and two sequential envelope clusters containing a peak were cross-correlated with each other (Figure 1C). The maximum of these correlation values, between 0 and 1, indicates the similarity between successive clusters of waxing and waning breathing cycles. We then defined the "full night similarity" as the ratio of time with high similarity (higher than 0.8) events to total sleep time, i.e. the percentage of sleep time in which high similarity was present.

We defined detected hypopneas as "central" only when similarity during the hypopnea event was higher than 0.8. From these automatically detected central events, CAI and CAHI (CAI including central hypopneas) were computed.

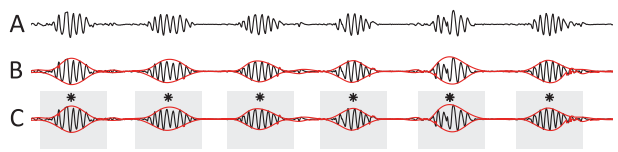

Figure 1. (A) Line of 5-minute respiratory tracing (abdominal RIP band). (B) Upper and lower envelope. (C) Peaks detected (*) and convolution applied.

REC prediction

Logistic regression with 5-fold cross-validation was used to create a model to predict REC vs. no REC. Means and standard deviations of the area under the receiver operating characteristic curve, and likelihood ratios (cutoff value defined as the highest Youden index) for the fivefolds were used to measure model performance.

Input features were the full night similarity and either the technologist-labeled CAI or the automatically generated CAI from the diagnostic night (split or full night) and the automatically generated CAHI.

Analysis of data enriched with central events

A subanalysis was performed on patients with a CAI higher than 5/hour of sleep labeled by the technologists in the diagnostic study. These patients were considered to be a subpopulation with possible more prominent HLG presentations in their respiratory tracings. The same prediction steps were performed as described above.

Results

The dataset included 8284 PSGs, of which 2466 pairs of diagnostic and CPAP PSGs met our inclusion criteria and were included in the training set. The pairs of diagnostic and CPAP PSG consisted of split-night PSGs and full-night diagnostic PSGs paired with CPAP titration PSGs, recorded from 2008 to 2016. Dataset characteristics and results of the automatically detected labels are provided in Table 1.

Figure 2 shows 15-minute tracings from four different patients with the corresponding similarity values for these tracings. The percentage shows how much of this 15-minute tracing similarity is higher than 0.8. These fragments show how similarity varies between patients.

Table 1. Dataset characteristics (mean ± SD)

Sex (male/female)		1683/783
Age (years)		55 ± 14
BMI		34.0 ± 7.6
Type of diagnostic PSG (*n*, split night/full night)		1923/543
CAI technologist labels	Diagnostic	4.5 ± 9.8
	CPAP titration	4.7 ± 9.1
AHI technologist labels	Diagnostic	42.3 ± 30.2
	CPAP titration	12.9 ± 15.1
CAI auto labels	Diagnostic	4.8 ± 8.7
	CPAP titration	3.6 ± 8.0
CAHI auto labels	Diagnostic	13.2 ± 15.9
	CPAP titration	6.6 ± 12.1

BMI, body mass index. CAHI was calculated only via the automated method, because technologist-scored central hypopneas were not available. AHI is calculated only based on technologist labels.

REC prediction

Based on technologist labels, 13% (n = 313) of patients had REC (CAI more than 10/hour of sleep), 75% (n = 1850) of patients had no REC (CAI less than< 5/hour of sleep), and 12% (n = 303) were excluded from the prediction analysis because of indeterminate outcomes (CAI between 5 and 10/hour of sleep).

Based on automatically generated labels, 10% (n = 244) of patients had REC, 81% (n = 2018) had no REC, and 10% (n = 244) were excluded from the prediction analysis because of indeterminate outcomes (CAI between 5 and 10/hour of sleep).

