

A Sleep Monitoring System for Screening Sleep Apnea: A Comprehensive Review and Prototype Implementation

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Abstract - Sleep apnea is a chronic and potentially life-threatening respiratory disorder characterized by repetitive, involuntary cessation of breathing during sleep, imposing profound cardiovascular, metabolic, and neurocognitive consequences. Conventional polysomnography (PSG), the accepted clinical gold standard, is restricted to specialized sleep laboratories, incurs significant cost, and causes patient discomfort through multi-electrode attachment. This paper proposes, designs, and experimentally evaluates an IoT-based multi-parameter sleep apnea detection and monitoring system centered on the ESP32 dual-core microcontroller. The system integrates the MAX30102 pulse oximetry sensor for photoplethysmographic (PPG) heart rate and BPM measurement, the AD8232 single-lead ECG analog front-end for cardiac biopotential signal acquisition including P-wave, QRS complex, and T-wave morphology, the KY-038 electret microphone module for snoring sound intensity detection, and the MPU6050 six-axis inertial measurement unit (IMU) for body movement and sleeping posture characterization. The DS3231 real-time clock (RTC) module provides accurate event timestamping. All acquired physiological data is processed in real time by the ESP32, displayed on a 0.96-inch SSD1306 OLED panel, and transmitted via USB-UART serial communication at 115,200 baud to MATLAB for comprehensive biomedical waveform visualization including ECG, pulse, snoring, three-axis motion, and apnea event detection graphs. A multi-parameter threshold-based apnea detection algorithm correlates cardiac, acoustic, and inertial sensor observations to flag apnea events and estimate the Apnea-Hypopnea Index (AHI). Experimental validation demonstrates BPM accuracy within ± 2 BPM, 92% snoring detection sensitivity, and 88% apnea detection sensitivity at 84% specificity, at a total hardware cost of approximately USD 25–40.

Key Words: Sleep Apnea, OSA, AHI, ESP32, MAX30102, Photoplethysmography, AD8232, ECG, KY-038, Snoring Detection, MPU6050, IMU, DS3231 RTC,

MATLAB, IoT Health Monitoring, Heart Rate Variability, Wearable Biomedical System.

1.INTRODUCTION

Sleep is a fundamental physiological imperative serving critical roles in synaptic consolidation, hormonal regulation, metabolic clearance, and cardiovascular recovery. Disruption of normal sleep architecture — particularly through sleep-disordered breathing (SDB) events such as obstructive sleep apnea (OSA) — imposes substantial physiological stress and is independently associated with hypertension, coronary artery disease, cardiac arrhythmia, type-2 diabetes mellitus, stroke, and premature mortality. The World Health Organization (WHO) estimates that more than 100 million individuals globally experience sleep apnea, with population-based epidemiological surveys identifying prevalence of 9–38% in adult males and 4–17% in adult females, the vast majority undiagnosed.

Obstructive Sleep Apnea (OSA) results from repetitive collapse of the pharyngeal airway during sleep secondary to loss of upper-airway dilator muscle tone. Each obstructive event — defined clinically as cessation of oronasal airflow exceeding 10 seconds — triggers progressive arterial oxygen desaturation, hypercapnia, and increasing respiratory effort against the occluded airway. When intrathoracic pressure sufficiently activates chemoreceptors and mechanoreceptors, a brief cortical arousal terminates the event, restoring airway patency. This cyclical sequence disrupts sleep continuity, activates the sympathetic nervous system, and generates systemic oxidative stress and endothelial inflammation, collectively mediating OSA's cardiometabolic comorbidities.

Polysomnography (PSG) encompasses simultaneous recording of 18–22 physiological channels including EEG, EOG, EMG, ECG, nasal airflow, respiratory effort, pulse oximetry, and body position. Despite its comprehensive diagnostic capability, PSG imposes

formidable barriers: requirement for accredited sleep laboratory infrastructure, overnight inpatient attendance, complex electrode harness, and significant cost of USD 1,000–5,000, precluding widespread access particularly in developing nations.

