Sleep states detection using Halfwave and Franklin transformation

Yash Paul\textsuperscript{a,1}, Prof. S.Fridli\textsuperscript{b,1}

\textsuperscript{a}PhD school of Informatics
Eotvos Loránd University, Budapest, Hungary, 1115
yash@inf.elte.hu

\textsuperscript{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 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 \cite{1} shown 27.6\% of the Italin population have sleep problem. Gupta et al. \cite{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.\cite{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 \cite{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 \cite{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 NREM2 and NREM3 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]. 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. $\delta$(1 to 4 Hz) = deep sleep, NREM sleep, unconsciousness. $\theta$(4 to 8 Hz) = light sleep, $\alpha$(8 to 13 Hz) = relaxed but not sleep, calmness and conscious. $\beta$(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 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 hardly 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 linear models in different domains is to make the system fast and accurate. These two models of piecewise linear functions 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.
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 sharp 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 sharp waves 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 easy 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. [8,21,23] 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 \textit{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 \textit{Halfwave}. The main advantage of halfwave is that normal and abnormal patterns 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 $f: [a, b] \rightarrow \mathbb{R}$ 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

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

with

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

such that minimum and maximum points are alternating.

In the $k$th step of the proposed algorithm ($k = 1, 2, 3, \ldots$) 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

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

the extremal function values,

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

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

$$D := \{ i \in \mathbb{N} : 1 \leq i < n - 1 \\
|\Delta_i| \leq |\Delta_{i+1}| \land |\Delta_i| \leq |\Delta_{i-1}| \} \cup \{n\}$$

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

$$\nu : \{0, 1, \ldots, N\} \rightarrow \{0, 1, \ldots, n\}.$$
defined by $\nu(0) = 0$ and
\[ \nu(j + 1) = \nu(j) + 2d + 1 \quad (j = 0, 1, \ldots N - 1; d \in \mathbb{N}), \]
such that
\[ \nu(j) + 2d + 1 \notin D, \]
\[ \nu(j) + 2\delta + 1 \in D \quad (\delta = 0, 1, \ldots, d - 1). \]
(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 get signal at next level (level 2) and so on until the 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].

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

and its scaling function function $\varphi(t)$ can be described as
\[ \varphi(t) = \begin{cases} 1 & 0 \leq t < 1 \\ 0 & \text{otherwise} \end{cases} \]

**Haar function and Haar system**

for every pair $n,k$ of integers in $\mathbb{Z}$, the Haar function $\psi_{n,k}$ is defined on the Real line $\mathbb{R}$ by the formula $\psi_{n,k}(t) = 2^{n/2}\psi(2^n t - k), \ t \in \mathbb{R}$. 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 $L^2(\mathbb{R})$. $\int_\mathbb{R} \psi_{n,k}(t) dt = 0$, $||\psi_{n,k}||_{L^2(\mathbb{R})}^2 = \int_\mathbb{R} \psi_{n,k}(t)^2 dt = 1$. The Haar functions are pairwise orthogonal. $\int_\mathbb{R} \psi_{n_1,k_1}(t)\psi_{n_2,k_2}(t) = \delta_{n_1,n_2}\delta_{k_1,k_2}$, where $\delta_{i,j}$ represents the Kronecker delta.

Haar system

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

6
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 with \(s_0 = 1\), 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:

\[
s_{n,k}(t) = 2^{1+n/2} \int_0^t \psi_{n,k}(u) du, \quad t \in [0,1], 0 \leq k < 2^n.
\]

These functions \(s_{n,k}\) are continuous, piecewise linear supported by the interval \(I_{n,k}\) that also supports \(\psi_{n,k}\). The function \(s_{n,k}\) is equal to 1 at the midpoint \(X_{n,k}\) 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 Haar basis for space \(C([0,1])\) of the continuous functions on \([0,1]\). For everywhere \(f \in C([0,1])\), the partial sum

\[
f_{n+1} = a_0 s_0 + a_1 s_1 + \sum_{m=0}^{n-1} \sum_{k=0}^{2^m-1} a_{m,k} s_{m,k}, \quad \psi_{m,k}, \in C([0,1])
\]

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 \(f_{n+2} - f_{n+1} = \sum_{k=0}^{2^n-1} (f(x_{n,k}) - f_{n+1}(x_{n,k})) s_{n,k} = \sum_{k=0}^{2^n-1} a_{n,k} s_{n,k}\).

