DOI: 10.15476/ELTE.2021.14

Eötvös Loránd University

Faculty of Informatics

Department of numerical analysis

Epileptic Seizures and Sleep States Detection Using Hybrid Approaches

PhD Dissertation

Supervisor:
Sándor Fridli
Dsc, Professor

Author:
Yash Paul

Budapest, Hungary , (2021)

Declarations

As the author of the doctoral dissertation, I agree to public disclosure of my doctoral dissertation after obtaining a doctoral degree in the storage of ELTE Digital Institutional Repository. I authorize Adina Kulcsar, the administrator of the ELTE Doctoral School of Informatics to upload the dissertation and the abstract to ELTE Digital Institutional Repository, and I authorize the administrator to fill all the declarations that are required in this procedure. I request in case the doctoral dissertation contains qualified data pertaining to national security, to disclose the doctoral dissertation publicly to the University Library and the ELTE Digital Institutional Repository ensuing the lapse of the period of the qualification process. I request to defer public disclosure to the University Library and the ELTE Digital Institutional Repository, in case there is a publishing contract concluded during the doctoral procedure or up until the award of the degree. However, the bibliographical data of the work shall be accessible to the public. If the publication of the doctoral dissertation will not be carried out within a year from the award of the degree subject to the publishing contract, I agree to the public disclosure of the doctoral dissertation and abstract to the University Library and the ELTE Digital Institutional Repository. As the author of the doctoral dissertation, I declare that the doctoral dissertation and abstract uploaded to the ELTE Digital Institutional Repository are entirely the result of my own intellectual work and as far as I know, I did not infringe anyone's intellectual property rights. The printed version of the doctoral dissertation and the abstract are identical with the doctoral dissertation files (texts and diagrams) submitted on electronic device. As the author of the doctoral dissertation, I agree to the inspection of the dissertation and the abstract by uploading them to a plagiarism checker software.

Signature of dissertation author

Contents

Chapter 1

Introduction

In this Chapter, we will give brief introduction of various techniques and terminologies used in our proposed methods. In the PhD duration, we did work on two important problems in biomedical signal processing namely, epileptic seizure detection and sleep states detection. In the proposed algorithms, both the problems are solved by using novel hybrid approaches. In the hybrid approaches the features are extracted from time and frequency domains. Final feature vectors are classified with different classifiers. We found that our proposed algorithms are performing better in terms sensitivity, specificity false alarm rate and Cohen's kappa coefficient as compared to the state of the art algorithms. The organization of the thesis is as follows. Thesis comprises of five Chapters. Chapter 1, is about the introduction of various biomedical signals, epilepsy, sleep states, piecewise linear functions and metrics used. Chapter 2, is about detection of seizures using EEG signals. Chapter 3 and 4 are about sleep states detection by combining different biomedical signals. Chapter 5, gives the summary about the thesis.

1.1 Epilepsy

Epilepsy is a chronic chaos of the central nervous system that influences individual's daily life by putting it at risk due to repeated seizures. Epilepsy affects more than 2% people worldwide of which developing countries like India, China, Brazil etc. are affected worse. A seizure is a transient irregularity in the brain's electrical activity that produces disturbing physical symptoms such as a lapse in attention and

memory, a sensory illusion, etc. Approximately one out of every three patients have frequent seizures, despite treatment with multiple anti-epileptic drugs. According to a survey, population aged 65 or above in European Union is predicted to rise from 16.4% (2004) to 29.9% (2050) and also this tremendous increase in aged population is also predicted for other countries by 2050. Anybody can be the victim of epilepsy. Epilepsy influences the two males and females, irrespective of their ages. Seizure side effects can change broadly. A few group with epilepsy basically gaze blankly for a couple of moments during a seizure, while others more than once jerk their arms or legs. Having a solitary seizure doesn't mean you have epilepsy. Treatment with drugs or here and there medical procedure can handle seizures for most of individuals with epilepsy. A few group require deep rooted treatment to control seizures, yet for other people, the seizures at last disappear. Few kids with epilepsy may grow out of the condition with age. The symptoms of the epilepsy are: confusion in mind (sometimes), a gazing spell, uncontrollable developments of the arms and legs, loss of cognizance or mindfulness, psychic manifestations like dread, uneasiness. An individual with epilepsy will in general have a similar sort of seizure each time, so the side effects will be comparative. Experts generally classify seizures as either focal or generalized, based on how the abnormal brain activity begins. At the point when seizures seem to result from strange action in only one area of your brain, they are called central focal seizures. These seizures fall into two classifications: focal seizures without loss of awareness. called basic simple partial seizures, these seizures don't cause a deficiency of awareness. They may adjust feelings or change the manner in which things look, smell, feel, taste or sound. They may likewise bring about compulsory jolting of a body part, like an arm or leg, and unconstrained tangible indications like shivering, dazedness and blazing lights. Focal seizures with impaired awareness. called complex partial seizures, these seizures include a change or loss of cognizance or mindfulness. During an intricate incomplete seizure, you may gaze into space and not react ordinarily to your current circumstance or perform tedious developments, for example, hand scouring, biting, gulping or strolling around and around. Seizures that seem to include all regions of the brain are called generalized seizures. Six kinds of generalized seizures exist.

Absence seizures.: recently known as petitmal seizures, frequently happen in

youngsters and are portrayed by gazing into space or inconspicuous body developments, for example, eye flickering or lip smacking. These seizures may happen in groups and cause a short loss of mindfulness. Tonic seizures: Tonic seizures cause solidifying of your muscles. These seizures for the most part influence muscles in your back, arms and legs and may make you tumble to the ground. Atonic seizures: Atonic seizures, otherwise called drop seizures, cause a deficiency of muscle control, which may make you unexpectedly breakdown or tumble down. Clonic seizures: Clonic seizures are related with rehashed or musical, snapping muscle developments. These seizures typically influence the neck, face and arms. Myoclonic seizures: Myoclonic seizures typically show up as unexpected brief jerks or jerks of your arms and legs. Tonic-clonic seizures: Tonic-clonic seizures, recently known as grand mal seizures, are the most emotional kind of epileptic seizure and can cause a sudden loss of awareness, body hardening and shaking, and at times loss of bladder control or staying quiet. In seizure signal, four states are identified, namely pre-ictal, ictal, inter-ictal and post-ictal. The portions of the signal before the first seizure and after the last are called pre-ictal and post-ictal. Ictal and inter-ictal indicate intervals of seizures and between seizures. When a seizure occurs, it might cause injuries or jeopardize the life of the patients especially when they are driving cars or working with different machinery. That is why there is a need to develop an automatic seizure detector to avoid different types of harms to epileptic patients. Most of the research work is carried out by using scalp EEG, because capturing the signal from the surface of the brain (iEEG) is quite risky and require lots of expertise in it.

1.2 Sleep Stages and Disorders

Sleep is fundamental and plays an important role to keep human healthy. In the recent years sleep-related issues are increasing day by day and lot of many people who are suffered from sleep disorder are also affected by their normal day-to-day life. Sleep disorders can be the indicator of a future disease e.g. depression. That is why sleep assessment now a days is an important part of any health checkup. Across the globe many health care systems set up the mechanisms to prevent and detect sleep disorders by offering specific plans in terms of education and awareness of good sleep

habits. Some traditional and new methods are available for sleep disorder detection, but such methods still have some shortcomings like accuracy and require more time for scoring of the entire sleep duration of the given biomedical signal. These methods are still dependent on experts of the sleep scoring to verify their results. Therefore, the limitations of manual sleep stage scoring stated the demand for developing an efficient and automatic sleep stage scoring method to improve sleep stage detection and classification accuracy. Two standards for scoring namely R&K and AASM are available for sleep stage scoring. As per R&K rule [1], analysis of the EEG signal is carried out by dividing each signal into periods of 30s small parts known as segments. Sleep stages identification process extract features from each 30 sec segment. Since last decade many sleep assessment techniques have been proposed with the new technologies such as mobile apps and novel advanced hardware sensors such as galvanic skin response measures. Simple methods can be used only to categories awake or sleep states but we need complex methods to distinguish all the sleep stages. A sleep detection method categories the sleep states of a patient. Most of the sleep detection methods e.g. wrist actigraphy or mobile apps used a binary function to classify Awake/Sleep states. Another sophisticated methods can be considered as a ternary function to classify$Awake/NREM/REM$. At last, the most advanced and powerful methods, such as polysomnography quinquenary function considered as the gold standard for more states like: $Awake/N1/N2/N3/REM$ [2]. Large number of methods are applied for sleep state detection and each one has one significant advantages and disadvantages. The obvious and common disadvantage of these methods is that they used advance technology like electroencephalograms, electrocardiograms, etc which cannot be used at home. On the other hand the merit is that these methods are extremely precise, and can be discrete which are able to differentiate different sleep phases. That is why these mentioned in the literature survey can be considered as the gold standard for sleep evaluation e.g. [3], [4] and many more. The term polysomnogram comes with poly (Greek) means many, somnus (Latun) which means sleep, and the gramma (Greek) which means drawing or diagram. A PSG (Robertson, Marshall & Carno, 2014; Pandi-Perumal, Spence & BaHammam, 2014; Armon et al., 2016) is a medical procedure comprises of various independent tests that look into the body functions while sleeping. The following tests and in-

formation can be collected while performing tests: Electroencephalogram (EEG), which measures and records the brainwave action to recognize sleep states and identify seizure action. Electrooculogram (EOG), records eye developments or activities, are significant for recognizing the diverse sleep stages, particularly the REM stage. Electromyogram (EMG), records muscle activity and is important necessary to distinguish REM from wakefulness. Electrocardiogram (ECG, used to records the heart rate and rhythm. Nasal and oral airflow sensor, used to records the airflow and the breathing rate. Blood pressure monitor, measures the blood pressure and its variations [2]. Sleep is a significant part of person's life and individuals used to sleep one-third of their entire life. Our research is motivated by the fact that there are large number of disorders like insomnia, breathing disorders, wake-sleep disorder sleep movement disorder found in human beings. Every sleep state has different group of neurological and physiological features. The correct identification of these features along with their states are important for diagnosis and the better treatment for such sleep disorders [5]. 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. Around 24% of the adult population have regular sleep disorders. Ohayon and Smirne [6] shown 27.6% of the Italian population have sleep problem. Gupta et al. [7] shown Indian population have 10-15% insomnia and 10% delayed sleep wave phase disorder. This problem is increasing worldwide day by day and according to Oliver et al. this problem costs around $100 billion USD per year. Following R&K rules sleep is categorized into six categories, REM, sleep stage1, stage2, stage3, stage4 and wake state. Later on NRME2 and NRME3 are also combined resulted as just four main classes namely light sleep, Deep sleep, REM and Awake state. For accurate diagnosis of sleep phases, an expert manual scoring for sleep stages using some standards is needed for the whole duration recordings of the selected biomedical signals. Manual scoring is time consuming, its availability is limited, therefore there is a need for automatic sleep phase detection to reduce cost and to increase access to diagnosis sleep stages. For instance in case of EEG (electroencephalograph) signals six 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 The main challenge to automatic sleep phase detection is heterogeneity. This means that individuals have different cranial structures which effect the patterns in the signal. For example 10 percent of the population don't produce alpha rhythm during stage W (wake) and 10 percent create just a constrained or limited alpha beat. This justifies the combination of EEG with other biomedical signals in order to improve the results.

1.3 Piecewise Linear Functions

A function is known as piecewise linear function if it is continuous and defined on a (possibly unbounded) interval of real numbers, such that there is a collection of intervals on each of which the function is an affine function. If the domain of the function is compact, there needs to be a finite collection of such intervals.

Figure 1.1: A continuous piecewise linear function

A piecewise linear function with four pieces or segments is shown in Figure 1.1.

$$\text{Example: } f(x) = \begin{cases} -x-3 & \text{if } x \leq -3 \\ x+3 & \text{if } -3 < x < 0 \\ -2x+3 & \text{if } 0 \leq x < 3 \\ 0.5x-4.5 & \text{if } x \geq 3 \end{cases}$$

In proposed methods we used two piecewise linear function reduction techniques for the signals. One in the time and other one in the frequency domain explained in coming sections. The reason for developing two piecewise liner models in different domains is to make the signal processing fast and accurate. Models make the signal simple and short by discarding the irrelevant information (not predominant peaks)

but retain important seizure and sleep properties in the original signal. 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. The nature of the seizure segments is that, usually they have high spikes rate and high amplitude which gives rise to high peaks in the signal [8], [9], [10].

1.4 Half-wave as Piecewise Linear Function

Traditionally, from mid of 20th century to end of 20th century, Half-wave was very popular method to detect epileptic activities (seizures) form the long EEG signals where the terms spikes and sharp waves also called SSWs [9] shown in following Figures 1.2, 1.3, 1.4 and 1.5 are the representative or interpretations of seizure and non seizure portions. Different methods by using Half-wave have been proposed to detect seizure and some of them are reviewed in coming sections. 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 epileptic activity is found at that instance. But traditional methods based on spikes and sharps were not reliable and therefore, Jasper and Kershman [11] divided focal epileptic activity into spikes i.e. 10 to 50 ms and sharp waves i.e. 50 to 500 ms. In 2005 Runarsson et al. [12] first time used Half-wave method in machine learning and in our proposed algorithm we used the Half-wave method proposed by Runarsson et al with certain modifications. Half-wave method works as, first find the local minima and maxima over the entire signal and then draw an edge between each extrema. Therefore, the original signal is converted into piecewise or segment wise wave where each segment is an edge between two consecutive extrema. Segments are alternate in direction i.e. if one segment is in upward direction (minima-maxima) next alternate segment will be downward in direction (maxima-minima) shown in Figure 1.3.

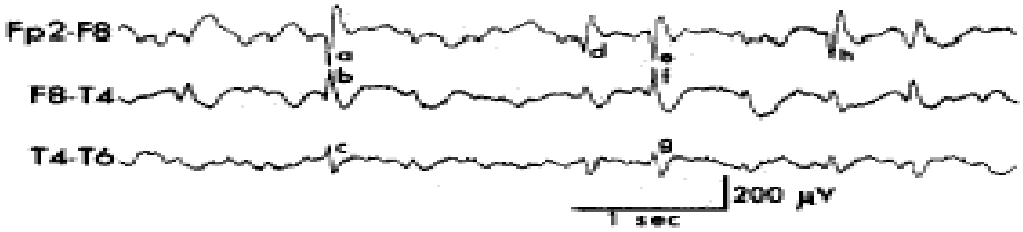

Figure 1.2: The letters a to h mark the SSWs detected by the system. Phase reversals at electrode F8 are detected by coincidence in time for a–b and e–f, by computation of the cross-correlation for d and h (since no SSW was found in channel F8–T4 at the time of d or h) [12].

In The existing methods [12] the following conditions are necessary criteria to add or reject the segment or sequence into the final wave and these conditions are given below:

1. A sequence of direction X (up or down) includes a segment S in the direction X, if the segment is larger (in duration) than either of two segments immediately adjacent to S.

2. A sequence of direction X may not include a segment S in the direction of X if the duration of the segment is equal to or greater than the 30 ms.

3. A sequence of direction X may not include a segment S in the direction of X if the relative amplitude of the segment is equal to 2 or greater than 2.

this method ensure and focused that a sequence of any direction is bound to add the segments having small duration i.e having relative amplitude less than 2 and duration is less than 30 ms.

Relative amplitude: Relative amplitude is associated with two terms i.e. Background activity and Background amplitude. The background activity is defined as EEG activity which contains normal and abnormal patterns and these patterns are differentiable from each other i.e. a spike or sharp wave is clearly distinguish from background activity. On the another hand, background amplitude is defined at every instant and is the mean amplitude of a sequence from the 5 sec directly proceeding that instant. Example, Let N and A be the number and sum of amplitudes (extrema points) sequences in an interval of 320 ms long Half-wave. The background

amplitude is calculated by $A/(N+6)$, here a constant 6 achieves the desired bias and the value of N is usually between 1 to 15. If there are 15 sequences then there are 16 extrema or amplitude points. For 5 sec long signal there are approximately 16 segments or duration of 320 ms, which means 16 numbers (extrema points) from 16 consecutive 230 ms long duration are truly averaged. Because of the addition of constant 6 while calculating the background amplitude, the background amplitude is 25 percent smaller than the actual value if the activity is mostly fast and is 50 or 75 percent less if the activity is mostly delta or theta. The problem with the background amplitude is that for each and every instant it needs to be updated which is not simple and requires lot of memory for its updation and therefore, it usually get updated after 1/3 second [8], [9], [10].

Relative amplitude of a segment or sequence is the ratio of its absolute amplitude to background amplitude and it is an integer value between 0 to 20.

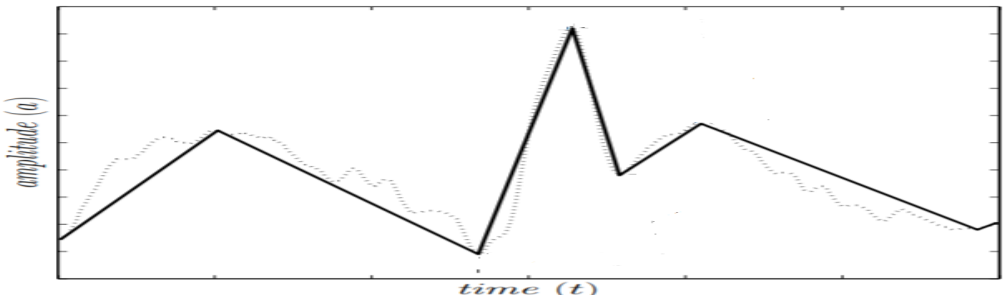

Figure 1.3: The original EEG (dotted) broken down into Half-waves (solid) [12]

In our research we modified this Half-wave method and instead of using 3 above mentioned principles we used only one guiding principle. New Half-wave method is iterative in nature and can be stopped after the desired reduction is achieved. The detailed explanation about new Half-wave is given in Chapter 2 and 3.

1.5 Franklin System

The classical Franklin system, introduced by Ph. Franklin [11] in 1928, is a complete orthonormal system of continuous, piecewise linear functions with dyadic knots. The idea of its construction is originated from the Haar system. The Haar system which later turned to be the simplest model for wavelets is a sequence of rescaled square shaped functions [13]. Although the Haar functions are not continuous

and so not differentiable the Haar system enjoys many nice properties which make this system a very special one from both theoretical and practical aspects.

