Apneic Events Detection Using Different Features of Airflow Signals

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ABSTRACT

Apneic-event based sleep disorders are very common and affect greatly the daily life of people. However, diagnosis of these disorders by detecting apneic events are very difficult. Studies show that analyzes of airflow signals are effective in diagnosis of apneic-event based sleep disorders. According to these studies, diagnosis can be performed by detecting the apneic episodes of the airflow signals. This work deals with detection of apneic episodes on airflow signals belonging to Apnea-ECG (Electrocardiogram) and MIT (Massachusetts Institute of Technology) BIH (Bastons’s Beth Israel Hospital) databases. In order to accomplish this task, three representative feature sets namely classic feature set, amplitude feature set and descriptive model feature set were created. The performance of these feature sets were evaluated individually and in combination with the aid of the random forest classifier to detect apneic episodes. Moreover, effective features were selected by OneR Attribute Eval Feature Selection Algorithm to obtain higher performance. Selected 28 features for Apnea-ECG database and 31 features for MIT-BIH database from 54 features were applied to classifier to compare achievements. As a result, the highest classification accuracies were obtained with the usage of effective features as 96.21% for Apnea-ECG database and 92.23% for MIT-BIH database. Kappa values are also quite good (91.80 and 81.96%) and support the classification accuracies for both databases, too. The results of the study are quite promising for determining apneic events on a minute-by-minute basis.

Key Words: Apneic Event Detection, Feature Extraction, Classification, OneR Attribute Eval Feature Selection, Random Forest.

1. INTRODUCTION

SBD (Sleep Breathing Disorders) generally include OSA (Obstructive Sleep Apnea) which may affect approximately 2% of females and 4% of males [1]. Events occurred during night as called apneic events. These events include apnea and hypopnea and they are characterized with cessation of airflow for at least 10 seconds [2]. In the day time following the night in which apnea and hypopnea events occur, subjects experienced situations such as sleepiness, tiredness, carelessnes, low concentration [3]. These situations can cause traffic and work accidents, depression, impaired learning etc. Moreover, apnea-induced sleep disorders can trigger heart disease, cardiovascular disfunction, hypertension and myocardial infarction [2-3]. Therefore, diagnosing and treatment of SBD is important. In a clinical environment, diagnosing is generally made by
polysomnography. Through polysomnography apneic events are specified and number of events are counted [4]. Calculation of apneic events number is important for diagnosis but the identification of events and determination of time intervals at which events occur are also important especially for treatment [4]. For determination of time intervals, apneic episodes of signal must be detected and separated from the normal episodes. In this way, both events can be identified and the time when events occur can be determined.

This study focuses on the detection of apneic episodes on a minute-by-minute basis. So, we can also learn the minutes at which apneic events occur. Although several signals have been used in many studies [5-8], airflow signals were selected for this study and detection of apneic episodes was made on the airflow signals. Because, these signals give the primary indication of apneic events [3]. Detection processes generally contain analysis of airflow signals and classification of the signals according to their specific characteristics. Therefore, characteristics of signals must be well defined. In order to define the signal characteristics, various feature sets including classical feature set, amplitude feature set and descriptive model feature set were produced in this study. And then these sets were used with a classifier RF (Random Forest) to detect the apneic events. In the study, it was aimed how successfully the apneic episodes were detected and which feature sets or features were more effective in this success.

2. MATERIALS AND METHOD

In this study experiments were performed with nasal airflow signals obtained from two separate databases, Apnea-ECG and MIT-BIH Polysomnographic [9-10]. These databases can be accessed on the PhysioNet website [11]. Using records obtained from these databases, this study was realized in four distinct stages; preprocessing, feature extraction, feature selection and classification. The block diagram of the study is shown in Fig. 1.

2.1 DATABASE

2.1.1 Apnea_ECG database

This database is described in Penzel et. al. [9] . Data were recorded in Philips University in Marburg, Germany. In this database, since only 5 airflow signals contain the apneic events. These 5 signals were selected for this study.

