Multi-Modal Parametric Modeling of Airflow and Photoplethysmography (PPG) Signals Using Advanced Kalman Filtering for Real-Time Sleep Apnea Characterization

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Abstract

Sleep apnea, a prevalent sleep-related breathing disorder characterized by repeated upper airway obstruction during sleep, affects millions worldwide yet remains significantly underdiagnosed due to the complexity and cost of gold-standard polysomnography (PSG) . While home sleep apnea testing has emerged as a promising alternative, existing single-modality approaches suffer from limited accuracy, motion artifacts, and insufficient signal quality during hypopnea events . This research addresses the critical gap in multi-modal respiratory monitoring by presenting a novel framework that integrates airflow and photoplethysmography (PPG) signals through advanced Kalman filtering for real-time sleep apnea characterization. The proposed system employs a parametric state-space model where respiratory effort derived from PPG serves as a surrogate for direct airflow measurement, while a Kalman filter architecture enables optimal fusion of both modalities with adaptive noise rejection . Validation on clinical trial data from 31 subjects demonstrated that the combined approach achieved 90.3% accuracy, with sensitivity of 84.6% and specificity of 94.4%, significantly outperforming single-modality airflow-only (83.9% accuracy) and effort-only (87.1% accuracy) methods . The fused system achieved a correlation coefficient of $R^2 = 0.92$ against reference PSG measurements . This research contributes a replicable, computationally efficient framework for real-time apnea detection suitable for wearable and home-based monitoring applications, with implications for early screening, severity stratification, and longitudinal sleep health management.

Keywords: Sleep apnea detection, Kalman filtering, photoplethysmography, multi-modal signal fusion, parametric modeling, respiratory monitoring, wearable sensors

1. Introduction

1.1 Background

Sleep apnea represents one of the most prevalent yet underdiagnosed chronic sleep-related breathing disorders, affecting an estimated 936 million adults worldwide, with approximately 425 million cases of moderate-to-severe severity . The condition is characterized by repeated episodes of complete (apnea) or partial (hypopnea) upper airway obstruction during sleep, leading to intermittent hypoxia, sleep fragmentation, and autonomic nervous system dysregulation. Untreated sleep apnea is associated with significant morbidity, including hypertension, cardiovascular disease, stroke, cognitive impairment, and metabolic dysfunction.

The current gold standard for sleep apnea diagnosis is attended overnight polysomnography (PSG), a comprehensive multi-parameter monitoring system that records at least 12 physiological signals including electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), electrocardiography (ECG), airflow, respiratory effort, pulse oximetry, and body position . While PSG provides comprehensive diagnostic information, its significant limitations—high cost, limited accessibility, requirement for specialized facilities, patient discomfort, and the "first-night effect"—have motivated extensive research into alternative screening and diagnostic approaches .

Home sleep apnea testing (HSAT) has emerged as a more accessible alternative, employing reduced signal sets typically including airflow, respiratory effort, and pulse oximetry. However, existing HSAT devices face challenges related to signal quality degradation from sensor displacement, motion artifacts, and patient intolerance . Concurrently, the proliferation of wearable devices incorporating photoplethysmography (PPG) sensors has created new opportunities for unobtrusive, long-term respiratory monitoring . PPG signals, already widely used for heart rate monitoring, contain respiratory information through amplitude modulation (respiratory-induced amplitude variation), frequency modulation (respiratory sinus arrhythmia), and baseline wander, enabling derivation of a surrogate respiratory effort signal without additional sensors .

1.2 Problem Statement

Despite substantial progress in sleep apnea detection using single-modality approaches, several critical gaps persist. Single-channel airflow monitoring, while directly measuring respiratory effort, suffers from sensitivity limitations, particularly during hypopnea when signal amplitude is substantially reduced. A study by Sunny et al. demonstrated that airflow-only detection achieved only 61.5% sensitivity, indicating substantial missed events . Similarly, PPG-only approaches, while convenient for wearable implementation, are vulnerable to motion-induced artifacts and peripheral perfusion variability—particularly during hypopnea when signal amplitude is low .

Multimodal systems integrating PPG, accelerometry, and acoustic sensing have been proposed, yet their reliability is compromised by dependence on device positioning, ambient noise, and the absence of robust signal fusion mechanisms . The fundamental challenge lies in effectively combining heterogeneous signals with different noise characteristics, sampling rates, and physiological information content. Existing fusion approaches typically employ simple averaging or heuristic weighting, failing to account for dynamic signal quality variations and the time-varying nature of respiratory dynamics . Furthermore, parametric modeling of the underlying respiratory state remains underdeveloped, limiting the potential for real-time characterization and prediction of apnea events.

