IJCRT.ORG ISSN : 2320-2882
INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Real-Time Fuzzy System for Apnea and Hypopnea Events Detection

[1]Bijoy Laxmi Koley
[1]Department of Electrical Engineering,
[1]Dr. B C Roy Engineering College Durgapur, India

Abstract: Sleep-related disorders are prevalent for older people in our modern society. Among many sleep disorders, sleep apnea is often found to be critical. A subject suffering from sleep apnea often found loud snoring during sleep due to restriction in the upper airway. As per standard, sleep apnea/hypopnea is defined as complete or partial cessation of airflow to the lungs during sleep for 10 sec or more. For treatment, assessment of apnea severity is essential and therefore requires sleep study. The laboratory-based sleep study is cost-intensive and also scare. This work attempts to develop a FUZZY based automated apnea event detection system with the help of an oro-nasal airflow signal that can be used in home-based monitoring of suspected subjects.

Two-time domain-based indexes have been extracted from the measured oro-nasal airflow signal: instantaneous volume flow rate and variance. These indices are fed to the FUZZY system for the detection of Apnea/Hypopnea events. This work analyses overnight sleep recordings of oro-nasal airflow signals from 16 subjects diagnosed with obstructive sleep apnea syndrome. For validation, an independent test has been performed on four randomly chosen recordings. The result was found to be very promising, with 92% accuracy in the case of apnea event detection and 85.6% accuracy for hypopnea event detection. The proposed system can be used for home-based screening of suspected apneic subjects and can count a total number of apnea and hypopnea events during sleep.

***Index Terms* - Apnea-hypopnea event detection, respiration signal, fuzzy inference system, variance, volume flow rate.**

I. INTRODUCTION

Sleep apnea is a prevalent sleeping problem, with a prevalence of 4% in adult males and 2% in adult women [1]. Apnea is the complete stopping of airflow to the lungs for 10 seconds or longer during sleep. Hypopnea is a respiratory episode in which breathing does not stop but the volume of air entering the lungs with each breath is drastically reduced. Daytime sleepiness, loud snoring, irritation, weariness, reduced attention, and impaired learning are the most prevalent sleep apnea symptoms [2]. Undiagnosed and untreated apnea can have substantial health repercussions, according to epidemiological research [3].

1.1 Background

Polysomnography (PSG) is the gold-standard method for definitive diagnosis of sleep apnea, which entails nightly recordings of various electrophysiological signals with the assistance of specialised equipment and trained staff [4]. The captured signals are then analysed by a sleep specialist to determine the disease's ultimate diagnosis. The severity of the condition is determined by the PSG's apnea-hypopnea index (AHI). It calculates how many apnea-hypopnea occurrences occur on average each hour of sleep.

AHI less than: is the absence of the syndrome
AHI in between 5 and 15: mild syndrome
AHI in between 15 and 30: moderate syndrome
AHI greater than 30: severe syndrome

PSG, on the other hand, is a difficult, time-consuming, and costly technique. As a screening test for a public health checkup, it is unfeasible. As a result, a quick, relatively cost, and reliable diagnosis option is desirable. Several solutions have been offered as simpler alternatives to PSG in the last decade. Most of them are based on fewer biological signals. For example, detections based on pulse oximetry [5], [6], ECG [7]-[9], airflow [10], [11], and snoring [12] have been developed. Airflow measurement-based strategies are one of them, and they provide direct evidence of apnea and hypopnea occurrences [4]. As a result, numerous single-channel airflow measurement-based approaches for home-based automated apnea assessment have been developed in recent years [10], [13]-[15]. The most common methods are time domain algorithms that measure the amplitude and frequency of breathing [11]. Airflow signals have also been examined using frequency domain and later nonlinear analysis [10], [15]. Furthermore, multiple machine learning techniques have been utilized to automatically recognize OSA based on the parameters acquired from the airflow signal, such as neural networks [11] and mixture discriminant analysis [15].

Subject categorization (sleep apnea positive/sleep apnea negative) and epoch classification are two of the most common approaches for detecting sleep apnea. The research [5], [9] made a definitive conclusion on participants who did not have a valid estimate of AHI, whereas the studies [6], [8] created procedures for detecting sleep apnea on an epoch basis. Estimating AHI without accurately identifying individual breathing events may result in an inaccurate evaluation of the severity of sleep apnea. In this regard, many studies have proposed the automatic event detection and scoring of sleep apnea [16]-[18]. These studies used different machine learning algorithms such as neural network [11], fuzzy logic [18], support vector machine [18], deep learning [19] etc. The study in [13] showed an accuracy of 93.3% for detecting positive apnea patients using a neural network model with oxygen saturation features. The authors in [19] predicted the sleep apnea events using long short term memory neural networks from respiratory signals. Nowadays, deep learning approaches have unfolded their applications in sleep apnea detection, including long short term memory (LSTM), CNN, pre-trained CNN models. Despite their promising results, most of the studies have used publicly available datasets.

1.2 Motivation

Most of the earlier have applied ECG signal for detection of apnea subjects. The measurement of ECG is much difficult need multiple contact point with the body. A much simpler and economic measurement is the measurement of oro-nasal airflow. Thus, the present work aims to develop an automatic model for identifying apnea and hypopnea events from single-channel respiration signals using a much simpler fuzzy–logic based algorithm. The system also estimates AHI according to the AASM criteria [20]. Moreover, apneic subjects are also prone to heart related disease.

