Sleep states detection using Halfwave and Franklin transformation

Yash Paul[a,1], Prof. S.Fridli[b,1]

[a] *PhD school of Informatics*
Eotvos Loránd University, Budapest, Hungary,1115
yash@inf.elte.hu
[b] *PhD school of Informatics*
Eotvos Loránd University, Budapest, Hungary,1115
fridli@inf.elte.hu

Abstract

Sleep is a physiological phenomenon and a sufficient amount of sleep is mandatory for a human for his/her health. Three biomedical signals namely Blood, EEG and Nasal are used to identify various sleep stages. The discrete version of these signals is piecewise linear function and applied two piecewise linear data reduction techniques namely a new **Halfwave** method in bf time domain and **Franklin transformation** in frequency domain on the discrete versions of these selected signals. As a result we obtained two piecewise linear functions with low complexity that still preserve the characteristics of the stages of the sleep in the signals. The components of the feature vector are generated from the parameters of the two reduced piece wise linear functions. Algorithm is tested on MIT-BIH Polysomnographic Database having more than 70 hours long term EEG, Blood and Nasal signals with six different sleep classes. Proposed method shows better performance so far on such long duration data in terms of Sensitivity, Specificity, Accuracy and False Alarm Rate/hour. Algorithm achieved an average sensitivity, specificity accuracy and false alarm rate of 98.35% and 97.32%, 96.96%, 0.029 respectively for two classes, 96.62% and 97.10%, 93.94%, 0.030 for 4 classes, 96.13% and 98.33%, 93.84%, 0.016 for all (six) classes.

Key words: Sleep states, Halfwave, Faber Schauder, Franklin system, K-Nearest Neighbor, ADASYN, EEG, Blood, Nasal signal.

1. Introduction

Sleep is an important part of individuals life and people used to sleep one-third of their whole life. There are large number of disorders like insomnia, breathing disorders, wake- sleep disorder sleep movement disorder found in human beings . Around 24% of the adult population have regular sleep disorders. Ohayon and Smirne [1] shown 27.6% of the Italin population have sleep problem. Gupta et al. [2] shown Indian population have 10-15% insomnia and 10% delayed sleep wave phase disorder. Worldwide this problem is increasing day by day and according to Oliver et al.[3] this problem costs around $100 billion USD per year. Every sleep state has different group of neurological and physiological features and correct identification of these features along with their states are important for diagnosis and the better treatment for such sleep disorders [4]. Sleep classification process is not a standardized one i.e. different experts have different criteria to mark a specific period of sleep. Usually sleep scientists make classifications by using visual method to predict or decide in which state the patient is for a specific time [5].The human sleep is categorized into 3 main

categorized name wake, REM and NREM. (Non Rapid Eye Movement) sleep [6]. A state is called slow wave sleep or synchronized sleep when sleep is analyzed with EEG characteristics and same sleep can be known as quiet sleep when behavioral correlates are utilized. When eye movements are used such state is called as NREM. According to R&K [6] rules sleep is categorized into six categories, REM, sleep stage1, stage2, stage3, stage4 and wake state. Stage3 and stage 4 were combined as slow wave sleep (SWS) stage. Due to high nonuniform and nonlinear nature of the majority of the biomedical signals single domain analysis is not sufficient to extract the desired information from the signal.Therefore there is a need to combine the features from different domains to extract comprehensive information from the signal. Generally NREM are high in magnitude as compared to REM but breathing and heart rate is more regular than REM. In the recent sleep state classification research, researcher has combined NREM3 and NREM4 as a single state and hence total number of classes remaining are 5 [7]. Later on NRME2 and NRME3 are also combined resulted as just four main classes namely light sleep, Deep sleep REM and Awake state. Most of the researcher who are involved in automatic sleep state detection research rely on PSG (Polysomnography), a multi-parametric test that look after many body activities using EEG (electroencephalography), EOG (electrooculography), EMG (Electromyography). The implementation of Faber Schauder system with halfwave is obvious because Faber Schauder system and halfwave decomposition both are linear piecewise systems and the discrete version of the biomedical signals is also piecewise linear [8] [9],[10]. Polysomnogram is a collection of various signals useful for monitoring the sleep of an individual. For accurate diagnosis of sleep phases, whole duration recordings of the selected biomedical signals needs an expert manual scoring for sleep stages using some standards. Therefore there is a need for automatic sleep phase detection to reduce cost and to increase access to diagnosis sleep stages. The main challenge to automatic sleep phase detection is : Heterogeneity : people around the world have different cranial structures which demographically and physiologically effects the patterns in the signal. Example 10 percent people don't generate alpha rhythm during stage W (wake) and 10 percent generate only a limited alpha rhythm. Therefore this issue motivate us to combine the other signals with EEG to improve the results. Six EEG wave patterns are used to differentiate wake and sleep states and classify sleep stages: (1) alpha activity, (2) theta activity, (3) vertex sharp waves, (4) sleep spindles, (5) K complexes, and (6) slow wave activity [6][11] [12] [4].These are summarized we believe that results would be good and more reliable as compared with the state of the art methods. Relationship between EEG rhythms and sleep states and brain states are given below. δ(1 to 4 hz) = deep sleep, NREM sleep, unconsciousness.
θ(4 to 8 hz) = light sleep.
α81 to 13 hz) = relaxed but not sleep, calmness and conscious.
β(14 to 30 hz) = consciousness of self and surroundings.
According to NHTSA in USA drowsiness while driving causes around 100000 accidents per year out of which 1500 cases faces death and 71000 suffer from major injuries [13]. Polysomnography is commonly used for sleep state detection, monitoring scoring for sleep related diseases[14]. Manual process of sleep states scoring is time consuming, therefore an automatic system of sleep states scoring is needed to aid sleep technologies. The proposed automatic system of sleep states uses two piecewise linear models to decompose the signals into a simple form. Features are extracted from the decomposed signals (EEG, Respiratory and Blood) and the sleep states classification is achieved by using KNN classifiers.