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 each 1-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 using different combinations of the signals

| Signal       | Class - pair | featureused | Train FTest | Sensitivity(%) | Specificity(%) | Accuracy(%) |
|--------------|--------------|-------------|-------------|----------------|----------------|-------------|
| Blood        | 4            | $6T + 16F$  | 60 - 40     | 91.02          | 97.5           | 96.09       |
| Blood        | 4            | $6T + 8F$   | 80 - 20     | 96.11          | 98.70          | 96.09       |
| Blood        | 4            | $6T + 8F$   | 60 - 40     | 90.64          | 96.86          | 90.66       |
| Resp         | 4            | $6T + 8F$   | 80 - 20     | 91.11          | 97.05          | 91.15       |
| Resp         | 4            | $6T + 8F$   | 80 - 20     | 96.37          | 98.79          | 96.38       |
| Resp         | 4            | $6T + 16F$  | 80 - 20     | 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          | 98.38          | 95.63       |
| EEG          | 4            | $6T + 8F$   | 60 - 40     | 90             | 96.7           | 90          |
| EEG          | 4            | $6T + 16F$  | 80 - 20     | 90.64          | 96.86          | 90.66       |
| Blood RESP   | 4            | $6T + 8F$   | 60 - 40     | 93.28          | 97.76          | 93.28       |
| Blood RESP   | 4            | $6T + 8F$   | 80 - 20     | 97.28          | 99.09          | 97.27       |
| Blood RESP   | 4            | $6T + 16F$  | 80 - 20     | 92.82          | 97.60          | 92.84       |
| Blood RESP   | 4            | $6T + 32F$  | 60 - 40     | 96.92          | 98.97          | 96.93       |
| Blood RESP   | 4            | $6T + 32F$  | 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 [14, 32, 33]. 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, 

$$d(x, x_1) = \sqrt{(x_1 - x_1)^2 + (x_2 - x_2)^2 + \cdots + (x_n - x_n)^2}$$

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 [33] 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)[10] to detect epileptic seizures and sleep states classifications in an efficient 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 overall 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:

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \times 100
\]
Specificity = \( \frac{TN}{TN+FP} \times 100 \)

Accuracy = \( \frac{TP+TN}{TN+FP+TP+FN} \times 100 \)

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 [45], 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 instantaneous frequencies | alert and drowsiness | LSTM | 94.31 % |
| Paukung et al. [51], 2019 | 06 | statistical features | NREM (s1-s4), REM, Wake | W-SVM | 85.29 |
| Junming at al. [52], 2020 | 18 | Hilbert Huang coefficients | REM, REM, wake | CNN | 87.6, 87.81 |
| **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.

Funding and Acknowledgments

The first author was supported by EFOP-3.6.3-VEKOP-16-2017-00001: Talent Management in Autonomous Vehicle Control Technologies - The Project is supported by the Hungarian Government and co-financed by the European Social Fund. This research of the second author was supported by the Hungarian Scientific Research Funds (OTKA) No K115804.

References

[1] M. Ohayon, S. Smirne, Prevalence and consequences of insomnia disorders in the general population of Italy, Sleep Medicine 3 (2) (2002) 115 – 120. doi:https://doi.org/10.1016/S1389-9457(01)00158-7.

[2] R. Gupta, S. Das, K. Gujar, N. M. A. Mishra, K Kand Gaur, Clinical practice guidelines for sleep disorders, Indian J Psychiatry; 59, Suppl S1:116-38 59 (2017) 116–38.

[3] O. Faust, H. Razaghi, R. Barika, E. Ciaccio, U. R. Acharya, A review of automated sleep stage scoring based on physiological signals for the new millennia, Computer Methods and Programs in Biomedicine 176 (Sep. ,2019) 19-30. doi:10.1016/j.cmpb.2019.04.032.

[4] L. J. Herrera, C. M. Fernandes, A. M. Mora, D. Migotina, R. Largo, A. Guillen, A. C. Rosa, Combination of heterogeneous eeg feature extraction methods and stacked sequential learning for sleep stage classification, International Journal of Neural Systems 23 (03) (2013) 1350012. doi:10.1142/S0129065713500123.

