

Obstructive Sleep Apnea Detection from Single-Lead ECG Using Signal Processing and Machine Learning

Sona Semsari Parapari

Dept. of Electrical and Electronics Engineering
Istanbul Kültür University
Istanbul, Turkey
s.semsari@gmail.com

Esra Saatçi

Dept. of Electrical and Electronics Engineering
Istanbul Kültür University
Istanbul, Turkey
esra.saatci@iku.edu.tr

Abstract—Obstructive Sleep Apnea (OSA) is a common sleep disorder characterized by the temporary cessation of breathing during sleep. Polysomnography (PSG), considered the gold standard for OSA diagnosis, is costly and labor-intensive due to the requirement of recording multiple physiological signals. In this study, a non-invasive method for OSA detection using only single-lead Electrocardiogram (ECG) signals is proposed. The ECG signals were denoised using a bandpass filter and the Savitzky–Golay filter to reduce noise and artifacts. R-peaks were detected using the Pan–Tompkins algorithm, and R-R interval time series were derived. ECG-derived respiration (EDR) signals were extracted in three forms: QRS area variation, QRS slope, and R-peak amplitude. In addition to time and frequency domain features, cardiopulmonary coupling (CPC) features based on Continuous Wavelet Transform (CWT) were also obtained. Classification was performed using the Random Forest algorithm, and feature selection was conducted via the minimum redundancy maximum relevance (mRMR) method. The model was applied to identify the presence or absence of apnea events on a per-minute basis during sleep. Using the top 10 selected features, an accuracy of 88.99%, a sensitivity of 0.878, and a specificity of 0.898 were achieved. The results indicate that this ECG-based approach may serve as an effective alternative for OSA detection.

Keywords — Obstructive Sleep Apnea; EDR; R-R intervals; CWT; Random Forest; Machine Learning

I. INTRODUCTION

Sleep apnea is a sleep disorder characterized by recurrent episodes of complete or partial cessation of breathing during sleep, which is prevalent and may lead to significant adverse health outcomes. It is broadly classified into three subtypes: obstructive sleep apnea (OSA), central sleep apnea (CSA), and mixed sleep apnea (MSA). OSA arises from physical obstruction of the upper airway, whereas CSA results from a deficiency in the neural signals that activate the respiratory muscles [1]. MSA, on the other hand, is characterized by the coexistence of both obstructive and central events within the same episode or during the same sleep period. Among these, OSA is recognized as the most common subtype.

OSA causes recurrent apnea, oxygen desaturation, and sleep fragmentation, leading to inadequate and non-restorative sleep. This condition has been associated with cardiovascular diseases, cognitive impairments, car accidents, and a marked decline in quality of life. Globally, approximately one billion individuals are affected by OSA when using a diagnostic

threshold of five or more events per hour. The prevalence of OSA is known to increase with age and is strongly associated with obesity rates [2].

Polysomnography (PSG) is regarded as the gold standard for the diagnosis of OSA; however, its high cost, time-consuming nature, and limited accessibility necessitate the development of more practical and widely available diagnostic alternatives [3]. In this context, various approaches have been proposed, including home sleep apnea testing (HSAT) systems, smart wearable technologies, pulse oximetry, and automated detection methods based on single-lead ECG signals [4]. Among these, ECG-based apnea detection methods stand out due to their low cost, non-invasive nature, and applicability to large patient populations, and they can also be integrated with other diagnostic approaches to enhance practicality and improve accuracy.

In 1984, Guilleminault et al. identified a potential association between heart rate variability observed in ECG signals and sleep apnea, thereby establishing the groundwork for subsequent research on ECG-based apnea detection [5]. Since then, the performance of various algorithms has been evaluated using signal processing techniques such as Fourier analysis [6] and wavelet transform [7]. These studies demonstrated that variations in R–R intervals are effective in distinguishing between apneic and non-apneic periods. For example, classifiers such as Support Vector Machines (SVM) and k-Nearest Neighbors (kNN) have achieved accuracies of up to 89% [8]. More recently, multi-task learning frameworks that process ECG and respiratory effort signals simultaneously have yielded promising results in predicting the Apnea–Hypopnea Index (AHI) [9].