Reference annotation file associated with each signal was created by a sleep expert to indicate the presence or absence of apnea during 1 minute. Each minute is labeled as ‘A’ when apnea was in progress at the beginning of the associated minute, otherwise this minute is labelled as ‘N’ [2].
In this database, apneas were associated with 90% drops in airflow. Also, minutes containing hypopneas (defined as intermittent drops in airflow below 50%, accompanied by drops in oxygen saturation of at least 4%, and followed by compensating hyperventilation) were scored as minutes containing apnea [11].

2.1.2 MIT-BIH Polysomnographic Database

The MIT-BIH Polysomnographic Database consists of multiple physiologic signal recordings in sleep. Recordings were gathered in BIH Sleep Laboratory for evaluation of chronic OSA syndrome [10]. Also, database include annotation file associated with signals. File contains apnea information and sleep stage. Annotation was made by sleep experts according to the presence or absence of apneic events during 30 second periods [11]. Because rules of apneic event scoring was not specified for this database, it was accepted general apnea, hypopnea scoring rules as 90% drops in airflow signal for apnea, 50 or 70% drop in airflow signal for hypopnea [12].

2.2 Pre-Processing

Proper pre-processing can cause to be obtained better results in all signal processing area. Filtering and segmentation processes constituted as pre-processes of our study.

In the various studies carried out by airflow signal, the filters whose frequency range is varying from 0.01 and 15Hz have been used. Bandpass filter with cut-off frequency of 0.01-0.15 was used in study of Koley and Dey [3]. Diaz et. al. [4] and Huang et. al. [13] used 0.05-5Hz bandpass filter. Selvaraj and Narasimhan [14] applied lowpass filter with frequency of 0.7 Hz. As can be seen, there is no definite frequency range for these signals in literature studies. The reason for this can be explained by Varady et. al. [15] as that airflow signals are specific to the applied sensor and they can change during measurements because of sensor or patient movements. Therefore, different filters with various frequency range were tried during the study. As a consequence of the experiments, frequency values were determined that would allow the apnea region to appear more clearly on the signal. While fourth-order Butterworth bandpass filter with cut-off frequency of 0.1-0.15Hz were applied to airflow signals of Apnea-ECG database, second-order Butterworth bandpass filter with cut-off frequency of 0.01-0.5Hz were used for airsflows of MIT-BIH database. Fig. 2 shows airflow signals which are filtered by bandpass filter with various frequency values.

As seen from Fig. 2, areas in the red circle are apneic events and they are seen more clearly in determined frequency ranges.

Generally, it is expected that the airflow signals will show a sinusoidal pattern. The period of these signals represents respiratory cycle and amplitudes are always normalized between -1 and 1 [8]. As a usual, all the signals used in our work were normalized between -1 and 1.

After the filtering and normalization processes, both Apnea-ECG database airflow signals and MIT-BIH database airflow signals were segmented into 1-min episodes. As mentioned before, reference annotation file associated with each signal of Apnea-ECG database were created by a sleep expert to indicate the presence or absence of apnea during 1 minute [2,9]. Same annotations were made by sleep experts according to the presence or absence of apneic events during 30 sec periods by MIT-BIH polysomnographic database. For Apnea-ECG
database, if airflow signals were segmented into 30 sec
segments, we cannot decide that how many seconds of
apneic events are included in the segment and which
segment will be called apneic without sleep experts.
Therefore, we can only use 1 minute annotations for this
database. However, we can convert 30 seconds
annotations of MIT-BIH polysomnographic database to
1 minute annotations. If one of the 30 seconds of the 1-
minute segments is named apneic, we can assume that
this minute is apneic. If none of the 30 seconds of the 1-
minute segments include apneic events, this minute is
called normal. For these reasons, air flow signals were
segmented at 1-minute episode.

Reference annotation file of MIT-BIH database were
rearranged according to 1 minute. Segmented minutes of
two databases were evaluated according to whether they
contained apneic event or not.

For MIT database, although some episodes included the
air flow cessation, they were ignored because the patient
is awake at that time. Airflow cessations are not valid for
apnea scoring clinically when the patient is awake.

At the end of the pre-processing stage, 2513 and 1699
episodes with 1-minute length were created from Apnea-
ECG database and MIT-BIH database, respectively.