2. Database and Channel Selection

2.1. Dataset

MIT-BIH Polysomnographic Database (Physionet,https://www.physionet.org /physiobank/database/slpdb/), collected and described by Ichimaru Y, Moody GB et al. [15] [16] at Boston's Beth Israel Hospital Sleep Laboratory. It is a data collection from 16 subjects whose average weight and age are 119kg and 43 years respectively.The database contains over 80 hours' long data of four(C3-O1), six (C3-A1), and seven(O2-A1)-channel polysomnographic recordings, each with an ECG signal annotated beat-by-beat, and EEG and respiration signals annotated with sleep states and apnea. Each signal is divided into 20 and 30 sec long epoch and each epoch belongs to the one of the sleep stages.The sampling rate of the measured signal is 250 Hz and 30 seconds duration of the EEG and other signals are labeled by associated experts. Available standard databases usually contains data of one type of signal like EEG, ECG (ECG=ElectroCardioGram) etc. or combination of EEG, ECG. We used blood, nasal and EEG signal in proposed method and we found that this is standard and long enough database which containing blood, nasal and EEG signal, where we can test our proposed method. In our research, due to some technical problem we are not able to read 3 records out of 18 therefore we performed our tests only on remaining 15 records (patients)

2.2. Channel Selection

The channel selection is one of the most challenging tasks in sleep state detection and prediction algorithms. Considering of large number of channels will make signal processing system computationally slow. In proposed method we used data from only one channel given by the database experts, but our method least dependent on some specific number or set of channels. We believed and saw that our method gives comparatively equally good results when channel number along with patient has been changed (as per the expert of the database) i.e. any randomly selected channel can be used in proposed method which hardely reduces the performance of the algorithm and this is one of the main advantages of our proposed method (channel independent) . Our algorithm does not require any mechanism for channel selection and we require only one channel that can be random.

3. Methodologies Used

In proposed method we developed two piecewise linear time domain and frequency domain models called new halfwave decomposition [8] and Faber-Schauder (Franklin) [9],[10] system to extract the best discriminatory features from three biomedical signals. The reason for developing two piecewise liner models in different domains is to make the system fast and accurate. These two models of piecewise linear funtions make the signals simple and short by discarding the irrelevant information but retain important sleep stage properties in the original signals. Thus, after applying the models on the signal we have a simple, reduced but more assertive signal for analysis, which gives best insight into the signal. In literature survey we have found that recent research in signal processing is surrounding around very famous transformations like wavelets, EMD, Fourier, Hilbert and Fast Fourier etc [17]. Therefore there is a need of adaptive methods and transformations which can solve the signal processing problems efficiently and we believe that using adaptive methods and transformations on these selected signals can perform better than all other existing methods. We have chosen piecewise models because the nature of the discrete version of selected biomedical signal is also piecewise linear and piecewise functions have low computational cost and hence fast. The framework of the proposed algorithm is shown in figure 1.