The Haar function $\psi_{2^n+k} = \psi_{n,k}$ $(n, k \in \mathbb{N},\ k = 0, \ldots, 2^n - 1)$ is defined as follows

$$\psi_0 = \begin{cases} 1, & \text{if } t \in [0, 1/2) \\ -1, & \text{if } t \in [1/2, 1) \end{cases},$$

$$\psi_{2^n+k}(t) = \psi_{n,k}(t) = \begin{cases} 2^{n/2}, & \text{if } t \in [k2^{-n}, (2k+1)2^{-(n+1)}) \\ -2^{n/2}, & \text{if } t \in [(2k+1)2^{-(n+1)}, (k+1)2^{-n}) \\ 0, & \text{otherwise} \end{cases}.$$

The Haar system $(\psi_{n,k} : n, k \in \mathbb{N})$ is a complete orthonormal basis in $L^2[0, 1)$. Moreover the Haar series of continuous functions converge to the function at every point, which failed to hold to any orthogonal system constructed prior to the Haar system in 1910. On the other hand the element of the system are in the space of continuous function.

In order to construct a basis within the space of continuous function Faber [14] ([15]) considered the system of indefinite integrals of the Haar system supplemented by the function that is identically equal to one. In the general case, the construction was carried out by J. Schauder. The elements of the so called Faber-Schauder system are defined as follows

$$s_0 \equiv 1\ , \quad s_n(t) = \int_0^t \psi_{n-1}(u)du \quad (t \in [0, 1], n \in \mathbb{N},\ 0 \leq k < 2^n).$$

We note that the definition of the Faber–Schauder functions may differ according to the normalization applied. Historically, the Faber–Schauder system was the first example of a basis of the space of continuous functions. These functions s_n are continuous, piecewise linear and supported on the same interval that also supports ψ_{n-1}.

The Faber–Schauder system is a basis in $C[0, 1)]$, but the elements are not orthogonal to each other. An orthogonal basis is derived from the Faber–Schauder system by applying Gram-Schmidt orthogonal procedure. The resulting system is called Franklin system [17], [18], [19]. Clearly, the Franklin system has the same linear span as that of Faber Schauder systems and this span is dense in C([0,1]).

1.6 Metrics Used

The performance of the most of the techniques in different domains is measured by following quantities and the same metrics are used in our proposed methods:

1.6.1 Binary Classification Problem

When there are only two classes to identify e.g. in seizure detection case, the following metrics are used:

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

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

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

TP, means true positive, is the number of epochs which are marked as seizure by both algorithm and doctor.

TN, true negative, is the number of epochs which are marked as non seizure by both algorithm and doctor.

FN, false negative, the number of seizure epochs which are misclassified by the algorithm, i.e. recognized as non seizure but actually they are seizures.

FP, false positive, the number of non seizures epochs which are misclassified by the algorithm, i.e. recognized as seizure but actually they are non seizures.

The performance of the seizure detection algorithm primarily depends on following parameters:

Transformation technique, feature selection, classifier used, window size, type of window or mother wavelet, the levels of decomposition of the original signal and optimization algorithm, etc. The literature survey will also help the readers to become familiar with different types of public and non-public epilepsy databases.

1.6.2 Multi-Class Problem

For multi-class problem, the performance evaluation is achieved by following metrics.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \quad \text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\,,$$
$$\text{Average Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TN} + \text{FP} + \text{TP} + \text{FN}} \times 100\,.$$

TP, stands for true positives which is the sum of the diagonal values of confusion matrix. TN, i.e. true negative is the sum of all rows and columns excluding that class's rows and column. FN, false negative is the sum of the values in corresponding rows excluding TP's. FP, is the sum of values in corresponding columns excluding TP's. TP+FN, total numbers of test examples of the considered class. Therefore in case of multi-class problem TN, FN, TP, FP, FN here are the overall values for all classes. The "False alarms per hour" (Fph) is the ratio of total number of false detection and the time length of the test data in hour. For more details please follow the link (https://towardsdatascience.com/confusion-matrix).

Chapter 2

Epileptic seizure detection using piecewise linear reductions

2.1 Abstract

This Chapter is based on our paper published in Lecture Notes in Computer Science (LNCS,Q2) Springer [20], where we proposed a hybrid approach to detect seizure segments in a given EEG signal. In our model the discrete EEG signal is naturally associated with a piecewise linear function. We apply two data reduction techniques within the model space, a new Half-wave method in the time domain, and orthogonal projection with the Franklin system in frequency domain. The later one is a complete orthogonal system of piecewise continuous functions. As a result we obtain two reduced piecewise linear functions with low complexity that still preserve the main characteristics of the seizures in the signals. Then the components of the feature vector are generated from the parameters of the two reduced functions. Our choice for the model space, i.e. the space of piecewise continuous functions, is justified by its simplicity on the one hand, and flexibility on the other hand. Accordingly the proposed algorithm is computationally fast and efficient. The algorithm is tested on 23 different subjects having more than 100 hours long term EEG in the CHB-MIT database in several respects. It showed better performance compared to the state of the art methods for seizure detection tested on the given database.

keywords: epilepsy, seizure detection, signal modeling, Half-wave method, Franklin system.

Before doing the actual research, we wrote a survey paper namely "Various epileptic seizure detection techniques using biomedical signals: A review" [21], published in Brain Informatics,(Q2), Springer, where a thorough study of various existing methods and results has done.

2.2 Problem Statement and Motivation

We propose a hybrid approach to detect seizure segments in a given EEG signal. There are a number of algorithms proposed to detect seizures and the majority of the algorithms is based on *multichannels*. The problem with the multichannel algorithms is that they require a huge amount of data to process in order to get good results. It slows down the speed of the method. Such algorithms are not accepted in small devices and in real time applications where response is expected in very short time with high accuracy. On the other hand state of the art single channel methods are fast but they are not as reliable and accurate as multichannel methods. We propose a single channel approach to detect seizures in a given EEG signal. Our method is a so called hybrid method, i.e. a combination of a time domain and a frequency domain method.

2.3 Introduction and Background

Epilepsy is a neurological disorder which creates severe effects to human brain. According to the latest study, more than 2% of the population worldwide is affected from epilepsy where 85% of those live in developing countries and has adverse effects on their daily life and productivity. Each year 2.4 million new cases are estimated to occur globally [22], [23]. EEG signals are usually used by experts for the diagnosis of the epilepsy. EEG signals are classified into two types: (a) scalp EEG and (b) intracranial EEG (iEEG). Scalp EEG is captured by placing the electrodes on the surface of scalp by using international standard 10–20 system [24]. iEEG signals are captured by placing the electrodes directly on the surface of brain to record the brain activity from the cerebral cortex. Detecting and locating the seizure period in EEG recordings manually is difficult and time-consuming because EEG recordings

are usually tens or even hundreds of hours long. According to [25], [26], the seizure detection process is classified as single-channel or multichannel process. In single-channel process, a channel or signal which is strong and close to the seizure origin is selected based on some measures like local variance. Combining the information from more than one channel through some data fusion techniques [27] gives better results in seizure detection process. Another attempt to classify seizure detection as linear and nonlinear techniques is made in [28], [29], [30]. Tzallas et al.[31] classified seizure detection methods as pattern recognition methods, morphological analysis methods, parametric methods, decomposition methods, clustering methods and data mining methods. Alotaiby et al. [32] classified seizure detection methods based on time, frequency wavelet and empirical mode decomposition (EMD) domains. Because of the application of various transforms like discrete Fourier transform (DFT), discrete wavelet transform (DWT), Hilbert transform, Gabor transform, rational transform, etc., decomposition techniques like empirical mode decomposition, singular value decomposition, etc., and data reduction techniques like principal component analysis (PCA) and independent component analysis (ICA) have played an important role in seizure detection. In the literature survey the state of the art methods are discussed under time domain, frequency (DFT) domain, wavelet domain (time–frequency), empirical mode decomposition (EMD) and rational transform functions. Most of the techniques discussed here are noninvasive. we also summarize some papers which adopted other biomedical signals like electrocardiogram (ECG), electrocorticography (ECoG), etc., or combination of different signals for seizure detection. We focused on scalp EEG databases-based techniques and methodologies.

Time Domain or Threshold-based Methods

Time domain refers to how the value of the signals varies over time, in other words time parameter is the independent variable of the signal. Time domain methods are usually patient-specific or problem-specific and do discrete time analysis, and do analysis of the given epochs (time window). Thus, this is value-time analysis of a given signal x(t). The main objective here is to demonstrate the various approaches, interconnection among approaches and different possibilities in time domain so that we can further do improvement in seizure detection devices. To this end, we selected seven different latest papers with different ideas. The selected papers have

high accuracy, sensitivity, specificity and low false detection rate. It may be beneficial to the researchers who are interested to develop seizure detection devices with high speed and more accuracies. The performance in terms of accuracy, sensitivity, specificity and false detection rate of below mentioned algorithms depends mainly on core ideas, selection of the features and classifiers being used. Since these methods do not require transformations and are generally fast and are used in seizure detection devices like smart watch, tablets, etc., proposed algorithms are tested on CHB-MIT, Bonn database [33] and self-recorded data, whereas last two papers are purely hardware based.

Shanir and Khan [34], proposed method for automatic seizure detection based on mean and minimum value of energy per epoch, i.e. mean of the energy of each sample point in a epoch and sample point having minimum energy in a epoch are used as features for classification. The window size was chosen as 1 s. The classifier used here is linear classifier. The algorithm was tested on CHB-MIT database on three subjects with 60 and 40% of data used as training and test data, respectively. They obtained an average detection accuracy of 99.81%, sensitivity 100%, and specificity 99.81%. Alotaiby et al. [35], they proposed patient-specific method for channel selection and seizure detection by estimating the histograms of multichannel scalp EEG signals.The method is tested on CHB-MIT dataset using 309.9 h of EEG including 26 seizures of five patients. They have shown an average sensitivity and specificity off 97.14% of 98.58%, respectively.

Runarsson and Sigurdsson [12], the idea behind this paper is: first, find the Galf-wave form of the EEG epoch at hand and then find the consecutive peaks and minima in that Half-wave signal segment. The histograms are estimated for two variables: the amplitude difference (Δ, Y-axis) and time separation (τ, X-axis) between two consecutive peak values as well as minima. Here we have two histograms one for minima and other for maxima. The features used for classification of an epoch as a seizure or non-seizure are these estimated values like Δ and τ from local minima and maxima. Actual features used are the frequencies of co- occurrences of τ and Δ and each feature is generated from 8 s long signal with 2 s overlap 12 h self-recorded data using 10 EEG channels with 256 sampling. Support vector machines (SVMs) with chunking method are used as classifiers. An average sensitivity of about 90%

is achieved. Problem with this method is that actual processing of the signal like extraction of the features starts only after finding the Half-wave representation of the original signal. Once the Half-wave is in hand this could be very fast algorithm in time domain applications with large amount of dataset and can be used as on-line seizure detection method. In [36] the researchers designed the seizure detector (hardware) and implemented the algorithm (software) in the designed processor. In [37] they have developed a improved network of seizure detection devices.

Mursalin et al. [38], present a hybrid approach where features from time and frequency domains are analysed to detect epileptic seizure from EEG signal. Time domain features like mean, median, mode, minimum, maximum, skewness, standard deviation, kurtosis, first quartile (Q1), third quartile (Q3) and interquartile range (Qir), mobility and complexity, Hurst exponent and the detrended fluctuation analysis with frequency domain features like maximum of the wavelet coefficients, minimum of the wavelet coefficients, mean of the wavelet coefficients, standard deviation of the wavelet coefficient. Alejandro and Ramon-Lozano [39], in this paper, authors used energy of the signal in a different way. They used smaller window as the foreground windows and larger window as the background while windowing the signal. Energy is calculated in every foreground and background window, and the energy ratio is calculated by dividing the foreground energy by the corresponding background window energy resulting a series of energy ratios and can be treated as a time series distribution where some values are more higher than average or threshold values are part of seizure. The algorithm is tested on CHB-MIT database and found that the number of false positives is very small, and it is 0.39 per 24 h in average, which less than most state-of-the-art methods.

Yoo et al. [36], they designed a multichannel-based processor called system on chip (SoC) for detecting the seizure, and energy of the signal is used as features. They used SVM as classifier and is trained to detect rapid-eye blink patterns as this is similar to the generalized seizure and has more energy as compared to non-seizure patterns. The SoC was tested on CHB-MIT scalp EEG database [40] and it showed an accuracy of 84.4% with a total time of 2 s and 2.03 μJ/classification energy. The advantage of this processor as compared to IAS processor is that it enlarges the EDO filtering range 4 times better and consuming the same power of 2.5 μW.

Frequency Domain

Time domain method does the analysis of the signal based only the time and magnitude components of signal [magnitude (Y-axis), time (X-axis)], and there is no information about frequency component of the signal. But if we want the deep analyses of the signal then frequency component is also required. Frequency domain tells about the frequency spectrum [magnitude (Y-axis), frequency (X-axis)] of the signal. The advantage of the transformation of signal from one domain to another domain is that it provides insight and points out the important properties of the signals which cannot be seen by visual inspection of the original signal and or hidden signal in time domain. Bhople et al.[20], authors proposed epileptic seizure detection method by using fast Fourier transform (FFT). The FFT-based features are extracted and are fed to the neural networks. They used multi-layer perceptron (MLP) and generalized feed-forward neural network (GFFNN) as a classifier. The algorithm is tested on Bonn database, and results show they are able to achieve 100% accuracy.

Hills [21], the author participated in a competition "UPenn and Mayo Clinic's Seizure Detection Challenge" and he used fast Fourier transform (FFT) to each one second long window and taking magnitude in the range 1–47 Hz and leaving phase information. Then correlation coefficients and eigenvalues are computed in both frequency and time domains and added to the FFT data to form the feature vector; these features are classified using random forest classifier with 3000 trees.

Rana et al. [19], they proposed a multichannel algorithm for seizure detection, and their algorithm is based on phase slope index (PSI). The performance of the algorithm is tested on 258-h-long recorded EEG data of five patients with different types of epilepsy. ECoG data of five patients ranges from 41 to 63-h-long and have 5–15 seizures in each case. A unique strength of this paper is that it is designed and evaluated on long-term recordings. They also showed that their algorithm can be used to find the channels among various channels having strong activity.

Khamis et al. [40], it is a single channel, patient-specific and with no threshold parameter method of seizure detection. Frequency domain features like frequency moment signatures are used to distinguish a seizure segment from non-seizure. A sensitivity of 91% and false alarm rate of 0.02 false positives per hour is achieved

as per this method. Acharya et al. [41], they designed a method for the detection of three states of EEG signal, i.e. normal, pre-ictal, and ictal conditions from recorded EEG signals. They combine the features from two domains, i.e. time domain and frequency domain and found that this combined features method is performing good in situations when signal has nonlinear and non-stationary nature. Four entropies (measure of randomness), phase entropy 1 (S1), phase entropy 2 (S2), approximate entropy (ApEn), and sample entropy (SampEn) are used as features. Results showed that Fuzzy classifiers are optimal, with an accuracy of 98.1%.

Observations: Frequency domain methods are good choices when recorded data is large, i.e. for long-term data but time component of the signal is missing here. On the other hand, combination of features from different domains may produce very promising results.

Wavelet Domain (Time–Frequency)

A wavelet can be defined as a waveform with certain properties: (a) effectively limited duration and (b) zero average value.

Here basis functions are wavelets called mother wavelets, e.g. Har, Daubechies, etc. The mother wavelet is a reference wavelet, whose coefficients are evaluated for the entire range of dilation and translation factors [42]. Next six papers investigate the appropriate decomposition levels of the signal for efficient seizure detection, and last paper is hardware based. Different classifiers are discussed in all ten papers.

Polat et al.[43], proposed a new method for seizure detection by using Wavelet and Hilbert transforms. The features like mean, maximum, minimum, standard deviation and average power of absolute values of wavelet and Hilbert transform coefficients are extracted separately. The decomposition level 2 was chosen because dynamics of EEG signals contain important sub-bands. Daubechies wavelet of order 4 (db4) is chosen as mother wavelet. The K-Nearest Neighbourhood (KNN) classifier is applied separately on these extracted features. The performance is tested on Bonn database [44], and they found that the results obtained by using Hilbert transform are quite promising. Accuracy: for wavelet case, 100 and 96% for the A–E and B–E datasets, and for Hilbert case, 100 and 100% for the A–E and B–E datasets, respectively. Zainuddin et al. [45], in this paper, the authors first take the wavelet transform of EEG signals to generate a set of coefficients, and then, maximum, min-

imum, and standard deviation of the absolute values of the wavelet coefficients in each sub-band are extracted as features. The extracted features are then classified by WNNs (Wavelet Neural Networks) classifier. Niknazar et al. [46], they used recurrence quantification analysis (RQA) a well-known and well-suited analysis technique for nonlinear data on recorded EEG, and their alpha, beta, delta, theta, and gamma sub-bands are extracted by a four-level Daubechies wavelet transform. The signal is decomposed into five levels. After extracting the features, an error-correcting output coding (ECOG) classifier is used on Bonn database to classify the three states like normal or healthy, inter-ictal, and ictal. They achieved an accuracy of 98.67%.

Zhou et al.[47], this paper used lacunarity and fluctuation index as features, and Bayesian Linear Discriminant Analysis (BLDA) is used as classifier.

The performance of this algorithm is evaluated and investigated on Freiburg EEG database [48], and it is found a sensitivity and false detection rate of 96.25% and 0.13/h, respectively.

Guangyi et al. [49], in this paper, they decompose the EEG signals up to six wavelet scales without down-sampling. Scales 3, 4, 5, and 6 are chosen for further processing. The fast Fourier transform on selected scales has been performed, and magnitude of the Fourier coefficients is chosen as features for seizure detection. Nearest neighbor classifier is used to classify the input EEG signal into the seizure and non-seizure class. The performance of the proposed algorithm is tested on Bonn database and perfect correct classification rates achieved (100%) for all seven binary classification problems, and it is better than existing methods like [43], [45] in terms of classification rate.

Liu et al. [50], it is also a five-level decomposition technique. Three wavelet sub-bands are selected for feature extraction and feature selection. The feature used is relative amplitude, relative energy, coefficient of variation, and fluctuation index from the selected three levels. The results are tested on 509 h for 21 epilepsy patients, and they found sensitivity, specificity and false detection rate of 94.46, 95.26%, and 0.58/h, respectively. This algorithm is robust as compared to above-mentioned techniques because algorithm is performing exceptionally well on long-range data.