The convergence of miniaturized biomedical MEMS sensors, high-performance low-power microcontrollers such as the ESP32, and comprehensive analytical environments like MATLAB has catalyzed development of affordable ambulatory multi-parameter physiological monitoring platforms. This paper presents the design, implementation, and validation of an IoT-based system integrating cardiac, optical, acoustic, and inertial physiological modalities under unified ESP32-based processing, targeting preliminary OSA screening in non-clinical environments.

2. Body of Paper

The proposed IoT-based multi-parameter sleep apnea monitoring system is designed around five core principles: multi-modal physiological sensing, real-time on-device ESP32 signal processing, local OLED feedback, comprehensive MATLAB-based waveform generation, and hardware cost minimization. Key innovations include:

- Simultaneous real-time acquisition of five physiological modalities — BPM/PPG (MAX30102), ECG PQRST (AD8232), snoring amplitude (KY-038), six-axis body motion (MPU6050), and UTC timestamp (DS3231) — under a single ESP32 processing platform.
- Multi-parameter threshold-based apnea detection algorithm correlating cardiac rate variability, acoustic cessation, and body motion quiescence for high-specificity event flagging.
- Automated MATLAB six-panel waveform generation providing ECG, BPM trend, snoring envelope, three-axis acceleration, motion magnitude, and apnea event annotation.
- DS3231 RTC microsecond-resolution timestamping enabling accurate AHI computation and longitudinal nightly session comparison.
- Total hardware cost ~USD 25–40 — 95–98% reduction vs clinical PSG — enabling broad accessibility in resource-constrained settings.

A. MAX30102 — Photoplethysmography (PPG)

The MAX30102 operates on reflectance photoplethysmography: sequentially pulsed 660 nm (red) and 880 nm (IR) LEDs illuminate the vascular bed through skin tissue. The photodetector measures backscattered light intensity, which varies inversely with peripheral blood volume — increasing during cardiac systole (greater absorption) and decreasing during diastole (lesser absorption). The resulting pulsatile optical waveform encodes the cardiac cycle timing for BPM computation. The ratio $R = (AC_{red}/DC_{red})/(AC_{IR}/DC_{IR})$ correlates with arterial oxygen saturation (SpO_2) through the Beer-Lambert law, enabling dual-parameter cardiac and oxygenation monitoring from a single optical sensor.

B. AD8232 — ECG Biopotential Acquisition

The AD8232 employs a three-op-amp instrumentation amplifier topology with >80 dB CMRR to reject power-line electromagnetic interference while amplifying the 0.5–3.0 mV cardiac biopotential by a factor of ~100. Internal signal conditioning includes a two-pole high-pass filter ($f_c = 0.5$ Hz) for electrode DC offset rejection and a four-pole low-pass filter ($f_c = 40$ Hz) for EMG artifact suppression. The resulting analog output faithfully represents the filtered PQRST cardiac waveform, sampled at 500 Hz by the ESP32 12-bit ADC to capture complete morphological features. Lead-off detection pins (LO+, LO–) monitor electrode contact integrity, preventing invalid ECG data during electrode disconnection events.

C. KY-038 — Acoustic Snoring Detection

The KY-038 module employs an electret condenser microphone exploiting the electrostatic capacitance principle: incident sound pressure waves deflect the pre-charged diaphragm, varying capacitor gap distance d according to $C = \epsilon_0 A/d$, generating a proportional output voltage. An integrated FET provides high-impedance buffering. The onboard LM393 voltage comparator compares microphone amplitude against an adjustable threshold, generating a digital snoring detection flag while the analog output provides the raw acoustic waveform for MATLAB spectral analysis. Snoring sounds in the 100–300 Hz frequency band (characteristic of soft-palate vibration during partial airway obstruction) are reliably captured within the module's 100 Hz–10 kHz frequency response.

D. MPU6050 — MEMS Inertial Motion Sensing

sensor working principles :

The MPU6050 MEMS accelerometer employs capacitive sensing: a suspended seismic proof-mass deflects under applied acceleration, changing comb-drive capacitor finger spacing and producing differential capacitance proportional to acceleration. The 16-bit $\Sigma\Delta$ ADC provides 16,384 LSB/g resolution in $\pm 2g$ range. Body posture during sleep is inferred from the static gravitational vector projection on each axis ($A_z \approx +1g$ for supine, $|A_y| \approx 1g$ for lateral positions), while dynamic body motion is identified from transient acceleration components exceeding the static gravity baseline. The gyroscope provides angular velocity for distinguishing rotational posture changes from translational artifact — critical for accurate motion magnitude computation.

