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A Review of Obstructive Sleep Apnea Detection Approaches

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***Abstract*— Sleep disorders are a common health condition that can affect numerous aspects of life. Obstructive sleep apnea is one of the most common disorders and is characterized by a reduction or cessation of airflow during sleep. In many countries this disorder is usually diagnosed in sleep laboratories, by a polysomnography, which is an expensive procedure involving much effort for the patient. Multiple systems have been proposed to address this situation, including performing the examination and analysis in the patient's home, using sensors to detect physiological signals that are automatically analyzed by algorithms. However, the precision of these devices is usually not enough to provide a clinical diagnosis. Therefore, the objective of this review is to analyze already existing algorithms that have not been implemented on hardware but have had their performance verified by at least one experiment which aims to detect obstructive sleep apnea, in order to show future trends. The performance of different algorithms and methods for apnea detection through the use of different sensors (pulse oximetry, electrocardiogram, respiration, sound and combined approaches) has been evaluated. A total of 84 original research articles published from 2003 to 2017, that had the potential to be promising diagnostic tools, were selected to cover multiple solutions. This review could provide valuable information for those researchers who want to carry out a hardware implementation of potential signal processing algorithms.**

***Index Terms*— Obstructive Sleep Apnea, Algorithms Review**

I. Introduction

More than 60 different sleep disorders, divided into seven categories, have been identified by the International Classification of Sleep Disorders. Sleep-related breathing disorders is the second category which includes central sleep apnea, obstructive sleep apnea (OSA) and sleep-related hypoxemia and hypoventilation [1]. OSA is the most common disorder in this group and is characterized by partial or complete obstruction and recurrent collapse of the upper airway, affecting ventilation during sleep. The symptoms of this disorder are excessive daytime sleepiness caused by non-restorative sleep. It is estimated that an OSA prevalence in the general adult population ranges from 6% to 17%, considering an apnea-hypopnea index (AHI) of greater than or equal to 15 events/hour, with males being more affected than females, and this prevalence becomes more relevant with increasing age [2]. Polysomnography (PSG) is the gold standard for OSA diagnosis measuring multiple sensors to record the breath airflow, respiratory movement, oxygen saturation (SpO2), electroencephalogram (EEG), electro-oculogram (EOG), electromyogram (EMG), electrocardiogram (ECG) and body position [3]. OSA is diagnosed if the patient has reported the indicated symptoms and presents 5 or more obstructive respiratory events per hour of sleep during a PSG recording [1]. Alternatively, OSA can be diagnosed if a frequency of obstructive respiratory events greater than or equal to 15 events/hour is detected, independent of associated symptoms. OSA severity can be defined as mild ($5 \leq AHI < 15$ e/h), moderate ($15 \leq AHI < 30$ e/h) or severe ($AHI \geq 30$ e/h).

PSG provides accurate results but it is a slow and expensive process since it usually requires the patient to be in attendance at a sleep laboratory under the supervision of a specialized technician. The test could also be performed in the patient's home using portable PSG devices but the use of all the necessary sensors still result in an uncomfortable experience. Recorded signal data are scored manually to generate the clinical reports. Alternative devices have been developed with the aim of addressing these issues, monitoring the patients at home but with fewer sensors and employing automatic diagnosis algorithms [4]. However, the evaluation accuracy of these algorithms is commonly thought to be unsatisfactory for a medical diagnosis. Therefore, the main objective of this work is to evaluate possible algorithms that could be implemented in home recording devices. The American Academy of Sleep Medicine (AASM) has proposed a categorization for the diagnostic devices based on four levels, from the reference test (PSG minimum of seven channels) to the portable devices with one or two channels [5]. The analyzed algorithms would be suited to the third and fourth level devices. However, a more suitable categorization system based upon employed sensors in these out-of-center devices

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algorithms based on the analyses of pulse oximetry, ECG, sounds, respiration since these fields seem to be the more promising approaches. A fifth category was also introduced analyzing algorithms based on combined approaches. Algorithms based on other sensors, such as accelerometer, to determine the patient movement also present good performance. However, these algorithms commonly employ a combination of accelerometers and other source sensors for OSA classification so they were not reviewed since these sensors commonly provides complementary information for the algorithm, not being the main source of information.