2.3 Feature Extraction

When apneic events occur at night, airflow signals exhibit
different characteristics. In order to separation of apneic
episodes from normal, changing characteristics must be
specified. In this study, classic features set, amplitude
features set and descriptive model features set were
created to define different characteristics of the airflow
signals for both databases separately. Subsequently,
features that were more sensitive to apneic events were
identified.

2.3.1 Classic Features Set (Set-1)

Set-1, generally include descriptive statistic
features called as classic because the features in this
group are commonly used in various signal processing
applications [3,16-17]. It enable to us a brief knowledge
about data and their distributions. The 1-minute airflow
signal episodes generally include both apneic event

FIG. 2. AIRFLOW SIGNALS FILTERED BY DIFFERENT FREQUENCY RANGE
patterns and normal patterns. If there are no apneic events in the episodes, a more periodic structure is observed without any major changes. This case facilitates the separation of normal and apneic episodes. In this study, 22 features were extracted to find out the changes within 1-minute episodes. Features in this data set are described in Table 1. The “//” sign in the tables represents the distinction between features. For example, S9 represents the mean absolute deviation, and S10 represents the median absolute deviation.

### 2.3.2 Amplitude Features (Set-2)

According to AASM criteria [12] and previous studies, amplitudes of airflow signals [3, 15] or peaks of the signals [13] vary during apneic events. Events are called as apnea, if there is a decrease in the peak or amplitude of signal by \( \geq 90\% \) [12]. AASM guidelines [12] define events as hypopnea if there is a decrease in the peak or amplitude of signal by \( \geq 50\% \) or \( \geq 30\% \). This decrease should be accompanied by \( \geq 3 \) or \( \geq 4 \) oxygen desaturation. It is also necessary that these reductions last for at least 10 seconds. Based on this definitions of apneic events, Set-2 was created. Table 2 shows the features of Set-2.

In order to extract amplitude features, firstly, peak and trough points and corresponding times of these points in the airflow signal were determined for any apneic episode as shown in Fig. 3. Then, features between A1-A15 were calculated using these peaks and trough points. Amplitude was calculated as shown in Equation (1).

\[
A[i] = p[i] - t[i]
\]

| Feature Number | Description of Features |
|----------------|-------------------------|
| S1             | Energy                  |
| S2             | Minimum                 |
| S3             | Maximum                 |
| S4             | Mean                    |
| S5             | Standard Deviation      |
| S6             | Variation               |
| S7             | Skewness                |
| S8             | Kurtosis                |
| S9 // S10      | Mean Absolute Value // Median Absolute Value |
| S11            | Root Mean Square Level  |
| S12            | Peak Magnitude to RMS Ratio |
| S13 // S14     | Hjorth Parameters : Mobility / Complexity |
| S15            | Sum of Absolute Signal Value |
| S16            | Sum of Absolute 1st Order Derivative Signal Value |
| S17 // S18 // S19 | Mean // Standard Deviation // Variation of Absolute 1st Order Derivative Signal Value |
| S20            | Mean of Signal Envelope |
| S21            | Standard Deviation of Signal Envelope |
| S22            | Mean of Signal Envelope to Standard Deviation of Signal Envelope ratio |
Since hypopnea is expressed by a 30 or 50% amplitude and a peak reduction, A2, A3, A5, A6, A8 and A9 features were used to define these apneic events. In the same way, A4, A7, A12 and A13 features was used to detect apneic events called apnea. When we set the baseline as the mean of the highest 20% of the peaks or signal amplitudes, peaks values and troughs values less than 50% of baselines, duration between the peaks values higher than 50% of baselines and amplitude values were obtained as in Fig. 4. For example, A3, A6, A10 and A11 were computed using these important points and intervals.