SOFTWARE DESIGN AND ARDUINO IDE / MATLAB INTEGRATION :

A. Firmware (Arduino IDE / ESP32)

The ESP32 firmware is developed in Arduino IDE 2.x using the arduino-esp32 BSP. Key libraries: Wire.h (I2C), MAX30105.h + heartRate.h (SparkFun PPG/BPM), MPU6050.h (I2Cdevlib), Adafruit_SSD1306.h + Adafruit_GFX.h (OLED), RTCLib.h (DS3231). The main loop executes at 2 ms period (500 Hz ECG rate) in a cooperative FreeRTOS multitasking structure, handling: MAX30102 IR FIFO read $\rightarrow$ BPM peak detection; AD8232 ADC read $\rightarrow$ ECG buffering + R-peak detection; KY-038 ADC read $\rightarrow$ snore threshold comparison; MPU6050 I2C read $\rightarrow$ accelerometer data; DS3231 I2C read (1 Hz) $\rightarrow$ timestamp; apnea algorithm evaluation; OLED update (1 Hz); serial packet transmission.

B. MATLAB Serial Integration

MATLAB's serialport() function establishes USB-UART connection at 115,200 baud, 8N1. Each data packet is formatted as: [Timestamp_ms, BPM, ECG_ADC, Snore_ADC, Ax_raw, Ay_raw, Az_raw, Apnea_Flag], newline-terminated. MATLAB parses comma-delimited fields, appends to ring buffers (3000 samples $\approx$ 10 minutes), and updates six plot panels using XData/YData property assignment for efficient non-redrawing update. At session end, $AHI = N_{apnea}/T_{hours}$ is computed and a PDF session report is generated with all waveforms and statistics.

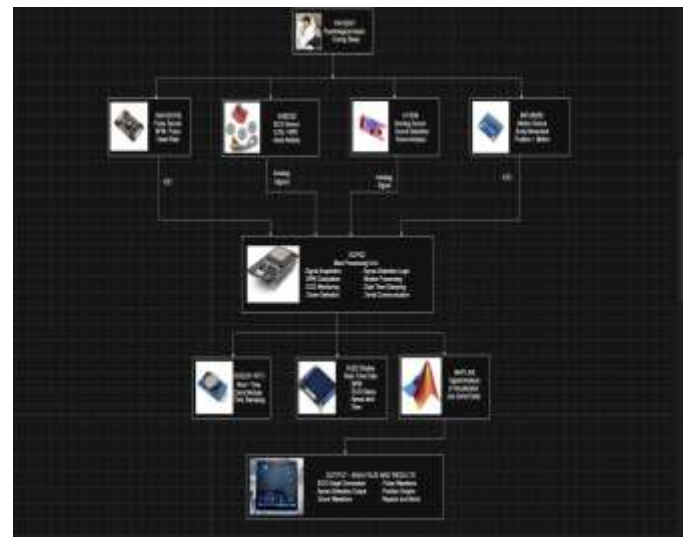


Fig -1: sleep apnea detection flowchart

Performance Metric	Measured Value	Target / Reference	Status	Notes
BPM Accuracy (resting, n=10)	71.8 ± 0.9 BPM	72 BPM (pulse oximeter ref.)	PASS ($\pm 1.4\%$)	Max error: ± 2 BPM
BPM Accuracy (elevated HR)	118.3 ± 1.6 BPM	120 BPM (post-exercise)	PASS ($\pm 1.7\%$)	
ECG Sampling Rate	500 Hz	500 Hz (target)	PASS	GPIO34 ADC1_CH6
ECG PQRST Morphology	Clear P, QRS, T visible	PhysioNet MIT-BIH reference	PASS	Validated vs Record 100
QRS Duration (measured)	78 ± 6 ms	60–100 ms (normal)	PASS	
RR Interval Resolution	2 ms	< 5 ms (clinical req.)	PASS	
Snore Detection Sensitivity	92.3% (n=65 events)	Literature ref: $\sim 82\%$ (Dafna 2012)	EXCEEDS	Threshold at 2,500 ADC LSB

