Study on Automatic Sleep Disorders Classification Using Electrocardiogram

A doctoral dissertation in partial fulfillment for the
degree of Doctor of Philosophy

February 2021

Interdisciplinary Graduate School of Agriculture and Engineering
Department of Materials and Informatics
UNIVERSITY OF MIYAZAKI

Edita Rosana Widasari

Declaration

I certify that except where due acknowledgement has been made, the work presented in it are my own; the work has not been submitted previously in whole or in part to qualify for any other academic award; the work was done wholly or mainly while in candidature for a research degree at this University; where I have consulted the published work of others, this is always clearly attributed; I have acknowledged all main sources of help; and ethics procedures and guidelines have been followed.

Miyazaki, February 2021

Signed: Edita Rosana Widasari

Supervisor: Prof. Koichi Tanno

UNIVERSITY OF MIYAZAKI

Abstract

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Sleep disorder is a medical disease of the sleep patterns, which is commonly suffered by the elderly. Sleep disorders diagnosis and treatment are considered to be challenging due to a time-consuming and inconvenient process for the patient. It is caused a Polysomnography (PSG) which is the gold standard to assess sleep condition involves a lot of multichannel signals, such as Electroencephalogram (EEG), Electromyogram (EMG), Electrooculogram (EOG), Electrocardiogram (ECG), respiratory effort signal, and pulse blood oxygen saturation. These multichannel signals will be recorded when patients fall asleep in a specialized laboratory or hospital. Moreover, the use of PSG in sleep disorder diagnosis is a high-cost process, so they refused the observation.

A clinical study widely used the spectrum analysis of Heart Rate Variability (HRV) to assess the personal condition, such as sleep, fatigue, stress, and sudden cardiac death in the last decade. HRV is measured from the variation of heartbeat or known as a cardiac rhythm that can be captured over a certain period of time from the electrocardiography (ECG) signal. HRV also indexes neurocardiac function and is generated by heart-brain interactions and dynamic non-linear Autonomic Nervous System (ANS) processes. The various HRV parameters can show significant differences in each sleep stage, which is associated with ANS activity. Hence, the variation of HRV according to the sleep stage, thereby reflecting the activity of ANS. It is implied that it is also possible to detect a sleep disorder using an ECG signal instead of complicated signal recordings. Therefore, this doctoral dissertation proposes an efficient classification method of sleep disorder by merely using an electrocardiogram to simplify the sleep disorders diagnosis process.

Different from many current related studies that applied a five-minute epoch to observe the main frequency band of the ECG signal, we perform a pre-processing technique that suitable for the 30-seconds epoch of the ECG signal. By this simplification, the proposed method has a low computational cost so that suitable to be implemented in a portable hardware device. Structurally, the proposed method consists of five stages: (1) pre-processing, (2) spectral features extraction, (3) sleep stage detection using the

Decision-Tree-Based Support Vector Machine (DTB-SVM), (4) assessment of sleep quality features, and (5) sleep disorders classification using an ensemble of bagged tree classifiers.

This doctoral dissertation is organized as follows. **Chapter 1** provides a research background, aims, scopes, contributions, and findings. The definitions of sleep are discussed in **Chapter 2**. This chapter also describes the sleep disorders in the elderly, sleep scoring standard and the sleep assessment. **Chapter 3** describes the sleep database and the proposed methods. As mentioned above, the proposed method is consisting of five stages. Subsequently, to reach the aims of this doctoral dissertation, the proposed method can be divided into three parts: (1) pre-processing, (2) automatic sleep stage detection, (3) automatic sleep disorders classification. The pre-processing part, which includes a new-processing technique suitable for the 30-seconds epoch of ECG signals during sleep is presented in **Chapter 4**. The automatic sleep stage detection part, which includes spectral features extraction and sleep stage detection stage provided in **Chapter 5**. **Chapter 6** presents the automatic sleep disorders classification part, which includes assessment of sleep quality features and sleep disorders classification stage. We summarize the conclusion and describe the future work of this doctoral dissertation in **Chapter 7**.

The selected pre-processing techniques are used to decompose the 30-second of ECG signal in the pre-processing part. Then, two features are obtained from spectral features extraction i.e., normalized Low Frequency and normalized High Frequency. These features were then used as inputs for sleep stage detection. Furthermore, most commonly used learning classifiers are implemented to detect the sleep stage, namely KNN, NN, DT, SVM, and proposed DTB-SVM in the automatic detection part. The proposed method using DTB-SVM based on spectral features of ECG signal achieved a good performance to obtain all sleep stage conditions.

In the automatic sleep disorders classification part, we evaluate the effectiveness of the proposed method in the task of classifying the sleep disorders into four classes (insomnia, Sleep-Disordered Breathing (SDB), REM Behavior Disorder (RBD), and healthy subjects) from the 51 patients of the Cyclic Alternating Pattern (CAP) sleep data. Based on experimental results, the proposed method presents 84.01% of sensitivity, 94.17% of specificity, 86.27% of overall accuracy, and 0.70 of Cohen's kappa. This result indicates that the proposed method able to reliably classify the sleep disorders merely using the 30-seconds epoch ECG in order to address the issue of a multichannel signal such as the PSG.

Acknowledgements

First and foremost, I would like to thank Allah SWT Almighty for giving me the age of blessing, happiness, and health. Praise the presence of Allah SWT that gives me the strength and opportunity to undertake this study and to persevere and complete it satisfactorily. Without his blessings, this achievement would not have been possible. Blessings and greetings may always be devoted to our lord the Great Prophet Muhammad SAW, who brings and illuminates our conscience, becomes the light for all noble deeds.

I would like to express my high appreciation and gratitude to my supervisor, *Prof. Koichi Tanno*, for his patience, knowledge, support, enthusiasm, opportunity, and valuable guidance throughout my doctoral study. His criticism and advice made me grow not only as an engineer or a researcher but also as a person. I would also like to thank the committee members: *Prof. Hiroki Tamura, Prof. Ichijo Hodaka, and Prof. Masahiro Tasumi*, for their generous time in giving their thoughtful suggestions and constructive advice for the improvement of this doctoral thesis.

I would like to acknowledge the *Ministry of Education, Culture, Sports, Science, and Technology (MEXT) of Japan* for the scholarship during the doctoral study and *University of Brawijaya (UB)* for the kind support for me during my study. This study would not possible without their support. Then, thanks to *Physionet* for providing the MIT-BIH Polysomographic and Cyclic Alternating Pattern (CAP) sleep data.

I would like to thank *Mrs. Takako Toyama* for supporting and helping me in laboratory activities. Thanks to all *Center for Integration Technology (CITE) laboratory* members for their accessibility whenever I had daily questions and requires. I would like to thank the members of Indonesian Student Association of Miyazaki and the other foreign students for their social contribution to my experience as a student at University of Miyazaki.

Special thanks are due to my parents *Haryati Usbandiyah*, *Warno Edy Supomo*, *Siti Indahsyah*, and *Wiwik Sudarto Darsono*. They worked very hard to support the family and to raise me. Thanks for their unconditional love, pray, and support throughout my life. Last but very special, many thanks to my husband *Barlian Henryranu Prasetio* and my daughter *Khayyira Quinza Prasetio*. Without their greatest love, support, encouragement, and understanding, it would have been impossible for me to finish my doctoral study.

List of Publications

This doctoral dissertation is a unity of several publications, as follows:

Journal articles

1. Widasari, E.R., Tanno, K., Tamura, H. A New Investigation of Automatic Sleep Stage Detection using Decision-Tree-Based Support Vector Machine and Spectral Features Extraction of ECG Signal. *IEEJ Transactions on Electronics, Information and Systems*, vol. 139(7), pp. 820–827, 2019.

2. Widasari, E.R., Tanno, K., Tamura, H. Automatic Sleep Disorders Classification using Ensemble of Bagged Tree based on Sleep Quality Features. *Electronics*, vol. 9(3), pp. 512(1-20), 2020.

3. Widasari, E.R., Tanno, K., Tamura, H. Spectrum Analysis of HRV During Sleep using an ECG Signal. *IEEJ Transactions on Electronics, Information and Systems*, 2020. *(resubmitted)*

International Conferences

1. Widasari, E.R., Tanno, K., Tamura, H. Automatic Sleep Stage Detection Based on HRV Spectrum Analysis. In Proceeding of IEEE International Conference on Systems, Man, and Cybernetics (SMC), Miyazaki, Japan, pp. 869–874, 2018.

2. Widasari, E.R., Tanno, K., Tamura, H. Heart Rate Variability Spectrum Analysis for Automatic Sleep Stage Detection. NOKOH Regular Seminar, University of Miyazaki, Japan, 2018.

3. Widasari, E.R., Tanno, K., Tamura, H. Automatic Sleep Quality Assessment for Obstructive Sleep Apnea Patient Based on HRV Spectrum Analysis. In Proceeding of IEEE International Conference on Systems, Man, and Cybernetics (SMC), Bari, Italy, pp. 1193–1198, 2019. *(Achieved the Best Student Paper Award in Cybernetics Category)*

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Dedication

I dedicate this doctoral thesis to my parents and brothers, especially to my father who in heaven now. Thank you for always inspiring and motivating me since I was a child, Dad. You are a great source of inspiration for me to become good lecturer, researcher, and person like you.
Without their pray, drive, and support that they have given me, I might not be the person I am today.

To my husband who taught me inquisitiveness and persistence. To my beloved daughter who are my greatest support, my strongest motivation, my favorite, and my everything. Both of you have stood with me during this long and challenging endeavour.

And to my home country, Indonesia.
"Tanah airku tidak kulupakan, kan terkenang selama hidupku, biarpun saya pergi jauh, tidak kan hilang dari kalbu, tanahku yang kucintai, engkau kuhargai."

Chapter 1

Introduction

This Chapter presents the research background, aims, and scopes. The findings and contributions are also provided in this Chapter. An outline structure of this doctoral dissertation is also given.

1.1 Backgrounds

A recent studies show that the elderly are easier to experience a sleep disorders compared to younger people. More than 40 thousand elderly from eight countries in Asia-Africa suffer a sleep disorder [1]. In America, there are 50-70 million elderly suffer at least one sleep disorder category [2]. The sleep disorder relates to some factors such as unhealthy diet, smoking, alcohol consumption, stress, bad lifestyle, and sleep habits. In advanced, sleep disorders can increase the risk of morbidity, mortality, and chronic diseases, such as obesity, cancer, cardiovascular disease, hypertension, and depression. Therefore, an elderly (aged 60 years or older) is recommended to take asleep around 6-6.5 hours per night and spend in bed for 7.5-8 hours without a disturbance to prevent the effect of sleep disorders [3][4].

Generally, there are two types of sleep disorders in the elderly, i.e., insomnia and primary sleep disorders [5] [6] [7]. Insomnia is the most reported sleep disorder that is typically defined as a difficulty for falling asleep or staying asleep as long as desired. A study reported that insomnia was affecting almost 40-50% of the elderly [6]. Primary sleep disorders are the other sleep disorder that not attributable to another medical or psychiatric condition. There are three primary sleep disorders in terms of frequently

suffered in the elderly, namely sleep-disordered breathing (SDB), REM Behavior Disorder (RBD), and Restless Legs Syndrome (RLS).

The prevalence of SDB in the elderly is about 20-40% [8]. It indicates that SDB in the elderly is at least double than younger people. While based on the RBD questionnaire, the prevalence of RBD in the elderly is 4.6-7.7%. It is much higher for certain neurodegenerative diseases [9]. Furthermore, a study estimate that there are 9-20% of the elderly suffers the RLS. However, this estimation may include a substantial portion of the Periodic Limb Movement of Sleep (PLMS) patients because RLS is often related to PLMS. Approximately, 70% of the patients with RLS also have PLMS, but only 20% of the patients with PLMS are reported RLS. Thus, it is essential to consider RLS in the differential diagnosis of any patient with PLMS [6]. Based on this respect, we considered that insomnia, SDB, and RBD could represent the most common sleep disorder in the elderly.

Polysomnography (PSG) is the standard method used to diagnose sleep disorders. The PSG method involves a lot of wired sensors to record the activities of the multiple physiological signals (such as brain waves, skeletal muscles, heart rate, eye movement, etc.). This method is conducted for all overnight long in a specialized laboratory or hospital. Moreover, misdiagnosis and mistreatment may occur though the patients had been monitored as long as full sleep observation. This observation method makes the patients feel inconvenience so that many patients refused the observation since they consider this method as need an extra effort, time-consuming, high-cost, and labor intensive [10]. It makes the elderly with sleep disorders are undiagnosed and untreated in clinical practice.

In the last decade, a clinical study [11] mentioned that it is possible to detect a sleep stage and sleep disorder in the elderly using an Electrocardiogram (ECG) signal instead of complicated signal recordings. It is because each sleep stage has different cardiac dynamics, which are represented in the average of the heartbeat interval [12]. To estimate the sleep stage, we can use the differences between the Autonomic Nervous System (ANS) activities from Heart Rate Variability (HRV) signal [13]. HRV performs a fluctuation analysis in the heartbeat interval so that the variation of HRV is according to the sleep stage, and reflect the activity of ANS.

To this end, we propose an efficient non-intrusive method to classify sleep disorders automatically for the elderly using the ECG signal alone. This method offers a more comfortable method than the conventional method but able to provide the result as effective as the PSG method. In addition, the advantage of ECG is more convenient to used and recorded, although without specialized trainers. A key process of our proposed method is the selection techniques of the pre-processing stage with regards to decompose the 30-seconds epoch of the ECG signal. Furthermore, we used a supervised machine learning in the task of classification. We perform two approaches: (1) automatic sleep stage detection using Decision-Tree-Based Support Vector Machine (DTB-SVM) based on spectral features of ECG signal, and (2) automatic sleep disorders classification using ensemble of bagged tree based on sleep quality features. Finally, the proposed method able to classify the sleep disorders of the patients into four classes i.e., healthy, insomnia, SDB, and RBD.

1.2 Research Aims

The main objective of this doctoral dissertation is to propose an efficient classification method of sleep disorder by merely using an electrocardiogram in order to address the issue of a multichannel signal such as the PSG and simplify the sleep disorders diagnosis process. To reach that objective, the research aims can best be presented in the following manner:

1. Develop new pre-processing technique that suitable for 30-seconds epoch of ECG during sleep.

2. Develop an automatic sleep stage detection method by utilizing DTB-SVM based on spectral features of ECG.

3. Develop an automatic sleep disorders classification by utilizing ensemble of bagged tree based on sleep quality features.

1.3 Research Scope

In order to reach the aims of this doctoral dissertation. Firstly, this doctoral dissertation concentrates on addressing the issue of a multichannel signal, such as the PSG merely using an ECG signal during sleep. Therefore, we used the MIT-BIH Polysomnographic

database in the first part of the experiment. This database includes a normal heart rate and cardiac stroke volume during sleep. The detailed information about MIT-BIH Polysomnographic database is explained in section 3.1.1.

Secondly, this doctoral dissertation concentrates on the most common sleep disorder in the elderly i.e. insomnia, SDB, and RBD. Therefore, we used Cyclic Alternating Pattern (CAP) sleep database that containing sleep disorder in the elderly. Labeled sleep data from CAP were used in the second and third part of the experiments. The automatic sleep stage detection was classified into four stages i.e. wakefulness, light sleep, deep sleep, and REM sleep. Furthermore, the automatic sleep disorders classification was classified into four classes i.e. healthy, insomnia, SDB, and RBD. The number of epoch and subject data of CAP sleep database is explained in more detail in Chapter 3.1.2.

1.4 Contributions and Findings

This doctoral dissertation proposed and evaluated several new methods for automatic sleep disorders classification using an ECG signal. The effectiveness of the proposed methods were compared with existing classical approaches. The proposed methods led to the following major findings and conclusions:

- Different from most current ECG-based automatic sleep stage systems that applied a five-minutes epoch to observe the main frequency band of ECG signal, we perform a new pre-processing technique that suitable for 30-seconds epoch without detecting each PQRST peak. We take advantage that the proposed method more efficiently to be implemented in an embedded hardware device as a consideration of the complexity requirements and computational cost.

- A set of efficient ECG signal features (normalized LF and normalized HF) is extracted by analyzing the HRV frequency band of Power Spectrum Density (PSD) using a Hanning window with the welch method, which is then used to identify the sleep stages.

- All sleep stage conditions are observed to patients and non-patients subjects. It is an essential factor for a robust automatic sleep stage system.

- Since the proposed method present an effective and efficient in classifying sleep disorders of the elderly, we expect this method could be used as a general framework

in modeling sleep disorders and become a fundamental model for future research. Moreover, we expect that our proposed method can contribute to the International Classification of Sleep disorders (ICSD-3) study and aim as a new alternative for diagnosing the sleep disorders, besides using the questionnaire-based method, such as Pittsburgh Sleep Quality Index (PSQI),Brief Insomnia Questionnaire (BIQ), and REM Sleep Behavior Disorder Screening Questionnaire (RBDSQ).

1.5 Thesis Outline

We organized this thesis as follows:

Chapter 1 provides research background, aims and scopes. We also present the research's contributions and findings.

Chapter 2 introduces definitions of sleep. It describes the expression of what is sleep and human sleep. We also describe the sleep disorders in the elderly i.e., insomnia, SDB, and RBD. Then, the sleep scoring and the sleep assessment using PSG & ECG-based also presented in this chapter.

Chapter 3 describes the sleep database and the proposed methods used in the doctoral dissertation, i.e., pre-processing, spectral features extraction, automatic sleep stage detection, assessment of sleep quality, and automatic sleep disorders classification.

Chapter 4 explain in detail the pre-processing part, which includes pre-processing stage. We also well describe the experimental setup, results, discussion, and conclusion.

Chapter 5 explain in detail the automatic sleep stage detection part, which include spectral features extraction and sleep stage detection stage. We also well describe the experimental setup, results, discussion, and conclusion.

Chapter 6 explain in detail the automatic sleep disorders classification part, which includes assessment of sleep quality and classification of sleep disorders stage. We also well describe the experimental setup, results, discussion, and conclusion.

Chapter 7 summarizes the conclusion and describes the future work of this doctoral dissertation.

Chapter 2

Literature Review

In this Chapter, we discuss the basic of sleep, sleep in human, type of sleep disorders in the elderly, and sleep stage scoring. We also present a standard for sleep assessment using PSG method. The ECG-based automatic sleep monitoring are also discussed.

2.1 Basic of Sleep

Sleep is a complex and dynamic process that affects our function scientifically. This section describes what is sleep and how sleep influenced in human life.

2.1.1 What is sleep

The sleep phenomenon has gained reasonable scientific interest for an extended time. Sleep refers to a behavioral state that varies from wakefulness by a loss of reactivity readily and reversible in relation to events within one‘s environment [14]. The reversibility of sleep differentiates it from other types of states of consciousness, such as altered states of consciousness like the state of anesthesia or coma characterized by unresponsiveness and others. Different theories offer insight about the reasons that people sleep. According to the passive theory, sleep occurs because of a lack of sensory stimulation or to prevent tiredness [15][16]. For many years sleep was considered as a passive state of the brain and the opposite of wakefulness. It was assumed that the excitatory regions of the brainstem and other areas of the brain get exhausted and turn inactive. Hence, sleep was brought about by this inactiveness. The active theories also indicate that the brain aggressively deters consciousness [17].

2.1.2 Human sleep

Sleep plays a vital role in the human being. One-third of human lives is spending on sleep. There are some functions of sleep i.e., energy conservation, increasing an anabolic hormone and decreasing catabolic hormones, memory reinforcement and consolidation, and synaptic and neuronal network integrating [18]. Moreover, sleep manages significant effects on the systemic hemodynamics, cardiac function, endothelial function, and coagulation [19]. Sleep deprivation can lead to loss of daytime performance, disturbance in circadian rhythm, impairments such as mental or physical fatigue, reduced immune system, reduced cognitive functioning, metabolic syndrome, diabetes, and other health risks [19–22]

In epidemiology and pathophysiology, it has been found that sleep disorders or abnormalities are linked to depression, diabetes, metabolic syndrome, sudden death, and other cardiovascular diseases such as cardiac arrhythmias, hypertension, atherosclerosis, stroke, and heart failure [19][23][24]. Human sleep is a complex biological process with its own internal architecture expressed by sleep states or stages [26][27].

2.2 Sleep Stage Scoring

A technicians and physicians will score the sleep stage condition based on visual examination of neurophysiologic signal patterns. The original sleep scoring rules was proposed by Rechtschaffen and Kales. Furthermore, American Academy of Sleep Medicine Scoring (AASM) was updated the scoring rules, as shown in Figure 2.1.

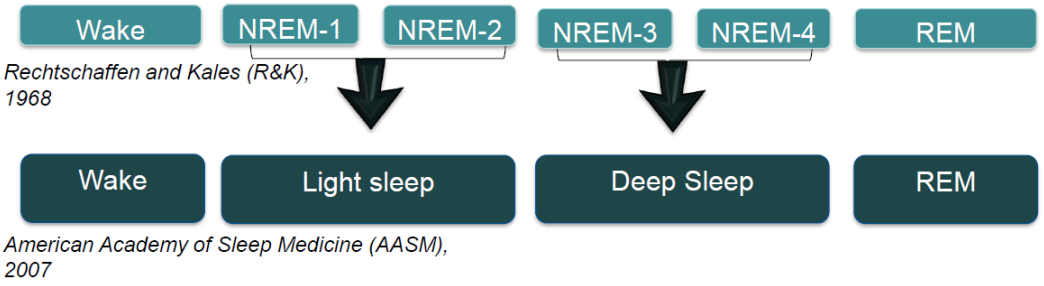


FIGURE 2.1: Sleep stage scoring rules

2.2.1 The Rechtscaffen and Kales (R & K) scoring rules

In 1968, Rechtschaffen and Kales (R&K) presented sleep stage scoring rules. Each epoch is classified as Wakefulness (W), Rapid Eye Movement (REM) sleep and Non-REM (NREM) sleep. Then, NREM sleep is divided into stage NREM 1 - 4 [28]. The details information of each sleep stage scoring rules is described as follows:

- Wakefulness is a daily recurring brain state and state of consciousness in which an individual is conscious and engages in coherent cognitive and behavioral responses to the external world. Being awake is the opposite of the state of being asleep in which most external inputs to the brain are excluded from neural processing.