### TABLE 2. SET-2: AMPLITUDE FEATURES

| Features Number | Description of Features |
|-----------------|-------------------------|
| A1              | Average Amplitude       |
| A2              | The total number of signals peak values less than 70% of the baseline peak |
| A3              | The total number of signals peak values less than 50% of the baseline |
| A4              | The total number of signals peak values less than 10% of the baseline |
|                 | (The baseline peak is the mean value of the highest 20% of the signal peaks) |
| A5              | The total number of signals amplitude values less than 70% of the baseline amplitude |
| A6              | The total number of signals amplitude values less than 50% of the baseline |
| A7              | The total number of signals amplitude values less than 10% of the baseline |
|                 | (The baseline amplitude is the mean value of the highest 20% of the signal amplitudes) |
| A8 // A9        | Mean // Maximum of time between peaks higher than 70% of baseline peak |
| A10 // A11      | Mean // Maximum of time between peaks higher than 50% of baseline peak |
| A12 // A13      | Mean // Maximum of time between peaks higher than 10% of baseline peak |
| A14             | Average of absolute differences between two successive amplitudes of 60 sec signal |
| A15             | Average of absolute differences between two successive mean values of 60 sec signal over 4 second interval |

**FIG. 3. PEAK, TROUGH POINTS AND TIME OF POINTS**
2.3.3 Descriptive Model Features (Set-3)

Descriptive models give information related to dataset by simulating them. This dataset consists of 17 features named as M1-M17 extracted from parametric normal (Gaussian) model, non-parametric kernel model, histogram model and clustering model of every 1-minute signal episode.

Nowadays, probability distribution plays an important role in various research areas [18]. The probability distribution is a mathematical function and it gives the probability of each value of the variable or gives the probability that the variable falls in a particular interval [19]. The most frequently used models, the parametric normal (Gaussian) model and non-parametric kernel model, were preferred in this study because data can be described efficiently by a model consisting of probabilistic distributions for facilitating analysis and classification [20-23]. In addition to these models, the histogram model was used since histograms give graphical representation of data distribution. These three models were applied to peak values of every 1-minute signal episodes. Fig. 5 summarizes this process. The upper part of the Fig. 5 shows the normal, histogram and kernel model of any apneic episode. The lower part of the Fig. 5 shows the kernel functions for both normal and apneic episodes. Also calculation of M11 and M12 features mentioned in Table 3 is seen from the lower part of Fig. 5. As seen from the lower parts of the Fig. 5, when normal episodes were considered, the peak values corresponding to maximum function values are higher than those of apneic episodes. In addition it can be said that when compared to normal episodes the area between -0.2 and 0.2 belongs to apneic episodes is greater.

Moreover, clustering model analysis helps to distinguish data samples to subgroups called as cluster. Samples in every cluster represents similar characteristics. Therefore, determination of cluster features can provide meaningful information for detection of apneic episodes. In this study, the samples of peaks for every 1-minute signal episode
were separated into 3 clusters and absolute mean of every cluster was calculated. The minimum of these three mean values was selected as a feature (M17). First cluster contains high positive peak values. Second cluster is consisted of low positive signal values. Hence, this cluster represents the value of apneic events. Values forming the negative parts of the sinisoidal signal pattern are in the third cluster. This cluster does not important for this study. Table 3 shows the features created by descriptive models.

### 2.4 Feature Selection

Determination of best features that represents the data better than others increases the discrimination of apneic episodes from normals [3]. In this study, 54 features were extracted in different categories and best features must be determined to obtain the best performance. For this purpose, OneR Attribute Eval Feature Selection Algorithm which calculates the value of a features using the OneR classification algorithm was used [24]. The OneR

![FIG. 5. NORMAL, KERNEL, NON-PARAMETRIC AND HISTOGRAM DISTRIBUTIONS OF DATA AND PEAKS](image-url)
classification algorithm ranks effectiveness of each individual feature and choose the top few to use [25]. In this study, attribute selection process was carried out with 10 fold cross-validation and average rank were obtained for every features. Firstly top 5 features were evaluated by a classifier. Then the properties were added sequentially according to the effectiveness values respectively, and the classification process was performed each time. Finally, best feature sets were determined so that it gives maximum classification result.