[5] R. Norman, I. Pal, C. Stewart, J. Walsleben, D. Rapoport, Interobserver agreement among sleep scorers from different centers in a large dataset, Sleep 23 (7) (2000) 901—908.

[6] A. Rechtschaffen, A. Kales, A manual of standardized terminology, techniques and scoring system for sleep stages of human subjects, Public Health Service, US Government Printing Office, Washington DC doi:10.1109/IJCNN.2008.4633969.

[7] C. Iber, S. Ancoli-Israel, A. Chesson, S. Quan, The aasm manual for the scoring of sleep and associated events: Rules, terminology and technical specifications, Westchester, IL: American Academy of Sleep Medicine.

[8] J. Gotman, P. Gloor, Automatic recognition and quantification of inter-ictal epileptic activity in the human scalp eeg, Electroencephalography and Clinical Neurophysiology 41 (1976) 513–529.

[9] G. Faber, Über die orthogonalfunktionen des herrn haar, Deutsche Math.-Ver (in German) 19 (1910) 104–112.
[10] B. Golubov, Faber–schauder system, in Hazewinkel, Michiel, Encyclopedia of Mathematics, Springer Science+Business Media B.V. / Kluwer Academic Publishers, ISBN 978-1-55608-010-4 (1994, 2001) 317–320.

[11] http://www.ninds.nih.gov/, National institute of neurological disorders and stroke.

[12] U. R. Acharya, O. Faust, N. Kannathal, T. Chua, S. Laxminarayan, Non-linear analysis of eeg signals at various sleep stages, Computer methods and programs in biomedicine 80 (2005) 37–45. doi:10.1016/j.cmpb.2005.06.011.

[13] L. E. A. Garces Correa, L. Oroso, Automatic detection of drowsiness in eeg records based on multimodal analysis, Med. Eng. Phys 36 (2014) 244–249.

[14] R. Tripathy, Application of intrinsic band function technique for automated detection of sleep apnea using hrv and edr signals, Biocybernetics and Biomedical Engineering 38(1) (2018) 136–144. doi:https://doi.org/10.1016/j.bbe.2017.11.003.

[15] Y. Ichimaru, G. Moody, Development of the polysomnographic database on cd-rom, PCN Psychiatry and clinical neurosciences 53 (1999) 175–177. doi:https://doi.org/10.1046/j.1440-1819.1999.00527.x.

[16] A. Goldberger, L. Amaral, L. Glass, J. Hausdorff, P. Ivanov, R. Mark, J. Mietus, G. Moody, C.-K. Peng, H. Stanley, Physiobank, physiotoolkit, and physionet: Components of a new research resource for complex physiologic signals 101 (23) (2000) 215–220. doi:10.1161/01.CIR.101.23.e215.

[17] Y. Paul, Various epileptic seizure detection techniques using biomedical signals: a review, Brain Inf. 5 (6) (2018) 429 – 436. doi:https://doi.org/10.1186/s40708-018-0084-z.

[18] H. Jasper, J. Kershman, Electroencephalographic classification of the epilepsies, Archives of Neurology and Psychiatry 45 (6) (1941) 903–943.

[19] G. Chatrian, L. Bergamini, M. Dondey, D. W. Klass, M. Lennox-Buchthal, I. I Petersén, Glossary of terms most commonly used by clinical electroencephalographers, Electroencephalography and Clinical Neurophysiology 37 (1974) 538–548.

[20] K. Kooi, Voltage-time characteristics of spikes and other rapid electroencephalographic transients: semantic and morphological considerations., Neurology (Minneap.) 16 (1) (1996) 59–66. doi:10.1212/wnl.16.1.59.

[21] D. O. Walter, H. F. Muller, R. M. Jell, Semiautomatic quantification of sharpness of eeg phenomenon, IEEE Trans. biomed. Engng BME 20 (1973) 53–54.

[22] B. Saltzberg, L. S. Lustick, R. G. Heath, Detection of focal depth spiking in the scalp eeg of monkeys, Electroenceph. clin. Neurophysiol 31 (1971) 327–333.