Abbasi and Esmaeilpour [51], the objective of this paper was improving the precision of prediction and classifying different states of EEG signals into healthy,

convulsive, and epileptic states. In this approach, they divide the signal into 5 levels. For further processing, they chose first 4 levels and last, i.e. 5th low-frequency level is rejected. Features like maximum, minimum, average and standard deviation for each sub-band are extracted. A Multi-Layer Perceptron (MLP) neural network was used as classifier. The confusion matrix was used to calculate the performance, and the algorithm tested on Bonn database achieved an accuracy, sensitivity and specificity of 98.33, 100, and 97.1%, respectively. Mother wavelet used here is Daubechies-4.

Panda et al. [52], it is also a five-level decomposition technique for features extraction. The extracted features are energy, standard deviation, and entropy. Reference wavelet used here is Daubechies (db-2), and SVM is used as a classifier. They compared the results of individual features and found energy feature has highest accuracy of 91.2%. The algorithm is tested by detecting the seizure activity on 500 epochs of EEG data (100 epochs from each activity) from five different brain activities like eye close, eye open, seizure, hippocampal region, and opposite of epileptogenic zone.

Khan et al.[53], authors use the same technique as Panda et al. [52], but choose different set of features like relative energy and a Normalized Coefficient Of Variation (NCOV). It works on wavelet coefficients acquired in the frequency range of 0–32 Hz. The algorithm is tested on five patients from CHB-MIT scalp EEG database and they found the performance of NCOV over the traditionally used COV is better. Reference wavelet used here is Daubechies (db-4), and they achieved an overall accuracy, sensitivity, specificity, and precession of 83.6, 100, 91.8, and 86.7% respectively. Shoaib et al. [54], they develop a processor for seizure detection that directly uses compressively sensed electroencephalograms for embedded signal analysis. Their main aim to present this method is that it saves energy of the processor through compressive sensing. The wavelet energy is used as features. By analyzing the compressed signals directly, it avoids reconstruction costs, computational energy of signal analysis due to the reduced number of signal samples. Their results showed that, because of compressive sensing there is 4% decline in sensitivity, 0.15 per hour increase in false alarm rate, and a latency of 1 s as compared to baseline performance. The results were tested on CHB-MIT database with SVM as classifier. For linear SVMs, the total processor energy lies in the range of 0.3–2.2 μJ, for nonlinear support vector machines energy lies in the range of 12.6 to 38.5 μJ by

using fourth-order polynomial kernel, and 18.1 to 53.3 μJ for SVMs with an RBF kernel. After every 2 s, classification results are produced, and for all SVMs kernels the total processor power appears in the range 0.6–107 W.

Observations: Applications of wavelets in signal processing tremendously increased the accuracy in signal processing techniques. We can conclude that decomposition level up to 5 is sufficient for seizure detection. It is difficult to recommend a particular classifier while dealing with wavelets but SVM, artificial neural network and KNN may be good options for classifications. Daubechies wavelet is frequently used, and results are quite interesting.

Hilbert Transform and Empirical Mode Decomposition

Instantaneous Frequency (IF) is a frequency of the signal at particular instant of time t. In Fourier analysis, one complete oscillation of a sine or cosine function is needed to find out the local frequency [55], but it could not make sense for non-stationary signals like EEG. There are dissimilar techniques to determine instantaneous frequency, but the preamble of the Hilbert transform with EMD is made easy and meaningful to discover IF.

IMF is a capacity or function with a similar number of extrema (minima and maxima) and zero intersections or crossing points, where envelopes are symmetric concerning zero. Therefore, definition of IMF guarantees a well-behaved Hilbert transform of the IMF. Hilbert Spectral Analysis (HSA), i.e. examination of each IMF's instantaneous frequency as functions of time results in a frequency-time distribution of signal amplitude or energy, which allows the identification of localized features. Eftekhar et al. [56], well-known time–frequency techniques like spectrograms and wavelet analysis have some issues like: both require some a priori knowledge of the signal and the assumption of linearity. Eftekhar et al. apply a new time–frequency technique called Hilbert-Huang technique or empirical time–frequency technique in seizure detection using EEG and ECG signal, and it is a combination of two famous methodologies of signal processing like Hilbert and Huang transform (Hilbert–Huang). Tafreshi et al. [57], in this paper, they used means of the absolute values of the IMF's Hilbert transform as feature. They also compared their approach with another approach where feature extraction is done with wavelet transform. Algorithm used Self-Organizing Map (SOM) neural net-

works and Multi-Layer Perceptron (MLP) classifiers for classification, and they showed that MLP are better than SOM networks. Results are tested on Freiburg database, where data is taken from 5 patients using 128 channels with 256-Hz samples. For each of the patients, there are datasets called "ictal" and seizures "interictal". The MLP networks are superior in performance with 90.69% accuracy to the SOM networks having 87.28% accuracy for same four empirical modes.

Other similar methods are explained in [58], [59], [60]. [61]. Alam and Bhuiyan [62], here combined statistical and chaotic features like kurtosis, skewness, largest Lyapunov exponent, variance, approximate entropy, and correlation dimension from the first 4 IMFs components of EEG signals are used. Here an IMF is segmented into 16 blocks using a rectangular window of length 256. For each window, three chaotic features (LLE, CD, ApEn) and three statistical features (variance, skewness, kurtosis) are calculated. They used Artificial Neural Network classifiers (ANN) for classification. The results are tested on Bonn database and algorithm achieved a sensitivity, specificity, and accuracy for (D,E) set using IMF3 and IMF4 of 100, 100, and 100%, respectively.

Bajaj and Pachori [63], they proposed an EMD-based seizure detection method to detect focal temporal lobe epilepsy. Algorithm used Hilbert transformation of IMFs which were obtained by an EMD process. The performance of this algorithm was evaluated on Freiburg database. The sensitivity, specificity and error rate are of 90, 89.31, and 24.25%, respectively. It is a patient-specific algorithm.

In summary, we say that combination of EMD with Hilbert transform is performing exceptionally well as compared to other time–frequency domains. Up to four IMFs are sufficient to detect the onset seizure.

Rational Transform

This is also a time–frequency domain which is based on rational functions. It is adaptive in nature, i.e. basis functions are not fixed unlike Fourier and wavelet transforms. This method of feature extraction is already used in control theory and system to control the behaviour and identification of the system. The application of rational transform in seizure detection is totally new area. The coefficients of the rational transform decay very fast as compared to above-mentioned time–frequency domains.

Samiee et al. [64], proposed a new method of feature extraction in time–frequency domain called MT rational DSTFT which relies on rational function, and it is adaptive in nature. Their method proposed a sparse representation of the signal while the components remain orthogonal. They investigated that the best window and coefficients size are 256 samples (1.5 s) and first 32 coefficients of the proposed transform. Authors applied stochastic hyperbolic Particle Warm Optimization (PSO) algorithm to find the optimal position of the pole of each EEG epoch which gives the compact t–f representation of the proposed system. The performance of the proposed method is evaluated on Bonn database and showed that the algorithm has more accuracy (in terms of sensitivity keeping specificity fixed) than other t–f transforms like DSTFT and 13 Cohen's transforms with the same number of nonzero coefficients and achieved an accuracy of 99.8 and 99.3 for the combination of E–A and E–B datasets, respectively.

Samiee et al. [65] here, they concentrated and solved the problem of off-line supervised detection of epileptic seizures in long-term EEG recording. To achieve the goal, they developed a new feature extraction method, which is based on the sparse rational decomposition and the Local Gabor Binary Patterns (LGBP). The proposed algorithm is tested on CHB-MIT scalp EEG database from PhysioNet using EEG recording of 163 h. Their proposed technique performs better over dedicated and well-known techniques (wavelet, STFT, etc.) by showing an overall sensitivity and specificity of 70.4 and 99.1%, respectively. Their algorithm detects commencement of seizures with an average overall sensitivity of 91.13% and false alarms per hour rate of 0.35.

Fridli et al.[66], used rational function system for the analysis of the ECG signals. Their technique has many advantages over the previously used generalized techniques like wavelet transform. Their system is very specific for ECG signals and shape of the individual term correspond to the natural shape of the ECG signals. The system is flexible, i.e. the coefficients and the system itself can be optimized even from heartbeats to heartbeats. The system is simple and less number of calculations are required.

2.4 Proposed Method

The various steps of the proposed algorithm are shown in Figure 2.1. The **novelty** of the proposed algorithm is that we apply two data reduction techniques namely a new Half-wave method in the time domain, and orthogonal projection with the Franklin system in frequency domain. The later one is a complete orthogonal system of piecewise continuous functions. As a result we obtain two reduced piecewise linear functions with low complexity that still preserve the main characteristics of the seizures in the signals. The feature vector is constructed from these two reduced models. For classification we used KNN classifier which is best suited to our problem as compared to the other well known classifiers.

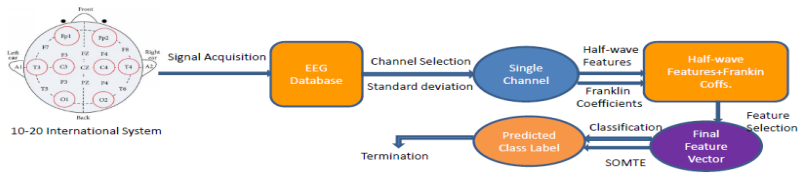

Figure 2.1: Framework of the proposed method

2.5 Database and Channel Selection

2.5.1 Database

For our tests we used CHB-MIT Scalp EEG Database collected by Ali Shoeb [67] (Physionet,https://www.physionet.org/pn6/chbmit/) at the Children's Hospital Boston. It consists of EEG recordings from paediatrics subjects with intractable seizures. Recordings, grouped into 23 cases, were collected from 22 subjects (5 males, ages 3–22 yrs ; and 17 females, ages 1.5–19 yrs). The start and end of each seizure is annotated. The signals were recorded with 23 common EEG channels at a sampling rate of 256 Hz. Signals were recorded with 23 common EEG channels.

Table 2.1: CHB-MIT Database

Patient number	$Age(years)$	Sex	$Seizureduration$	$Non-seizureduration$	$Numberofseizures$
1	11	F	499	23475	7
2	11	M	175	7983	3
3	14	F	409	24791	7
4	22	M	382	37976	4
5	7	F	563	17437	5
6	1.5	F	147	93051	9
7	14.5	F	328	32208	3
8	3.5	M	924	17076	5
9	10	F	280	34218	4
10	3	M	454	50008	7
11	12	F	809	9249	3
12	2	F	1565	44119	40
13	3	F	547	28253	12
14	9	F	117	25023	8
15	16	M	2012	8420	20
16	7	F	94	21506	10
17	12	F	296	10528	3
18	18	F	323	19951	6
19	19	F	239	10307	3
20	6	F	302	19732	8
21	13	F	203	13587	4
22	9	F	207	10593	3
23	6	F	431	31823	7
24	NR	NR	527	42673	16

2.5.2 Channel Selection

The channel selection is a challenging part in seizure detection and prediction algorithms. Taking many channels results in slow algorithms because of the higher computation demand. In the proposed method we use only one channel and show that it works well for seizure detection. For channel selection we follow the method proposed in [68]. Namely, we chose the one with least standard deviation (SD). The idea behind it is that unwanted artifacts, like eye blink or muscular movement, may produce sudden changes and so increase SD even in seizure free intervals in the signal. In our study we tested different channels, with different SD and found that channel having least SD gives the best result.

2.6 Methodologies Used

In our study we propose a novel EEG seizure detection hybrid method. In both domains, time and frequency, we use signal reduction processes. Then features are extracted from the reduced models. Our aim was to construct an effective but simple and fast method. Keeping these guiding principles in mind we came to the conclusion that the model of piecewise linear functions will be appropriate. The EEG devices provide a discrete signal, i.e. sequence of the sample values, that can be considered as a time series, or a piecewise constant function. A representation equivalent to them can be obtained by linear interpolation. This way we associate the discrete signal with a continuous piecewise linear function (pl-function), i.e. the signal is viewed as a piecewise continuous analog signal. Throughout the whole process we stay within this model space. This space is simple but it is rich enough for preserving the necessary properties of the signal. In addition, using a time window with 256 samples the point at which such functions are non-differentiable are all dyadic rationals. Such functions are easy to represent, because they are completely characterized by the endpoints of the linear segments. Moreover, all of the calculations reduce to simple arithmetic operations. In the time domain we develop a new Half-wave method for reducing the original function to a more simple one. The idea is to keep the relevant tendencies but eliminate the irrelevant ones in the signal. The nature of the seizure segments is that, usually they have high spikes rate and high amplitudes [8]. In the

frequency domain we use orthogonal projection for reduction. We show that the Franklin system is the proper choice for that.

2.6.1 Signal Reduction in Time Domain: Half-Wave Method

The history of the so called Half-wave method goes back to 40 years. Starting from the 70's of the 20th century to the first decade of this century this method was very popular to detect epileptic activities (seizures) form long EEG signals. It was used to identify spikes and sharp waves [9] as representatives of seizure and non seizure portions. Its main advantage is that normal and abnormal patterns of very long signals can be examined and identified easily. Different versions of Half-wave methods have been proposed to this order. In them several criterion were applied for the definition and identification of Half-wave formations within the signal. Also, various parameters like duration of the wave, frequencies, amplitude etc. and sophisticated methods based on them have been utilized for concluding whether epileptic activity is found at that instance. Here we can not go into details. Instead we refer the readers to the following relevant publications [69], [70], [8], [11], [71]. Our motivation differs from those above. Namely, we do not want to identify individual spikes. Instead, we take a 1 sec portion of the EEG signal which consists of 256 samples. Then we consider it as a pl-function, and we want to simplify it by eliminating irrelevant details. To this purpose we developed yet another Half-wave method which is simple and fast.

Proposed Method of Half-wave Generation

The idea behind the proposed Half-wave method is to reduce the complexity of the signal and to retain prominent peaks in the signal. First we calculate the extremal points of the original signal, drop the other values, and take the pl-function generated by the extremal points. Since the minimum-maximum values alternate in the sequence of extremal points, the graph of the resulting pl-function is a kind of wave form. We find that in intervals when there is a tendency of increase the decrease in the individual maxima→minima intervals are very small. They do not seem to contribute much in seizure detection process. Therefore, their inclusion in the Half-wave is not necessary and can be dropped. Similar process is applied to

opposite direction, i.e. when the signal shows a decreasing tendency. In the proposed method we apply only one condition, which is very simple, in the reduction process. After applying this condition the first time, the outcome is again a pl-wave with less extremal points, and is called first level Half-wave decomposition. The process can be repeated. It is easy to see that after some steps it will not make any further change, i.e. the next level decomposition coincides with the previous one. Then it is called final or complete Half-wave, and the previous versions are called semi-half-wave decompositions. When we move from lower to higher levels in Half-wave decomposition we loose more and more details. It is part of the reduction problem to decide which level is the best suitable for seizure detection. Now we provide the mathematical formalization of the proposed method. To this order let $N \in \mathbb{N}$, and let $f : [0,1] \mapsto \mathbb{R}$ be a continuous function that is linear on every subinterval of the form $[k/N, (k+1)/N]$ $(k = 0, \ldots, N-1)$. In the first step we select the points of local extrema. Namely those for which the following condition holds

$$f(k/N) > f\big((k-1)/N\big) \qquad \text{and} \qquad f(k/N) > f\big((k+1)/N\big),$$

$$\text{or}$$

$$f(k/N) < f\big((k-1)/N\big) \qquad \text{and} \qquad f(k/N) < f(\big(k+1)/N\big).$$

Adding the two endpoints 0, and 1 to those satisfying the condition we obtain an alternating sequence $0 = x_0 < x_1 < \cdots < x_{N_0} = 1$ of maximum-minimum points ordered in increasing way. The points of this sequence along with the values at them define the starting Half-wave function f_0, which is the continuous pl-function that is linear on the intervals $[x_k, x_{k+1}]$ $(k = 0, \ldots, N_0 - 2)$.

In the following steps we use criteria for the differences rather than for the individual values of the corresponding function. Suppose that f_j is a continuous pl-function with alternating extremal points $0 = x^{(j)} < x_1^{(j)} < \cdots < x_{N_j-1}^{(j)} = 1$. Set $\Delta_k^{(j)} = x_{k+1}^{(j)} - x_k^{(j)}$ $(k = 0, \ldots, N_j - 1)$. Then for every pair $(x_k^{(j)}, x_{k+1}^{(j)})$ $(k = 1, \ldots, N_j - 2)$ we check weather the condition

$$|\Delta_k^{(j)}| > |\Delta_{k-1}^{(j)}| \qquad \text{or} \qquad |\Delta_k^{(j)}| > |\Delta_{k+1}^{(j)}|.$$

holds. If this condition holds for k then we consider that the segment connecting the values at $x_k^{(j)}$ and $x_{k+1}^{(j)}$ represents a significant change in the signal. Otherwise

we consider that portion as an irrelevant detail and we will erase the points $x_k^{(j)}$ and $x_{k+1}^{(j)}$ from the sequence of extremal points. It is easy to see that if the condition doesn't hold for a k then it does hold for $k+1$. Consequently, despite of taking overlapping pairs of consecutive points the erasure process goes pairwise. It means, that also the remaining sequence $0 = x^{(j+1)} < x_1^{(j+1)} < \cdots < x_{N_{j+1}-1}^{(j+1)} = 1$ is an alternating sequence of maximum-minimum points. This sequence again defines a continuous pl-function function f_{j+1}, a reduced Half-wave function.

Then the starting pl-function is reduced from level to level. The process of course can be stopped at any point but it terminates at some level, when no points are dropped from the sequence of extrema. The final Half wave-function generated by the original pl-function f.

2.6.2 Signal Reduction in Frequency Domain: Franklin Transform

The frequency domain part in our hybrid classification is an orthogonal projection using a proper orthogonal system. Recall that the our model space for the EEG signals is the family of continuous piecewise continuous functions. In order to perform an orthogonal projection, reduction in the frequency domain, that complies with our model we need an orthogonal system that consists of continuous piecewise continuous functions. This guarantees that the subspace spanned by the elements of the system is a subspace of our model space. Moreover, since we take 1 sec long segments with 256 samples linearity must hold between any dyadic rationals of the form $k2^{-8}$ $(k = 0, \ldots, 256)$. The combination of these requirements leads to the Franklin system as a natural choice.

