Doctoral Dissertation
博士論文

A Simple Detection System of Sleep Stage and Apnea Syndrome by Breath Sound Measurement

「呼吸音計測による睡眠状態ならびに睡眠時無呼吸症候群の簡易検出システム」

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Abstract

Sleep is indispensable to keep healthy functions and further physical functions and it plays a fundamental role to improve the quality of life. However, in modern society, we have sacrificed sleep so much that living activities and economic interests are emphasized and more and more adults are suffering from disturbed sleep. Recently monitoring sleeping conditions has gained more interest, which is an important step to solve the sleeping problem and to improve sleep quality.

In sleep studies and evaluation the polysomnography (PSG) system represents the gold standard in the state of art. The patient has to hospitalized at least one night and measuring a lot of physiological signals such as, electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), respiration (RSP) and diagnose the sleep stage and apnea/hypopnea situation. Since many sensors are attached to the body, it is uncomfortable all-night laying down on the bed. Almost patients could not get sleeping well as usual in the home. Further, the medical checking cost is also very high. It make the most patient undergo unchecking.

Recently, various measuring systems and applications have been developed and marketed in order to simply monitor the sleeping state. These systems basically evaluate sleep stages by sensing and analyzing the body movements caused generated due to the respiration and heartbeat, the turning over in the bed etc.

Different from conventional study, this study is paying the main attention to respiratory ventilation state, by measuring and analyzing the respiratory sound in sleep with a wireless microphone. In this study, the breathing rhythm and the variation in amplitude are taken into account to

analyze sleep apnea syndrome and the sleeping stages. The sleep stage monitoring system and the detecting analytical method are developed and the aim of this study is to provide sleep measurement apparatus for general households that is superior in operability, performance, and cost.

This doctoral dissertation consists of 6 chapters.

In chapter 1, generalities and basics about sleep study are explained. The outline of the thesis is also given.

In chapter 2, the sleeping breath sound measurement system developed previously by our research group is described first. The possibility and the usefulness of detecting sleeping state and apnea state from respiratory sound waveform is demonstrated in detail. The measurement system consists of Bluetooth microphone, smartphone and analysis server. Sleeping breathing sound during sleeping is collected by the Bluetooth microphone and sent and saved to the smartphone in real time. The breath sound data stored on the smartphone is sent to the analysis server automatically at a given time intervals for analysis, record and management.

In chapter 3, in order to evaluate sleep stage, the breath strength, respiratory variation, breath period are defined from the sleep breathing sound waveform as sleep evaluation parameters and the these parameters calculation algorithm are explained in detail. A simple algorithm multiplying these evaluation parameters by weighting coefficients is proposed to distinguish the four sleep stages. These weighting coefficients are determined by trial and error on many sleep data. In order to verify the effectiveness of the algorithm proposed in this research, the sleep experiments are conducted in combination with the commercial SleepScan made by TANITA. It is shown that the results of the four sleep stages (wake, REM, shallow sleep, deep sleep) detected by SleepScan are almost similar to the results obtained by the sleeping breath sound method proposed in this study. It is confirmed that the proposed measuring system and sleep stage evaluation method is useful and effective.

In chapter 4, in order to automatically determine sleep stages, a support vector machine (SVM) classifying method is introduced. Firstly how to construct a sleep state database representing four sleep stages is describe. In order to construct the sleep state database corresponding to each sleep stage, the result of the sleep stage according to the weighting coefficient method as described in Chapter 3, the result obtained by using the SleepScan device, and the result estimated by observing the respiratory waveform, are considered integrally. Next, using the support vector machine (SVM) classifier learned based on the sleep state database, the sleep stage is predicted. As the sleep evaluation parameter, six characteristic parameters were adopted, the average values of respiratory strength, respiratory variation, and breath period proposed in Chapter 3 and their deviation values. Similarly, compared with the results of TANITA's SleepScan device, it is succeeded in obtaining more accurate estimation results compared with the SleepScan’s ones. In addition, the contribution of these six characteristic parameters to the sleep stage estimation was examined and it was found that the average value of the respiratory period contributed most.

In chapter 5, a simple method based on the processing of breath sound signal for the detection of apnea episodes is explained. Measurement of SpO2 during whole night sleep was conducted together with the breath sound measurement at the same time. The value of SpO2 was found being strongly correlated with the respiratory variation presented in this study. This means that the respiration variation can be used to estimate arterial oxygen saturation. In this study, the apnea episodes are detected by calculating the difference between respiratory variation and its moving average of respiration variation. As the result it was demonstrated that the number of apnea episodes were detected almost perfectly comparing with the breath sound waveform. Furthermore, as an example, the clinical diagnosis result of an apnea syndrome patient is used for comparison. It is confirmed again the number of apnea episodes during the whole night, which is detected by the respiratory sound calculation, is almost in same number. It can be said that the sleep state inspection system based on the breathing sound proposed in this research is in a level usable for clinical examination.

In Chapter 6, summary of this thesis and future work are described.

要　旨

睡眠は、身体の健康な機能を維持するために不可欠であり、生活の質を向上させるための基本的な役割を果たす。しかし、現代社会では、生活習慣や経済的利益が重視されるほど睡眠を犠牲にしてきており、多くの人が睡眠障害に苦しんでいる。最近、睡眠の問題を解決し、睡眠の質を改善するための重要なステップとして、常に睡眠状態をモニタリングすることの重要性が挙げられている。

睡眠の研究と評価には、睡眠ポリグラフ（PSG）システムがゴールドスタンダードとして使用されている。患者が一晩入院し、脳波（EEG）、眼電図（EOG）、筋電図（EMG）、心電図（ECG）、呼吸（RSP）などの生理学的信号を計測し総合解析することで、睡眠のステージや無呼吸・低呼吸状態を判断する。しかし、多くのセンサが身体に取り付けられているため、一晩中ベッドの上で動けず、大変不快を感じ、通常の睡眠ができないケースが多い。さらに入院が必要で検査コストも非常に高い。そのため、睡眠ポリグラフ検査を受けない人が多い。簡易的に睡眠状態をモニタリングする方法として、最近様々な計測システム並びにアプリケーションが開発され市販されている。これらのシステムは、基本的に睡眠時に発生する寝返り、呼吸や心拍などによる動きをセンシングし、その動きを解析することで睡眠ステージを評価するものである。

本研究では、呼吸による酸素と二酸化炭素の換気状態に着目し、寝息呼吸音を無線マイクロフォンで計測し、呼吸のリズム、呼吸強さの変動などを解析することで、睡眠時無呼吸状態ならびに睡眠ステージを検出できる簡便な睡眠計測システム並びに解析方法を開発し、操作性と機能性さらにコスト面が共に優

れる、一般家庭向けの睡眠計測装置を提供することを目指している。

本論文は、6 章から構成されている。

第 1 章では、睡眠研究に関する研究背景と目的、現状を説明する。また、本論文の概要について述べる。

第 2 章では、当研究グループが今までに開発した寝息呼吸音の計測システムを説明し、呼吸音波形から睡眠状態と無呼吸状態を検出する可能性とその有用性について述べる。本計測システムは、Bluetooth マイク、スマートフォンと解析サーバーから構成されている。睡眠時の寝息呼吸音を Bluetooth マイクで採集し、リアルタイムでスマートフォンに送信・保存する。スマートフォンに保存されている音声データを一定間隔で解析サーバーに送信し、解析・記録・保存を行う。

第 3 章では、初めに寝息呼吸音波形から、呼吸強さ、呼吸変動、呼吸周期を睡眠評価パラメータとして定義、その算出方法を説明する。次にこれらの睡眠評価パラメータに重み係数をかけ、睡眠ステージを判別することを試みる。これらの重み係数は、数多くの睡眠データに対して試行錯誤で決定する。本研究で提案するアルゴリズムの有効性を検証するため、市販の TANITA 社 SleepScan 装置と併用して睡眠実験を行う。SleepScan により得られた 4 段階の睡眠ステージ（覚醒、REM、浅い睡眠、深い睡眠）結果が本研究の寝息呼吸音により得られた結果とほぼ一致していることを確認でき、本研究で提案する睡眠計測システムと睡眠ステージ評価方法の有用性と有効性が確認された。

第 4 章では、睡眠ステージを自動判別するため、サポートベクターマシン（SVM）分別方法を導入する。初めに、4 つの睡眠ステージを表す睡眠状態データベースの構築について述べる。睡眠状態データベースを構築するに当たり、第 3 章で述べた重み関係数による睡眠ステージの結果と、SleepScan 装置を用いた得られた結果と、さらに呼吸波形を観察して推定した結果と照らし合わせ

て、4 つの睡眠ステージに対応する睡眠状態データベースを構築する。次に睡眠状態データベースに基づき学習されたサポートベクターマシン（SVM）分類器を用いて、睡眠ステージを予測する。睡眠評価パラメータとして、第 3 章に提案した呼吸強さ、呼吸変動、呼吸周期の平均値にさらにそれぞれの偏差値を加え、合計 6 つの特徴パラメータを採用した。TANITA 社の SleepScan 装置の結果と比較したところ、より高い精度の推定結果を得ることに成功した。また、これらの 6 つの特徴パラメータが睡眠ステージへの寄与度についても調べ、呼吸周期の平均値が最も寄与していることを判明した。

第 5 章では、無呼吸発作の検出について、寝息呼吸音信号から簡単に求める方法を説明する。睡眠時の SpO2 の計測を同時に行った。 SpO2 の値は本研究で提示した呼吸変動と強い相関があることが判明した。これは呼吸変動を用いて動脈血酸素飽和度を推定することができることを意味する。本研究では、呼吸変動と呼吸変動の移動平均との差を算出し、無呼吸発作の検出に試みた。その結果を実際の睡眠時の寝息呼吸波形と比較した結果、無呼吸発作回数がほぼ正確に検出されたことを実証した。さらに無呼吸症候群患者の臨床診断結果の一例と比較したところ、無呼吸の回数がほぼ一致していることから、本研究で開発している寝息呼吸音による睡眠障害検出アルゴリズムは、臨床検査にも使用可能なレベルを有することが言える。

第 6 章では、本論文のまとめと今後の展望について述べる。

Chapter 1

Introduction

1.1 Background

Sleep is the circadian rhythm which is essential for human life. Humans spend approximately one-third of their life to sleep. Sleep is necessary for optimal health, as the person sleeps, his body repairs itself. Blood pressure fluctuates, heart rate slows down, hormone fluctuates, muscles and other tissues relax and repair and the replacement of aging or dead cells occur during sleep. Without sleeping, the humans do not function as well as they can [1]. Many experts suggest that quality sleep is as important to your health and well-being as good nutrition and exercise.

More and more adults are suffering from disturbed sleep, monitoring sleeping condition has gained more interest as a effective method to solve this problem and to improve sleep quality. Indeed, sleep diseases remain extremely under-diagnosed in spite of their high impact in public health. In fact, according to the world health organization (WHO) [2], it is estimated that 2% to 4% of middle-aged adults are concerned with sleep related diseases, 1% to 3% of preschool children are also concerned. A dramatic issue is to be expected if an early diagnostic is not made; for instance, it should be known that 1 out of 3 of motor vehicle accidents are caused by driver fatigue. Unfortunately, around 95% of people concerned with sleep diseases are undiagnosed.

1.2 Side effects of of sleep deprivation

You know lack of sleep can make you grumpy and foggy. You may not know what it can do to your memory, health, looks, and even ability to lose weight. Here are side effects of sleep loss:

1) Sleepiness Causes Accidents

Sleep deprivation was a factor in some of the biggest disasters in recent history: the 1979 nuclear accident at Three Mile Island, the massive Exxon Valdez oil spill, the 1986 nuclear meltdown at Chernobyl, and others.But sleep loss is also a big public safety hazard every day on the road. Drowsiness can slow reaction time as much as driving drunk. Studies show that sleep loss and poor-quality sleep also lead to accidents and injuries on the job. In one study, workers who complained about excessive daytime sleepiness had significantly more work accidents, particularly repeated work accidents. They also had more sick days per accident.

2) Sleep loss dumb you down

Sleep plays a critical role in thinking and learning. Lack of sleep hurts these cognitive processes in many ways. First, it impairs attention, alertness, concentration, reasoning, and problem solving. This makes it more difficult to learn efficiently. Second, during the night, various sleep cycles play a role in “consolidating” memories in the mind. If you don’t get enough sleep, you won’t be able to remember what you learned and experienced during the day.

3) Sleep loss can lead to serious health problems

According to some estimates, 90% of people with insomnia (a sleep disorder characterized by trouble falling and staying asleep) also have another health condition. Sleep loss may cause many illness, such as, heart disease, heart attack, heart failure, irregular heartbeat, high blood pressure, stroke, diabetes.

4) Sleepiness cause depressing

Over time, lack of sleep and sleep disorders can contribute to the symptoms of depression. In a 2005 Sleep in America poll, people who were diagnosed with depression or anxiety were more likely to sleep less than six hours at night.

5) Sleep deprivation may damage your skin

Most people have experienced sallow skin and puffy eyes after a few nights of missed sleep. But it turns out that chronic sleep loss can lead to lackluster skin, fine lines, and dark circles under the eyes.

6) Sleepiness makes you forgetful

In 2009, American and French researchers determined that brain events called “sharp wave ripples” are responsible for consolidating memory. The ripples also transfer learned information from the hippocampus to the neocortex of the brain, where long-term memories are stored. Sharp wave ripples occur mostly during the deepest levels of sleep.

7) Losing sleep can make you gain weight

Not only does sleep loss appear to stimulate appetite. It also stimulates cravings for high-fat, high-carbohydrate foods. Ongoing studies are considering whether adequate sleep should be a standard part of weight loss programs.

8) Lack of sleep may increase risk of death

In the “Whitehall II Study,” British researchers looked at how sleep patterns affected the mortality of more than 10,000 British civil servants over two decades. The results, published in 2007, showed that those who had cut their sleep from seven to five hours or fewer a night nearly doubled their risk of death from all causes. In particular, lack of sleep doubled the risk of death from cardiovascular disease.

1.3 Detection of sleep loss subjects

The lack of the number of proper diagnosis materials in hospitals and the increasing high demand due to the pandemic character of the mentioned problems combined to the constant evolution of technology pushed the researchers to look for a novelty kind of diagnosis aid systems. These systems aim to simplify the existing health evaluation devices in order to be used in home or as portable systems. This trend is not aimed to replace the existing diagnosis systems but in order to improve it and to help health professionals in diagnosis tasks. This is clear in the sleep study where a complex system exclusively used in hospitals is needed. This system called polysomnography (PSG) consists of a multi-parametric testing, which means the acquisition of different physiological signals during a whole night (sometimes during 24h). It records the breath airflow, respiratory movement, oxygen saturation, body position, electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), and electrocardiogram (ECG). A subject mounting device for PSG is shown in Fig.1. It is obvious that a simplified system for sleep study can not include all these records. In addition, the conventional method of sleep study is based on treating signals manually, which means that a professional sleep technician should visualize the whole night signals in order to get valuable results. In contrary, by definition a portable system or an in-home sleep study system should be independent, in other words, the signal processing should be automatic rather than manual. This shows the importance of developing new systems for healthcare and sleeping condition evaluation.

Fig.1. A subject mounting device for PSG (cited from http://www.nikko-memorial-hos.or.jp/sleep.html).

Except PSG used in hospital, many products aim to simplify detection sleeping condition in order to be used in home or as portable systems. This trend is not aimed to replace the PSG but in order to improve it and to help health professionals in diagnosis sleep tasks. We introduce several products as fellow:

The Tanita SleepScan SL-501 is a mat that you place under your bedding to monitor sleep patterns. The device uses a vibration microphone to sense body motion, heart rate and breathing patterns, and then stores that information on an SD card. Put that data into your PC and the accompanying software will display the user’s sleep patterns in easy-to-understand graphs. Users can then evaluate the quality of your sleep (how long you really slept, how often you woke up during the night etc.) through graphs and a “sleep score” the software gives you, based on information coming from the capacitor microphone inside the mat that tracks vibrations.The mat is sized at 863×314×26mm and weighs 1.3kg as shown in Fig. 2. A 2GB SD card is enough to store the data of about 500 sleep cycles. All-night sleeping condition measured by SleepScan is represented in Fig. 3. TANITA is a nearly 100-years-old health equipment company, is also committed to the cause of health well-known international brands. TANITA global cumulative sales of up to 30 million units, Japan's market share of 60%, in Europe and the United States sales are also stable leadership position. Due to SleepScan including more sensitive sensors which can detect comprehensive analysis of the parameters and the official accurate is 83% compared with PSG, so SleepScan was chose as my research comparison object.

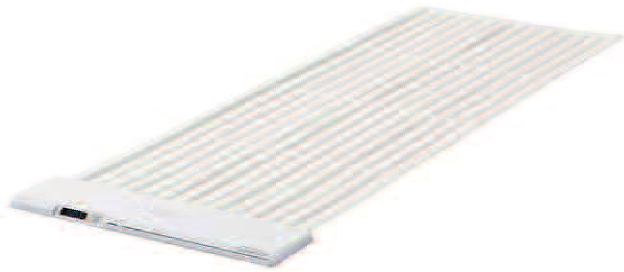


Fig. 2. Tanita SleepScan SL-501.

測定開始	07月01日	02:42	覚 醒	03分00秒	1.3%
測定終了	07月01日	07:11	R E M	01時間03分00秒	27.4%
睡眠時間	03時間50分00秒		浅睡眠	02時間12分30秒	57.6%
実睡眠時間	03時間47分00秒		深睡眠	31分30秒	13.7%

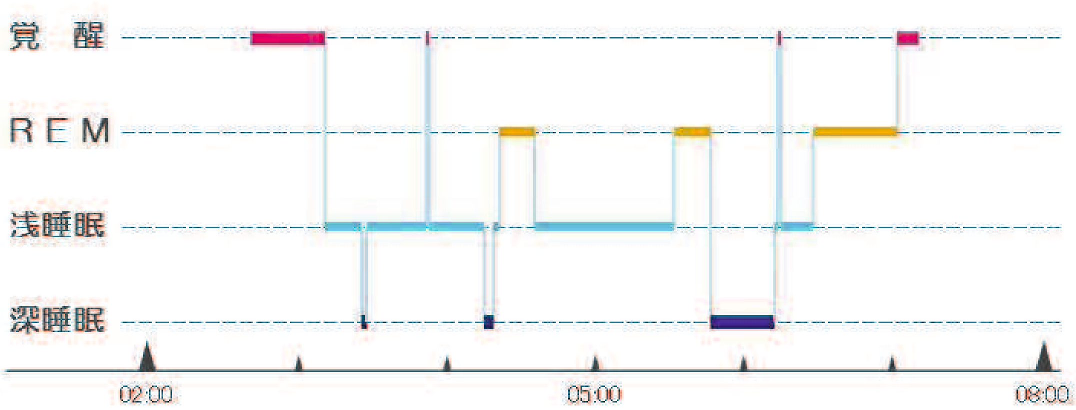


Fig. 3. All-night sleeping condition measured by SleepScan.

The Fig. 4 shows the commercial system in the smart device. ThinkPillow, in combination with ThinkSleep, is the most effective sleep system to make you sleep and feel better. As a pillow, it is fully adjustable in both softness and height, so comfortable it feels like a custom-made pillow for you. Not only does ThinkSleep track how you sleep, it also knows the ideal time to wake you up, so you will feel alert and refreshed to face the day. All easy to use by smartphone apps. ThinkPillow reinvents the bed pillow, changing the way of we sleep forever.

Fig. 4.   ThinkPillow (cited from https://www.kickstarter.com/).

Omron Sleep Meter HSL-101 is shown in Fig. 5. Set in the bedside, it captures the movement of body using wave sensor to estimate the sleeping / awake state. The HSL-101 has a radio frequency sensor that sends out waves over a roughly 5-foot range. It stands by the bedside and starts scanning once you press the "good night" button.

Fig. 5. Omron Sleep Meter HSL-101(cited from http://www.omron.co.jp/).

Due to above products are expensive, difficult portable or no easy to carry for business trip, a monitoring sleep condition system was developed in our laboratory [3]. This system described in details in next chapters of this thesis is aimed to acquire breath sound signals used the bluetooth sound sensor during sleep. The signals acquired with the bluetooth sound sensor are subject to strong noise, which make its use very difficult without proper signal processing. In the following, we introduce the sleeping condition study, its problems and proposed solutions.

1.4 Sleeping condition study

Sleep is a natural state of rest, characterized by unconsciousness, which is necessary to the physical and physiological recovery in humans. Studying the dynamics governing sleep leads to a better comprehension and evaluation of several health states such as sleep apnea, cardiac arrhythmias, mental stress, daytime sleepiness and so on. Actually, sleep consists of six different stages, wakefulness stage, four non rapid eye movement (NREM) sleep stages numbered from 1 to 4 and rapid eye movement (REM) sleep stage. Rechtschaffen and kales [4] established the standard for the sleep stage scoring more than four decades ago, where sleep stages are visually scored by an expert according to changes in the physiological signals acquired during night, which are mainly the EEG, the EOG and the EMG. As mentioned earlier these signals are acquired, among others, using a multi-parametric testing system known as PSG, which is exclusively used in the hospital environment. The information related to sleep stages changing is very important to evaluate sleep quality, sleep quantity and sleep related problems.

Above statements, show clearly the importance of sleep study. However, many problems arise concerning sleep study. In the following, we list the main problems related to sleep study:

1) The sleep study system called PSG is very expensive and exclusively used in hospitals. This unavailability make that large number of sleep related problems sufferers are undiagnosed.