The left graph in Figure 3 shows the AUC values resulting from REC prediction in mean ± standard deviation of the 5-fold cross-validation prediction. Our proposed full night similarity as input for a logistic regression model resulted in a (mean ±SD) AUC value of 0.70 ± 0.02 to predict REC based on technologist labels. In the case of automatically generated labels to calculate CAI, full night similarity resulted in an AUC of 0.78 ± 0.02. The most accurate prediction of REC based on technologist labels resulted from the diagnostic CAI based on technologist labels (AUC = 0.82 ±0.03). However, based on automatically generated labels, the combination of the full night similarity and the automatically generated CAI resulted in an AUC for the prediction of REC of 0.85 ±0.02.

To find a clinical threshold to predict REC, the positive predictive value (PPV) was plotted for both input variables in

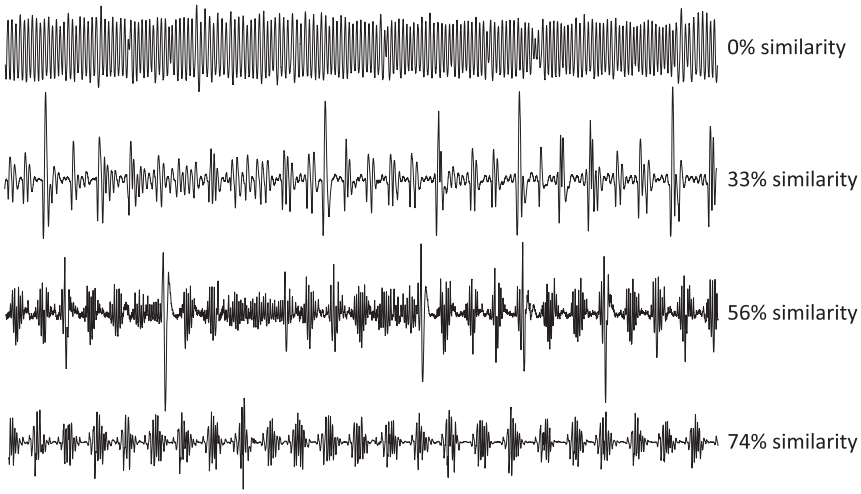

Figure 2. Examples of 15-minute respiratory tracings from four different patients; similarity values indicate the percentage during which similarity values were higher than 0.8 for these fragments.