The importance of the role of the Haar system [13] in many applications, including signal processing problems, is hard to exaggerate. It is, among others, the simplest model for wavelets. Originally, in the construction of his system Alfred Haar was motivated by the problem of Schauder basis in the space of continuous functions $C([0,1])$. At that time no orthogonal system Ψ was known such that the Ψ-Fourier partial sums of every continuous function converge to the given function uniformly. The Haar system was the first example for such an orthogonal system. Ever since it turned out that the Haar system $(\mathcal{H})$ enjoys several nice and impor-

tant properties in mathematics as well as in applications. There was, however, one imperfection in the construction from the point of the original motivation. Namely, the Haar functions themselves are not continuous, ie. do not belong to the space $C([0,1)]$. In order to overcome this problem Faber [14], [15] came to the idea to take the integral functions of the Haar functions. Then he of course received continuous functions, and hoped that the system Φ of these functions preserve the convergence property of $\mathcal{H}$. Indeed, the system Φ now called as Faber-Schauder system turned to be Schauder basis in $C([0,1])$. Recall that $h_n \in \mathcal{H}$ ($n \in \mathbb{N}$, $n = 2^m + k$, $0 \leq k < 2^m$) is defined as

$$h_n = 2^{m/2}\chi_{[k/2^m,(2k+1)/2^{m+1})} - 2^{m/2}\chi_{[(2k+1)/2^{m+1}),(k+1)/2^m)} \tag{2.1}$$

where χ_A stands for the characteristic function of the set $A \subset [0,1]$. Hence we have that the nth Faber-Schauder function $\varphi_n(x) = \int_0^x h_n(t)\,dt$ is a roof shape function, continuous pl-function, on $[k/2^m, (k+1)/2^m]$. Finally, the Franklin system $\mathfrak{F} = \{\mathfrak{f}_n : n \in \mathbb{N})$ is generated from Φ by Gram-Schmidt orthogonalization and normalization. Then $\mathfrak{F}$ is an orthonormal basis in $C[0,1)$. We note that it follows from the construction that $\mathfrak{f}_n$ ($n \in \mathbb{N}$, $n = 2^m + k$, $0 \leq k < 2^m$) is a continuous pl-function, which is linear on every dyadic interval $[k/2^{m+1}, (k+1)/2^{m+1}]$. We conclude that $\mathfrak{F}$ satisfies all of the properties we formulated above with respect to the desired orthogonal system. We note that if f is a pl-function that corresponds to the EEG samples in a 1 sec long record then the Franklin coefficients [17], [18], [19].

$$\widehat{\mathfrak{f}}_n = \int_0^1 f \cdot \mathfrak{f}_n \tag{2.2}$$

can be accurately calculated by finite many arithmetic operations.

2.7 Feature Extraction and Classification

2.7.1 Feature Extraction

In the proposed method a hybrid feature vector is constructed from two piecewise linear models. Rectangular windows of size 1 sec. are applied with 256 samples in

each window. This size turned to be appropriate and that agrees with the conclusion in [64], [65]. In the time domain features are extracted from the Half-wave reduction: total number of extremal points, slopes of linear segments, maximum of slopes, mean of extremal points, absolute minimum and maximum within the window. In the frequency domain we take the first 16 coefficients of the Franklin transform. The final feature vector is constructed after performing tests using different combinations shown in Table 2.1. We found that the above mentioned six features from time domain in the 4th level Half-wave reduction and the first 16 Franklin coefficients form the best combination with KNN classifier for seizure classifications. In the performance evaluation the metrics used are mentioned in section 1.6.1 of chapter 1.

2.7.2 Classification

We have tested several classifiers commonly used for seizure detection, like k-Nearest Neighbor (KNN) algorithm, artificial neural network and support vector machines. We concluded that the KNN performs the best in our case. We had to address the problem that the database is highly imbalanced. Namely, the CHB-MIT database has 10218 seizure seconds, which is only 1.6% of the total duration of the EEG signal (6400086 sec). This makes the classifier biased to detect majority (non-seizure) class because of the unequal prior probabilities of the two classes. There are two popular methods to handle this problem:

a) over-sampling (increasing the samples of minority class).

b) under-sampling (reducing the samples of majority class).

Most of the pattern classification methods use over-sampling because there is no loss of information. In the proposed method, we applied the well known over sampling technique called Synthetic Minority Over-Sampling Technique (SMOTE) [72]. It neither exaggerates the Receiver Operating Characteristic curve of the extracted features, nor causes any over-fitting problem [73]. We used 3 iterations of SMOTE for each patient as recommended by Bhattacharya et al [68]. Each iteration increases the number of minority samples by 100%. After applying the classifier, we analyzed the class labels. We experienced that in non-seizure time intervals some segments are mistakenly classified as seizure segments. The opposite situation occurs in seizure

intervals. Therefore, we studied the result of the classification not only for the individual segment but for its 4 neighbors on each side. This way we could correct the status of most of the misclassified segments.

Table 2.2: Various combinations to find best features

Halfwave level	$SMOTElevel$	$Featuresused$	$\#seizures$	$\#seizuredetected$	$Specificity(\%)$	$Sensitivity(\%)$	$Accuracy(\%)$
03	03	$(6time + 16Franklin)$	03	03	98.8	91	98.7
03	03	$(6time + 8Franklin)$	03	03	97.4	91.6	97.3
04	**03**	$(\mathbf{6time + 16Franklin})$	**03**	**03**	**99.9**	**95.2**	**99.8**
04	03	$(6time + 8Franklin)$	03	03	99.3	97	99.3
05	03	$(6time + 8Franklin)$	03	03	99.3	94	99.2
05	03	$(6time + 16Franklin)$	03	03	99.3	73.7	98.5

2.8 Results and Test Comparisons

Results of the proposed algorithm on CHB-MIT database are shown in Table 2.3. Table 2.4 shows the comparisons with state of the art algorithms. From Table 2.4, we can see in 2017 Bhattacharyya [68] proposed best method tested on the same database for seizure detection. But the problem with the method is that it is multichannel method which may slow down the speed of system and in real time applications such heavy systems (multichannel) may not be accepted. Our method is simple and based on only one channel which may be used in real time applications. They achieved and average sensitivity, specificity and accuracy of 97.91%, 99.57%, 99.41%. Whereas, our proposed method achieved an average sensitivity, specificity, accuracy, false alarm rate and kappa of 99.45%, 99.75%, 99.01%, 0.0039, 0.964 respectively and these results are comparatively good than [68] and other state of the art methods.

2.9 Conclusion

A novel hybrid approach has been developed to extract the features from EEG signals. The main idea behind the piecewise linear models is to morph the signals

in such a way that they become simple and smooth but at the same the important characteristics of the sleep states are retained.The novelty of the proposed algorithm is that we apply two data reduction techniques namely a new Half-wave method in the time domain, and orthogonal projection with the Franklin system in frequency domain. The later one is a complete orthogonal system of piecewise continuous functions. As a result we obtain two reduced piecewise linear functions with low complexity that still preserve the main characteristics of the seizures in the signals. Different time domain and frequency domain features are extracted and tested, and the final feature vector is their best combination. The feature vectors are classified by using KNN classifier on long data of CHB-MIT polysomnography database. Proposed algorithm achieved an average sensitivity, specificity, accuracy, false alarm rate and kappa of 99.45%, 99.75%, 99.01%, 0.0039, 0.964 respectively, which is higher than the existing state of the art methods.

Table 2.3: Results of proposed algorithm on CHB-MIT database

Patient number	TP	FN	$Sensitivity(\%)$	TN	FP	$Specificity(\%)$	$Accuracy(\%)$	$Falsealarmrate/hr$
1	11458	0	100	9083	25	99.7	99.9	0.0069
2	4474	0	100	2933	58	98.1	99.2	0.016
3	10503	0	100	9090	104	98.9	99.5	0.028
4	9619	0	100	14633	145	99	99.4	0.040
5	14375	0	100	9284	68	99.3	99.7	0.0188
6	2276	0	100	9744	190	98.1	98.4	0.052
7	3935	0	100	7028	26	99.6	99.8	0.007
8	11869	7	99.9	2999	110	96.5	99.2	0.030
9	3254	0	100	7515	89	98.8	99.2	0.024
10a	5940	0	100	10658	117	98.9	99.3	0.032
10b	4233	0	100	4988	102	98	98.9	0.028
11	20659	0	100	3225	49	98.5	99.8	0.013
12	0	0	0	0	0	0	0	0
13	8602	36	99.6	6677	231	96.7	98.3	0.064
14	4527	3	99.9	8119	211	97.5	98.3	0.058
15	9416	7	99.9	4174	218	95	98.4	0.060
16	2359	40	98.3	7993	118	98.5	98.5	0.032
17	7612	0	100	3991	15	99.6	99.9	0.0049
18	7396	0	100	7670	28	99.6	99.8	0.0077
19	6122	0	100	3348	123	96.5	98.7	0.0341
20	7739	0	100	7004	77	98.9	99.5	0.021
21	5198	0	100	4962	70	98.6	99.3	0.0194
22	4926	3	99.9	3821	36	99.1	99.6	0.01
23	4650	0	100	6632	48	99.3	99.6	0.0133
24	8418	12	99.9	7551	99	98.9	99.4	0.02
Average			99.92			98.38	99.3	0.027

Table 2.4: Comparison with latest state of the art methods

Reference and year	$channel - patients$	$training/testdata$	$classifier$	$AverageSensitivity - Specificity - Accuracy(\%)$	$Falsealarmrate$
Bhattacharyya [68] [2017]	$multichannel - 23$	$10foldcrossvalidation$	RF	$97.91 - -99.57 - -99.41$	$--$
Sina [74] [2017]	$multiple - 23$	$leave - one - record - out$	$ADCD$	$96.00 - - - -$	0.12
Miaolin [75][2019]	$multichannel - 23$	$--$		$98.48 - - - -$	8.61
Chen [76][2017]	$multichannel - 23$	$leave - one - subject - outcrossvalidation$	SVM	$91.71 - -92.89 - -92.30$	$--$
Birjandtalab [77][2017]	$multichannel - 23$	$10foldcrossvalidation$	$RF - t - sne, KNN$	$- - - - 89.80$	2.2
Tsiouris [78][2017]	$multichannel - 23$	$notraining$	$rulebased$	$88 - - - -$	8.1
Samiee [64][2015]	$multichannel - 23$	$25\%training$	$SVM, Logregg, RF$	$71.6 - -99.2$	0.35
Khan [53][2012]	$multichannel - 5$	$80\%training$	LDA	$100 - -83.6 - -91.8$	$--$
Proposed work	$singlechannel - 23$	$60\%training$	KNN	$\mathbf{99.92 - -98.38 - -99.3}$	**0.027**

Chapter 3

Sleep states detection using Halfwave and Franklin transformation

3.1 Abstract

Sleep is a physiological phenomenon and a sufficient amount of sleep is mandatory for a human for his/her health. In this Chapter we present results published in [79], where we develop an efficient algorithm to detect the various sleep states by combining biomedical signals. The novelty of the algorithm that, we have extended our method proposed in Chapter 2 and instead of one biomedical signal i.e. EEG, we applied it on three biomedical signals with certain modification. We use two piecewise linear data reduction techniques namely a new Half-wave method in time domain and Franklin transformation in frequency domain. The obtained two piecewise linear forms of signals have 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 Pressure and Respiratory (Nasal) signals with six different sleep classes. Proposed method shows better performance than state of the art methods.

keywords: sleep states, Half-wave, Faber Schauder, Franklin system, K-Nearest Neighbor, ADASYN, EEG, blood pressure, nasal signal. The research presented in this Chapter was accepted by MACS-2020, [79] Hungary and is to appear in "Annales Universitatis Scientiarium Budapestinensis de Rolando Eötvös Nominatae. Sectio

Computatorica and Annales Universitatis Scientiarium Budapestinensis de Rolando Eötvös Nominatae. Sectio Mathematica".

3.2 Problem Statement and Motivation

The aim of the research is to detect the various sleep states by combining biomedical signals. Our research is motivated by the fact that there are large number of disorders like insomnia, breathing disorders, wake-sleep disorder sleep movement disorder found in human beings. Every sleep state has different group of neurological and physiological features. The correct identification of these features along with their states are important for diagnosis and the better treatment for such sleep disorders and avoid unwanted accidents (especially while driving). Sleep classification process is not a standardized one, i.e. different experts have different criteria to mark a specific period of sleep. Around 24% of the adult population have regular sleep disorders. Ohayon and Smirne [6] shown 27.6% of the Italian population have sleep problem. Gupta et al.[7] shown Indian population have 10-15% insomnia and 10% delayed sleep wave phase disorder. This problem is increasing worldwide day by day and according to Oliver et al. [80] this problem costs around $100 billion USD per year. Manual scoring is time consuming, its availability is limited, therefore there is a need for automatic sleep phase detection to reduce cost and to increase access to diagnosis sleep stages [81], [82], [83], [5], [84], [85]. The main challenge to automatic sleep phase detection is heterogeneity. This means that individuals have different cranial structures which effect the patterns in the signal. For example 10 percent of the population don't produce alpha rhythm during stage W (Wake) and 10 percent create just a constrained or limited alpha beat. This justifies the combination of EEG with other biomedical signals in order to improve the results.

3.3 Introduction and Background

Sleep is an important part of person's life and individuals used to sleep one-third of their entire life. Around 24% of the adult population have regular sleep disorders. Ohayon and Smirne [6] shown 27.6% of the Italian population have sleep

problem. Gupta et al.[7] shown Indian population have 10-15% insomnia and 10% delayed sleep wave phase disorder. 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 [86]. Following R&K [1] rules sleep is categorized into six categories, REM, sleep stage1, stage2, stage3, stage4 and wake state. Later on NRME2 and NRME3 are also combined resulted as just four main classes namely light sleep, Deep sleep REM and Awake state [87]. For accurate diagnosis of sleep phases, an expert manual scoring for sleep stages using some standards is needed for the whole duration recordings of the selected biomedical signals. For instance in case of EEG (electroencephalograph) signals six 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 [81], [82], [83], [5], [84], [85].

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, Laypunov exponent, approximate entropy, mean, energy of the signal, slopes, etc. to extract comprehensive information from non linear signals like EEG, blood and respiratory. Originally the Half-wave method was used in seizure detection but the new Half-wave method proposed by us can be used with Franklin transformation (a hybrid approach) [20] 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 different problems in biomedical field in an efficient way. Dihong et al.[88] used three biomedical signals - EEG, Electrooculogram (EOG), and Electromyography (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. [89] proposed single channel automated detection of sleep states using EEG signals. Time domain and frequency domain features are classified for four and two sleep stages separately with 90.81%, 83.2% respectively. They achieved an overall accuracy of 86.7%. Tripathy et al. [90] used dispersion entropy and the variance features from the different bands of EEG signal. The RR-time series features and the EEG features were fed 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. Over all average accuracy was 91.71%. Silverira et al. [91] proposed a single channel method where EEG signal is decomposed by using wavelet transform. The features such as kurtosis, skewness and variance of the wavelet coefficients are classified using random forest classifier. They obtained 90% over all accuracy for 2 to 6 classes. Budak et al. [92] proposed a 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 instantaneous 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) states. Taran et al. [93] utilized Hermite functions as basis functions. Then 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%. In the subject specific approach [94] 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 [95], where the average accuracy using EEG is 76%, and using ECG signals is 75%.

3.4 Proposed Method

In the proposed method the signals are modeled as piecewise linear functions in a natural way. Then reduction methods are used both in time and frequency domains. To this order we develop a so called Half-wave type method [8], [9], [10] in time domain and use the Franklin system [14], [15] for orthogonal projection. Here we *extend* our method [20], originally developed and successfully applied for epilepsy seizure detection. The **novelty** of the algorithm is the adaptation of the Half-wave and Franklin transformation for the actual problem and we are combining three

biomedical signals instead of one to detect various sleep phases. Class imbalance problem is addressed by using advance version of SMOTE called Adaptive Synthetic Sampling Approach for Imbalanced Learning (ADASYN).

The study done by Shayan et al. [81] collected 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. Proposed method is a so called hybrid one, i.e. we utilize both time and frequency domains to extract components for the feature vector. The main idea is to use the piecewise linear function model for data reduction in time and frequency domain. Piecewise linear functions are of low complexity that still preserve the characteristics of the signal that are relevant in context of stages of the sleep. To this order we took the so called Half-wave method and modified it according to our need. The frequency space is generated by Franklin transformation. The Franklin system an orthogonal system which is strongly related with the well-known Haar system, and its elements piecewise linear functions. Then the feature vector elements are generated from the piecewise linear models in both domains. We applied this technique for synchronized EEG, blood pressure, and respiratory signals. Framework of proposed method is shown in Figure 3.1.

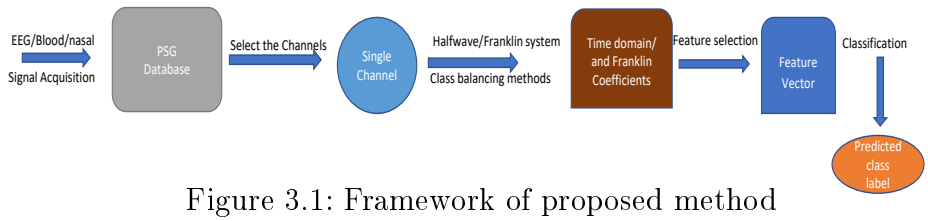

Figure 3.1: Framework of proposed method

3.5 Database and Channel Selection

3.5.1 Database

In our research we used the standard MIT-BIH Polysomnographic database, collected and described by Ichimaru et al. [96], [33] at Boston's Beth Israel Hospital Sleep Laboratory. It is open source, freely available database (https://www.physionet.org/physiobank/database/slpdb/). Data collection consists of records from 16 individuals. 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 (electrocardiogram) 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 contain data of one type of signal like EEG, ECG etc. only or combination of EEG, ECG. We used blood pressure, nasal and EEG signal in the proposed method. This database contains all of the three signals and they are long enough to test our method. In our research, due to some technical problem we were not able to read 3 records out of 18 records hence, we performed our tests only on remaining 15 records from 13 different patients shown in Tables 3.2, 3.3 and 3.4.