1.3 Objectives and Outcome

The main contribution of the work are as follows;

- This paper presents a simpler alternative for detecting apnea and hypopnea events for real-time assessment of apnea severity.
- The proposed system uses an adaptive normalizing scale that improves the event detection ability under different breading conditions.

The specific and explanatory features, i.e., instantaneous volume flow rate and variance of the preprocessed airflow signal, are fed to the fuzzy system. The proposed fuzzy system uses a fuzzy logic approach to validate the proposed method by evaluating its ability to detect abnormal events using specific and defining physiological features.

A brief literature review of very recent time is presented in Section 2. The details of the signals that have been used in the study are presented in Section 3. Section 4 presents the details of the method that have been applied for the detection of apnea and hypopnea events with the help of the FUZZY system. All the results as obtained for the validation study are presented in Section 5, followed by discussion in Section 6, and conclusions in Section 7.

II. Literature Review

In the recent time the authors in [21] developed automated sleep apnea detection from cardio-pulmonary signals using bivariate fast and adaptive EMD. The bivariate CP signal is produced by combining the electrocardiogram (ECG) signal's HR and RR signals. A simple method for detecting obstructive sleep apnea. was developed by [22] by representing the electrocardiogram (ECG) signals in time-domain.

The authors in [23] detected apnea events from ECG segments using the Fourier decomposition method. In this case the ECG signal is transformed using the Fourier decomposition method.

The Performance evaluation of the spectral autocorrelation function and autoregressive models for automated sleep apnea detection with a single-lead ECG signal was created by [24]. The autors in [25] reported a HRV analysis index based on the temporal dependency complexity.

The authors in [26] created obstructive sleep apnea detection using statistical features based on discrete wavelet transforms.

The authors in [27] created deep learning methods for detecting sleep apnea events from an electrocardiogram. Six deep learning models were analysed and compared in terms of performance.

An algorithm for automatically classifying apnea and normal subjects based on new features extracted from HRV and ECG-derived respiration signals was developed in [28]. The EDR signal is extracted from a single-lead ECG using six algorithms, and the results are compared. To select the most effective features, the sequential feature selection method is used. In terms of per-segment classification, the proposed automatic OSA detection system outperforms other existing state-of-the-art methods.

Detection of sleep apnea using deep neural networks and single-lead ECG signals was developed also developed in [29]. The Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) recurrent networks were combined to create the automatic feature extraction method. The apnea-hypopnea index (AHI) is then used to distinguish between apnea and healthy subjects. Some experiments are carried out using the publicly available Apnea-ECG and UCDDB datasets.

Automated detection of sleep apnea using sparse residual entropy features with various dictionaries extracted from heart rate and EDR signals was developed in [30]. The analysis of these two signals reveals important information about sleep Apnea. To select the best performing classifier, the proposed SRE features are fed into a combination of fuzzy K-means clustering and support vector machine (SVM).

Detection of obstructive sleep apnea (OSA) using single-lead electrocardiogram (ECG) signals using a scalogram-based convolutional neural network (SCNN) was proposed in [31]. SCNN converts ECG signals into conventional scalograms using the continuous wavelet transform.

In [32] an information-based similarity approach to develop a sleep apnea screening based on photoplethysmography data from wearable bracelets. The goal of this study is to identify SA using wearable devices. This novel method could be used to evaluate SA and provide new insights into its pathophysiology.

The detection of obstructive sleep apnea (OSA) using common polysomnographic signals prior to cessation of breathing activates ventilation-aided machines such as Continuous Positive Airway Pressure (CPAP) (CPAP). Using recurrence plots and convolutional neural networks, the authors [33] devised a novel method for predicting OSA events. OSA events of 30, 60, 90, and 120 seconds are predicted before they occur.

The authors in [34] created a Bispectral analysis of overnight airflow to aid in the diagnosis of paediatric sleep apnea. When indicated, bispectral analysis of overnight airflow (AF) is proposed as a potential approach to replace PSG.

Obstructive sleep apnea-hypopnea (OSAH) syndrome is a common but often undiagnosed sleep disorder. The Apnea Hypopnea Index (AHI) is used to quantify the severity of the pathology. The average number of apnea and hypopnea events per hour of sleep is used to calculate this index. The majority of traditional methods fail to differentiate between these two types of events [35]. In the paper the authors used a structured dictionary learning method that has been found to be suitable for automatically differentiating between apnea and hypopnea using blood oxygen saturation signals as a unique input.
The authors in [36] created a robust automated non-contact algorithm for detecting central apnea in real time using video cameras. Central apneas that occur as a result of epileptic seizures can result in sudden death. To distinguish between apnea events and movements, two event features were calculated.
The authors in [37] created a convolutional neural network optimization based on Greedy for detecting apnea. The primary goal of the work was is to create a classifier based on a convolution neural network that can detect apnea events from a one-dimensional SpO2 signal.
Respiratory gating training is a popular method for improving patient proprioception [38]. The method is based on morphological analysis of respiratory signals and the use of an autoencoder trained on regular breathing and apnea detection. Results:
In the work [39] an accelerometry-derived respiratory index for sleep apnea screening that estimates the apnea-hypopnea index. Overnight physiological monitoring with the proposed ADR solution, which employed a machine learning approach, yielded a clinically relevant estimate of AHI for SAS screening. In [40] the authors used an enhanced frequency extraction network to develop a novel approach to diagnosing sleep apnea. The most direct indicator of the severity of SAHS is nasal airflow (NA). They present an automatic detection approach for SAH events using single-channel signals.
The authors [41] observed polysomnography (PSG) recordings provide detailed information that can be used to diagnose obstructive sleep apnea. The Respiratory Fluctuation Index (RFI) quantifies the distribution of respiratory drops in a PSG time series without the need for manual counting of episodes. Regression models based on nasal airflow RFI had the best agreement with manually scored AHIs, as shown by Bland-Altman plots. The highest sensitivities and specificities in detecting OSA were achieved by a threshold detection model based on RFI of nasal airflow.
Automatic detection of non-apneic sleep arousal regions from polysomnographic recordings was developed in [42]. The regions targeted are those where RERA and Non-RERA-Non-Apnea events occur. To reduce the feature space dimension, the features were ranked using a combination of feature selection strategies and a method of rank aggregation. The Non-Dominated Sorting Genetic Algorithm was used as the optimization algorithm to find a feature set that conveys the most discriminative information of detection in designated learning models.

