EDITORIAL

Modeling sleep-disordered breathing using overnight polysomnography—opportunities for patient-oriented research and patient care

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Overnight polysomnograms (PSG) provide a rich source of information on various physiological processes that occur during sleep [1]. Advancements in sensor, computer processing, and data storage technologies have enabled us to capture an array of data. For example, changes in bioelectric potentials such as electroencephalography (EEG) are recorded with the precision of nanovolts every few milliseconds. Depending on the number of recording channels, amplitude resolution, and sampling rate, a single sleep study may capture about 500 megabytes of information, i.e. 4 194 304 000 bits. Yet, for clinical decision-making on the presence of sleep-disordered breathing (SDB), all this information is reduced to one single bit, answering the simple categorical question: is sleep apnea present?

The average rate at which apneas and hypopneas occur during sleep, the apnea-hypopnea-index (AHI) or variations thereof, is the clinically employed metric to define the presence and severity of SDB. This single numerical value could be expressed in as few as 8 bits. Arguably, the vast amount of data collected during overnight PSG may capture largely redundant information, some of which may be irrelevant for SDB diagnosis. But undoubtedly, condensing an entire PSG into a single 8-bit number cannot occur without significant information loss [2].

Admittedly, a typical PSG report provides more sleep insights, including a hypnogram, traces of body position, oximetry, and respiratory and limb movement events. Sleep stage summary statistics and cross-tabulation of AHI against sleep stage and body position may further add to the clinical picture and allow for phenotyping of SDB.

In this issue of the journal, Chen et al. [3] propose a dynamic point process model to characterize the temporal association between respiratory events, sleep stage, body position, and the history of preceding respiratory events. Point process models provide a powerful statistical framework for analyzing event time series and have been successfully applied to various problems, including sleep stage transitions [4].

While the relationship between AHI and sleep stage and body position, respectively, could be qualitatively gauged from the summary charts and cross tabulations, the estimation of statistical models from observed data is attractive. It yields robust, easily interpretable information on the strength of multiple associations, including confidence intervals.

In the dynamic point process model developed by the authors, the study participants' sleep stage and body position explain a significant amount of temporal variations in AHI, confirming the well-documented observation that SDB is often prevalent during REM sleep [5] and in the supine position [6]. Importantly, the model allows assessing the influence of multiple variables simultaneously. The authors show that the history of preceding respiratory events, in particular, adds significantly to the model's predictive power yielding an accuracy

of 86% (ROC area under the curve). Aside from reducing the model error and delivering a better estimate of AHI, considering the history of respiratory events provides additional insights into the individual manifestation of SDB that would be difficult to gauge from conventional PSG summary reports. The authors propose a set of metrics to quantify the increased propensity of respiratory events, including the "refractory period" between events. By estimating point process models for a large cohort study, they illustrate how variables obtained within their statistical framework could be effectively used to quantify SDB better and identify phenotypes.

The authors have made their tool for assessing the temporal association between respiratory events, sleep stage, and body position publicly available, and researchers are encouraged to incorporate the dynamic AHI analysis in their research. Conventional parameters from PSG (sleep scoring and respiratory event detection) fall short of predicting or showing modest associations with disease-specific symptom burden; hence, there is significant room for improvement. There are several areas where the model might be beneficial. For example, quantifying the propensity of respiratory events may provide valuable markers of Cheyne–Stokes respiration. Markers provided by the dynamic point process model may also be more effective for distinguishing between patients whose symptoms and/or hypertension improve on sleep apnea treatment, given the association between REM-related sleep apnea and prevalent and incident hypertension [7–9].