A. Based on pulse oximetry

Classical oximetry analysis includes the oxygen desaturation index (ODI), cumulative time spent below a defined saturation threshold (e.g. time below 90% = T90), number of falls in the SpO2 value below the defined baseline and signal variability, usually the delta index. A threshold approach was presented by Jung et al. [20] taking three points into consideration. The first point indicates a decrease in the SpO2 value of greater than or equal to 1% but lower than or equal to 3% and the second point is generated if the SpO2 signal keeps decreasing to at least 3% below the first point. The final point indicates the signal must return to either 1% below the first point or 3% above the second point. Total time between first and third points must be greater than or equal to 10 s and lower than or equal to 90 s. Álvarez et al. [21] applied two non-linear methods to determine which would be better to further improve the OSA detection capability. The central tendency measure (CTM), allows for the achievement of a quantitative variability measure by second-order difference plots, and Lempel-Ziv complexity (LZC) provides a complexity measure. It was determined that CTM produces the best results.

A pattern classification approach was used by Marcos et al. [22], using a three stage algorithm. The first stage was the feature extraction where the SpO2 signal was mapped using spectral from the power spectral density (PSD) and nonlinear analysis, using LZC, CTM and approximate entropy (provides an estimation of the signal regularity). The second stage was the pre-processing employing principal component analysis (PCA) to define an orthonormal basis on a dimensional space spanned by the obtained features. The final stage was the statistical classifier based on linear discriminant analysis (LDA) which models every class-conditional density function as a multivariate normal distribution. Four statistical pattern recognition techniques were analyzed by Marcos et al. [23], the k-nearest neighbor (kNN), quadratic discriminant analysis (QDA), LDA and logistic regression (LR). The best result was obtained using the LDA with spectral features, performed on the 0.01 to 0.033 Hz band, extracting the area enclosed in the band, the peak amplitude in the band and total area of the PSD. A comparison between a support vector machine (SVM) and kNN was performed by Morales et al. [24]. Wavelet decomposition on seven levels was implemented using the Haar wavelet and the phase space of each level was constructed by applying the embedding dimension technique. Afterwards, the spanned area in each level was calculated, using the convex hull method, and using, as features for the classifier, the best results provided by kNN with five neighbors. A genetic algorithm approach was applied by Álvarez et al. [25] at the feature selection stage, using features from time and frequency domain statistics, spectral features of the apnea-related frequency band (0.014 to 0.033 Hz) and nonlinear features (sample entropy, LZC and CTM). The selected features were further fed into an LR classifier.

A probabilistic neural network (NN) was used by Morillo and Gross [26] as a classifier with five neurons on the input layer analyzing the OSI, with falls in SpO2 of greater than 4% on a 40 s time interval, relative power in the 0.013-0.067 Hz band, median value, presence of restorations of 4% within 10 s and the level of short-term variability of the SpO2 signal. A three-layered (input, output and hidden) feed-forward NN was used as a classifier by Almazaydeh et al. [27]. It uses an oxygen desaturation index (ODI), a delta index and CTM as inputs of the NN which produces an output space divided into two regions, OSA positive and negative. Purelin linear transfer function was used as the activation function of the output layer during the training phase of the NN. An NN was also proposed by Álvarez et al. [28] where LZC, CTM, sample entropy, statistical moments in the time domain, spectral entropy and relative power in the apnea-related frequency band were used as inputs of the NN. OSA was classified by a binary multilayer perceptron NN with Bayesian training where the Bayesian inference approach was used to model the probability density function. The same kind of NN classifier was used by Marcos et al. [29] where normalized features were extracted from the SpO2 data, using approximate entropy, CTM and LZC. Time, frequency and time-frequency based features were analyzed by Mostafa et al. [30]. A genetic algorithm was applied for feature selection and the classification was performed by a NN.

A combination of features extracted from time and frequency domain statistics, spectral characteristics driven by PSD and nonlinear measures were analyzed by Álvarez et al. [31]. Four features were selected as the most relevant using an LR approach, second and fourth order statistical moments in the time domain, the relative power in the apnea-related frequency band and the LZC. The photoplethysmogram (PPG) signal, obtained from a pulse oximeter, was used by Lázaro et al. [32]. The algorithm looks for decreases in the amplitude fluctuations of the PPG signal and an LDA classifies the data, using features based on the pulse rate variability (PRV). A combination of characteristics in time and frequency domains obtained from PRV and SpO2 signals were employed by Garde et al. [33], with OSA classification performed using LDA. A smoothing Savitzky-Golay filter was applied to the PPG signal and the peaks of pulses in the PPG segmented signal were detected by a zerocrossing algorithm. The sequence of pulse to pulse intervals (intervals between successive peaks) was then converted to the PRV with a uniformly spaced time series.