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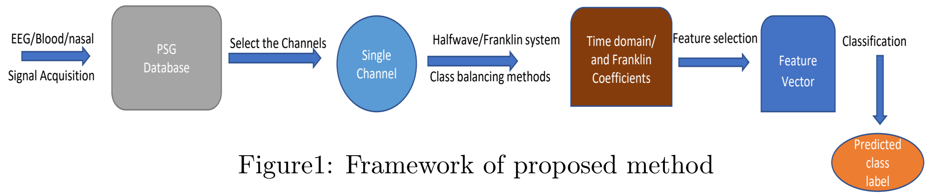

Figure1: Framework of proposed method

3.1. Halfwave Construction

Traditionally, from mid of $20th$ century to end of $20th$ century, halfwave was very popular method to detect epileptic activities (seizures) form the long EEG signals where the terms spikes and sharp waves also called SSWs [8] were the representative or interpretations of seizure and non seizure segments. Different methods to detect seizure by using halfwave have been proposed and some of them are reviewed here. Traditionally authors detect seizures by knowing the number and nature of the waves called spikes or sharps waves and if sharp and spikes waves are found at a particular instant, they conclude that epileptiform activity is found at that instance. But traditional methods based on spikes and sharps were not reliable and therefore, Jasper and Kershman [18] divided focal epileptic activity into spikes i.e. 10 to 50 ms and sharp waves i.e. 50 to 500 ms. Chatrain et al. [19] gave different duration for spikes (20 to 70 ms) and sharp waves (70 to 200ms). In coming methods definitions of sharp and spikes waves are purely qualitative, and the method of measurement of the duration of spikes and sharp waves was never mentioned. Koo et al. [20] conclude that epileptic activity can be identified in a signal by segmental velocities of more than 2 uv/msec. Walter et al. [21]. From the above methods authors conclude that systems were efficient for spike detection but sharp waves are not detected accurately and the muscle artifacts largely degrade the performance of the of the system. Saltzberg et al. [22] used a matched filtering technique to detect a particular wave shape in the scalp of monkey. This methods is very power when we know the shape of the wave in advance. But this method is not useful for EEG signal of human because subjects have different shapes of wave at different times which is not east to know in advance. Lopes da Silva et al. [23] all used auto-regressive model to find non-stationeries in the signal and the method is powerful because reveal epileptic activity which cannot be seen by the expert. But the model (Gotman et al) has the disadvantage that it requires lot of computations. Apart from above mentioned methods Gotman et al. [8][24][25] studied other existing methods of halfwave too and they incorporate the above ideas into their original idea to generate an efficient halfwave which is more reliable and not misleading the results as compared to existing halfwave methods. In the classical or traditional method of wave generation, they broken down the EEG signal into segments and a segment is the section between two consecutive extrema of amplitude and it has duration, amplitude and direction. This method of analysis has drawback that when noise is superimposed on wave (beta, muscle) there are large number of small segments instead of single long segment. Gevins et al. [26] used digital filter at 20c/sec to eliminate the fast activity. Now Gotman et al. [8] all have designed a new way of developing wave from original signal where segments are regrouped into sequences, generating slow frequency wave in the presence of low amplitude fast activity. According to Gotman a *wave* is defined as a set of two segments, two sequences or a segment and a sequence, where both the elements (segments or sequences) must be adjacent and of opposite direction. As it becomes a part of wave a segment or sequence is called a $Halfwave$. The main advantage of halfwave is that normal and abnormal patters of very long signals can be examined and identified easily. Halfwaves are easily implemented in small computers. Another

advantage of halfwave is that the most common artifacts like EMG and eye movements are usually not distributed in halfwave. In 2005 Runarsson and Sigurdsson used half-wave method given in [8] and halfwave's features are classified with support vector machine and they achieved an accuracy of 90 percent. From the history of the halfwave method we have seen that the the scope of this method was restricted to seizure detection only and was not applied in other problems available in signal processing. We proposed a new, simple and fast method to construct halfwave decomposition which can act as filter itself in the signal processing and can be used for better analysis of the signal in various areas like sleep states, seizure detection etc.

Mathematical formalization of proposed Halfwave method:

Let us suppose, that the $f\colon [a,b] \to \mathbb{R}$ signal is continuous on the $[a,b]$ compact interval, and suppose that f has finitely many extrema on $[a,b]$. Let us first collect the extrema points in two sets:

$$M_1 := \{x \in [a,b] \ : \ f \text{ has a local maximum in } x\},$$

$$m_1 := \{x \in [a,b] \ : \ f \text{ has a local minimum in } x\}.$$

And let us denote the set of all extremal points by

$$X_1 := M_1 \cup m_1 = \{x_0, x_1, x_2, \dots, x_n\}$$

with

$$x_0 < x_1 < x_2 < \cdots < x_n \ (n \in \mathbb{N}),$$

such that minimum and maximum points are alternating.

In the kth step of the proposed algorithm ($k = 1, 2, 3, \dots$) we delete some extremal points from M_k, m_k and X_k, and we will keep only the important extremal points to get the new sets M_{k+1}, m_{k+1} and $X_{k+1} = M_{k+1} \cup m_{k+1}$. The algorithm will converge, i.e.

$$\exists K \in \mathbb{N} : \forall k \geq K : M_k = M_K,\ m_k = M_K,$$

but we will stop at a suitable iteration number k^*.