[23] F. L. da Silva], K. V. Hulten], J. Lommen, W. S. V. Leeuwen], C. V. Veen], W. Vliegenthart, Automatic detection and localization of epileptic foci, Electroencephalography and Clinical Neurophysiology 43 (1) (1977) 1 – 13. doi:https://doi.org/10.1016/0013-4694(77)90189-4.
[24] J. Gotman, P. Gloor, W. Ray, A quantitative comparison of traditional readings of the EEG and interpretation of computer-extracted features in patients with supratentorial brain lesions, Electroencephalography and clinical neurophysiology 38 (6) (1975) 623–639. doi:https://doi.org/10.1016/0013-4694(75)90163-7.

[25] G. Jean, D. R. Skuce, C. J. Thompson, P. Gloor, J. R. Ives, W. F. Ray, Clinical applications of spectral analysis and extraction of features from electroencephalograms with slow waves in adult patients, Electroenceph, clin. Neurophysio 35 (3) (1973) 225–235. doi:https://doi.org/10.1016/0013-4694(73)90233-2.

[26] A. Gevins, H. Leong, M. E. Smith, J. Le, R. Du, Mapping cognitive brain function with modern high-resolution electroencephalography, Trends in Neurosciences 18 (10) (1995) 429–436. doi:https://doi.org/10.1016/0166-2236(95)94489-R.

[27] A. Haar, Zur theorie der orthogonalen funktionensysteme, Mathematische Annalen 69 (3) (1910) 331–371.

[28] J. Lindenstrauss, L. Tzafriri, Classical banach spaces i, sequence spaces, Ergebnisse der Mathematik und ihrer Grenzgebiete, Springer-Verlag,ISBN 3-540-08072-4 (1977) 3.

[29] Z. Ciesielski, Properties of the orthonormal franklin system, Encyclopedia of Mathematics 23 (1963) 141–157. doi:http://eudml.org/doc/217068.

[30] B. Golubov, Franklin system (originator), URL : http://www.encyclopediaofmath.org/index.php?title=Franklin_system&oldid=16655.

[31] P. Franklin, A set of continuous orthogonal functions, Math. Ann 100 (1928) 522–529.

[32] K. Samiee, P. Kovacs, M. Gabbouj, Epileptic seizure classification of EEG time-series using rational discrete short-time fourier transform, IEEE Transactions on Biomedical Engineering 62 (2) (2015) 541–552. doi:10.1109/TBME.2014.2360101.

[33] B. Dasarathy, Nearest neighbor norms: Nn pattern classification techniques, IEEE Computer Society Press 100.

[34] T. Mitchell, Machine learning, McGraw-Hill.

[35] P. Ren, S. Tang, F. Fang, L. Luo, L. Xu, M. L. Bringas-Vega, D. Yao, K. M. Kendrick, P. A. Valdes-Sosa, Gait rhythm fluctuation analysis for neurodegenerative diseases by empirical mode decomposition, IEEE Transactions on Biomedical Engineering 99 (2016) 1–1.

[36] N. Chawla, K. Bowyer, L. Hall, W. Kegelmeyer, Smote: synthetic minority over-sampling technique, Journal of Artificial Intelligence Research 16 (2002) 321–357. doi:10.1613/jair.953.

[37] H. He, Y. Bai, E. Garcia, S. Li, Adasyn: Adaptive synthetic sampling approach for imbalanced learning, Proceedings of the International Joint Conference on Neural Networks (2008) 1322–1328 doi:10.1109/IJCNN.2008.4633969.
[38] V. López, A. Fernández, J. Moreno-Torres, F. Herrera, Analysis of preprocessing vs. cost-sensitive learning for imbalanced classification. open problems on intrinsic data characteristics, Expert Systems with Applications 39 (7) (2012) 6585–6608. doi:10.1016/j.eswa.2011.12.043.

[39] Z. Liu, J. Sun, Y. Zhang, P. Rolfe, Sleep staging from the eeg signal using multi-domain feature extraction, Biomedical Signal Processing and Control 30 (2016) 86–97. doi:10.1016/j.bspc.2016.06.006.

[40] Y. Paul, S. Fridli, Epileptic seizure detection using piecewise linear reduction, In: Moreno-Díaz R., Pichler F., Quesada-Arencibia A. (eds) Computer Aided Systems Theory – EUROCAST 2019. EUROCAST 2019. Lecture Notes in Computer Science, Springer 2014. doi:10.1007/978-3-030-45096-0-45.