2.5 Classification

The classification process was carried out to detect apneic episodes of entire airflow signals using RF classifier in Weka 3.9 [26]

The RF algorithm was suggested by Brierman [27]. It is an ensemble of decision tree classifiers [1]. The RF has alot of advantages such as rapidness, robustness to noise and outliers, resistance to overfit [1,28]. Moreover, in the algorithm, there are very few parameters to be determined such as number of features (m) to be used for each node and the number of trees (N) to be created [29]. Also, in the literature, RF has shown successful results for two-class problems [28-30]. Due to these positive properties, the RF classification algorithm has been found suitable for this study and it was preferred to classify the 1-minute airflow signal episodes.

CA (Classification Accuracy), Prec (Precision), recall, kappa statistic and area under of ROC curve measures were used to evaluate performance of classifier and study [31].

3. EXPERIMENTAL RESULTS

In this study, it was aimed to detect apneic episodes of all airflow signals with RF using two different databases. In order to achieve this aim, pre-processing, feature extraction, feature selection and classification stages were realized.

In the pre-processing stage, filtering and segmentation processes were carried out. After the pre-processing stages, 2513 episodes from Apnea-ECG database [9] and 1699 episodes from the MIT-BIH database [10] were

| Features Number | Description of Features |
|-----------------|-------------------------|
| M1 // M2 // M3 // M4 | Mean // Median // Standard deviation // Variance of Normal (Gaussian) probability density function belongs to peaks value |
| M5              | The peak value corresponding to the maximum of normal density function value |
| M6              | The area between -0.2 and 0.2 in the normal density function |
| M7 // M8 // M9 // M10 | Mean // Median // Standard deviation // Variance of Kernel probability density function belongs to peaks value |
| M11             | The peak value corresponding to the maximum of kernel density function value |
| M12             | The area between -0.2 and 0.2 in the kernel density function |
| M13 // M14 // M15 // M16 | Mean // Median // Standard deviation // Variance of histogram of peaks |
| M17             | Minimum of mean peak values belongs to each cluster |
created in 1-minute length. In the feature extraction stage, 54 features in 3 different categories were built for each database separately. These features were grouped as classic features, amplitude features and descriptive model features. After the creation of these feature sets, normalization process were applied to the features.

In the classification stage, representative features extracted from 1-minute signal episodes were classified as two class, either apneic or not. Apneic class includes apnea and hypopnea events because these events have not been evaluated separately.

Classification process using RF was repeated 50 times for every feature set with 10 fold cross validation. The maximum of 50 classification results were accepted as the classification result of that set. Number of tree (N) is set to 100 for RF classifier. The number of features (m) to be used for each node was left at the default value. Firstly, Set-1, Set-2 and Set-3 were classified separately. Following these classifications, features of sets were merged and classification was carried out with all 54 features. Finally, OneR attribute eval algorithm was applied to 54 features of Apnea-ECG database. Thus, effective features were specified. Feature selection process was not reapplied on the airflow signals obtained from MIT-BIH database. Same effective features were used for this database and classification was performed again with them.

Table 4 presents the classification results of Set-1, Set-2, Set-3, all features and selected 28 features for Apnea-ECG database, separately. It was seen that from the results, classification result of Set-1 are slightly better than both of Set-2 and Set-3. The lowest classification results were obtained with descriptive model features (Set-3). It was also observed that obtained classification accuracy, precision, recall, kappa and ROC values for all 54 features of Apnea-ECG database are better than the results of each three individual classifications. As shown in Table 4, classification of selected 28 effective features produces the best classification accuracy as 96.21%. Moreover, precision, recall and kappa values with selected features are the best among all classification results.

Confusion matrices are also shown in Table 4. It can be seen from confusion matrices in Table 4, that total number of episodes with apneic and normal events are 1608 and 905, respectively. In the classification with selected 28 features, only 46 normal and 49 apneic episodes were classified wrongly. 2418 episodes were correctly classified. The number of misclassifications with the previous 4 feature sets is higher. Consequently, Table 4 illustrated that the best performance was obtained with the selected features, when all results in Table 4 were compared in terms of all evaluation criteria.