2) A sleep expert technician makes the sleep stages scoring manually. This fact make the sleep study very consuming in time and not very precise since it is related to the subjectivity of the human scorer.

3) Many health problems have mild or vague symptoms during daytime. Therefore, a sufferer of such diseases can not be detected unless his situation becomes serious.

4) Sleep study is very complex and includes several aspects which make it quite impossible to study all aspects.

A Solution to the first problem can be the simplification of the conventional sleep study system the PSG. However, no valuable system was proposed as an alternative to the PSG, which is still the gold standard system of sleep study. Conversely, the second problem was widely discussed in literature. Actually, many algorithms of automatic sleep stages scoring were proposed [5-10]. These algorithms are based on the processing of many signals, such using the EEG signal, as it is the most important one. This approach may be better in the accuracy; however, we are loosing in simplicity. Such a system can not be used for in-home applications since an EEG recorder is a complex device that can not be used without an expert technician assistance. This fact is directly related to the third problem cited above. The solution to such problem is the development of easy use devices to be used for in-home environment. Since a simplified system is needed, the use of complex recordings such as EEG is to be excluded. In addition, the fourth point above point out the complexity of the sleep study. On other words, one can not evaluate all aspect of sleep in one study. Conversely, we should focus on a specific aspect of sleep and study it. Along with this is the alternative approaches using more simple signals such as breath sound signals.

1.5 Aim of this thesis

This thesis focuses on the development of sleeping condition evaluation system. In particular, the work focuses on two points. First, the detection of sleep and wake times during night sleep recording; this allow us to evaluate the sleeping condition. Second the detection of sleep apnea episodes during night sleep; this allows us to evaluate the health state of a subject. This study includes signal processing methods and proposed algorithms that can be used for portable and in-home healthcare systems, in particular the sleeping condition monitoring system developed earlier in our laboratory. The entire work is summarized as follows:

Chapter 1 introduces the thesis where the sleep studies background and sleep study problems are summarized.

Chapter 2 provides a comprehensive explanation about sleep study in literature. In addition, the wireless sound sensor and sleep conditions monitoring system are introduced.

Chapter 3 the sleep stages discrimination using the breath characteristic parameters for sleeping condition estimation was fulfilled. The results of estimated sleeping condition are compared to the commercial product. The sleeping condition discrimination was fulfilled by a classification method where several features are extracted from the breath characteristic parameters. More precisely, the breath sound signal obtained with the bluetooth sound sensor is prone to high grade noise which necessitated a algorithm to deal with them. It was tested on data sets acquired in our laboratory using the aforementioned sleeping conditions monitoring system.

Chapter 4 built sleeping condition data sets and use in a support vector machine (SVM) classifier to evaluate and predict sleep state based on sleeping condition database. The results of estimated sleeping condition are compared to the commercial product and the Chapter 3 proposed algorithm. By the way, the classification efficiency is calculated. In addition, the RBF(Radial Basis Function) kernel is adopted in our case which is non-linear problem in the SVM classifier.

Chapter 5 discusses the development of a simple method of apnea detection during sleep using breath sound signal. In particular, the signal acquired using the sound bluetooth sensor is processed to obtain the breath sound signal. Then, respiratory variance have strongly relationship with oxygen saturation (SpO2) that we proposed is used to detect the apnea events. The results showed that the apnea index (AI) values obtained from the our method are close to the values obtained using breath sound wavefrom and the gold standard PSG results have a good efficiency and accuracy.

Chapter 6 provides conclusions to the thesis work.

1.6 References

[1] N. S. Sleeping Sickness Pill May Work as Well as Injections[J]. Science News, 2007, 172(22):350-350.

[2] World Health Organization (2004). Annex Table 2: Deaths by cause, sex and mortality stratum in WHO regions, estimates for 2002. The world health report 2004 - changing history. http://www.who.int/entity/whr/2004/annex/topic/en/annex_2_en.pdf. Accessed: 5 March, 2009.

[3] Y Luo, Z Jiang, A simple method for monitoring sleeping conditions by all-night breath sound measurement, Journal of Interdisciplinary Mathematics 2017; 20(1): 307- 317.

[4] A. Rechtschaffen and A. Kales, A Manual of Standardized Terminology,Techniques, and Scoring System for Sleep Stages of Human Subjects.Washington, DC: US Public Health Service, US Government Printing Office, 1968.

[5] A. Saastamoinena, E. Huupponena, A. Värri, J. Hasanb and S-L. Himanenb, Computer program for automated sleep depth estimation, computer methods and programs in biomedicine 2006; 82(1): 58-66.

[6] K. Šušmáková and A. Krakovská, Discrimination ability of individual measures used in sleep stages classification, Artificial Intelligence in Medicine 2008: 44(3): 261-277.

[7] L. Zoubek, S. Charbonnier, S. Lesecq, A. Buguet and F. Chapotot, Feature selection for sleep/wake stages classification using data driven methods, Biomedical Signal Processing and Control 2007; 2(3): 171-179.

[8] A. Flexer, G. Gruber and G. Dorffner, A reliable probabilistic sleep stager based on a single EEG signal, Artificial Intelligence in Medicine 2005; 33(3): 199-207.

[9] R. Agarwal and J. Gotman, Computer-Assisted Sleep Staging, IEEE Transactions on Biomedical Engineering 2001; 48(12): 1412-1423.

[10] S.J. Redmond and C. Heneghan, Cardiorespiratory-based sleep staging in subjects with obstructive sleep apnea, IEEE Transactions on Biomedical Engineering 2006; 53(3): 485-496.

[11] https://www.kickstarter.com/.

[12] http://www.omron.co.jp/.

[13] http://www.nikko-memorial-hos.or.jp/.

Chapter 2

Sleeping conditions monitoring system

2.1 Introduction

Indirect technologies offer a more ambient, practical approach to long term sleep monitoring and can ideally avoid any conscious participation by the subject. A number of non-contact technologies have been proposed for this purpose and these can be broadly divided into systems which detect physiological signals and/or movement detection technologies. A brief overview of some of these technologies is given below:

2.1.1 Physiological signal sleep monitoring systems

Shin et al. [1] investigated direct contact respiration estimation using an air mattress, composed of separate air cells with a balancing tube based pressure sensor, and reported a mean difference of 0.5 (SD of±0.63) breaths per minute and an MPE of 2.85%. Estimates of heart beats, body movement, snoring events and apnoeic episodes were also produced with high sensitivity and high positive prediction values. Carlson et al. [2] developed a non-invasive respiratory monitoring system (NIRMS) for sleeping subjects (in direct contact with the sensor) which monitors pressure changes on an air mattress using a pressure transducer. They reported on eleven subjects over three sleeping postures each (supine, prone and side) for a duration of 5 minutes per condition (33 data sets in total). A mean of absolute differences between the estimated respirations and the actual respirations of 0.79±0.6 breaths per five minutes and a mean error of 1.38% were reported. Brink et al. [3] investigated the use of high resolution force sensors (also known as load cells) placed underneath the bed posts for non-contact measurement of respiration, heart rate and body movements during sleep. Data was captured from fourteen subjects (seven male) over a five minute duration in a prone, supine or side position. This produced a mean absolute difference of 0.03 (SD of ±0.33) breaths per minute (0.15 ± 1.65 breaths per five minutes) between the estimated and actual breaths and a mean error of 1.2%. Zhu et al. [4] developed an under-pillow pressure based respiration and heart rate estimation sensor. Data was recorded from thirteen recumbent subjects (8 male) for an average of approximately 115 minutes. A mean absolute difference of 0.04 (SD of ±0.06) breaths per minute (0.24 ± 0.34 breaths per five minutes) was reported, resulting in a mean error of 0.38%. However the accuracy of this underpillow technique might vary over different sleeping positions (supine, prone or side-lying) as the carotid pulse might not be present in all postures. Mack et al. [5] proposed pressure sensitive pads placed on top of the mattress, in contact with the participant through bed sheets as a potential technology for sleep monitoring. An algorithm was developed, from data collected from 40 subjects, which detected the ballistocardiogram and accurately reported the heart rate to within 2.72 beats per minute and respiration to within 2.1 breaths per minute. Brueser et al. [6] used 4 strain gauges, sampling at 128 Hz, fitted to a segment of the bed frame to detect heart rate. An automated, dynamic technique was developed for heart rate estimation and validated on data collected from 16 individuals. A beat to beat interval error of 1.79% was reported and the algorithm was found to work for over 95% of data. Choi et al. [7] investigated load cells, placed underneath the bed posts and sampled at 200 Hz, to extract the ballistocardiogram (the physical manifestation of heart beat and breathing). Heart rate variability analysis was then applied and the derived features were found to be able to discriminate deep sleep (stage 3 and stage 4 sleep) from the other stages of sleep with a 92.5% accuracy. Kortelainen et al. [8] developed an under-mattress pressure sensitive capacitive foil electrode grid sampled at 50 Hz to extract the various heart rate features from the ballistocardiogram.The combination of a movement detection system and another system, based on the application of hidden Markov models on heart beat interval data to discriminate between Rapid Eye Movement (REM) and Non-Rapid Eye Movement (NREM) sleep, reported an accuracy of 79%.

2.1.2 Movement detection sleep monitoring systems

Video-based sleep monitoring solutions offer impressive utility in detecting body movement during sleep [9,10], however participants are often uncomfortable with the presence of video recording equipment in the home and especially in the bedroom. Passive InfraRed (PIR) based systems are also optical systems, however they do not record an image but register movement whenever differential changes are recorded across the infrared radiation sensing grid upon which environmental radiation is focussed. A high accuracy for movement detection has been reported in PIR-based sleep monitoring systems [11,12]. However, a number of potential usability issues remain including the presence of heaters (which emit disruptive infrared radiation) and the varying location of heaters between environments and the presence and types of bed sheets shielding the bodily infrared from the detector. Radar based technologies [13], placed on the bedside locker, report high accuracies in detecting movement compared to wrist actigraphy. However, this technology requires line-of-sight between the participant and the system (often placed on a bed-side locker).

To sum up above systems that they are more or less not have high accurate, expensive, lack of portable or uncomfortable. Additionally, it's very difficult to apply at home or business trip in hotel. Meanwhile, above literature have proposed to use radar to acquire signals, as everyone knows, radar have more or less electromagnetic radiation to the human body and not easy to install.

In order to monitor the sleeping disorders in-home with less constraint, our laboratory has developed a wireless sound sensor, which can measure breath sound signals [14]. Using breath sound signals, we aim to evaluate sleeping condition. Therefore, in this chapter, we proposed a method to extract characteristic parameters of breath sound signals and then evaluate sleeping condition classification based them. The algorithm was designed for breath sound signals and was tested with several all-night days data acquired with our laboratory-made sleeping condition monitoring system. Furthermore, a commercial system(SleepScan) were compared for validating the efficiency of our proposed algorithm.

One of the most studied aspects of sleep (may be the most studied) is the evaluation of sleep dynamics [15-20], which means the sleep chronology and the sleep stages. This aspect tends to explain the mechanisms of sleep (normal and abnormal) and extract features to evaluate the quality of sleep. In fact, sleeping condition includes six different stages, wakefulness stage, four non rapid eye movement (NREM) sleep stages numbered from 1 to 4 and rapid eye movement (REM) sleep stage. As mentioned earlier these signals are got, among others, using a multi-channel collecting system known as PSG, which is exclusively used in the hospital or laboratory. The information related to sleeping condition changing is very important to assess sleep quality and sleep related illness. Unfortunately, PSG is intrusive, expensive, time consuming and often scares the subjects. However, current sleep monitoring methods suffer from several defects, such as invasive, contact, lack of comfortable, and high-cost. These drawbacks prevent people from the existing sleep monitoring systems. Instead, portable devices that subjects can convenient and easy to use while asleep seem to be very attractive and highly demand.

Another aspect of sleep study is the detection or evaluation of health problems related to sleep mainly the apnea problems. Sleep Apnea (SA) is becoming a more common cause of sleepiness in children and adults. It is characterized by abnormal pauses of breathing or abnormally low breath during sleep. These pauses of breathing can range in frequency and duration. The duration of the pause might be ten to thirty seconds and upwards to as much as four hundred pauses per night in those with severe SA. This kind of illnesses is difficult to detect during day even though some strong clinical indicators exist for example dizziness and day sleepiness. These indicators are very common among population, and then it becomes difficult to diagnose such illnesses without studying night sleep.

In our work we have chosen two aspects of sleep study. The first one is deducing a sleep quality marker by studying sleep dynamics. Our research target is to develop and validate a high performance method to classify sleeping condition into several stages based on breath sound signals. The second aspect is the detection of apnea during night sleeping. These two aspects should be studied using only breath sound signals. Actually, our work is a continuity of a previous work which is the development of a wireless sound sensor.

The evaluation of the methods we developed is, naturally, made using data acquired with our wireless sound sensor. However, some other information data are needed for the evaluation of our methods, and then we used the mainstream product of monitoring sleeping conditions in the market is SleepScan (TANITA SL-503). Unlike the past studies, we described a simple method to monitor sleeping condition using breath sound signals. The location of monitoring sleeping conditions is flexible. To the best of our knowledge, this is the first attempt to monitor sleeping conditions only using breath sound. The collection and use of physiological signals was approved by the ethics committee of the mechanical engineering department of Yamaguchi University.

2.2 Materials studied

Two kinds of materials were used in our experiments: a laboratory made wireless sound sensor and a sleeping conditions monitoring system. In the following the description of each system.

2.2.1 Wireless sound sensor

Our laboratory developed a wireless sound sensor for the acquisition of breath sound signals. The wireless sound sensor is composed of a microphone, a bluetooth module and a battery module. These modules are assembled together into a sensor as shown in Fig. 2. Microphone is chose Plantronics M70 whose specifications is shown in Fig. 3. Plantronics that is a world leader in professional audio and audio communications. We made the changes in the bottom in order to let the air flow into the device more easily.

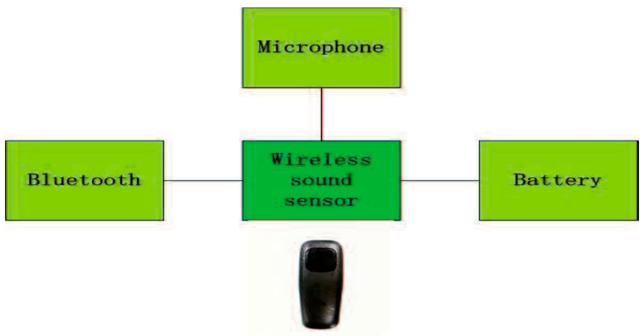


Fig. 2. Architecture of Bluetooth breath sound sensor.

Talk Time	Up to 11 hours*
Standby Time	Up to 16 days*
DeepSleep Standby Mode	Up to 180 days*
Weight	8 grams
Multipoint Technology	Pair and maintain connections with two phones and answer calls from either phone
Wideband for HD Audio	Enhances clarity when used with wideband-ready phones and networks
Bluetooth Version	Bluetooth v3.0
Bluetooth Profiles	Advanced Audio Distribution Profile (A2DP), Audio Video Remote Control Profile (AVRCP), Hands-Free (HFP) Profile 1.6 and Headset (HSP) Profile 1.2
Charge Connector	Micro USB
Battery Type	Rechargeable, non-replaceable lithium ion polymer
Charge Time (Maximum)	2 hours for full charge
Operating + Storage Temperature	32°F – 104°F (0 – 40°C)
Service and Support	1-year limited warranty

* Performance is dependent upon battery and may vary by device

Bluetooth

Fig. 3. Plantronics M70 specifications (cited from http://www.plantronics.com/).

2.2.2 Sleeping condition monitoring system

Acquisition of physiological information during sleep is evaluation standard for the sleeping conditions. In the light of that, we developed the sleeping conditions monitoring and analysis system. In this study, focus on the all-night breath sound during sleep, research the connection between breath sound and sleeping conditions. Fig. 4 shows sleeping conditions monitoring and analysis system. The breath sound signal send to ②tablet/smartphone by ① wireless sound sensor (using medical tape placed at a distance of 1 cm near nostril) in home/group house. ②Tablet/smartphone upload sound data to ③analysis server via the WiFi. After analyzing by ③ analysis server, the results of the analysis can download by ② tablet/smartphone from ③ analysis server. At the same time, doctors can view ④ sleeping conditions monitoring results viewer in hospital/clinic. Tablet/smartphone app user interface is shown in Fig. 5. Analysis server is represented in Fig. 6. Sleep state viewer which doctors can view sleeping conditions monitoring results is shown in Fig. 7.

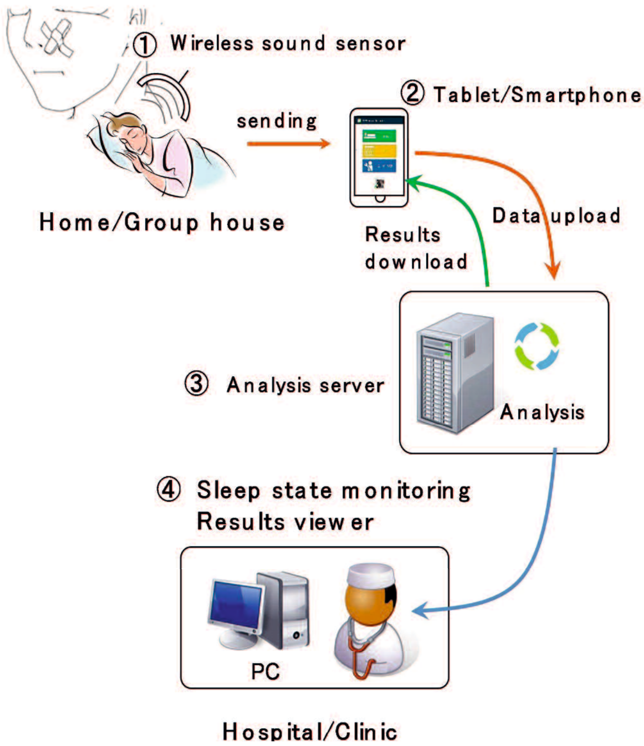


Fig. 4. All-night breath sound measuring and sleeping condition analysis system.

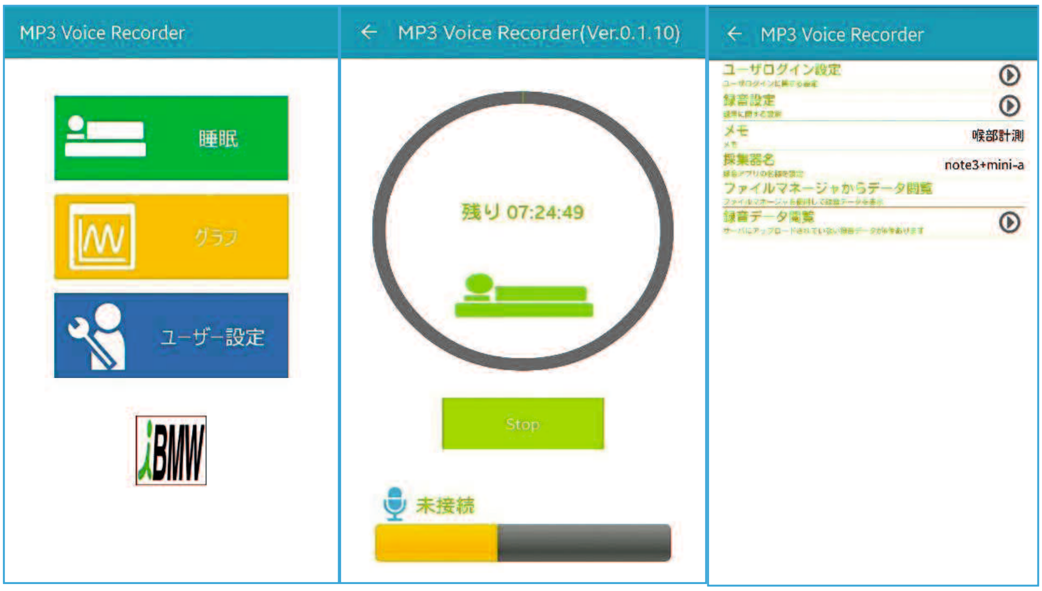


Fig. 5. Tablet/smartphone app user interface.

Fig. 6. Analysis server.

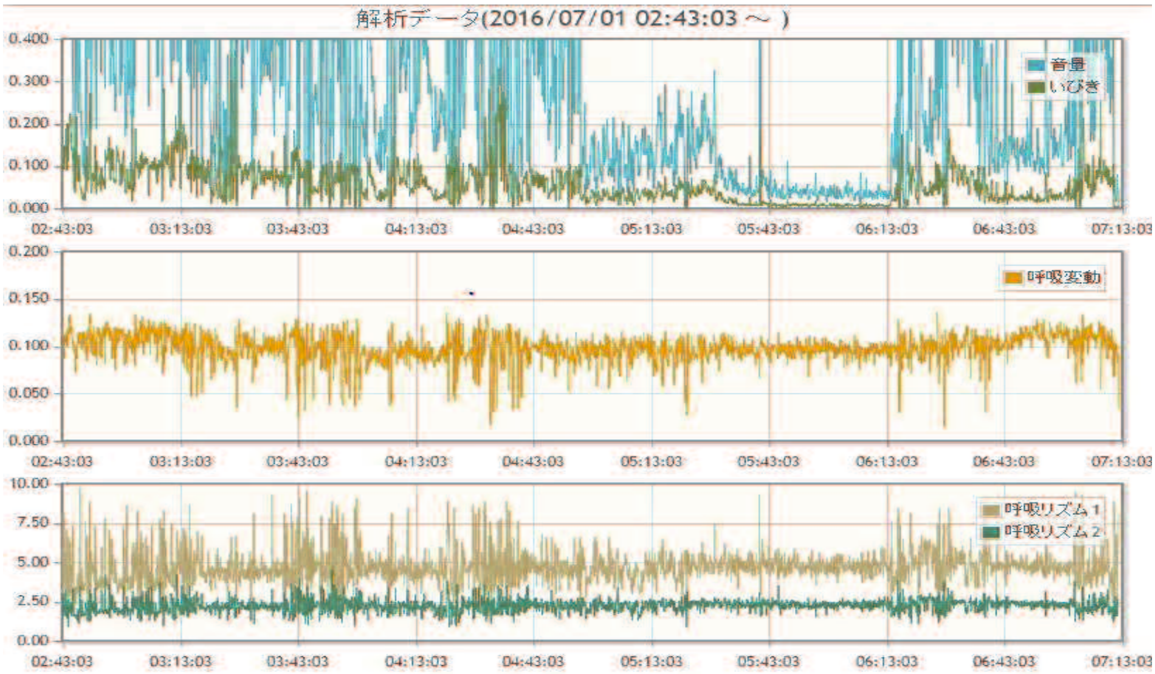


Fig. 7. Sleep state viewer.