3.5.2 Channel Selection

The channel selection is usually a challenging tasks in EEG signal processing, in particular, in sleep state detection and prediction algorithms. Multichannel processing may be computationally demanding and make signal processing slow. On the other hand single channel methods may not be sufficiently effective. In this research on the given database, however, we had no choice. Namely, only one EEG channel is available for each patient. Moreover, that particular channel varies from patient to patient and signal to signal. The author of the database did not provide any background about the channel selection process. We note that in [15] we addressed the channel selection problem for seizure detection. Our aim was the same in this case as well but we had no options.

3.6 Methodologies Used

3.6.1 New Half-wave Method: Time Domain

In the last quarter of the 20th Half-wave was a very popular method to detect epileptic activities (seizures) form the long EEG signals. Half-wave mechanism is explained in details in Chapter 2. In Half-wave method, the crucial part of the

reduction problem to decide which level is the best suitable for the problem studied, in our case for sleep detection. In sleep states problem we found that level 2 may be considered as best level. For seizure detection we used Half-wave having level 4. Biomedical signals in sleep states cases have not much high speed and peaky activities as compared to the signals in seizure states. Therefore if we go higher level of Half-wave in sleep case, in some of the selected windows we will not get any information (extremal points). For more details about the algorithm of new Half-wave please refer the Chapter 2.

3.6.2 Frequency Domain: Franklin Transform

The frequency domain part in our hybrid classification is an orthogonal projection using a proper orthogonal system. Our model space for the EEG and other biomedical signals is again the family of piecewise linear functions. In order to perform an orthogonal projection, reduction in the frequency domain, that matches with our model we need an orthogonal system that consists of such type of functions. We applied Franklin transformation on three selected biomedical signals instead of only on EEG (Chapter 2) and then selected Frequency domain features from three signals are merged with the time domain features to form the feature vector also explained in coming sections. For more details about Franklin system system and its applications, readers are requested to refer Chapter 1, 2, [13], [14], [15] . [17], [18], [19], [16].

3.7 Feature Extraction and Classification

3.7.1 Feature Extraction

The elements of the feature vector are derived from three types of biomedical signals. 30 seconds duration of the signals are labeled by associated experts to categorize different states of the sleep. The sampling rate is 250 Hz.

Feature Extraction in Time Domain: Half-wave Method. Following the other studies and methods cited we work window size of 30 sec including 7500 sample points. Half-wave up to level 2 only method is applied to reduce the signals.

The reason for not going higher levels is that when we increase the level in blood pressure, nasal and EEG signals, the signals become so simple that in some of the 30 sec long segments 1 extremal point remains. Consequently, the reduced signal does not contain enough information anymore, we cannot extract effective features. In the selected signals this type of situation occurs in very early levels. It is because the nature of the signals in case of the sleep states. It means slow activities and results in less peaky signals. This is quite different from epileptic seizure periods [20], when fast and peaky activities occur. One of the advantages of Half-wave method is that we can customize the method based on the problems in hands.

The time domain features we use are: total number of extremal points, mean of the absolute values of the extremal points, maximum of the absolute values of the extremal points, maximum of the absolute values of the slopes, mean of absolute values of slopes and the last feature is the sum of the squares of extremal points. The latter one is related to the energy of the signal are extracted. The reason of choosing these features is that these are the simple and very common statistical features. Moreover, several studies and surveys including [20], [81], [21] concluded that these are effective features in time domain for the analysis of the different biomedical signals. In fact, during our studies we extracted a number of statistical features in time domain. Then an analysis was made on these features by using histograms [20]. We found that the selected 6 time domain features are the best discriminatory ones and their combination with selected Franklin coefficients gives better results than any other combination as shown in Table 3.1.

Feature Extraction in Frequency Domain: Franklin Transformation. We found, that in order to calculate Franklin transform 2^8 sample points the appropriate one to apply. Therefore the rectangular of length 30 sec long with 7500 should be resampled. Reduction from 7500 to 256 samples seems to be drastic, and there is a chance that we loose some important information. At this point we only note that comparisons with state of the art methods proves that features from Franklin transform with this resolution is still effective.

After applying the Franklin transformation on the selected segment we made some combinations (see Table 3.1), and we found that the first 8 coefficients are the best

discriminatory features.

3.7.2 Final Feature Vector Construction

From each of the three biomedical signals (EEG, blood pressure, nasal) we have three feature vectors. Each feature vector is constructed by merging the 6 time domain and first 8 frequency domain features with a total of 14 entries. If V1, V2, V3 and are the feature vectors extracted from EEG, blood pressure and nasal respectively. Let the final feature vector F is constructed by concatenation F= [V1 V2 V3]. Thus the final feature vector used for classification here has 42 features. In Table 1, 6T means, six best time domain features and 8F = First Eight Franklin coefficients. Final results with different sets of classes are shown in Tables 3.2, 3.3, 3.4, 3.5 and 3.6 where training and Testing data is taken in the ratio of 60:40 respectively.

3.7.3 Classification

After the feature vector construction we applied the K-Nearest Neighbor algorithm (KNN) for classification. We tested other classification algorithms like Support Vector Machine (SVM), Artificial Neural Network (ANN) and we found that KNN performs better in this task. We note that the sets of sleep stages in the databases are not balanced. This means that the numbers of tuples of different classes are significantly different. Therefore, before applying the classifier, the class imbalance problem needs to be addressed otherwise results would be biased. In the proposed method we used an advanced form of Synthetic Minority Over-Sampling Technique (SMOTE) [72] to address the issue of class imbalance. It is called Adaptive Synthetic Sampling Approach for Imbalanced Learning [97].

3.8 Results and Comparison Tests

Tests were performed on 15 records (out of 18 records) and total duration of selected 15 long term EEG, blood and nasal signals with six different sleep classes is more than 70 hours. First we have optimized our method then we have carried out comparison tests. The results obtained are presented in Tables 3.1. There we

summarized how the various feature value combinations perform in to detect sleep states. It shows that the best choice is the combination of the three signals - EEG, blood pressure, nasal - using 6 time domain and 8 Franklin feature values for each of them.

Tables 3.2, 3.3, 3.4 show how the proposed method performs in the classification problem for randomly selected 2, 4, and 6 classes respectively. For 2 classes in Table 3.2, we achieved an average accuracy of 96.96% which higher than state of the art methods [95], [98], [94], [90], [99], [93] based on two classes. Similarly, in Table 3.4 and 3.5 for randomly selected 4 and 6 classes we achieved an average accurcies of 93.94% and 93.84% respectively which is also higher than states of the art methods [100], [101] using same number of classes.

Tables 3.5, and Table 3.6 contain the comparison of the proposed method with state of the art methods using the same (Table 3.5) and different databases (Table 3.6) respectively. It shows that our algorithm performed better than other state of the art methods. Our method is patient specific and the state of the methods used for comparisons are also patient specific, therefore it justifies the comparisons. In the performance evaluation the metrics used are mentioned in section 1.6.2 of Chapter 1.

3.9 Conclusion

A novel hybrid approach of two piecewise linear models have been developed to extract the features from three biomedical signals. The main idea behind the two piecewise linear models is to morph the signals in such a way that they become simple and smooth but at the same the important characteristics of the sleep states are retained. Different time domain and frequency domain features are extracted and tested, and the final feature vector is their best combination.The novelty of the algorithm is the adaptation of the Half-wave and Franklin transformation for the actual problem and we are combining three biomedical signals instead of one to detect various sleep phases. Class imbalance problem is addressed by using advance version of SMOTE called Adaptive Synthetic Sampling Approach for Imbalanced Learning (ADASYN). The feature vectors are classified by using KNN classifier on

Table 3.1: Feature selection using different combinations of the signals

Signal	$Class-pair$	$Features$	$Train\&Test$	$Sensitivity(\%)$	$Specificity(\%)$	$Accuracy(\%)$
Blood	4	$6T+16F$	$60-40$	91.02	97	91
Blood	4	$6T+16F$	$80-20$	96.11	98.70	96.09
Blood	4	$6T+8F$	$60-40$	90.64	96.86	90.60
Blood	4	$6T+8F$	$80-20$	96.03	98.67	96.02
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	$6T+8F$	$60-40$	90.00	96.7	90.00
EEG	4	$6T+8F$	$80-20$	95.63	98.58	95.63
EEG	4	$6T+16F$	$80-20$	90.64	96.86	90.60
Blood Resp	4	$6T+16F$	$60-40$	92.37	97.45	92.37
Blood Resp	4	$6T+16F$	$80-20$	96.71	98.99	96.77
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	$6T+32F$	$80-20$	96.51	98.83	96.50

Table 3.2: 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	0.023
2b	100	96.30	96.69	0.037
03	100	97.00	97.10	0.035
04	100	95.45	96.01	0.045
14	100	96.00	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	0.023
60	95.52	100	96.08	0.010
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 3.3: 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	0.017
2a	96.51	98.64	95.89	0.014
2b	100	95.41	95.89	0.041
03	97.12	97.65	94.00	0.022
04	93.71	93.85	91.00	0.060
14	95.90	97.14	93.00	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	91.00	0.061
59	96.51	98.64	95.89	0.024
60	95.62	97.07	92.23	0.029
61	96.84	98.32	94.48	0.017
66	93.55	96.87	91.53	0.013
66x	96.47	98.12	94.81	0.019
Avg	**96.62**	**97.10**	**93.94**	**0.030**

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 than the existing state of the art methods.

Table 3.4: Results of proposed algorithm with 5 and 6 randomly selected classes

Patient number	$Sensitivity(\%)$	$Specificity(\%)$	$Accuracy(\%)$	$Falsealarmrate/hr$
01a	97.09	98.77	97.09	0.012
01b	98.05	98.68	93.31	0.013
2a	93.69	98.11	98.78	0.012
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	0.012
16	97.67	98.78	95.39	0.001
37	NA	NA	NA	NA
48	94.25	97.40	90.59	0.026
59	94.79	98.58	93.10	0.019
60	NA	NA	NA	NA
61	96.94	98.63	94.19	0.014
66	NA	NA	NA	NA
66x	NA	NA	NA	NA
Avg	**96.13**	**98.33**	**93.84**	**0.016**

Table 3.5: Comparison of results with previous algorithms tested on the same database

Author and year	#records	Features	Classesused	Classifierused	AverageAccuracy(%)
Redmond and Heneghan [95], 2003	17	HRVandEEG	Lightsleepvsdeepsleep	QDA	89
Adnane et al. [94], 2012	17	HRV, DFAandWDFA	Sleepvswake	SVM	79.99
Hayet and Slim [98], 2012	09	RR − timeseriesandHRV	Sleepvswake	ELM	83.59
Werteni et al. [99], 2015	17	HRV	SleepvswakeREM	SVM	56.81
R.K Tripathi et al. [90], May, 2018	17	Dispersionentropyandvariance	wakevslight, sleepvsdeep, sleepvsREM	Neuralnetwork	91.71
Taran et al. [93], 2018	16	Hermitecoefficients	alert(w)anddrowsiness(s1)	ELM	92.28
Budak et al. [92], 2019	16	Spectrogramimagesandinstaniousfrequencies	alertanddrowsiness	LSTM	94.31
Proposed method, 2 classes	15	TimedomainandFranklincoefficients	2randomclasses	KNN	**96.9**
Panfeng et al. [100], 2019	06	Statisticalfeatures	NREM(s1 − s4), REM, Wake	W − SVM	85.29
Junming at el. [101], 2020	18	HilbertHuangcoefficients	REM, NREM, wake	CNN	87.6
Proposed method, 4 classes	15	TimedomainandFranklincoefficients	4randomclasses	KNN	**93.94**
Proposed method, 5 and 6 classes	15	TimedomainandFranklincoefficients	Wake, Sleep(all), REM	KNN	**93.84**

Table 3.6: Comparison with other algorithms tested on the different database

Author and year	features	Classesused	Classifierused	AverageAccuracy(%)
Prucnal et al. [102]	Waveletbasedfeatures	Fiveclass(wake, S1, S2, deepsleep, REM)	NeuralNetwork	74.2
Prucnal et al. [102]	EMDbasedfeatures	Fiveclass(wake, S1, S2, deepsleep, REM)	NeuralNetwork	57.6
Hasan et al. [103]	EnsembleEMDbasedfeatures	Sixclasses(wake, S1, S2, S3, S4, REM)	RUSBoost	71.98
Da Silveira et al. [91]	DWTandstatisticalfeatures	(wake, S1, S2, S3, S4, REM)	Randomforest	63.51
R.K Tripathi et al. [85], May, 2018	HRVfeatures	(NREM(all), REM)	DNN	73.70
Proposed method (5 and 6 classes)	TimedomainandFranklincoeffi.	Wake, Sleep(all), REM	KNN	**93.84**
Proposed method (4 classes)	TimedomainandFranklincoefficients	4randomclasses	KNN	**93.94**
Proposed method (2 classes)	TimedomainandFranklincoeffi.	2randomclasses	KNN	**96.96**

Chapter 4

A hybrid approach for sleep states detection using blood pressure and EEG signals

4.1 Abstract

Sleep is fundamental to every human being and it is a physiological phenomenon. This Chapter is about the paper accepted by ICRIC-2021 and is to appear in Lecture Notes in Electrical Engineering [104]. The aim of the research is to develop a hybrid approach using time and frequency domain features for automatic sleep states detection. In time domain, statistical and morphological features are extracted from the blood pressure signal and in frequency domain, a piecewise linear reduction namely Franklin transformation is applied on EEG signal. The Franklin coefficients are used as discriminatory features in frequency domain. The novelty of the proposed method is that we considered two cases, the blood pressure signal by itself, and the combination of it with EEG signal. The motivation behind the first one is that in certain cases, e.g. smart personal mobile devices, only the blood pressure signal is available. In both cases the algorithm is tested on MIT-BIH Polysomnographic database having more than 80 hours long term EEG and Blood Pressure signals. In both cases we performed comparison tests with relevant state-of-the-art methods, and our algorithm showed better or equal performance in terms of sensitivity, specificity, accuracy and false alarm rate.

keywords: sleep states, Faber-Schauder, Franklin system, K-Nearest Neighbor, ADASYN, EEG, blood pressure, Systolic and Diastolic temperature, Dicrotic notch.

4.2 Problem Statement and Motivation

The aim of the research work is to develop a hybrid approach using time and frequency domain features for automatic sleep states detection. The problem statement of the research work proposed in Chapter 3 and 4 is same but their aim and motivation are different. Our motivation in this research is to use the blood pressure signal alone and combination of it with EEG signal so that algorithm can be used in real time systems. Blood pressure signals are well defined and are easily available in handheld and smart devices devices. Most of the state of the art methods are based on EEG signals. In real time scenario, the implementation and processing of EEG signal is quite challenging because capturing and processing of the EEG signals requires complex system of placing the electrodes inside or on the scalp. Most of the cases EEG acquisition needs to be done in the supervision of the experts or doctors and sometimes it is a bit risky too. On the other hand, blood pressure signals are periodic, well behaved, can be used in real time scenario and are relatively easy to measure. Blood pressure signal can be measured even by using smart devices like wrist watch and other handheld applications. Therefore, in our proposed method, to detect various sleep states, first we used only blood signal, and then the combination of the blood and EEG signals. The motivation behind the combination of blood signal with EEG is to get better results as compared to the relevant state of the art methods. No doubts the results of the combined approach (blood and EEG) the better than only blood, but at the same time results using only blood pressure signals are comparatively good or equal as compared to the state of the art methods.

4.3 Introduction and Background

In the recent years sleep-related issues are increasing. The normal day-to-day life of those many people who suffer from sleep disorders are heavily affected. Sleep disorders can be the indicator of a future disease like depression and mental illness.

Now a days sleep assessment is an important part of any health checkup. Some traditional and new methods are available for sleep disorder detection, but such methods still have some shortcomings like they are mainly based on EEG, and are slow in nature which require more time for scoring the entire sleep duration of the given biomedical signal. These methods are still dependent on experts of the sleep scoring to verify their results. Therefore, the limitations of manual sleep stage scoring stated the demand for developing an efficient and automatic sleep stage scoring method which has good classification accuracy, and it is simple and fast. The main challenge to automatic sleep phase detection is heterogeneity. This means that individuals have different cranial structures which effect the patterns in the signal. For example 10 percent of the population don't produce alpha rhythm during stage W (wake) and 10 percent create just a constrained or limited alpha beat. This justifies the combination of EEG with other biomedical signals in order to improve the results. We proposed automatic sleep stage scoring algorithm by combining blood and EEG signals. In the proposed method the EEG signal is modeled as piecewise linear functions. We are motivated to apply Franklin system by Yash and Fridli [20], [79] originally developed and successfully applied for epilepsy seizure and sleep states detection. Two standards for scoring namely R&K and AASM [1] are available for sleep stage scoring. As per R&K rule, analysis of the EEG signal is carried out by dividing each signal into periods of 30 seconds small parts known as segments. Following R&K rules sleep is categorized into six categories, REM, sleep stage1, stage2, stage3, stage4 and wake state. Later on NRME2 and NRME3 are also combined resulted as just four main classes namely Light sleep, Deep sleep, REM and Awake state [86], [6]. Large number of methods are applied for sleep state detection and each one has one significant advantages and disadvantages. The obvious and common disadvantage of these methods is that they used advance technology like electroencephalograms, electrocardiograms, etc. which cannot be used at home [3], [80]. Since manual scoring is time consuming, its availability is limited, therefore there is a need for automatic sleep phase detection to reduce cost and to increase access to diagnosis sleep stages, [5], [7], [80], [87], [81], [82], [83], [5], [84], [85]. More details about the background of sleep disorders, phases and latest techniques are explained in Chapter 3. .

4.4 Proposed Method

The literature survey done by Shayan et al. and Santosh et al. [81], [105] collected various advantages and disadvantages of the existing research done by using some adaptive and hybrid methods. Our aim is to increase the overall accuracy of sleep states detection process as compared to the existing methods. Proposed method is a so called hybrid one, i.e. we utilize both time and frequency domains to extract components for the feature vector. The main idea is to use the piecewise linear function model for data reduction in frequency domain, morphological and statistical features are used from blood signal in time domain. The **novelty** of the proposed method is that we considered two cases, the blood pressure signal by itself, and the combination of it with EEG signal. The motivation behind the first one is that in certain cases, e.g. smart personal mobile devices, only the blood pressure signal is available. Piecewise linear functions have low complexity but still preserve the characteristics of the signal that are relevant in context of stages of the sleep. Then the feature vector elements are generated from the piecewise linear model and the statistical features from blood signal. Framework of the proposed system is shown in Figure 4.1.