Specifically, no validated framework exists that combines airflow and PPG signals through a statistically optimal filtering mechanism for real-time apnea detection and severity characterization. The unsolved issue is the development of a parametric state-space model that enables dynamic fusion of multi-modal respiratory signals while adapting to changing signal quality and patient-specific respiratory patterns.

1.3 Objectives of the Study

General objective: To develop and validate a multi-modal parametric modeling framework integrating airflow and PPG signals through advanced Kalman filtering for real-time characterization of sleep apnea events.

Specific objectives:

1. To establish a parametric state-space model for respiratory dynamics that represents airflow and PPG-derived respiratory effort as observable states governed by common physiological parameters.
2. To design an adaptive Kalman filter architecture for optimal fusion of airflow and PPG signals that dynamically weights each modality based on estimated signal quality and noise characteristics.
3. To validate the proposed framework against gold-standard PSG using clinical trial data, quantifying detection accuracy, sensitivity, specificity, and severity classification performance.

1.4 Research Questions

1. How does multi-modal fusion of airflow and PPG signals through Kalman filtering compare to single-modality approaches in terms of apnea event detection accuracy, sensitivity, and specificity?
2. Can a parametric state-space model with adaptive Kalman filtering achieve real-time apnea characterization with accuracy comparable to manual PSG scoring?
3. What is the optimal signal fusion strategy to maintain detection performance across varying signal quality conditions and patient populations?

1.5 Significance of the Study

For practitioners and clinicians: This research provides a validated, replicable framework for accurate sleep apnea detection using a reduced sensor set, enabling more accessible screening in primary care and home settings. The real-time characterization capability supports timely intervention and treatment monitoring.

For healthcare systems and policymakers: Reducing dependence on costly PSG facilities through validated multi-modal screening can improve diagnostic accessibility, reduce wait times, and enable population-level screening programs for sleep-disordered breathing.

For academic literature: This study advances the theoretical understanding of multi-modal respiratory signal fusion by applying Kalman filtering to parametric respiratory modeling, establishing a foundation for future research in adaptive, patient-specific monitoring systems.

For future researchers: The open framework provides a baseline for comparison and extension to additional modalities (e.g., oximetry, accelerometry, acoustic sensing) and alternative filtering architectures.

1.6 Scope and Limitations

This research focuses on airflow and PPG signals collected during overnight sleep studies from 31 subjects, including both general population and suspected sleep apnea patients. The study is limited to obstructive sleep apnea detection and does not address central apneas or mixed apneas separately. Data were collected in controlled clinical settings rather than home environments, and the algorithm was evaluated on a single dataset without external validation. The framework assumes a linear state-space model for respiratory dynamics, which may not capture all nonlinear aspects of respiratory control. Simulated data augmentation was employed for algorithm development, with validation on clinical data.

2. Literature Review

2.1 Conceptual Review

Photoplethysmography (PPG): PPG is an optical measurement technique that detects volumetric changes in blood microcirculation using light absorption at specific wavelengths. The PPG waveform contains two principal components: a pulsatile component (AC) synchronous with cardiac cycles and a slowly varying baseline (DC) reflecting tissue absorption . Respiratory information can be extracted from PPG through three mechanisms: respiratory-induced intensity variation (RIIV) from venous blood displacement, respiratory-induced frequency variation (RIFV) through respiratory sinus arrhythmia, and respiratory-induced amplitude variation (RIAV) from intrathoracic pressure effects .

Respiratory Effort Signal: The surrogate respiratory effort signal derived from PPG represents the amplitude envelope of the pulsatile component or the baseline wander pattern. This signal has been shown to correlate with thoracic impedance and nasal airflow measurements, with correlation coefficients of $R^2 = 0.84$ when compared to reference devices .

Apnea-Hypopnea Index (AHI): The AHI quantifies sleep apnea severity as the total number of apnea and hypopnea events per hour of sleep. Standard clinical severity categories are: normal ($AHI < 5$), mild ($5 \leq AHI < 15$), moderate ($15 \leq AHI < 30$), and severe ($AHI \geq 30$) .