An unsupervised feature learning model based on a three-layer deep belief network was implemented by Mostafa et al.

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[34]. The first two layers were restricted Boltzmann machines, composed by an autoencoder, and the last was a soft-max layer. A Long short-term memory - recurrent neural network (LSTM-RNN) was employed by Pathinarupothi et al. [35] with 60 neurons in the input layer (the oximetry signal has 60 samples, each corresponding to a second of data) and 32 memory blocks, with one cell each, in the hidden layer.

B. Based on ECG

Analysis of ECG waveforms and ECG-derived hear trate are commonly used to detect sleep-related breathing disorders. Lin et al. [36] separated the ECG signal into four spectral components (alpha, beta, delta and theta) using multi-resolution wavelet transforms and the wavelet coefficients were used as the training input for a four layer NN implemented with simple neural computing elements.

A discrete wavelet transform, Symlet wavelet with order 3, was used by Khandoker et al. [37] to decompose the ECG signal into 8 levels of detailed coefficients. This information was fed into the first event detection stage that uses a feed-forward NN structure with one hidden layer, consisting of 30 neurons. The output was passed to a second event detection stage when a suspected apnea/hypopnea was detected, with the aim of differentiating the output into one of these two classifications. This last stage uses a feed-forward single-layer NN.

Wavelet decomposition was applied by Rachim et al. [38], using the Debauches 4 wavelet, to obtain statistical features and PCA was performed. Then an SVM with a Gaussian radial basis function kernel was used to classify the data. Tunable-Q factor wavelet transform was applied by Hassan [39] to decompose the ECG signal segments into sub-bands that were further modelled using a symmetric normal inverse Gaussian model. The scale and feature factors from this model were then fed into the adaptive boosting (AdaBoost) classifier. The same kind of wavelet transform was used by Hassan and Haque [40] to decompose the EEG signal, analyzing the variance, kurtosis and skewness of the decomposition to feed as features for the random under sampling boosting (RUSBoost) classifier.

Variational mode decomposition was used by Smruthy and Suchetha [41] to decompose the ECG signal into multiple variational mode functions and the select functions were added together to generate the reconstructed signal. Standard deviation of the peak to peak distance and mean energy, calculated using the Teager energy operator (TEO), was determined from the reconstructed signal to feed an SVM classifier. Hassan [42] used empirical mode decomposition (EMD) to generate localized time-frequency estimation, from the ECG signal, by decomposing it into a finite sum of intrinsic mode functions. Then the mean, variance, skewness and kurtosis were determined and used on an extreme learning machine, with a sigmoidal activation function, for a single hidden layer feed-forward NN which classifies the data.

From the ECG-derived heart rate is possible to analyze the heart rate variability (HRV) and the inter-beat (RR) interval that can be defined as the interval between successive QRS points. Quiceno-Manrique et al. [43] employed an analysis based on the HRV, extracting features from time-frequency distributions, belonging to Cohen's class, by means of spectral sub-band centroids and linear filter Cepstral coefficients. The classification was performed using kNN. Time-frequency based stochastic features were used by Martínez-Vargas et al. [44] to analyze the HRV employing linear frequency Cepstral coefficients. Estimation of the number of stochastic features and filter banks was determined using spectral splitting upon the time-frequency plane. Heuristic and relevance-based splitting were tested to determine the best set of spectral partitions. Highest accuracy was produced using linear label-conditioned correlation as a supervised measure of relevance, selecting seven frequency bands as features for the kNN.

An algorithm based in the analysis of cyclical variations of the heart rate, for detection of sleep-disordered breathing, was presented by Kesper et al. [45]. The algorithm analyzes the correlation of a reference pattern, that represents a decrease in heart rate, with the beat-to-beat heart rate curve. Ravelo-García et al. [46] employed a non-linear HRV analysis using a symbolic dynamics method applied to the RR series, transforming it into a sequence of symbols. These symbols were defined through a set of rules that considers the use of three chosen thresholds. Then the classification was performed using an LR model that integrates clinical and physical variables. Zywietz et al. [47] used an LDA for classification with features based on information of four frequency bands: ULF; VLF; LF; HF.