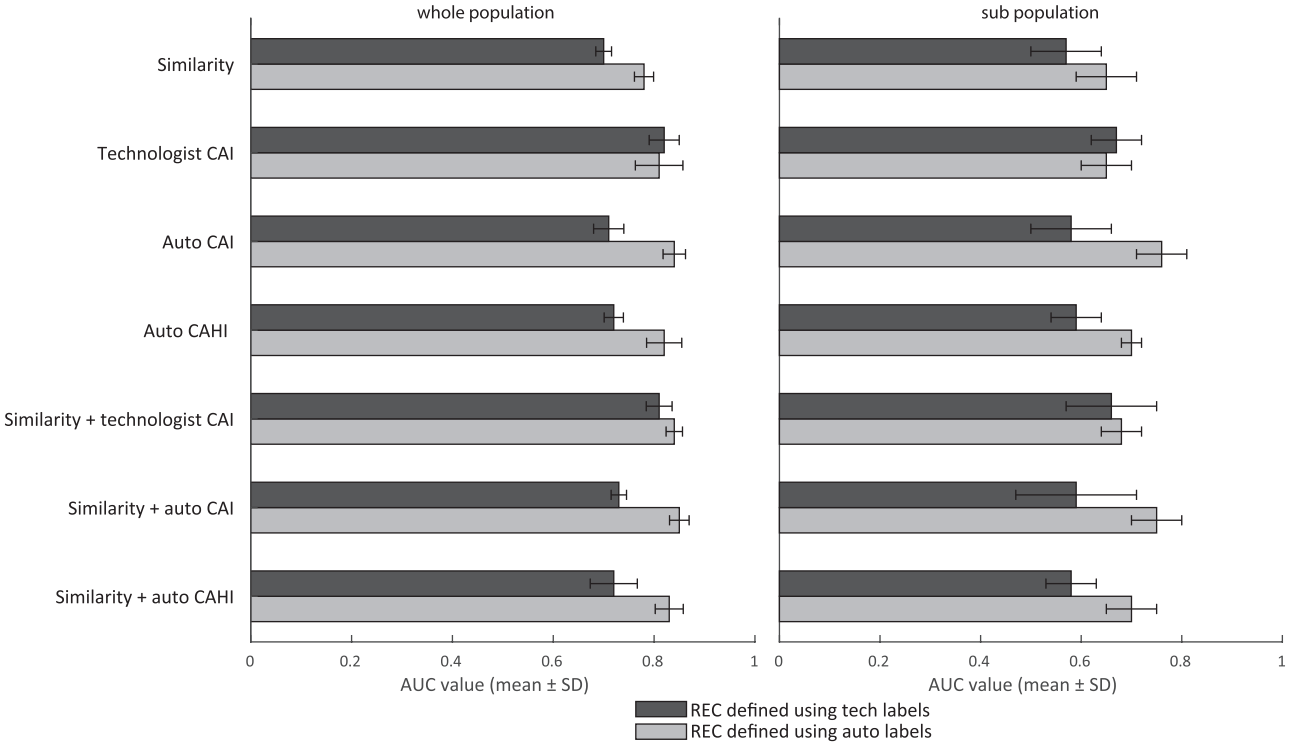

Figure 3. Area under the curve as the outcome of logistic regression to predict REC for the whole population (left) and the subpopulation (right) as mean and standard deviation of 5-fold cross-validation.

Figure 4. The red dot shows a PPV of 30%, implying that when similarity is equal to or higher than 17% or auto CAI equal to or more than 3 events per hour of sleep, the probability of REC was 30%.

Figure 5 shows the positive and negative likelihood ratios resulting from the REC prediction in mean ± standard deviation of the 5-fold cross-validation prediction.

The highest positive likelihood ratio to predict REC based on technologist labels was 3.44 ± 1.20 with the technologist-labeled CAI as input. The highest positive likelihood ratio to predict REC based on automatically generated labels was 4.06 ± 1.16 also with the technologist-labeled CAI as input.

The best (smallest) negative likelihood ratio to predict REC based on technologist labels was 0.28 ± 0.03 with the automatically generated CAHI and full night similarity as input. The best (smallest) negative likelihood ratio to predict REC based on automatically generated labels was 0.16 ± 0.04 with the automatically generated CAI and full night similarity as input.

Subanalysis

Based on technologist labels, a subpopulation was defined consisting of 515 patients with CAI higher than 5/hour of sleep in the diagnostic PSG. Dataset characteristics are shown in Table 2. Based on technologist labels, 35% (n = 182) of patients had REC (CAI more than 10/hour of sleep), 42% (n = 220) of patients had no REC (CAI less 5/hour of sleep), and 22% (n = 113) of patients had indeterminate results (CAI during CPAP between 5 and 10/hour of sleep).

Based on automatically generated labels, 29% (n = 150) of patients had REC, 55% (n = 285) of patients had no REC, and 10% (n = 80) of patients had indeterminate outcomes (CAI during CPAP between 5 and 10/hour of sleep).

The right graph in Figure 3 shows the AUC values resulting from the REC prediction in mean ± standard deviation of the 5-fold cross-validation prediction. In this subpopulation, our proposed full night similarity as input for a logistic regression model resulted in an AUC value of 0.57 ± 0.07 to predict REC based on technologist labels, near chance performance. However, using automatically generated labels to calculate CAI, the full night similarity resulted in an AUC of 0.65 ± 0.06, moderately better than chance. A similar performance was obtained based on the CAI from technologist labels (AUC 0.67 ± 0.05). CAI based on automatically predicted labels resulted in an AUC to predict REC (based on automatically generated labels) of 0.75 ± 0.05.

Figure 6 shows the positive and negative likelihood ratios resulting from the REC prediction in the mean ± standard deviation of the 5-fold cross-validation for the subpopulation.