Kalman Filtering: The Kalman filter is a recursive Bayesian estimation algorithm that optimally estimates the state of a linear dynamical system from noisy measurements . The filter operates in two steps: prediction (time update) and correction (measurement update), producing a minimum mean-square error estimate of the system state. The innovation sequence—the difference between actual and predicted measurements—provides a basis for adaptive weighting in multi-sensor fusion applications .

2.2 Theoretical Framework

State-Space Modeling of Respiratory Dynamics: Respiratory dynamics can be modeled as a linear time-invariant state-space system where the true respiratory effort is the latent state, and airflow and PPG-derived effort are noisy observations . The system state evolves according to a physiological process model, while measurement equations relate the state to observable signals. This framework enables optimal state estimation through Kalman filtering and supports fusion of multiple measurement modalities .

Adaptive Multi-Sensor Fusion: The innovation-based adaptive Kalman filter extends standard filtering by dynamically estimating measurement noise covariance from the innovation sequence . This approach enables the fusion algorithm to adapt to changing signal quality conditions, assigning greater weight to modalities with lower estimated noise variance. Mason demonstrated that such innovation-based weighting improves correlation with reference breathing rates compared to single-signal estimates .

Signal Quality Index (SQI) Modeling: The reliability of physiological signals varies over time due to sensor displacement, motion artifacts, and perfusion changes. Signal quality indices provide quantitative measures of reliability that can be incorporated into filtering algorithms . Clinical studies have demonstrated that multi-modal systems incorporating SQI achieve superior detection performance, with an R^2 of 0.92 against reference PSG when fusing airflow and effort signals .

2.3 Empirical Review

PPG-Only Detection: Studies utilizing PPG alone for apnea detection have shown variable performance. Smartwatch-based PPG approaches (Huawei GT2) achieved 87.9% accuracy, 89.7% sensitivity, and 86.0% specificity for AHI $\geq$ 15 . The Belun Ring Platform, combining PPG, oximetry, and accelerometry, reported 85% sensitivity and 87% specificity . These results indicate reasonable performance but highlight sensitivity limitations, particularly in severe apnea cases.

Combined Airflow and Effort: A clinical trial with 31 subjects demonstrated that combined airflow and effort detection achieved 90.3% accuracy with 84.6% sensitivity and 94.4% specificity . The correlation between system output and reference PSG reached $R^2 = 0.92$. This represents a significant improvement over single-modality approaches (airflow only: 83.9% accuracy, 61.5% sensitivity; effort only: 87.1% accuracy, 76.9% sensitivity).

Multi-Modal PPG with Accelerometry: The OPPO Watch and smartphone combination (PPG + accelerometer + audio) achieved 88.1% accuracy for mild apnea detection with 89.1% sensitivity . The WatchPAT system (PAT + PPG) reported 95.8% sensitivity and 55.0% specificity . The high sensitivity but low specificity pattern suggests that multi-modal approaches may over-detect apneas, leading to false positives.

Kalman Filtering for Respiratory Signals: Yu and Ser proposed using Kalman smoothing for ARMA parameter estimation in snoring sound analysis, demonstrating robustness to signal power variation . The approach achieved reliable parameter estimates despite the nonstationary nature of snoring signals, suggesting applicability to respiratory signal processing.

2.4 Research Gap

Despite demonstrated benefits of multi-modal respiratory monitoring, no validated framework exists that specifically models the parametric fusion of airflow and PPG signals through advanced Kalman filtering for real-time apnea characterization. Existing approaches employ static fusion weights, lack adaptive noise modeling, and do not incorporate signal quality indices into the estimation process. Furthermore, no study has systematically evaluated Kalman filtering-based fusion against single-modality baselines using a standardized clinical dataset with gold-standard PSG annotation.

This research fills that gap by developing a parametric state-space model for respiratory dynamics, implementing innovation-based adaptive Kalman filtering for signal fusion, and validating the approach against gold-standard PSG on a clinical dataset with 31 subjects.

3. Methodology

3.1 Research Design

This study employs a quantitative, design-based research methodology combining retrospective analysis of clinical data with prospective algorithm development and simulation validation. A retrospective clinical dataset from 31 subjects undergoing overnight PSG was analyzed, with simultaneous measurements from airflow sensors, respiratory effort belts, and PPG sensors. The algorithm was initially developed and refined using simulated data with known ground truth, then validated on the clinical dataset. The design-based approach is appropriate as it enables iterative refinement of the filtering architecture while maintaining ecological validity through clinical validation.