[41] D. Jiang, Y. MA, Y. Wang, Sleep stage classification using covariance features of multi-channel physiological signals on riemannian manifolds, Computer Methods and Programs in Biomedicine 178 (2019) 186–190. doi:10.1016/j.cmpb.2019.06.008.

[42] N. Michielli, U. R. Acharya, F. Molinari, Cascaded lstm recurrent neural network for automated sleep stage classification using single-channel eeg signals, computers in biology and science 106 (3) (2019) 71–78.

[43] R. Tripathy, U. R. Acharya, Use of features from rr-time series and eeg signals for automated classification of sleep stages in deep neural network framework, Biocybernetics and Biomedical Engineering 38 (4) (2018) 890–902.

[44] T. da Silveira, A. Kozakevicius, C. Rodrigues, Single channel eeg sleep stage classification based on a streamlined set of statistical features in wavelet domain., Med Biol Eng Comput 55(2) (2017) 343–52.

[45] U. Budak, V. Bajaj, Y. Akbulut, O. Atila, A. Sengur, An effective hybrid model for eeg-based drowsiness detection, IEEE Sensors Journal 19 (17) (2019) 7624–7631. doi:10.1109/JSEN.2019.2917850.

[46] S. Taran, V. Bajaj, Drowsiness detection using adaptive hermite decomposition and extreme learning machine for electroencephalogram signals, IEEE Sensors Journal 18. doi:10.1109/JSEN.2018.2869775.

[47] M. Adnane, Z. Jiang, Z. Yan, Sleep-wake stages classification and sleep efficiency estimation using single-lead electrocardiogram, Expert Systems with Applications: An International Journal 39 (2012) 1401–1413. doi:10.1016/j.eswa.2011.08.022.

[48] S. Redmond, C. Heneghan, Electrocardiogram-based automatic sleep staging in sleep disordered breathing, Computers in cardiology. IEEE 30 (2003) 609–612.

[49] W. Hayet, S. Yacoub, Sleep-wake stages classification based on heart rate variability, Biomedical Engineering and Informatics (BMEI), 5th International Conference (2012) 996–999doi: 10.1109/BMEI.2012.6513040.

[50] H. Werteni, S. Yacoub, N. Ellouze, Classification of sleep stages based on eeg signals, International Review on Computers and Software (IRECOS) 10 (2015) 174.
[51] P. An, W. Si, S. Ding, G. Xue, Z. Yuan, A novel eeg sleep staging method for wearable devices based on amplitude-time mapping, 2019 IEEE 4th International Conference on Advanced Robotics and Mechatronics (ICARM) (2019) 124–129.

[52] J. Zhang, R. Yao, W. Ge, J. Gao, Orthogonal convolutional neural networks for automatic sleep stage classification based on single-channel eeg, Computer Methods and Programs in Biomedicine 183 (2020) 105089. doi:https://doi.org/10.1016/j.cmpb.2019.105089.
URL http://www.sciencedirect.com/science/article/pii/S0169260719311617

[53] M. Prucnal, A. Polak, Effect of feature extraction on automatic sleep stage classification by artificial neural network., Metrol Meas Syst 24(2):229–40.

[54] P. Hasan, S. O. Mehmet, Epileptic seizure detection from eeg signals by using wavelet and hilbert transform, MEMSTECH 2016 7(4).

[55] S. Motamedi-Fakhr, M. Moshrefi-Torbati, M. Hill, C. M. Hill, P. R. White, Signal processing techniques applied to human sleep eeg signals—a review, Biomedical Signal Processing and Control 10 (2014) 21 – 33. doi:https://doi.org/10.1016/j.bspc.2013.12.003.
URL http://www.sciencedirect.com/science/article/pii/S174680941300178X
| 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 (S3), 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), 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(%) | Falsealarmrate/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(%) | Falsealarmrate/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       | 0.0202           |
| 03            | 96.78          | 98.59          | 94.11       | 0.0142           |
| 04            | 94.25          | 97.40          | 90.59       | 0.0262           |
| 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       | 0.0262           |
| 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**        |