III. Materials

The present study uses 16 subject's polysomnography databases from the popular MIT-BIH database [21]. The database contains airflow, Sao2, abdominal and thoracic movement in the subject wise recordings. Each record includes a period of eight hours. The airflow signal is measured through a nasal thermistor. The demographic details of the subjects are given in [21].

The score for the MIT-BIH dataset was discovered to be 30s epoch wise, with the start and stop times of events not noted. In the current study, apnea and hypopnea events associated to the start and endpoints of each event were indicated on the respiratory signal in collaboration with a clinical expert, in addition to database rating. According to AASM [20] recommendations, these two points were marked from the nadir preceding the first breath that is reduced to the beginning of the first breath, approaching the baseline breathing amplitude. Among the 16 records, six randomly chosen records were kept for independent testing, and the remaining ten were used for training validation.

IV. Methods

The raw respiratory signals from the MIT-BIH database were analysed to count the number of apnea and hypopnea occurrences per person. Signal processing, feature extraction, and fuzzy theory are all used in the event detection process. Different portion of raw respiration of 150s duration for the subject with ID 14 are shown in Fig. 1, Fig. 2 and Fig. 3. Fig. 1 shows an apnea event in between normal breathing. A hypopnea event is shown in Fig. 2. From Fig. 2, it can be observed during the hypopnea event; the respiration does not almost wholly collapse as in the case of an apnea event. Fig. 1 shows normal respiration without any disturbance as observed during apnea and hypopnea events.

4.1 Signal Pre-processing

Artifacts from a variety of sources were discovered in the raw respiration data. The respiratory signal has a relatively low frequency, ranging from 0.18 to 0.42 Hz. The respiration signal was filtered using a 10th order low pass Butterworth filter with a cutoff frequency of 3 Hz to reduce distortions produced by patient or sensor movements. To eliminate subject-dependent fluctuations, all signals were amplitude normalised by dividing the signal by the subject's maximum respiration amplitude.
Respiration amplitude is subjective specific; from the close observation of the breathing pattern for all the subjects, it is concluded that a subjective specific normalization can be applied using the zero mean units standard deviation technique using (1).

$$x_n(i) = \frac{x_r(i)-\bar{x}}{\sigma} \qquad (1)$$

The sample numbers are represented with $i=1,2, ...N$, $x_r(i)$ and $x_n(i)$ are the i^{th} sample for the raw and normalized respiration signal. $\bar{x}$ is the mean and σ is the standard deviation of the signal.

4.2 Adaptive normalization

Although found the application of the normalisation mentioned above, inter-subject normalisation was necessary, as the breathing amplitude during a subject's sleep was found to vary significantly over the night. In this case, a novel adaptive normalisation process has been adapted similar to adaptive filtering. The normalisation process is explained with the help of Fig. 4.

The adaptive normalisation system consists of a normalising scale factor unit that scales the signal with an adjustable coefficient(s) and the LMS algorithm to change the coefficient value for scaling each sample. In the adaptive system, the popular least mean square algorithm (LMS) algorithm has been applied. The LMS algorithm employs a technique known as the "method of steepest descent," which continuously updates weights to estimate results. The least mean square method provides certain learning curves. This concept is found to pursuing convergence, in which the iterative learning process resolves into a cohesive result rather than deviating. The learning rate for the adaptive process is obtained heuristically. An example of adaptively normalised signals applied on the signals shown in Fig. 1, Fig. 2, and Fig. 3 are shown in Fig. 5, Fig. 6, and Fig. 7 respectively.

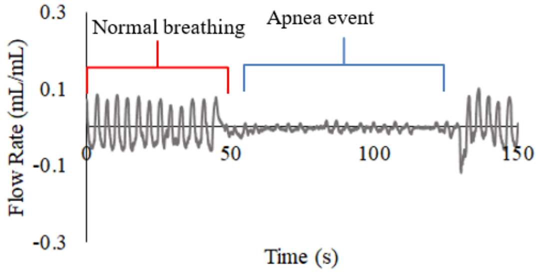

Fig. 1. An oro-nasal airflow signal during apnea event.

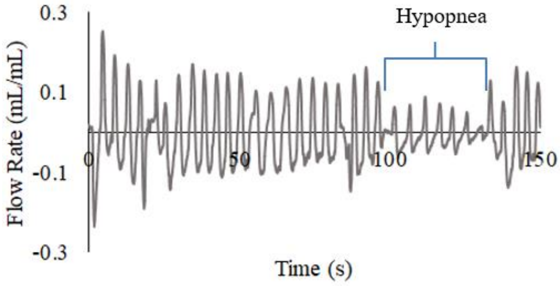

Fig.2. An oro-nasal airflow signal during hypopnea.