One step of the proposed algorithm (deleting unwanted extrema) can be formulated as follows. We start with M_k, m_k and $X_k = M_k \cup m_k$, with the elements of X_k indexed in ascending order, as above. Now define

$$y_i = f(x_i) \ (i = 0, \dots, n)$$

the extremal function values,

$$\Delta_i := y_{i+1} - y_i \ (i = 0, \dots, n-1),$$

the differences between two consecutive extreme values (a minimum and a maximum), and

$$\begin{aligned} D := \quad & \{i \in \mathbb{N} \ : \ 1 \leq i < n-1 \\ & |\Delta_i| \leq |\Delta_{i+1}| \ \wedge \ |\Delta_i| \leq |\Delta_{i-1}|\} \cup \{n\} \end{aligned}$$

the set of indexes of segments with not significant difference (less than both neighboring segments). To formulate the set of important extremal points we will use the strictly increasing index function

$$\nu : \{0, 1, \dots, N\} \to \{0, 1, \dots, n\}.$$

defined by $\nu(0) = 0$ and

$$\nu(j+1) = \nu(j) + 2d + 1 \; (j = 0, 1, \ldots N-1; \; d \in \mathbb{N}),$$

such that

$$\nu(j) + 2d + 1 \notin D,$$
$$\nu(j) + 2\delta + 1 \in D \; (\delta = 0, 1, \ldots, d-1).$$

(It will turn out that $\nu(N) = n$). And then the set of important extremal points can be written as

$$X_{k+1} := \{x_{\nu(j)} \in X_k \; : \; j = 0, 1, \ldots, N\} \subset X_k.$$

As a consequence of the definition the values in X_{k+1} are alternatingly minimum and maximum points. Furthermore we can also formulate

$$M_{k+1} = X_{k+1} \cap M_k,$$
$$m_{k+1} = X_{k+1} \cap m_k$$

the sets of the new maximum and minimum values.

After the completion of first level, we will repeat the same procedure for the outcome (M_{k+1}, m_{k+1} and X_{k+1}) of the first level to ge signal at next level (level 2) and so on untill required level is found.

3.2. Piece-wise linear transform

Haar wavelet

is the simplest possible wavelet which is a sequence of re scaled square shaped functions which together form a wavelet family or basis [27].

$$\psi(t) = \begin{cases} 1 & 0 \leq t < 1/2 \\ -1 & 1/2 \leq t < 1 \\ 0 & otherwise \end{cases}$$

and its scaling function function $\varphi(t)$ can be described as

$$\varphi(t) = \begin{cases} 1 & 0 \leq t < 1 \\ 0 & otherwise \end{cases}$$

Haar function and Haar system

for every pair n,k of integers in Z , the Haar function $\psi_{n,k}$ is defined on the Real line R by the formula $\psi_{n,k}(t) = 2^{n/2}\psi(2^n t - k)$, $t \in R$. This function is supported on right-open interval $I_{n,k} = [k2^{-n}, (k+1)2^{-n})$ i.e. it vanishes outside the interval. It has integral 0 and norm 1 in the Hilbert space $L^2(R)$. $\int_R \psi_{n,k}(t)dt = 0$, $||\psi_{n,k}||^2_{L^2(R)} = \int_R \psi_{n,k}(t)^2 dt = 1$. The Haar functions are pairwise orthogonal. $\int_R \psi_{n_1,k_1}(t)\psi_{n_2,k_2}(t) = \delta_{n_1,n_2}\delta_{k_1,k_2}$, where $\delta_{i,j}$ represents the Kronecker delta.

Haar system

On the real line is the set of functions. $\psi_{n,k}(t); n \in Z, k \in Z$. It is complete in $L^2(R)$; The Haar system on the line is an orthonormal basis in $L^2(R)$.

Faber Schauder System

The Faber-Schauder System [9],[10] is the family of continuous functions on$[0,1]$ consisting of the constant function one and of the multiples of indefinite integrals of the functions in the Haar system on$[0,1]$ chosen to have norm 1 in the maximum norm. This system begins w $s_0 = 1$, then s(t)=t is the indefinite integral vanishing at 0 of the function 1, first element of the Haar system on[0,1],next for every integer$n \geq 0$, functions $S_{n,k}$ are defined by the formula.