- NREM-1 is a occurs mostly in the beginning of sleep, with slow eye movement. This state is sometimes referred to as relaxed wakefulness. However, if aroused from this stage of sleep, a person might feel as if he or she has not slept. This stage might last for five to 10 minutes. People aroused from this stage often believe that they have been fully awake.

- NREM-2 is a condition with no eye movement occurs, and dreaming is very rare. The sleeper is quite easily awakened. The brain also begins to produce bursts of rapid, rhythmic brain wave activity known as sleep spindles. Body temperature starts to decrease and heart rate begins to slow.

- NREM-3 is formerly the transition between NREM-2 and NREM-4 where "deep" sleep began to occur. During this stage, people become less responsive and noises and activity in the environment may fail to generate a response. This stage lasts only a few minutes.

- NREM-4 is approximately 20 to 40 minutes in the first cycle. The arousal threshold is highest for all NREM stages in stage 4. This stage is characterized by increased amounts of high-voltage, slow-wave activity on the brain activity.

- REM is characterized by eye movement, increased respiration rate, and increased brain activity. REM sleep is also referred to as paradoxical sleep because while the brain and other body systems become more active, muscles become more relaxed. Dreaming occurs due to increased brain activity, but voluntary muscles become immobilized.

2.2.2 The American Academy of Sleep Medicine Scoring (AASM) rules

In 2007, the American Academy of Sleep Medicine (AASM) presented an improvement of sleep stages rules which combine the NREM-3 and NREM-4 into Slow Wave Sleep (SWS) or called "deep sleep". While NREM-1 and NREM-2 usually correspond to "light sleep" [29]. The sleep stages should not be viewed as distinct entities, but rather as a gradual transition of a waveform. The scoring rules were devised to allow uniformity between sleep laboratories and to offer a conceptual simplicity rather than a rigid framework. Therefore, this research also use this new sleep stage scoring. The details information of light and deep sleep is described as follows:

- Light sleep, or shallow sleep, is called light sleep because it is easier to wake one up during this period. External stimuli such as noise, temperature, touch, and movement can wake us up. But they wake us up more readily, with less effort, when we are in light sleep than in heavy sleep. When people are awakened from NREM-2, they often deny they were sleeping or claim they were already awake. Sleep inertia is less severe when awakening from light sleep than from REM or deep sleep.

- Deep sleep, or slow-wave sleep, is the sleep stage that is associated with the slowest brain waves during sleep. The heartbeat and breathing become their slowest as muscles relax. Then, it is difficult to awaken even with loud noises. The first stage of deep sleep lasts anywhere from 45 to 90 minutes. It lasts for longer periods in the first half of the night and becomes shorter with each sleep cycle.

2.3 Polysomnography (PSG) - Standard for Sleep Assessment

In clinical practice, overnight polysomnography (PSG) is currently regarded as the gold standard for objective assessment of sleep stage and occurrence of sleep-related disorders such as insomnia, parasomnia, sleep-disorder breathing (apnea and hypopnea), and REM sleep behavior disorder. This method records multiple physiological signals during overnight sleep including Electroencephalogram (EEG), Electromyogram (EMG), Electrooculogram (EOG), Electrocardiogram (ECG), respiratory effort signal and pulse

blood oxygen saturation [10]. PSG method is typically very intrusive and conducted for all overnight long in a specialized laboratory or hospital as shown in Figure 2.2. According to the R&K or the AASM rules overnight sleep stages are typically scored by trained sleep technicians on continuous 30-seconds epoch.

FIGURE 2.2: A subject was being monitored with PSG method

Figure 2.3 shows an example of a PSG recording (20 minutes) of a healthy adult. According to the R&K rules overnight sleep stages are typically scored by trained sleep technicians on continuous 30-s epochs through visually inspecting the EEG, EMG, EOG, ECG, airflow, respiratory effort, respiratory effort, and SaO_2 channels in PSG, forming a hynogram throughout the entire night.

2.4 Sleep Disorders in the Elderly

Sleep disorder refers to a medical condition, also known as somnipathy [31]. Contemporary studies have argued that severe sleep disorders can interfere with the normal mental, social, emotional and physical functioning of an individual [32]. PSG is the standard method that have been used in the diagnosis of sleep disorders.

In 2014, the American Academy of Sleep Medicine (AASM) released the third edition of the International Classification of Sleep disorders (ICSD-3) [33]. The ICSD is a clinical textbook to diagnostic, epidemiology, and resource for the physician and researchers in the sleep disorders studies. The ICSD-3 describes six primary clinical sleep disorders,

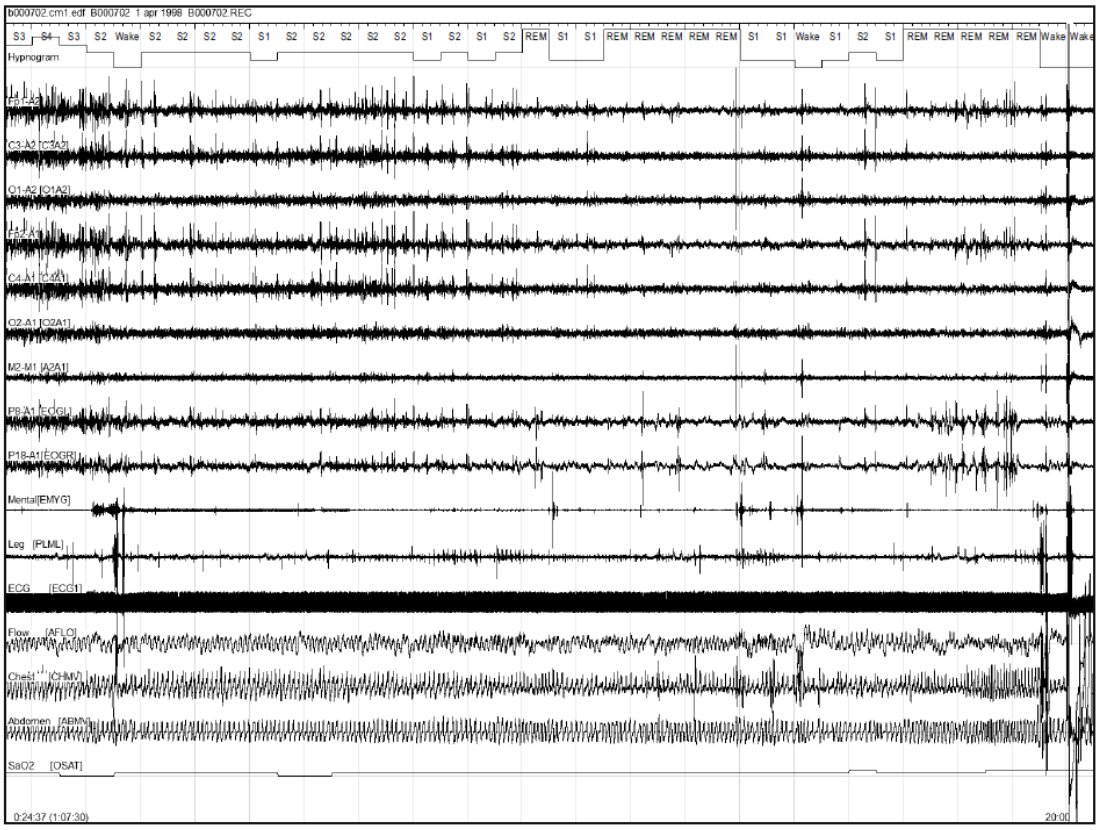


FIGURE 2.3: An example of an continuous PSG recording (20 minutes) with multiple channels of bio-signals from a healthy adult *(Source: [30])*

i.e., insomnia, sleep-disordered breathing, central disorders of hyper-somnolence, circadian rhythm sleep-wake disorders, parasomnias, and sleep-related movement disorders. ICSD presents the detail diagnostic procedures and criteria for each sleep disorder. On the other hand, some researchers [6–8] specifically described the common elderly suffered sleep disorders with their causes and treatments. In general, there are two types of sleep disorders in the elderly, i.e., insomnia and primary sleep disorders. Primary sleep disorders consist of three common sleep disorders that frequently suffered in the elderly, such as SDB, RBD, and RLS.

Each sleep disorder has different characteristics of related sleep quality parameters. Sleep quality is defined as one's satisfaction of the sleep experience, integrating aspects of sleep initiation, sleep maintenance, sleep quantity, and refreshment upon awakening. Most of the conventional methods used the Pittsburgh Sleep Quality Index (PSQI) to evaluate sleep quality [34]. The PSQI is a self-report questionnaire that assesses sleep quality over a one-month time interval.

In PSQI, several questions are related to the psychometric properties of sleep quality. The details information of each sleep quality parameters is described as follows [35–37]:

- Total Time in Bed (TIB) is the total investigation time or the total in-bed duration (in minutes). TIB has a clinical significance for diagnosing sufficient sleep.
- Total Sleep Time (TST) is the total sleep duration or total non-wake conditions (in minutes). TST has a relation for diagnosing the effects of medications, sleep deprivation, and medical condition.
- Sleep Onset Latency (SOL) is the duration time from the wake condition until getting the first non-wake condition (in minutes). SOL represents sleep time habits.
- Sleep Efficiency (SE) is the ratio of total sleep duration (TST) and the total in-bed duration (TIB) (in percentage). In normal sleep conditions, it should at least 85% of TIB. SE represents how well the subject slept.
- The percentage of wakefulness stage is used to measures awake condition.
- The percentage of light sleep stage is associated with the transition between being awake and asleep. The increasing percentages of light sleep indicate the patient has a sleep disorder. Typically, the percentage of light sleep is around 55% of the total sleep duration for normal sleep conditions.
- The percentage of deep sleep stage is associated with the rebound sleep and side effect of medications. The normal percentage of deep sleep is around 20% of total sleep for normal sleep conditions.
- The percentage of the REM sleep stage is sensitive to the effect of medications and sleep deprivation. Nevertheless, the REM sleep stage remains approximately 25% of the total sleep in normal sleep conditions. The increasing percentages of the REM sleep indicate a recovery of sleep deprivation.

2.4.1 Insomnia

Insomnia commonly include difficulty in initiating or/and maintaining sleep. They include extended periods of initiating or/and maintaining insomnia amounts of nighttime sleep [38]. The diagnostic and symptom category of insomnia are best denoted by their

subcategory. These subcategories are described by different combinations of repeated sleep problems with sleep duration, initiation, quality and impairment during the daytime [31]. Insomnia complaints can be associated with the perception of non-restorative or poor quality sleep even if the quantity and quality of sleep episodes are perceived as adequate or regular. The meaning of insomnia being a complaint of sleep maintenance, sleep initiation, non-restorative sleep or associated with daytime impairment [39].

The ICSD-3 defines insomnia as a difficulty in maintaining sleep (early morning awakening or mid-sleep awakening), a difficulty in initiating sleep or even non-restorative sleep which is chronic and persists for more than three weeks, notwithstanding that one has adequate opportunity for rest/sleep and it impairs daytime performance [40, 41]. Many abnormalities have been reported with insomnia patients in the elderly [7]. These can be measured using PSG, with insomnia most often suffer from difficulty falling asleep as well as intermittent wakefulness during sleep [40]. The characteristics in insomnia patients show an increase in light sleep and a decrease in sleep efficiency. Moreover, Brief Insomnia Questionnaire (BIQ) can be also used to diagnose insomnia [42]. Table 2.1 describes the sleep quality parameters of insomnia disorders in the elderly.

Table 2.1: Sleep quality parameters of insomnia

Parameters	Conditions
Total Time in Bed (min)	Decrease
Total Sleep Time (min)	Decrease
Sleep Onset Latency (min)	Increase
Sleep Efficiency (%)	Decrease
Wakefulness (%)	Increase
Light sleep (%)	Increase
Deep sleep (%)	Decrease
REM sleep (%)	Decrease

2.4.2 Sleep-disordered breathing (SDB)

SDB is a syndrome of upper airway dysfunction during sleep characterized by snoring and/or increased respiratory effort secondary to increased upper airway resistance and pharyngeal collapsibility. Several conditions characterized by disordered respiration during sleep i.e., obstructive sleep apnoea (OSA) disorders, central sleep apnoea disorders,

sleeprelated hypoventilation disorders, and sleep-related hypoxaemia disorder. It is expected that more than one of these conditions are often present in the same patient and, in particular, obstructive and central sleep apnoea are often found in combination. OSA is also referred to as obstructive sleep apnea-hypopnea, is a sleep disorder that involves cessation or a significant decrease in airflow in the presence of breathing effort.

The term of obstructive SDB is used when symptoms of intermittent upper airway obstruction during sleep are present, but the severity of airway obstruction has not been defined by objective measures such as PSG. The general characteristic of OSA is the increased collapsibility of the upper airway during sleep resulting in markedly reduced (hypopnea) or absent (apnea) airflow at the nose and/or mouth which is usually accompanied by oxyhemoglobin desaturation and is typically terminated by a brief microarousal. Repeated episodes of apnea lead to a sustained reduction in oxyhemoglobin saturation and sleep fragmentation with diminished amounts of deep sleep and rapid eye movement (REM) sleep [43]. Table 2.2 describes the sleep quality parameters of SDB disorders in the elderly.

TABLE 2.2: Sleep quality parameters of SDB

Parameters	Conditions
Total Time in Bed (min)	Decrease
Total Sleep Time (min)	Decrease
Sleep Onset Latency (min)	Increase
Sleep Efficiency (%)	Decrease
Wakefulness (%)	Increase
Light sleep (%)	Increase
Deep sleep (%)	Increase
REM sleep (%)	Decrease

2.4.3 REM behavior disorder (RBD)

RDB is a sleep disorder that predominantly affects elderly, in which patients appear to be enacting their dreams while in REM sleep. The behaviours may be simple or complex, including talking, singing, shouting, grabbing, strangulating, and jumping from the bed. The majority of enacted dreams have violent content and associated violent behaviors, although non-violent behaviours can also occur. Because of the violent nature of the actions, the potential for serious self-harm or bed-partner harm is high. Despite

the aggressive and violent content of dreams, however, RBD patients are not aggressive during the day [44].

While PSG remains the diagnostic gold standard, the diagnosis of RBD can be made based on REM Sleep Behavior Disorder Screening Questionnaire (RBDSQ)[45] . There are ten questions to assess the various aspects of sleep behavior. The higher score of RBDSQ will be associated with RBD. However, the reliability and validity of those questionnaires still need further evaluation for some patients. The evaluation result shows the RBDSQ is invalid for Parkinson's disease patients [46]. Table 2.3 describes the sleep quality parameters of RBD disorders in the elderly.

TABLE 2.3: Sleep quality parameters of RBD

Parameters	Conditions
Total Time in Bed (min)	Decrease
Total Sleep Time (min)	Decrease
Sleep Onset Latency (min)	Increase
Sleep Efficiency (%)	Decrease
Wakefulness (%)	Increase
Light sleep (%)	Increase
Deep sleep (%)	Decrease
REM sleep (%)	Decrease

2.5 Electrocardiogram (ECG) - based Automatic Sleep Systems

In the scientific world, sleep stage detection is a standard way to analyze sleep condition. Some works have developed an automatic sleep stage detection using EEG, EMG, and EOG. However, since the complexness of the recording process and signal analysis of those signals, it makes those methods are not recommended to be implemented as a portable system of home appliances. To this end, the use of the ECG signal for detecting the sleep stage is lately massively explored.

2.5.1 What is ECG

ECG is a simple test that can be used to check the heart's rhythm and electrical activity [47]. Sensors attached to the skin are used to detect the electrical signals produced by

the heart each time it beats. The role of the heart is crucial for living beings. Indeed, it is through the pumping movement of the heart that blood circulates trough the different vessels of the organism and brings oxygen and nutrients to its different cells.

Each heart beat corresponds to a specific pattern in the ECG. This pattern comprises five waves (P, Q, R, S, and T) as it can be seen in Figure 2.4. The first wave is the P wave. It corresponds to the atrial depolarization initiated by the sinoatrial node (SA node). It is during this phase that the contraction of the auricles occurs (atrial systole). Then it is the QRS complex consisting of the ventricular depolarization just before its contraction for the ventricular systol. During this complex, there is also the atrial repolarization (atrial diastole). Finally, the last wave is the T wave corresponding to the ventricular repolarization leading to the ventricular diastole as shown in Figure 2.5.

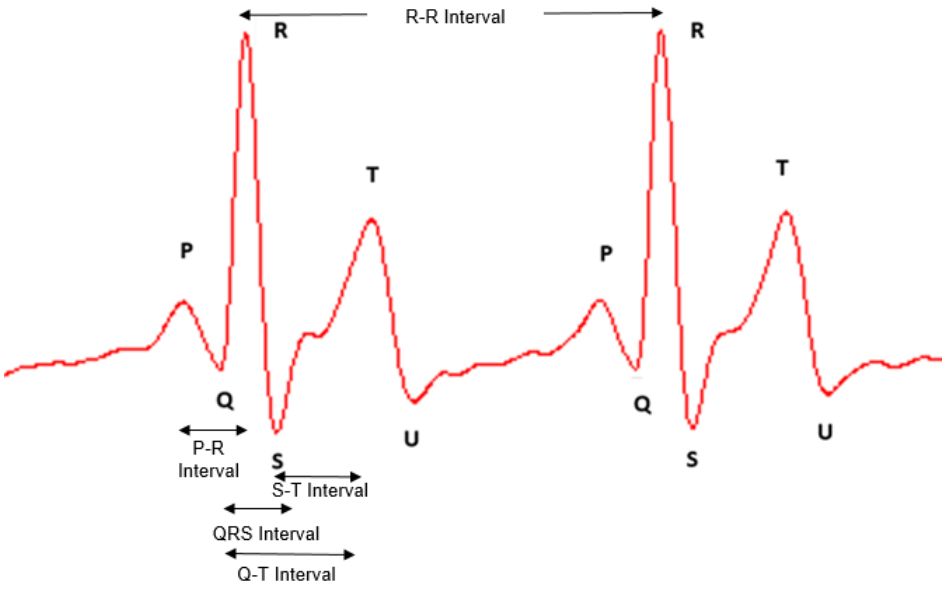


FIGURE 2.4: The ECG signal

The heart has the ability to autonomously generate depolarization at a specific frequency. This phenomenon can be seen for instance during heart transplant. The heart continues to beat when it is extracted from the body of the donor. This ability comes from the pacemaker cells present in the heart. These cells slowly depolarize themselves from their resting potential. After a certain time, the potential of the membrane will reach the threshold potential. Therefore, an action potential will be generated resulting in a heart

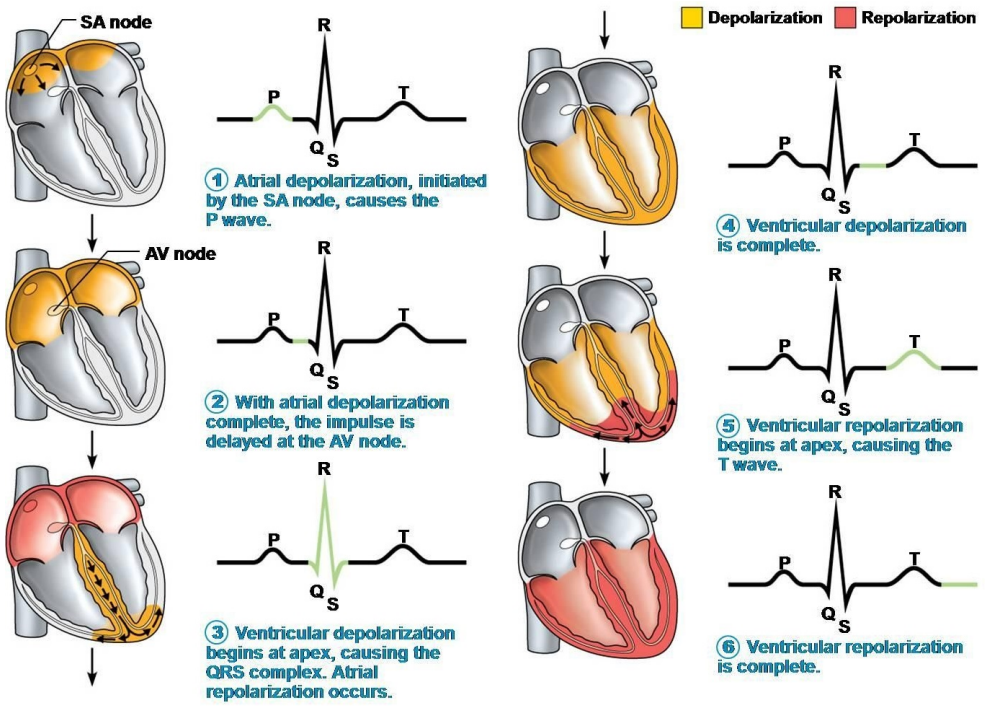


FIGURE 2.5: Depolarization wave trough the heart *(source:[48])*

beat. There are three main parts for the pacemakers cells [49] as it can be seen in Figure 2.6, such as :

- Sinotrial node is situated at the junction between the superior vena cava and the right atrium. This node has frequency of 60 to 100 beats per minute. Action potential is transferred from this node in the atrium until the atrioventricular node.
- Atrioventricular node is situated near the valve of the right atrium. The propagation signal is delayed during a small time at this node to allow the full contraction of the atria. Then, it is transmitted trough the ventricles.
- Bundle is a link between the atrium and the ventricle. This bundle is thus spitted in two parts to reach the two ventricles. The propagation goes down trough this bundle until reaching the Purkinje fibers. It is in the Purkinje fibers that the myocardial cells are excited leading to the ventricular contraction.