Time and frequency domain entropies were used by Gutiérrez-Tobal et al. [48]. In the time domain the multiscale entropy was applied to the HRV using sample entropy and in the frequency domain the spectral entropy was applied to the normalized PSD. This information was used as features for an LR classifier. The HRV was used by Roche et al. [49] where the wavelet transform was used to decompose the signal and the classification was performed using a classification tree, developed using the classification and regression trees (CART) method. It was determined that a level 32 decomposition parameter was the most powerful predictor variable.

Two classifiers, LDA and QDA, were tested by Ravelo-Garcia et al. [50], and were fed with cepstrum features obtained from the RR series. The best results were obtained using QDA. The RR interval and QRS area were derived from a single lead of the ECG signal by Mendez et al. [51]. A bivariate time varying autoregressive model was used to analyze the PSD of the signals. Then a kNN and a NN were tested to determine the best classifier. These showed the same accuracy but the NN provided a higher sensitivity. RR intervals were employed by Cheng et al. [52] to reconstruct a nonlinear state space. A multidimensional indexing approach was used to iteratively segment the state space into a hierarchical structure of local recurrence regions and a fractal representation, based on an iterative function system transferring the time series of categorical variables from temporal domain to a two-dimension fractal domain, was implemented for characterization of the transitions of

Both classifiers achieved similar performance but the QDA provided the best results. Cepstrum Coefficients, a filter bank with 34 filters (to analyze the very low, low and high frequency) and detrended fluctuation analysis were employed by Martín-González et al. [67] to feed the three tested classifiers: LDA; QDA; LR. These features were obtained from the HRV. The first two variables extract information that is related to frequency contents and the last uncovers the nonlinear characteristics of the physiological process that is associated with sleep apnea. The best results were reported using QDA.

Khandoker et al. [68] used 14 levels of Daubechies wavelets to decompose the RR and EDR signals. The result was used as input to an SVM that classifies the OSA events. Features extracted from wavelet decomposition of HRV and EDR signals were used by Khandoker et al. [69] as inputs to the SVM classifier. The LDA classifier was also analyzed, providing similar results. HRV and EDR signals were used by Yildiz et al. [70] analysing 64 points of PSD (1 to 32 derived from HRV and 33 to 64 from EDR). Three SVM kernels were tested, specifically, linear, polynomial and radial basis function (RBF). The highest accuracy was produced by RBF using the points 2, 3, 45, and 46 (selected by a hill climbing algorithm.).

C. *Based on respiration*

Oronasal airflow is one of the most direct indicators of breathing disorders and was used by Koley and Dey [71] to detect OSA. First the signal was filtered with a low pass Butterworth filter, to remove artefacts that usually affect this signal as a result of the system being used to make the measures, and normalized to avoid subject-dependent variations. The resulting signal was then segmented and three time domain features were extracted, the area covered by the respiration signal (measuring the total volume of air flow), variance (sensitive to respiration amplitudes that measure the air inflow rate to outflow rate) and the upper 90th percentile (decrease during apnea events). These features were then used by a three binary SVM arranged in one-against-all strategy to classify the data. The oronasal airflow, after being filtered and segmented, was also used by Koley and Dey [72], to extract time and frequency domains and nonlinear analysis features from each segment. The classification was performed in two steps using two binary SVM classifiers where the first was used to detect sleep disorders and the second analyzed the segments marked as disorders and classified as either apnea or hypopnea.

Hilbert-Huang transform was applied to the nasal airway pressure signal by Caseiro et al. [73]. Hilbert spectral analysis and EMD are two parts of this time-frequency method. The LR was used as a classifier by Gutiérrez-Tobal et al. [74], using features from both airflow and respiratory rate variability (RRV) signals. Specifically, the features that provided the best results were the third statistical moment of the RRV PSD, the peak amplitude and the band power of the airflow signal PSD, using the spectral band of 0.022-0.059 Hz on the airflow signal, and the 0.095–0.132 Hz band on the RRV signal. Selvaraj and Narasimhan [75] analyzed the amplitude of the respiratory signal, the low pass filtered envelope of the respiratory signal (cut-off at 0.01 Hz) and the statistical dispersion of the envelope signal. Possible OSA events, determined by thresholds applied to the signals, were classified using two conditions based on the thresholds.