$s_{n,k}(t) = 2^{1+n/2} \int_0^t \psi_{n,k}(u)du$, $t \in [0,1], 0 \leq k < 2^n$. These functions $s_{n,k}$ are continuous, piecewise linear supported by by the interval $I_{n,k}$ that also supports $\psi_{n,k}$ .The function $s_{n,k}$ is equal to 1 at the mid point $X_{n,k}$ of the interval $I_{n,k}$, linear on both halves of that interval . It takes values between 0 and 1 everywhere. The Faber Schauder system is the Schauder basis for space C([0,1]) of the continuous functions on [0,1]. For everywhere f in C([0,1]) , the partial sum $f_{n+1} = a_0 s_0 + a_1 s_1 + \sum_{m=0}^{n-1} \sum_{k=0}^{2^m-1} a_{m.k} s_{m,k}$,$\in C([0,1])$ The series expression of f in the Faber Schauder System is the continuous piecewise linear function[28] that agrees with f at $a^n + 1$ points $k2^{-n}$ where, $0 \leq k \leq 2^n$. The formula $f_{n+2} - f_{n+1} = \sum_{k=0}^{2^n-1} (f(x_{n,k}) - f_{n+1}(f(x_{n,k})) s_{n,k} = \sum_{k=0}^{2^n-1} a_{n,k} s_{n,k}$.

Franklin System

A Franklin system is an orthogonal system of basis which is derived from Faber Schauder system of basis by applying Gram-Schmidt orthogonal procedure [29][30][31] on Faber Schauder system. The Franklin system has the same linear span as that of Faber Schauder systems and this span is dense in C([0,1]), hence $L^2([0.1])$ consists of continuous piecewise linear function.

Feature Extraction

In proposed method a hybrid approach of feature extraction i.e. the features from two piecewise linear models i.e.halfwave and Franklin system in time domain and frequency domain respectively are used to construct final feature vector for sleep states detection. A rectangular 1 sec (250 samples, over sampled to 256) long window is used for windowing the halfwave. Window size used here is 1 second [32] [17] for both time domain and frequency domain is considered as a best size window. Time domain features like total number of extrema points, slopes of extrema points, maximum of slopes, mean of extrema points, minimum of extrema points, maximum of extrema points have been chosen from each1-s-long window after analyzing their properties by means of histograms. For frequency domain features, we applied the Franklin piecewise linear transformation on the original discrete signal to transform the signal from time domain to frequency domain and we selected first 8 Franklin coefficients with 8 time domain features to construct the final feature vector for the classification as shown in table I .

Some of the combinations are shown in table I and we found that combination number 12 and 13 are better than others. In the table I, 6T means, six best time domain features out of 8 features and 8F = First Eight Franklin coefficients. Final results with different set of classes are shown in table II, III, IV where training and Testing data is taken in the ratio of 60:40 respectively. First algorithm is tested on around 6 hours long data (Table I) to find best set of features from time and frequency domain. The final feature vector is constructed by making different different combinations of features from time domain and frequency domain and based on the results of classification. We applied the piece-wise linear transform on the original signal resulting piece-wise signal with 256 coefficients in each and every window segment. Here we over sampled the signal from 250 sample to 256 (because Franklin coefficients used here are 256)

Table 1: Feature selection usind different combinations of the signals

Signal	$Class-pair$	$featureused$	$Train\&Test$	$Sensitivity(\%)$	$Specificity(\%)$	$Accuracy(\%)$
Blood	4	$6T+16F$	$60-40$	91.02	97	91
Blood	4	$6T+16F$	$80-20$	96.11	98.70	96.09
Blood	4	$6T+8F$	$80-20$	96.03	98.67	96.02
Blodd	4	$6T+8F$	$60-40$	90.64	96.86	90.60
Resp	4	$6T+8F$	$60-40$	91.11	97.05	91.15
Resp	4	$6T+8F$	$80-20$	96.37	98.79	96.38
Resp	4	$6T+16F$	$60-40$	90.87	96.98	90.97
Resp	4	$6T+16F$	$80-20$	96.15	98.72	96.17
EEG	4	$6T+8F$	$80-20$	95.63	98.58	95.63
EEG	4	$6T+8F$	$60-40$	90	96.7	90
EEG	4	$6T+16F$	$80-20$	90.64	96.86	90.60
Blood RESP EEG	**4**	$\mathbf{6T+8F}$	$\mathbf{60-40}$	**93.28**	**97.76**	**93.28**
Blood RESP EEG	**4**	$\mathbf{6T+8F}$	$\mathbf{80-20}$	**97.28**	**99.09**	**97.27**
Blood resp EEG	4	$6T+16F$	$60-40$	92.82	97.60	92.84
Blood resp EEG	4	$6T+16F$	$80-20$	96.92	98.97	96.93
Blood resp EEG	4	$6T+32F(114)$	$80-20$	96.51	98.83	96.50
Blood resp	4	$6T+16F.(44)$	$80-20$	96.71	98.99	96.77
Blood resp	4	$6T+16F.(44)$	$60-40$	92.37	97.45	92.37