In a normal heart, it is the sinotrial node that has the highest depolarization frequency. It is thus this node that determines the heart beat.

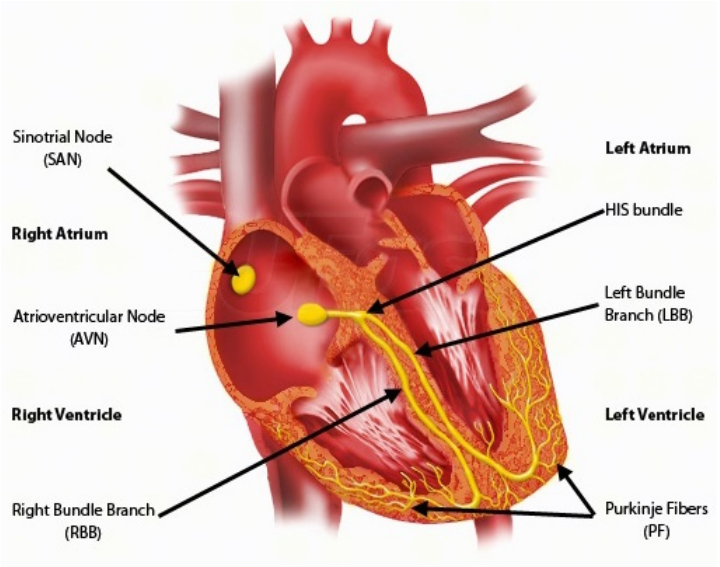


FIGURE 2.6: Cardiac conduction system *(source:[50])*

2.5.2 Action of the nervous system on the heart

The heart has the ability to generate heart beat autonomously thanks to pacemaker cells. However, the Autonomic Nervous System (ANS) is able to interact with the heart to change its activity. It is the part of the nervous system that controls and regulates the internal organs without any conscious recognition or effort by the organism. As seen in Figure 2.7, this system is divided in two parts: parasympathetic and sympathetic nervous system.

The parasympathetic uses the vagal nerve as the main road. This is why the parasympathetic action is also called the vagal activity. The nerve fibres of the parasympathetic nervous system are the cranial nerves, primarily the vagus nerve, and the lumbar spinal nerves. When stimulated, these nerves increase digestive secretions and reduce the heartbeat. The second system is the sympathetic nervous system. It connects the internal organs to the brain by spinal nerves. When stimulated, these nerves prepare the organism for stress by increasing the heart rate, increasing blood flow to the muscles, and decreasing blood flow to the skin. Moreover, ANS influence a sleep, fatigue, and stress activity[52]. The regulation of our cardio-respiratory system also depends on the ANS activity [53][54].

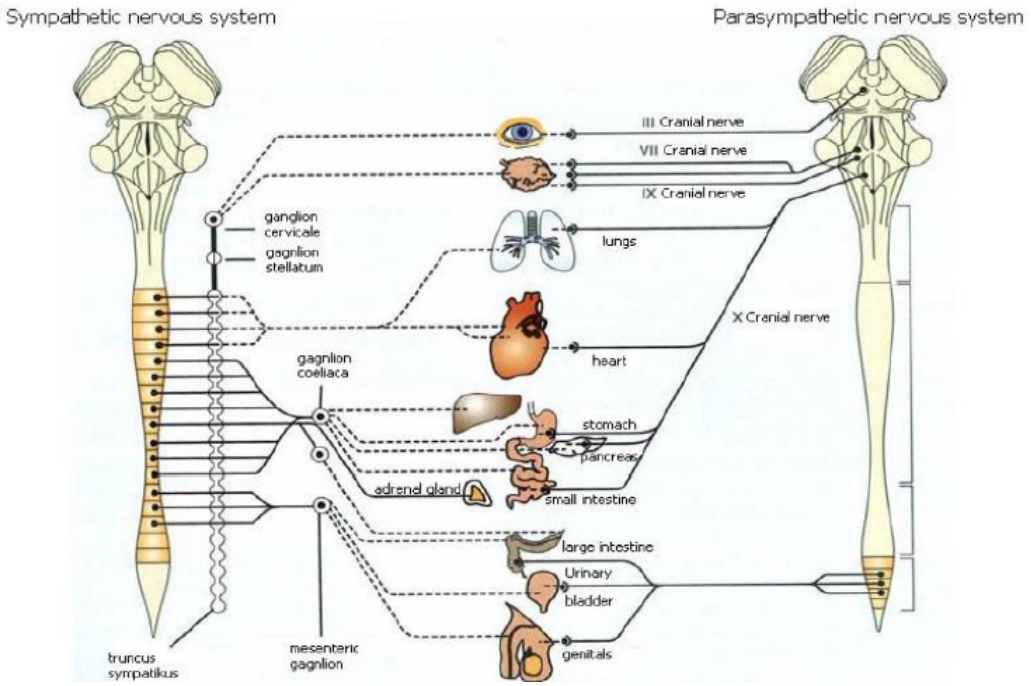


FIGURE 2.7: Autonomic nervous system *(source:[51])*

2.5.3 Heart rate variability (HRV)

HRV is measured from the variation of heartbeat or known as a cardiac rhythm that can be obtained from the ECG signal. Because of its easy and straightforward implementation, HRV has been chosen as a tool to study ECG for more than two decades. [13] have investigated various HRV parameters that can show significant differences in each sleep stages, which is associated with ANS activity. Therefore, the variation of HRV according to the sleep stage, thereby reflecting the activity of ANS.

The HRV spectrum primary frequency consists of Very Low Frequency (VLF) ranges 0.003–0.04 Hz, Low Frequency (LF) ranges 0.04–0.15 Hz, and High Frequency (HF) ranges 0.15–0.4 Hz as shown in Figure 2.8. There were few studies explore the significance of VLF fluctuations, and it is still ongoing. While LF fluctuation represents the activity of the parasympathetic and the sympathetic nervous system, and HF fluctuation only reflects the activity of the parasympathetic nervous systems.

Typically, the band power measurement of VLF, LF, and HF are represented in absolute values of power (ms^2). Since the variation of normalized LF and normalized HF could reflect the balanced and controlled behaviors of the ANS [55], both of them are

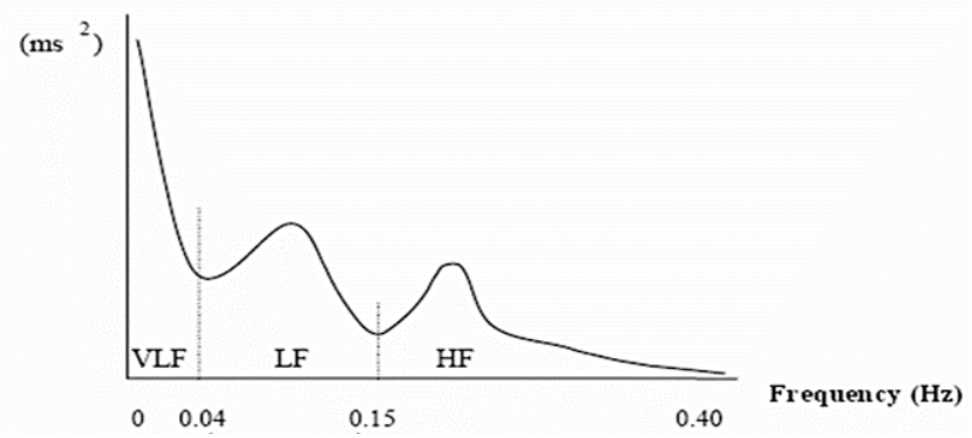


FIGURE 2.8: HRV spectrum band

considered as a good discriminator in distinguishing the sleep stage. Hence, we use the normalized LF and normalized HF feature to recognize the sleep stage. The LF and HF in the normalized unit represent the absolute value of LF and HF in the total distribution of power in spectrum analysis. Thus, the normalized LF and normalized HF band power describe the relative value of LF and HF in proportion to the total spectral power (TSP) minus the VLF band power, as formulated in Equations (2.1) and (2.2). The TSP is the total spectral power of HRV (up to 0.4 Hz).

$$Normalized\ LF = \frac{LF}{TSP - VLF} \tag{2.1}$$

$$Normalized\ HF = \frac{HF}{TSP - VLF}. \tag{2.2}$$

The variation of obtained HRV from ECG signals is associated with the ANS activity for distinguishing the sleep stage. HRV represents the changes between beat-to-beat variations in the time intervals of the heart rate, called inter-beat or R-R intervals. Furthermore, time-domain describes quantifying the amount of measured HRV in the R-R intervals, such as Standard Derivation of NN Intervals (SDNN) and Root Mean Square of Successive R-R Interval Differences (RMSSD). The burst of parasympathetic and sympathetic can increase the R-R intervals of the heartbeat. Higher values of the SDNN indicate the wakefulness and REM sleep. Thus, the LF band power makes a significant contribution to SDNN. It implies that the parasympathetic and sympathetic HRV measurement is sensitive to SDNN, while the HF band power correlates to RMSSD. Therefore, parasympathetic HRV measurement is sensitive to RMSSD but it not across

to the sleep stage [56, 57]. A study [58] investigated a certain degree of HRV reduction using SDNN and RMSD. The result shows that there are no significant differences between young and elderly subjects in terms of the linear scale-invariant correlations, nonlinear scale-invariant correlations, the fractal measure of directionality, and nonlinear fractal measure.

2.5.4 Assessment of the HRV

The HRV signal is usually obtained from an ECG recording that is captured over a certain period of time using an electrocardiography device. The researches [59] [60] has applied five-minutes segments of HRV signals since it is the recommended record length for ECG signals analysis. However, a study [61] has investigated that the computation of the nonlinear HRV indexes needs even longer segments (at least five minutes), and it may reduce the resolution of the estimated sleep staging results.

The ECG data are transferred from an electrocardiography device to a computer for further processing and analysis. The ECG signal may contain noise, irregular rhythm, or frequently varying morphology of the QRS complex. These kinds of disturbances appear since it is impossible to obtain steady-state conditions throughout the entire recording for several hours in a specialized laboratory or hospital. In fact, the QRS complex and R-peak are usually used as the fiducial point due to its readily distinguishable amplitude. Moreover, detection of the R-peak is a crucial stage in the acquisition of the HRV. Thus, it requires a robust algorithm, i.e., the more accurate the R-peak detection, the less error in the R–R interval time series, and in the subsequent HRV spectrum analysis [62].

A study [63] proposed Elgendi's algorithm to evaluate the best algorithm to detect R-peak in portable devices. Although this algorithm is computationally efficient, it needs a global ECG record to calculate the threshold. On the other hand, the Pan-Tompkins algorithm has been widely used for the pre-processing stage of the ECG signal [64] due to its effectiveness in detecting the position of the QRS complex. As mentioned before, accurate detection of the QRS complex position is a crucial factor in ECG-based systems. Separating the noise from the ECG signal without destroying the QRS waveform is a complicated process due to noise is usually broadband and overlaps to the QRS

complex [65]. Furthermore, the Pan-Tompkins algorithm presents a high complexity and the detection accuracy is moderate compared to Elgendi's algorithm [66].

In order to form R-R intervals, first, the difference in time of each of two consecutive R-peak is computed. Then, the duration of the consecutive R-R interval time domain is defined and they might be formed to the frequency domain as the HRV spectrum. According to [67], due to HRV apply fixed boundaries for specifying the frequency bands, it may fail to reflect certain aspects of ANS activity accurately. It may limit their discrimination power, e.g., in sleep and wakefulness classification. Therefore, the adapt HRV spectral features are implemented to discriminate the power in classifying sleep and wakefulness. The results showed that the combination between adapted HRV spectral features and other selected HRV non-spectral features significantly improve the overall classification performance, including sleep and wakefulness. Nevertheless, the overlapped part of the spectrum components will influence the computed features for both bands (LF and HF). It may have an impact on the decreasing accuracy of the classifier. Therefore, a more harmonious method is needed for defining a threshold that is needed to separate the two bands.

2.5.5 ECG-based automatic sleep staging detection

A study [68] proposed to detect the sleep stage to analyze the sleep condition of the patient. Sleep stage detection is a standard way to analyze sleep. Some works have developed an automatic sleep stage detection using Electroencephalogram (EEG), Electromyogram (EMG), and Electrooculogram (EOG). However, since the complexness of the recording process and signal analysis of those signals, it makes those methods are not recommended to be implemented as a portable system of home appliances. To this end, the use of the ECG signal for detecting the sleep stage is lately massively explored. The diverse feature extraction techniques and machine learning classifiers have been applied in classifying the sleep stage [69–71]. However, most of them just observed some of the sleep stages. In this paper, we observe all sleep stages (i.e., the wakefulness, light sleep, deep sleep, and REM sleep). Structurally, the automatic sleep stage system consists of a preprocessing phase and feature extraction phase. The results of this sleep stage system are used to compute sleep quality features.

Some research [72, 73] has used ECG in assessing sleep quality. In the back-end phase, a multi-class Support Vector Machine (SVM) classifier was used to classify sleep quality [74]. This approach presents a good promising in terms of sleep efficiency index, delta-sleep efficiency index, and sleep onset latency. The work of [75] also has investigated a binary classification of sleep stages (sleep-wake stages), and sleep efficiency estimation using the ECG signal. This system achieved an average error of 4.52% for 12 features input and 4.64% for ten features input. Furthermore, the difference between healthy subjects and Obstructive Sleep Apnea (OSA) patients in terms of sleep quality index has been considered by [76] and was developed by [77] on their automatic sleep quality system. It proves that the ECG signals can be used to obtain the sleep quality features.

Even though several works have applied a minimal physiological signal to detect sleep conditions, but only a few works have applied it to diagnose and treat the various sleep disorders instead of the use of a multichannel signal (PSG). A study [78] has developed an algorithm for detecting the sleep arousal. By using K-nearest Neighbours (KNN) classifier, this method achieved averagely 79% of sensitivity, 95.5% specificity, and 93% accuracy. However, the types of arousal and sleep disorder are not distinguished.

Chapter 3

Materials and Proposed Methods

In this Chapter, we describes the materials and the proposed methods includes the detail data description of the data used in this work and the main part of the proposed methods i.e., spectrum analysis of HRV, automatic sleep stage detection, and automatic sleep disorders classification.

3.1 Data Description

In this section describes the two PSG database used in this work. The following section 3.1.1 describes the PSG for subject during sleep condition and section 3.1.2 describes the PSG for healthy subjects and the most common elderly's sleep disorders.

3.1.1 MIT-BIH Polysomnographic Database

In order to obtain the fist aim of this doctoral dissertation about develop new pre-processing technique that suitable for 30-seconds epoch of ECG signals during sleep, the MIT-BIH Polysomnographic database [79] is used. This database contains EEG, EOG, EMG of the chin muscle, invasive blood pressure, oxygen saturation, two respiration signals and ECG. The study was conducted at the Boston's Beth Israel Hospital Sleep Laboratory. There are 18 recordings in total. The average age of subjects is 43 years, ranges 32 - 56 years. Record-slp01a and Record-slp01b are segments of the same subject and Record-slp02a and Record-slp02b are segments of another subject. All the remaining 14 records are from different subjects. The sleep recording time for each of the subject varied from 1:17 to 6:30 hours. In order to obtain the objective, this work only use the ECG signals from each subject to the experiments. Each ECG signal annotated

beat-by-beat and sleep stages.

Each 30-seconds of the PSG recordings in this database is labeled into six sleep stages condition according to R&K rules (i.e., Wake, NREM 1-4, and REM) [28]. Afterward, it is re-label according to the American Academy of Sleep Medicine (AASM) guidelines [29]. It is an improvement of sleep stages rules. The labels are wakefulness, light sleep (a combination of NREM 1&2), deep sleep (a combination of NREM 3&4), and REM sleep.

3.1.2 Cyclic Alternating Pattern (CAP) Sleep Database

In order to obtain the second and third aims of this doctoral dissertation about develop an automatic sleep stage detection and automatic sleep disorders classification, the Cyclic Alternating Pattern (CAP) [80] sleep database is used. It is caused, in those aims, we concentrated on healthy subjects and the most common elderly's sleep disorders (i.e., insomnia, SDB, and RBD). CAP data contains various physiological sleep conditions, non-sleep disorders (or healthy), and sleep disorders, such as Bruxism, Insomnia, Narcolepsy, Epilepsy, PLMS, RBD, and SDB. The average age of subjects is more than 60 years. It means that CAP data represents the age of the elderly.

In the CAP data, the PSG recordings contain the data of EEG channels, EOG channels, EMG signals, respiration signals, and ECG signals. We only use the ECG signals from each subject to the experiments. Based on R&K rules, each epoch (30-seconds) is label into six sleep stages (i.e., wake, NREM 1-4, and REM) [28]. We then re-label each epoch according to the American Academy of Sleep Medicine (AASM) guidelines [29]. The labels are wakefulness, light sleep (a combination of NREM 1&2), deep sleep (a combination of NREM 3&4), and REM sleep. On each epoch, we evaluate 51-subjects that consist of 23–42 years old sixteen healthy subjects (7 males and 9 females), 47–82 years old nine insomnia patients (4 males and 5 females), 65–78 years old four SDB patients (4 males), and 65–78 years old twenty-two RBD patients (19 males and 3 females). Table 3.1 shows detail information about the total number of epoch in terms of each stage and subject.

TABLE 3.1: Detailed information about the total number of epoch

Subject	**Sleep Stage**			
	wakefulness	**Light Sleep**	**Deep Sleep**	**REM Sleep**
Healthy	400 (8.45%)	2080 (43.95%)	1185 (25.05%)	1067 (22.55%)
Insomnia	1114 (34.93%)	1227 (38.48%)	437 (13.71%)	411 (12.88%)
SDB	196 (20.31%)	473 (49.02%)	231 (23.94%)	65 (6.73%)
RBD	1322 (23.55%)	2084 (37.12%)	1330 (23.69%)	878 (16.64%)

3.2 General Proposed Methods

Structurally, the proposed methods consists of five-stages, as shown in Figure 3.1. The first stage is the pre-processing of the ECG signal. Afterward, we extract the spectral features from the ECG signal in the second stage. The third stage is the sleep stage detection process by applying the DTB-SVM. The assessment of sleep quality performs in the fourth stage. In the final stage, sleep disorder classifies using an ensemble of bagged tree classifier.

Subsequently, to reach the aims of this doctoral dissertation, the proposed methods can be divided into three part, as shown in Figure 3.2. The general information of each part is describes as follows:

- The first part is pre-processing. In this part we propose a new pre-processing technique that suitable for 30-second epoch of ECG signals during sleep. This method address the issue of a multichannel signal of PSG by merely using an ECG signal during sleep. In addition, the advantage of ECG signal is more convenient to used and recorded, although without specialized trainers. A key process of our proposed method is the selection techniques to decompose the 30-seconds of the ECG signal.

- The second part is automatic sleep stage detection. In this part, we investigate an easy, fast, and effective method for automatic sleep stage detection using spectral features extraction of ECG signal alone. Two features is obtained from spectral features extraction i.e., normalized Low Frequency and normalized High Frequency. These features were then used as inputs for sleep stage detection. Therefore, this method offers the simplification of sleep stage assessment process. Then, mostly

commonly used learning classifiers is implemented to detect sleep stage, namely KNN, NN, DT, SVM, and proposed DTB-SVM. The proposed method using DTB-SVM based on spectral features of ECG signal achieved a good performances to obtain all sleep stage condition.

- The third part is automatic sleep disorders classification. In this part, we propose an efficient classification method of sleep disorder by merely using ECG signals to simplify the sleep disorders diagnosis process. This part also the compilation of all stage of the proposed methods. The assessment of sleep quality performs is investigated in this part. Furthermore, sleep disorder will classified using an ensemble of bagged tree classifier

We use Matlab software for all computations in the proposed method. The detailed information of the main part is explained in next Chapter.