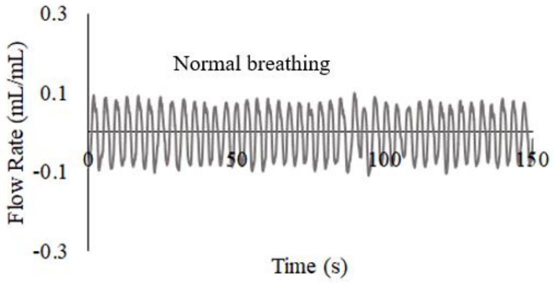

Fig. 3. An oro-nasal airflow signal during normal breathing condition at sleep.

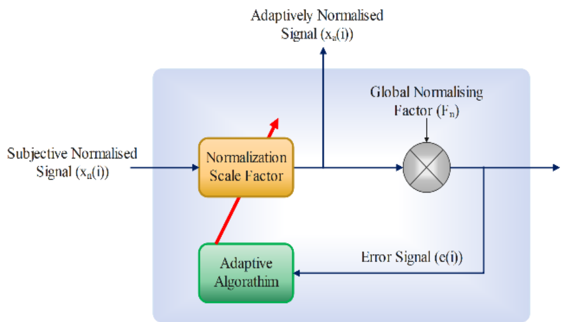

Fig. 4. Functional block diagram of the adaptive normalization process.

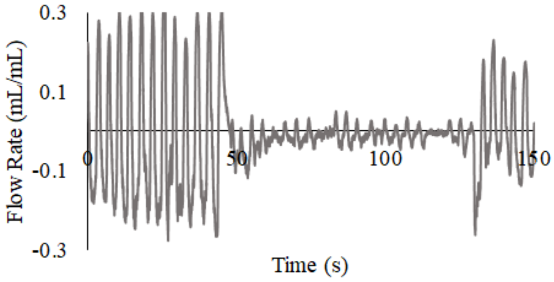

Fig. 5. Adaptively normalised oro-nasal airflow signal during apnea event for the signal shown in Fig. 1.

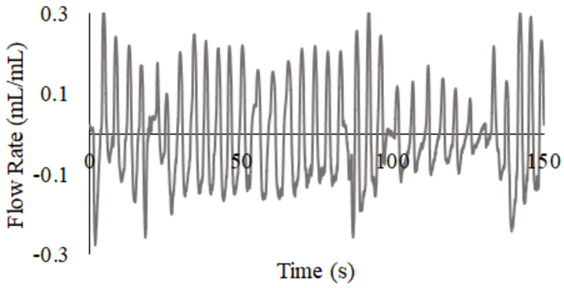

Fig. 6. Adaptively normalised oro-nasal airflow signal during hypopnea event for the signal shown in Fig. 2.

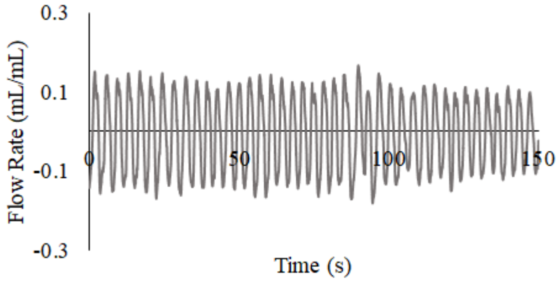

Fig. 7. Adaptively normalised oro-nasal airflow signal during normal respiration for the signal shown in Fig. 3.

4.3 Feature extraction

The instantaneous volume flow rate and variance have been calculated with a time horizon of six seconds. Then, for each section of respiration signal both of the time domain based measures are performed.

4.3.1 Instantaneous Volume flow rate:

The volume flow rate covered by the respiration signal was calculated over a base line (b) determined from the previous five minutes recordings. This measure is sensitive to the total volume of air flow occurs over the time period, and was calculated using equation (1).

$$Area\ (A) = \frac{1}{F_s}\sum_{n=1}^{N}(x_n - b) \qquad (2)$$

where N is the total number of samples in the segmented signal x_n and F_s is the sampling frequency.

4.3.2 Variance:

Variance is sensitive to respiration amplitudes (air inflow flow rate to outflow rate) and was calculated by equation (3).

$$\text{Variance}\ (V) = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \bar{x}_n)^2 \qquad (3)$$

where $\bar{x}_n = \frac{1}{N}\sum_{n=1}^{N} x_n$.

The variation of the variance and instantaneous volume flow rate during the apnea vent is shown in Fig. 7, and 8 respectively. Similarly the variations of these two features during the hypopnea and normal breathing are shown in Fig. 9, Fig. 10, Fig 11, and Fig. 12 respective sequential manner.

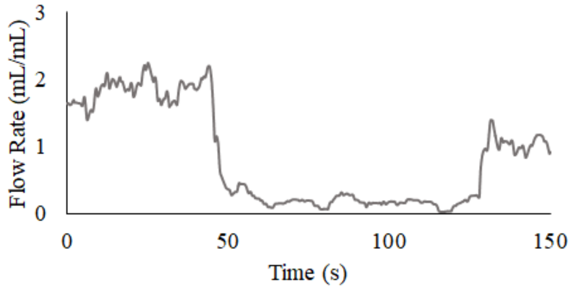

Fig. 8. Variance of airflow signal during apnea event as shown in Fig. 5.