Classification results of Set-1, Set-2, Set-3, all features, selected 28 features and selected 31 features for MIT-BIH database with RF as shown in Table 5. Unlike Apnea-ECG database, results of Set-2 features are slightly better than Set-1. Likewise, the lowest results were obtained with Set-3. When the features of three feature sets were merged for this database, the performance was better than individual results of feature sets, as in the other database. In addition, the same selected features used for Apnea-ECG database were also experimented for this database, initially. Although higher results were obtained than the individual classifications (Set-1, Set-2 and Set-3), lower results were acquired from classification with all features for MIT-BIH database. The reason of
classification result can be explained that, definition of apneic events have been made according to least 50% drop in airflow signal for Apnea-ECG database. The selected features A3, A4, A6, A7, A10, A13

### TABLE 4. CLASSIFICATION RESULTS OF FEATURES SETS FOR APNEA-ECG DATABASE

| Database: Apnea-ECG | CA      | Confusion Matrix | Other Measurements |
|---------------------|---------|------------------|--------------------|
|                     |         | Normal | Apneic | Precision | Recall | Kappa | ROC  |
| Set-1 Classic Features (22 Features) | 95.62   | 848    | 57     | 94.1      | 93.7   | 90.49 | 98.3 |
| Set-2 Amplitude Features (15 Features) | 95.54   | 849    | 56     | 93.8      | 93.8   | 90.33 | 98.1 |
| Set-3 Descriptive Model Features (17 Features) | 95.22   | 841    | 64     | 93.8      | 92.9   | 89.62 | 98.5 |
| All Features Set-1, Set-2 and Set-3 (54 Features) | 95.98   | 854    | 51     | 94.5      | 94.4   | 91.28 | 99.1 |
| S1, S5, S6, S7, S8, S9, S10, S11, S13, S15, S16, S20, S21, S22, A1, A3, A4, A6, A7, A10, A13, A15, M5, M10, M11, M12, M13, M17 (28 Features) | 96.21   | 859    | 46     | 94.6      | 94.9   | 91.80 | 99.1 |

### TABLE 5. CLASSIFICATION RESULTS OF FEATURES SETS FOR MIT-BIH DATABASE

| Database: MIT-BIH | CA      | Confusion Matrix | Other Measurements |
|-------------------|---------|------------------|--------------------|
|                   |         | Normal | Apneic | Precision | Recall | Kappa | ROC  |
| Set-1 Classic Features (22 Features) | 91.40   | 455    | 78     | 87.0      | 85.4   | 79.94 | 95.4 |
|                  |         | 68     | 1098   | 93.4      | 94.2   |        |      |
| Set-2 Amplitude Features (15 Features) | 91.46   | 463    | 70     | 86.1      | 86.9   | 80.23 | 95.4 |
|                  |         | 75     | 1091   | 94.0      | 93.6   |        |      |
| Set-3 Descriptive Model Features (17 Features) | 90.16   | 450    | 83     | 84.3      | 84.4   | 77.18 | 95.5 |
|                  |         | 84     | 1082   | 92.9      | 92.8   |        |      |
| All Features Set-1, Set-2 and Set-3 (54 Features) | 92.23   | 465    | 68     | 87.9      | 87.2   | 81.92 | 96.3 |
| S1, S5, S6, S7, S8, S9, S10, S11, S13, S15, S16, S20, S21, S22, A1, A3, A4, A6, A7, A10, A13, A15, M5, M10, M11, M12, M13, M17 (28 Features) | 92.05   | 468    | 65     | 87.0      | 87.8   | 81.59 | 92.2 |
|                  |         | 70     | 1096   | 94.4      | 94.0   |        |      |
| Selected Features S1, S5, S6, S7, S8, S9, S10, S11, S13, S15, S16, S20, S21, S22, A1, A2, A3, A4, A5, A6, A7, A9, A10, A13, A15, M5, M10, M11, M12, M13, M17 (31 Features) | 92.23   | 467    | 66     | 87.6      | 87.6   | 81.96 | 96.4 |

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support this expression. However, apneic event
definition was not made for MIT-BIH database.
According to AASM [12], 30% fall in the airflow signal
can also describe hypopnea which is one of the apneic
events. Therefore, it was added A2, A5 and A9
features in to the selected features and the number of
selected features were reached 31 for MIT-BIH
database. As a result of classification with 31 features,
high classification accuracy was achieved as 92.23%.
This accuracy value is the same as the classification
accuracy of all 54 features. However, feature set with
31 features is always preferred because the number
of features is less and the results are better in terms
of Kappa and ROC.