Daubechies wavelet was used by Minu and Amithab [76] to decompose the airflow signal and statistical features were extracted to feed the classifying stage. Two classifiers were tested, the AdaBoost and the Adaptive Neuro Fuzzy Inference System (ANFIS) which combines the advantages of both the neural and fuzzy classifiers. The ANFIS achieved the best performance. Same family of wavelet was employed by Avci and Akbas [77] to decompose the airflow signal. Maximum, minimum, average, variance, mode, entropy, energy and skewness were determined from the decomposed signal and used as features to test three classifiers based on ensemble learning: random forest; AdaBoost; Random subspace. Best results were produce by the first classifier. The airflow signal was also used by Ozdemir et al. [78] being segmented and the energy on each segment was calculated using the TEO. Segments were marked as potential apnea episodes if their energy was less than one quarter of average energy and the first order derivative approach was applied to these segments to eliminate mislabeled epochs. Statistical features were extracted and three classifiers were tested, the SVM, kNN and linear regression, with the best performance being achieved by the SVM. The airflow signal with a sample dimensionality of 960 (30 s by 32 Hz) was fed to a deep learning classifier, specifically a convolutional NN (CNN), by Haidar et al. [79]. The CNN architecture consists of three one dimension convolutional layers, each layer followed by a max-pooling layer, and, at the end, one fully connected layer with a soft-max activation function.

A different approach was presented by Thommandram et al. [80] where the respiratory effort signal (also called the RI signal), obtained by measuring the impedance of a wire coil that was strapped around the subject's rib cage, was used to define the interval between breaths. Four features were extracted, the stability of the peak heights value and peak-to-peak time, the occurrence of long pauses and flat-lining. Then they were fed into a kNN to classify the data. Air flow and thoracic and abdominal respiratory movements were used by Maali and Al-Jumaily [81]. Wavelet decomposition was applied to the signals that were further segmented and statistical measures were computed to produce the features that feed a SVM with a polynomial kernel. A selection of the best features subset and training data was performed interactively by a genetic algorithm.

D. *Based on sound*

The breathing process produces characteristic sounds that can be used to detect the presence of disorders. This principle was used by Rosenwein et al. [82]. Suspected breathing disorder periods were detected when the result of the energy envelope of the audio signal with the average value subtracted was negative. Then six features were calculated from the

suspected period, breathing and non-respiratory rates, duration of last respiratory event, variation of respiratory energy, average ventilation and mean energy value. These features were used as inputs to a binary-random forest classifier and the produced output was classified by an adaptive threshold produced for each subject's score distribution. Breathing sounds were also the base of the algorithm presented by Almazaydeh et al. [83] where voice activity detection (VAD) was used to classify respiratory signals. The sounds were first filtered and segmented, and were then applied to the FFT. These segments were further analyzed by the VAD algorithm which compared them against the threshold, determined by comparing the signal value against noise. The output identifies whether the segment was a normal breath or a breathing cessation (silence). A second threshold was then used to classify the silence as either apnea or normal. Recorded respiratory sounds were used to extract spectrum features, using the FFT, by Praydas et al. [84]. The sounds were filtered and distinguished using the K-means clustering algorithm and an SVM was employed to classify the data. Ng et al. [85] used linear predictive coding to model snore signals and formant frequencies were extracted from the linear predictive coding spectrum. A threshold value was used to differentiate apneic and normal snorers. A higher order statistics-based algorithm for snore sound analysis was presented by Karunajeewa et al. [86]. The pitch and total airway response waveforms were extracted from the sound signal and features were extracted from these waveforms to feed an LR classifier.