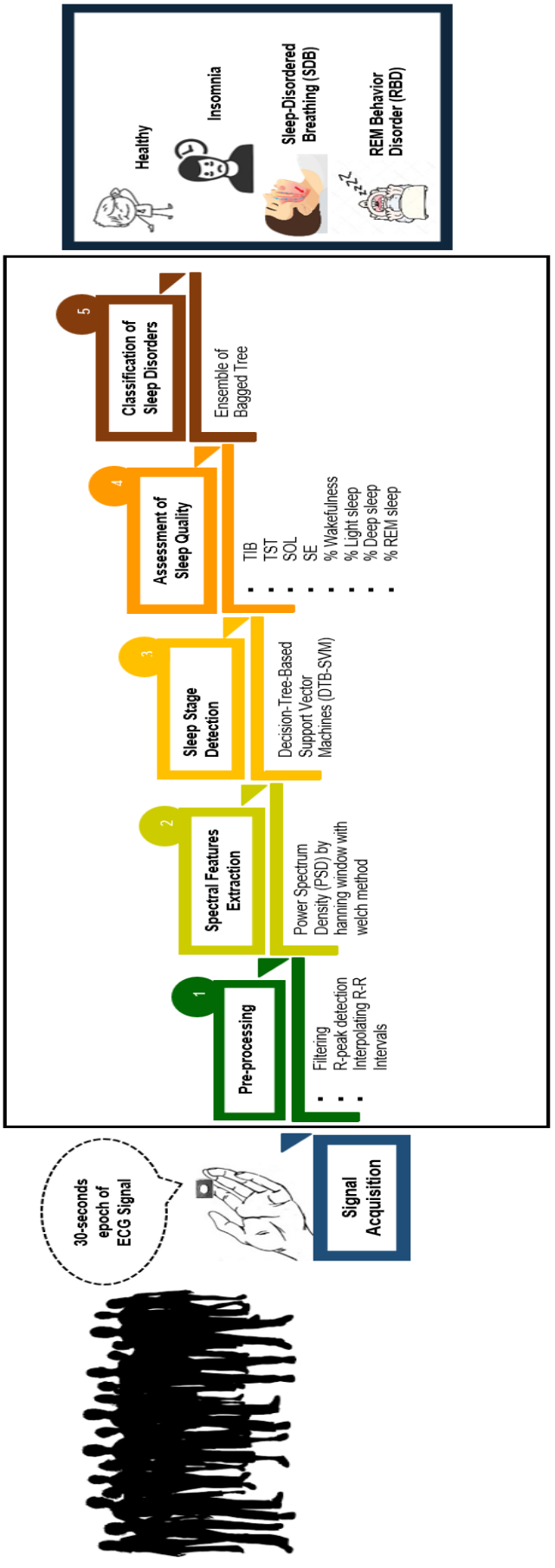


FIGURE 3.1: General scheme of the proposed method

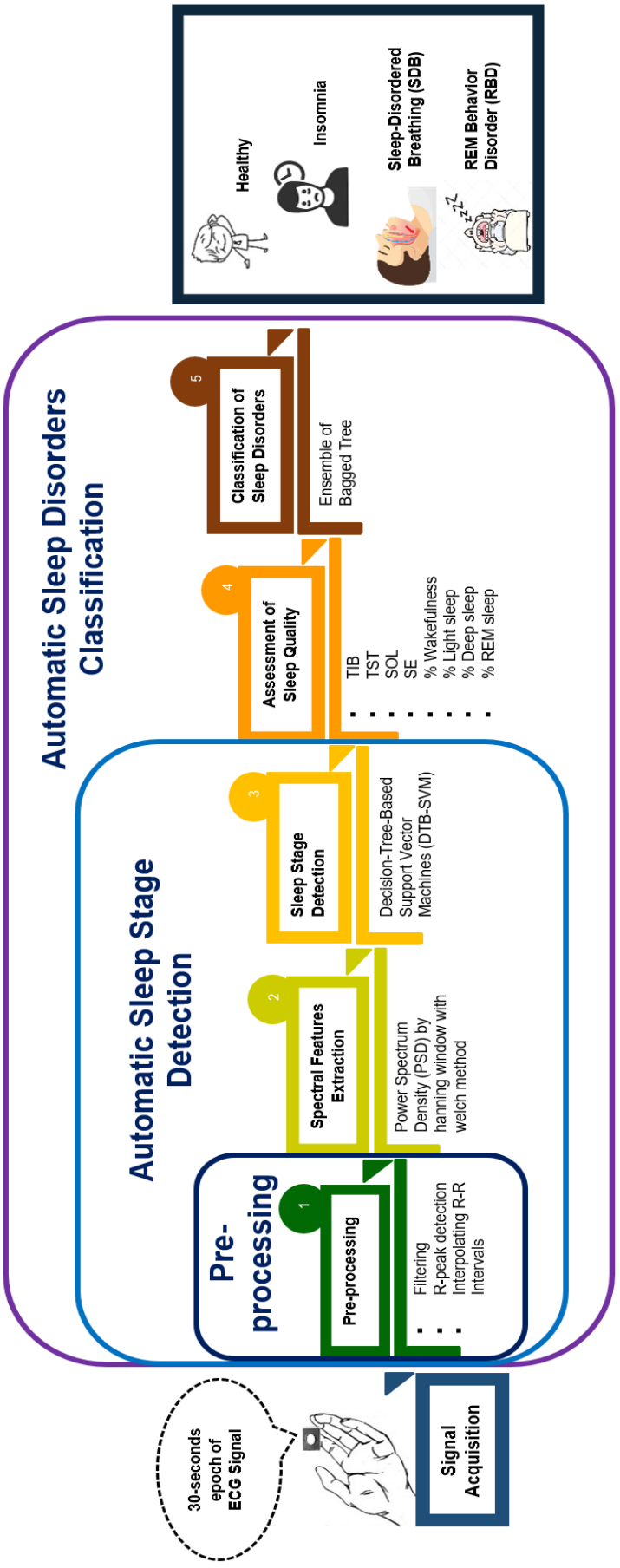


FIGURE 3.2: Three main part of proposed method

Chapter 4

Pre-processing

In this Chapter, we describes the first part of the proposed methods: Pre-processing. This part focused on the first stage of the proposed methods is the pre-processing of the ECG signal.

4.1 Proposed Method

In this part we propose we propose a new pre-processing technique that suitable for 30-second epoch of ECG signals during sleep. This method offers the simplification of sleep stage assessment process and address the issue of a multichannel signal of PSG by merely using an ECG signal during sleep. The proposed method of pre-processing as shown in Figure 4.1 . Therefore, the pre-processing of the ECG signal includes the procedure for filtering ECG, procedure for R-peak detection, procedure for interpolating R-R Intervals as desribed in section 4.1.1.

4.1.1 Pre-processing

The pre-processing stage consists of three-steps. The first step is the filtering of the ECG signal. Afterward, we detect R-peak from ECG signal in the second step. The third stage is the interpolating R-R intervals.

4.1.1.1 Procedure for Filtering ECG

A ECG signal is often corrupted by noise during acquisition or transmission. The de-noising process is to remove the noise while retaining and not distorting the quality of the processed signal. The traditional way of signal de-noising is filtering. In our work,

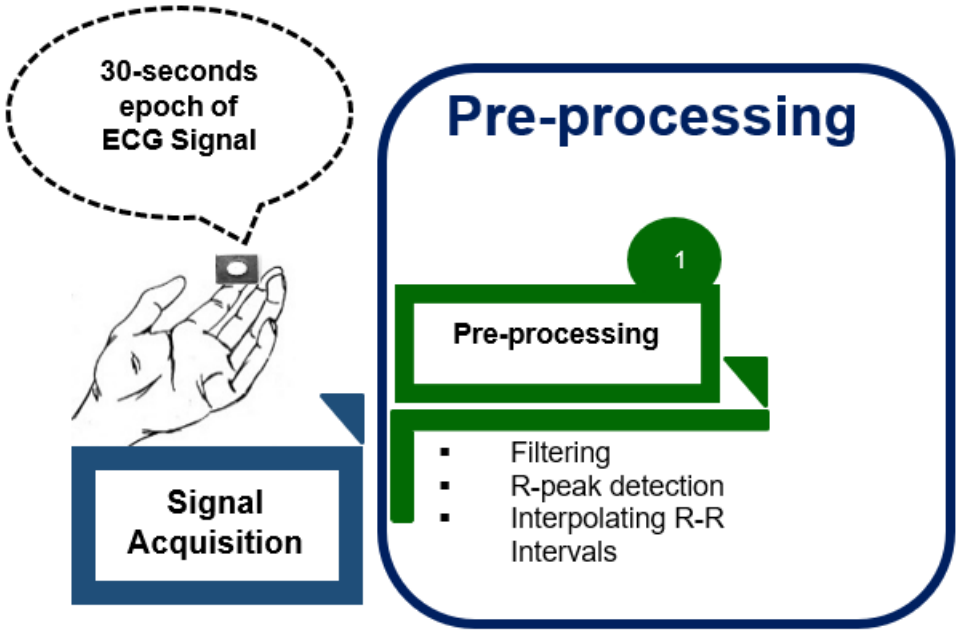


FIGURE 4.1: Proposed method of pre-processing technique

the proposed algorithm is developed by combining Infinite Impulse Response (IIR) notch and moving average filter.

The notch (band-stop) filter is a filter that passes all the frequencies except those in a specific frequency range. Thus, it is having a very narrow band. Furthermore, digital notch filters can be constructed as either Finite Impulse Response (FIR) and IIR filter. Signal processing by traditional digital filtering techniques brings some problems, such as the transient response at the beginning of the signal. Its duration mainly depends on the filter order. This causes problems when particularly short signals are filtered or when the initial part of a processed signal is of great importance. In this case, the useful signal can considerably be distorted owing to the transient response, or it can entirely be lost in the transient. Due to this problem, filters of possibly small order are often used. In general, IIR filter structures can be designed with a much lower order than their FIR counterparts for meeting equivalent magnitude specifications.

For designing notch filter through optimization technique, an ideal IIR notch filter is

required for calculating the value of objective function which is to be minimized using minimax optimization technique. The ideal IIR notch filter is defined in terms of magnitude frequency response of the filter. For ω_o the notch frequency the amplitude response is given as Equation (4.1). Where, ω is in the range of [0, π] and $H_i(\omega)$ is the ideal frequency response.

$$|H_i(\omega)| = \begin{cases} 0, \omega = \omega_o \\ 1, otherwise \end{cases} \tag{4.1}$$

In this work, using two order Z transfer function pole zero placement method of direct design of second order IIR notch filter. The purpose of the second order IIR notch filter is to eliminate the power line and skin-electrode interferences. In addition, it can also does not affect the effective of signal transmission even though the 50Hz power interference is eliminated. The analysis in the work by the authors of [81] shows that the use of second order IIR notch filter for digital signal processing is simple, practical and effective. The transfer function of the filter is expressed as Equation (4.2).

$$H_o(z) = K_0 \frac{(z - e^{j\omega_o})(z - e^{-j\omega_o})}{(z - re^{j\omega_o})(z - re^{-j\omega_o})} \tag{4.2}$$

where K_0 is the gain factor of the filter, $\omega_o = (2\pi\ f_0)\ /\ f_s$, f_0 is the is the frequency that has to be removed from a signal, f_s is the sampling frequency, and r is the radius of a pair of complex conjugate poles placed at the angle ω_o, the same angle as the zeros of the designed filter. Thus, we assumed $f_0 = 50$ Hz, $f_s = 250$ Hz, and r = 0.99 due to closer the pole radius approaches the unit circle the frequency. By using Euler formula, Equation (4.2) is simplified as Equation (4.3).

$$H_o(z) = K_0 \frac{1 - 2cos\omega_o z^{-1} + z^{-2}}{1 - 2rcos\omega_o z^{-1} + r^2\ z^{-2}} \tag{4.3}$$

The output of the transfer function of the second order IIR notch filter can be expressed in the discrete time domain by the following difference equation:

$$\begin{aligned} y(n) =& x(n) + b_1 x(n-1) + x(n-2) - a_1(n-1)y(n-1) \\ & - a_2(n-2)y(n-2) \end{aligned} \tag{4.4}$$

where *y(n)* is the second order IIR notch filter output and *x(n)* is the input ECG signal. The coefficient b_1 is equal to -2cos(ω_o), a_1 *(n)* = *2r(n)*cos(ω_o), and a_2*(n)* = r^2 *(n)*. Furthermore, the moving average filter is applied to provide information for detecting R-peak with robustness to noise.

4.1.1.2 Procedure for R-peak Detection

In order to detect R-peak detection, the signal is decomposed into shifted and scaled versions of the original mother Wavelet Daubechies 6 (db6). It is because the wavelet db6 closely matches with the shape of QRS complex. The R-peak detection is managed in the following steps:

1. The filtered 30-seconds ECG signal is read, and the length is calculated.

2. The wavelet db6 is applied in the signal.

3. The smoothing of the signal is achieved by averaging signal samples over longer time windows.

   The first element of the moving average is obtained by taking the average of the initial fixed subset of the number series in Equation (4.4). Then, the subset is modified by shifting forward, exclude the first number of the series and including the next number following the original subset in the series. It creates a new subset of numbers, which is averaged. This process is repeated over the entire data series.

4. The threshold value is calculated corresponding to 70% from the maximum amplitude of the ECG signal.

   A study [82] has investigated 70% of the maximum peak of the ECG signal can calculated to insure the R peak.

5. R-peak is detected when the fiducial point of the signal is higher than the threshold.

4.1.1.3 Procedure for Interpolating R-R intervals

We interpolate the R-R intervals in the time domain using a cubic spline and re-sampled it at 2.5 Hz. With cubic spline, it is possible to ensure smoothness of the resulting curve of the R-R interval. Moreover, a time-series signal should be re-sampled using frequency sampling at least two-times of the considered maximal frequency. It aims to estimate the HRV spectrum (maximum HF band power is 0.4 Hz) for satisfying the Nyquist-Shannon sampling theorem.

4.2 Experimental setup

This part concentrates on addressing the issue of a multichannel signal, such as the PSG merely using an ECG signal during sleep. Therefore, we used the MIT-BIH Polysomnographic database [79].

4.3 Results and Discussion

The raw (original) ECG signal loaded from the MIT-BIH Polysomnographic database usually is corrupted with noise as a shown in Figure 4.2. Therefore, it is needed to purify before R-peak detection stage. Filtering ECG is also the initial procedure for HRV spectrum analysis. The first step is to filter the ECG using second order IIR notch filter in each 30-seconds of the ECG signal. The result of filtering the signal with the second order IIR notch filter described above is shown in Figure 4.3. Although the noise level has been reduced, some noise is still present in the result. The moving average filter offers another approach to dealing with this problem in detecting R-peak with a robust approach to noise and smoothing the result of the ECG signal, as shown in Figure 4.4. Furthermore, the detection of R-peak using a 70% threshold from the maximum amplitude of the ECG signal is shown in Figure 4.5.

The performance of the R-peak detection is essential for R-R intervals and HRV spectrum analysis in different sleep stages. The proposed R-peak detection algorithm is evaluated using quantitative comparisons in term of sensitivity (S), positive predictivity (P), and detection error (DER), as defined in Equations (4.5) - (4.7). The true positive (TP) is defined as the number of R-peak detected as R-peak. False negative (FN) is the

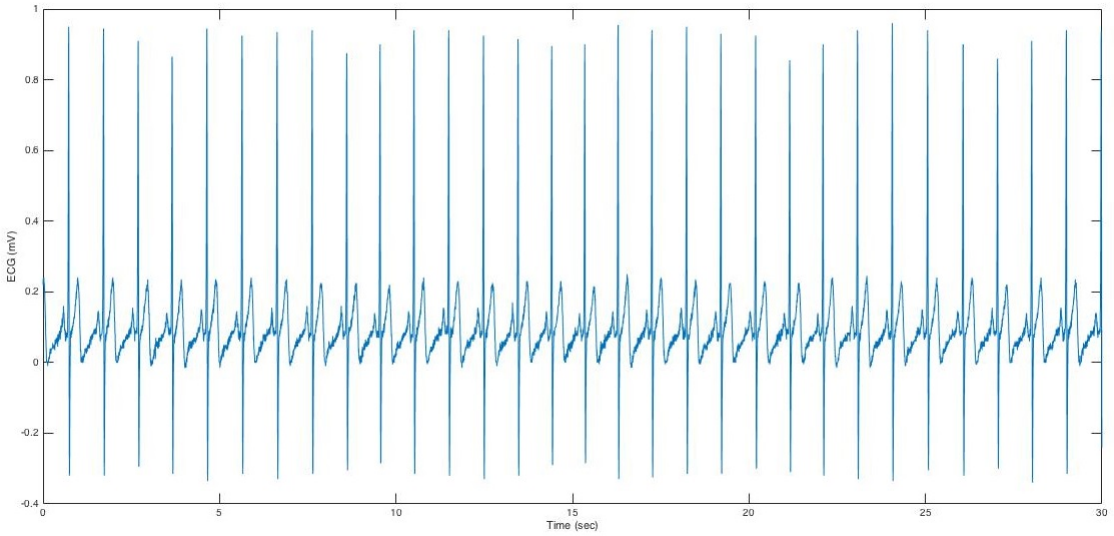


FIGURE 4.2: Original ECG signal of MIT-BIH polysomnographic for first 30-seconds Record-slp01b

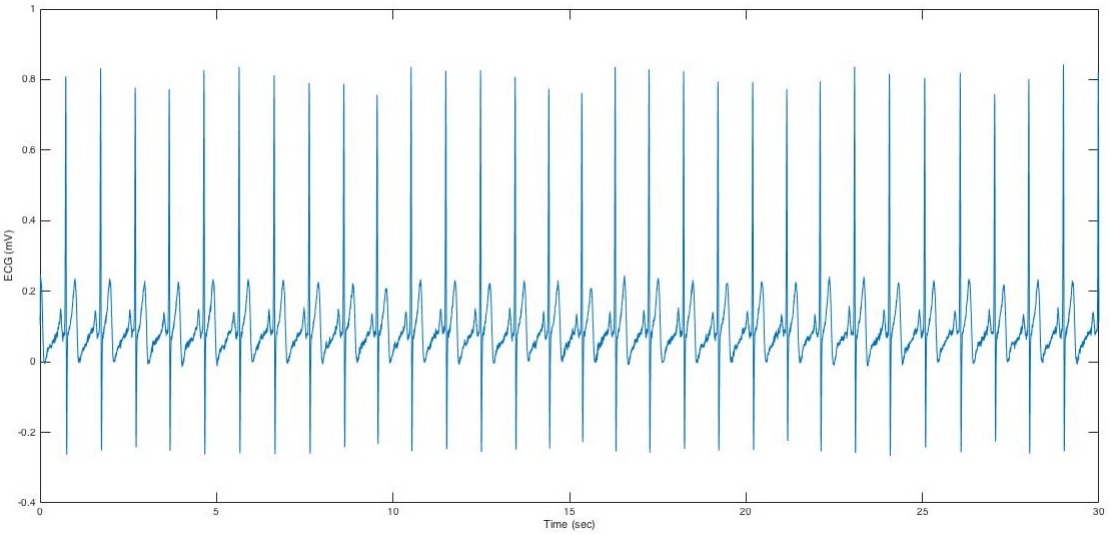


FIGURE 4.3: Filtering ECG signal using second order IIR notch filter of first 30-seconds Record-slp01b

number of R-peak which have not been detected, and false positive (FP) is the number of non R-peak detected as R-peak.

$$S\,(\%) = \frac{TP}{TP + FN} \tag{4.5}$$

$$P\,(\%) = \frac{TP}{TP + FP} \tag{4.6}$$

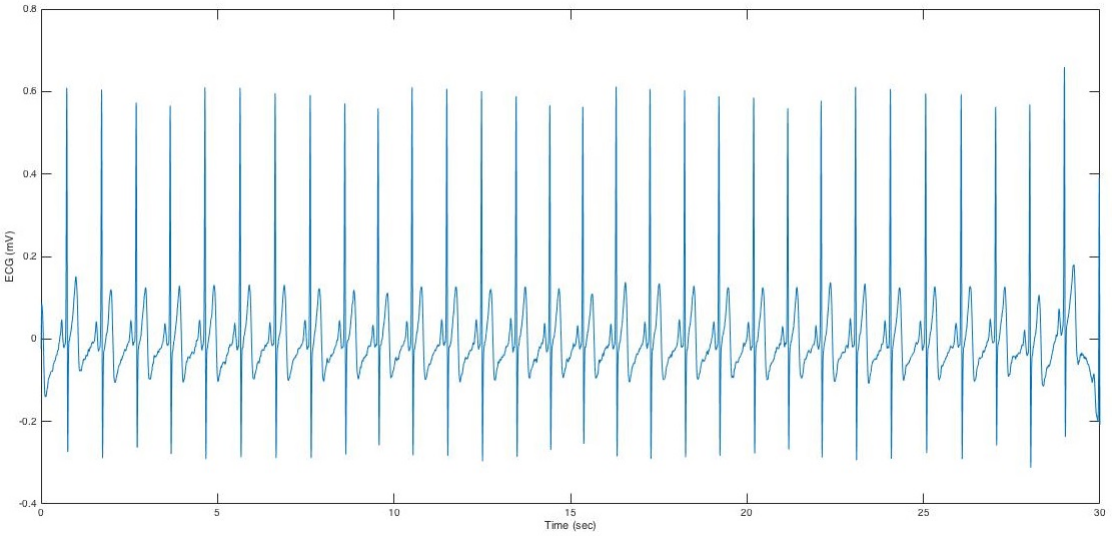


FIGURE 4.4: Final filtering ECG signal of first 30-seconds Record-slp01b

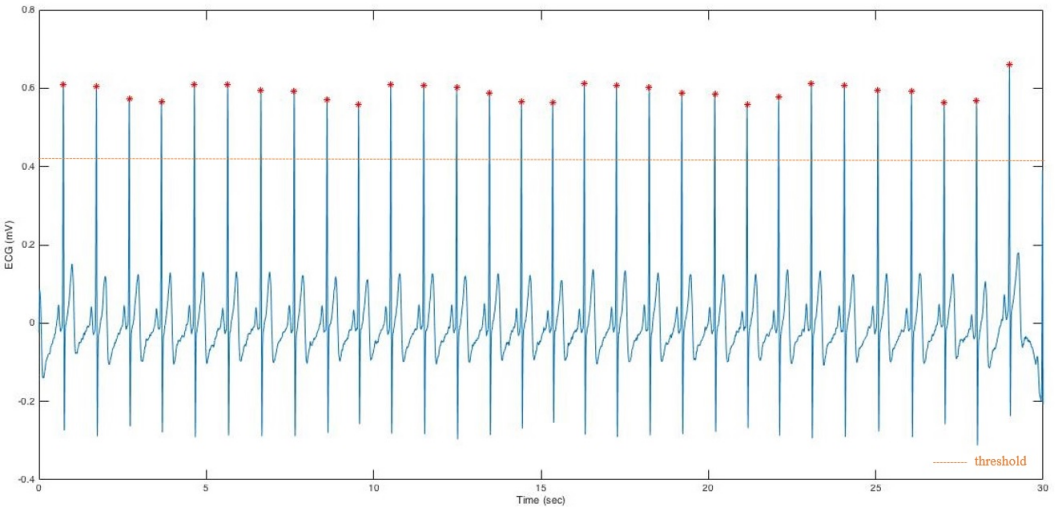


FIGURE 4.5: R-peak detection using 70% threshold in first 30-seconds ECG signal Record-slp01b

$$DER\,(\%) = \frac{FN + FP}{TP + FN} \tag{4.7}$$

Table 4.1 presents the performance of the R-peak proposed algorithm with its default parameters against all records. The average DER value is 0.09%. The proposed algorithm performs well on most records and their maximum DER is below 0.31%, except on Record-slp45. The error of the Record-slp45 occurs due to the significant false negative and false positive errors during the flutter episodes. MIT-BIH Polysomnographic database has considered Record-slp45 as an extremely difficult record. Moreover, the R-peak proposed algorithm achieves Sensitivity = 90.92% and Positive Predictivity =

99.57%. The sensitivity represents the percentage of true beats that are correctly detected, whereas the percentage of detected true beats is presented by the positive predictivity.