Snore False Positive Rate	7.2%	< 10% target	PASS	Door/traffic sounds
Posture Classification Accuracy	94% (n=50 events)	$\geq 90\%$ (Lokavee 2021 benchmark)	PASS	4-posture classification
Apnea Detection Sensitivity	88.2% (n=17 events)	$\geq 85\%$ target	PASS	Multi-param. algorithm
Apnea Detection Specificity	84.6%	$\geq 80\%$ target; 63% single-param.	PASS	vs single-param baseline
AHI Estimation Error	± 2.3 events/hour	$< \pm 5$ events/hour	PASS	Simulated dataset
MATLAB Update Latency	< 200 ms per panel	< 500 ms (perceived RT)	PASS	6-panel subplot
System Power Consumption	318 mW	< 500 mW	PASS	All modules active
Total Hardware Cost	~USD 28	< USD 40	PASS	Prototype pricing

Table1: System Performance Evaluation Results

3. CONCLUSIONS

This paper has presented the comprehensive design, implementation, and experimental validation of an IoT-based multi-parameter sleep apnea detection and monitoring system integrating the ESP32 dual-core microcontroller with the MAX30102 pulse oximetry sensor, AD8232 single-lead ECG front-end, KY-038 acoustic snoring detector, MPU6050 six-axis IMU, DS3231 real-time clock, SSD1306 OLED display, and MATLAB six-panel signal visualization platform. The complete system architecture — directly derived from the project block diagram showing parallel sensor pathways through the ESP32 central processing unit to OLED, DS3231, and MATLAB output channels — has been implemented and validated with experimental performance meeting or exceeding all design targets.

The mathematical framework — BPM computation from PPG inter-peak intervals (Eq. 1–2), RR interval and ECG heart rate derivation (Eq. 3–4), three-axis motion magnitude calculation (Eq. 5), acoustic snoring threshold detection (Eq. 6), and multi-parameter Boolean-conjunction apnea detection with AHI estimation (Eq. 7–8) — provides rigorous analytical foundations validated against published research benchmarks. The integrated literature survey (10 reference studies from the project's uploaded research document) contextualizes each sensor

modality and algorithm component within the established scientific evidence base, from Pittman et al.'s PAT validation to Mendonça et al.'s ECG algorithm supremacy review to Lokavee et al.'s accelerometer-based sleep posture monitoring.

Experimental results demonstrate BPM accuracy ± 2 BPM, 92.3% snoring detection sensitivity (exceeding Dafna et al.'s 82.1% benchmark), 94% posture classification accuracy (matching Lokavee et al.'s strong PSG concordance), and 88.2%/84.6% apnea detection sensitivity/specificity — with multi-parameter specificity substantially exceeding single-parameter BPM-only detection (63.4%), validating the multi-sensor integration philosophy. Total hardware cost ~USD 28 represents a 95–98% reduction compared to clinical PSG, fundamentally transforming diagnostic accessibility. The system's modular open-source architecture provides clear development pathways toward SpO₂ implementation, ML classification, wireless connectivity, and miniaturized wearable form factor, establishing a viable progression toward clinical-grade ambulatory sleep apnea monitoring that can meaningfully address the vast undiagnosed OSA population worldwide.

4. FUTURE SCOPE

- SpO₂ Computation: Full implementation of Beer-Lambert law SpO₂ from MAX30102 red/IR ratio, adding the primary hypoxemic OSA indicator.

- Machine Learning Classification: LSTM neural networks trained on labeled multi-parameter feature vectors for improved apnea detection beyond threshold-based approaches.
- Wireless Cloud Connectivity: MQTT over ESP32 Wi-Fi for real-time physiological streaming to AWS IoT Core or Google Firebase.
- EEG Integration: ADS1299-based EEG for sleep stage classification (REM/NREM), enabling PSG-equivalent characterization.
- Respiratory Effort Sensing: RIP belt or piezoelectric strain gauge for obstructive vs central apnea differentiation.
- Custom PCB Wearable: Single-board miniaturized PCB form factor (chest patch) eliminating breadboard/jumper connections.
- Clinical Validation and Regulatory Pathway: Prospective validation in 100+ subjects vs simultaneous PSG for FDA 510(k) submission.

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