As a result, the high classification accuracy for both
databases were obtained with 96.21% and 92.23% values.
Kappa values are quite good (91.80% and 81.96%) and
support the CA values for both databases, too. If the
features sets were compared, it can be said that there are
no major differences between results of the classical
feature set (Set-1) and the amplitude feature set (Set-2).
However, when only descriptive model feature set was
used, the achieved of RF was decreased. The study
shows that the successful results were obtained when
the features which reveal different characteristics of data
were combined and effective features were selected from
this combined dataset.

28 features including 14 classical features, 8 amplitude
features and 6 descriptive model features were
determined as effective features for Apnea-ECG
database. For the MIT-BIH database, 31 features have
been defined as effective features. These features contain
14 classical features, 11 amplitude features and 6
descriptive features.

Tables 6-7 show the average rank for every selected
feature according to 10 fold cross-validation using
OneR Attribute Eval Feature Selection Algorithm.
Rankes of other features have not been shown because
they are lower than those of selected features.
According to Table 7, most effective features are
amplitude features because 8 of the top 10 features are
amplitude features for MIT-BIH database. Likewise, 6
of the top 10 features are amplitude features for Apnea-
ECG database. When the top 20 features are considered
for MIT-BIH database and Apnea-ECG database 11 and
9 of these features are amplitude features respectively,
6 of the features are descriptive model features for two
database and 3 and 5 features are classical features for
MIT and Apnea-ECG database respectively. So, it can
be said that most effective features are amplitude
features. Second-order effective features are
descriptive model features and last effective features
are classical features.

Most of selected classic features are statistical and they
represents the changes that take place in the 1-minute
signal episode. The features selected from amplitude
feature set are associated with the AASM criteria. Selected
6 descriptive model features comprised of 1 feature related
to normal density function, 3 features related to kernel
density function and 2 histogram model features. The
effective features used for both databases are the same
except for the 3 added features (A2, A5 and A9 ) the MIT-
BIH database. These used effective features make it
possible to clearly identify the apneic events in both
databases.

Literature studies, the results obtained from these
studies and the comparison with this study are shown
in Table 8.
Apneic Events Detection Using Different Features of Airflow Signals

It can be seen from Table 8, when this study has been compared with the studies [1,17,32] in literature, it generally outperformed the others. Only CA value of the study is less than CA value of the study performed by Avcý and Akbas. Avcý and Akbas [1] used 8 airflow signals from Apnea-ECG database. However, only 5 airflow signals were used in this study. Three signals of Apnea-ECG database do not have apneic event. These signals are not important for our study. Therefore, 5 airflow signals were preferred by us. We think that the difference between the CAs is due to the number of used signals.

**TABLE 6. APNEA-ECG DATABASE**

| No. | Average Rank | Features |
|-----|--------------|----------|
| 1   | 88.51        | S8       |
| 2   | 87.52        | A10      |
| 3   | 87.43        | A3       |
| 4   | 87.10        | A6       |
| 5   | 86.35        | A1       |
| 6   | 82.35        | M11      |
| 7   | 80.09        | A4       |
| 8   | 77.96        | A7       |
| 9   | 77.58        | S22      |
| 10  | 77.56        | M13      |
| 11  | 76.61        | A13      |
| 12  | 76.43        | M5       |
| 13  | 75.24        | A15      |
| 14  | 75.09        | M17      |
| 15  | 73.56        | S10      |
| 16  | 72.33        | M12      |
| 17  | 68.58        | M10      |
| 18  | 68.13        | S9       |
| 19  | 67.78        | A1       |
| 20  | 67.71        | S20      |
| 21  | 67.08        | S21      |
| 22  | 65.47        | S7       |
| 23  | 65.23        | S11      |
| 24  | 65.13        | S5       |
| 25  | 64.73        | S13      |
| 26  | 64.26        | S1       |
| 27  | 64.24        | S6       |
| 28  | 63.26        | S16      |