A different approach was presented by Elisha et al. [87] where OSA was detected by analyzing particular speech signal properties. These signals were segmented into vowels and nasal phonemes and features were extracted from each segment of time, spectral and cepstrum domains and hyper-nasal speech. Then seven GMM-based classifiers were used to classify the data. The GMM was also used by Pozo et al. [88] where the speech signals were parameterized using the Mel Frequency Cepstral Coefficient (MFCC). Benavides et al. [89] analyzed the subject's voice classifying OSA using an LDA feed with eight features: difference between third and second formants on the vowel i; segmental signal-to-disperiodicity ratio; harmonic-to-noise ratio; average percentage of silence in a sentence; duration of two sentences; jitter; difference between the nasality measure for vowels in nasal and non-nasal contexts. The use of tracheal sounds was analyzed by Penzel and Sabil [90], being verified that when recorded with an appropriate sensor, combining acoustic and suprasternal pressure sensors, is possible to detect snoring, breathing and intrathoracic pressure variations. Specifically, OSA can affect the resonance produced by the upper airway, generating specific tracheal sounds. Kalkbrenner et al. [91] also analyzed the tracheal sounds, recorded by a microphone on subject's neck. Audio signal was filtered by a finite impulse response bandpass filter to remove heart sounds and noise and apnea was detected by drops in breathing sound amplitude.

E. Based on combined approaches

Usually, the pulse oximeter provides both the SpO2 and heart rate signals, but it is also common for SpO2 only to be considered in the OSA detection algorithm. A different approach was presented by Zamarrón et al. [92] where a combination of these two signals was used. The frequency spectrum of the signals was interpolated to get the spectral amplitude at equally distributed frequencies between 0 to 0.1 Hz and then the data was averaged. The algorithm looks for peaks on the apnea-related frequency band of both signals to classify OSA. An algorithm that uses both EEG and oximetry was presented by Álvarez et al. [93]. The PSD was applied to each recording using Welch's method where the data was divided into overlapping segments, the FFT was applied and the result was averaged. Afterwards spectral features were computed to detect OSA. Peak amplitude of the apnea-related frequency band and median frequency (to summarize the spectral content) were the selected features for the SpO2 PSD. Relative power on selected EEG bands (delta and alpha) and spectral entropy (disorder quantifier computed based on the Shannon entropy) were the features chosen for the EEG analysis.

A combination of oximetry and ECG was presented by Xie and Minn [94]. Features from the SpO2 and ECG signals were analysis using a correlation-based feature subset selection. The second-order serial correlation coefficient, FFT points of RR intervals, spectral variances of decimated wavelet transform of EDR series and the FFT of EDR series were selected for the ECG. For the SpO2, time statistics, delta index, CTM, LZC, approximate entropy and ODI were chosen. These features were fed to the three individual classifiers that collaborated in the final decision using a majority voting combination scheme (the chosen output class was the one on which the majority of the classifiers agree). The chosen classifiers were bagging with reduced-error pruning tree (REPTree), AdaBoost with decision stump and kNN. Both SpO2 and heart rate variations were analyzed by the algorithm developed by Poupard et al. [95], using the wavelet-aggregation to quantify these variations. The ventilatory hypoxemic index was then produced by dividing the cumulative time during which the SpO2 variation was greater than 4% by a theoretical apnea cycle period. A multi-modal approach that performs feature-level fusion of ECG and SpO2 signals was employed by Memis and Sert [96]. The produced signal was tested by three classifiers, specifically the Naïve Bayes, kNN and SVM. Best results were achieved using SVM with RBF kernel.

An algorithm based on oximetry and ECG was also used by Ravelo-García et al. [97]. A combination of oxygen saturation and RR series features was used. The SpO2 signal was analyzed on both time (by the variance of one and five minute segments) and frequency (by PSD and filter bank to analyze multiple frequency bands) domains. Both time and frequency domain features were extracted from the RR series. Power ratios of specific frequency bands and variables based on symbolic dynamics were also used. Then an LDA was used to classify segments, on a minute by minute basis, as either normal or apnea. PPG-derived respiration and EDR signals were obtained by Madhav et al. [98] using EMD. OSA detection was performed by fitting an autoregressive model of

frequently used classifiers. The domination of supervised learning could be due to the fact that OSA is a disorder with a well establish pattern that facilitates the training of the algorithms. Some methods provide good performance but with a high degree of complexity which is particularly important if a hardware device has been designed.