The highest positive likelihood ratio to predict REC based on technologist labels was 3.13 ± 3.73 with the full night similarity and the automatically generated CAI as input. The highest positive likelihood ratio to predict REC based on automatically generated labels was 3.55 ± 2.55 also with the full night similarity and the automatically generated CAI as input.

The best (smallest) negative likelihood ratio to predict REC based on technologist labels was 0.45 ± 0.07 with the automatically generated CAHI and full night similarity as input. The best (smallest) negative likelihood ratio to predict REC based on automatically generated labels was 0.32 ± 0.05 with the full night similarity as input.

Discussion

The current study provides a measure for cyclical self-similarity of breathing patterns during sleep. Our study makes two main contributions. First, our results show that breathing pattern self-similarity as an indicator of manifest (expressed) HLG predicts REC. Second, central apnea labels were derived in an automated way and we showed that short-term REC (acute treatment-emergent central

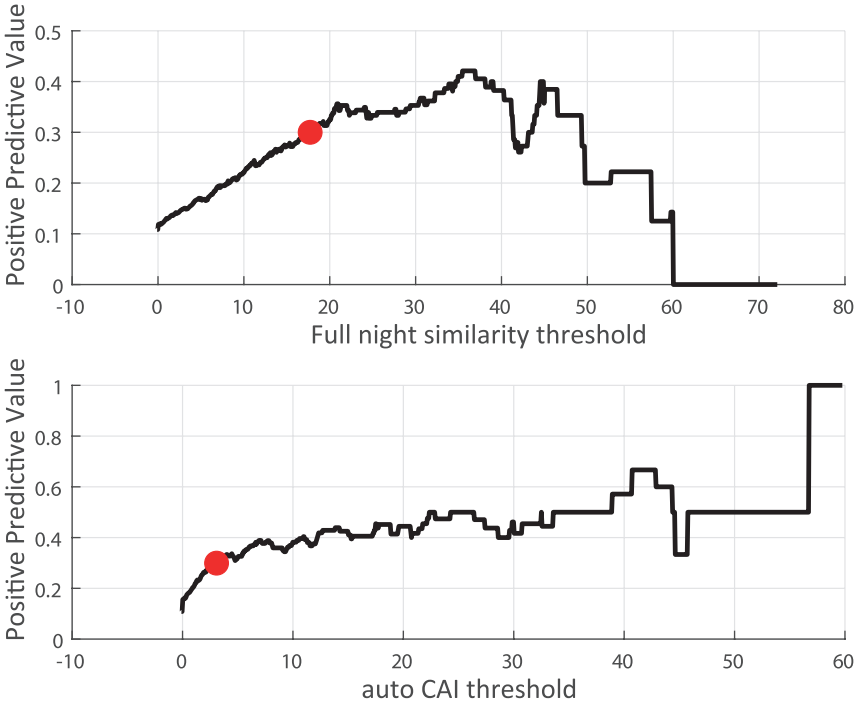

Figure 4. PPVs for full night similarity and auto CAI to find a clinical threshold to predict a high probability of CPAP failure, based on automatically generated labels.