One of the key components in this field is heart rate variability (HRV), which represents the natural variation in R–R intervals and serves as an indicator of autonomic nervous system activity. Reduced HRV levels have been reported to be associated with OSA, and classifiers based on HRV have achieved accuracies of up to 85% [10]. Similarly, the EDR signal, obtained from morphological variations in the QRS complex without the need for direct respiratory measurement, has been considered an effective metric for apnea detection [11].

Another prominent approach is cardiopulmonary coupling R–R intervals and EDR time series. CPC enables the assessment of

sleep quality and apnea detection, offering complementary capabilities in situations where HRV or EDR alone may be insufficient. Recently, spectral features obtained using the SST-CPC method proposed by Wang et al. have been applied in apnea classification through various machine learning algorithms [13].

Despite these advances, there remains a need for methods that are simultaneously accurate, low-cost, and practical for home use. To address this, we propose an approach for detecting OSA using only R–R intervals and EDR signals derived from single-lead ECG recordings. By integrating signal processing, CPC analysis, and machine learning, our method aims to provide a portable and accessible alternative to existing diagnostic tools, while offering improved applicability in real-world home environments.

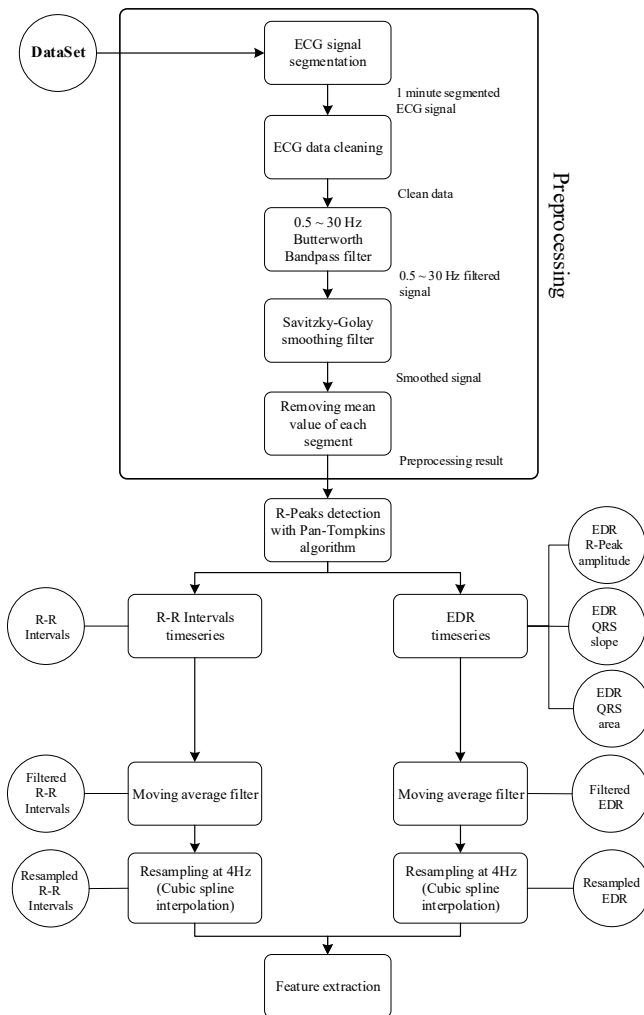


Figure 1: Preprocessing and feature extraction block diagram.

II. MATERIALS AND METHODS

In this section, the database and the signal processing methods employed are described. Figure 1 presents the preprocessing and feature extraction steps in a flow diagram. The subsequent section details the machine learning methodology.

A. Dataset

Real ECG data were obtained from the publicly available Physionet Sleep Apnea dataset [14] (<http://www.physionet.org/physiobank/database/apnea-ecg/>). The dataset consists of a total of 70 single-lead ECG recordings, which are evenly divided into training and test sets, each containing 35 recordings. The recordings have a sampling frequency of 100 Hz. All recordings were manually annotated on a per-minute basis, indicating whether each minute corresponded to a normal or apnea-affected period. The dataset comprises a total of 34,278 labeled minutes, including 13,064 minutes affected by apnea and 21,214 minutes without apnea.