2.3 Discussion

Two all-night breath sound signals waveform acquired by our sleeping condition monitoring system and sleeping condition measured by SleepScan are depicted in Fig. 8 and Fig. 9. When breath sound signal is the most smooth and steady, we marked by D in this state. The second smooth and steady curve depict C. At the period of A, breath sound signal have more amplitude and variance. When the amplitude of breath sound signal become a little less than wake, marked by B. Compared sleeping conditions measured by SleepScan, we found A, B, C, D are denoting wake, REM, shallow, deep in sleeping condition which measured by SleepScan, respectively. Then, we can evaluate sleep stages based on breath sound. At the very least, we can conclude breath sound have a strong relationship with sleep stage.

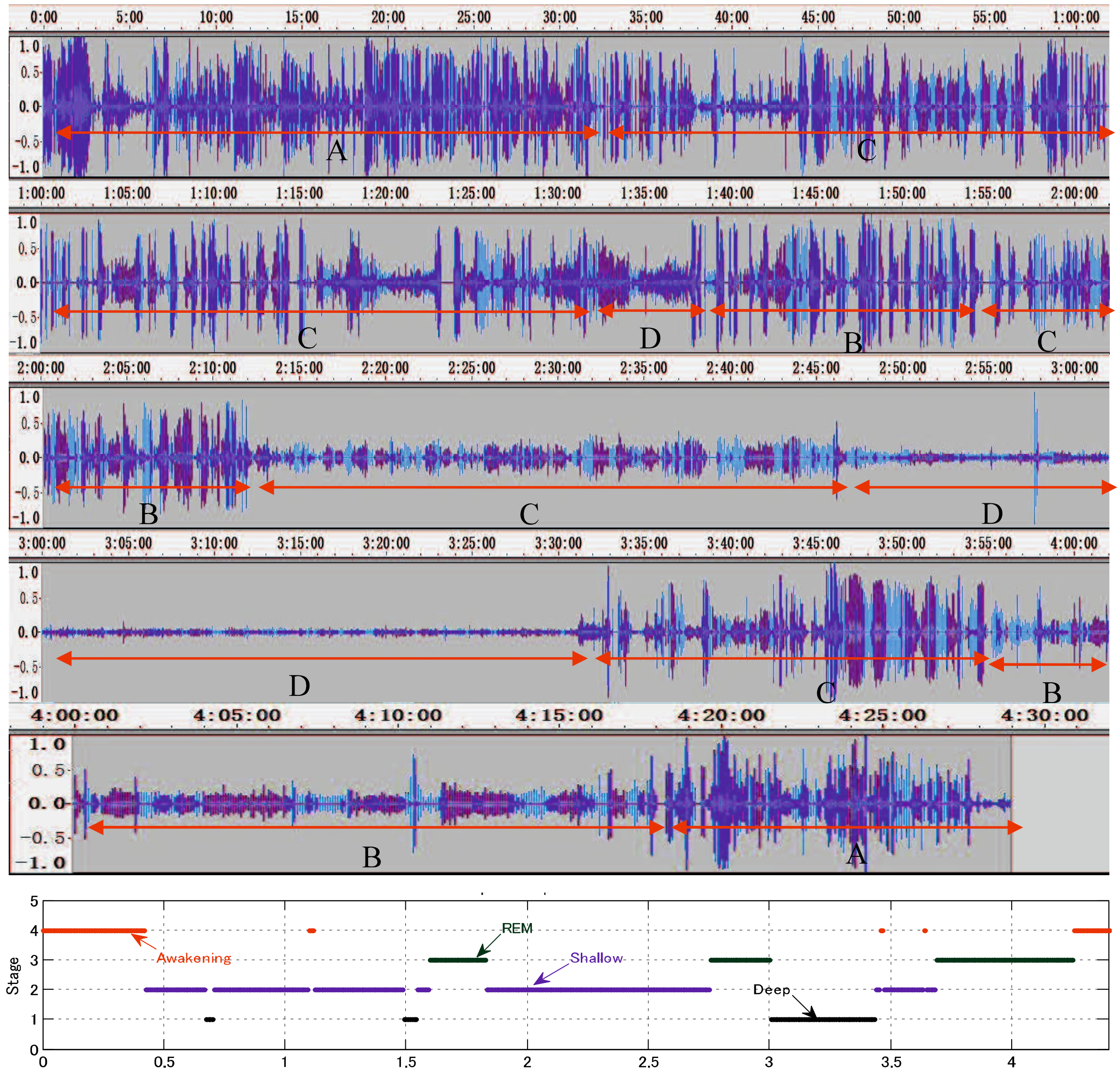


Fig. 8. All-night breath sound signal waveform and sleeping condition measured by SleepScan (data 0701).

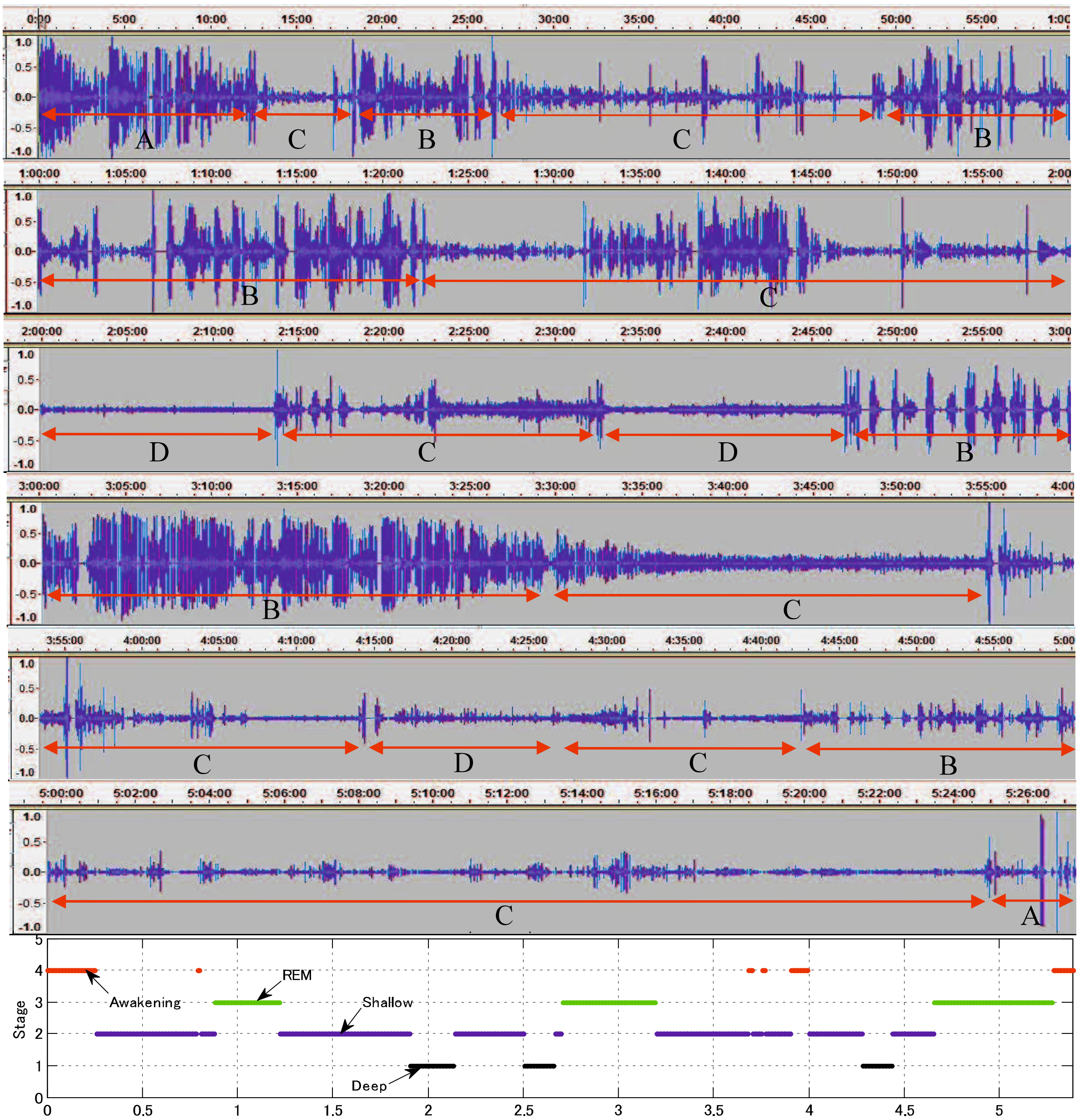


Fig. 9. All-night breath sound signal waveform and sleeping condition measured by SleepScan (data 0702).

2.4 Summary

In this chapter, we first introduced some sleep study methods in literature:

1. Sleep dynamics study (sleep stages and sleep chronology).
2. Sleep-related health problems detection during night.
3. Interaction between sleep and some daily life aspects.

Then, we fixed the target of our research in two aspects. First, one sleep dynamic aspect which is the discrimination between sleep and wake stages in night sleep in order to evaluate sleep quality. Second, the detection of apnea episodes in night sleep. To fulfill these tasks we introduced the systems used for the acquisition of data:

1. Laboratory made wireless sound sensor.
2. Sleeping condition monitoring system.

Finally, we introduced the product necessary to the evaluation of our method.

2.5 References

[1] J.H. Shin, Y.J. Chee, D. Jeong and K.S. Park, Nonconstrained sleep monitoring system and algorithms using air-mattress with balancing tube method, IEEE Trans. Inf. Technol. Biomed. 14(1) (Jan. 2010), 147 – 156.

[2] B.W. Carlson, V.J. Neelon and H. Hsiao, Evaluation of a noninvasive respiratory monitoring system for sleeping subjects, Physiol. Meas. 20(1) (Feb. 1999), 53 – 63.

[3] M. Brink, C.H. Muller and C. Schierz, Contact-free measurement of heart rate, respiration rate, and body movements during sleep, Behav. Res. Methods 38(3) (August 2006), 511 – 521.

[4] X. Zhu, W. Chen, T. Nemoto, Y. Kanemitsu, K.I. Kitamura K.I. Yamakoshi and D. Wei, Real-time monitoring of respiration rhythm and pulse rate during sleep, IEEE Trans. Biomed. Eng. 53(12) (Dec. 2006), 2553–2563.

[5] D.C. Mack, J.T. Patrie, P.M. Suratt, R.A. Felder, and M.A. Alwan, Development and preliminary validation of heart rate and breathing rate detection using a passive, ballistocardiographybased sleep monitoring system, IEEE Transactions on Information Technology in Biomedicine 13(1) (Jan. 2009), 111–120.

[6] C. Brueser, K. Stadlthanner, S. de Waele, and S. Leonhardt, Adaptive Beat-to-Beat Heart Rate Estimation in Ballistocardiograms, IEEE Transactions on Information Technology in Biomedicine 15(5) (Sep. 2011), 778–786.

[5] D.C. Mack, J.T. Patrie, P.M. Suratt, R.A. Felder, and M.A. Alwan, Development and preliminary validation of heart rate and breathing rate detection using a passive, ballistocardiographybased sleep monitoring system, IEEE Transactions on Information Technology in Biomedicine 13(1) (Jan. 2009), 111–120.

[6] C. Brueser, K. Stadlthanner, S. de Waele, and S. Leonhardt, Adaptive Beat-to-Beat Heart Rate Estimation in Ballistocardiograms, IEEE Transactions on Information Technology in Biomedicine 15(5) (Sep. 2011), 778–786.

[7] B.H. Choi, G.S. Chung, J.-S. Lee, D.-U. Jeong, and K.S. Park, Slow-wave sleep estimation on a load-cell-installed bed: A non-constrained method, Physiological Measurement 30(11) (Nov. 2009), 1163–70.

[8] J.M. Kortelainen, M.O. Mendez, A.M. Bianchi, M. Matteucci, and S. Cerutti, Sleep staging based on signals acquired through bed sensor, IEEE Transactions on Information Technology in Biomedicine 14(3) (2010), 776–785.

[9] K. Nakajima, Y. Matsumoto and T. Tamura, Development of real-time image sequence analysis for evaluating posture change and respiratory rate of a subject in bed, Physiological Measurement 22 (2001), 21–28.

[10] S. Okada, Y. Ohno, Goyahan, K. Kato-Nishimura, I. Mohri and M. Taniike, Examination of non-restrictive and noninvasive sleep evaluation technique for children using difference images, in: Conf. Proc. IEEE Eng. Med. Biol. Soc., 2008, pp. 3483–3487.

[11] J.M. Choi, B.O. Kim, B.S. Hwang, R.H. Sohn and K.S. Park, Unobtrusive body movement monitoring during sleep using infrared motion detector and ZigBee protocol, in: Proc. 3rd IEEE/EMBS International Summer School on Medical Devices and Biosensors, 2006, pp. 32 – 33.

[12] J.W. Shin, Y.R. Yoon, and J.C. Principe, Evaluation of body movement during sleep by thermopile using wavelet and neuro-fuzzy, in: Conf. Proc. IEEE Eng. Med. Biol. Soc., 2003, pp. 2406 – 2407

[13] P. de Chazal, E. O’ Hare N. Fox and C. Heneghan, Assessment of sleep/wake patterns using a non-contact biomotion sensor, in: Conf. Proc. IEEE Eng. Med. Biol. Soc., 2008, pp. 514 – 517.

[14] Y Luo, Z Jiang, A simple method for monitoring sleeping conditions by all-night breath sound measurement, Journal of Interdisciplinary Mathematics 2017; 20(1): 307- 317.

[15] Publications K. Sleep Dynamics[J]. Publications Office.

[16] Phillips A J, Robinson P A, Kedziora D J, et al. Mammalian sleep dynamics: how diverse features arise from a common physiological framework[J]. Plos Computational Biology, 2010, 6(6):e1000826.

Chapter 3

Sleeping conditions classification algorithm

3.1 Introduction

One of the main important markers of sleep quality is the sleep efficiency. This marker is useful to evaluate the kind of sleeper a subject is normal or insomniac. The calculation of this marker is done by the estimation of the ratio of sleep times over total sleep spent in bed during a night sleep recording. The method to do this is the detection of sleep stages and wake stages in the night recording. Actually, sleep consists of six different stages, wakefulness stage, four non rapid eye movement (NREM) sleep stages numbered from 1 to 4 and rapid eye movement (REM) sleep stage.

We have seen in previous chapters that the study of sleep dynamics is usually done using polysomnography (PSG) system. This system is complex because it uses several physiological recordings such as EEG, EMG and EOG. Then, our laboratory developed a wearable breath detect system that can measure breath sound signals [1]. In addition, a algorithm has been developed, for this system, for evaluating sleeping condition. This algorithm will be described in the chapter 3.

Main researchers were interested in the development of automatic sleep staging systems using EEG, EOG and EMG [2]. Even though high performance can be reached with such methods, it can not be used for in-home systems. Actually, the EEG, EOG and EMG recordings require special instrumentation and acquisition settings. Indeed, particulars are, for instance, unable to set, by themselves, the electrodes placements correctly for EEG acquisition. Along with this, researchers in the literature [3-6] have proposed many approaches for sleep stages scoring. Redmond and Heneghan [7] proposed a cardiorespiratory-based sleep staging, where they used ECG, estimated respiratory frequency and respiratory effort signals to extract 27 features used in quadratic discriminant classifier. Classification accuracy was moderately good (79%) in the case of subject-specific system and quite poor (67%) in the case of subject-independent system, even though 36 subjects were merged to form the training data and the 37th subject used as the tested data. Although, good methods were developed in this paper a lack concerning the impact of each signal, taken alone, in the sleep staging is noticed. Penzel et al. [8] made a comparison between spectral analysis for HRV and detrended fluctuation analysis (DFA) applied to sleep ECG. Some features were tested and good results were reported. However, no details were given on how the scoring of sleep stages was fulfilled. In addition, the sleep stages transition effect on HRV were taken off. This makes the staging task easier but not reproducing the real situation. In the real scheme, we dispose only of physiological signals such as breath sound without any information on the sleep stages transition times. Telser et al. [3,4] and Staudacher et al. [5] introduced and tested a new method for change-point detection in time series called progressive detrended fluctuation analysis (PDFA). This method, inspired by the DFA, is used to detect changes in low range times. The authors showed that their method is sensitive to sleep stages transitions but did not propose a precise sleep staging scheme. Instead, they counted the occurrence or not of an event, called PDFA event, corresponding to a transition in the hypnogram. This approach neglects the effect of other events, which do not correspond to any sleep stage occurrences. Bunde et al. [9] used DFA analysis to study the correlated and uncorrelated regions in HRV during sleep. Their results can be used for sleep stages scoring. We should notice that in their work Bunde et al. have studied the different sleep stages separately, i.e., taking off the effect of sleep stages transitions. We notice also that very few researches interested to the exclusive use of breath sound signals for sleep stages, this might be explained by the high complexity of sleep process and the conventional methods for sleep stages. However, such a simple method will be easier to implement for in-home and portable systems, which will help greatly improving health quality assessment.

In this chapter, the sleep stages discrimination using the breath characteristic parameters for sleeping condition estimation was fulfilled. The results of estimated sleeping condition are compared to the commercial product. More precisely, the breath sound signal obtained with the wireless sound sensor is prone to high grade noise which necessitated a algorithm to deal with them. The tested breath sound acquired using the aforementioned sleeping conditions monitoring system. The performance results of algorithm is also calculated.

3.2 Sleeping conditions

Approximately 2 h after we fall asleep our eyes start to move back and forth irregularly. Based on this fact scientists have divided sleep stages into two main stages, namely REM sleep stage (Rapid Eye Movement) and NREM sleep stage (Non Rapid Eye Movement). NREM sleep is divided into another four sub-stages in which a sleep gets gradually deeper and deeper [10]. During a healthy sleep, REM and NREM stages interchange several times. Most of the dreams happen during the REM stage. Body muscles are completely relaxed, waking up at this stage is refreshing. During the deep sleep stages (NREM 3 and 4), blood pressure is decreasing, which an lower the risk of cardiovascular disease[11]. And in adolescence, a growth hormone is produced at maximum levels [12]. To summarize, the sleep stages are as follows:

(a) Wake (Awake)
(b) REM—we dream in this stage
(c) NREM1—falling asleep
(d) NREM2—light sleep
(e) NREM3—deep sleep
(f) NREM4—deepest sleep

Table 1 describes and outlines the processes in the human body during the individual sleep stages. It shows the relationships between biological manifestations and the different sleep stages [11]. This table and information therein are taken into account in the our algorithm.

Table 1. Biological manifestations in sleep states

Physiological Process	During NREM	During REM
Brain activity	Decreases from wakefulness	Increase in motor and sensory areas,while other areas are similar to NREM
Heart rate	Slows from wakefulness	Increases and varies compared with NREM
Blood pressure	Decreases from wakefulness	Increases(up to 30%) and varies from NREM
Blood flow to brain	Does not change from wakefulness in most regions	Increases by 50% to 200% from NREM, depending on brain region
Respiration	Decreases from wakefulness	Increases and varies from NREM, but may show brief stoppages (apnea); coughing suppressed
Airway resistance	Increases from wakefulness	Increases and varies from wakefulness
Body temperature	Is regulated at lower set point than wakefulness; shivering initiated at lower temperature than during wakefulness	Is not regulated; no shivering or sweating; temperature drifts toward that of the local environment
Muscle tension	Decreasing with increasing of NREM	Increase from NREM

Hypnograms are usually obtained by visually scoring the recordings from electroencephalogram (EEG), electrooculography (EOG) and electromyography (EMG). The output from these three sources is recorded simultaneously on a graph by a monitor or computer as a hypnogram. Certain frequencies displayed by EEG, EOG and EMG are characteristic and determine which stage of sleep or wake the subject is in. There is a protocol defined by the American Academy of Sleep Medicine (AASM) for sleep scoring, whereby the sleep or wake state is recorded in 30 seconds epochs. Prior to this the Rechtschaffen and Kales (RK) rules were used to classify sleep stages. Sleep cycles in 9 hours of sleep, both stage 3 and stage 4 (these are often combined as stage 3) are shown in Fig. 1. Sleep cycle is an important part of sleep which consists of REM and NREM cycles that alternate 90-110 minutes. In each hour of sleep some portions are REM sleep and some are NREM sleeps repeated 4 to 6 times per night. Transition of sleep stages in a complete 9 hour sleep is shown in Fig. 1. As hours of sleep increase period of REM sleep increases. In morning hour it is all REMs, Non REM 1 and Non REM 2. Non REM 1 is the transition from wake to sleep. Non REM 2 is the light sleep period when eye movement stops. Non REM 3 and Non REM 4 is the deep sleep period. REM sleep is the active period of sleep marked as intense brain activity. This is the phase of dreaming.