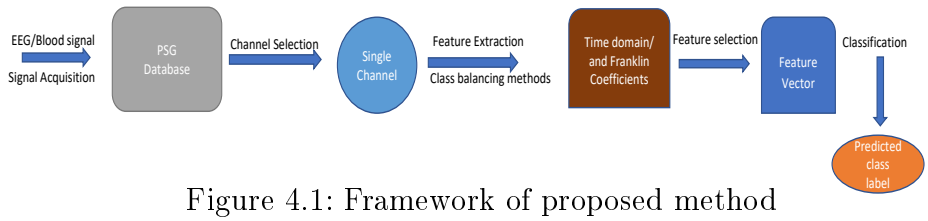

Figure 4.1: Framework of proposed method

4.5 Database and Channel Selection

4.5.1 Database

In our research we used the standard MIT-BIH Polysomnographic database, collected and described by Ichimaru et al. [96], [33] at Boston's Beth Israel Hospital Sleep Laboratory. It is open source, freely available database explained in Chapter 3.

4.5.2 Channel Selection

The channel selection is usually a challenging task in EEG signal processing, in particular, in sleep state detection and prediction algorithms. In the given database, the data is given by the database expert from only one channel. Therefore, there is no choice left for us to work on channel selection mechanism.

4.6 Methodologies Used

4.6.1 Blood Pressure: Time Domain

We used feature detection algorithm for arterial blood pressure that is based on derivatives and threshold [106], [107], [108] implemented by Alexandre Laurin in Matlab [108]. After implementing the algorithm index points of diastolic and systolic values, index points of minimum or foot of the dicrotic notch, and index points of peaks of the dicrotic notch are identified. The time domain features used are basically the statistics from diastolic index points and values, systolic values, minimum values of dicrotic notch, and the peaks of dicrotic notch. Since blood signal is annotated for 30 sec therefore, in time domain and frequency domain we used rectangular window of size 30 sec.

4.6.2 EEG Signal: Frequency Domain

In the frequency domain, we applied Franklin transformation on EEG signal and Franklin coefficients are used as discriminatory features. For more details about the application of Franklin system on EEG and other signals are we refer to our previous works [20], [79].

4.7 Features Extraction and Classification

4.7.1 Feature Extraction in Time Domain: Blood Signal

Before extracting the features from blood pressure signal, let us have a look at the nature and the basic terms used for the blood pressure signal. Figure 4.2 shows the arterial blood pressure waveform. The main terms used in the blood pressure

waveform are diastolic blood pressure, systolic blood pressure, dicrotic notch. Due to the rate and character of the arterial pulse, blood pressure signal is used for the diagnosis of a wide range of disorders, like sleep disorder. *Systolic* blood pressure: the highest value with in the heart beat, measures the force, your heart exerts on the walls of your arteries each time it beats. *Diastolic* blood pressure: the lowest value with in the heart beat, measures the force your heart exerts on the walls of your arteries in between beats. From Figure 4.2 we can see that blood pressure signals have two types of waves i.e. Systole and Diastole. Dicrotic notch is a part of diastole wave. The *dicrotic* notch: designates the closure of the aortic valve. It is the foot or minimum value of the dicrotic notch wave. All these points are shown in Figure 4.2. After selecting the 30 sec long window we take the diastolic and systolic points along with the foot and peak points of the dicrotic notches with in every heart beat. After finding these points, the actual time domain features are calculated from them. We have calculated number of morphological and statistical features from blood signal and we found that the selected 13 time domain features are the best discriminatory features in sleep state detection in both the cases, i.e. when only blood signal is used or when it is combined with EEG signal.

For a fixed 30 second long window let the number of total heartbeats included it be N. Then we take the N dimensional vectors of the systolic values $\mathbf{S}$, the diastolic values $\mathbf{D}$, the foots of dicrotic notches $\mathbf{F}$, and the peaks of dicrotic notches $\mathbf{P}$. Let $\mathbf{D_\Delta t}$ be the $N-1$ dimensional vector that consists of the time lengths that elapsed between the adjacent diastolic points. $\mathbf{D_\Delta y}$ be the $N-1$ dimensional vector that is formed from the differences of the consecutive diastolic values. Using these vectors we calculate the following feature values.

a) Averages: Avg($\mathbf{S}$), Avg($\mathbf{D}$), Avg($\mathbf{F}$), Avg($\mathbf{P}$), Avg($\mathbf{D_\Delta t}$).

b) Variances: Var($\mathbf{S}$), Var($\mathbf{D}$), Var($\mathbf{F}$), Var($\mathbf{D_\Delta y}$), Var($\mathbf{P}$).

c) The sum of the squares of systolic and diastolic values: $Q = \sum_{k=1}^{N}(D_k^2 + S_k^2)$.

d) Mean average pressure: MAP$=\dfrac{2\text{Avg}(\mathbf{D}) + \text{Avg}(\mathbf{S})}{3}$.

Along with N, i.e. with the number of heartbeats in the window, these 12 quantities form the 13 dimensional feature vector. MAP (Mean Average Pressure) is a calculation that doctors use to check whether there's enough blood flow, resistance, and

pressure to supply blood to all your major organs, and experts think the number between 70 and 100 mmHg can be considered as normal value. For more details about the features and estimations of the blood pressure signal readers are refereed to follow [109], [110].

During sleep cycle, the blood pressure changes, and it is seen by the doctors that change in the blood pressure has a impact on the heart rate. Therefore, the number of heartbeats can be considered as a one of the discriminatory features. As the sleep cycle goes from wake to NREM and REM states, it is seen that the nature of the blood pressure wave also changes and in deep sleep states like s3, s4, REM the blood pressure waves become very slow as compared to wake and light sleep. Slow waves have small values (not much peaky) of systolic, diastolic, foot and peaks of dicrotic notches as compared to the normal wave. Therefore, the nature of blood pressure wave may impact the statistical features like variance, average and energy. The other reason of choosing such features is that these features are very simple and commonly used features and their combination with 8 Franklin coefficients gives better results so far. Various combinations to find best set of discriminatory features are presented in Table 4.1.

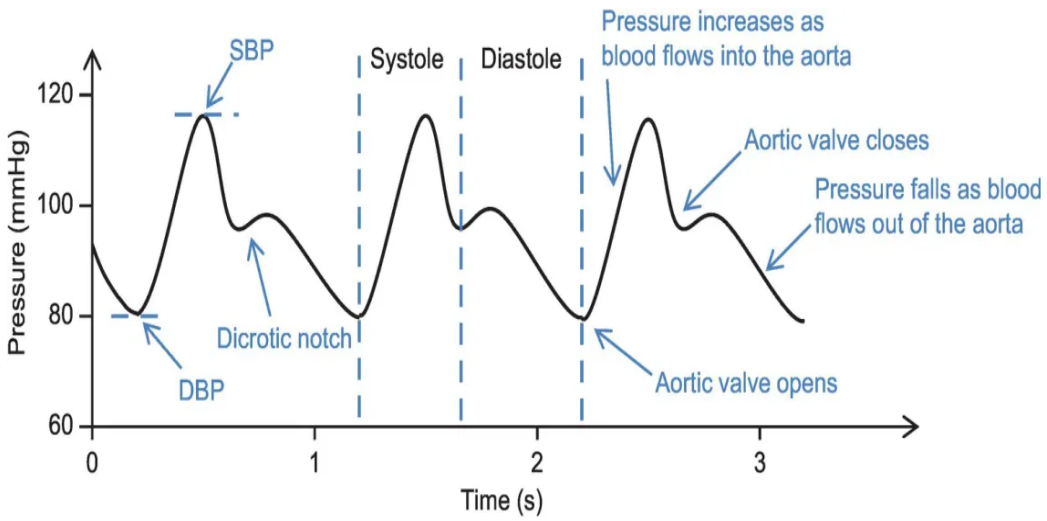

Figure 4.2: Arterial blood pressure waveform from a normal person[Anesthesia]

4.7.2 Feature Extraction in Frequency Domain: EEG Signal

In frequency domain we use orthogonal projections utilizing system. The preference of the Franklin system over other orthogonal systems is based on our previous studies and experience [20], [79]. After performing the tests shown in Table 4.1 we can see that considering 8 or 16 coefficients are effective. Theoretically, Franklin coefficients are the scalar product of the corresponding function and the elements of the Franklin system. Now we have a discrete signal with 7500 samples in 30 sec. After proper normalization we found that the numerical calculation of the Franklin coefficients is appropriate, i.e. provides the desired accuracy, on discretization level of 256 samples. To this order, we used down-sampling by using resample function of the MATLAB. The results of the proposed method are compared with state of the art methods which shows that features from Franklin transform with this resolution is still effective. To find the best features, various combinations are made and we found that the first 8 Franklin coefficients (EEG) are the best discriminatory features with the thirteen time domain features (blood) when KNN classifier is used. Bold rows of Table 4.1 shows the best combination on sample data.

4.7.3 Final Feature Vector Construction

There are two feature vectors, one in time domain, derived from from blood signal and other one from frequency domain derived from EEG signal. The final feature vector is constructed by merging the 13 time domain and first 8 frequency domain features with a total of 21 entries which are quite less than the best method [79] (42 entries) so far in terms of accuracy. Final results with different sets of classes using blood and "blood + EEG" are shown in Tables 4.3 and 4.4 where training and testing data is taken in the ratio of 60:40 respectively.

4.7.4 Classification

After the feature vector construction we applied the K-Nearest Neighbor algorithm (KNN) for classification recommended by various studies [20], [21], [79]. The reason to choose KNN for classification in our approach is that it is simple and fast as compared to popular classifier like SVM, Artificial neural network. We tested the

algorithm on SVM and KNN and the results are shown in Tables 4.1 and 4.2. We noted that the sets of sleep stages in the databases are not balanced. This means that the numbers of tuples of different classes are significantly different. Therefore, before applying the classifier, the class imbalance problem needs to be addressed otherwise results would be biased. Problem is addressed by using Adaptive Synthetic Sampling Approach for Imbalanced Learning (ADASYN) [97].

4.8 Results and Comparison Tests

Tests were performed on all the 18 records and total duration of 18 selected long term EEG and blood and with six different sleep classes is more than 80 hours. First we have optimized our method then we have carried out comparison tests. The results presented in Tables 4.1 and 4.2 are made by using sample data (#61 patient, 6 hour data of the same dataset). Such combinations give us hints about what type of classifier and features can be used as the best set of discriminatory features. The combinations "blood", and "blood+EEG", (bold rows) of Table 4.1 are the best combinations in case of only blood and blood+EEG signals. We used the same combinations to produce overall results. Therefore, the best choice is the combination of 13 time domain (blood signal) and 8 Franklin feature values (EEG signal) for each of them. The results of proposed algorithm using blood and the combination of the blood with EEG are shown in Tables 4.3 and 4.4.

Table 4.2 shows the results of SVM and we can see that SVM classifier is not performing well in our case. In the performance evaluation the metrics used are mentioned in section 1.6.2 of Chapter 1.

Table 4.5, contains the comparison of the proposed method with state of the art methods using the same database. It shows that our algorithm performed better than other state of the art methods. Our method is patient specific and the state of the methods used for comparisons are also patient specific, therefore it justifies the comparisons. After comparison with state of the art methods in Table 5 we can conclude that our proposed method using only blood signal is performing comparatively good as compared to the best method [79] in terms of accuracy. On the other hand, combined signal approach using blood and EEG gives best results so far on

Table 4.1: Results with different combinations using KNN

Signal	*Classifier*	*Features*	*Train&Test*	*Sensitivity*(%)	*Specificity*(%)	*Accuracy*(%)
Blood	**KNN**	**13T**	**60 − 40**	**98.44**	**99.43**	**97.95**
Blood	KNN	$10T$	$60-40$	95.43	97.79	93.51
Blood	KNN	$8T$	$60-40$	96.44	94.43	94.70
EEG	KNN	$8F$	$60-40$	94.64	96.70	94.89
EEG	KNN	$16F$	$60-40$	92.86	96.72	93.25
Blood EEG	**KNN**	**13T + 8F**	**60 − 40**	**99.33**	**99.65**	**98.47**
Blood EEG	KNN	$13T+16F$	$60-40$	95.63	98.58	95.63
Blood EEG	KNN	$8T+16F$	$60-40$	98.92	97.82	97.93
Blood EEG	KNN	$8T+8F$	$60-40$	98.62	99.82	98.10
Blood EEG	KNN	$10T+8F$	$60-40$	98.88	99.68	98.20

Table 4.2: Results with different combinations using SVM

Signal	*Classifier*	*Features*	*Train&Test*	*Sensitivity*(%)	*Specificity*(%)	*Accuracy*(%)
Blood	SVM	$13T$	$60-40$	69.52	90.48	60.33
EEG	SVM	$8F$	$60-40$	31.82	82.72	31.11
EEG	SVM	$16F$	$60-40$	31.86	80.60	30.90
Blood EEG	SVM	$16F$	$60-40$	69.33	90.30	60.21

the selected database.

4.9 Conclusion

A novel hybrid approach has been developed to extract the features from two biomedical signals. The novelty of the proposed method is the application of blood signal (alone) and combination with the EEG signal for sleep states detection. The idea behind the piecewise linear models used for EEG signal is was elaborated in our previous paper [20]. Different time domain and frequency domain features are extracted and tested on sample data, the final feature vector is their best combination. The feature vectors are classified by using KNN classifier on long data of CHB-MIT polysomnography database. From the Table 5 we can see that best state of the art methods mentioned in [93], [92], [100], [79] that are based on EEG or combination of EEG with other biomedical signals and their accuracies are: 92.28%, 94.31%, 85.29%, 93.84% respectively. In case of blood signal, our proposed algorithm achieved an average sensitivity, specificity, accuracy, false alarm rate and kappa of 95.45%, 98.27%, 93.78 %, 0.0170, 0.0224 respectively which is good or comparatively equal to the best state of the art methods and 99.45%, 99.75%, 99.01%, 0.0039, 0.964 respectively using blood and EEG signals, which is higher than the existing state of the art methods so far.

Table 4.3: Results of proposed algorithm with 13 time domain features using Blood signal only

Patient_Id	Total classes	Sensitivity(%)	Specificity(%)	Accuracy(%)	False alarm rate/hr	kappa
01a	$1, 2, 3, 4, W, R$	97.79	99.19	96.22	0.0081	0.8644
01b	$1, 2, W, R$	98.86	99.78	99.44	0.0020	0.985
2a	$1, 2, 3, 4, W, R$	99.03	99.32	96.59	0.0068	0.8773
2b	$1, 2, W, R, M$	96.66	98.31	95.54	0.0169	0.88
03	$1, 2, , 3, W, R$	96.26	98.51	93.89	0.0149	0.8090
04	$1, 2, 3, W, R$	98.09	98.84	94.86	0.0027	0.8390
14	$1, 2, 3, 4, W, R$	95.83	98.86	94.39	0.0114	0.7980
16	$1, 2, 3, 4, W, R$	97.36	98.87	94.52	0.0113	0.8029
32	$1, 2, 3, 4, W$	97.24	99.07	95.78	0.0093	0.868
37	$1, 2, W, R$	98.07	98.56	96.69	0.0026	0.9
41	$1, 2, 3, W, R$	72.43	91.19	67.31	0.088	0.0212
45	$1, 2, 3, 4, W, R$	98	98.90	94.18	0.0110	0.7905
48	$1, 2, 3, W, R$	97.37	98.57	96.36	0.0030	0.957
59	$1, 2, 3, 4, W, R$	98.60	99.50	98.11	0.0030	0.936
60	$1, 2, W, R$	99.93	99.96	99.86	0.0032	0.996
61	$1, 2, 3, W, R$	96.60	98.62	94.17	0.0138	0.8177
66	$1, 2, 3, W$	85.54	95.28	86.79	0.0472	0.6477
67x	$1, 2, 3, W$	94.63	97.54	93.51	0.0246	0.8268
Avg		**95.45**	**98.27**	**93.78**	**0.0170**	**0.0224**

Table 4.4: Results of proposed algorithm with combined features(8F+13T) from Blood and EEG signals

Patient_Id	Total classes	Sensitivity(%)	Specificity(%)	Accuracy(%)	False alarm rate/hr	kappa
01a	$1, 2, 3, 4, W, R$	99.59	99.84	99.16	0.0011	0.969
01b	$1, 2, W, R$	98.86	99.78	99.44	0.0020	0.985
2a	$1, 2, 3, 4, W, R$	99.51	99.68	98.30	0.0031	0.938
2b	$1, 2, W, R, M$	99.35	99.71	99.35	0.0029	0.970
03	$1, 2, , 3, W, R$	99.42	99.73	98.89	0.0027	0.965
04	$1, 2, 3, W, R$	99.59	99.73	98.75	0.0027	96.09
14	$1, 2, 3, 4, W, R$	99.42	99.75	98.74	0.0025	0.954
16	$1, 2, 3, 4, W, R$	99.84	99.92	99.57	0.0015	0.984
32	$1, 2, 3, 4, W$	99.82	99.93	99.69	0.0014	0.990
37	$1, 2, W, R$	100	99.67	99.67	0.0034	0.952
41	$1, 2, 3, W, R$	98.43	99.44	97.95	0.0051	0.935
45	$1, 2, 3, 4, W, R$	99.58	99.76	98.68	0.0020	0.952
48	$1, 2, 3, W, R$	99.29	99.65	98.55	0.0031	0.947
59	$1, 2, 3, 4, W, R$	98.70	99.61	98.25	0.0030	0.937
60	$1, 2, W, R$	99.93	99.96	99.86	0.0032	0.996
61	$1, 2, 3, W, R$	99.33	99.65	98.47	0.0035	0.952
66	$1, 2, 3, W$	99.45	99.71	98.75	0.0029	0.960
67x	$1, 2, 3, W$	100	100	100	0	1.00
Avg		**99.45**	**99.75**	**99.01**	**0.0039**	**0.964**

Table 4.5: Comparison of results with previous methods tested on the same database