B. Preprocessing

During the preprocessing stage, the dataset was initially segmented into one-minute intervals. Subsequently, to exclude segments containing high-amplitude, transient artifacts, segments with excessive amplitude within each recording were removed, and a 300-minute clean segment was selected from the middle portion of each recording. Following this, a zero-phase Butterworth bandpass filter with a passband of 0.5–30 Hz was applied to eliminate noise in both low and high-frequency ranges. Finally, a Savitzky–Golay filter was employed to smooth the signal. Figure 2 illustrates the effect of the filtering procedures on a representative one-minute signal segment.

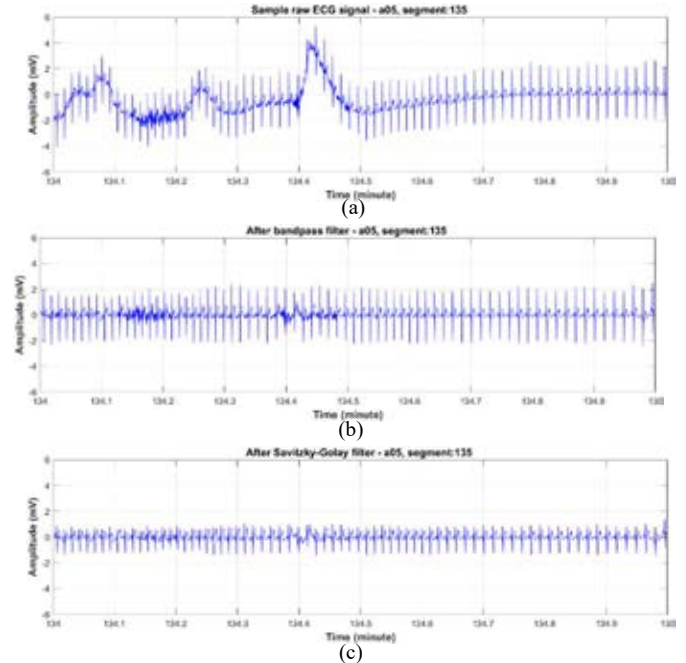


Figure 2:(a) Raw ECG signal, (b) bandpass filtered (c) smoothed ECG signal

C. R-R Intervals and EDR

Following preprocessing, R-peaks were automatically detected using the Pan–Tompkins algorithm, and the intervals between consecutive peaks were computed as R–R intervals. Based on the detected R-peaks and preprocessed ECG signals, the EDR time series were extracted in three forms: QRS area variation, QRS slope, and R-peak amplitude. Both the R–R intervals and EDR signals were then resampled at 4 Hz using cubic spline interpolation. The resulting signals are illustrated in Figure 3.