Classification

From the literature survey we concluded that KNN (k-Nearest Neighbor) Artificial Neural Network and support vector machines are commonly used classifiers for the classification of the features extracted from biomedical signals [17] [33],[34]. KNN is non parametric, instance-based simple, robust, versatile, fast and supervised learning algorithm and in many applications it performs better than other modern classifiers like Artificial Neural Networks (ANN) and Support Vector Machines (SVM) [17]. Let x to denote a feature vector and y is class label, KNN Categorizing query points based on their distance (Euclidean distance, Minkowski distance, Chebychev distance etc) to points in a training data set. It chooses K-most nearest or similar tuples to the query tuple and uses majority voting, weighted average of the K similar tuples to find the new class label for the query point. Similarity between two data points is calculated by means of a distance metric. A popular choice is the Euclidean distance. $d(x, x_1^{'}) = (\sqrt{(x_1 - x_1^{'})^2 + (x_2 - x_2^{'})^2 + \cdots + (x_n - x_n^{'})^2}$ [33],[34]. Usually the given sleep states databases are not balanced i.e the number of tuples of different classes are not almost same. Therefore before applying any classifier, the class imbalance problem needs to be addressed otherwise results would be biased. There are two popular methods [35] address this problem and are given below:

1. Over-sampling (increasing the samples of minority class
2. Under-sampling (reducing the samples of majority class

Most of the pattern classification methods used over-sampling because there is no loss of information. In proposed method, we have applied advance version of a well known over sampling technique Synthetic Minority Over-Sampling Technique (SMOTE) [36] to solve the problem of class imbalance problem of sleep states called (ADASYN) Adaptive Synthetic Sampling Approach for Imbalanced Learning [37], which neither exaggerate the Receiver Operating Characteristic (ROC) curve of the extracted features, nor cause any over-fitting problem [38]. ADASYN approach improves learning with respect to the data distributions in two ways: (1) Reducing the bias introduced by the class imbalance, and (2) Adaptively shifting the classification decision boundary toward the difficult

examples. This technique is designed to handle two class problem but we have used it for multi-class problem where each and every class is balanced with respect to the class having highest training tuples.

4. Related Work

In the literature survey we studied number of sleep states detection techniques and we found that recent research is focusing on dynamic parameters like correlation dimension, Lyponov exponent, approximate entropy etc to extract comprehensive information from non linear signals like EEG, blood and respiratory[39]. Originally the halfwave was used in seizure detection but new halfwave method proposed by us can be used with Franklin transformation (a hybrid approach) [40] to detect epileptic seizures and sleep states classifications in an efficent way by using different biomedical signals. We believe that this method with slight modification in the parameters if needed can be useful to solve many problems in biomedical field in an efficient way. Dihong et al. [41] used three biomedical signals like using EEG, EOG and EMG and on an average, accuracy of 81.2% and a Cohen's Kappa coefficient of 0.722 are obtained under leave-one-subject-out cross validation. Nicola et al. [42] proposed single channel automated detection of sleep states using EEG signals. Time domain and frequency domain features are classified for four and two stages separately with 90.81% 83.2% respectively. They achieved an overall accuracy of 86.7%. Tripathy et al. [43] they used dispersion entropy and the variance features from the different bands of EEG signal. The RR-time series features and the EEG features feed to the deep neural network (DNN) to carry out the classification of sleep stages. They achieved an average accuracy of 85.51%, 94.03% and 95.71% for the classification of 'sleep vs wake', 'light sleep vs deep sleep' and 'rapid eye movement (REM) vs non-rapid eye movement (NREM)' sleep stages. Silverira et al. [44] proposed a single channel method where EEG signal is decomposed using wavelet transform. The features such as kurtosis, skewness and variance of the wavelet coefficients are classified using random forest classifier and they obtained an over all accuracy for 2 to 6 classes is 90%. Budak et al. [45] they proposed new method to detect driver drowsiness.They decompose the signal using Q-factor wavelet transform in sub-bands. The Spectrogram images of the obtained sub-bands and statistical features like standard deviation of instanious frequencies are calculated. Features are classified by long-short term memory (LSTM) for classification. They obtained an over all accuracy of 94.31 for awake and drowsy (S1) state. Taran et al. [46] used Hermite functions as basis functions and the Hermite coefficients are used as features to classify alertness and drowsiness states.With ELM (Extreme Learning Method) their detection rate for alert and drowsiness are 95.45% and 87.92%. The over all accuracy was 92.28%. A subject specific approach [47] where 12 features are extracted by three methods namely, the heart rate variability (HRV), detrended fluctuation analysis (DFA) and windowed DFA (WDFA). They reported an average accuracy of 79.99 and kappa coefficient 0.43. Another subject specific approach is mentioned in [48] where average accuracy are using EEG is 76% and using ECG signals is 75%.