Ultimately, any new metric should be more predictive of patient outcomes and/or easier to assess than established ones. Future studies are mandatory to validate the clinical value of these metrics, testing whether the novel phenotypes/quantification measures are related to disease-specific symptom burden, nocturnal hypertension [10], and cardiac arrhythmias [11]. In addition, the new metrics can be integrated with an important clinical context, when—as mentioned by the authors—it is possible to predict the efficacy of various therapies of SDB including positive airway pressure, mandibular advancement devices, positional therapy, and upper airway stimulation. Efficacy of such treatments includes the normalization of breathing, hypoxemic burden [12], and sleep, surrogates that may lead to a relief of disease-specific symptom burden such as sleepiness and quality of life as well as to an improvement of hypertension [13].

Evidently, SDB cannot be condensed into a single number. A relatively simple, highly predictive model with few parameters that can be estimated from PSG or polygraphy, making more effective use of hundreds of megabytes of data that are easily interpretable, would seem highly beneficial for patient-oriented research and patient care. In addition to the variables included in the model, other candidates may add predictive value, for example, arousal [14].

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References

1. Mehra R, *et al*. Sleep-disordered breathing and cardiac arrhythmias in adults: mechanistic insights and clinical implications: a scientific statement from the american heart association. *Circulation*. 2022;**146**(9):e119–e136.
2. Linz D, *et al*. Assessment and interpretation of sleep disordered breathing severity in cardiology: clinical implications and perspectives. *Int J Cardiol*. 2018;**271**:281–288. doi:10.1016/j.ijcard.2018.04.076
3. Chen S, *et al*. Dynamic models of obstructive sleep apnea provide robust prediction of respiratory event timing and a statistical framework for phenotype exploration. *Sleep*. 2022:zsac189. https://doi.org/10.1093/sleep/zsac189.
4. Kishi A, *et al*. NREM sleep stage transitions control ultradian REM sleep rhythm. *Sleep*. 2011;**34**(10):1423–1432. doi:10.5665/SLEEP.1292
5. Alzoubaidi M, *et al*. Obstructive sleep apnea during REM sleep: clinical relevance and therapeutic implications. *Curr Opin Pulm Med*. 2016;**22**(6):545–554. doi:10.1097/MCP.0000000000000319
6. Joosten SA, *et al*. Supine position related obstructive sleep apnea in adults: pathogenesis and treatment. *Sleep Med Rev*. 2014;**18**(1):7–17. doi:10.1016/j.smrv.2013.01.005
7. Mokhlesi B, *et al*. Obstructive sleep apnea during REM sleep and hypertension. results of the Wisconsin Sleep Cohort. *Am J Resp Crit Care*. 2014;**190**(10):1158–1167.
8. Kumagai H, *et al*. Nocturnal blood pressure fluctuations in patients with rapid eye movement-related obstructive sleep apnea. *J Clin Med*. 2021;**10**(21). Article No.:5023.
9. Sasai-Sakuma T, *et al*. Prevalence, clinical symptoms and polysomnographic findings of REM-related sleep disordered breathing in Japanese population. *Sleep Med*. 2021;**80**:52–56. doi:10.1016/j.sleep.2021.01.009
10. Khoshkish S, *et al*. The association between different features of sleep-disordered breathing and blood pressure: a cross-sectional study. *J Clin Hypertens*. 2018;**20**(3):575–581.
11. Linz D, *et al*. Nightly sleep apnea severity in patients with atrial fibrillation: potential applications of long-term sleep apnea monitoring. *Int J Cardiol Heart Vasc*. 2019;**24**:100424.
12. Linz D, *et al*. Nocturnal hypoxemic burden during positive airway pressure treatment across different central sleep apnea etiologies. *Sleep Med*. 2021;**79**:62–70.
13. Patil SP, *et al*. Treatment of adult obstructive sleep apnea with positive airway pressure: an American Academy of Sleep Medicine systematic review, meta-analysis, and GRADE assessment. *J Clin Sleep Med*. 2019;**15**(2):301–334.
14. Eckert DJ, *et al*. Arousal from sleep: implications for obstructive sleep apnea pathogenesis and treatment. *J Appl Physiol*. 2014;**116**(3):302–313.