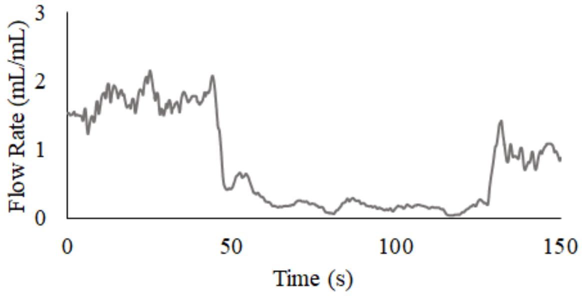

Fig. 9. Volume flow rate of airflow signal during apnea event as shown in Fig. 5.

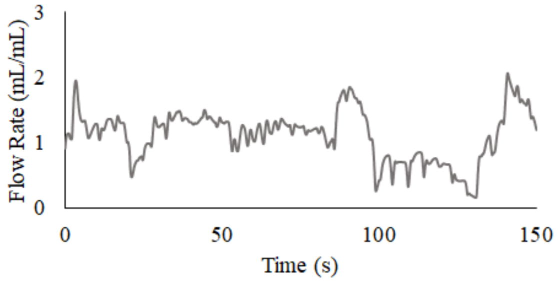

Fig. 10. Variance of airflow signal during hypopnea event as shown in Fig. 6.

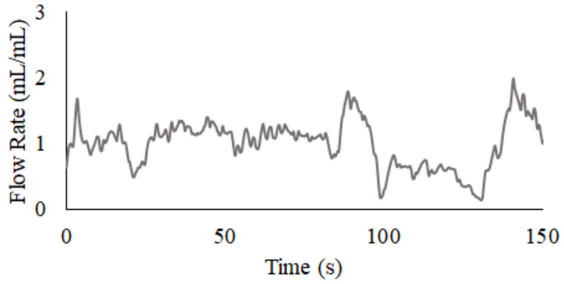

Fig. 11. Volume flow rate of airflow signal during hypopnea event as shown in Fig. 6.

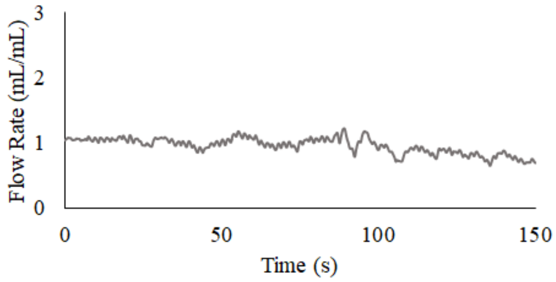

Fig. 12. Variance of airflow signal during hypopnea event as shown in Fig. 7.

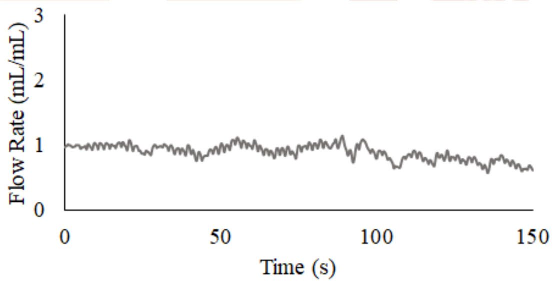

Fig. 13. Volume flow rate of airflow signal during hypopnea event as shown in Fig. 7.

The two measures' values were derived using the graph of respiration signals and a six-second sliding window. The time series instantaneous volume flow rate and variance of airflow signal grow during normal breathings, moderately reduce during hypopnea, and further decrease during apnea occurrences. It was discovered that the features originating from distinct classes overlap in feature space, making it difficult to determine a specific range of threshold values to separate the classes.
From the graph of respiration signals, as well as the calculated values of the two measurements in time order. The time series instantaneous volume flow rate and variance of airflow signal grow during normal breathings, moderately reduce during hypopnea, and further decrease during apnea occurrences, as seen in the signal graphs. It was discovered that the features originating from distinct classes overlap in feature space, making it difficult to determine a specific range of threshold values to separate the classes. However, because physiological inputs from various subjects give varied findings, a threshold that is appropriate for one person may not be appropriate for another; in this case, a fuzzy logic-based approach might improve risk classification for apnea patients.

4.4 Fuzzy Logic Modelling

Fuzzy logic is based on the concept of fuzzy sets. Fuzzy sets have the greater flexibility to capture faithfully various aspects of incompleteness and imperfection in a situation [43]. Fuzzy systems approve or disapprove a word or a phrase based on relativity. It is well known that biological systems do not have precisely defined criteria of membership. Moreover, it contains uncertainty and ambiguity. This means that rather than completely rejecting or accepting words, they are given a degree of acceptability or rejection. These systems convert environmental challenges to fuzzy systems (fuzzifying), then make a choice based on the rules established by an expert and de-fuzzify system outputs based on the extracted rules.

Variables for input of the fuzzy system is given the instantaneous volume flow rate and variance determined for the six second sliding windowed respiration signal; the fuzzy system's result and outputs are used as a criterion to detect apnea. Instantaneous volume flow rate are variance were divided into three groups "very high", "high", and "normal" and three groups as "very low", "low", and "normal", respectively. The output variable outcome risk score was categorised into "very high", "high", very low medium. The two input variables are divided into A rule-based expert system which uses generalised modusponens (GMP) from fuzzy logic as a rule of inference is implemented here for the classification of three different breathing patterns. GMP is considered as the categorical inference rule offered by the fuzzy logic by drawing inferences.