In order to facilitate the research, Non REM 1 and 2 are defined into shallow stage and Non REM 3 and 4 are defined into deep stage. Then, we divide the sleep quality into four stages (awake, REM, shallow, deep). This classification method is widely used in the research of sleep evaluation and market products.

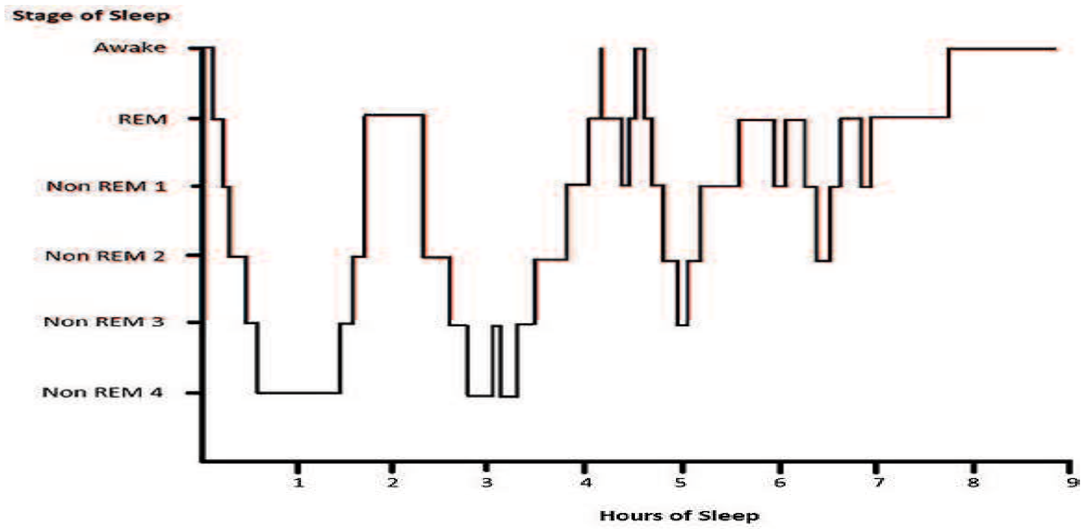


Fig. 1. Sleep cycles in 9 hours of sleep.

3.3 Breath sound signals analysis Methods

Example waveform of exhale and inhale in sleeping condition is shown in Fig. 2. Example of apnea in sleeping condition is shown in Fig. 3. All signal pre-processing, time-frequency analyses and data visualizations described throughout this study were performed using custom code written in MATLAB (Mathworks Inc., MA, USA).

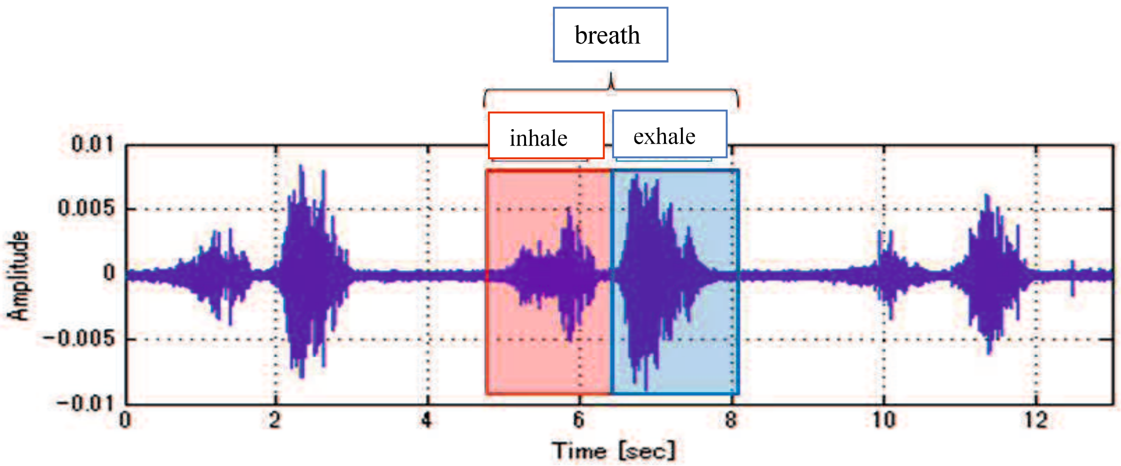


Fig. 2. Example waveform of exhale and inhale in sleeping condition.

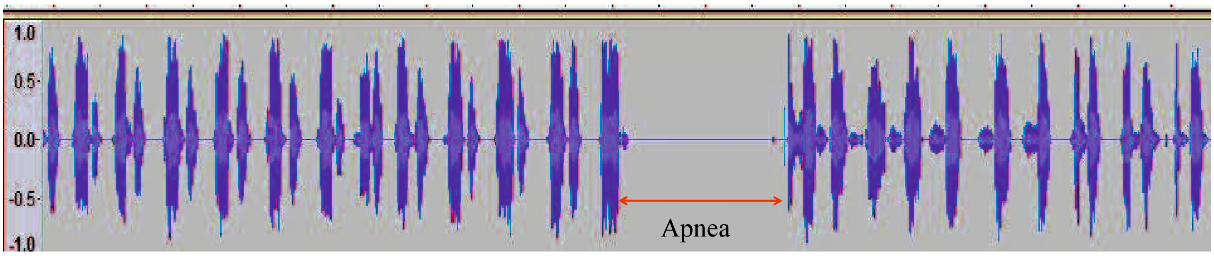


Fig. 3. Example of apnea in sleeping condition.

3.3.1 Signal preprocessing

In this chapter, the original breath sound signal x(t) is recorded by sleeping condition monitoring system and with 20kHz or 40kHz sampling frequency. Every area where the subject is sleeping and where is being recorded is typically full of noise and other interfering signals. These signals need to be filtered out in order to ensure the necessary signal quality for further REM/NREM stage signals analysis and detection. A FIR noise cancelation filter is used in this algorithm. In this case, FIR filter library functions are used to filter out environmental noises. The LMS (Least Mean Squares) method is used to adapt filter coefficients recursively. This method is one of the most favored coefficient adaptation method for its simplicity and steep descent. Equations (1) describing the adaptive general transversal filter are shown below. The filter equation is supplemented with an LMS algorithm update step Δ(n) describing the adaptation rate of a filter. Example of used FIR filter window function is shown in Fig. 4.

$$
\begin{aligned}
\mathrm{y}(n) &= d(n) - w^{T}(n-1)u(n) \\
w(n) &= w(n-1) + \Delta(n)y(n) \\
\Delta(n) &= \mu u(n)
\end{aligned}
\tag{1}
$$

The spectrum of frequencies below 72 Hz and above 1378 Hz are not desired as they do not contain any valid information for us, thus they are filtered out.

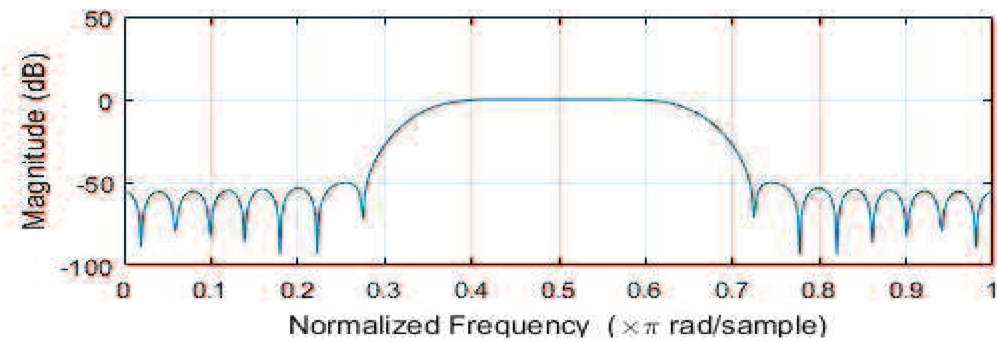


Fig. 4. Example of used FIR filter window function.

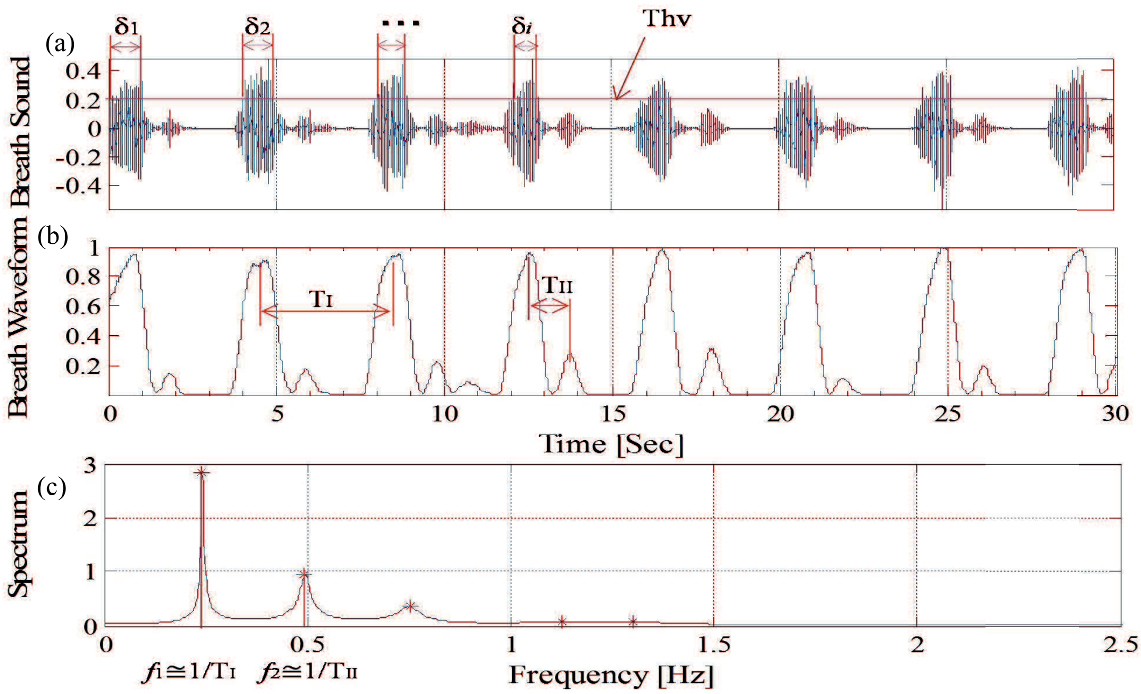


Fig. 5. Concept of analysis methods for sleeping condition estimation.

3.3.2 Envelop waveform extraction

Concept of analysis methods for sleeping condition estimation is shown in Fig. 5. The resultant signals can be expressed as s(t). We set a signal s(t), the random noise signal as n(t), and the output signal as x(t)=s(t)+n(t), and x(t) is showed in Fig. 5(a). It is easy to express their variances by $\sigma^2(x)=\sigma^2(s)+\sigma^2(n)$, Where σ(·) denotes as the variance of a signal. The output signal $\sigma^2(s)$ is defined as envelope waveform of breath sound signal, here we assume $\sigma^2(n)$ is only an unknown constant, and the mean is 0, and variance is 1. Therefore, output signal can be viewed as $\sigma^2(x)$. The envelop waveform of the breath sound signal is denoted as e(t,σ), which is defined as the variance signal of actual output signal x(t) and expressed as $e(t,\sigma)=\sigma^2(x)$, Where δ is neighborhood of time t, called the width δ time scale [8], and then

$$\mathrm{e}(t,\delta)=\int_{t-\delta}^{t+\delta}(x(\tau)-\bar{x}(t))^2\,d\tau \tag{2}$$

$$\bar{\mathrm{x}}(\mathrm{t})=\frac{1}{2\delta}\int_{t-\delta}^{t+\delta}x(\tau)d\tau \tag{3}$$

Therefore , e(t, δ) can be computed by

$$\mathrm{e}(t,\delta)=\int_{t-\delta}^{t+\delta}(x(\tau))^2\,d\tau-2\delta(\bar{x}(t))^2 \tag{4}$$

And the envelop waveform of the breath sound signal is showed in Fig. 5(b).

3.4 Breath characteristic parameters

Fig. 6 shows breath characteristic parameters for sleeping condition estimation. Breath characteristic parameters consist of four parameters as follows:

1) Breath peak:

Breath sound peak amplitude is calculated by equation(5),

$$\mathrm{Pk}=\frac{1}{100}\sum \mathrm{e}(t,\delta)_{\max}(1:100) \tag{5}$$

where Pk is breath sound peak amplitude, t is 10s, window is 10s and movement speed is 5s, $\sum \mathrm{e}(t,\delta)_{\max}(1:100)$ is the sum of 100 points of maxim amplitude in a time of window.

2) Breath snore:

Breath sound events are classified two parts. The one is normal breath in sleep, the other is abnormal breath including snore, apnea. Breath sound events are automatically detected and segmented using an adaptive amplitude threshold. The schematic FFT drawing of normal breath shown in Fig. 7 and snore state shown in Fig. 8, then we can get snore frequency is located in the peak of spectrum between 100-200 Hz frequency band. Then, signals applied band pass filter between in 100-200 Hz and calculated by equation(5), the result we defined SnoreV.

3) Respiratory variance:

Respiratory variance is correlation to snore. Respiratory variance is calculated by equation (6),

$$\mathrm{RespVar}=\frac{1}{10}P \tag{6}$$

where RespVar is denoting respiratory variance value, P is the amount of points which amplitude is five multiple of the mean value of feature waveform amplitude in 10s. Less RespVar value connect with snore, awakening and apnea, normal value is the state of normal respiratory.

4) Respiratory period:

Respiratory period value is defined Resp which is correlating with the time of expiration and inspiration. Applying FFT to breath sound signal waveform e(t, δ) in 10 s, defined the reciprocal of peak frequency band is respiratory period that is shown in Fig. 2(c). Respiratory variance is calculated by equation (7),

$$\mathrm{Resp} = 1/f \tag{7}$$

Due to sleep cycle in NREM is more steady than REM, we could conclude that larger amplitude variance band of respiratory period is REM, smooth and steady band is NREM. Example of respiratory period is shown in Fig. 9.

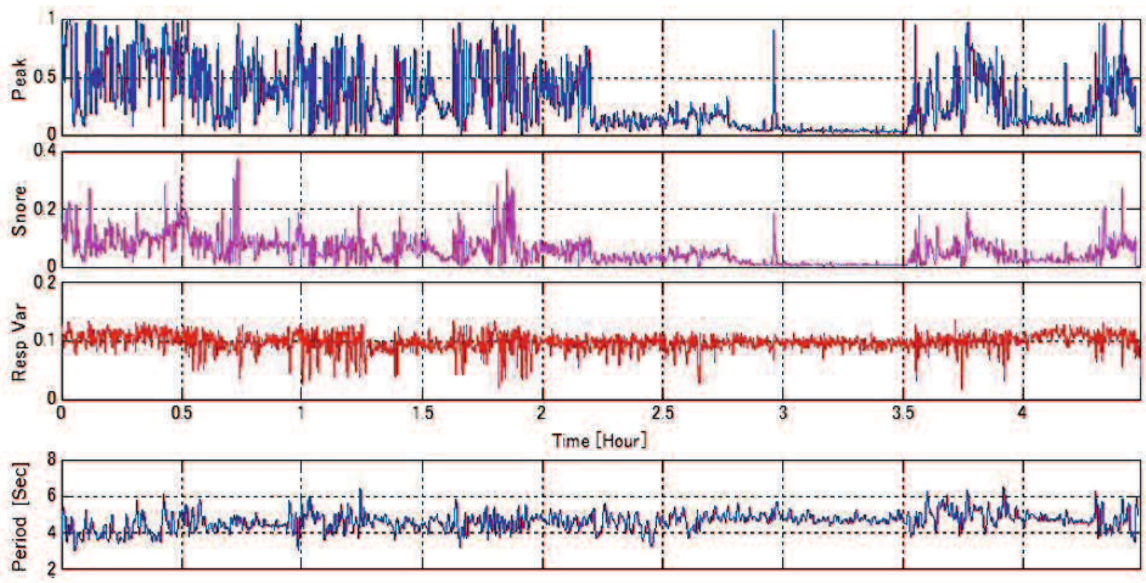


Fig. 6. Breath characteristic parameters for sleeping condition estimation.

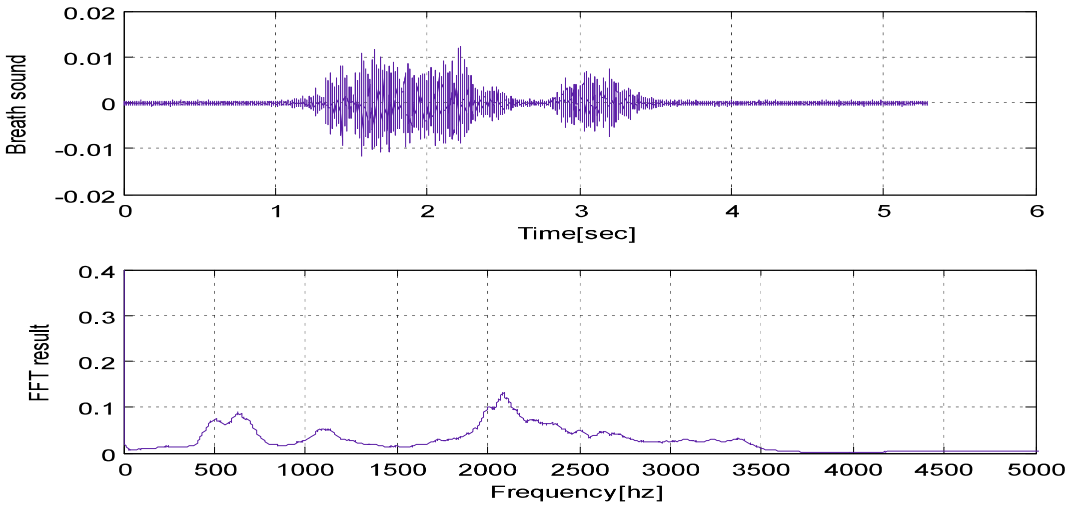


Fig. 7. FFT of normal breath.

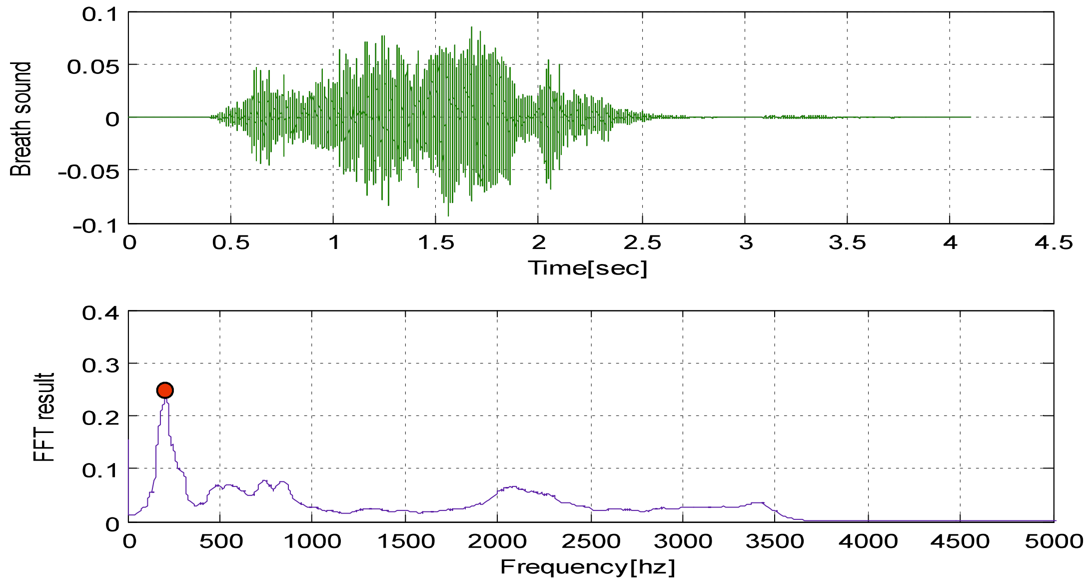


Fig. 8. FFT of snore state (red points are the location of snore event).

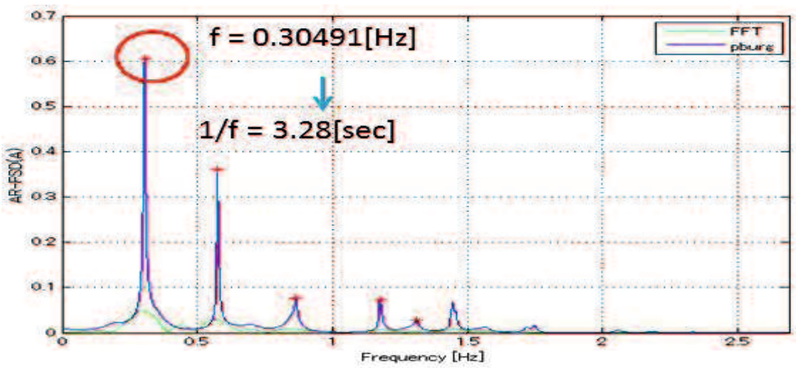


Fig. 9. Example of respiratory period.