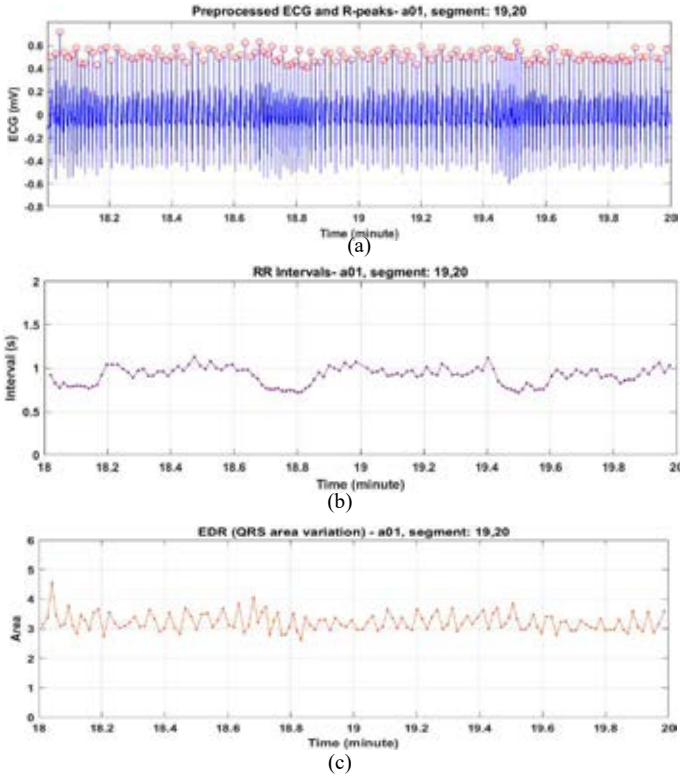


Figure 3: Sample a01, segment 19 and 20, (a) detected R-peaks on preprocessed ECG signal, (b) R-R intervals (c) EDR (QRS area variation)

D. Feature Extraction

For the detection of OSA using ECG signals, a comprehensive set of 33 baseline features reflecting both cardiac and respiratory dynamics was extracted. To improve classification performance, CPC features, representing the interaction between R–R intervals and ECG-derived respiration (EDR) signals, were additionally incorporated. In this context, the continuous wavelet transform (CWT) was employed to compute CPC features from three different EDR derivation methods, resulting in 27 features in total (9 per method). Consequently, 60 features were extracted for use in classification.

E. Machine Learning

In this study, a machine learning-based Random Forest algorithm was employed for apnea classification. This method reduces variance and enhances model generalizability by constructing a large number of decision trees and aggregating their outputs [15]. After partitioning the dataset into 80% training and 20% testing subsets, model evaluation was conducted using cross-validation. Classification was performed on three distinct feature sets: (1) time–frequency based features, (2) continuous wavelet transform–based cardiopulmonary coupling (CWT-CPC) features, and (3) a combined feature set. During each cross-validation iteration, feature selection was carried out using the Minimum Redundancy Maximum Relevance (mRMR) algorithm. As illustrated in Figure 4, overfitting occurred when the TopK value exceeded 20. Accordingly, TopK values of 10 and 15 were selected, yielding six classification results across the three feature sets. For the case of 15 features selected from the combined feature set, the following features were identified: SDS2, mean EDR area, peak-to-peak, mean ECG, standard deviation of EDR area,

SD2, SD ratio, standard deviation of EDR slope, LF/HF (CPC-slope), LF/HF (CPC-area), PSE, minimum RR, minimum ECG, standard deviation of RR, and mean EDR slope.

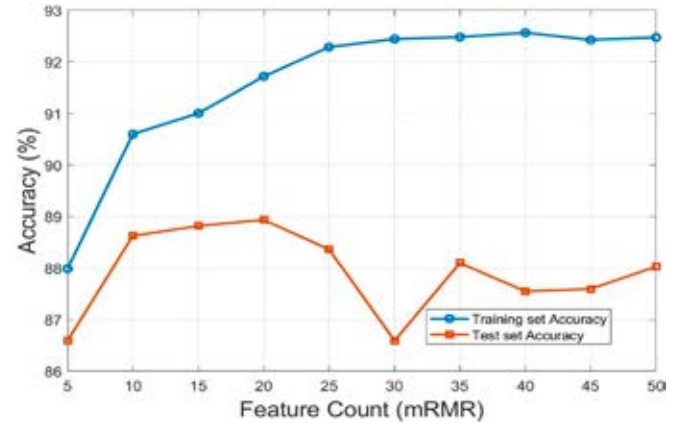


Figure 4. Variation of cross-validation accuracy on the training set (blue curve) and test set accuracy red curve) with respect to the number of features.

III. RESULTS AND DISCUSSION

Tables I and II summarize the classification results for TopK values of 10 and 15. The combined feature set consistently yielded the best performance, achieving a test accuracy of 88.99%, sensitivity of 0.878, and specificity of 0.898 at TopK=15. This indicates that integrating CPC features with time–frequency features enhances the discrimination between apneic and non-apneic segments.