Author and year	$\#records$	$feature$	$Classesused$	$Classifierused$	$AverageAccuracy(\%)$	$Cohen'skappa$
Redmond and Heneghan [95], 2003	17	$HRVandEEGFeatures$	$Lightvsdeepsleep$	QDA	89	0.51
Adnane et al. [94], 2012	17	$HRV, DFAandWDFA$	$Sleepvswake$	SVM	79.99	0.43
Hayet and Slim [98], 2012	09	$RR-timeseriesandHRVfeatures$	$Sleepvswake$	ELM	83.59	$--$
Werteni et al. [99], 2015	17	HRV	$SleepvswakeREM$	SVM	56.81	$--$
R.K Tripathi et al [90], (May, 2018)	17	$Dispersionentropyandvariance$	DNN	$Neuralnetwork$	$85.51, 94.095.71$	$--$
Taran et al. [93], 2018	16	$Hermitecofficents$	$alert(w)anddrowsiness(s1)$	ELM	92.28	$--$
Budak et al. [92], 2019	16	$spectroramimagesandInstaniousfrequencies$	$alertanddrowsiness$	$LSTM$	94.31	$--$
Panfeng at el [100], 2019	06	$statisticalfeatures$	$NREM(s1-s4), REM, Wake$	$W-SVM$	85.29	$--$
Junming at el [101], 2020	18	$HilbertHuangcoefficients$	$REM, REM, wake$	CNN	87.6	0.81
Yash at el.[79], 2021	18	$Half-waveandFranklinCoefficients$	$Wake, Sleep(all), REM$	KNN	93.84	$--$
Proposed method, 6 classes	18	$timedomainandFranklincoefficients$	$Wake, Sleep(all), REM$	KNN	**99.01**	**0.964**

Table 4.6: Comparison with other algorithms tested on the different database

Author and year	features	$Classesused$	$Classifierused$	$AverageAccuracy(\%)$
Prucnal et al. [102]	$Waveletbasedfeatures$	$Fiveclass(wake, S1, S2, deepsleep, REM)$	$NeuralNetwork$	74.2
Prucnal et al. [102]	$EMDbasedfeatures$	$Fiveclass(wake, S1, S2, deepsleep, REM)$	$NeuralNetwork$	57.6
Hasan et al. [103]	$EnsembleEMDbasedfeatures$	$Sixclasses(wake, S1, S2, S3, S4, REM)$	$RUSBoost$	71.98
Da Silveira et al. [91]	$DWTandstatisticalfeatures$	$(wake, S1, S2, S3, S4, REM)$	$Randomforest$	63.51
R.K Tripathi et al. [85], May, 2018	$HRVfeatures$	$(NREM(all), REM)$	DNN	73.70
Proposed method(6 classes)	$TimedomainandFranklincoeffi.$	$Wake, Sleep(all), REM$	KNN	**99.01**

Chapter 5

Summary

Since couple of decades, biomedical signal processing plays an important role to the improve the quality of human life. The recent research in the field of biomedical signal processing is carried out by using important biomedical signals like EEG, EMD, ECG, blood pressure and nasal signals. Thesis is divided into 5 chapters including summary. Chapter 1, gives the introduction about Epilepsy, sleep states, piecewise linear functions and metrics used for performance evaluation. In Chapter 2, we proposed a hybrid approach for seizure detection using EEG signals. We used two piecewise linear models namely Halfwave and Franklin transformation. The reason of preferring the linear models over other models is that linear models are simple, computationally fast and efficient. The algorithm is tested on 23 different subjects having more than 100 hours long term EEG in the CHB-MIT database in several respects. It showed better performance compared to the state-of-the art methods for seizure detection tested on the given database. In 2017 Bhattacharyya et al.[68] proposed best method for seizure detection based on multichannel, which may not be used for real time applications efficiently, achieved average sensitivity, specificity and accuracy of 97.91%, 99.57%, 99.41%. Whereas, our proposed method achieved an average sensitivity, specificity, accuracy, false alarm rate and kappa of 99.45%, 99.75%, 99.01%, 0.0039, 0.964 respectively and these results are comparatively good than [68] and other state of the art methods. In Chapter 3, various sleep states are detected by using the extended version of the method proposed in Chapter 2. The aim of the algorithm proposed in Chapter 3 is to detect the various sleep states by combining different biomedical signals like EEG, blood pressure, and nasal signals.

Algorithm is tested on MIT-BIH Polysomnographic database having more than 70 hours long term EEG, blood pressure and respiratory (nasal) signals with six different sleep classes. Proposed method shows better performance than state of the art methods. 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 than the existing state of the art methods. To use the algorithm in real time scenario, and to increase the further accuracy of the method proposed in Chapter 3 we proposed a new approach for sleep states in Chapter 4. We used two biomedical signals i.e. blood pressure signal, in time domain and EEG signal, in frequency domain. In time domain, statistical and morphological features are extracted from the blood pressure signal and in frequency domain, a piecewise linear reduction namely Franklin transformation is applied on EEG signal. The Franklin coefficients are used as discriminatory features in frequency domain. The novelty of the proposed method is that we considered two cases, the blood pressure signal by itself, and the combination of it with EEG signal. The motivation behind the first one is that in certain cases, e.g. smart personal mobile devices, only the blood pressure signal is available. In both cases the algorithm is tested on MIT-BIH Polysomnographic database having more than 80 hours long term EEG and blood Pressure signals. In both cases we performed comparison tests with relevant state-of-the-art methods, and our algorithm showed better or equal performance in terms of sensitivity, specificity, accuracy and false alarm rate. Our proposed algorithm in case of using only blood signal, achieved an average sensitivity, specificity, accuracy, false alarm rate and kappa of 95.45%, 98.27%, 93.78 %, 0.0170, 0.0224 respectively which is good or comparatively equal to the state of the art methods. Where as, an average sensitivity, specificity, accuracy, false alarm rate and kappa of 99.45%, 99.75%, 99.01%, 0.0039, 0.964 respectively is achieved using blood and EEG signals, which is higher than the existing state of the art methods so far.

5.1 My Publications

1. Y. Paul, A Comparative Study of Famous Classification Techniques and Data Mining Tools LECTURE NOTES IN ELECTRICAL ENGINEERING (Q3) (1876-1100 1876-1119): 597 597 pp 627-644 Paper Chapter 45. (2020), Accepted and Published.

2. Y. Paul, Various epileptic seizure detection techniques using biomedical signals: A review, BRAIN INFORMATICS (Q2) (2198-4018): 5 p. 1. Paper 6. 6 p. (2018), Accepted and published.

3. Y. Paul and S. Fridli, Epileptic Seizure Detection Using Piecewise Linear Reduction LECTURE NOTES IN COMPUTER SCIENCE (Q2) (0302-9743 1611-3349): 12014 pp 364-371 (2020), Accepted and Published.

4. Y. Paul and S. Fridli, Sleep states detection using halfwave and Franklin transformation, MACS-2020, Annales Universitatis Scientiarum Budapestiensis de Rolando Eotvos Nominatae Sectio Computatorica, 2021, accepted.

5. Y. Paul and S. Fridli, Sleep states detection using EEG and blood pressure signals, ICRIC-2021, LECTURE NOTES IN ELECTRICAL ENGINEERING (Q3) 2021, ISSN: 1876-1100

   accepted.

Bibliography

[1] A. Kales and A. Rechtschaffen. "A manual of standardized terminology, techniques and scoring system for sleep stages of human subjects." In: *Allan Rechtschaffen and Anthony Kales, editors, University of California, Los Angeles. Brain Information Service, NINDB Neurological Information Network (U.S.)* (1968).

[2] V. Ibáñez et al. "A survey on sleep assessment methods". In: *Speerj* 6.e4849 (2018), 231–236. DOI: 10.7717/peerj.4849.

[3] H. Firat et al. "Comparison of four established questionnaires to identify highway bus drivers at risk for obstructive sleep apnea in Turkey". In: *Sleep Biol. Rhythms* 10 (2012), 231–236. DOI: https://doi.org/10.1111/j.1479-8425.2012.00566.x.

[4] G.E. Silva et al. "Obstructive sleep apnea and quality of life: comparison of the SAQLI, FOSQ, and SF-36 questionnaires". In: *Southwest Journal on Pulmonary Critical Care* 13.3 (2016), 137–149. DOI: 10.13175/swjpcc082-16.

[5] L. J. Herrera et al. "Combination of heterogeneous EEG feature extraction methods and stacked sequential learning for sleep stage classification". In: *International journal of neural systems* 23(3).1793-6462 (2011). DOI: 10.1142/S0129065713500123.

[6] M. Ohayon Maurice and S. Salvatore. "Prevalence and consequences of insomnia disorders in the general population of Italy". In: *Sleep Medicine* 3.2 (2002), pp. 115–120. ISSN: 1389-9457. DOI: https://doi.org/10.1016/S1389-9457(01)00158-7. URL: https://www.sciencedirect.com/science/article/pii/S1389945701001587.

[7] R. Gupta et al. "Clinical Practice Guidelines for Sleep Disorders". In: *Indian journal of psychiatry* 59.1 (2017), S116–S138. ISSN: 1998-3794. DOI: 10.4103/0019-5545.196978.

[8] j. Gotman and p. Gloor. "Automatic recognition and quantification of interictal epileptic activity in the human scalp EEG". In: *Electroencephalography and Clinical Neurophysiology* 41.5 (1976), pp. 513–529. ISSN: 0013-4694. DOI: https://doi.org/10.1016/0013-4694(76)90063-8. URL: https://www.sciencedirect.com/science/article/pii/0013469476900638.

[9] J. Gotman, P. Gloor, and W.F. Ray. "A quantitative comparison of traditional reading of the EEG and interpretation of computer-extracted features in patients with supratentorial brain lesions". In: *Electroencephalography and clinical neurophysiology* 38.6 (June, 1975), 623—639. ISSN: 0013-4694. DOI: 10.1016/0013-4694(75)90163-7.

[10] J. Gotman et al. "Clinical applications of spectral analysis and extraction of features from electroencephalograms with slow waves in adult patients". In: *Electroencephalography and Clinical Neurophysiology* 35.3 (1973), pp. 225–235. ISSN: 0013-4694. DOI: https://doi.org/10.1016/0013-4694(73)90233-2. URL: https://www.sciencedirect.com/science/article/pii/0013469473902332.

[11] H. Jasper and J. Kershman. "Electroencephlographic Classification of the Epilepsies". In: *Archives of Neurology and Psychiatry* 45.6 (June 1941), pp. 903–943. ISSN: 0096-6754. DOI: 10.1001/archneurpsyc.1941.02280180015001. eprint: https://jamanetwork.com/journals/archneurpsyc/articlepdf/648886/archneurpsyc_45_6_001.pdf. URL: https://doi.org/10.1001/archneurpsyc.1941.02280180015001.

[12] T.P. Runarsson and S. Sigurdsson. "On-line detection of patient specific neonatal seizures using support vector machines and half-wave attribute histograms". In: *CIMCA-IAWTIC,vienna* (28-30 Nov 2005), 673–677.

[13] A. Haar. "Zur Theorie der orthogonalen Funktionensysteme". In: *Mathematische Annalen* 69.3 (1910), pp. 331–371. DOI: https://doi.org/10.1007/BF01456326.

[14] G. Faber. "uber die Orthogonalfunktionen des Herrn Haar". In: *Deutsche Math.-Ver (in German)* 19 (1910), pp. 104–112. URL: http://eudml.org/doc/145217.

[15] B.I. Golubov. "Faber–Schauder system". In: *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.

[16] L. Tzafriri J. Lindenstrauss. "Classical Banach Spaces I, Sequence Spaces". In: *Ergebnisse der Mathematik und ihrer Grenzgebiete, Springer-Verlag,ISBN 3-540-08072-4* (1977), p. 3.

[17] Z. Ciesielski. "Properties of the orthonormal Franklin system". In: *Encyclopedia of Mathematics* 23 (1963), 141–157.

[18] B.I. Golubov. "Franklin system (originator)". In: *URL: http://www.encyclopediaofmath.org* 1402006098 ().

[19] P. Franklin. "A set of continuous orthogonal functions". In: *Math. Ann* 100 (1928), pp. 522–529.

[20] Y. Paul and S. Fridli. "Epileptic Seizure Detection Using Piecewise Linear Reduction". In: *Lecture Notes in Computer Science, Springer* 45 Cham. (2020), pp. 364–371. ISSN: 12014. DOI: 10.1007/978-3-030-45096-0\underline{\;\;}45.

[21] Y. Paul. "Various epileptic seizure detection techniques using biomedical signals: a review". In: *Brain Informatics* 5 (2018). DOI: 10.1186/s40708-018-0084-z.

[22] National Institute of Neurological Disorders and Stroke. "http://www.ninds.nih.gov/". In: *accesed 15* (15 Sept 2014).

[23] World Health Organization. "Fact sheet on epilepsy". In: (January 2009). DOI: http://www.who.int/mediacentre/factsheets/fs999/.

[24] Trans Cranial Technologies. "10/20 System Positioning Manual". In: *rans Cranial Technologies Ltd, Kowloon* (2012).

[25] U. Rajendra Acharya et al. "Automated EEG analysis of epilepsy: A review". In: *Knowledge-Based Systems* 45 (2013), pp. 147–165. ISSN: 0950-7051. DOI: https://doi.org/10.1016/j.knosys.2013.02.014. URL: https://www.sciencedirect.com/science/article/pii/S0950705113000798.

[26] K. Binder Devin and R. Haut Sheryl. "Toward new paradigms of seizure detection". In: *Epilepsy and Behavior* 26.3 (2013). The Future of Translational Epilepsy Research, pp. 247–252. ISSN: 1525-5050. DOI: https://doi.org/10.1016/j.yebeh.2012.10.027. URL: https://www.sciencedirect.com/science/article/pii/S1525505012006476.

[27] H. Borbála et al. "Incorporating structural information from the multichannel EEG improves patient-specific seizure detection". In: *Clinical Neurophysiology* 123.12 (2012), pp. 2352–2361. ISSN: 1388-2457. DOI: https://doi.org/10.1016/j.clinph.2012.05.018. URL: https://www.sciencedirect.com/science/article/pii/S1388245712004208.

[28] P. E. McSharry, L. A. Smith, and L. Tarassenko. "Comparison of predictability of epileptic seizures by a linear and a nonlinear method". In: *IEEE Transactions on Biomedical Engineering* 50.5 (2003), pp. 628–633. DOI: 10.1109/TBME.2003.810688.

[29] P. E. McSharry et al. "Linear and non-linear methods for automatic seizure detection in scalp electro-encephalogram recordings." In: *Med. Biol. Eng. Comput. 40, (2002)* 40 (2002), 447–461. DOI: https://doi.org/10.1007/BF02345078.

[30] V. Sakkalis et al. "Absence seizure epilepsy detection using linear and nonlinear eeg analysis methods". In: (2013), pp. 6333–6336. DOI: 10.1109/EMBC.2013.6611002.

[31] T. Tzallas Alexandros et al. "Automated Epileptic Seizure Detection Methods: A Review Study". In: (2012). Ed. by Dejan Stevanovic. DOI: 10.5772/31597. URL: https://doi.org/10.5772/31597.

[32] T. N. Alotaiby et al. "EEG seizure detection and prediction algorithms: a survey". In: *EURASIP Journal on Advances in Signal Processing* (2014). DOI: 10.1186/1687-6180-2014-183.

[33] A. L. Goldberger et al. "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals". In: *circulation* 101.23 (), e215–e220. DOI: 10.1161/01.cir.101.23.e215.

[34] P.P. Shanir and U. Khan Yusuf. "Time Domain Analysis of EEG for Automatic Seizure Detection". In: *ETEEE-2015* (2015).

[35] N. Alotaiby Turky et al. "Channel selection and seizure detection using a statistical approach". In: *5th International Conference on Electronic Devices, Systems and Applications (ICEDSA)* (19 jan, 2017). DOI: 10.1109/ICEDSA.2016.7818505.

[36] J. Yoo et al. "An 8 channel scalableEEG acquisition SoC with patient-specific seizure classification and recording processor". In: *IEEE J. Solid State Circuits* 48(1) (2012), 214–228. DOI: https://doi.org/10.1109/JSSC.2012.2221220.

[37] A. Dalton et al. "Development of a Body Sensor Network to Detect Motor Patterns of Epileptic Seizures". In: *IEEE Transactions on Biomedical Engineering* 59.11 (2012), pp. 3204–3211. DOI: 10.1109/TBME.2012.2204990.

[38] M. Md et al. "Automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier". In: *Neurocomputing* 241 (2017), pp. 204–214. ISSN: 0925-2312. DOI: https://doi.org/10.1016/j.neucom.2017.02.053. URL: https://www.sciencedirect.com/science/article/pii/S0925231217303442.

[39] A. Baldominos and C. Ramón-Lozano. "Optimizing EEG energy-based seizure detection using genetic algorithms". In: (2017), pp. 2338–2345. DOI: 10.1109/CEC.2017.7969588.

[40] R. Puneet et al. "Seizure detection using the phase-slope index and multi-channel ECoG". In: *IEEE Trans. Biomed.Eng. 59(4)* (2012), pp. 1125–1134. DOI: 10.1109/TBME.2012.2184796.

[41] U. Acharya et al. "Automated diagnosis of epileptic EEG using entropies". In: *Biomed. Signal Process. Control.* 7 (2012), pp. 401–408.

[42] M. Vetterli and C. Herley. "Wavelets and filter banks: theory and design". In: *IEEE Transactions on Signal Processing* 40.9 (1992), pp. 2207–2232. DOI: 10.1109/78.157221.

[43] H. Polat and M. S. Ozerdem. "Epileptic seizure detection from EEG signals by using wavelet and Hilbert transform". In: (2016), pp. 66–69. DOI: 10.1109/MEMSTECH.2016.7507522.

[44] K. et al. Lehnertz. "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: dependence on recording region and brain state". In: *Department of Epileptology, University of Bonn, Sigmund-Freud-Strasse 25, 53105* (), p. 2003. DOI: 10.1103/PhysRevE.64.061907..

[45] Z. Zarita, H. Lai Kee, and P. Ong. "On the Use of Wavelet Neural Networks in the Task of Epileptic Seizure Detection from Electroencephalography Signals". In: *Proceedings of the 3rd International Conference on Computational Systems-Biology and Bioinformatics,Procedia Computer Science* 11 (2012), pp. 149–159. ISSN: 1877-0509. DOI: https://doi.org/10.1016/j.procs.2012.09.016. URL: https://www.sciencedirect.com/science/article/pii/S1877050912005996.