5. Experimental Results and Discussions

The proposed algorithm is tested on 15 patients of around 70 hours long data with three different biomedical signals from single channel of the CHB-MIT Polysomnography database mentioned above. The performance of the proposed algorithm is is measured by following quantities:

Sensitivity $= \frac{\text{TP}}{\text{TP+FN}} \times 100$

Specificity = $\frac{\text{TN}}{\text{TN+FP}} \times 100$

Accuracy = $\frac{\text{TP+TN}}{\text{TN + FP + TP + FN}} \times 100$

False alarms per hour (Fph)= the total number of false detection divided by the length of the test data in hour.

where TP is true positive, TN is true negative, FN is false negative .

Table 2: Comparison of results with state-of-the art algorithms tested on the same database

Author and year	Number of records	feature	Classes used	Classifier used	Average Accuracy(%)
Redmond and Heneghan [48],2003	17	HRV features and EEG Features	Light sleep vs deep sleep	QDA	89
Adnane et al.[47] ,2012	17	HRV, DFA and WDFA	Sleep vs wake	SVM	79.99
Hayet and Slim[49] 2012	09	RR-time series and HRV features	Sleep vs wake	ELM	83.59
Werteni et al.[50],2015	17	HRV	Sleep vs wake REM	SVM	56.81
R.K Tripathi et al[43] (May,2018)	17	Dispersion entropy and variance	wake, light sleep, deep sleep, REM	Neural network	85.51, 94.0 95.71
Taran et al. [46],2018	16	Hermite coefficients	alert(w) and drowsiness(s1)	ELM	92.28
Budak et al. [45] ,2019	16	spectrogram images and instanious frequencies	alert and drowsiness	LSTM	94.31 %
Panfeng et al.[51],2019	06	statistical features	NREM (s1-s4), REM, Wake	W-SVM	85.29
Junming at el[52],2020	18	Hilbert Huang coefficients	REM,REM,wake	CNN	87.6 0.81
Proposed method	15	time domain and Franklin coefficients	Wake, Sleep(all), REM	KNN	**96.9,93.94, 93.84**

The study done by Shayan et al. [55] suggests various disadvantages of the existing studies. The study motivate the researcher to do research by using some adaptive methods. Our focus is to increase the speed as well as accuracy of sleep states detection process as compared to the existing methods. We have applied KNN classifier because it is faster as compared to other classifier but cannot work fine when data is large. We found that our method works well when data is not very large to process. In near future work we plan to work on two biomedical signals instead of three signal with different set of features from different domains. The various results obtained are shown in table I, II, III, IV and table V. The table I help us to choose best set of discriminatory features among large number of features and we found that the combination in row number 12 and 13 can be consider as best combination to detect various sleep states. Table II and table III shows the comparison with state of the art methods and we found that proposed method is performing better than other existing methods in terms of accuracy.

6. ABBREVIATIONS

EEG= ElectroEncephaloGraphy
ECG=ElectroCardioGram
PSG= PolySomnoGraphy
EOG= ElectroOculoGraphy
EMG=ElectroMyoGraphy
REM= Rapid Eye Movement
NREM= Non Rapid Eye Movement
SWS=Slow Wave Sleep
SSW=Spikes and Sharp Wave
KNN= K-Nearest-Neighbor
EMD=Empirical Mode Decomposition
ADSSYYN= Adaptive Synthetic Sampling Approach for Imbalance Learning
ROC= Receiver Operating Characteristics
SMOTE=Synthetic Minority Over Sampling
ANN =Artificial Neural Network
LSTM= Long-Short Term Memory
DNN =Deep Neural Network
SVM=Support Vector Machine
HRV=Heart rate Variability
DFA= Detrended Fluctuation Analysis

7. Conclusion and future work

A novel hybrid approach of two piecewise linear models has been developed to extract the features from the biomedical signals. The main idea behind the two piecewise linear models is to morph the signals in such a way that signal should become simple and smooth but at the same it must retain the important characteristics of the sleep states in it. Different time domain and frequency domain features are extracted, and these features are combined to construct final feature vector. Features are classified by using KNN classifier on long data of CHB-MIT polysomnography database. Proposed algorithm achieved an average sensitivity, specificity, accuracy and false alarm rate of 98.35% and 97.32%, 96.96%, 0.029 respectively for two randomly picked classes, 96.62% and 97.10%, 93.94%, 0.030 for randomly picked any 4 classes, 96.13% and 98.33%, 93.84%, 0.016 for all six classes, which is higher so far than state of the art methods. In future algorithm will be tested on very long data of different databases. In this algorithm we have used three biomedical signals which may slow down the speed of the system instead of two or less signal being used under this method. Therefore in near future we will try to use only two or less signals with different set of features from different signals so that further results can be improved in an more efficient way. In future, we plan to use EEG and blood signal where Franklin system may be used on EEG and some time domain features can be extracted from blood signal.