TABLE 4.1: Performance evaluation of the R-peak proposed algorithm for the MIT-BIH Polysomnographic database

Record	**Total**	**TP**	**FN**	**FP**	**S(%)**	**P(%)**	**DER(%)**
slp01a	7806	7806	0	0	100.00	100.00	0.00
slp01b	11465	11465	0	0	100.00	100.00	0.00
slp02a	16135	11160	4975	0	69.17	100.00	0.31
slp02b	11282	8640	2642	0	76.58	100.00	0.23
slp03	24890	24890	0	0	100.00	100.00	0.00
slp04	27026	20160	6866	0	74.59	100.00	0.25
slp14	22892	22892	0	0	100.00	100.00	0.00
slp16	27603	27603	0	0	100.00	100.00	0.00
slp32	21707	21707	0	0	100.00	100.00	0.00
slp37	30610	25200	5410	0	82.33	100.00	0.18
slp41	25668	25668	0	0	100.00	100.00	0.00
slp45	27678	9120	17798	760	33.88	92.31	0.69
slp48	24692	24692	0	0	100.00	100.00	0.00
slp59	16901	16901	0	0	100.00	100.00	0.00
slp60	25016	25016	0	0	100.00	100.00	0.00
slp61	25410	25410	0	0	100.00	100.00	0.00
slp66	15774	15774	0	0	100.00	100.00	0.00
slp67x	5372	5372	0	0	100.00	100.00	0.00
Mean	**367927**	**329476**	**37691**	**760**	**90.92**	**99.57**	**0.09**

In addition, the total computational resource cost of the R-peak proposed algorithm was presented in Table 4.2. We compared the processing time of each method from other related studies ([63] and [64]). The chosen methods were implemented in MATLAB version 2015b on a desktop of Intel i7 4-core CPU and 8 GB RAM. Table 2 shows the comparison results on average computational time over ten trials in processing the MIT-BIH Polysomnographic database. The R-peak proposed method runs faster than the other algorithms, even with a low error rate for a huge potential suitable to be implemented in portable hardware device and real-time applications.

R-R intervals are calculated by computing the difference in time of each of two consecutive R-peak. The values of R-R intervals are then plotted versus time, giving a curve called tachogram as shown in Figure 4.6. Furthermore, the time-series ECG signal

TABLE 4.2: Comparison of processing time

Methods	Error rate (%)	Processing time (second)
Elgendi's algorithm [63]	0.69	40.99
Pan-Tompkin's algorithm [64]	1.72	101.54
This work	**0.09**	**5.28**

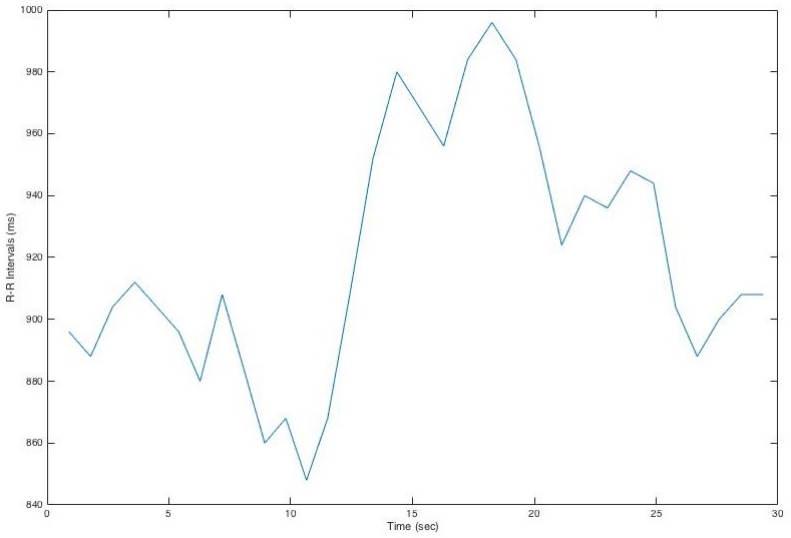


FIGURE 4.6: R-R intervals of first 30-seconds ECG signal Record-slp01b

should be re-sampled for estimating the HRV spectrum. The result of power spectrum of HRV by applied PSD is shown in Figure 4.7.

Table 4.4 shows the normalized LF and normalized HF component differed significantly between the individual sleep stage. During REM sleep, the normalized LF is increased substantially compared to other sleep stages since the highest value is observed in REM sleep. This spectrum component in the supine position is mediated both by sympathetic and parasympathetic activity. In contrast, the normalized HF shows higher values in other sleep stages in comparison to REM sleep since the lowest value being observed in REM sleep. It may be estimated that the parasympathetic activity is reduced, and sympathetic activity increased in REM sleep.

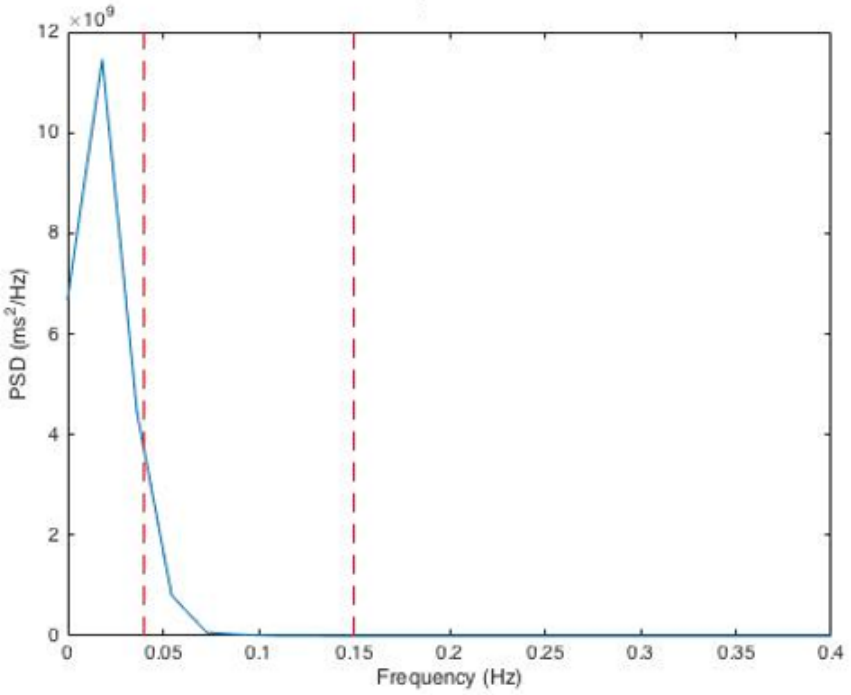


FIGURE 4.7: Power spectrum of HRV

4.4 Conclusion

The proposed method of this part is concentrated to address the issue of a multichannel signal, such as the PSG by merely using an electrocardiogram. In filtering stage, we presented a suitable method for 30-seconds of the ECG signal. Furthermore, R-peak was detected using a threshold without detecting each PQRST peak. The experiment results shows that the R-peak proposed algorithm performs better compared to previous works in robustness to noise and low processing time.

This approach is proven reliable in modeling automatic sleep stage or sleep disorder system without preoccupied with a multichannel signal of PSG. Moreover, it reinforce the practical feasibility of the proposed method for implementing in portable hardware device and real-time applications.

Chapter 5

Automatic Sleep Stage Detection

In this Chapter, we describes the second part of the proposed methods: Automatic Sleep Stage Detection. This part includes the first and second stage of the proposed methods, i.e., spectral features extraction and sleep stage detection,respectively. A well-known classifiers also applied and compared in this Chapter i.e., KNN, NN, DT, SVM and our proposed DTB-SVM.

5.1 Proposed Method

In this part, we investigate an easy, fast, and effective method for automatic sleep stage detection on patients and non-patients subjects. As shown in Figure 5.1, the proposed method of automatic sleep Stage detection consists of three stage, i.e., pre-processing, spectral features extraction, and sleep stage detection. However, pre-processing stage was described in detail on the Chapter 4. Therefore, the following section 5.1.1 describes the spectral features extraction includes HRV spectrum analysis by using Power Spectrum Density (PSD). Section 5.1.2 describes automatic sleep stage. In addition, the results of first, second, and third stages is presented and discussed.

5.1.1 Spectral features extraction

The pre-processing stage consists of two-steps. The first step is the HRV spectrum analysis by using PSD. Afterward, we analyze the spectrum analysis of the HRV in different sleep stages in the second step.

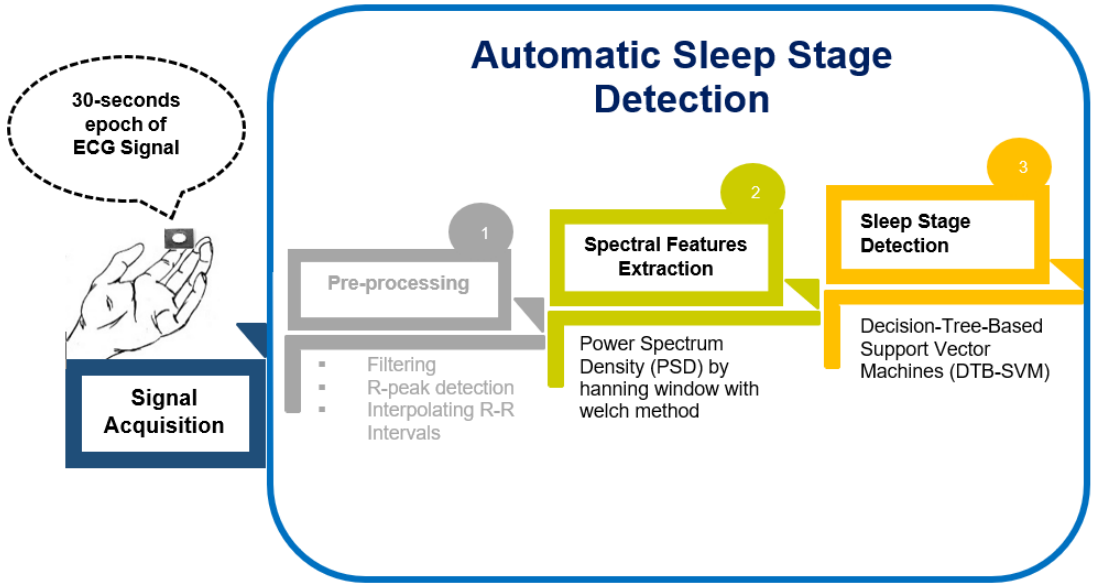


FIGURE 5.1: Proposed method of automatic sleep stage detection

5.1.1.1 HRV Spectrum Analysis by using PSD

We use the Fast Fourier Transform (FFT)-based welch method to transform from the time domain into the frequency domain. Welch method is a non-parametric technique (includes the periodogram) that provides an excellent resolution and estimation of the spectrum calculation. Then, to reduce spectral leakage on the resulting spectrum, we apply the Hanning window on each 30-seconds of the ECG signal. Furthermore, we perform the HRV analysis to the PSD representation.

5.1.1.2 Spectrum analysis of the HRV in Different Sleep Stages

As mentioned in Chapter 2, HRV spectrum can be distinguished into three main frequency bands (VLF, LF, and HF). Typically, the band power measurement of VLF, LF, and HF are represented in absolute values of power (ms^2). Since the variation of normalized LF and normalized HF could reflect the balanced and controlled behaviors of the ANS, both of them are considered as a good discriminator in distinguishing the sleep stage. Hence, we use the normalized LF and normalized HF to recognize the sleep stage (wakefulness, light sleep, deep sleep, and REM sleep). The LF and HF in the normalized unit represent the absolute value of LF and HF were calculated using Equations (2.1) and (2.2).

5.1.2 Sleep stage detection

In this stage, the DTB-SVM is used to detect the sleep stage. DTB-SVM is a combination of SVM and Decision Tree (DT) [84]. The learning function form of NN and SVM is statistically the same. A single hidden layer of NN uses the same model with an SVM. SVM is a machine learning algorithm that uses the structural risk minimization principle for estimating the objection function. It is performed by minimizing the upper bound of the generalization error. The SVM attempts to seek an optimized linear division, that is, construct a hyperplane that is then used to separate the classes. The general equation of SVM in defining the hyperplane *y(a)* is given in Equation (5.1), where, w is the support vector, a is the input vector, and b is the bias term.

$$y(a) = w.a + b \tag{5.1}$$

According to the binary SVM rules that (*x-1*), where x is a class problem, for classifying four sleep stages conditions, we use three SVMs. Firstly, we trained the SVM using as input the normalized LF and normalized HF features. It aims to find the optimal hyperplane with the maximum margin (m), where the margin can be calculated by dividing the integer two with the absolute function of support-vector. Then, the DT is used to find the maximum margin of each SVM until the four-targeted conditions (i.e., wakefulness, light sleep, deep sleep, and REM sleep) are reached. The detailed scheme for DTB-SVM is illustrated in Figure 5.2. We evaluate the DTB-SVM performance using the cross-validation method with k = 5.

In addition, well-known classifiers were applied in this doctoral dissertation, including KNN, NN, DT, SVM and proposed DTB-SVM. It is caused KNN, NN, DT, and SVM that have been widely used in the sleep stage detection system. The reported data shows that 10%, 23% 5%, 31% sleep stage detection was using KNN, NN, DT, SVM, respectively. While 31% other used nine another classifier. Nevertheless, DTB-SVM is proposed for automatic sleep stage detection. The classification performance was evaluated to investigate an easy, fast, and effective method that feasible to implement in-home and portable system. The sleep stage classification using KNN classifier requires the majority of its neighbors, with objects being applied to the most common class among their closest neighbors (k nearest neighbors). For the NN classifier using 1 input

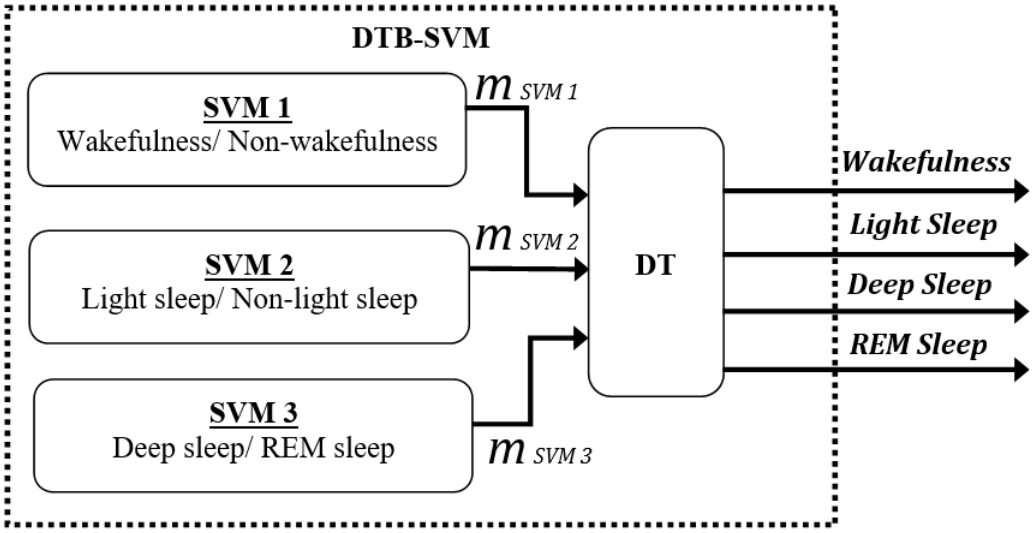


FIGURE 5.2: General Scheme of DTB-SVM

layer, 1 output layer, and 1 hidden layer feedforward backpropagation NN. Furthermore, in the output layer using an equal number of neuron and number of classes. For DT classifier using the binary tree algorithm to sleep stage classification. This method requires to split each epoch into two different groups, start from the top of the decision tree and calculate the bottom decision function. Lastly, for SVM classifiers using a one-against-all approach which combined with kernel functions. In this research used a linear kernel.[85][86][87] reported a detailed description and equation of these classifiers. DTB-SVM classifier is proposed for detecting the four stages of sleep, i.e., wakefulness, light sleep, deep sleep, and REM sleep.

5.2 Experimental setup

This part concentrates on investigating an easy, fast, and effective method for automatic sleep stage detection on patients and non-patients subjects. Therefore, we used the Cyclic Alternating Pattern (CAP) sleep database [80].

5.3 Results and Discussion

As mentioned above, after generating an ECG signal from every 30 seconds (one epoch), filtering processes were involved. Then R-peaks position for each epoch was detected based on a threshold value. Furthermore, the R-R interval was developed as the sequence of R-peaks. The first 30-seconds epoch of the pre-processing ECG signal of patient-1

with insomnia is shown in Figure 5.3.

When a time series of R-R intervals is obtained. Spectral features extraction for each epoch is performed by PSD. The first 30-seconds epoch of PSD representation (patient-1 with insomnia) is shown in Figure 5.4. It also provides the ability to distinguish HRV spectrum bands: VLF, LF, and HF. Then, the two features applied were LF (n.u.) and HF (n.u.) band power that obtained using Equations (2.1) and (2.2). These extracted features were then used as inputs for sleep stage detection.

According to achieve classification purposes, several machine learning algorithms were applied. The different classifier was tested to obtain the best performance in automatic sleep stage detection. In addition, three standard measures [88] which are specificity, sensitivity, and accuracy were used to evaluate the performance of the proposed system. This standard involved the calculation of the True Positives (TP), False Positives (FP), False Negative (FN) and True Negative (TN) values. These obtained by comparing the classification results to the expert classification. The equations of the standard classification performance measure as shown in Equations (5.2) - (5.4)[89].

$$Specificity = \frac{TN}{TN + FP} \tag{5.2}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{5.3}$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{5.4}$$

Table 5.1 - 5.4 shows the comparison of specificity, sensitivity, and accuracy of each sleep stages detection in different classification method and subjects. Table 5.1 shows that the greatest classification problem of healthy subjects was related to wakefulness and light sleep was almost indistinguishable when applied NN and SVM. It is caused the characteristics of both sleep stage was similar. This is proven the sensitivity of both the

sleep stage has very low value. It implies that the ability to determine the wakefulness and light sleep cases correctly is low, respectively. Otherwise, the ability to determine other sleep cases correctly (specificity) is high. Moreover, REM sleep was almost indistinguishable when applied NN and DT. It caused almost REM sleep was classified as deep sleep, because of characteristics of both sleep stage was similar.

Table 5.2 shows the greatest classification problem of patients with insomnia were related to deep sleep and REM sleep were almost indistinguishable when applied KNN and SVM. Moreover, almost wakefulness sleep was classified as light sleep. Whereas, wakefulness and light sleep were almost indistinguishable when applied NN. It is caused the characteristics of both the sleep stage in insomnia was similar. This is proven the sensitivity of both the sleep stage has very low value. Table 5.3 shows the greatest classification problem of patients with sleep-disorder breathing was related to REM sleep were almost indistinguishable when applied KNN, NN, DT, and SVM. This is proven the sensitivity of both the sleep stage has very low value. Table 5.4 shows the greatest classification problem of patients with rem behavior disorder were related to deep sleep and REM sleep was almost indistinguishable when applied KNN. Moreover, wakefulness was almost indistinguishable when applied KNN, NN, DT, and SVM. This is proven the sensitivity of both the sleep stage has very low value.

On the other hand, in this research found that the proposed DTB-SVM classifier can obtain the highest specificity, sensitivity, and accuracy in all sleep stage condition and all tested subjects compared to another classifier as shown in Table 5.1 - 5.4 and Figure 5.5. The DTB-SVM achieved an average classification specificity, sensitivity and overall accuracy of 98.31%, 91.84%, 95.06%, respectively. The evaluation of classification performance using K-fold cross-validation where 80% data was used for training and 20% data was used for testing. Moreover, all sleep stage condition can be well distinguished using DTB-SVM classifier. It is useful to solve the similarity of both sleep stage that occurred in another classifier. In addition, Table 5.5 shows the DTB-SVM classifier has the fastest computation time. When applied DTB-SVM classifier the computation time only takes around 1 second of each data.

Tables 5.6 – 5.9 present the confusion matrix of the sleep stage detection for health and sleep disorders subjects. These matrices represent the performance of the DTB-SVM in

terms of true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN). TP presents the number of sleep stages that labeled correctly and TN for the number of sleep stages that correctly identified as not correspond to the sleep stages. FP indicates the number of sleep stages that incorrectly labeled. FN denotes the number of sleep stages that unidentified in sleep stage classes. Furthermore, the TP, TN, FP, and FN are used to evaluate the performance of sleep stage detection, such as specificity, sensitivity, and overall accuracy.