V. Results

Table 1 shows the classification results of the FUZZY classifier model; the performance on the observed dataset is the average classification performance of each class. The classification performance results are shown in terms of sensitivity, specificity, predictivity, and accuracy.The classification performance on an unknown dataset is reflected in the findings on an independent test dataset. The FUZZY classifier model was trained with the training dataset, which was the observed dataset in this case. The resulting classification performance reveals that normal breathing class detection is pretty good, followed by apnea class, and hypopnea class is the least discriminating class. When previously unseen data is supplied, categorization performance drops slightly, but not significantly.

Table 2 shows the event detection performance in terms of accuracy acquired from the event detector. Table 2 shows that while the accuracy for detecting hypopnea events is poor, the accuracy for detecting event (apnea + hypopnea) is best, indicating that there is some inaccuracy in differentiating hypopnea from apnea events. The non-linearity of thermistor-based sensors causes hypopnea to be missed.

Table 1 FUZZY Classification Performance in (%)

Dataset	Class	Sens.	Spec.	Pred.	Acc.
Seen	Normal	89.3	93.4	87.3	92.3
	Hypopnea	76.2	88.2	84.2	86.1
	Apnea	87.2	91.3	85.1	88.5
Unseen	Normal	87.5	89.8	85.4	90.6
	Hypopnea	77.2	88.1	82.0	83.2
	Apnea	83.3	90.3	81.1	91.5

Table 2 Event Detection Accuracy of the FUZZY Model in (%)

Dataset	Hypopnea	Apnea	Event (Apnea + Hypopnea)
Seen	89.1	92.4	94.6
Unseen	88.5	91.7	92.2

A comperative analysis for the performance of the proposed system with the other relevant works of recent time are presented in the Table 3.

Table 3. Comparison of the proposed system with the other works of recent time.

Ref.	Signal/Method	Perf. (%)
[21,22,23]	ECG derived features	73, 97
[24]	ECG, autoregressive models	95.65
[25]	HRV temporal complexity	93.3
[26]	ECG, Discrete Wavelet	90
[27]	ECG, Deep learning	99
[28]	HRV and respiration signals	90
[29]	ECG, CNN + LSTM	94.4
[30, 31]	ECG, residual entropy/SCNN	>90.1
[32]	Pathophysiology	84
[33]	Pathophysiology, CNN	90.7
[35]	blood oxygen saturation	90.1
[36,37]	SpO2	>90
[38]	Respiration, morphological analysi	87.6
[39,40]	Respiration, accelerometer	>90
Proposed	**Oro-nasal airflow, Fuzzy**	**92.2**

VI. DISCUSSION

In the work, only one signal measured through thermistor based oro-nasal airflow sensor has been utilized. Though this make the system simple and cost competitive. However, the thermal airflow sensor is highly non-linear and less sensitive particularly during hypopnea event. Thermal airflow sensors estimate airflow and detect mouth breathing by measuring the temperature difference between exhaled and ambient air. The use of temperature as a surrogate for airflow measurement works well for detecting apnea because it detects both nasal and oral airflow. Nasal cannulas are pressure sensors that detect changes in pressure during inspiration and expiration. To ensure an oronasal flow measurement, most sleep laboratories use signals from a thermistor and nasal pressure (NP). This sensor combination improves the detection of apneas that thermistors miss or overestimate in the case of mouth breathing. These two sensors, on the other hand, can cause patients a great deal of discomfort and even interfere with their sleep.

VII. CONCLUSIONS

The current study provides a strategy for identifying events that is clinically more significant than identifying one-minute apneic epochs [6], [8], because the number of apneic epochs does not always equal the number of events. FUZZY classifier judgments on time series sequences are employed to identify events in the current study, where one or two misclassification results may not effect event identification, rather than treating classifier conclusions as final [6]-[9]. Apnea and hypopnea events are detected separately from normal breathings in this study, whereas prior studies [6], [8] on apneic epoch classification attempted to determine whether apnea or non-apnea occurred. The proposed model attained an overall event identification accuracy of 92.2 percent in unseen data. As a result, it could be used as a screening tool to detect apnea events and kinds (apnea/hypopnea).

Future scope of work, involves incorporation of SpO2 signal measurement for improving the low hypopnea event detection accuracy. The proposed system will need to be tested on a larger database. Furthermore, advanced methods available in the fields of information theory and coding can be used to improve the performance of the event detector. Other classifier combiner rules, such as Error Correcting Output Code, Majority Voting, and others, can be used instead of winner-takes-all to examine classification performance.

Acknowledgment

The author acknowledge the support provided by the Dr. B C Roy Engineering College, Durgapur, West Bengal, India

Conflicts of interest

The authors have no conflicts of interest to declare.