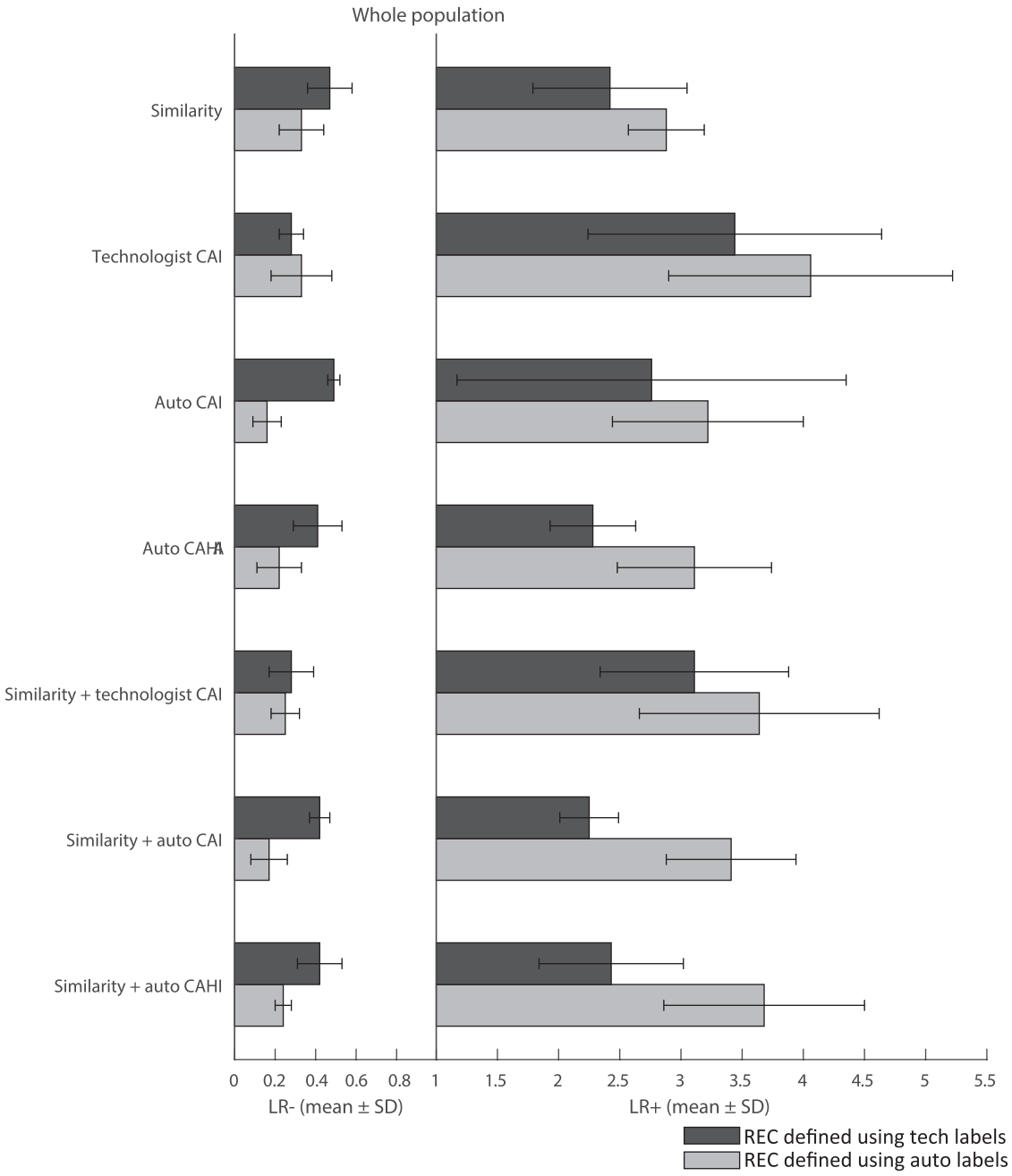

Figure 5. Negative likelihood ratio (left) and positive likelihood ratio (right) as model performance measure to predict REC for the whole population.

sleep apnea) is predicted at least as well based on labels generated by automated analysis as by manual scoring. Our results show that the computational estimation of central apneas, hypopneas, and self-similarity is feasible and may have clinical value to complement other methods of disease phenotyping. Though we used a laboratory polysomnographic dataset, our method should work as well on home-study data and in other conditions where breathing pattern estimation may be informative.

Although automatically generated CAI and full night similarity were highly correlated (Pearson Rho = 69%), we believe that similarity provides additional useful information not captured by CAI alone, as it reflects more directly HLG. We showed that either a high auto CAI or a high full night similarity means that the risk of REC is high. Choosing a probability of REC higher than 30% as a clinically meaningful trigger warranting further investigation, we find that this condition is met when either full night similarity is equal to or higher than 17% or auto CAI equal to or more than 3 events per hour of sleep, as shown in Figure 4. It should be noted in Figure 4 that PPV appears to worsen as similarity increases; however, this is likely due to the limitations of data. Sufficient data were not available to calculate statistically reliable estimates of PPV above full night similarity values of ~25% (396 of 2466 PSGs).