The main diagonals of each confusion matrix denote the TP values. A shown in Tables 5.6 – 5.9, the TP values are the highest value on each row and column. It indicates that the proposed method able to detect the sleep stages accurately. In more particular, the specificity, sensitivity, and overall accuracy of the sleep stage detection for 16 healthy subjects achieve 96.36%, 84.63%, and 90.42%, respectively. Table 5.6 shows that deep sleep is well classified, while wakefulness tends to be miss-classified than the others. It is because wakefulness and light sleep have a similar LF power level for healthy subjects so that they are difficult to distinguish. The lowest value of the LF power level occurs during the deep sleep, while the HF power level during wakefulness is comparable with deep sleep and REM sleep, but different from the light sleep [90].

The specificity, sensitivity, and overall accuracy of the sleep stage detection for nine patients with insomnia achieve 99.15%, 97.16%, and 97.55%, respectively. Table 5.7 shows that the best classification is provided by light sleep, matching with the PSG scoring. Then, the specificity, sensitivity, and overall accuracy of the sleep stage detection for four patients with SDB are 96.79%, 77.85%, and 89.89%, respectively. The specificity, sensitivity, and overall accuracy of the sleep stage detection for 22 patients with RBD achieved 99.54%, 97.92%, and 98.57%, respectively. Tables 5.8 and 5.9 show that deep sleep and REM sleep tend to be miss-classified than the others, while wakefulness and light sleep are well classified for patients with SDB and RBD. It is due to some of the REM condition cannot be detected in patients with SDB and RBD. SDB and RBD distinguish wakefulness and light sleep better than healthy subjects. It is because hypopnea or apnea may have affected the pulse during sleep. RBD patients frequently have SDB. The hypopnea or apnea index (AHI) of SDB and RBD patients is higher than 15. Moreover, RBD is an intriguing parasomnia characterized by repeated episodes of dream enactment behavior and REM Sleep Without Atonia (RSWA). RSWA is characterized

by increased tonic muscle activity. Therefore, it could be said that RSWA also influences a diagnostic feature of RBD in REM sleep [91].

DTB-SVM is the combination between SVM and DT. SVM is the classifier was designed for binary classification. A multi-classes classification problem cannot directly have applied SVM. Therefore, multi-classes classification problem in automatic sleep stage detection can be solved effectively using DTB-SVM. Firstly, the highest SVMs are trained in these two classes. However, three SVM is required for four sleep stage condition. Then, the classification procedure goes from the root node to the leaf node with the help of binary SVM when testing a sample. Furthermore, when the maximum hyperplane margin is found, only the points located closest to the hyperplane are called support vectors. That means the points can provide a representation of the classifier. These data points serve as support vectors in each SVMs. Finally, DT is trained based on the maximum hyper-plane margin in each SVMs. Start at the highest of the DT and calculate the decision function from the root.

Table 5.10 shows a comparison of this research approach with several related studies. The comparison was made with another research that also used ECG signal for sleep stage detection but using a different type of classifier, subjects, and features. [92] investigate the sleep stage detection using heart rate (HR) two-dimensional features vector each 30-second and Hidden Markov Model (HMM) on 15 healthy subjects. Then, [93] report the sleep stage detection using time-domain features, non-linear-dynamic features and time-frequency features of HRV at least 5 minutes by using Linear Discriminant (LD) classifier on 30 healthy subjects. The performance of our proposed method although using minimal spectral features and different type of subject can obtain high accuracy in all sleep stage condition when compared with another research. While the specificity and sensitivity were not reported in these related studies.

The three primary frequency bands of HRV spectrum are computed according to the main frequency band of the HRV spectrum i.e., VLF ranges 0.003–0.04 Hz, LF ranges 0.04–0.15 Hz, and HF ranges 0.15–0.4 Hz. According to the ANS study, LF spectrum fluctuation represents the activity of the parasympathetic and the sympathetic nervous system, and HF spectrum fluctuation only reflects the activity of the parasympathetic nervous systems. Then, the changes of the power spectrum between different sleep stage

also influenced the absolute value of its spectrum components. In order to eliminate this effect of total spectrum fluctuations between different sleep stage, only the normalized value of individual spectrum components were assessed. Specifically, normalized LF and normalized HF were assessed since both of them are considered as a good discriminator in distinguishing the sleep stage.

Thus, to verify that two extracted features suggested can be distinguished among all sleep stage condition and subjects, a boxplot method or also called Box-and-Whisker plot method was conducted. In Box-and-Whisker plot method, the sleep stage data is split to quartiles. Furthermore, it has a minimum value, lower quartile, mean, median, upper quartile, and maximum value. The difference between upper quartile and lower quartile is the length of the box. Then, one vertical line is drawn inside the box as the median of the sleep stage data. Median of the lower samples is called 'lower quartile' and median of the higher samples is called 'upper quartile'. Afterward, in the outside of the box, two more vertical lines are drawn near upper quartile is called 'upper whisker' and another one line near lower quartile is called 'lower whisker'. The mean of the sleep data is marked with 'x' As results showed, the mean, median, upper and lower quartile, upper and lower whisker of extracted features normalized low frequency and normalized high frequency was significantly different between every two stages on patients and non-patients as shown in Figure 5.6 - 5.9.

During REM sleep, the normalized LF is increased substantially compared to other sleep stages since the highest value is observed in REM sleep. This spectrum component in the supine position is mediated both by sympathetic and parasympathetic activity. In contrast, the normalized HF shows higher values in other sleep stages in comparison to REM sleep since the lowest value being observed in REM sleep. It may be estimated that the parasympathetic activity is reduced, and sympathetic activity increased in REM sleep.The applied classifier of DTB-SVM provides an effective analysis to distinguish all sleep stage condition: wakefulness, light sleep, deep sleep, and REM sleep with good specificity, sensitivity, and overall accuracy on patients and non-patients subjects. Even though, the number of subjects was limited. In this work has a different type of subjects: healthy, insomnia, sleep-disordered breathing, and REM behavior disorder. It is reliable for modeling and making statistical comparisons. Finally, the proposed method that used minimal spectral extraction of ECG signal and DTB-SVM was a major contribution

and advantage as an easy, fast, and effective for automatic sleep stage detection instead of using a multichannel signal.

5.4 Conclusion

An automatic sleep stage detection was proposed in this part. It is consisting of normalized LF band power, normalized HF band power, and DTB-SVM classifier for distinguishing four sleep of sleep based on 30-second segments of ECG signals, instead of using a multichannel signal. This can pave a way for developing an easy, fast, and effective automatic sleep stage detection on healthy subjects and sleep disorders patients in dissomnias class such as insomnia, sleep-disordered breathing, and REM behavior disorders.

Furthermore, the proposed method is able to obtain all sleep stage condition. Based on this research, it becomes a great foundation to implement in-home and portable system. Moreover, a sleep physician may be improving an evaluating of sleep stages. It is also reliable to suspect a treatment and diagnosis of sleep disorders though sleep stage detection. In addition, we can further extend the use of the proposed model in classifying of sleep disorders based on the automatic system, in that it can make the screening or diagnostic processes much easier, faster, and more effective than with other methods.

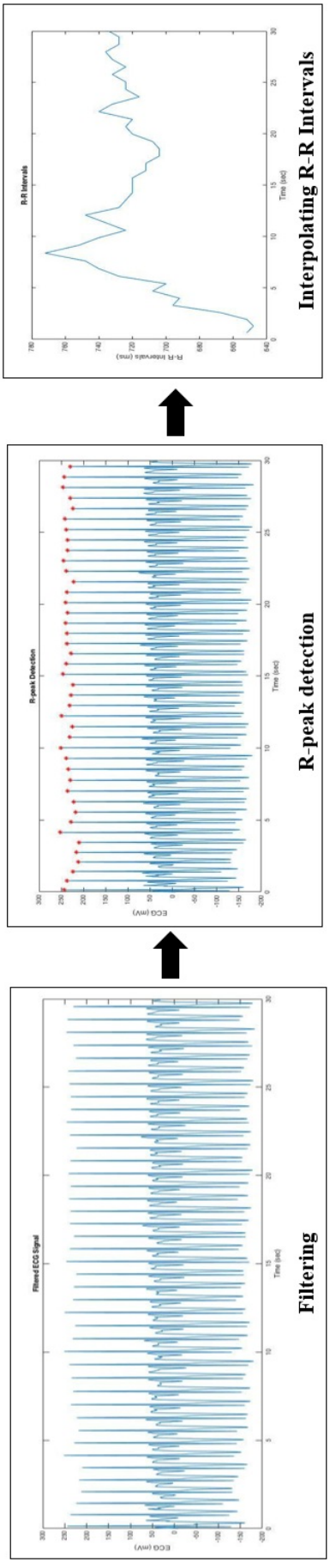


FIGURE 5.3: Example of pre-processing for first 30-seconds epoch from patient-1 with insomnia

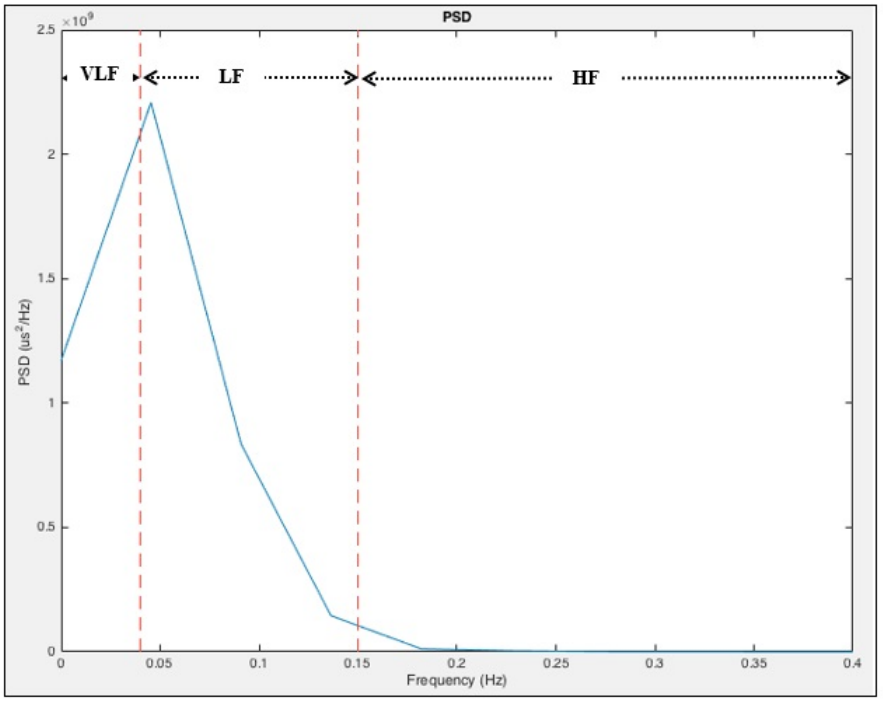


FIGURE 5.4: Example of PSD for first 30-seconds epoch from patient-1 with insomnia

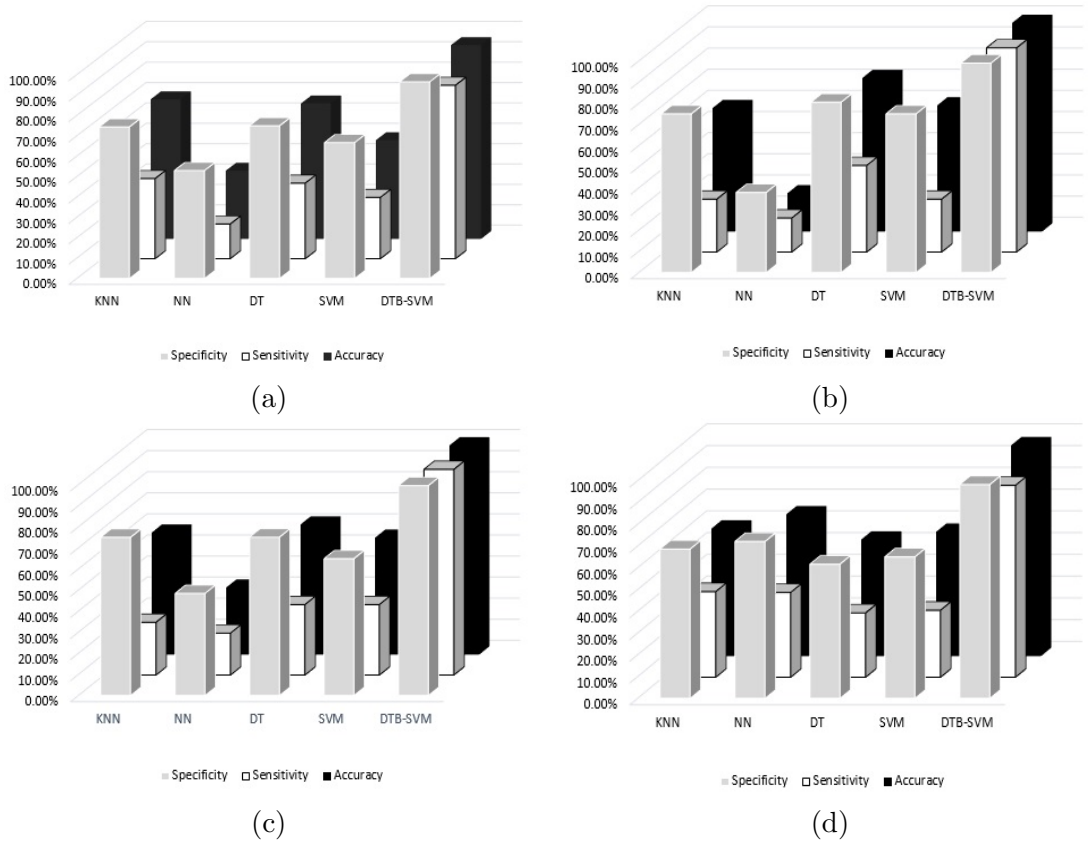


FIGURE 5.5: The average of performance results for (a) healthy subjects, (b) patients with insomnia, (c) patients with sleep-disorder breathing, (d) patients with rem behavior disorder in different classifier

TABLE 5.1: The average classification performance results of a healthy subjects (n1-n16)

Sleep stage	KNN			NN			DT			SVM			DTB-SVM		
	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy
Wakefulness	100.00%	6.25%	83.09%	100.00%	0.00%	64.17%	100.00%	0.00%	82.33%	100.00%	0.00%	74.93%	**96.72%**	60.64%	**93.52%**
Light sleep	35.18%	78.09%	57.75%	65.42%	0.00%	22.90%	33.30%	83.27%	55.14%	98.31%	0.00%	38.79%	**93.62%**	93.13%	**93.52%**
Deep sleep	70.59%	59.03%	66.67%	0.00%	67.87%	19.31%	66.25%	65.01%	61.30%	13.85%	79.36%	31.40%	**95.57%**	100.00%	**96.76%**
REM sleep	91.49%	13.85%	66.76%	46.30%	0.00%	27.58%	100.00%	0.00%	67.12%	54.46%	40.90%	48.69%	100.00%	86.65%	**96.76%**

TABLE 5.2: The average classification performance results of a patients with insomnia (ins1-ins9)

Sleep stage	KNN			NN			DT			SVM			DTB-SVM		
	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy
Wakefulness	100.00%	0.00%	51.52%	100.00%	0.00%	22.18%	92.26%	46.66%	72.97%	100.00%	0.00%	52.91%	**98.60%**	**95.42%**	**97.83%**
Light sleep	0.00%	100.00%	36.06%	22.81%	0.00%	10.27%	30.50%	92.01%	54.29%	0.00%	100.00%	37.81%	**98.89%**	**100.00%**	**99.35%**
Deep sleep	100.00%	0.00%	71.21%	0.00%	64.31%	18.98%	100.00%	0.00%	79.05%	100.00%	0.00%	72.35%	**98.63%**	**92.63%**	**97.86%**
REM sleep	100.00%	0.00%	74.73%	28.57%	0.00%	20.42%	99.31%	25.04%	85.00%	100.00%	0.00%	75.76%	**100.00%**	**98.14%**	**99.77%**

TABLE 5.3: The average classification performance results of a patients with sleep-disorder breathing (sdb1-sdb4)

Sleep stage	KNN			NN			DT			SVM			DTB-SVM		
	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy
Wakefulness	54.53%	62.85%	54.60%	66.78%	53.69%	62.41%	61.29%	33.13%	52.82%	58.35%	47.47%	54.58%	**100.00%**	**100.00%**	**100.00%**
Light sleep	85.25%	11.86%	44.47%	64.71%	39.53%	51.22%	50.61%	32.78%	40.29%	50.87%	33.69%	41.25%	**100.00%**	**100.00%**	**100.00%**
Deep sleep	34.43%	82.57%	49.21%	56.64%	60.99%	58.57%	46.15%	43.73%	44.21%	50.72%	36.99%	46.81%	**98.31%**	**76.48%**	**93.63%**
REM sleep	100.00%	0.00%	86.01%	100.00%	1.56%	88.28%	88.41%	8.51%	76.80%	100.00%	5.00%	85.83%	**94.52%**	**76.08%**	**93.63%**

TABLE 5.4: The average classification performance results of a patients with rem behavior disorder (rbd1-rbd22)

Sleep stage	KNN			NN			DT			SVM			DTB-SVM		
	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy
Wakefulness	100.00%	0.00%	61.88%	99.68%	0.00%	43.99%	95.50%	9.33%	64.95%	93.86%	0.00%	59.85%	**98.82%**	**100.00%**	**99.13%**
Light sleep	0.00%	100.00%	37.32%	42.04%	2.89%	22.57%	11.45%	93.53%	42.36%	25.18%	70.80%	45.76%	**99.99%**	**100.00%**	**99.99%**
Deep sleep	100.00%	0.00%	62.20%	3.44%	75.05%	27.13%	98.61%	0.00%	64.21%	73.32%	30.54%	57.64%	**99.71%**	**98.07%**	**99.42%**
REM sleep	100.00%	0.00%	70.05%	48.42%	1.50%	33.44%	94.66%	30.72%	75.40%	67.09%	32.30%	58.61%	**99.56%**	**92.16%**	**98.54%**

TABLE 5.5: The computation time of different classifier

KNN	NN	DT	SVM	**DTB-SVM**
2 s	1.5 s	2 s	92 s	**1 s**

TABLE 5.6: Confusion matrix for healthy subjects

		Automatic Scoring			
		wakefulness	**Light Sleep**	**Deep Sleep**	**REM Sleep**
PSG Scoring	wakefulness	**238**	155	0	0
	light sleep	120	**1873**	0	0
	deep sleep	0	0	**1185**	0
	REM sleep	0	0	169	**894**

TABLE 5.7: Confusion matrix for patients with insomnia

		Automatic Scoring			
		wakefulness	**Light Sleep**	**Deep Sleep**	**REM Sleep**
PSG Scoring	wakefulness	**893**	6	35	0
	light sleep	0	**1145**	0	0
	deep sleep	19	3	**432**	0
	REM sleep	0	7	0	**321**

TABLE 5.8: Confusion matrix for patients with SDB

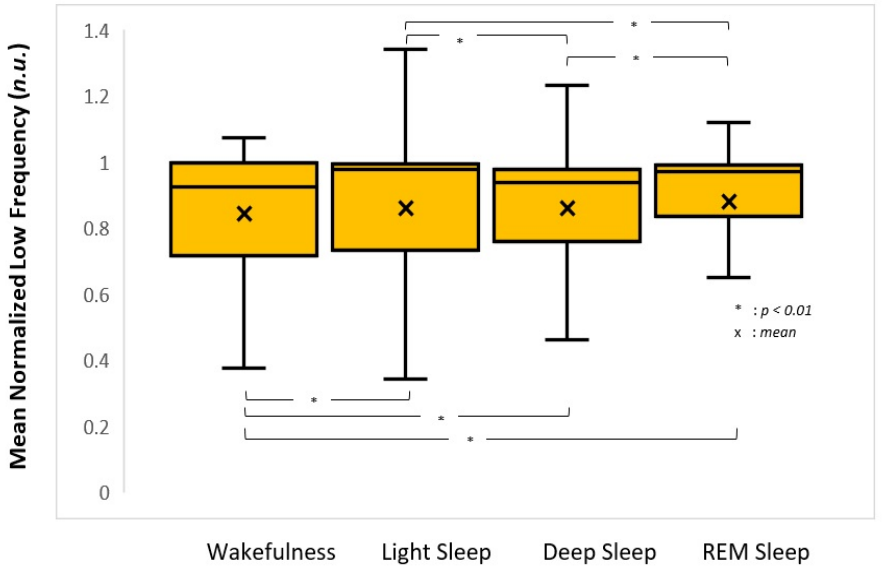
		Automatic Scoring			
		wakefulness	**Light Sleep**	**Deep Sleep**	**REM Sleep**
PSG Scoring	wakefulness	**1372**	0	0	0
	light sleep	0	**2329**	0	0
	deep sleep	0	0	**1418**	20
	REM sleep	51	1	15	**898**