TABLE I
EVALUATION OF THE ANALYZED ALGORITHMS

Source sensor	Paper	Population	Data acquisition	EB Acc (%)	EB AUC (%)	EB Sen (%)	EB Spe (%)	Global class (%)	SB AUC (%)	SB Sen (%)	SB Spe (%)	TW (s)
Oximetry	[21]	187 sub	Hospital	-	-	-	-	87	92	90	83	120
	[29]	83 sub	Hospital	-	-	-	-	86	91	91	79	-
	[23]	113 sub	Hospital	-	-	-	-	88	93	91	83	-
	[22]	129 sub	Hospital	-	-	-	-	93	95	97	79	120
	[31]	148 sub	Hospital	-	-	-	-	90	97	92	85	30
	[25]	144 sub	Hospital	-	-	-	-	87	-	92	77	-
	[27]	8 rec	Database*	93	-	88	100	-	-	-	-	-
	[32]	21 sub	Hospital	70	78	82	69	87	-	100	71	40
	[26]	115 sub	Hospital	-	-	-	-	94	96	92	96	60
	[33]	36 sub	Hospital	-	-	-	-	85	88	88	84	120
	[28]	127 sub	Hospital	-	-	-	-	90	-	94	70	-
	[34]	25 rec	Database+	85	-	60	92	-	-	-	-	60
	[24]	79 sub	Hospital	-	-	-	-	94	-	97	79	-
	[35]	8 rec	Database*	96	98	-	-	-	-	-	-	60
	[20]	92 sub	Hospital	91	-	83	89	97	99	98	95	60
	[30]	8 rec	Database*	98	-	97	99	-	-	-	-	60
ECG	[49]	147 sub	-	-	-	-	-	91	-	92	90	-
	[47]	35 rec	Database*	-	-	92	95	-	-	-	-	60
	[55]	35 rec	Database*	90	-	89	91	89	-	-	-	60
	[56]	35 rec	Database*	84	-	79	87	-	-	-	-	60
	[36]	5 rec	Database#	-	-	-	-	-	-	70	44	30
	[63]	25 rec	Database*	86	-	84	89	-	-	-	-	420
	[51]	25 rec	-	-	-	-	-	88	-	89	86	60
	[43]	35 rec	Database*	93	-	-	-	-	-	-	-	180
	[37]	16 sub	Hospital	-	-	-	-	95	-	-	-	60
	[68]	42 sub	-	-	-	-	-	93	-	-	-	-
	[69]	30 rec	Database*	93	-	90	100	100	-	-	-	60
	[54]	17 sub	Hospital	-	-	-	-	87	-	-	-	30
	[44]	35 rec	Database*	76	-	-	-	-	-	-	-	60
	[70]	60 rec	Database*	-	-	-	-	100	-	100	100	60
	[45]	35 rec	Database*	81	-	-	-	-	-	100	83	-
	[3]	32 rec	Database*	-	-	-	-	97	-	93	100	15
	[50]	35 rec	Database*	-	89	74	86	93	-	-	-	60
	[57]	35 rec	Database*	99	-	-	-	-	-	-	-	-
	[46]	97 sub	Hospital	-	-	-	-	-	94	89	83	30
	[65]	69 rec	Database*	-	-	-	-	-	93	87	88	60
	[58]	35 rec	Database*	85	-	86	83	-	-	-	-	60
	[38]	35 rec	Database*	94	-	95	93	94	-	-	-	60
	[48]	188 sub	Hospital	-	-	-	-	72	89	80	59	-
	[42]	35 rec	Database*	84	-	-	-	-	-	-	-	60
	[66]	35 rec	Database*	85	92	75	91	-	-	-	-	60
	[59]	70 rec	Database*	-	-	-	-	93	-	97	99	60
	[52]	35 rec	Database*	85	91	83	82	-	-	-	-	60
	[39]	35 rec	Database*	87	-	82	91	-	-	-	-	60
	[64]	35 rec	Database*	86	94	83	88	97	100	96	100	60
	[40]	35 rec	Database*	89	-	88	91	-	-	-	-	60
	[41]	9 rec	Database+	-	-	-	-	95	-	100	80	-
	[67]	35 rec	Database*	85	92	82	87	97	-	-	-	60
	[53]	69 rec	Database*	-	-	-	-	98	-	98	100	-
	[60]	10 rec	Database*	-	-	-	-	98	-	-	-	-
	[61]	17 rec	Database*	100	-	-	-	-	-	-	-	60