[46] M. Niknazar et al. "A new framework based on recurrence quantification analysis for epileptic seizure detection". In: *IEEE journal of biomedical and health informatics* 17.3 (2013), 572—578. ISSN: 2168-2194. DOI: 10.1109/jbhi.2013.2255132.

[47] W. Zhou et al. "Epileptic seizure detection using lacunarity and Bayesian linear discriminant analysis in intracranial EEG". In: *IEEE Trans. Biomed.Eng* 60(12) (2013), 3375–3381. DOI: 10.1109/tbme.2013.2254486.

[48] "Seizure Prediction Project Freidburg (University of Freiburg, 2014), University of Freidberg". In: *http://epilepsy.uni- freiburg.de/freiburg-seizure prediction project/eeg-database. Accessed* 17(3) (Sept 2014), 572–578. DOI: http://epilepsy.uni-freiburg.de/freiburg-seizurepredictionproject/eeg-database..

[49] G. Guangyi et al. "Automatic Epileptic Seizure Detection in EEG Using Non-subsampled Wavelet– Fourier Features". In: *J. Med. Biol. Eng.* 60(12) (2017). DOI: 10.1007/s40846-016-0214-0(2017).

[50] Y. Liu et al. "Automatic Seizure Detection Using Wavelet Transform and SVM in Long-Term Intracranial EEG". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 20.6 (2012), pp. 749–755. DOI: 10.1109/TNSRE.2012.2206054.

[51] R. Abbasi and M. Esmaeilpour. "Selecting Statistical Characteristics of Brain Signals to Detect Epileptic Seizures using Discrete Wavelet Transform and Perceptron Neural Network". In: *International Journal of Interactive Multimedia and Artificial Intelligence* 4.5 (2017), pp. 33–38. DOI: 10.1109/TNSRE.2012.2206054.

[52] R. Panda et al. "Classification of EEG signal using wavelet transform and support vector machine for epileptic seizure diction". In: *2010 International Conference on Systems in Medicine and Biology* (2010), pp. 405–408. DOI: 10.1109/ICSMB.2010.5735413.

[53] Y.U. Khan, N. Rafiuddin, and O. Farooq. "Automated seizure detection in scalp EEG using multiple wavelet scales". In: *2012 IEEE International Conference on Signal Processing, Computing and Control* (2012), pp. 1–5.

[54] M. Shoaib et al. "A 0.6–107 µW Energy-Scalable Processor for Directly Analyzing Compressively-Sensed EEG". In: *IEEE Transactions on Circuits and Systems I: Regular Papers* 61.4 (2014), pp. 1105–1118. DOI: 10.1109/TCSI.2013.2285912.

[55] E. Huang Norden et al. "The Empirical Mode Decomposition and the Hilbert Spectrum for Nonlinear and Non-Stationary Time Series Analysis". In: *Proceedings: Mathematical, Physical and Engineering Sciences* 454.1971 (1998), pp. 903–995. ISSN: 13645021. URL: http://www.jstor.org/stable/53161.

[56] A. Eftekhar et al. "Hilbert-Huang transform: Preliminary studies in epilepsy and cardiac arrhythmias". In: *2008 IEEE Biomedical Circuits and Systems Conference* (2008), pp. 373–376. DOI: 10.1109/BIOCAS.2008.4696952.

[57] A. K. Tafreshi, A. M. Nasrabadi, and A. H. Omidvarnia. "Epileptic Seizure Detection Using Empirical Mode Decomposition". In: *2008 IEEE International Symposium on Signal Processing and Information Technology* (2008), pp. 238–242. DOI: 10.1109/ISSPIT.2008.4775717.

[58] L. Orosco et al. "An epileptic seizures detection algorithm based on the empirical mode decomposition of EEG". In: *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (2009), pp. 2651–2654. DOI: 10.1109/IEMBS.2009.5332861.

[59] C. Guarnizo and E. Delgado. "channel seizure recognition using empiricalmode decomposition and normalized mutual information". In: *in Proceedings ofthe IEEE International Conference on Signal Processing (ICSP),* (28 Oct 2010), 1–24.

[60] S. Belhadj et al. "Whole brain epileptic seizure detection using unsupervised classification". In: *2016 8th International Conference on Modelling, Identification and Control (ICMIC)* (2016), pp. 977–982. DOI: 10.1109/ICMIC.2016.7804256.

[61] A. Torse Dattaprasad, D. Veena, and K. Rajashri. "EEG Signal Classification into Seizure and Non-Seizure Class using Empirical Mode Decomposition and Artificial Neural Network". In: *(IJIR) ISSN: 2454-1362* Vol-3,1 (march,2017).

[62] S. M. S. Alam and M. I. H. Bhuiyan. "Detection of epileptic seizures using chaotic and statistical features in the EMD domain". In: *2011 Annual IEEE India Conference* (2011), pp. 1–4. DOI: 10.1109/INDCON.2011.6139341.

[63] V. Bajaj and R. B. Pachori. "Epileptic seizure detection based on the instantaneous area of analytic intrinsic mode functions of EEG signals". In: *Biomedical Engineering Letters* 3 (2013), pp. 17–21. DOI: 10.1007/S13534-013-0084-0.

[64] K. Samiee, Kovacs P., and M. Gabbouj. "Epileptic Seizure Classification of EEG time-series using Rational Discrete Short Time FourierTransform". In: *IEEE Transactions on Biomedical Engineering* vol. XX.10 (SEP, 2011), pp. 541–52. DOI: 10.1109/TBME.2014.2360101.

[65] K. Samiee, P. Kovcs, and M. Gabbouj. "Epileptic Seizure Detection in Long-Term EEG Records Using Sparse Rational Decomposition and Local Gabor Binary Patterns Feature Extraction". In: *Knowledge-Based Systems,Elsevier Science Publishers B. V.* 118.228–240 (2017). DOI: 10.1016/j.knosys.2016.11.023. URL: https://doi.org/10.1016/j.knosys.2016.11.023.

[66] S. Fridli, L. Lócsi, and F. Schip. "Rational Function Systems in ECG Processing". In: *project is supported and financed by the European Social Fund (grant agreement no.TAMOP 4.2.1./B-09/1/KMR- 2010-0003)* vol. XX.10 (2010). DOI: https://doi.org/10.1007/978-3-642-27549-4_12.

[67] A. Shoeb and J. Guttag. "Application of Machine Learning to Epileptic Seizure Detection". In: *Proceedings of the 27th International Conference on International Conference on Machine Learning* (2010), 975–982.

[68] A. Bhattacharyya and R. B. Pachori. "A Multivariate Approach for Patient-Specific EEG Seizure Detection Using Empirical Wavelet Transform". In: *IEEE Transactions on Biomedical Engineering* 64.9 (2017), pp. 2003–2015. DOI: 10.1109/TBME.2017.2650259.

[69] A. S. Gevins et al. "Automated analysis of the electrical activity of the human brain (EEG): A progress report". In: *Proceedings of the IEEE* 63.10 (1975), pp. 1382–1399. DOI: 10.1109/PROC.1975.9966.

[70] K. A. Kooi. "Voltage-time characteristics of spikes and other rapid electroencephalographic transients". In: *Neurology* 16.1 (1966), pp. 59–59. ISSN: 0028-3878. DOI: 10.1212/WNL.16.1.59. URL: https://n.neurology.org/content/16/1/59.

[71] L. Silva, A. Dijk, and H. Smits. "Detection of nonstationarities in EEGs using the auto-regressive model. an application to EEGs of epileptics." In: *Dolce, G., K unkel, H.(eds.) CEAN Computerized EEG Analysis* Fischer, Stuttgart (1975), 180–199. DOI: 10.1109/MEMSTECH.2016.7507522.

[72] N. V. Chawla et al. "SMOTE: Synthetic Minority over-Sampling Technique". In: 16.1 (2002). ISSN: 1076-9757.

[73] L. Victoria et al. "Analysis of preprocessing vs. cost-sensitive learning for imbalanced classification. Open problems on intrinsic data characteristics". In: *Expert Systems with Applications* 39.7 (2012), pp. 6585–6608. ISSN: 0957-4174. DOI: https://doi.org/10.1016/j.eswa.2011.12.043. URL: https://www.sciencedirect.com/science/article/pii/S0957417411017143.

[74] S. Khanmohammadi, Khanmohammadi S., and C. Chou. "Adaptive Seizure Onset Detection Framework Using a Hybrid PCA-CSP Approach". In: *IEEE journal of biomedical and health informatics* 22.1 (Jan.,2018), pp. 154–160. DOI: 10.1109/JBHI.2017.2703873.

[75] M. Fan and C. A. Chou. "Detecting Abnormal Pattern of Epileptic Seizures via Temporal Synchronization of EEG Signals". In: *IEEE Transactions on Biomedical Engineering* 66.3 (2019), pp. 601–608. DOI: 10.1109/TBME.2018.2850959.

[76] D. Chen et al. "A high-performance seizure detection algorithm based on Discrete Wavelet Transform". In: *PLOS ONE* 12.3 (2017), pp. 1932–6203. DOI: 10.1371/journal.pone.0173138.

[77] J. Birjandtalab et al. "Automated seizure detection using limited-channel EEG and non-linear dimension reduction". In: *2011 IEEE 11th International Conference on Bioinformatics and Bioengineering, Computers in biology and medicine* 82.0010-4825 (march,2017), pp. 49–58. DOI: 10.1016/j.compbiomed.2017.01.011.

[78] Kostas M Tsiouris et al. "A robust unsupervised epileptic seizure detection methodology to accelerate large EEG database evaluation". In: *Biomedical Signal Processing and Control* 40 (2018), pp. 275–285. DOI: https://doi.org/10.1016/j.bspc.2017.09.029.

[79] Y. Paul and S. Fridli. "Sleep states detection using halfwave and Franklin transformation". In: (2020). DOI: 10.21203/rs.3.rs-27562/v1.

[80] F. Oliver et al. "A review of automated sleep stage scoring based on physiological signals for the new millennia". In: *Computer Methods and Programs in Biomedicine* 178 (Sep.,2019), pp. 19–30. ISSN: 0169-2607. DOI: https://doi.

org/10.1016/j.cmpb.2019.04.032. URL: https://www.sciencedirect.com/science/article/pii/S0169260718313865.

[81] S. Motamedi-Fakhr et al. "Signal processing techniques applied to human sleep EEG signals—A review". In: *Biomedical Signal Processing and Control* 10 (2014), pp. 21–33. ISSN: 1746-8094. DOI: https://doi.org/10.1016/j.bspc.2013.12.003. URL: https://www.sciencedirect.com/science/article/pii/S174680941300178X.

[82] http://www.ninds. nih.gov/. "15 Sept 2014". In: ().

[83] R. Acharya et al. "Non-linear analysis of EEG signals at various sleep stages". In: *Computer methods and programs in biomedicine* 80.1 (2005), pp. 37–45. DOI: https://doi.org/10.1016/j.cmpb.2005.06.011.

[84] A. Garcés Correa, L. Orosco, and E. Laciar. "Automatic detection of drowsiness in EEG records based on multimodal analysis". In: *Medical engineering and amp; physics* 36.2 (2014), 244—249. ISSN: 1350-4533. DOI: 10.1016/j.medengphy.2013.07.011.

[85] R.K. Tripathy. "Application of intrinsic band function technique for automated detection of sleep apnea using HRV and EDR signals". In: *Biocybernetics and Biomedical Engineering* 38.1 (2018), pp. 136–144. DOI: https://doi.org/10.1016/j.bbe.2017.11.003.

[86] R. G. Norman et al. "Interobserver Agreement Among Sleep Scorers From Different Centers in a Large Dataset". In: *Sleep* 23.7 (oct,2000), pp. 1–8. ISSN: 0161-8105. DOI: 10.1093/sleep/23.7.1e. URL: https://doi.org/10.1093/sleep/23.7.1e.

[87] C. Iber and American Academy of Sleep Medicine et al. "The Aasm Manual for the Scoring of Sleep and Associated Events: Rules, Terminology and Technical Specifications". In: *Westchester, IL: American Academy of Sleep Medicine* (2007). URL: https://www.worldcat.org/title/aasm-manual-for-the-scoring-of-sleep-and-associated-events-rules-terminology-and-technical-specifications/oclc/438914652.

[88] J. Dihong, M.A. Yu, and W. Yuanyuan. "Sleep stage classification using covariance features of multi-channel physiological signals on Riemannian manifolds". In: *Computer Methods and Programs in Biomedicine* 178 (2019), pp. 19–30. ISSN: 0169-2607. DOI: https://doi.org/10.1016/j.cmpb.2019.06.008. URL: https://www.sciencedirect.com/science/article/pii/S0169260719305838.

[89] M. Nicola, U. Rajendra Acharya, and M. Filippo. "Cascaded LSTM recurrent neural network for automated sleep stage classification using single-channel EEG signals". In: *Computers in Biology and Medicine* 106 (2019), pp. 71–81. ISSN: 0010-4825. DOI: https://doi.org/10.1016/j.compbiomed.2019.01.013. URL: https://www.sciencedirect.com/science/article/pii/S0010482519300137.

[90] R.K. Tripathy and U. Rajendra Acharya. "Use of features from RR-time series and EEG signals for automated classification of sleep stages in deep neural network framework". In: *Biocybernetics and Biomedical Engineering* 38.4 (2018), pp. 890–902. ISSN: 0208-5216. DOI: https://doi.org/10.1016/j.bbe.2018.05.005. URL: https://www.sciencedirect.com/science/article/pii/S0208521618300949.

[91] T.L. da Silveira, A.J. Kozakevicius, and C.R. Rodrigues. "Single channel EEG sleep stage classification based on a streamlined set of statistical features in wavelet domain." In: *Med Biol Eng Comput* 55.2 (2017), 343–52. DOI: 10.1007/s11517-016-1519-4.

[92] U. Budak et al. "An Effective Hybrid Model for EEG-Based Drowsiness Detection". In: *IEEE Sensors Journal* 19.17 (2019), pp. 7624–7631. DOI: 10.1109/JSEN.2019.2917850.

[93] S. Taran and V. Bajaj. "Drowsiness Detection Using Adaptive Hermite Decomposition and Extreme Learning Machine for Electroencephalogram Signals". In: *IEEE Sensors Journal* 18.21 (2018), pp. 8855–8862. DOI: 10.1109/JSEN.2018.2869775.

[94] A. Mourad and Y. Zhongwei J.and Zhonghong. "Sleep–wake stages classification and sleep efficiency estimation using single-lead electrocardiogram".

In: *Expert Systems with Applications* 39.1 (2012), pp. 1401–1413. ISSN: 0957-4174. DOI: https://doi.org/10.1016/j.eswa.2011.08.022. URL: https://www.sciencedirect.com/science/article/pii/S095741741101133X.

[95] S. Redmond and C. Heneghan. "Electrocardiogram-based automatic sleep staging in sleep disordered breathing". In: *Computers in cardiology. IEEE* (2003), pp. 609–612.

[96] Y. Ichimaru and G. B. Moody. "Development of the polysomnographic database on cd-rom". In: *Psychiatry Clin Neurosci.* 53(2) (1999). DOI: doi:10.1046/j.1440-1819.1999.00527.x.

[97] H. He et al. "ADASYN: Adaptive Synthetic Sampling Approach for Imbalanced Learning". In: *Proceedings of the International Joint Conference on Neural Networks* (July 2008), pp. 1322 –1328. DOI: 10.1109/IJCNN.2008.4633969.

[98] W. Hayet and S. Yacoub. "Sleep-wake stages classification based on heart rate variability". In: (Oct. 2012), pp. 996–999. DOI: 10.1109/BMEI.2012.6513040.

[99] W. Hayet, S. Yacoub, and N. Ellouze. "Classification of Sleep Stages Based on EEG Signals". In: *International Review on Computers and Software (IRECOS)* 10 (2015), p. 174.

[100] P. An et al. "A Novel EEG Sleep Staging Method for Wearable Devices Based on Amplitude-time Mapping". In: (2019), pp. 124–129. DOI: 10.1109/ICARM.2019.8833661.

[101] Z. Junming et al. "Orthogonal convolutional neural networks for automatic sleep stage classification based on single-channel EEG". In: *Computer Methods and Programs in Biomedicine* 183 (2020), p. 105089. ISSN: 0169-2607. DOI: https://doi.org/10.1016/j.cmpb.2019.105089. URL: https://www.sciencedirect.com/science/article/pii/S0169260719311617.

[102] A. Prucnal Monika and A. Polak. "Effect of Feature Extraction on Automatic Sleep Stage Classification by Artificial Neural Network". In: *Metrology and Measurement Systems* 24 (2017), pp. 229–240.

[103] H. Ahnaf Rashik and B. Mohammed Imamul Hassan. "Automated identification of sleep states from EEG signals by means of ensemble empirical mode decomposition and random under sampling boosting". In: *Comput Methods Programs Biomed* vol. 140 (2017), pp. 201–210. ISSN: 0169-2607. DOI: https://doi.org/10.1016/j.cmpb.2016.12.015. URL: https://www.sciencedirect.com/science/article/pii/S0169260716305132.

[104] Y. Paul and S. Fridli. "Sleep states detection using EEG and blood pressure signals". In: *ICRIC-2021, Lecture Notes in Electrical Engineering, Springer* Indo-HUN-02 (2021), pp. 364–371.

[105] S. K. Satapathy and D. Loganathan. "A Comprehensive Survey and New Investigation on Sleep Disorder Detection Using EEG Signal". In: (2021), pp. 499–513. DOI: 10.1007/978-981-15-5077-5_45.

[106] J. Pan and W .J. Tompkins. "A real-time QRS detection algorithm". In: *IEEE transactions on biomedical engineering* 3 (1985), pp. 230–236. DOI: 10.1109/TBME.1985.325532.

[107] J. X. Sun, A. T. Reisner, and R. G. Mark. "A signal abnormality index for arterial blood pressure waveforms". In: *2006 Computers in Cardiology* (2006), pp. 13–16. DOI: doi=10.1.1.309.3848.

[108] L. Alexandre. "*BP_annotate*". In: *MATLAB Central File Exchange* (2021). DOI: $https://www.mathworks.com/matlabcentral/fileexchange/60172-bp_annotate$.

[109] H. M. Fillit, K. Rockwood, and J. B. Young. "Brocklehurst's textbook of geriatric medicine and gerontology E-book". In: (2010, seventh edition).

[110] B. P. Fuhrman et al. "Pediatric critical care". In: (2006 fourth edition,and 2016).

List of Figures

List of Tables