Table I. Classification results for TopK = 10

Criteria	Time Frequency Features	CWT-CPC Features	Combined Features
Training Accuracy	90.13%	79.83%	90.19%
Test Accuracy	86.76%	80.20%	88.77%
Sensitivity (Recall)	0.8329	0.8072	0.8895
Specificity	0.4702	0.3628	0.8867

Table II. Classification results for TopK = 15

Criteria	Time Frequency Features	CWT-CPC Features	Combined Features
Training Accuracy	90.44%	80.40%	90.94%
Test Accuracy	85.64%	81.42%	88.99%
Sensitivity (Recall)	0.7918	0.8246	0.8779
Specificity	0.54	0.3443	0.897

As shown in Table II, the highest classification performance was achieved when the combined feature set was used at TopK=15.

A comparative evaluation with existing studies is presented in Table III. The proposed method outperformed several conventional machine learning approaches [10,13,16]. While deep learning methods, such as the CNN-based model by Thompson [17], achieved higher accuracy (95.28%), the proposed method demonstrated competitive performance with the advantages of reduced computational complexity, interpretability, and suitability for portable applications.

Table III. Comparison of similar studies and their results

No	Author	Reference	Dataset	Feature	Method	Accuracy (%)	Sensitivity (Recall)	Specificity
1	Wang	[13]	PhysioNet Apnea-ECG Dataset	R-R intervals/EDR/SST-CPC	Decision tree	82.49	0.781	0.757
2	Tuncer	[16]		CWT	Random forest	82.43	N/A	N/A
3	Mendez	[10]		HRV	kNN	85.55	0.839	0.885
4	Liu	[19]		ECG signals	Random forest	88.4	0.87	N/A
5	Thompson	[17]		ECG signals	1D-CNN	95.28	0.961	0.973
6	Nabil	[18]		ECG signals	1D-CNN	93	0.95	N/A
-	Proposed Method	-		R-R intervals EDR (amplitude, slope, area) CWT-CPC	Random forest	88.99	0.878	0.898

IV. CONCLUSION

In this study, a machine learning-based approach for obstructive sleep apnea detection was proposed using R-R intervals and EDR signals from single-lead ECG recordings. A comprehensive feature set was constructed by combining time-frequency features with CWT-based cardiopulmonary coupling (CPC) features, followed by mRMR-based feature selection and Random Forest classification. The combined feature set achieved the highest performance, with an accuracy of 88.99%, sensitivity of 0.878, and specificity of 0.898, outperforming several conventional methods. Although deep learning may provide higher accuracy, the proposed method demonstrated practical benefits in terms of computational efficiency, interpretability, and feasibility for portable and home-based applications.

Despite these strengths, limitations remain due to the inherent constraints of machine learning techniques and the relatively small and limited PhysioNet Apnea-ECG dataset, which may not fully represent variability across populations. Moreover, since CPC features had tiny improvements in results, their inclusion may be less beneficial in future work. Moving forward, research should focus on larger and more diverse clinical datasets, including hospital-sourced data, and the integration of advanced deep learning architectures. These efforts aim to enable reliable, efficient, and widely deployable diagnostic tools for the early detection and management of sleep apnea in both clinical and home-care environments.

ACKNOWLEDGMENT

This work is partially supported by the Scientific Research Projects Coordination Unit of Istanbul Kültür University.

References

- [1] M. K. Moridani, M. Heydar, and S. S. Jabbari Behnam, "A reliable algorithm based on combination of EMG, ECG and EEG signals for sleep apnea detection," in *Proc. 5th Conf. Knowl. Based Eng. Innov. (KBEL)*, 2019, pp. 256–262, doi: 10.1109/KBEL.2019.8734992.
- [2] P. E. Peppard, T. Young, J. H. Barnet, M. Palta, E. W. Hagen, and K. M. Hla, "Increased prevalence of sleep-disordered breathing in adults," *Am. J. Epidemiol.*, vol. 177, no. 9, pp. 1006–1014, 2013, doi: 10.1093/aje/kws342.
- [3] K. H. Levin and P. Chauvel, "Jessica Vensel Rundo and Ralph Downey III," in *Clinical Neurophysiology: Basis and Technical Aspects*, vol. 160. Elsevier, 2019, p. 381.