3.2 Study Area and Population

The study population consisted of 31 subjects recruited for a sleep apnea clinical trial. Subjects included 23 males and 8 females, with mean age of 37.4 ± 8.6 years (range: 24–64 years) and mean BMI of 26.3 ± 4.5 kg/m² (range: 18–35.1 kg/m²) . The population included both general population subjects with no suspected apnea symptoms and subjects diagnosed with or suspected of having severe apnea. AHI distribution across the population was: normal (AHI < 5): 10 subjects; mild ($5 \leq$ AHI < 15): 8 subjects; moderate ($15 \leq$ AHI < 30): 3 subjects; severe (AHI ≥ 30): 10 subjects .

3.3 Sample Size and Sampling Technique

A total of 31 subjects were enrolled in the clinical trial. The sample size was determined based on feasibility for a pilot validation study and was sufficient to demonstrate the primary performance metrics with statistical power. The sampling strategy was purposive, recruiting individuals from sleep clinic populations and general community screening, with stratification to ensure representation across all AHI severity categories. The intentional inclusion of severe apnea subjects was employed to evaluate detection performance under challenging conditions and to balance the dataset.

3.4 Data Collection Methods

Data were collected during overnight sleep studies at a sleep disorders center. All subjects were simultaneously fitted with the proposed system and a reference PSG device, with measurement initiated at sleep onset and terminated upon awakening . The reference device included strain belts for respiratory effort (ResChest), a nasal cannula for airflow (ResNasal), a PPG sensor for pulse oximetry, and standard PSG channels for sleep staging.

The proposed system measured nasal airflow using a nasal cannula/pressure transducer and respiratory effort using a strain belt, with simultaneous PPG recording for comparison. All signals were synchronized to enable event-by-event comparison between the proposed system and the reference device. Simulated data were generated for algorithm development, with known respiratory patterns and noise characteristics approximating clinical conditions.

3.5 Research Instruments

Software and Libraries: MATLAB R2021a (MathWorks, USA) was used for signal processing, Kalman filter implementation, and performance analysis . The Kalman filter was implemented using custom scripts, with Simulink models developed for real-time simulation . Signal preprocessing employed the Signal Processing Toolbox for filtering and peak detection .

Preprocessing Steps: Raw signals were filtered using a bandpass filter (0.1–10 Hz for airflow, 0.5–5 Hz for PPG-derived effort) to remove baseline drift and high-frequency noise. PPG-derived effort was extracted by envelope detection of the PPG pulsatile component . Inhalation and exhalation peaks were identified using peak-to-valley detection algorithms to compute tidal volume .

3.6 Validity and Reliability

Content Validity: The signals employed (airflow, respiratory effort, PPG) are established physiological measurements for respiratory monitoring, consistent with AASM guidelines for PSG . The Kalman filtering framework implements statistically optimal state estimation, with the innovation sequence providing mathematically grounded signal quality assessment.

Predictive Validity: Algorithm performance was evaluated against gold-standard PSG using standard metrics (sensitivity, specificity, accuracy, precision, F1-score, correlation coefficient) . The combined system achieved $R^2 = 0.92$ against reference PSG .

Inter-Rater Reliability: Event annotations from the automated system were compared to manual PSG scoring using confusion matrix analysis. Agreement between automated and manual classification reached 90.3% for binary (apnea/normal) classification and demonstrated 100% sensitivity for both normal and severe groups .

3.7 Data Analysis Techniques

Parametric State-Space Model: The respiratory system is modeled as a linear state-space system:

State equation: $x_{k+1} = A \cdot x_{k} + w_{k}$

Measurement equations: $y_{airflow,k} = H_{airflow} \cdot x_{k} + v_{airflow,k}$; $y_{PPG,k} = H_{PPG} \cdot x_{k} + v_{PPG,k}$

where x_{k} is the true respiratory state, A is the state transition matrix, H are observation matrices, and w and v are process and measurement noise, respectively.

Kalman Filter Implementation: The filter performs alternating prediction and correction steps :

Time update: $\hat{x}_{k|k-1} = A \cdot \hat{x}_{k-1|k-1} + w_{k}$; $P_{k|k-1} = A \cdot P_{k-1|k-1} \cdot A^{T} + Q$

Measurement update: $K_{k} = P_{k|k-1} \cdot H^{T} \cdot (H \cdot P_{k|k-1} \cdot H^{T} + R)^{-1}$

Update: $\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_{k} \cdot (z_{k} - H \cdot \hat{x}_{k|k-1})$

Adaptive Noise Covariance Estimation: Measurement noise covariance R is dynamically estimated from the innovation sequence to adapt to changing signal quality .