TABLE 5.9: Confusion matrix for patients with RBD

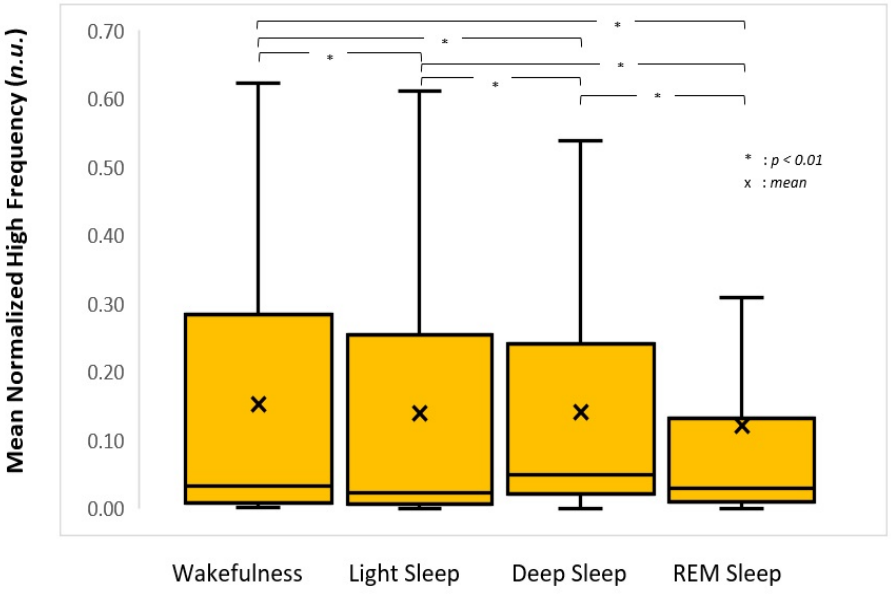
		Automatic Scoring			
		wakefulness	**Light Sleep**	**Deep Sleep**	**REM Sleep**
PSG Scoring	wakefulness	**332**	0	0	0
	light sleep	0	**620**	0	0
	deep sleep	0	0	**324**	41
	REM sleep	0	0	106	**31**

TABLE 5.10: Comparison table

	Extracted features	**Groups**	**Classifier**	**Performance**	
				sleep stages	**accuracy**
[92]	Combined the mean and SD values of HR into a two-dimensional feature vector	15 healthy	HMM	wake light sleep deep sleep REM sleep	85.5% 76.0% 82.2% 76.1%
[93]	Time-domain features, non linear-dynamic features and time-frequency of HRV	30 healthy	LD	wake Stage2 SWS REM sleep	90.49% 63.38% 78.99% 79.2%
This work	Normalized LF band power and Normalized LF band power	51 (Healthy and sleep disorders)	DTB-SVM	wakefulness light sleep deep sleep REM sleep	97.62% 98.22% 96.92% 97.17%

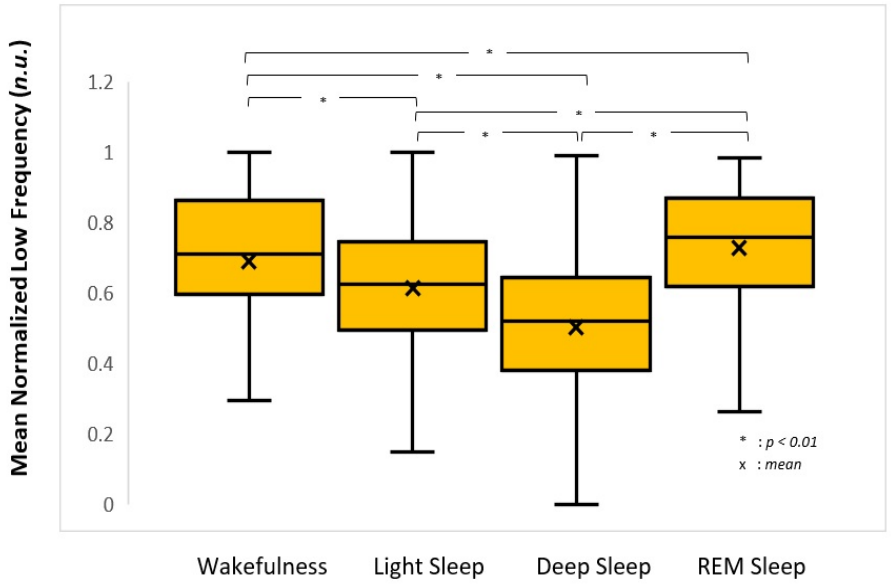


(a)



(b)

FIGURE 5.6: Box-and-Whisker plots of mean (a) normalized low frequency and (b) high frequency in healthy subject



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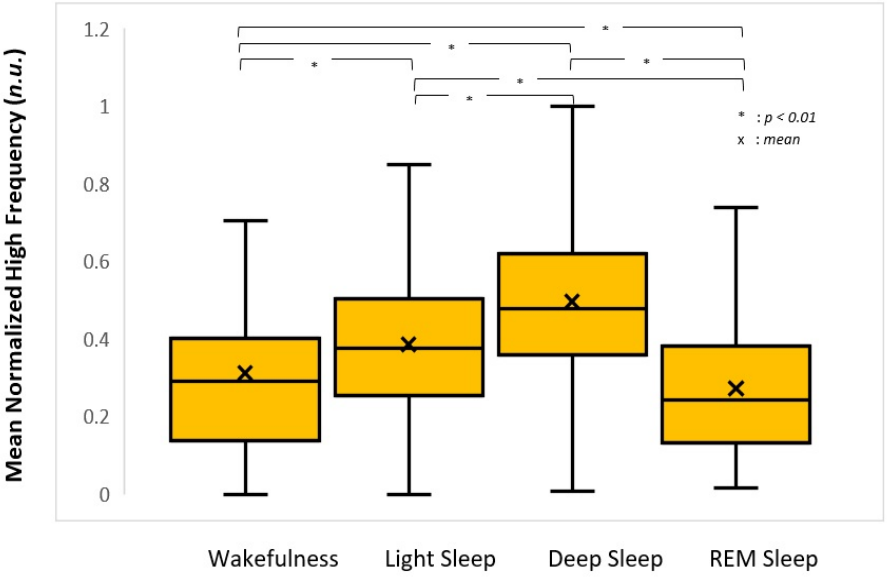
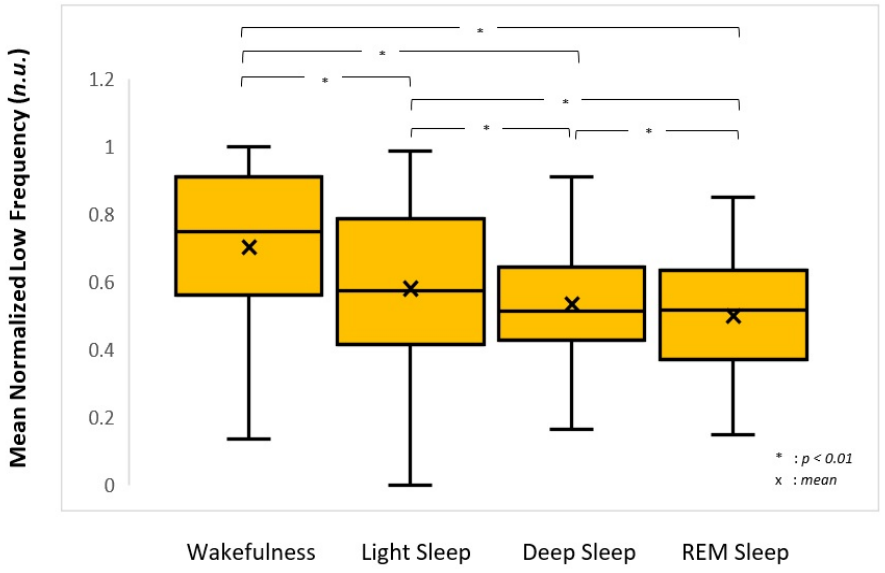
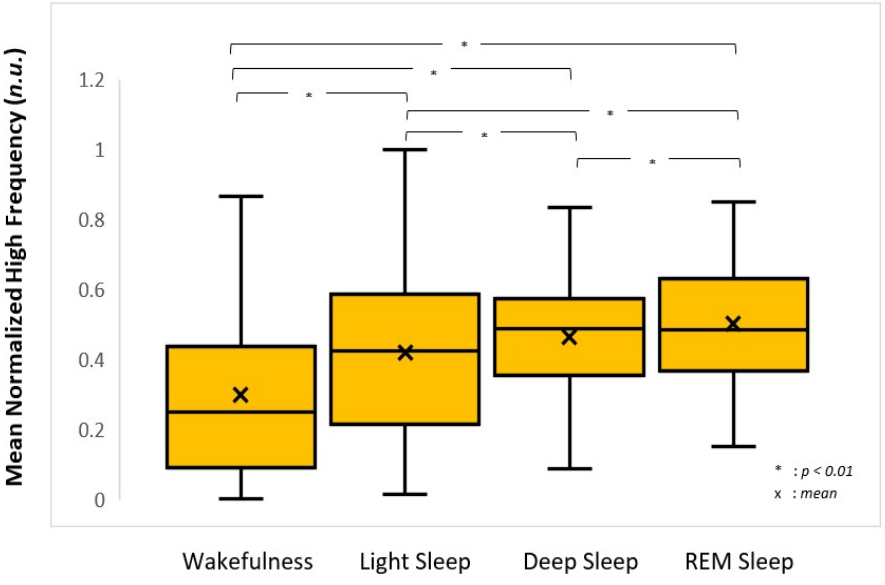


(b)

FIGURE 5.7: Box-and-Whisker plots of mean (a) normalized low frequency and (b) high frequency in patients with insomnia

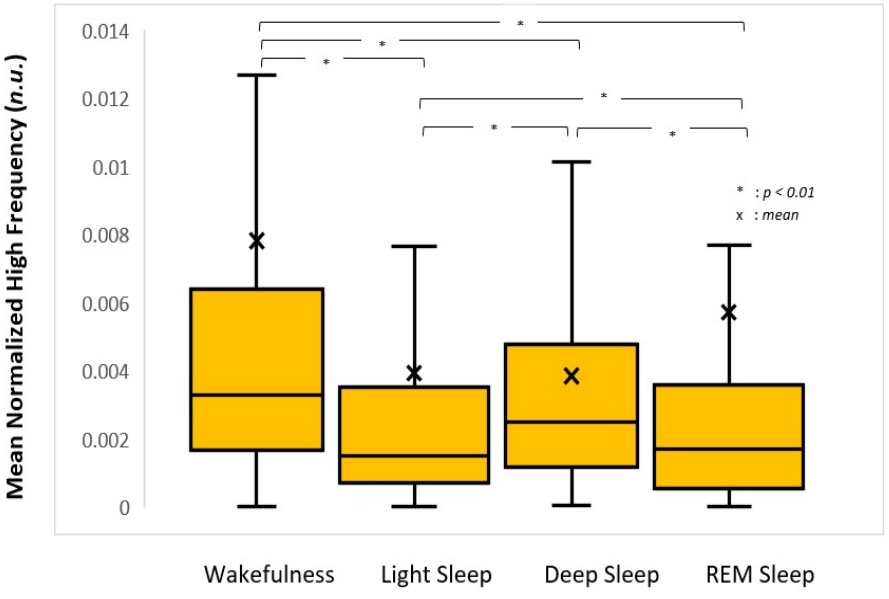


(a)

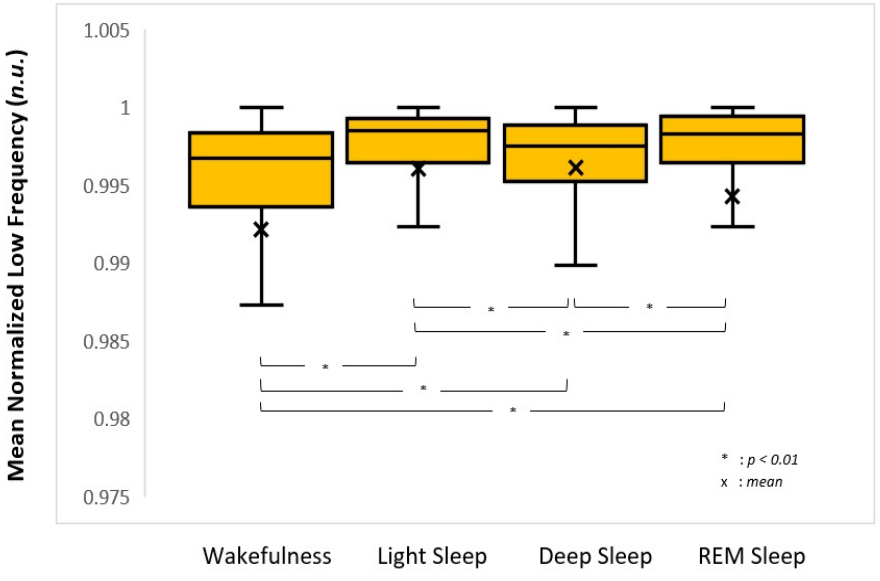


(b)

FIGURE 5.8: Box-and-Whisker plots of mean (a) normalized low frequency and (b) high frequency in sleep-disorder breathing



(a)



(b)

FIGURE 5.9: Box-and-Whisker plots of mean (a) normalized low frequency and (b) high frequency in rem behavior disorder

Chapter 6

Automatic Sleep Disorders Classification

In this Chapter, we describes the third part of the proposed methods: Automatic Sleep Disorder Classification. This part focused on the fourth and fifth stage of the proposed methods i.e., assessment of sleep quality and classification of sleep disorders.

6.1 Proposed Method

In this part, we propose an efficient classification method of sleep disorder by merely using ECG signals to simplify the sleep disorders diagnosis process. As shown in Figure 6.1, the proposed method of automatic sleep Stage detection that consists of five stages i.e., pre-processing, spectral features extraction, sleep stage detection, assessment of sleep quality, and classification of sleep disorders. However, pre-processing and spectral feature extraction stage was described in detail on the Chapter 4. Then, sleep stage detection was described in detail on the Chapter 5. Therefore, in this section, we will focus on assessment of sleep quality and classification of sleep disorders as described in section 6.1.1 and 6.1.2, respectively.

6.1.1 Assessment of sleep quality

The fourth stage is the assessment of the sleep quality of the subjects. This stage conducts in two steps. The first step is the measurement of sleep quality based on the result of sleep stage detection (previous stage), as shown in Figure 6.2. We use eight sleep quality parameters. In the second step, we analyze the eight parameters using one-way

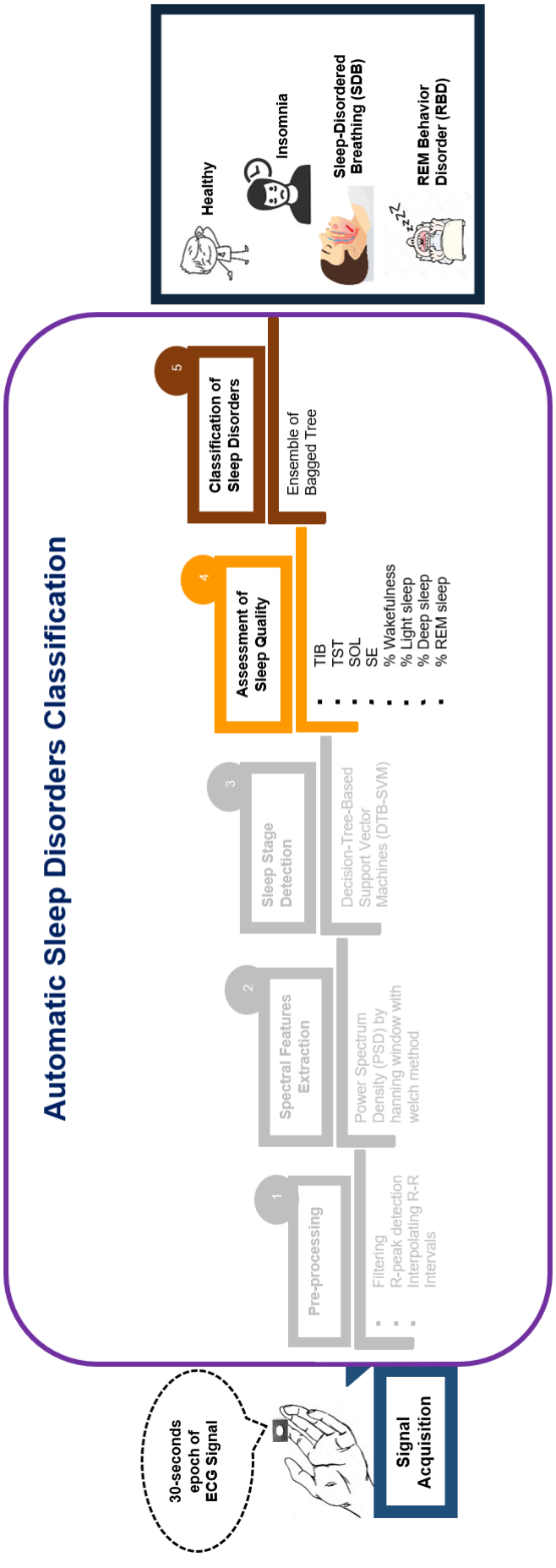


FIGURE 6.1: Proposed method of automatic sleep disorders classification

ANOVA and post hoc Scheffe test and select the parameters that have the most significant differences (we called them as the sleep quality features).

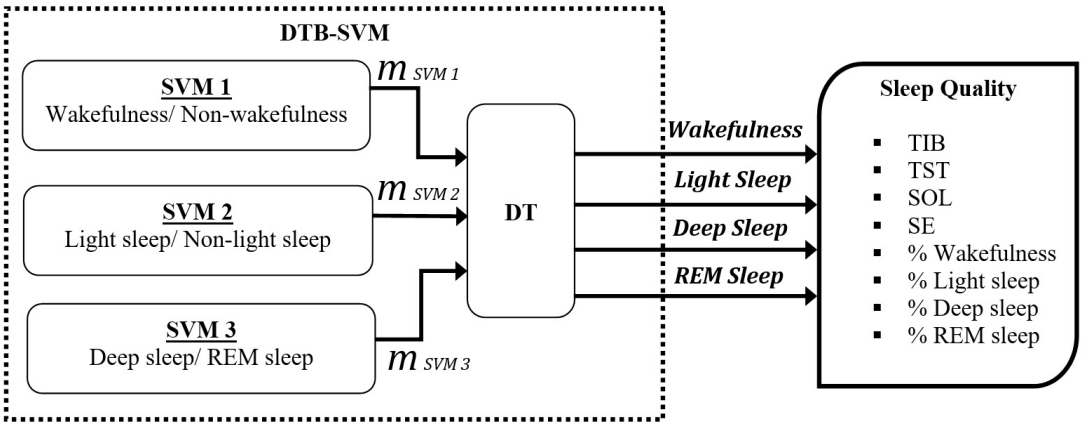


FIGURE 6.2: General Scheme of DTB-SVM for assessing sleep quality

Table 6.1 presents the differences characteristic of the sleep disorders between patient and healthy subjects based on eight sleep quality parameters, i.e., Total Time in Bed (TIB), Total Sleep Time (TST), Sleep Onset Latency (SOL), Sleep Efficiency (SE), and the percentage of each sleep stages (i.e., wakefulness, light sleep, deep sleep, and REM sleep) of insomnia, SDB, and RBD disorders.

TABLE 6.1: Sleep quality parameters of insomnia, Sleep-Disordered Breathing (SDB) and REM Behavior Disorder (RBD) disorders

Features	**Insomnia** [94]	**SDB** [95, 96]	**RBD** [96, 97]
Total Time in Bed (min)	Decrease	Decrease	Decrease
Total Sleep Time (min)	Decrease	Decrease	Decrease
Sleep Onset Latency (min)	Increase	Increase	Increase
Sleep Efficiency (%)	Decrease	Decrease	Decrease
Wakefulness (%)	Increase	Increase	Increase
Light sleep (%)	Increase	Increase	Increase
Deep sleep (%)	Decrease	Increase	Decrease
REM sleep (%)	Decrease	Decrease	Decrease

We engage the one-way ANOVA [98] and post hoc Scheffe test [99] to select the most significant differences in the sleep quality parameters. This step is an essential part of an automatic classification system because the selected features are used to distinguish sleep disorders. One-way ANOVA defines whether one or more sleep disorder parameters are significantly different from each other based on an individual parameter. A null

hypothesis of one-way ANOVA describes that the mean (average) of all sleep disorder parameters is equal to the mean (average) of an individual parameter of sleep quality parameters. Otherwise, an against the hypothesis of one-way ANOVA described that at least one the mean (average) of the sleep disorder parameter is different. Furthermore, the mean (average) of the sleep disorder parameters in different sleep disorders data are determined by the post hoc Scheffe test.

6.1.2 Classification of sleep disorders

In this fifth stage, we use an ensemble of bagged tree classifier for classifying sleep disorders, namely, healthy, insomnia, SDB, and RBD. An ensemble of bagged tree classifier is a combination of the bagging algorithm and decision tree classifier [100]. The ensemble method is a machine learning technique that combines multiple machine learning classifiers that aims to improve the classification performance, robustness, and reduced over-fitting problem [101]. The Bagging algorithm (or bootstrap aggregation) is one of the most common ensemble methods [102]. The Bagging algorithm is the most accurate and efficient ensemble method compared to boosting and random forest because it can reduce a high variance of the algorithm, such as the decision tree algorithm [103]. Thus, the Bagged Tree algorithm is a bootstrap procedure implemented in the decision tree (DT) algorithm. The general scheme of the ensemble of bagged tree classifier illustrates in Figure 6.3. As shown in Figure 6.3, sleep quality data that consists of healthy, insomnia, SDB, and RBD disorders are used as the training data. Then, we divide this training data randomly into n new training data (random subset). Each random subset is used to train one DT classifier. Each DT classifier consists of a root, interior nodes, and leaf nodes. The interior nodes correspond to the attributes, and the leaf nodes correspond to decision results.

For classification problems, the predicted class for an observation is the class that yields the largest weighted average of the class posterior probabilities (classification score) computed using selected trees only. Let *H(x)* be an instance for the DT's output probability distributions $h_i(x, c_j)$, where $i = 1...n$ is the number of DT classifier, and $c_j, j = 1...k$ is the class labels, which is the estimated posterior probability of class c_j given observation x using tree i. Then, the result aggregation *H(x)*, for instance x is obtained using the majority vote. The predicted class is the class that yields the largest weighted average,

as expressed in Equation (4). Ensemble of bagged tree computes the optimal result aggregation *H(x)* from each DT classifier. The final prediction obtained from the decision of result aggregation. The sleep disorders determined according to the final prediction of the ensemble of bagged tree classifier.