- [4] I. M. Rosen *et al.*, "Clinical use of a home sleep apnea test: An updated American Academy of Sleep Medicine position statement," *J. Clin. Sleep Med.*, vol. 14, no. 12, pp. 2075–2077, 2018.
- [5] C. Guilleminault, S. Connolly, R. Winkle, K. Melvin, and A. Tilkian, "Cyclical variation of the heart rate in sleep apnoea syndrome: Mechanisms, and usefulness of 24 h electrocardiography as a screening technique," *Lancet*, vol. 323, no. 8369, pp. 126–131, 1984, doi: 10.1016/S0140-6736(84)90062-X.
- [6] M. Drinnan, J. Allen, P. Langley, and A. Murray, "Detection of sleep apnoea from frequency analysis of heart rate variability," in *Comput. Cardiol. 2000*, vol. 27, Cambridge, MA, USA, pp. 259–262, doi: 10.1109/CIC.2000.898506.
- [7] A. Hossen, "A soft decision algorithm for obstructive sleep apnea patient classification based on fast estimation of wavelet entropy of RRI data," *Technol. Health Care*, vol. 13, no. 3, pp. 151–165, 2005.
- [8] B. Yilmaz, M. H. Asyali, E. Arikan, S. Yektin, and F. Ozgen, "Sleep stage and obstructive apneic epoch classification using single lead ECG," *Biomed. Eng. Online*, vol. 9, 2010.
- [9] T. Osa, Y. Morita, T. Tsuji, *et al.*, "A multi-task learning model using RR intervals and respiratory effort to assess sleep disordered breathing," *Biomed. Eng. Online*, vol. 23, p. 16, 2024, doi: 10.1186/s12938-024-01240-0.
- [10] M. O. Mendez, D. Ruini, O. Villantieri, M. Matteucci, T. Penzel, and A. Bianchi, "Detection of sleep apnea from surface ECG based on features extracted by an autoregressive model," in *Proc. IEEE Eng. Med. Biol. Soc. (EMBS)*, Aug. 2007, pp. 6105–6108.
- [11] G. B. Moody, R. G. Mark, A. Zoccola, and S. Mantero, "Derivation of respiratory signals from multi-lead ECGs," in *Comput. Cardiol.*, vol. 12, 1985, pp. 113–116.
- [12] R. J. Thomas, J. E. Mietus, C.-K. Peng, and A. L. Goldberger, "An electrocardiogram-based technique to assess cardiopulmonary coupling during sleep," *Sleep*, vol. 28, no. 9, pp. 1151–1161, Sep. 2005.
- [13] Y. Wang, W. Shi, and C. H. Yeh, "A novel measure of cardiopulmonary coupling during sleep based on the synchrosqueezing transform algorithm," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 4, pp. 1790–1800, Apr. 2023.
- [14] T. Penzel, G. B. Moody, R. G. Mark, A. L. Goldberger, and J. H. Peter, "The apnea-ECG database," in *Proc. Comput. Cardiol.*, vol. 27, 2000, pp. 255–258.
- [15] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.
- [16] E. Tuncer, "Development of new machine learning based algorithm for the diagnosis of obstructive sleep apnea from ECG data," *J. Comput. Sci. Res.*, vol. 5, no. 3, pp. 15–21, 2023.
- [17] S. Thompson, P. Fergus, C. Chalmers, and D. Reilly, "Detection of obstructive sleep apnea using features extracted from segmented time series ECG signals using a one-dimensional convolutional neural network," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, 2020, pp. 1–8.
- [18] R. I. Nabil *et al.*, "End-to-end sleep apnea identification from raw ECG signals utilizing 1D convolutional neural networks," in *Proc. Int. Conf. Quantum Photon., Artif. Intell., Netw. (QPAIN)*, Rangpur, Bangladesh, 2025, pp. 1–6.
- [19] X. Liu and W. Liu, "Innovative machine learning approaches for real-time detection of obstructive sleep apnea using ECG signals in medical wireless systems," in *Proc. Cross Strait Radio Sci. Wireless Technol. Conf. (CSRSWTC)*, Macao, China, 2024, pp. 1–3.