Automation of event scoring

The most important advantage of automated event scoring in PSG is the saving of time, compared with manual labeling. It is already shown that the integrated analysis of PSG features can improve

Table 2. Dataset characteristics of subpopulation, technologist-labeled diagnostic CAI > 5 (mean ± SD)

Sex (male/female)		433/82
Age (years)		57 ± 14
BMI		33.9 ± 7.7
Type of diagnostic PSG (*n*, split night/full night)		452/63
CAI technologist labels	Diagnostic	17.8 ± 15.2
	CPAP titration	12.0 ± 15.4
AHI technologist labels	Diagnostic	61.3 ± 28.7
	CPAP titration	21.4 ± 20.3
CAI auto labels	Diagnostic	12.2 ± 13.1
	CPAP titration	8.7 ± 12.3
CAHI auto labels	Diagnostic	26.1 ±19.6
	CPAP titration	15.1 ± 17.6

BMI, body mass index. CAHI was calculated only via the automated method, because technologist-scored central hypopneas were not available. AHI is calculated only based on technologist labels.

the identification of central hypopneas [22]. Predominance during NREM rather than rapid eye movement (REM) sleep, lack of inspiratory airflow curve flattening or thoracoabdominal paradoxical breathing (chest wall moving inward with inspiration) during hypopnea, arousals in the middle of the recovery breath sequence [23], and gradual flow restoration pattern at hypopnea termination can help classify hypopneas as central. Automation of hypopnea phenotyping (obstructive vs. central) is possible [24], but the accuracy in comparison to electromyography is limited (69%). "Mixed" events are more problematic, as how much "mixture" of obstructive and central components" is required to differentiate from obstructive and central events suffers from visual bias and inaccuracies. Moreover, insurance coverage of treatments does not consider mixed events as equivalent to HLG.

Phenotyping of sleep disorders could be done more quickly, more objectively, and in a technologist-independent manner using computational methods. Automated detection of apneas and hypopneas may be especially useful in situations where central events are frequent but obstructive features may coexist, for example in heart failure, atrial fibrillation, and stroke. The presented automated labeling method is agnostic to the presence of flow limitation, mild degrees of which are frequently seen in central hypopneas. Lastly, our method is relatively insensitive to cycle length. AASM scoring rules state a minimum central hypopnea/periodic breathing cycle time of 40 seconds, but this is not likely a biologically valid cutoff; short (less than 30 s) cycle respiratory events are seen at high altitude and in non-REM dominant and HLG OSA, and in idiopathic central sleep apnea.

A more detailed example of the correlation between the automated and tech-scored central apneas and hypopneas is provided in the Supplementary Material and Supplementary figures S1 to S5.

Therapeutic implications of autoscoring central events

The diagnosis of central apnea syndromes has used arbitrary thresholds, such as more than 5/hour of sleep and more than 50% of events scored as central. In addition, manual scoring of central hypopneas is difficult and imprecise, considered "optional," and consequently is rarely performed. Current diagnostic criteria can pose a challenge to investigators and clinicians because reliably differentiating hypopneas as central versus obstructive is difficult. Evidence of upper airway obstruction on PSG, including flow limitation, does not rule out central apneas/hypopneas [25–27], and esophageal manometry is rarely used in practice. Unclassified hypopneas are thus summed into the overall AHI, biasing metrics toward obstructive sleep apnea.

This practice of lumping all hypopneas as obstructive has translated to scoring central apneas alone, underestimating the component of central events when hypopneas are significant. Thus, a CAHI/CAI of 4.9/hour of sleep and 49% central events is considered obstructive. There are real clinical implications of such arbitrariness, including insurance coverage of therapies such as oxygen and adaptive ventilation. Such thresholds also confound research studies and interpretation. Decision-making about the expressed phenotype is especially relevant to heart failure, where adaptive ventilation is contraindicated in those with systolic heart failure (ejection fraction ≤ 45%) and central sleep apnea. Therapy may be withheld when indicated, or the inappropriate therapy chosen, based on central event count errors.