8. Declarations

8.1. competing interests

The authors declare that they have no competing interests

8.2. *Authors contributions*

8.3. *consent for publication*

This is original work but we have all the necessary permissions and consents to publish this article too. Both the authors contributed equally.

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Table 3: Comparison of results with other algorithm tested on the different database

Author and year	feature	Classes used	Classifier used	Average Accuracy(%)
Prucnal et al. [53]	EMD and wavelet based features	Five class (wake, S1, S2, deep sleep, REM)	Neural Network	74.2 (using DWT features), 57.6 (using EMD features)
Hasan et al. [54]	Ensemble EMD based features	Six classes (wake, S1, S2, S3, S4, REM)	RUSBoost	42.05 (S1), 79.51 (S2), 86.61 (S3), 48.09 (S4), 95.16 (wake), 80.50 (REM sleep)
Da Silveira et al. [44]	DWT and statistical features	(wake, S1, S2, S3, S4, REM)	Random forest	5.80 (S1), 87.70 (S2), 51.50 (S3), 68.00 (S4), 99.3 (wake), 68.80 (REM sleep)
R.K Tripathi et al (May,2018)	HRV features	(NREM, REM)	DNN	83.84% (wake), 57.75% (light sleep), 72.66% (deep sleep), 80.11% (REM sleep), 73.70% (overall accuracy)
Proposed method	**time domain and Franklin coefficients**	**Wake, Sleep (all), REM**	**KNN**	**96.9,93.94, 93.84**

Table 4: Results of proposed algorithm with 2 randomly selected classes

Patient number	$Sensitivity(\%)$	$Specificity(\%)$	$Accuracy(\%)$	$False alarm rate/hr$
01a	100	96.30	96.61	0.037
01b	100	99.75	99.75	0.025
2a	96.53	97.69	97.21	0.0231
2b	100	96.30	96.69	0.037
03	100	97	97.10	0.035
04	100	95.45	96.01	0.045
14	100	96	97.02	0.030
16	97.01	92.16	93.95	0.078
37	100	97.46	97.56	0.025
48	94.31	95.61	94.21	0.065
59	96.53	97.69	97.21	0.0231
60	95.52	100	96.08	0.01
61	96.49	99.83	96.45	0.005
66	100	98.86	98.90	0.011
66x	100	99.72	99.73	0.002
Avg	**98.35**	**97.32**	**96.96**	**0.029**

Table 5: Results of proposed algorithm with 4 randomly selected classes

Patient number	$Sensitivity(\%)$	$Specificity(\%)$	$Accuracy(\%)$	$False alarm rate/hr$
01a	100	95.41	95.89	0.045
01b	97.15	98.31	94.45	0.0169
2a	96.51	98.64	95.89	0.0136
2b	100	95.41	95.89	0.041
03	97.12	97.65	94	0.022
04	93.71	93.85	91	0.0604
14	95.90	97.14	93	0.028
16	97.10	97.64	93.64	0.023
37	98.44	98.57	94.70	0.014
48	93.81	93.95	91	0.0605
59	96.51	98.64	95.89	0.0236
60	95.62	97.07	92.23	0.0293
61	96.84	98.32	94.48	0.0168
66	93.55	96.87	91.53	0.0131
66x	96.47	98.12	94.81	0.0188
Avg	**96.62**	**97.10**	**93.94**	**0.030**

Table 6: Results of proposed algorithm with 5 and six randomly selected classes

Patient number	$Sensitivity(\%)$	$Specificity(\%)$	$Accuracy(\%)$	$Falsealarmrate/hr$
01a	97.09	98.77	97.09	0.0123
01b	98.05	98.68	93.31	0.0132
2a	93.69	98.11	98.78	0.0122
2b	96.69	97.92	93.50	0.020
03	96.78	98.59	94.11	0.014
04	94.25	97.40	90.59	0.026
14	97.34	98.85	94.67	0.0115
16	97.67	98.78	95.39	0.00122
37	NA	NA	NA	NA
48	94.25	97.40	90.59	0.0260
59	94.79	98.58	93.10	0.0188
60	NA	NA	NA	NA
61	96.94	98.63	94.19	0.0137
66	NA	NA	NA	NA
66x	NA	NA	NA	NA
Avg	**96.13**	**98.33**	**93.84**	**0.016**