3.5 Sleep stage analysis algorithm

This section describes the algorithm used to classify sleep stage. Data used for this algorithm are breath characteristic parameters described in Section 3.3. In order to get the degree of breath, then get a new characteristic parameter RespR. Example of RespR curve is shown in Fig. 10. Times of breath in one minute defined RespR is calculated by equation(8),

$$\mathrm{RespR} = 60/\mathrm{Resp} \tag{8}$$

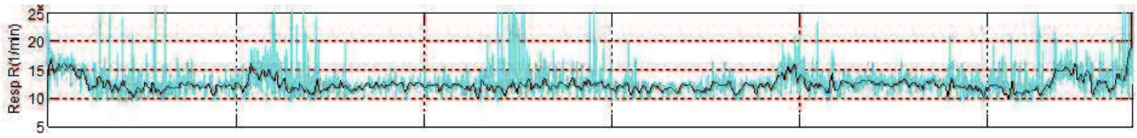


Fig. 10. Example of RespR.

Compared breath waveform and breath characteristic parameters, in additional empirical testing on several subjects results, we can conclude that low RespR value and smooth RespVar mean deep sleep stage. More RespR value and more variance of RespVar value infer to wake. At the same time, more Pk (breath sound peak amplitude) mean wake and steady Pk value is deep stage. Example classification awakening and deep sleep based on RespR and RespVar is shown in Fig. 11 and Fig. 12. If RespR value is lower than threshold and RespVar value is less variance, the stage conclude deep sleep. On the contrary, we can define wake. Because of REM is close to shallow sleep, accurately, REM is rapid eye movement, so is very difficult to divide into REM and shallow sleep, whether our or other commercial product (SleepScan), so we can define by life experience. In a word, sleep state in all-night can be descried by breath characteristic parameters. For the sake of accuracy, stage value is calculated by equation(9),

$$\mathrm{STG} = \alpha_1 * Pk + \alpha_2 * \mathrm{Re}sp + \alpha_3 * \mathrm{RespVar} \tag{9}$$

The initial value of (α_1, α_2, α_3) are defined by comparing sleep stage measured by SleepScan.

3.6 Experiments

In order to get the initial value of (α_1, α_2, α_3) which defined by comparing sleep stage measured by SleepScan. According to the empirical testing on several selected subjects results, we defined (α_1, α_2, α_3) is (0.04, 0.65, 0.01), value of STG are expressing deep sleep (STG <=1.45), wake (STG >=3.8), REM (STG >2.8 & STG <3.8), shallow sleep (STG >1.45 & STG <2.8). At the same time, applied same (α_1, α_2, α_3) parameters to all data for one subject. For the apply proposed method, we took experiments to a subject used our proposed sleeping condition monitoring system and measured by SleepScan, simultaneously. All-night sleep stage evaluated by our algorithm and all-night sleep stage measured by SleepScan are shown from Fig. 13 to Fig. 22.

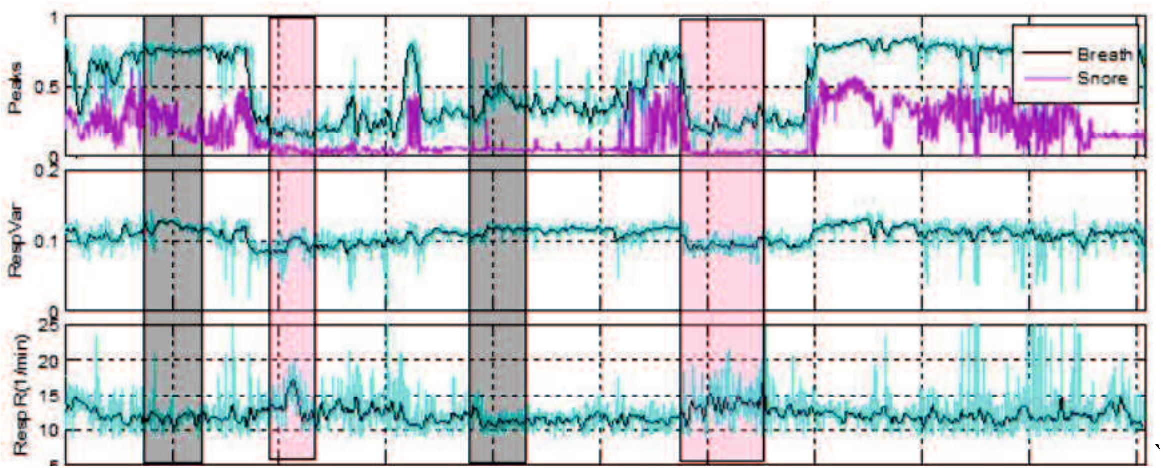


Fig. 11. Example classification awake and deep sleep based on RespR and RespVar (red parts are awake, black parts are deep sleep).

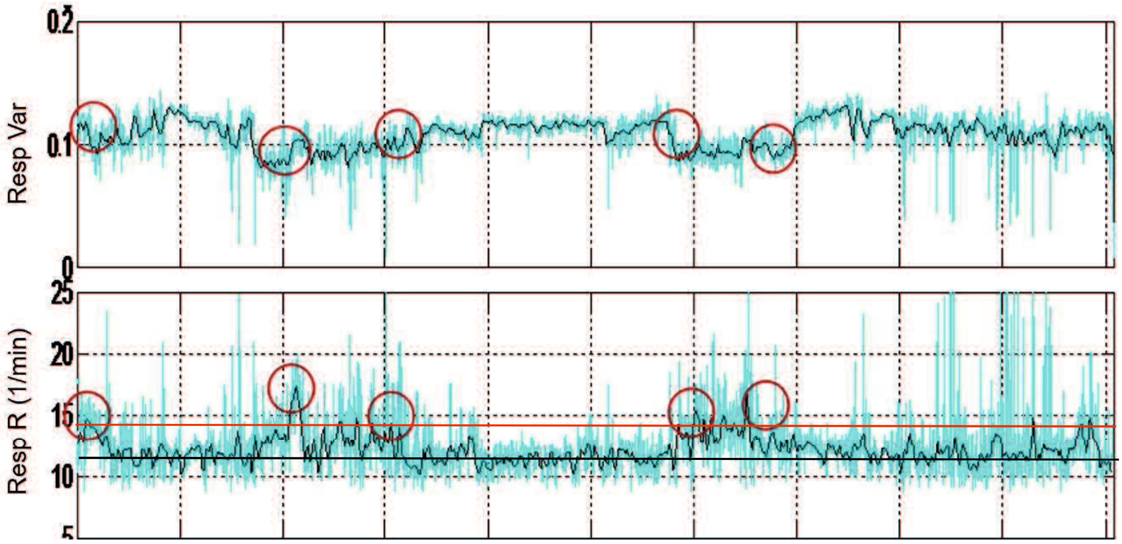


Fig. 12. Example of RespR value threshold for deep sleep and awake classification (higher than red line are wake, lower than black line are deep stages), strong variance of RespVar value indicate awake (red circles).

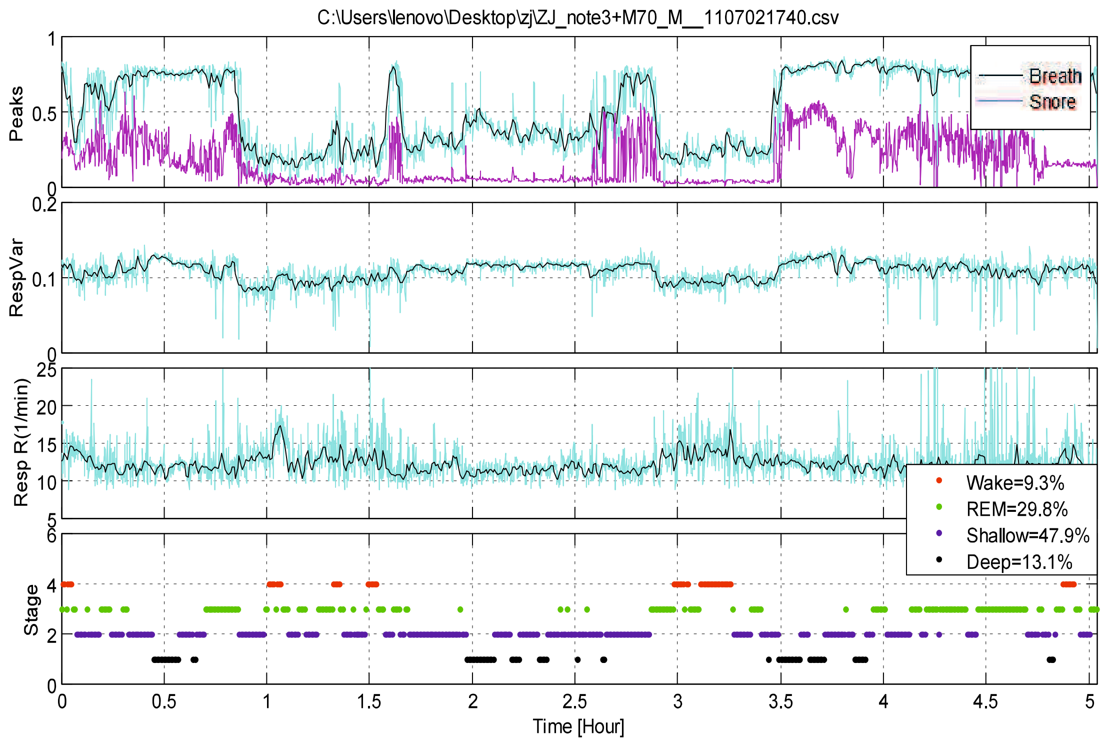


Fig. 13. All-night sleep stage evaluated by our algorithm(date 1107).

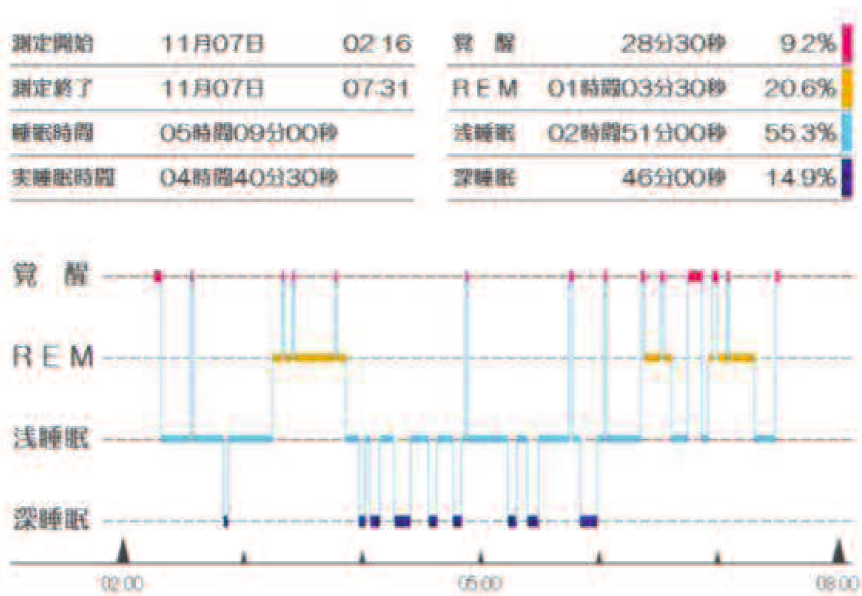


Fig. 14. All-night sleep stage measured by SleepScan(date 1107).

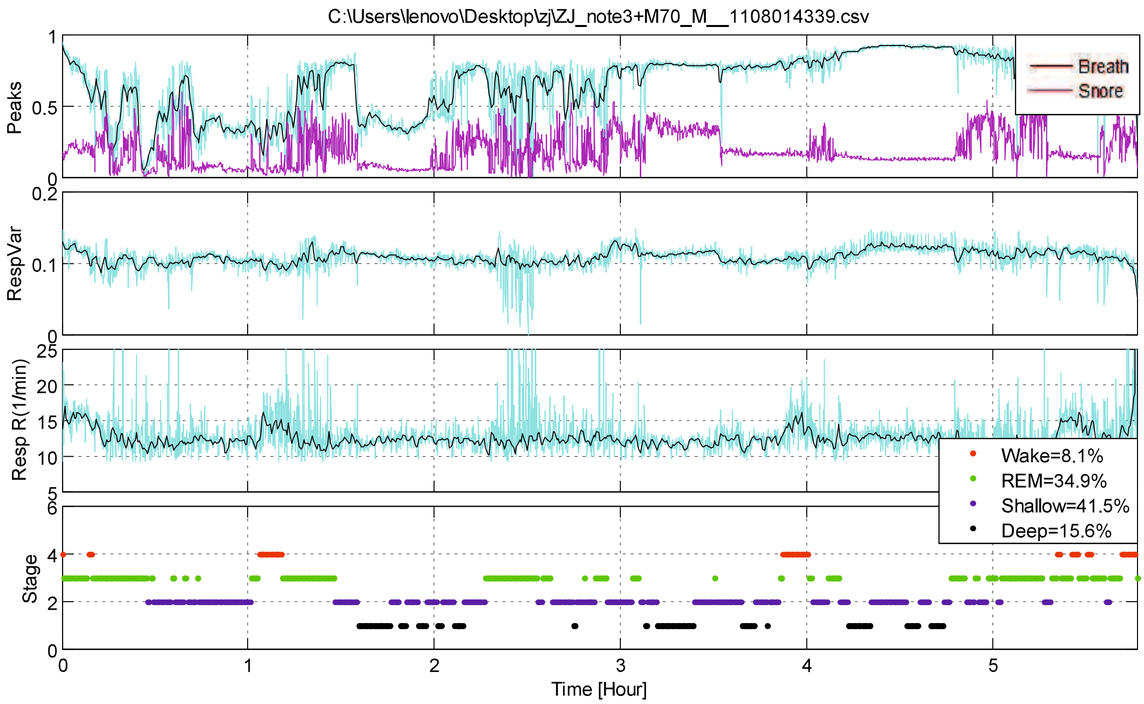


Fig. 15. All-night sleep stage evaluated by our algorithm(date 1108).

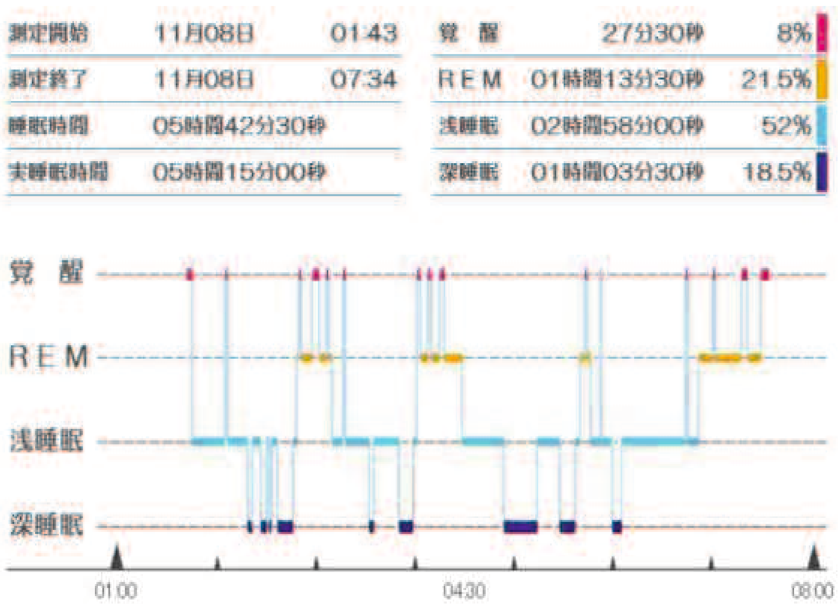


Fig. 16. All-night sleep stage measured by SleepScan(date 1108).

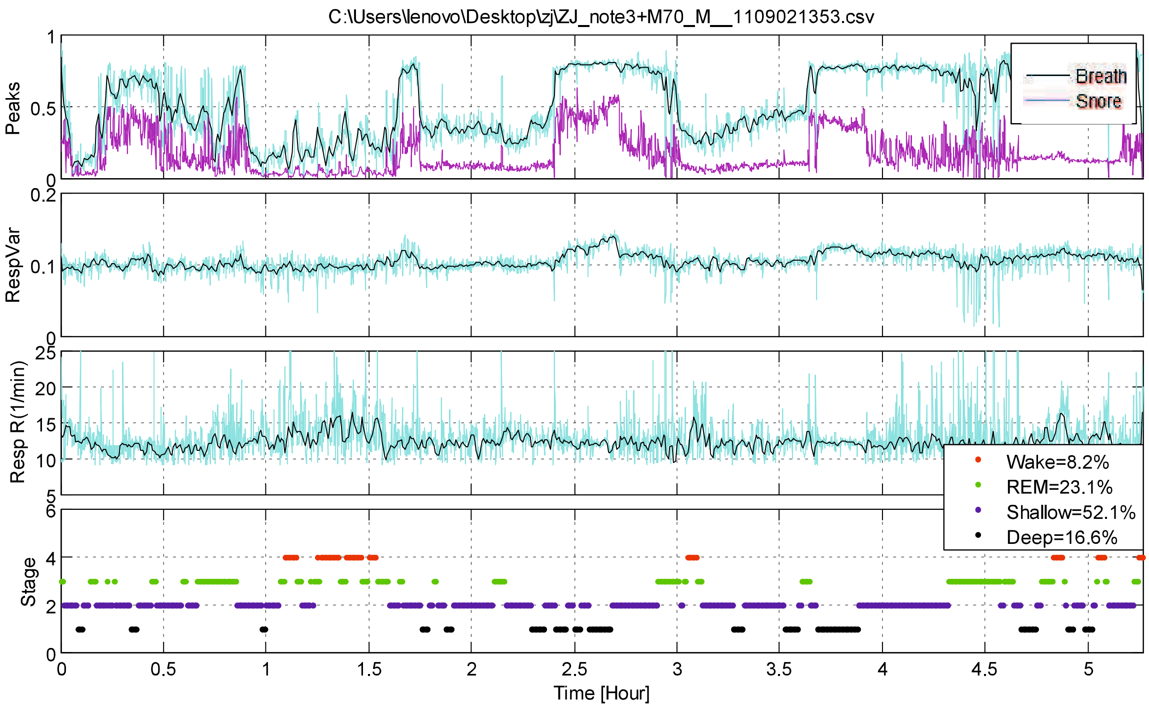


Fig. 17. All-night sleep stage evaluated by our algorithm(date 1109).

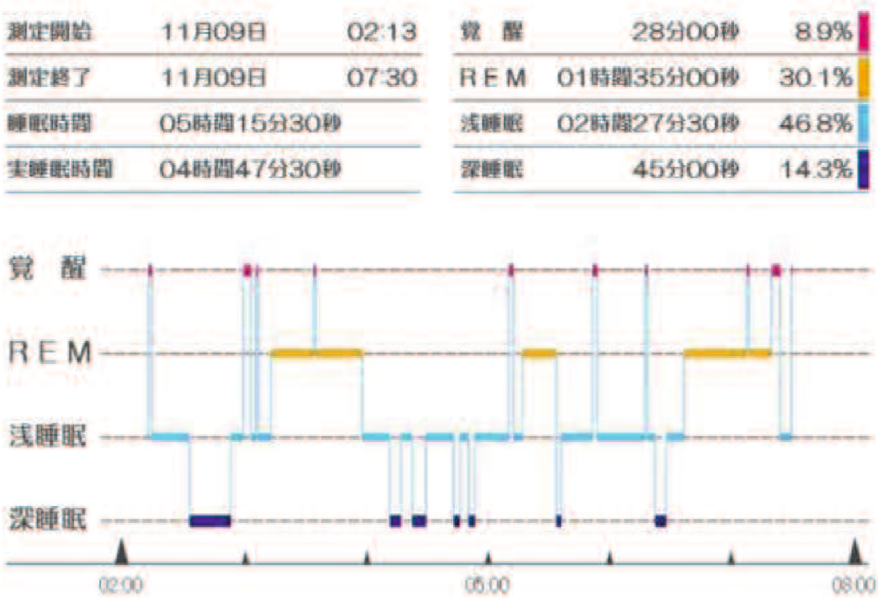


Fig. 18. All-night sleep stage measured by SleepScan(date 1109).

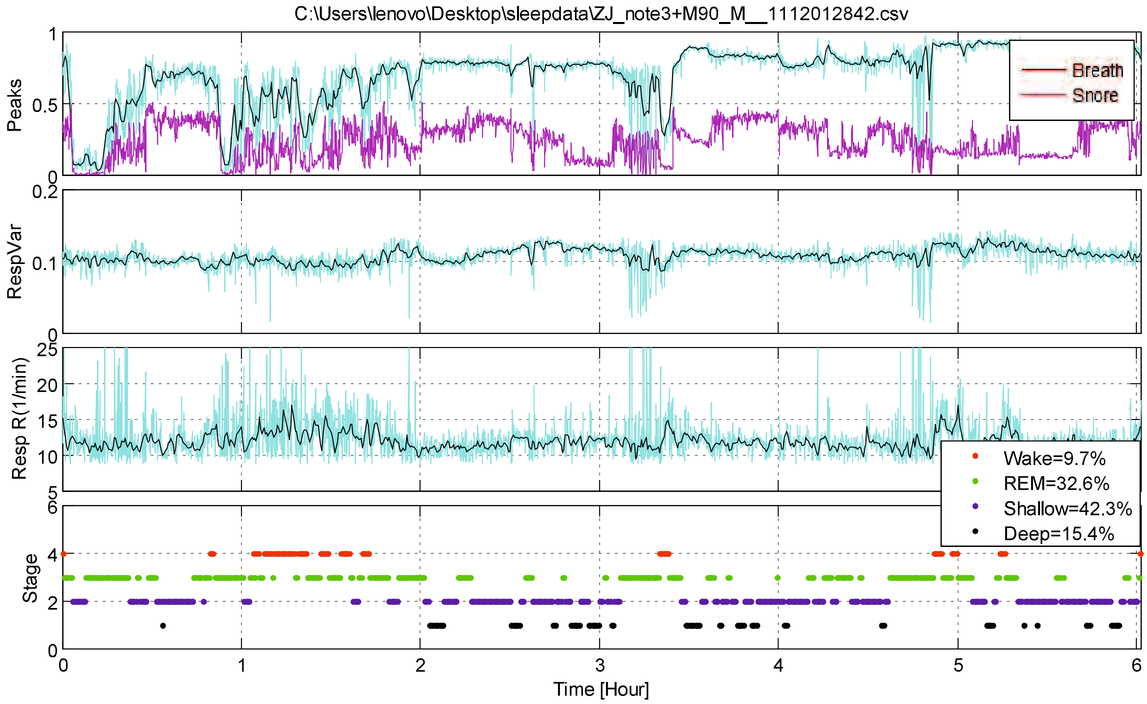


Fig. 19. All-night sleep stage evaluated by our algorithm(date 1112).