REFERENCES

[1] T. Young, M. Palta, J. Dempsey, J. Skatrud, S. Weber, and S. Badr, "The occurrence of sleep-disordered breathing among middle-aged adults," N. Engl. J. Med., vol. 328, pp. 1230–1235, 1993.
[2] D. P. White, "Sleep apnea," Proc. Amer. Thorac. Soc., vol. 3, pp. 124-128, 2006.
[3] T. Young, P. E. Peppard, and D. G. Gottlier, "Epidemiology of obstructive sleep apnea, a population health perspective," Amer. J. Respir. Crit. Care Med., vol. 165, pp. 1217-1239, 2002.
[4] Standards of Practice Committee of the American Sleep Disorders Association, "Practice parameters for the indications for polysomnography and related procedures," Sleep, vol. 20, pp. 406-422, 1997.
[5] D. Alvarez, R. Hornero, J. V. Marcos, and F. Del Campo, "Multivariate analysis of blood oxygen saturation recordings in obstructive sleep apnea diagnosis," IEEE Trans. Biomed. Eng., vol. 57, no. 12, pp. 2816-2824, Dec. 2010.
[6] Burgos, A. Goni, A. Illarramendi, and J. Bermudez, "Real-Time detection of apneas on a PDA," IEEE Trans. Inf. Technol. Biomed. Eng., vol. 14, no. 4, pp. 995-1002, July 2010.
[7] H. Khandoker, J. Gubbi, and M. Palaniswami, "Automated scoring of obstructive sleep apnea and hypopnea events using short-term electrocardiogram recordings," IEEE Trans. Inf. Technol. Biomed. Eng., vol. 13, no. 6, pp. 1057–1067, Nov. 2009.
[8] M. Bsoul, H. Minn, and L. Tamil, "Apnea MedAssist: Real-time sleep apnea monitor using single-lead ECG," IEEE Trans. Inf. Technol. Biomed. Eng., vol. 15, no. 3, pp. 416-427, May 2011.
[9] H. Khandoker, M. Palaniswami, and C. K. Karmakar, "Support vector machines for automated recognition of obstructive sleep apnea syndrome from ECG recordings," IEEE Trans. Inf. Technol. Biomed. Eng., vol. 13, no. 1, pp. 37–48, Jan. 2009.
[10] H. Nakano, T. Tanigawa, T. Furukawa, and S. Nishima, "Automatic detection of sleep-disordered breathing from a single-channel airflow record," Eur. Respir. J., vol. 29, pp. 728-736, 2007.
[11] P. Várady, T. Micsik, S. Benedek, and Z. Benyo, "A novel method for the detection of apnea and hypopnea events in respiration signals," IEEE Trans. Biomed. Eng., vol. 49, no. 9, pp. 936–942, Sep. 2002.
[12] U. R. Abeyratne, A. S. Wakwella, and C. Hukins, "Pitch jump probability measure for the analysis of snoring sound in apnea," Physiol. Meas., vol. 26, pp. 779-798, 2005.
[13] T. Shochat, N. Hadas, M. Kerkhofs, A. Herchuelz, T. Penzel, J. H. Peter, and P. Lavie, "The SleepStrip: An apnoea screener for the early detection of sleep apnoea syndrome," Eur. Respir. J., vol. 19, pp. 121-126, 2003.
[14] F. R. de Almeida, N. T. Ayas, R. Otsuka, H. Ueda, P. Hamilton, F. C. Ryan, and A. A. Lowe, "Nasal pressure recordings to detect obstructive sleep apnea," Sleep Breath, vol. 10, pp. 62–69, 2003.
[15] S. I. Rathnayake, I. A. Wood, U. R. Abeyratne, and C. Hukins, "Nonlinear features for single-channel diagnosis of sleep-disordered breathing diseases," IEEE Trans. Biomed. Eng., vol. 57, no. 8, pp. 1973-1981, Aug. 2010.
[16] B. Koley and D. Dey; "Automatic detection of sleep apnea and hypopnea events from single channel measurement of respiration signal employing ensemble binary SVM classifiers" Measurement, Elsevier, (Impact Factor 1.526), Volume 46, Issue 7, August 2013, pp. 2082 – 2092.
[17] B. Koley and D. Dey; "On-Line Detection of Apnea/Hypopnea Events Using SpO2 Signal: A Rule-Based Approach Employing Binary Classifier Models" IEEE Journal of Biomedical and Health Informatics, (Impact Factor 1.978), Volume, 18, Issue, 1, January 2014.
[18] B. Koley and D. Dey; "Real-Time Adaptive Apnea and Hypopnea Event Detection Methodology for Portable Sleep Apnea Monitoring Devices" IEEE Transaction on Biomedical Engineering, (Impact Factor 2.348), Volume 60, Issue, 12, December 2013, pp. 3354-3363.
[19] T.V. Steenkiste, W. Groenendaal, D. Deschrijver, and T. Dhaene, "Automated sleep apnea detection in raw respiratory signals using long-short term memory networks," IEEE Journal of Biomedical and Health Informatics, Volume 23, No. 6, November 2019, pp. 2354-2364.
[20] Iber C, Ancoli-Israel S, Chesson AL Jr, Quan SF, The AASM manual for the scoring of sleep and associated events: rules, terminology and technical specifications," Westchester, IL: American Academy of Sleep Medicine; 2007.
[21] R.K. Tripathy, Pranjali Gajbhiye, U. Rajendra Acharya, "Automated sleep apnea detection from cardio-pulmonary signal using bivariate fast and adaptive EMD coupled with cross time–frequency analysis," Computers in Biology and Medicine, Volume 120, 2020.