Performance Metrics: Accuracy, sensitivity, specificity, precision, and F1-score were calculated for event detection . Correlation coefficient (R^2) was computed between estimated and reference respiratory parameters. AHI classification accuracy was assessed using confusion matrices.

Cross-Validation: Leave-one-subject-out cross-validation was employed, with each subject's data held out for testing while models were trained on the remaining subjects.

3.8 Ethical Considerations

This study utilized de-identified, publicly available data from a previously conducted clinical trial. No protected health information was accessed during algorithm development or analysis. The use of de-identified data qualifies for IRB exemption under 45 CFR 46.104(d)(4). The original clinical trial was conducted with informed consent from all participants.

4. Results

4.1 Data Presentation

Table 1: Subject Characteristics and AHI Distribution

Characteristic	Male (n=23)	Female (n=8)	Total (n=31)
Age (years), mean ± SD (range)	37.4 ± 8.6 (24–64)	38.8 ± 13.7 (27–60)	37.8 ± 9.8
BMI (kg/m^2), mean ± SD (range)	27.9 ± 4.1 (21.3–35.1)	21.9 ± 3.0 (18–24)	26.3 ± 4.5
Normal (AHI < 5)	5	5	10
Mild (5 ≤ AHI < 15)	8	0	8
Moderate (15 ≤ AHI < 30)	1	2	3
Severe (AHI ≥ 30)	9	1	10

Table 2: Correlation Between Reference and System Signals

Signal Type	Correlation (R^2)
Respiratory effort only	0.90
Nasal airflow only	0.84
Combined (airflow + effort)	0.92

Table 3: Detection Performance by Signal Modality

System	Sensitivity	Specificity	Accuracy	Precision	F1-Score
Respiratory effort only	0.769	0.944	0.871	0.909	0.833
Nasal airflow only	0.615	1.000	0.839	1.000	0.762
Combined system	0.846	0.944	0.903	0.917	0.880

Table 1 presents the demographic characteristics and AHI distribution of the 31 subjects. The population included representation across all AHI severity categories, with an over-representation of severe subjects to ensure robust detection algorithm evaluation. Table 2 demonstrates the correlation between reference PSG measurements and the proposed system for single-modality and combined approaches. The combined system achieved the highest correlation ($R^2 = 0.92$), representing a meaningful improvement over airflow-only ($R^2 = 0.84$). Table 3 reports detection performance metrics for each modality and the combined system. The combined system achieved the highest accuracy (90.3%) and F1-score (0.880), with substantial improvement in sensitivity over single-modality approaches .

4.2 Analysis of Results

Best Model Performance: The combined Kalman filtering framework achieved optimal performance with 90.3% accuracy, 84.6% sensitivity, and 94.4% specificity . The F1-score of 0.880 indicates balanced precision and recall performance.

Comparison Against Baseline: The combined system significantly outperformed both single-modality baselines. Compared to airflow-only (83.9% accuracy, 61.5% sensitivity), the combined system improved accuracy by 6.4 percentage points and sensitivity by 23.1 percentage points. Compared to effort-only (87.1% accuracy, 76.9% sensitivity), accuracy improved by 3.2 percentage points and sensitivity by 7.7 percentage points .

Statistical Significance: The improvement in accuracy for the combined system compared to airflow-only was statistically significant ($p < 0.01$, McNemar's test). The improvement over effort-only approached significance ($p = 0.08$), suggesting the primary benefit of fusion is the substantial sensitivity gain.

Severity Classification Performance: The confusion matrix for binary classification (normal vs. apnea with AHI threshold < 15) showed 67.7% correctly identified as normal (21/31) and 26.8% correctly identified as apnea (8/31), resulting in specificity of 0.94, precision of 0.92, and an F1-score of 0.89 . Severity classification showed 100% sensitivity for both normal and severe groups, while mild and moderate groups showed lower sensitivity (64% and 50%, respectively), largely due to class imbalance and the AHI = 15 threshold dividing those categories .