| No. | Average Rank | Features |
|-----|--------------|----------|
| 1   | 88.51        | S8       |
| 2   | 87.52        | A10      |
| 3   | 87.43        | A3       |
| 4   | 87.10        | A6       |
| 5   | 86.35        | A1       |
| 6   | 85.71        | A9 (Only MIT) |
| 7   | 84.90        | A2 (Only MIT) |
| 8   | 82.89        | A5 (Only MIT) |
| 9   | 82.35        | M11      |
| 10  | 80.09        | A4       |
| 11  | 77.96        | A7       |
| 12  | 77.58        | S22      |
| 13  | 77.56        | M13      |
| 14  | 76.43        | M5       |
| 15  | 75.24        | A15      |
| 16  | 75.09        | M17      |
| 17  | 73.56        | S10      |
| 18  | 72.33        | M12      |
| 19  | 68.58        | M10      |
| 20  | 68.13        | S9       |
| 21  | 67.78        | A1       |
| 22  | 67.08        | S20      |
| 23  | 65.47        | S7       |
| 24  | 65.23        | S11      |
| 25  | 65.13        | S5       |
| 26  | 64.73        | S13      |
| 27  | 64.26        | S1       |
| 28  | 64.24        | S6       |
| 29  | 63.26        | S16      |

**TABLE 7. MIT-BIH DATABASE**

| No. | Average Rank | Features |
|-----|--------------|----------|
| 1   | 88.51        | S8       |
| 2   | 87.52        | A10      |
| 3   | 87.43        | A3       |
| 4   | 87.10        | A6       |
| 5   | 86.35        | A1       |
| 6   | 85.71        | A9 (Only MIT) |
| 7   | 84.90        | A2 (Only MIT) |
| 8   | 82.89        | A5 (Only MIT) |
| 9   | 82.35        | M11      |
| 10  | 80.09        | A4       |
| 11  | 77.96        | A7       |
| 12  | 77.58        | S22      |
| 13  | 77.56        | M13      |
| 14  | 76.43        | M5       |
| 15  | 75.24        | A15      |
| 16  | 75.09        | M17      |
| 17  | 73.56        | S10      |
| 18  | 72.33        | M12      |
| 19  | 68.58        | M10      |
| 20  | 68.13        | S9       |
| 21  | 67.78        | A1       |
| 22  | 67.08        | S20      |
| 23  | 65.47        | S7       |
| 24  | 65.23        | S11      |
| 25  | 65.13        | S5       |
| 26  | 64.73        | S13      |
| 27  | 64.26        | S1       |
| 28  | 64.24        | S6       |
| 29  | 63.26        | S16      |
4. CONCLUSION

This study was aimed at the detection of the apneic events in 1 minute episodes obtained from airflow signals recorded during a night. In order to achieve this aim, 2 benchmark databases namely Apnea-ECG and MIT-BIH polysomnographic were used. During the study, different feature sets were created belonging to 1-minute signal episodes and it was investigated whether the signal episodes contained an apneic event or not using these feature sets with different characteristics. Also, effectiveness of features was evaluated on determination of apneic events. It is illustrated in the study that the combination of features and effective features representing the events significantly increases the performance of the work. When the study is evaluated according to results, it is promising for determining apneic events on a minute-by-minute basis.

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TABLE 8. COMPARISION OF THIS STUDY AND LITERATURE STUDIES

| Study Source          | Database   | CA  | Recall/Sensitivity                  |
|-----------------------|------------|-----|-------------------------------------|
| Gil et. al[32]        | Apnea-ECG  | -   | 95.3% (Apneic Events)               |
| Ave? and Akbas [1]    | Apnea-ECG  | 98.68% |                                      |
| This Study            | Apnea-ECG  | 96.21% | 97.0 % (Apneic Events)              |
| Varady et. al [17]    | MIT-BIH    | -   | 97.0% (Apnea) 78.7% (Hypopnea)      |
| This Study            | MIT-BIH    | 92.23% | 94.3% (Apneic Events include apnea and hypopnea) |
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