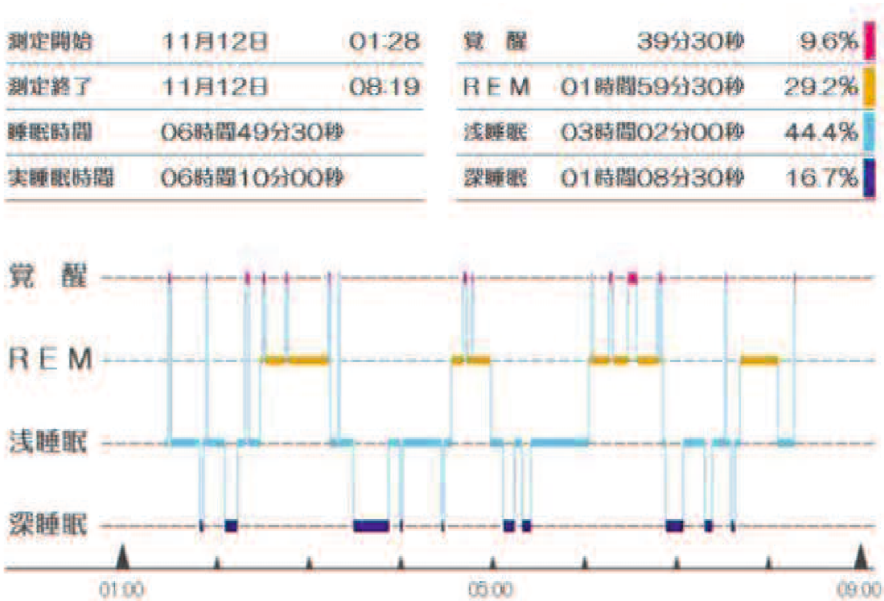


Fig. 20. All-night sleep stage measured by SleepScan(date 1112).

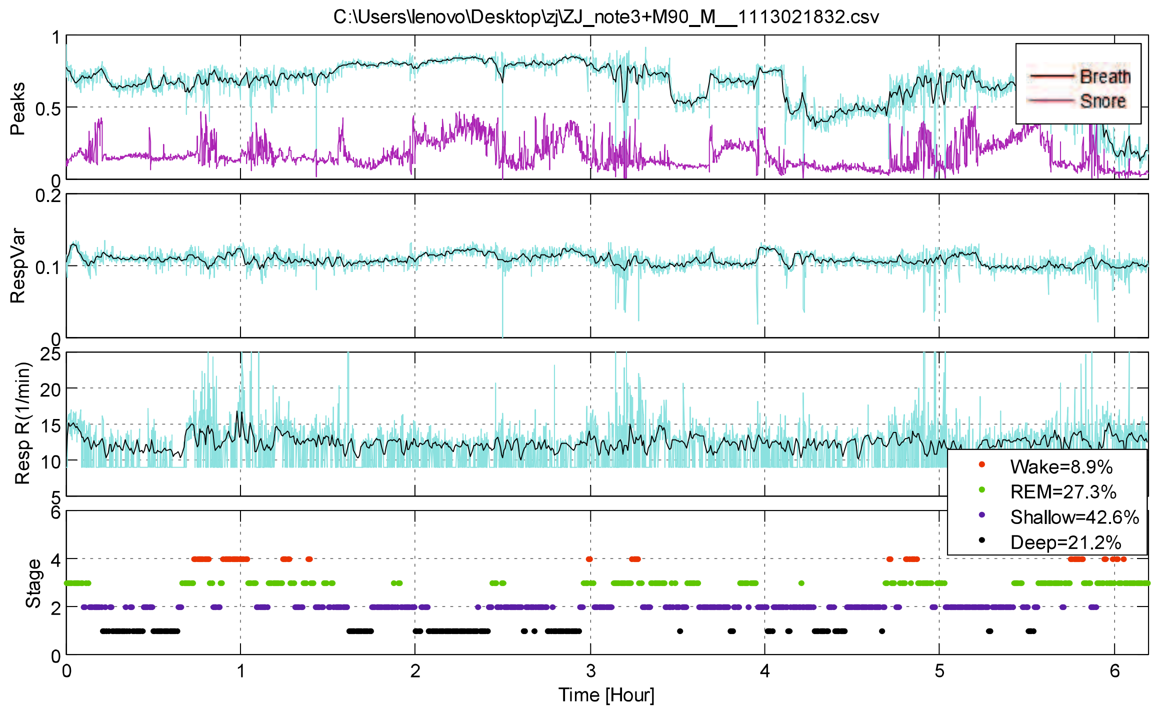


Fig. 21. All-night sleep stage evaluated by our algorithm(date 1113).

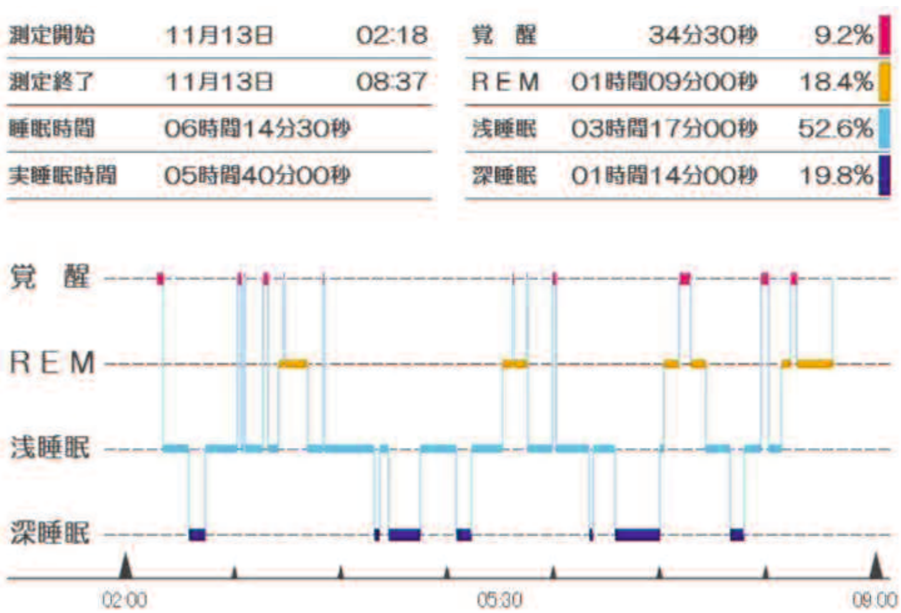


Fig. 22. All-night sleep stage measured by SleepScan(date 1113).

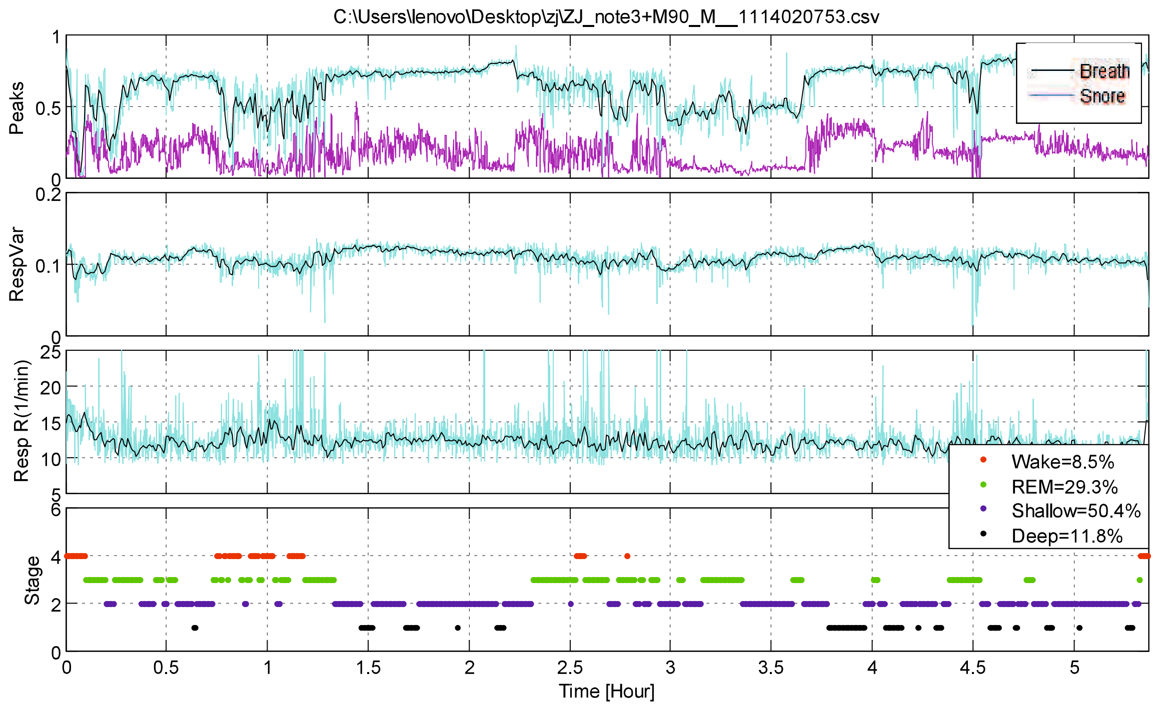


Fig. 23. All-night sleep stage evaluated by our algorithm(date 1114).

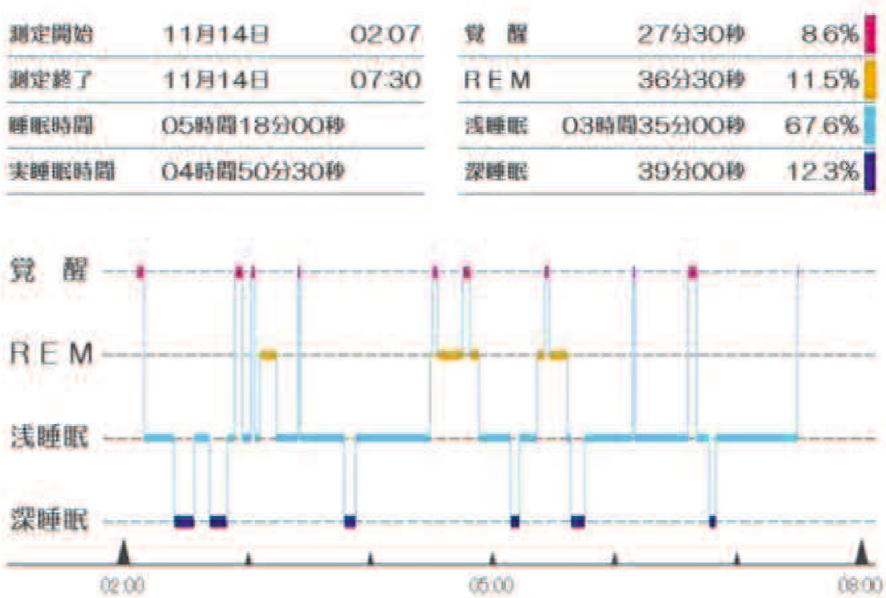


Fig. 24. All-night sleep stage measured by SleepScan(date 1114).

3.7 Results

In order to evaluate the performance of our algorithm, Table 2 is shown the performance results of our method. Table 3 is shown the performance results of measured by SleepScan. The result is the percentage of each stage in all-night time.

Table 2. The performance results of our method.

Date (month/day)	Wake (%)	REM and Shallow (%)		Deep (%)
11/07	9.3	29.8	47.9	13.1
11/08	8.1	34.9	41.5	15.6
11/09	8.2	23.1	52.1	16.6
11/12	9.7	32.6	42.3	15.4
11/13	8.9	27.3	42.6	21.2
11/14	8.5	29.3	50.4	11.8

Table 3. The performance results measured by SleepScan.

Date (month/day)	Wake (%)	REM and Shallow (%)		Deep (%)
11/07	9.2	20.6	55.3	14.9
11/08	8	21.5	52	18.5
11/09	8.9	30.1	46.8	14.3
11/12	9.6	29.2	44.4	16.7
11/13	9.2	18.4	52.6	19.8
11/14	8.6	11.5	67.6	12.3

Due to REM is the state of rapid eyes movement, and SleepScan is measured by vibration sensor, it is very difficult to divide REM to shallow exactly except using PSG. So, combined REM and shallow, we can get the Table 4 and Table 5 which are combing REM and shallow based on Table 2 and Table 3, respectively.

Table 4. The performance results of our method (combined REM and shallow).

Date (month/day)	Wake (%)	REM and Shallow (%)	Deep (%)
11/07	9.3	77.6	13.1
11/08	8.1	76.3	15.6
11/09	8.2	75.2	16.6
11/12	9.7	74.9	15.4
11/13	8.9	69.9	21.2
11/14	8.5	79.7	11.8

Table 5. The performance results measured by SleepScan (combined REM and shallow).

Date (month/day)	Wake (%)	REM and Shallow (%)	Deep (%)
11/07	9.2	75.9	14.9
11/08	8	73.5	18.5
11/09	8.9	76.9	14.3
11/12	9.6	73.6	16.7
11/13	9.2	71	19.8
11/14	8.6	79.1	12.3

Our algorithm reliability with SleepScan was assessed by the detection error rate D_e as follows:

$$D_e = \frac{\mathrm{OV-SV}}{\mathrm{SV}} * 100\% \qquad (17)$$

Where OV is the value of our method detections, SV is the value of SleepScan detections, used in the tables 3 and 4. The detection error D_e expresses the accuracy of the algorithm compared with SleepScan.

Table 6 shows the result of D_e.

Table 6. The results of D_e.

Date (month/day)	D_e(Wake) (%)	D_e(REM and shallow) (%)	D_e(Deep) (%)
11/07	1.08	2.24	12
11/08	1.25	3.8	20
11/09	-7.89	-2.21	16
11/12	1.04	1.76	-7.78
11/13	-3.26	-1.97	7.07
11/14	-1.16	0.76	-4.07

3.8 Discussion

We have developed an algorithm for a wearable breath detect system made previously in our laboratory. The algorithm was implemented in Matlab 7.1. We can find our method have a good performance comparing with SleepScan. The maker of SleepScan said, the accuracy is about 83% compared with the polysomnography (PSG). We can compare them with breath sound waveform. All-night sleeping conditions measured by SleepScan is shown in Fig. 25 and the typical sleeping breath sound waveforms is depicted in Fig. 26 simultaneously. In Fig. 25, the period of ① is awakening, ②③④⑥ are shallow sleep, ⑦ is REM, ⑤⑧ are the state of deep sleep.

Based on the previous research content, compared Fig. 25 and Fig. 26, ① should be shallow when we stay 30 min in bed according to our life experience, Fig. 26 is right. It's obvious that ③ is deep sleep due to breath sound waveforms is smooth and evenly in Fig. 26, but Fig. 25 is representing shallow sleep. In Fig. 26, the period of ⑥ don't have breath sound waveform, we can define apnea is appear in this time. Fig. 25 and Fig. 26 have same sleeping conditions in the period of ②④⑤⑦⑧. We can conclude that SleepScan is not completely accurate.

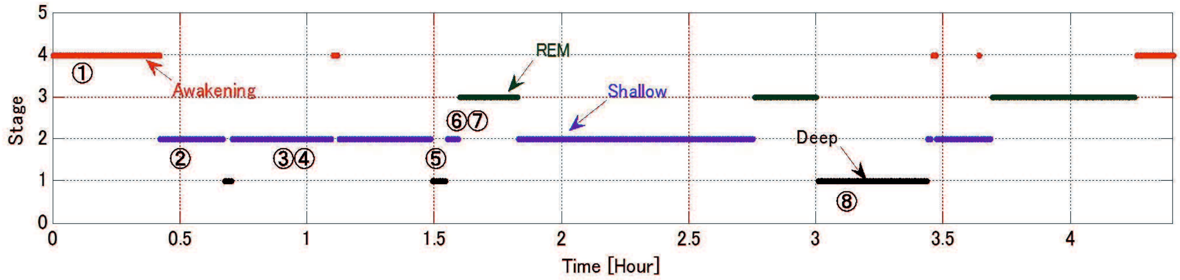


Fig. 25. All-night sleep stage measured by SleepScan (TANITA SL-503).

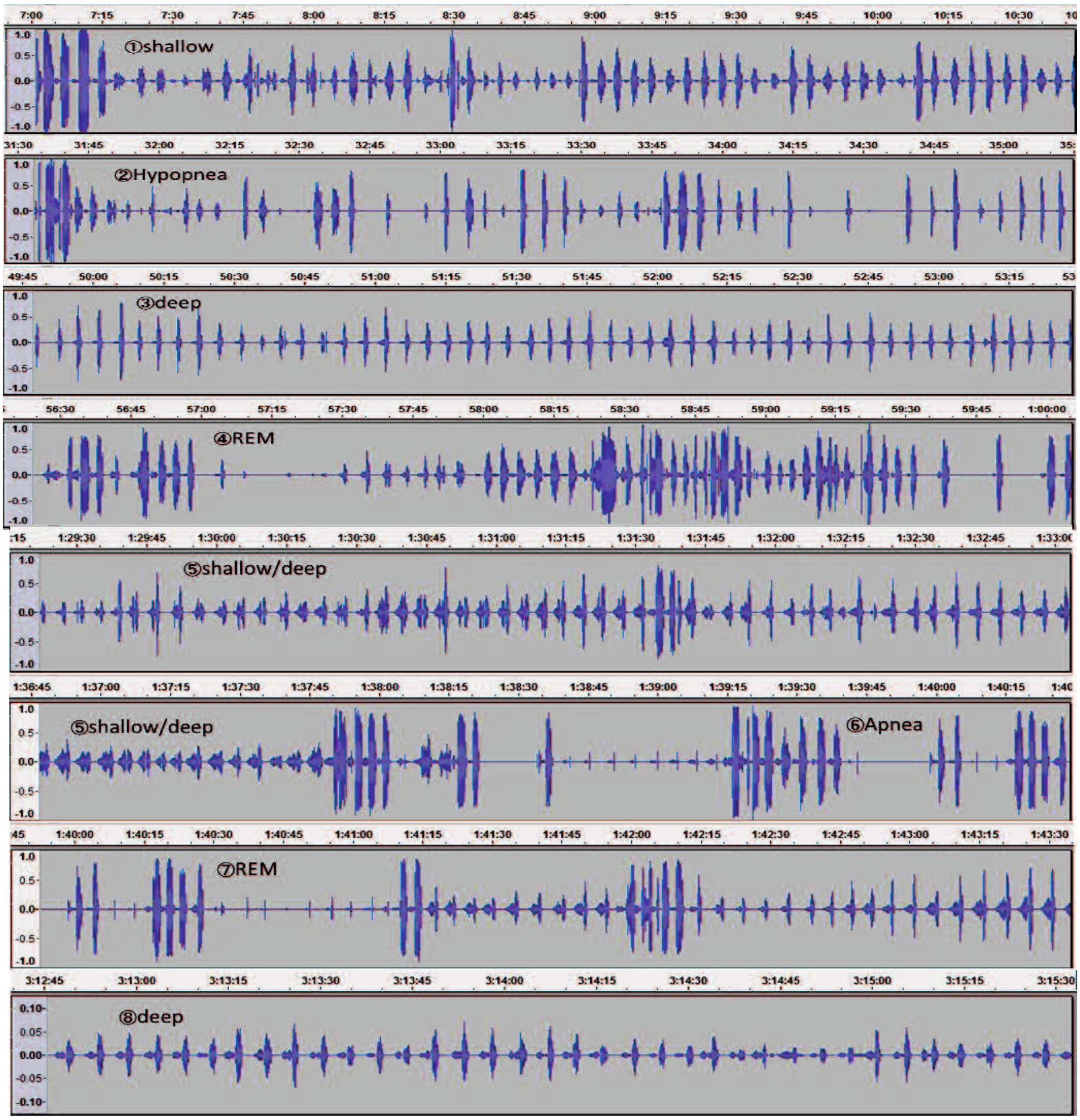


Fig. 26. Typical sleeping breath sound waveforms.

3.9 Summary

In this chapter, the algorithm combining extracting breath sound characteristic parameters features was developed. The algorithm's performance was evaluated both for 6 all-nights total about 35 hours data acquired using our self-made system and SleepScan. The sleeping condition discrimination was fulfilled by a classification method where several features are extracted from the breath characteristic parameters which are used in the next chapter for building sleeping condition database.

On the other hand, we notice that the main purpose of this chapter which is the sleep stages estimation was accurately done. Actually we can see from the detailed results in Table 6 that the low value detection error De expresses the accuracy of the algorithm compared with SleepScan have a good performance.