Accurately classifying SDB as predominantly central or obstructive has implications for treatment, as targeting HLG is possible with body positioning, low-dose acetazolamide, adaptive ventilation, oxygen, and sedatives. Moreover, although providing CPAP might resolve obstructive apneas, it can induce complex sleep apnea (CompSA): a condition defined by the emergence of problematic central sleep apnea and HCSR in the absence of obstructive events [28]. Patients who develop CompSA have a higher prevalence of coronary artery disease, a higher diagnostic CAI (central apneas per hour of sleep), and more preexisting periodic breathing [29].

Limitations of the presented automated labeling method

The presented method for automated labeling of central apneas is based on two major assumptions. First, HLG is a driver of central apneas. Second, HLG results in cyclical self-similar behavior of breathing patterns. However, we did not calculate or estimate HLG directly in our patients. Instead, we used the presence of high similarity as a surrogate for HLG. While this assumption is reasonable, and our method is thus likely to detect HLG effects on sleep-breathing patterns, we do not provide a direct loop gain estimate. Although the AASM provides rules to score central hypopnea, the database in our study did not provide labels for central hypopneas, as these were usually not scored by the sleep technologists. This is mainly because scoring of central hypopneas is difficult, considered "optional," and some of the components of the rules have been shown to be unsupported by research. In general, central hypopneas are not scored by clinical sleep services or are scored only when there is overt periodic breathing or HCSR. For these reasons, we could not compare manual/visual and the proposed automated detection of central hypopneas.

It should be noted that our data are cross-sectional, so the long-term impact of self-similarity and central event detection cannot be estimated from the present data. Features of respiratory control instability may decrease, persist, or emerge during long-term treatment with CPAP in apnea patients, dependent on an interaction of genetic and acquired factors, such as degree of hypoxia, associated disorders, such as heart