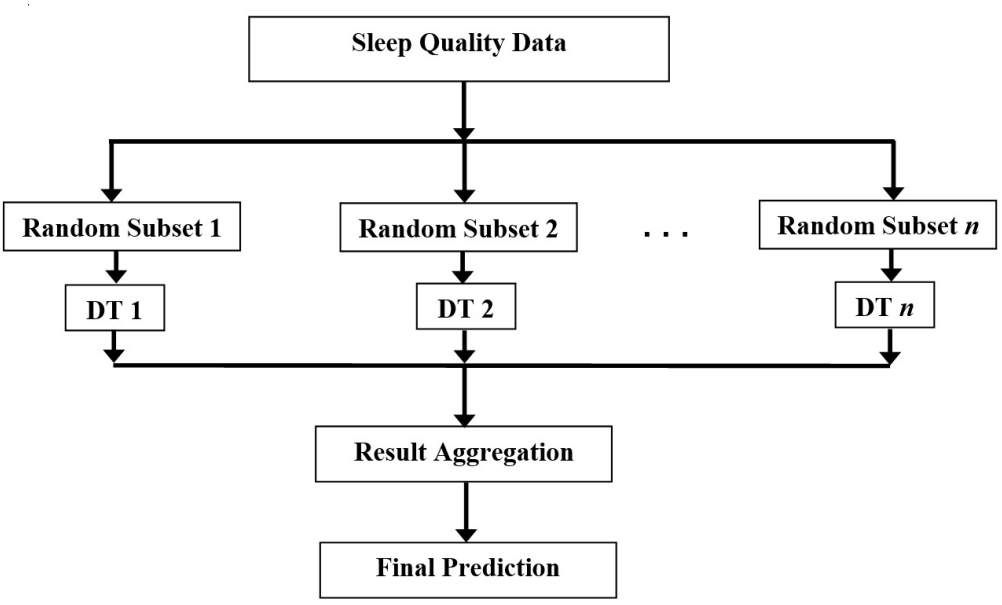


FIGURE 6.3: General scheme of ensemble of bagged tree classifier

$$H(x) = arg_{cj} max \sum_{i=1}^{k} h_i(x, c_j) \tag{6.1}$$

To create the decision trees, we use the standard the Classification and Regression Trees (CART) algorithm. In CART, all input data are examined to all possible binary splits on every predictor. At each node, it will scan over every possible threshold split for every feature, calculate the information gain for each of these different splits, and then choose the split that yielded the highest information gain. The information gain is the number of data points that lead to that node (on the left/right side of the threshold) with the classification, divided by the total number of data points. A split might lead to a child node having too few observations (less than the minimum leaf size parameter). To avoid this, we use a split that yields the best optimization criterion subject to the minimum leaf size constraint, namely "Gini impurity". Gini evaluates how many observations of each class would be split into each child node, expressed as follows:

$$Gini = 1 - \sum_{j=1}^{k} [p(c_j|t)]^2, \tag{6.2}$$

where $p(c_j|t)$ denotes the posterior probability of observation belonging to class c_j at a given node t.

6.2 Experimental setup

This part concentrates on efficient classification method of sleep disorder by merely using ECG signals to simplify the sleep disorders diagnosis process. Therefore, we used the Cyclic Alternating Pattern (CAP) sleep database [80].

6.3 Results and Discussion

We assess the effectiveness of the proposed method for classifying sleep disorders. The performance evaluation and comparison between our proposed method and AASM guidelines included some related clinical study.

Table 6.2 presents all sleep quality parameters for each subject. By paying attention to the standard deviation, most of the value of sleep quality parameters (for the patients with insomnia, SDB, and RBD compared to healthy subjects) accordance to the characteristics of clinical studies, as shown in Table 6.2. Furthermore, one-way ANOVA is used to obtain the sleep quality parameters. Then, we use a post hoc Scheffe test to compute the significant differences between two sleep disorder parameters. As shown in Table 6.2, all parameters of sleep quality (except the TST, percentages of light sleep, and percentages of deep sleep) present statistically significant differences in all sleep disorders at the level of significance (p) of 0.05. It indicates that TIB, SOL, SE, percentages of wakefulness, and percentages of REM sleep are the crucial parameters for identifying the elderly's sleep disorders.

Figure 6.4 shows the trained model of the ensemble of bagged tree classifier in classifying four classes of sleep disorders: healthy subjects, patients with insomnia, SDB, and RBD. The SOL is used to determine patients with insomnia. We found that most of the patients have a higher duration of SOL (above 36.5 min) than others feature. It corresponds to a recent clinical study result [104] that reported elderly patients with

insomnia (65 years or older) have more than 30 min of quantitative SOL criteria. Moreover, AASM also has treatment goals to reduce the SOL of insomnia patients with at least lower than 30 min [105]. This treatment aims to improve sleep quality.

Then, we determine that a healthy subject is a subject that has the duration of SOL below 36.5 min and the percentage of wakefulness below 17.505%. It corresponds to a recent clinical study that estimates the average SOL of healthy people (aged 60 years or older) is around 19 min [106], and we obtained below 36.5 min.

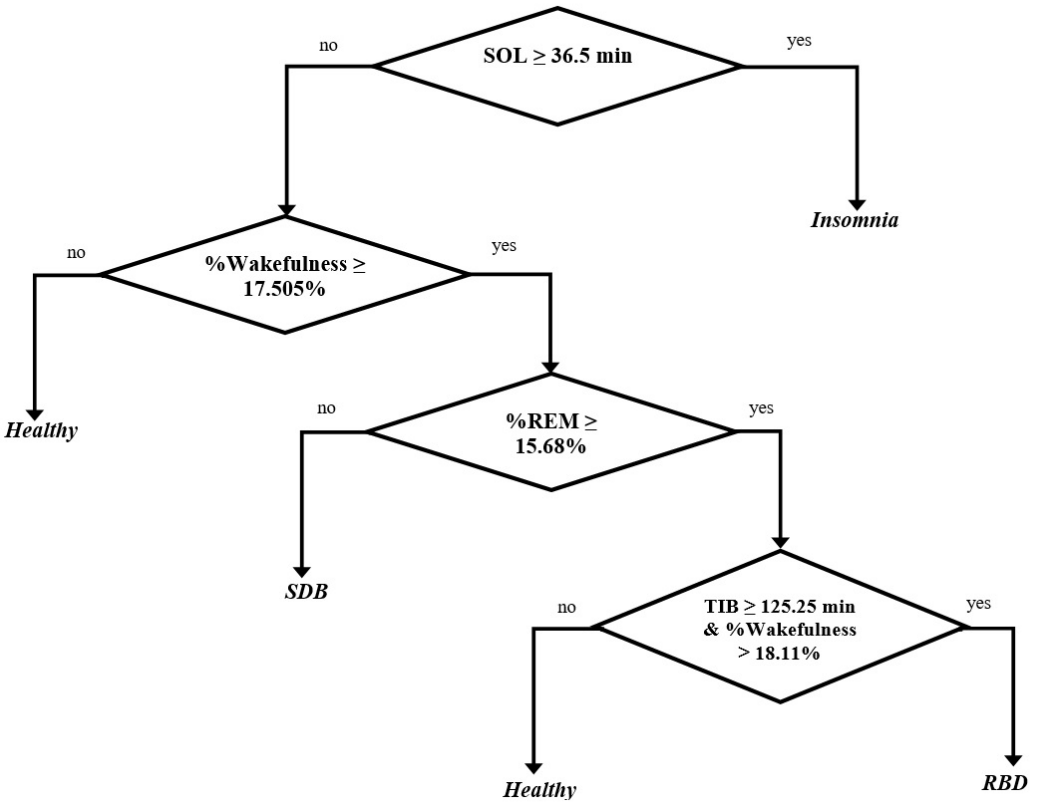


FIGURE 6.4: The trained model of the ensemble of bagged tree classifier in classifying four classes of sleep disorders

Furthermore, we found the specification of the duration of SOL, the percentage of wakefulness, and the percentage of REM sleep to determine the SDB patients. The specification describes as follows.

1. The longest duration of SOL for SDB patients was below 36.5 min It corresponds to a clinical study that estimated the average longest duration of SDB patients was around 9.5 min [107], and we obtained below 36.5 min.

2. The percentage of wakefulness was above 17.505%.

3. The longest percentage of REM was below 15.68%. It corresponds to a clinical study that estimated the prevalence percentage of REM in the SDB patients (such as OSA patients) was around 13.5% [108], and we obtained below 15.68%.

Other parameters such as the duration of SOL, the percentage of wakefulness, the percentage of REM sleep, and the duration of TIB were used to determine RBD patients with the specifications as follows.

1. The longest duration of SOL for RBD patients was below 36.5 min. It corresponds to a related clinical study that estimated the average duration of SOL in 8 RBD patients was around 11.1 min [109], and we obtained below 36.5 min.

2. The percentage of wakefulness was above 17.505%.

3. The longest percentage of REM was above 15.68%. It corresponds to a related clinical study that estimated the characteristics percentage of REM in 94 RBD patients was around 22.4% [97], and we obtained above 15.68%.

4. The duration of TIB and the percentage of wakefulness were generated simultaneously. Thus, the RBD patient is the subject that has the duration of TIB above 125.25 min and the percentage of wakefulness above 18.11%. It corresponds to a clinical study that estimated the average duration of TIB in 4 RBD patients is around 452.75 min [96], and we obtained above 125.25 min. In addition, [106] evaluated that healthy subjects have an average percentage of wakefulness around 10.55%, and we obtained below 17.505% and 18.11%.

Furthermore, the confusion matrix and the performance evaluation of the proposed method are presented in Tables 6.3 and 6.4, respectively. The highest sensitivity is achieved by RBD (90.0%) with none miss-classification in insomnia and SDB. Conversely, specificity and accuracy of RBD are lowest (82.76% and 86.27%, respectively) than the other. It is because the classification of RBD depends on four sleep quality features, i.e., SOL, wakefulness, REM, and TIB. Moreover, the miss-classification of RBD into healthy due to there are two subjects that have a percentage of wakefulness lower than 18.11%, but the TIB is above 125.25 min.

Specificity and accuracy of insomnia and SDB are the highest, but there is one subject on each classified as RBD. Insomnia is expected to be classified by SOL, but there is one subject that has a duration of SOL below 36.5 min. For the same reason, one subject of SDB has a percentage of REM higher than 15.68%. Furthermore, there are healthy subjects classified as RBD. It due to three subjects has a percentage of wakefulness higher than 18.11%, and the TIB is above 125.25 min.

The evaluation performance of the whole proposed method achieved 84.01% of sensitivity, 94.17% of specificity, 86.27% of overall accuracy, and 0.70 of Cohen's kappa. The specificity of 94.17% implies that the proposed method able to accurately distinguish the sleep disorder subjects and non-patients (healthy subjects). The sensitivity of 84.01% shows that the ability to recognize healthy subjects and elderly sleep disorder patients is quite robust. The proposed method also presents a good overall accuracy (86.27%). The Cohen's kappa that represents the inter-rater agreement with PSG scoring achieves 0.70. According to the rule of thumb values of Cohen's kappa [110], 0.70 implied a substantial level of agreement between proposed automatic scoring and actual PSG scoring. The proposed method is reliable as an automatic sleep disorders model and able to become a good foundation for classifying the elderly sleep disorders based on sleep quality features from the 30-seconds epoch ECG signal.

Table 6.5 shows a comparison of our work with several related studies that also distinguish sleep disorders. The researchers [111] developed an automated detection system of sleep disorders using related events from the EEG signal. This system has two types of events (i.e., arousal events and left & right leg movement events) that detected for discriminating SDB (such as OSA) and sleep-related movement disorders (such as RLS). They used a DT classifier to estimate the total accuracy of the arousal and left and right leg movement events. Based on their experimental result, this system presented the overall accuracy by 85.02%. The other approach [112] developed an automatic classification system for sleep apnea episodes. This approach used three types of features vectors, i.e., PSD estimation, Principal Component Analysis (PCA), and Partial Least Squares (PLS) scores from the EEG signal. Then, the SVM classifier used for discriminating SDB. This system achieved an overall accuracy of 85%. As mentioned above, both works [111, 112] presented good accuracy results. However, both of them have not reported their system performance in more detail, such as the specificity, sensitivity, and

Cohen's kappa yet.

As shown in Tables 6.3 and 6.4, the proposed method presents an improvement in classifying the healthy subjects and sleep disorders patients in the elderly (i.e., insomnia, SDB, and RBD) using ECG based-sleep quality features as the input and an ensemble of the Bagged tree as the classifier. Moreover, the total accuracy of the proposed method is higher compared to the works of [111, 112]. We also take advantage of the ECG signal usage that easy to record even though an untrained user. Thus, the proposed method is easy and efficient to implement in the real hardware system. Even though the number of subjects was limited in this work, but the number of epochs is large enough (over 14,000 epochs). Thus, we argue that it is reliable for modeling an automatic sleep disorder for the elderly based on sleep quality parameters from the ECG signal. We assume that it is advantageous to diagnose and treat the various sleep disorders instead of the use of a multichannel signal (PSG).

Finally, we present the trained model of the ensemble of bagged tree classifier for classifying four classes of sleep disorders: healthy subjects, patients with insomnia, SDB, and RBD, as shown in Figure 6.3. This model takes a decision tree structure and then applies bagging (bootstrap aggregating) to reduce variance and bias. Due to the decision trees divide the predictors by thresholds, so it does not difference how far is a data point from thresholds. Therefore, most likely outliers will have a negligible effect because the nodes are determined based on the sample proportions in each split region (and not on their absolute values). Thus, we ensure that the trained model of ensemble bagged tree (Figure 6.3) is universal for the entire elderly population.

6.4 Conclusion

In this part, an easy and efficient method for the automatic sleep disorders classification in the elderly using ensemble bagged tree has been proposed. In the pre-processing stage, we presented a suitable pre-processing technique for the 30-seconds epoch of the ECG signal. Furthermore, spectral features were extracted using PSD by the Hanning window with the welch method. The sleep stage detection was examined using the DTB-SVM. Then, the sleep quality parameters such as TIB, TST, SOL, SE, and the percentage of each sleep stage were computed and analyzed using ANOVA and post hoc Scheffe test to

evaluate and select the most important features of sleep quality parameters. The experiment result has been showed the ensemble of bagged tree classifier based on the sleep quality features is able to discriminate the sleep disorders (insomnia, SDB, and RBD) and healthy effectively by achieving a good specificity, sensitivity, overall accuracy, and Cohen's kappa.

We conclude that it is possible to determine sleep disorders based on sleep quality features from 30-seconds epoch of the ECG signal. This approach is proven reliable in modeling sleep disorders without preoccupied with a multichannel signal of PSG. Moreover, it also easy to be implemented in an embedded hardware device.

TABLE 6.2: One-way ANOVA and post hoc Scheffe test to evaluate the importance of sleep quality parameters

	Healthy	**Insomnia**	**SDB**	**RBD**	***p* value**
TIB	147.63 ± 101.17^{4}	159.17 ± 105.58^{4}	181.75 ± 127.33^{4}	$27.98 \pm 22.53^{1,2,3}$	0.000016
TST	136.44 ± 102.57	108.5 ± 96.25	140.25 ± 86.33	110.93 ± 66.43	0.75
SOL	11.56 ± 7.23^{2}	$85.55 \pm 81.07^{1,3,4}$	10 ± 7.52^{2}	14.10 ± 7.31^{2}	0.000011
SE	84.64 ± 5.23^{2}	64.15 ± 17.28^{1}	71.37 ± 11.61	74.69 ± 11.8	0.00083
% Wakefulness	$5.64 \pm 5.23^{2,3,4}$	$33.1 \pm 17.46^{1,3,4}$	$20.54 \pm 8.34^{1,2,4}$	$23.87 \pm 11.8^{1,2,3}$	0.0000017
% Light sleep	40.64 ± 7.36	36.85 ± 11.03	48.13 ± 18.55	37.32 ± 10.27	0.23
% Deep sleep	24.29 ± 6.19	16.20 ± 5.22	20.56 ± 10.11	22.99 ± 11.73	0.19
% REM sleep	$19.72 \pm 4.61^{2,3,4}$	$11.10 \pm 4.98^{1,3}$	$2.67 \pm 2.27^{1,2,4}$	$14.38 \pm 5.33^{1,3}$	0.00000046

Note. Values are expressed as mean ± standard deviation

[1](*) significantly different from healthy subjects

[2](*) significantly different from patients with insomnia

[3](*) significantly different from patients with SDB

[4](*) significantly different from patients with RBD

TABLE 6.3: Confusion matrix of an automatic classification system

		Automatic Scoring			
		Healthy	**Insomnia**	**SDB**	**RBD**
PSG Scoring	Healthy	**13**	0	0	3
	Insomnia	0	**8**	0	1
	SDB	0	0	**3**	1
	RBD	2	0	0	**20**

TABLE 6.4: Evaluation performance of each sleep disorder subjects and non-patients (healthy subjects)

	Sensitivity (%)	**Specificity (%)**	**Accuracy (%)**	**Cohen's Kappa (%)**
Healthy	81.25	93.94	89.80	0.71
Insomnia	88.89	100.00	97.78	0.71
SDB	75.00	100.00	97.78	0.60
RBD	90.91	82.76	86.27	0.73

TABLE 6.5: Comparison work

	Input Signal	**Features Extraction**	**Classifier**	**Sleep Disorders**	**Overall Accuracy**
[111]	EEG	Arousal events and Left & right leg movement events	DT	OSA RLS	85.02%
[112]	EEG	PSD estimation, PCA, and PLS	SVM	SDB	85%
This work	ECG	Sleep quality	Ensemble of Bagged Tree	Healthy Insomnia SDB RBD	86.27%

Chapter 7

Conclusions and Future Works

This Chapter presents the conclusion and describes the future work of this doctoral dissertation.

7.1 Conclusions

The main objective of this doctoral dissertation is to propose an efficient classification method of sleep disorder by merely using an ECG signal in order to address the issue of a multichannel signal such as the PSG and simplify the sleep disorders diagnosis process. Structurally, the proposed method consists of five stages i.e., pre-processing, spectral features extraction, sleep stage detection using the Decision-Tree-Based Support Vector Machine (DTB-SVM), assessment of sleep quality features, and sleep disorders classification using ensemble of bagged tree classifiers. The result of this study can be summarized as follows.

1. A new pre-processing technique that suitable for 30-seconds epoch without detecting each PQRST peak of ECG signal has been developed. We take advantage that the proposed method more efficiently to be implemented in an embedded hardware device as a consideration of the complexity requirements, robustness to noise, and low computational cost.

2. The proposed method of automatic sleep stage detection using DTB-SVM based on spectral features of ECG signal has been developed. Two features has been obtained from spectral features extraction of ECG signal i.e., normalized Low Frequency and normalized High Frequency. These features has been calculated

and analyzed so it can be used for distinguishing among all sleep stage condition. Moreover, it achieved a good performances to obtain all sleep stage condition compared to the most commonly used learning classifiers to detect sleep stage i.e., KNN, NN, DT, and SVM.

3. The proposed method of automatic sleep disorders classification using ensemble of bagged tree based on sleep quality features has been developed. It achieved a good performances to discriminate the sleep disorders (insomnia, SDB, and RBD) and healthy subject effectively. Thus, this doctoral dissertation shows that it is reliable for modeling an automatic sleep disorder for the elderly based on sleep quality parameters from 30-seconds epoch of the ECG signal. We assume that it is advantageous to diagnose and treat the various sleep disorders instead of the use of a multichannel signal, such as the PSG.

7.2 Future Works

The value of threshold in this proposed method is fixed. This value should be updated with real heart rate condition to provide more best performance. One possible alternative solution is to have a dynamic threshold based on the real heart rate condition, but it might expense of an increase computational cost. Moreover, in this doctoral dissertation, we used database that include a normal heart rate and cardiac stroke volume during sleep. However, for other heart disease i.e., arrhythmia, cardiomyopathy, congenital heart defects, coronary artery disease, and heart infections might have different characteristic of the heart rate signal. This aspect is need to consider in the future.

On the other hand, atrial fibrillation and other heart rhythm disorders are prevalent in the elderly population. It might have an impact on the HRV analysis. However, HRV able to assess sympathetic and parasympathetic influences on disease states. Hence, in further analysis, HRV can be improved following the intervention, and thus it has the ability to assess autonomic dysfunction in the elderly's heart rhythm disorders, such as atrial fibrillation, bradyarrhythmias, and ventricular arrhythmias. Therefore, we interest to observe the autonomic dysfunction in the elderly via HRV intervention in the future.

In addition, the proposed method presents easiness and efficiency in classifying sleep disorders by using the ECG signal alone. It indicates that the proposed method gives a big promise to be implemented in an embedded hardware device. Since sleep disorders may happen randomly during the entire sleeping period, we plan to monitor and process the ECG signal in real-time. The proposed method consists of five stages. Real-time monitoring and data processing is performed only for the first three stages (pre-processing, spectral features extraction, and sleep stage detection), while the assessment of sleep quality and the classification of sleep disorders are conducted after the night sleep. Pre-processing and features extraction process is applied to each epoch of the ECG signal. The spectral features (normalized LF and normalized HF) are used as the input of DTB-SVM. Then, by using the transfer function of trained DTB-SVM, the sleep stage label of each epoch is determined. We store the sleep stage label of each epoch in the d-dimensional labels, defined as follows:

$$S_i = (l_1, l_2, ..., l_j, l_d), \tag{7.1}$$

where, S_i is i^{th} patient, l_j is a sleep stage label for j^{th} epoch, and d is the number of total epochs. Hence, this proposed method can become a fundamental model for future research such as an early warning sleep disorders system and support current sleep tracking devices.

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