[22] Maryam Faal, Farshad Almasganj, "Obstructive sleep apnea screening from unprocessed ECG signals using statistical modelling," Biomedical Signal Processing and Control, Volume 68, 2021.
[23] Binish Fatimah, Pushpendra Singh, Amit Singhal, Ram Bilas Pachori, "Detection of apnea events from ECG segments using Fourier decomposition method," Biomedical Signal Processing and Control, Volume 61, 2020.
[24] Asghar Zarei, Babak Mohammadzadeh Asl, "Performance evaluation of the spectral autocorrelation function and autoregressive models for automated sleep apnea detection using single-lead ECG signal," Computer Methods and Programs in Biomedicine, Volume 195, 2020.
[25] Lan Tang, Guanzheng Liu, "The novel approach of temporal dependency complexity analysis of heart rate variability in obstructive sleep apnea," Computers in Biology and Medicine, Volume 135, 2021.
[26] Kandala.N.V.P.S. Rajesh, Ravindra Dhuli, T. Sunil Kumar, "Obstructive sleep apnea detection using discrete wavelet transform-based statistical features," Computers in Biology and Medicine, Volume 130, 2021.
[27] Urtnasan Erdenebayar, Yoon Ji Kim, Jong-Uk Park, Eun Yeon Joo, Kyoung-Joung Lee, "Deep learning approaches for automatic detection of sleep apnea events from an electrocardiogram," Computer Methods and Programs in Biomedicine, Volume 180, 2019.
[28] Asghar Zarei, Babak Mohammadzadeh Asl, "Automatic classification of apnea and normal subjects using new features extracted from HRV and ECG-derived respiration signals," Biomedical Signal Processing and Control, Volume 59, 2020.
[29] Asghar Zarei, Hossein Beheshti, Babak Mohammadzadeh Asl, "Detection of sleep apnea using deep neural networks and single-lead ECG signals," Biomedical Signal Processing and Control, Volume 71, Part A, 2022.
[30] ChS.S.S. Viswabhargav, R.K. Tripathy, U. Rajendra Acharya, "Automated detection of sleep apnea using sparse residual entropy features with various dictionaries extracted from heart rate and EDR signals," Computers in Biology and Medicine, Volume 108, 2019, Pages 20-30.
[31] Fazla Rabbi Mashrur, Md. Saiful Islam, Dabasish Kumar Saha, S.M. Riazul Islam, Mohammad Ali Moni, "SCNN: Scalogram-based convolutional neural network to detect obstructive sleep apnea using single-lead electrocardiogram signals," Computers in Biology and Medicine, Volume 134, 2021.
[32] Shan Wu, Mingjing Chen, Keming Wei, Guanzheng Liu, "Sleep apnea screening based on Photoplethysmography data from wearable bracelets using an information-based similarity approach," Computer Methods and Programs in Biomedicine, Volume 211, 2021.
[33] Yashar Taghizadegan, Nader Jafarnia Dabanloo, Keivan Maghooli, Ali Sheikhani, "Obstructive sleep apnea event prediction using recurrence plots and convolutional neural networks (RP-CNNs) from polysomnographic signals," Biomedical Signal Processing and Control, Volume 69, 2021,
[34] Verónica Barroso-García, Gonzalo C. Gutiérrez-Tobal, Leila Kheirandish-Gozal, Fernando Vaquerizo-Villar, Daniel Álvarez, Félix del Campo, David Gozal, Roberto Hornero, "Bispectral analysis of overnight airflow to improve the pediatric sleep apnea diagnosis," Computers in Biology and Medicine, Volume 129, 2021,
[35] R.E. Rolon, I.E. Gareis, L.D. Larrateguy, L.E. Di Persia, R.D. Spies, H.L. Rufiner, "Automatic scoring of apnea and hypopnea events using blood oxygen saturation signals," Biomedical Signal Processing and Control, Volume 62, 2020.
[36] Evelien E. Geertsema, Gerhard H. Visser, Josemir W. Sander, Stiliyan N. Kalitzin, "Automated non-contact detection of central apneas using video," Biomedical Signal Processing and Control, Volume 55, 2020.
[37] Sheikh Shanawaz Mostafa, Darío Baptista, Antonio G. Ravelo-García, Gabriel Juliá-Serdá, Fernando Morgado-Dias, "Greedy based convolutional neural network optimization for detecting apnea," Computer Methods and Programs in Biomedicine, Volume 197, 2020.
[38] Mariana Abreu, Ana Fred, João Valente, Chen Wang, Hugo Plácido da Silva, "Morphological autoencoders for apnea detection in respiratory gating radiotherapy," Computer Methods and Programs in Biomedicine, Volume 195, 2020.
[39] Aurélien Bricout, Julie Fontecave-Jallon, Jean-Louis Pépin, Pierre-Yves Guméry, "Accelerometry-derived respiratory index estimating apnea-hypopnea index for sleep apnea screening," Computer Methods and Programs in Biomedicine, Volume 207, 2021.
[40] Yitao Wu, Xiongwen Pang, Gansen Zhao, Huijun Yue, Wenbin Lei, Yongquan Wang, "A novel approach to diagnose sleep apnea using enhanced frequency extraction network," Computer Methods and Programs in Biomedicine, Volume 206, 2021.
[41] Fu-Tai Wang, Ming-Hung Hsu, Shih-Chin Fang, Li-Ling Chuang, Hsiao-Lung Chan, "The Respiratory Fluctuation Index: A global metric of nasal airflow or thoracoabdominal wall movement time series to diagnose obstructive sleep apnea," Biomedical Signal Processing and Control, Volume 49, 2019.
[42] Jamileh Karimi, Babak Mohammadzadeh Asl, "Automatic detection of non-apneic sleep arousal regions from polysomnographic recordings," Biomedical Signal Processing and Control, Volume 66, 2021.
[43] A.-Estevez and V. M.-Bonillo, "Fuzzy reasoning used to detect apneic events in the sleep apnea-hypopnea syndrome," Expt. Syst. Appl., vol. 36, pp. 7778-7785, 2009.