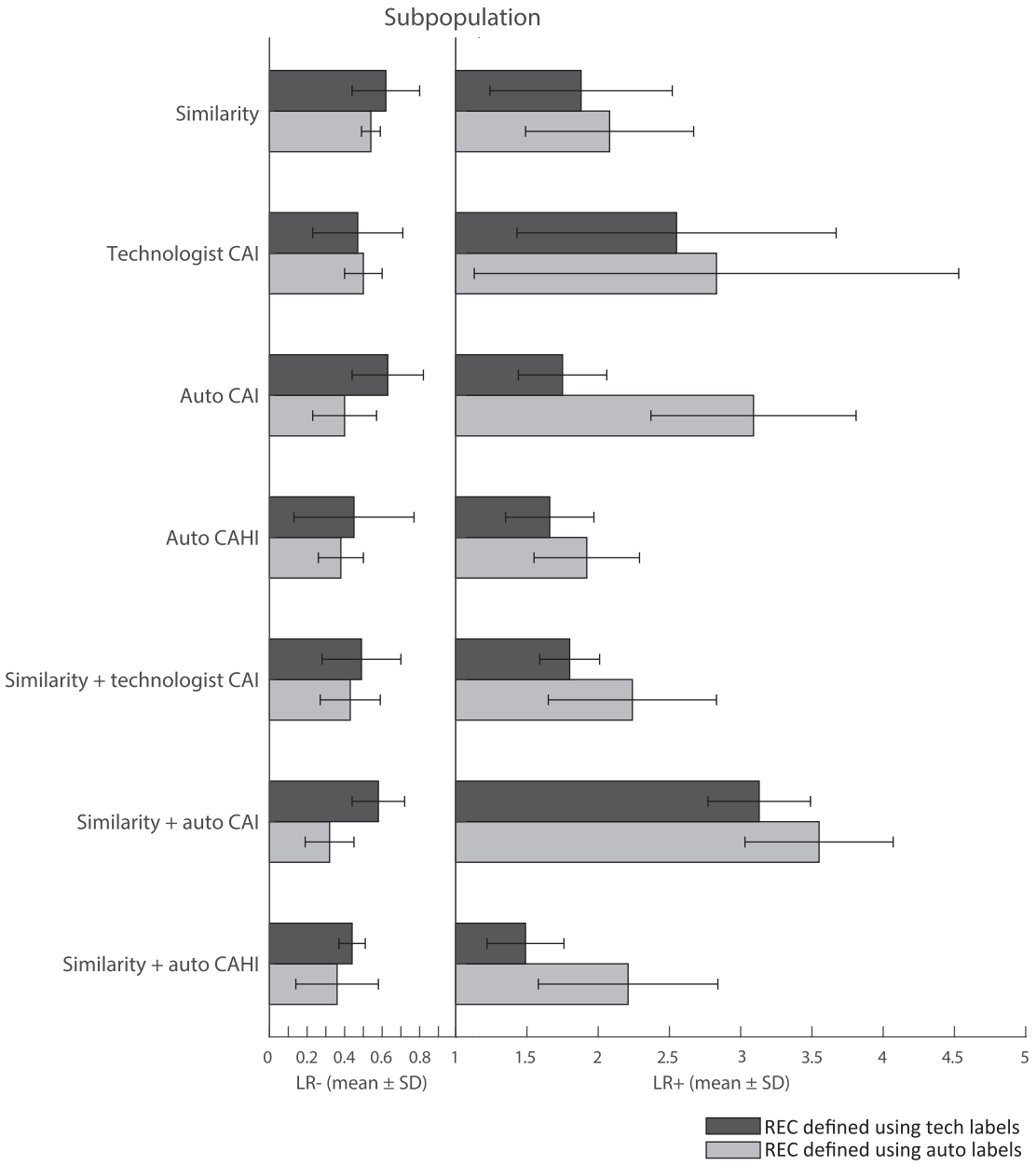

Figure 6. Negative likelihood ratio (left) and positive likelihood ratio (right) as model performance measure to predict REC for the subpopulation.

failure or atrial fibrillation, and gender. However, a high CAI does predict high residual AHI on CPAP and a high degree of self-similarity could help risk-stratify patients. Lastly, we did not have enough patients on opiates to estimate the accuracy in the detection of opiate-induced CSA, though inter-breath variability would be expected to decrease self-similarity. In a subanalysis of 496 patients with high CAHI (>10) and low similarity (<20%), the algorithm predicted that 70% of the patients not have REC versus 16% with REC. Another subgroup of 10 patients with high CAHI and high similarity (>70%), the algorithm predicted that 0% of the patients would have REC and 40% would have not. Although these are not enough patients to base firm conclusions on, it is speculative but possible that CSA detection without self-similarity may suggest ataxic breathing, as can be seen with opiates and high spinal/brain stem disorders.

Conclusions

This study presents an algorithm to automatically label central apneas and central hypopneas, based on envelope features in respiratory tracings. Our proposed full night similarity measure was able to predict REC based on automatically generated labels at least as well as manually scored labels by sleep technologists.

Supplementary material

Supplementary material is available at *SLEEP* online.

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Conflict of interest statement. R.J.T. declares the following "conflicts" (1) patent and license for the ECG-spectrogram to MyCardio, LLC, through the Beth Israel Deaconess Medical Center; (2) patent and license to DeVilbiss-Drive for an auto-CPAP algorithm; (3) consultant to Jazz Pharmaceuticals, Guidepoint Global, and GLC Councils; and (4) unlicensed patent for a device to regulate carbon dioxide in the positive airway pressure circuit. M.B.W. is a cofounder of Beacon Biosignals, Inc. Other authors report no conflicts of interest. None of the entities listed played any role in the present study.

Preprint Repositories: This manuscript is not preprinted or published prior to submitting to *Sleep*.

Data Availability: The code for the algorithm is open source with no restrictions and is available from https://github.com/mghcdac/self_similarity.

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