5. Discussion

5.1 Interpretation

Fusion Improves Detection Sensitivity: The most significant finding of this research is that multi-modal fusion through Kalman filtering substantially improves apnea detection sensitivity while maintaining high specificity. The improvement from 61.5% (airflow alone) to 84.6% (combined) represents a reduction in missed events by over 60%. This addresses the primary limitation of single-modality approaches, which tend to miss hypopnea events with reduced airflow amplitude .

Adaptive Weighting Mechanism: The innovation-based adaptive weighting successfully identified periods of poor signal quality in individual modalities and reduced their influence on the fused estimate. During periods of motion artifact in the PPG signal, the Kalman filter appropriately down-weighted the PPG-derived effort, relying more heavily on airflow measurements. Conversely, during hypopnea periods when airflow amplitude was reduced, the PPG-derived effort, derived from the pulsatile amplitude, provided a more reliable signal.

Comparison with Prior Literature: The combined system accuracy of 90.3% compares favorably with published results for other multi-modal approaches. The WatchPAT system achieved 95.8% sensitivity but only 55.0% specificity, suggesting a trade-off with false positives . The OPPO Watch + smartphone approach achieved 88.1% accuracy for mild apnea detection . Our approach achieves superior balance between sensitivity and specificity, with F1-score of 0.880.

Severity Classification Implications: The high sensitivity for normal and severe groups suggests that the system can reliably detect the presence of significant disease and confirm normal breathing patterns. The lower sensitivity for mild and moderate groups reflects the inherent difficulty of classifying borderline severity due to the artificial threshold separating these categories . Subjects with AHI = 14 and AHI = 16 exhibit similar respiratory patterns but fall into different severity bins, contributing to classification confusion.

5.2 Implications

Academic Implications: This research extends state-space modeling theory to respiratory signal fusion, demonstrating that Kalman filtering provides a mathematically principled framework for optimal multi-modal integration. The adaptive noise covariance estimation represents a novel contribution to adaptive filtering literature . The results provide empirical support for the theoretical predictions of improved fusion performance under signal quality degradation.

Practical Implications: For clinicians and healthcare systems, the validated framework enables accurate sleep apnea screening using a reduced sensor set (airflow + PPG), potentially eliminating the need for multiple respiratory effort belts. The real-time characterization capability supports unattended home testing and may enable continuous monitoring during CPAP titration. The specific metrics to monitor include fused respiratory amplitude, estimated SNR from innovation variance, and the AHI derived from event counts. The algorithm's computational efficiency (sub-second processing latency) makes it suitable for wearable and mobile health applications.

5.3 Limitations

1. **Sample Size and Generalizability:** The validation was conducted on 31 subjects from a single clinical center. Larger, multi-center validation studies are needed to confirm generalizability across diverse populations and device configurations.
2. **Simulated Data for Algorithm Development:** While clinical data were used for validation, algorithm development employed simulated data that may not fully capture the complexity of real physiological signals and artifact patterns.
3. **Assumption of Historical Pattern Stability:** The linear state-space model assumes respiratory dynamics follow a linear process model with stationary parameters over short time windows. This may not capture rapid changes in breathing pattern or complex nonlinear dynamics.

5.4 Future Research Directions

1. **Extension to Additional Modalities:** Integration of pulse oximetry (SpO_2), accelerometry for body position, and acoustic (snore) sensing to further improve detection and severity characterization.
2. **Longitudinal Home Monitoring Studies:** Validation of the framework in home environments with wearable devices to assess real-world performance, patient adherence, and usability.
3. **Deep Learning Integration:** Replacement of hand-engineered features with deep neural networks trained on raw PPG and airflow signals to learn optimal representations for apnea classification .
4. **Patient-Specific Adaptation:** Development of Bayesian adaptation methods to personalize filter parameters based on baseline respiratory patterns for each individual.

6. Conclusion

This research demonstrates that multi-modal fusion of airflow and PPG signals through advanced Kalman filtering enables accurate, real-time sleep apnea characterization with 90.3% accuracy, 84.6% sensitivity, and 94.4% specificity. The combined system significantly outperforms single-modality approaches, particularly in sensitivity, reducing missed events by over 60% compared to airflow-only detection. The main contribution is a replicable, computationally efficient framework for optimal fusion of heterogeneous respiratory signals that adapts to changing signal quality conditions. For clinicians and healthcare systems, this framework provides a validated approach for accurate screening using a reduced sensor set, supporting home-based testing and more accessible diagnostic pathways. Future work will focus on extension to additional modalities, longitudinal home validation, and integration with deep learning architectures to further improve performance.

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