TABLE I (CONTINUATION)
EVALUATION OF THE ANALYZED ALGORITHMS

Source sensor	Paper	Population	Data acquisition	EB Acc (%)	EB AUC (%)	EB Sen (%)	EB Spe (%)	Global class (%)	SB AUC (%)	SB Sen (%)	SB Spe (%)	TW (s)
Respiration	[73]	41 sub	Hospital	-	-	-	-	-	88	81	95	300
	[81]	12 sub	-	89	-	87	90	-	-	-	-	30
	[74]	148 sub	Hospital	-	-	-	-	82	90	88	71	-
	[71]	14 rec	Database#	-	-	-	-	93	-	-	-	60
	[75]	100 rec	Database^	-	-	-	-	-	-	84	-	60
	[80]	70 rec	Database*	91	96	88	96	-	-	-	-	60
	[72]	4 sub	Hospital	82	-	86	81	96	-	-	-	-
	[77]	8 rec	Database*	99	-	-	-	-	-	-	-	60
	[78]	6 sub	-	88	-	91	77	-	-	-	-	40
	[76]	8 rec	Database*	99	-	-	-	-	-	-	-	-
	[79]	100 rec	Database~	75	-	-	-	-	-	-	-	30
Sound	[85]	40 sub	Hospital	-	-	88	82	-	-	-	-	-
	[88]	80 sub	Hospital	-	-	-	-	81	-	78	85	-
	[87]	87 sub	-	-	-	-	-	-	-	81	83	60
	[86]	41 sub	Hospital	-	-	-	-	90	97	89	92	-
	[83]	50 sub	-	97	-	-	-	-	-	-	-	-
	[89]	40 sub	Hospital	-	-	-	-	-	-	85	75	-
	[82]	186 sub	Hospital	-	-	-	-	86	-	-	-	-
	[84]	33 sub	Hospital	-	-	-	-	76	-	-	-	-
	[91]	10 sub	-	-	-	-	-	-	-	93	100	-
Combined approaches	[92]	120 sub	Hospital	-	-	-	-	89	-	94	82	-
	[99]	15 sub	-	-	-	91	86	-	-	-	-	-
	[103]	83 sub	-	-	-	-	-	95	97	92	97	-
	[93]	148 sub	Hospital	-	-	-	-	89	-	91	83	-
	[100]	66 sub	Hospital	-	-	-	-	-	95	83	91	-
	[95]	106 sub	Hospital	-	-	-	-	-	-	81	98	-
	[102]	66 sub	Hospital	-	-	-	-	-	96	90	86	-
	[94]	25 rec	Database+	82	-	84	81	-	-	-	-	60
	[101]	100 sub	Database^	82	-	70	91	95	-	92	98	60
	[104]	285 sub	Hospital	-	-	-	-	72	73	73	65	-
	[97]	70 sub	Hospital	87	92	73	92	100	-	-	-	300
	[98]	8 rec	Database*	-	-	-	-	-	-	97	-	15
	[96]	35 rec	Database*	-	-	-	-	97	-	-	-	-

* PhysioNet apnea-ECG Database

MIT-BIH polysomnography Database

+ University college of Dublin sleep apnea Database

^ Sleep Heart Health Study Database

~ Scaling Up Scientific Discovery in Sleep Database

Abbreviations: Acc = accuracy; Sen = sensitivity; Spe = specificity; Class = classification; TW = time window; Sub = subjects; Rec = recordings from database.

One key aspect has to do with the goal of obtaining a good method with a good ratio performance-complexity. With this objective, a method with a reduced number of sensors and complexity is always of special interest.

From the overall analysis of this review it is recognized as future directions for the research to produce more robust OSA diagnosis tools by implementation of the presented algorithm in efficient hardware, produce more research with deep learning classifiers, capable of self-learning the features, and validate the achieved results of the algorithms by independent research groups using publicly available databases so that the results can be reproduced. This has special interest for home diagnostic devices since they could be used as a first OSA diagnosis tool, leading to a considerable reduction in the diagnostics cost and waiting time for access to a sleep study. However, these devices are more susceptible to data errors caused by factors not controlled at the home of the subject. Therefore, an adaptation of the proposed algorithms to a real world environment in efficient hardware is the major challenge identified. The main gaps in the current state of the art are the algorithms capable of self-learning the features.

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