3.10 References

[1] Y Luo, Z Jiang, A simple method for monitoring sleeping conditions by all-night breath sound measurement, Journal of Interdisciplinary Mathematics 2017; 20(1): 307- 317.

[2] K. Šušmáková and A. Krakovská, Discrimination ability of individual measures used in sleep stages classification, Artificial Intelligence in Medicine 2008: 44(3): 261-277.

[3] S. Telser, M. Staudacher, Y. Ploner, A. Amann, H. Hinterhuber and M. Ritsch-Marte, Can one detect sleep stage transitions for on-line sleep scoring by monitoring the heart rate variability?, Somnologie 2004; 8(2): 33-41.

[4] S. Telser, M. Staudacher, B. Henning, Y. Ploner, A. Amann, H. Hinterhuber and M. Ritsch-Marte, Temporally resolved fluctuation analysis of sleep ECG, Journal of Biological Physics 2007; 33(1): 19-33.

[5] M. Staudacher, S. Telser, A. Amann, H. Hinterhuber and M. Ritsch-Marte, A new method for change-point detection developed for on-line analysis of the heart beat variability during sleep, Physica A 2005; 349(3-4): 582-596.

[6] A. Bunde, S. Havlin, J.W. Kantelhardt, T. Penzel, J-H. Peter and K. Voigt, Correlated and uncorrelated regions in heart-rate fluctuations during sleep, Physical Review Letters 2000; 85(17) 3736-3739.

[7] S.J. Redmond and C. Heneghan, Cardiorespiratory-based sleep staging in subjects with obstructive sleep apnea, IEEE Transactions on Biomedical Engineering 2006; 53(3): 485-496.

[8] T. Penzel, J.W. kantelhardt, L. Grote, J-H. Peter and A. Bunde, Comparison of detrended fluctuation analysis and spectral analysis for heart rate variability in sleep and sleep apnea, IEEE Transactions on biomedical engineering 2003; 50(10): 1143-1151.

[9] A. Bunde, S. Havlin, J.W. Kantelhardt, T. Penzel, J-H. Peter and K. Voigt, Correlated and uncorrelated regions in heart-rate fluctuations during sleep, Physical Review Letters 2000; 85(17) 3736-3739.

[10] Zoubek, L.; Charbonnier, S.; Lesecq, S.; Buguet, A.; Chapotot, F. Feature selection for sleep/wake stages classification using data driven methods. J. Biomed. Signal Process. 2007, 2, 171-179.

[11] Fuller, P.M.; Gooley, J.J.; Saper, C.B. Neurobiology of the sleep-wake cycle: Sleep architecture, circadian regulation, and regulatory feedback. J. Biol Rhythm 2006, 21, 482-493.

[12] Rechtschaffen, A. Current perspectives on the function of sleep. J. Perspect. Biol. Med. 1998, 41, 359-390.

[13] HappyWakeUp Smart Alarm Clock Application for Nokia Mobile Phones. 2010. Available online: http://www.happywakeup.com/en/ (accessed on 31 May 2011).

[14] Scholle, S.; Schäfer, T. Atlas of states of sleep and wakefulness in infants and children. Somnologie 1999, 3, 163-241.

[15] Stoohs, R.; Guilleminault, C. Snoring during NREM sleep: Respiratory timing, esophageal pressure and EEG arousal. Respir. Physiol. 1991, 85, 151-157.

[16] OpenSource.NET Projects 2002–2010. Math.NET Documentation. Available online: http://mathnet.opensourcedotnet.info/doc/ (accessed on 31 May 2011).

[17] Microsoft Developer Network MSDN. Microsoft 1985–2010. Available online: http://msdn.microsoft.com/ (accessed on 31 May 2011).

[18] Comon, P.; Pham, D.T. Estimating the order of a FIR filter for noise cancellation. IEEE Trans. Inform. Theory 1990, 36, 429-434.

[19] Widrow, B.; Stearns, S.D. Adaptive Signal Processing; Prentice-Hall Inc.: Englewood Cliffs, NJ, USA, 1985.

[20] Recording and Playing Sound with the Waveform Audio Interface. Seth Demsey-Microsoft January 2004. Available online: http://msdn.microsoft.com/en us/library/aa446573.aspx (accessed on 31 May 2011).

[21] Penhaker, M.; Cerny, M.; Martinak, L.; Spisak, J.; Valkova, A. Home Care-Smart embedded biotelemetry system. IFMBE Proc. 2006, 14, 711-714.

[22] Krejcar, O.; Jirka, J.; Janckulik, D. Proactive User Adaptive System for Windows Mobile Devices—Processing of Sound Input Signal for Sleep State Detection. In Proceedings of 2nd International Conference on Mechanical and Electronics Engineering (ICMEE), Kyoto, Japan, 1-3 August 2010; Volume 1, pp. 374-378.

[23] Krejcar, O. Problem solving of low data throughput on mobile devices by artefacts prebuffering. EURASIP J. Wirel. Comm. 2009, ID 802523.

[24] Krejcar, O.; Janckulik, D.; Motalova, L.; Kufel, J. Mobile monitoring stations and web visualization of biotelemetric system—Guardian II. LNICST 2009, 16, 284-291.

Chapter 4

Automatic classifier system by SVM method

4.1 Introduction

In clinical routine, sleep studies are usually performed for the diagnosis of pathologies, such as insomnia, hypersomnia, circadian rhythm disorders, sleep apnea and so on. Sleep scoring often relies on visual analysis of the recordings to establish a hypnogram that depicts in time the different sleep stages.The analysis generally follows established guidelines for sleep stage classification, such as the ones introduced by [1] , where each segment of 30-s is labeled as wake, S1–S4 or REM. A more recent classification manual proposed by the American Academy of Sleep Medicine (AASM) in 2007 [2], combines the non-REM stages S3 and S4 into a single stage of deep sleep (called N3), also known as slow-wave sleep (SWS).

While visual scoring remains the gold-standard, recent years have witnessed a surge in method developments for automatic or semi-automatic sleep staging [3-5]. Although these results obtained so far are promising, there is still room and a need for improvement, especially given the time-consuming and tedious nature of visual sleep scoring. Across existing methods, a wide range of physiological signatures, or features, have been extracted from polysomnographic (PSG) signals, including time-domain, frequency-domain and time–frequency-domain features, and both linear and nonlinear features have been explored. While some studies rely only on one or two features to perform sleep stage classification [6], several studies provide evidence for the utility of searching for an optimum combination of features

[7]. Beyond the specific electrophysiological features used, existing methods also differ in the type of classification framework used. Some machine learning techniques such as artificial neural networks have been widely used for sleep staging [8-9]. A disadvantage of this method is the fact that the exact decision procedure remains hidden or implicit. Classification methods based on Bayesian probability (linear and quadratic discrimination, knearest neighbour), have also been used in sleep scoring[10]. The requirement of a Gaussian distribution of data in these methods can sometimes be a limitation. Other approaches for automatic sleep scoring based on mathematical modeling and hidden Markov Models have also been proposed [11]. Support vector machines (SVM) classification has also been used for sleep scoring [12]. Support vector machines, introduced in the early 90s [13] are used in a wide range of learning problems such as pattern recognition, text categorization and medical diagnosis and they continue to draw a lot of attention in many fields including basic and clinical neuroscience.

In this chapter, a classification for sleeping conditions database exposing in this section based on SVM technique is proposed to be used as the classifier to discriminate different sleep stages. As shown by experience of life, everyone has different sleep habit, the use of subject-independent system does not give good results for the sleep stages classification, because inter-individuals physiologies are so different and with less correlation ship to each other. Therefore, in this study we restrict the target to the use of subject-specific system. Support vector machine (SVM) training and classifying algorithms are applied to the sleeping database exposing in this section. A feature selection method known as SVM recursive features elimination (SVM-RFE) method is applied to the initially extracted 6 features. The sensitivity Se is estimated using classification results and the positive predictivity P+ is calculated and the set of best features ranking obtained using the SVM-RFE method. The mean classification accuracy is also calculated. At last, the predicting sleep stages using sleep database have a good performance.

4.2 Methods

The sleep stages classification process, as shown in Fig. 1, can be divided into two parts, the features extraction part and the classification part. In the extraction part, the breath sound is processed in order to obtain envelop waveform extraction, and then, features are extracted by our method which were proposed in chapter 3, so we built sleep stages database based on

SleepScan and our algorithm. The database is used as the training data and other input data is used as the testing data. In the classification part, the training data is used by the SVM system to find the optimum hyperplane separating sleep stages. Then, the separating hyperplane is applied to the testing data to obtain the classification. Then, the classifier system have functions for predicting and assessing sleeping conditions.

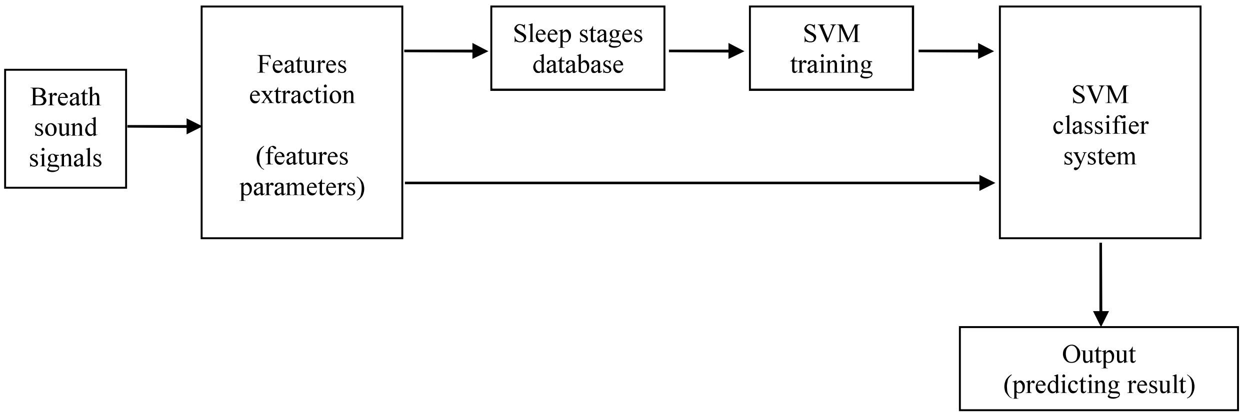


Fig. 1. Block diagram of sleep stages classification algorithm based on SVM..

4.2.1 Features extraction methods

In this work, 6 features are considered to be used for the evaluation of sleep stages. The sleep stages are defined every 30-s, as same as SleepScan which measured data every 30-s one time. Then, for every epoch time of 30-s length, 6 features are extracted. We try to summarize and find patterns by statistical analysis methods in the algorithm about these breath characteristic parameters. So we introduce three new parameters which are the mean and deviation of breath characteristic parameters. Based on the breath characteristic parameters proposed in chapter 3, we used statistics method to get six key sleeping condition characteristic parameters for dividing shallow sleep and REM. Then, every epochs have 6 parameters and a number evaluating in chapter 3 by our algorithm which is expressing the sleep stage in this period. In addition, a feature selection method was used to rank the features and select the best ones. In the following details about the features and the methods used for their extraction are presented.

For every epoch, 6 features detailed is shown in Table 1, are associated. Usual methods of classification involve a training step and a testing (classification) step. According to this, two methods emerge, such as subject-specific scheme where the training and tested data are taken from the same subject and subject-independent scheme where the training and tested data are taken from different subjects. In this work, we restrict ourselves to subject-specific scheme. The motivations of this choice are detailed in the discussion section. A support vector machine (SVM) algorithm is used for the training and classification of data, in the following an overview of SVM technique and the algorithm used in this work.

Table 1. List and description of features.

Features	Description of the feature
1	Mean value of breath peak
2	Standard deviation of breath peak
3	Mean of respiratory variance
4	Standard deviation of respiratory variance
5	Mean value of breath period
6	Standard deviation of breath period

4.2.2 Sleep stages database

In this work, we built sleep stages database. Example of Chapter 3 evaluating sleeping condition result with 6 parameters is shown in Table 2, Stage is the sleep stage in this point, 4,3,2,1 are awakening, REM, shallow, deep, respectively. Time of in the list is 30-s length, one night have 700 points total 5 hours in generally. Example of SleepScan result with parameters is shown in Table 3.

Table 2. Example of our evaluating all-night sleeping condition result with 6 parameters.

Time	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Stage
0	0.78102	0.15637	0.10669	0.015887	4.513	1.8451	4
30	0.62938	0.22709	0.090352	0.012999	4.6504	1.4916	4
60	0.51713	0.23222	0.092998	0.014057	4.5564	1.2231	3
90	0.42102	0.13692	0.094797	0.0079846	4.1109	0.44379	2
120	0.4035	0.099802	0.095451	0.005979	4.1833	0.34316	2
150	0.2952	0.14303	0.094471	0.0062916	4.1764	0.37456	2
180	0.12711	0.11349	0.094481	0.0065576	4.5247	0.42693	2
210	0.069889	0.043949	0.098121	0.0051236	4.5684	0.30555	2
240	0.11408	0.053409	0.093131	0.0073686	4.5404	0.23436	2
270	0.11489	0.058731	0.092201	0.0095408	4.9123	0.67394	2
300	0.12047	0.069508	0.093071	0.011118	4.8557	1.0449	1
330	0.10826	0.059099	0.09153	0.00888	4.8954	0.8857	1
360	0.078367	0.017517	0.087938	0.010044	4.9873	0.38277	1
...	...	...	...	...	...	...	...

Table 3. Example of SleepScan all-night sleeping condition result with parameters.

Time	respiration	heart_rate	stddev	body_move ment	Stage
0	5	34	391.1	1	4
30	7.2	33.8	401.4	0	2
60	7.7	37	105.4	0	4
90	7.9	30.7	109.6	0	4
120	7.2	30.6	104	0	4
150	7	23	108.7	0	2
180	7.4	30.2	110.2	0	2
210	7	28.5	85	0	2
240	6.6	28.1	95.5	0	2
270	6.7	28.5	90.6	0	2
300	6.6	28.6	86.9	0	2
330	6.6	29	81.8	0	2
360	6.4	28.9	70.3	0	2
...	...	...	...	...	...

Due to SleepScan can detect body movement in sleep which defined wake period, then we can get wake sleep database. According to breath waveform is most steady in deep sleep stage, then we can get deep sleep database, the example of breath sound waveform in deep sleep is shown in Fig. 1. At last, we test many all-night experiments and contrast SleepScan with our algorithm results, we choose the same stage in the same time by comparing all-night our evaluating result with all-night SleepScan result and breath sound waveform, process of comparing same sleep stages is shown in Table 4 (marked by red label). At last, Sleep stages database is shown in Table 5. One point is the epoch time of 30-s length have 6 parameters which are list in Table 1.

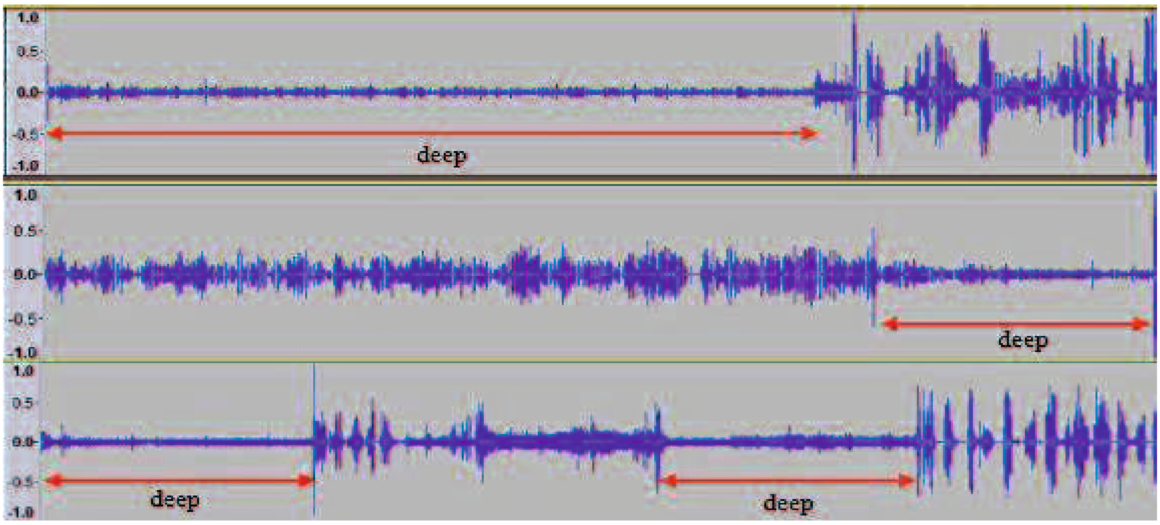


Fig. 1. Example of breath sound waveform in deep sleep stage.

Table 4. The process of comparing same sleep stages.

SleepScan stage	Chapter 3 stage	Breath waveform	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6
4	4	4	0.75759	0.094767	0.10222	0.01311	3.9807	0.86382
4	4	4	0.79407	0.10916	0.10431	0.01511	4.443	1.5545
4	4	4	0.82714	0.057828	0.11046	0.00902	4.8585	1.2845
4	3	4	0.79159	0.069908	0.10259	0.00905	5.4156	1.575
4	3	4	0.68365	0.14652	0.10244	0.00869	5.6627	1.3559
4	3	4	0.45619	0.27529	0.10043	0.00913	4.9796	0.8418
4	3	4	0.2464	0.19577	0.096098	0.00478	4.8214	0.54952
2	2	4	0.11507	0.066309	0.096432	0.00253	4.7622	0.59099
2	2	4	0.067334	0.024195	0.10238	0.00665	4.8702	0.64162
2	2	2	0.067747	0.021086	0.1072	0.00555	5.1683	0.59109
2	2	2	0.07343	0.020533	0.10799	0.00464	5.1553	0.54731
2	2	2	0.080855	0.028087	0.10057	0.01048	5.1737	0.41994
2	2	2	0.063139	0.031169	0.098416	0.00960	5.1058	0.42873
2	2	2	0.076902	0.049865	0.10596	0.00686	5.248	0.54068
2	2	2	0.089541	0.046244	0.10285	0.01126	5.1865	0.5344
2	2	2	0.1205	0.055775	0.09867	0.0131	4.9141	0.25609
2	2	2	0.14523	0.053366	0.10385	0.01133	5.0763	0.36509
2	2	2	0.13754	0.060294	0.10227	0.00891	5.4484	0.51733
2	2	2	0.083857	0.077849	0.09019	0.01323	5.8898	0.85731
2	2	2	0.059018	0.041806	0.091183	0.01380	5.6262	0.9851
2	2	2	0.072853	0.032212	0.10211	0.01256	5.3439	0.70373
2	2	2	0.08351	0.043046	0.10652	0.00532	5.4189	0.86261
2	3	2	0.085056	0.043059	0.10726	0.00546	5.1628	1.1725
2	3	2	0.045177	0.035079	0.099379	0.01315	5.5019	1.4122
2	3	2	0.025531	0.017189	0.091742	0.01239	5.7084	1.1575
2	3	2	0.039087	0.016263	0.096492	0.01295	5.3341	1.017
4	3	2	0.056633	0.019446	0.1028	0.00604	5.7173	0.81081
2	2	2	0.07602	0.07676	0.1028	0.00743	5.5437	1.3329
2	2	2	0.15947	0.1203	0.10336	0.00767	5.0176	1.1561
2	2	2	0.28621	0.10774	0.1023	0.00686	5.2103	0.51788
2	1	2	0.32148	0.14955	0.096823	0.00950	5.3539	0.47603
2	2	2	0.30052	0.155	0.098331	0.00956	5.5785	1.2414
2	2	2	0.32404	0.15044	0.1011	0.00650	5.5423	1.2729
2	1	1	0.33685	0.17751	0.10106	0.00926	5.7084	1.2063
2	1	1	0.2973	0.17709	0.098169	0.00920	5.349	1.1266
2	1	1	0.49124	0.1541	0.09896	0.01030	4.8332	1.3887
1	1	1	0.52762	0.12655	0.10355	0.00856	4.9234	1.3868
1	1	1	0.49084	0.10802	0.10227	0.00470	5.591	1.79
1	1	1	0.46759	0.082926	0.099617	0.00313	5.3789	1.7285
1	1	1	0.39545	0.079769	0.10011	0.00420	5.4138	1.1136
1	1	1	0.36847	0.07078	0.10145	0.00429	5.0517	1.0009
1	1	1	0.37343	0.082132	0.095784	0.00792	5.1034	1.2262
1	1	1	0.42127	0.114	0.094596	0.00757	4.905	1.683
1	1	1	0.5181	0.14508	0.10135	0.00679	5.2414	1.3574
...	...	...	...	...	...	...	...	...

Table 5. Sleep stages database.

Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Stage
0.92123	0.029251	0.12839	0.014359	4.3693	1.7039	4
0.88724	0.028779	0.12353	0.01017	3.8726	1.2577	4
0.8662	0.014628	0.11916	0.0069585	3.5341	0.21526	4
0.8577	0.019589	0.11851	0.011276	3.9153	0.39355	4
0.72479	0.051488	0.10734	0.010634	5.1674	1.5282	3
0.71104	0.068975	0.10722	0.0081884	5.1718	1.0043	3
0.53707	0.21254	0.1043	0.0098996	5.5805	0.92552	3
0.47267	0.20461	0.10052	0.0096539	5.5506	1.0704	3
0.64624	0.18856	0.10534	0.0078621	5.5078	1.3364	3
0.71896	0.11666	0.10027	0.0086245	5.6908	2.0862	3
0.7492	0.051446	0.10515	0.011522	5.1728	1.9159	3
0.69932	0.095704	0.102	0.0070919	5.0475	0.6987	2
0.61305	0.17603	0.094001	0.009952	5.0848	0.97369	2
0.52522	0.13796	0.094472	0.010555	5.1003	1.1071	2
0.4388	0.11251	0.10508	0.0063877	5.0439	0.69577	2
0.31322	0.066732	0.10828	0.0044017	4.7753	0.39744	2
0.69932	0.095704	0.102	0.0070919	5.0475	0.6987	2
0.34866	0.041531	0.10664	0.004839	4.8695	0.44177	1
0.33531	0.039833	0.10798	0.0030098	4.805	0.32009	1
0.31735	0.017049	0.10666	0.004975	4.6562	0.19709	1
0.32373	0.014523	0.10355	0.0046526	4.6877	0.47346	1
...	...	...	...	...	...	...

Along with experiments, sleep stages database can combine more data to as training set, more samples in database meaning more accuracy, then our system have study function by self. Up to now, sleep stages database have about 8000 points corresponding parameters and stages. The description of SVM is given subsequently.

4.3 Support vector machine classifier system

Support vector machine (SVM) is a widely used powerful learning machine. It can be used for training, classification and regression. First introduced by Cortes and Vapnik [13], it is based on the simple idea of finding an optimal hyperplane, separating different classes using a number of patterns (features), with maximum margin between the training set and the decision boundary. In the following a simple mathematical introduction of SVM, for more details see [14].

The SVM separating hyperplane:

$$w^T x - b = 0 \qquad (1)$$

Eq. (1) is calculated by solving the quadratic optimization problem:

$$\min_{\omega,b} \frac{1}{2} w^T w \qquad (2)$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1$$

Where x_i represents the ith training vectors, y_i represents the class value (±1), $\Phi(x_i)$ maps the input data to the feature space, i.e., applying a given function to the input data, for instance a polynomial function. Then, the classification of a given input x is made by finding the sign of the Eq. (1):

$$f(x) = \text{sgn}(w^T x - b) \qquad (3)$$

Where the class of the input vector x_i is:

$$\begin{cases} y_i = -1 \cdots f(x_i) \leq 0 \\ y_i = +1 \cdots f(x_i) \geq 0 \end{cases} \qquad (4)$$

This method is referred to as soft classifier. Actually, the impact of misclassified vectors does not appear in the Eq. (2). For approach that is more rigorous Eq. (2) is rewritten as:

$$\min_{\omega,b,\xi} \frac{1}{2} w^T w + C \sum_i \xi_i \qquad (5)$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i$$

$$\xi_i \geq 0 \forall i$$

Here the impact of misclassification is counted in the optimization step. ξ_i define slack variable that represent the degree of misclassification of a training vector and C the regularization parameter represents a bound on the Lagrange multipliers α such as:

$$\min_{\alpha} \frac{1}{2} \alpha^T L \alpha + e^T \alpha \qquad (6)$$

$$\text{subject to } y^T \alpha = 0,\ 0 \leq \alpha_i \leq C,\ \forall i$$

Where $y^T=[y_1, y_2, \ldots, y_N]$ is the vector of class values (±1), $e^T=[1, 1, \ldots, 1]$ is a vector of ones, $L_{ij}= y_i\ y_j\ K(x_i, x_j)$ and $K(x_i, x_j)= \Phi(x_i)^T\Phi(x_j)$ is the kernel function that performs the nonlinear mapping of the input data into the feature space. In our study, we used polynomial kernel of degree d=5 and the regularization parameter C=∞. The polynomial kernel is of the form:

$$K(x_i, x_j) = (x_i^T x_j + 1)^d \qquad (7)$$

The kernel function and C value choices were motivated by experimental tests of [15]. An important value used for the optimization of the solution in the SVM is the margin defined as m=2/||w||. The optimal solution is defined for the largest margin, i.e., maximizing 2/||w||. The architecture of SVM is shown in Fig. 2. It is to be noticed that all variables' notations used in this section are proper to it and do not have to be confound with the ones used in other sections. The SVM algorithm used in this work is the one developed by [16].

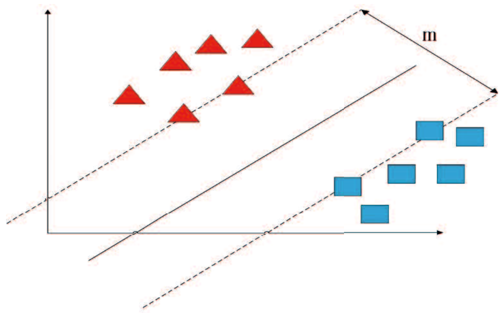


Fig. 2. Architectureof SVM.

4.3.1 Feature ranking method

Beyond the aim of sleep stages classification, one of the important goals behind this work is to estimate the best features, measured from breath sound signals for sleep study. First, it is useful to obtain the best classification accuracy with minimum number of features. Second, it can show which method is the best for sleep study and the most sensitive features to sleep stages changes. In general, feature selection methods are classified into, filter-based, wrapper-based and embedded-based methods [17]. Filter-based method is independent from the learning algorithm while wrapper-based uses the learning algorithm without exploiting its structure. Contrary to this, embedded-based method uses the learning algorithm and exploits its structure. In this work, we are using the SVM recursive feature elimination (RFE) method, which is an embedded-based method. The SVM-RFE was developed by [18] and used it in gene selection for cancer classification. The description of this method is given subsequently.

In the SVM-RFE method, the effect of removing a feature on an objective function is used as a ranking criterion. For classification problems, the ideal objective function is the expected value of the error, which is the error rate computed on an infinite number of examples [18]. The authors used the margin as objective function. In this work, the total error rate (TER) as ranking criterion was used, since the initial number of features is 6, which does not necessitate high computation costs. The steps of the SVM-RFE feature selection algorithm are:

(1) Remove one feature out of the number of features N_F (initially N_F=6) and compute the ranking criterion. This operation is repeated for every feature removed.

(2) Compare the ranking criterion values obtained for each subset of (N_F-1) features and sort out the feature with smallest ranking criterion, which is removed completely. A new subset of (N_F-1) features is then treated in (1). In the case of total error of classification used as ranking criterion (used in this work), the subset of (N_F-1) features with the lower error contains the best features, and the feature that was removed in the step (1) from the set (or subset) of N_F features is the worst one.

4.3.2 Results

In order to evaluate the performance of our algorithm, we tested it on the sleep stages database. We used sleep stages database to estimate one all-night sleeping condition, so we can predict and estimate sleeping condition using sleep stages database. Details of the number of, deep sleep, shallow sleep, REM, wake, training and testing data number of epochs in each all-night are presented in the Table 6. The reliability of our algorithm was assessed by the sensitivity S_e and the positive predictivity P_+ as follows:

$$S_e = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \qquad (8)$$

$$P_+ = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \qquad (9)$$

Table 6. Summary of sleep stages database and testing data.

Sleep stages database				Testing Data (sleep stage measured by SleepScan)				Date
Deep	Shallow	REM	Wake	Deep	Shallow	REM	Wake	
				105	348	128	52	11/09
2500	2500	2500	2500	106	440	133	65	11/12
				55	283	231	76	11/14

Where TP, FP, FN are explained as follows:

True positive (TP): the number of well classified this epochs;

False positive (FP): the number of epochs classified this stage (but actually other stage);
False negative (FN): the number of epochs classified other stages (but actually this stage).

The sensitivity Se is defined as the ability of the algorithm in the classification of sleep stages. The positive predictivity P+ is defined as the ability of the algorithm to discriminate this stage between other stages. A good classifier should have high sensitivity and positive predictivity values that should be nearly of the same order.

Then, we put into three all-night data as testing data, the three days total result of SVM algorithm are list in the Table 7. Table 8 - 10 are concrete result. In the Table 8- 10, the upper horizontal axis is the stage of data in initially which calculated by SleepScan, the left side vertical axis is the stage of SVM system estimation value.

Table 7. The result of SVM system.

Date	Result	Testing Data (all-night)			
		Deep	Shallow	REM	Wake
11/09	SleepScan	105	348	128	52
	SVM	102	343	135	53
11/12	SleepScan	106	440	133	65
	SVM	114	455	127	57
11/14	SleepScan	55	283	231	76
	SVM	87	235	269	54

Table 8. The concrete result of SVM system(11/09).

Value (Stage)	1 (Deep)	2 (Shallow)	3 (REM)	4 (Wake)
1 (Deep)	92	5	8	0
2 (Shallow)	5	5	116	2
3 (REM)	5	333	10	0
4 (Wake)	0	0	1	51

Table 9. The concrete result of SVM system(11/12).

Value (Stage)	1 (Deep)	2 (Shallow)	3 (REM)	4 (Wake)
1 (Deep)	89	5	12	0
2 (Shallow)	17	23	93	0
3 (REM)	8	421	19	1
4 (Wake)	0	6	3	56

Table 10. The concrete result of SVM system(11/14).

Value (Stage)	1 (Deep)	2 (Shallow)	3 (REM)	4 (Wake)
1 (Deep)	67	1	8	0
2 (Shallow)	18	16	248	1
3 (REM)	2	215	13	1
4 (Wake)	0	3	0	52

According to the equations (8), (9), (10), calculated the summary results for reliability of SVM system are list in Table 11-14, Deep, Shallow, REM, Wake, respectively. Reliability mean value of our algorithm is list in Table 15.

Table 11. Summary results for reliability of our algorithm (Deep).

Date	TP	FP	FN	Se(%)	P+(%)
11/09	92	10	13	87.6	90.2
11/12	89	25	17	83.9	78.1
11/14	67	20	9	90.5	77

Table 12. Summary results for reliability of our algorithm (Shallow).

Date	TP	FP	FN	Se(%)	P+(%)
11/09	333	10	15	95.7	94.4
11/12	421	34	28	93.8	92.5
11/14	215	20	16	93.1	91.5

Table 13. Summary results for reliability of our algorithm (REM).

Date	TP	FP	FN	Se(%)	P+(%)
11/09	116	19	12	90.6	85.9
11/12	93	34	40	70	73.2
11/14	248	22	35	87.6	91.9

Table 14. Summary results for reliability of our algorithm (Wake).

Date	TP	FP	FN	Se(%)	P+(%)
11/09	51	2	1	98.1	96.2
11/12	56	1	9	87.5	98.2
11/14	52	2	3	94.5	96.3

Table 15. Reliability mean value of our algorithm.

	Mean value	
Stage	Mean S_e (%)	Mean P_+ (%)
Deep	87.3	81.8
Shallow	94.2	92.8
REM	82.7	83.7
Wake	93.4	96.9

Table 16. 6 features ranking.

Rank	Feature description
1	Mean value of breath period
2	Mean value of breath peak
3	Mean of respiratory variance
4	Standard deviation of respiratory variance
5	Standard deviation of breath period
6	Standard deviation of breath peak

SVM-RFE feature ranking method was applied to the 6 features used in this work. The results show the following ranking (ordered from the best to the worst) in Table 16: 5, 1, 3, 4, 6, 2; where these numbers correspond to the ones in Table 1. It is to be noticed that all variables' notations used in this section are proper to it and do not have to be confound with the ones used in other sections.

4.3.3 Sleep stages evaluation

Due to we have built sleep stages database, then can predict sleep stages according to characteristic parameters. Then, we put different subjects all-nights data into SVM classifier system, sleep stages evaluated by SVM, measured by SleepScan are shown in Fig. 3 - Fig. 10 which include two days estimated sleeping condition by breath sound waveform, blue curve denote result of Chapter 3 algorithm, orange color denote result of SleepScan, green curve is sleeping condition evaluating by SVM.

All-night sleeping conditions (date 1107, 1109) measured by SleepScan and evaluated by SVM are shown in Fig. 3 and Fig. 6, the breath sound waveforms are depicted in Fig. 4 and Fig. 7. From Fig. 4, we can find ① is shallow and ② is deep, as same as sleep stage in Fig. 3 evaluated by SVM algorithm. The period of ① ② ③ are different stages between in SVM and SleepScan in Fig. 6. Then, we can find in Fig.7, the breath sound waveforms are most steady which are evaluated deep sleep stages in the period of ① ② ③. So, they can test SVM classifier may be more accuracy than SleepScan.

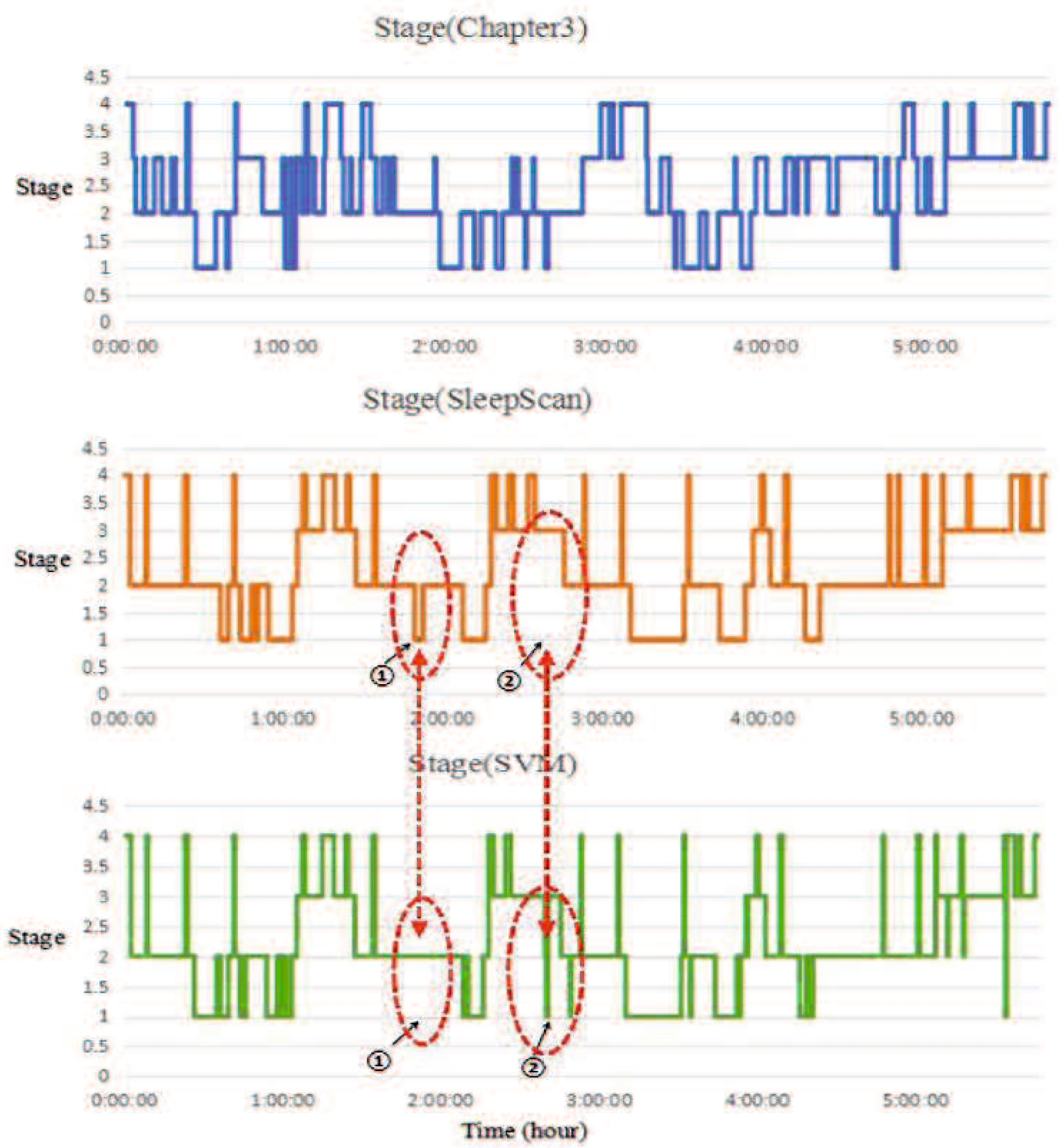


Fig. 3. All-night sleep stage evaluated by Chapter 3 algorithm, SVM and measured by SleepScan (date 1107).

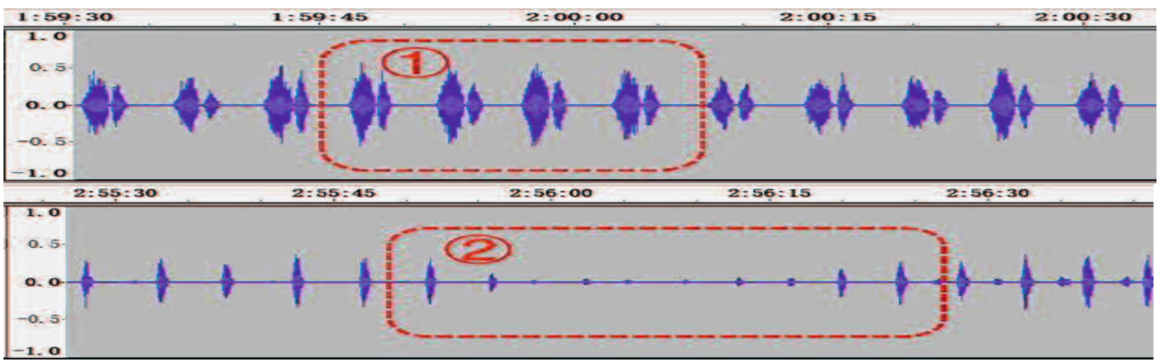


Fig. 4. ① ② breath sound signal and estimated sleeping condition (we could find that the ① is shallow, ② is deep) (date 1107).

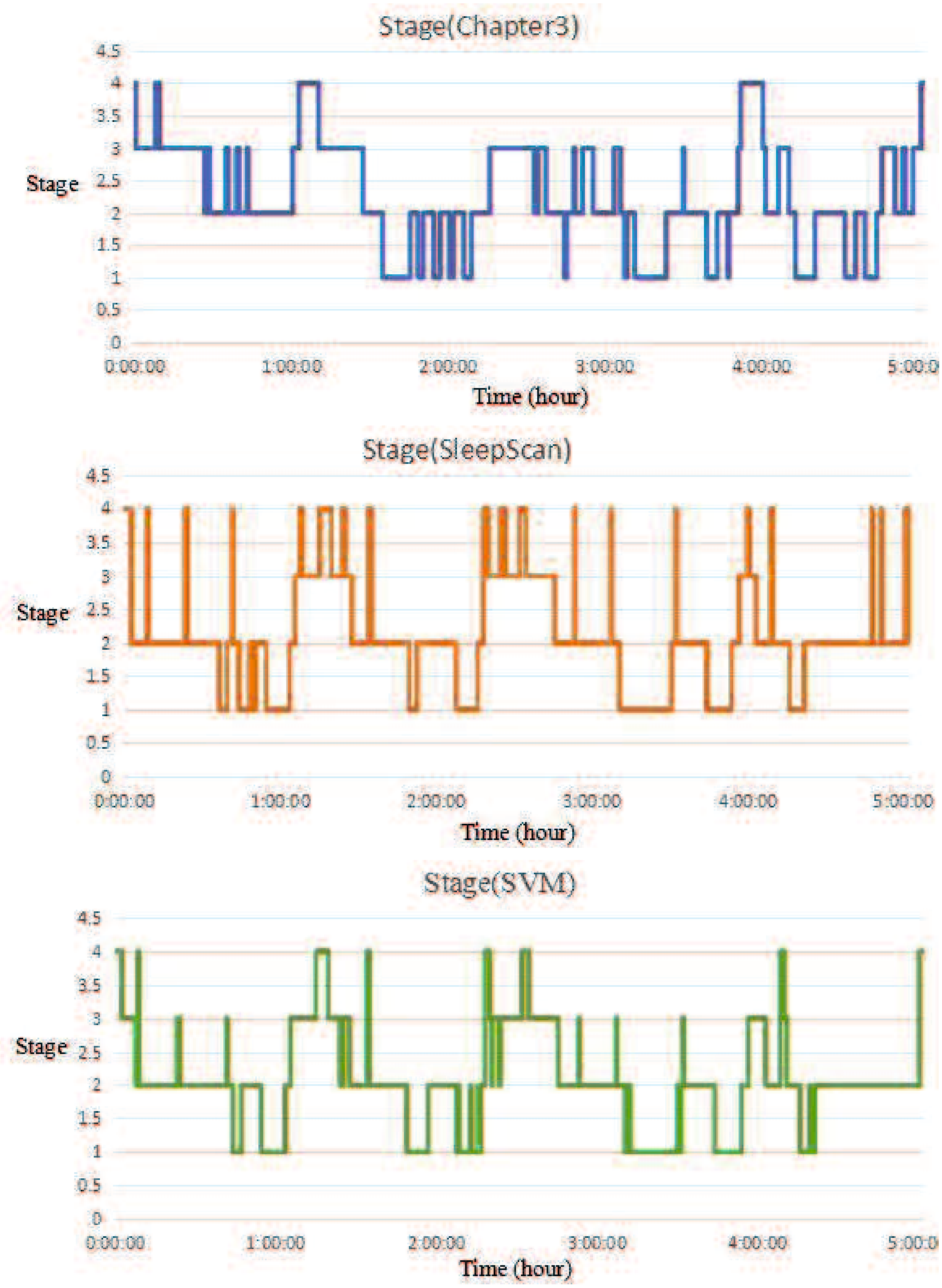


Fig. 5. All-night sleep stage evaluated by Chapter 3 algorithm, SVM and measured by SleepScan (date 1108).

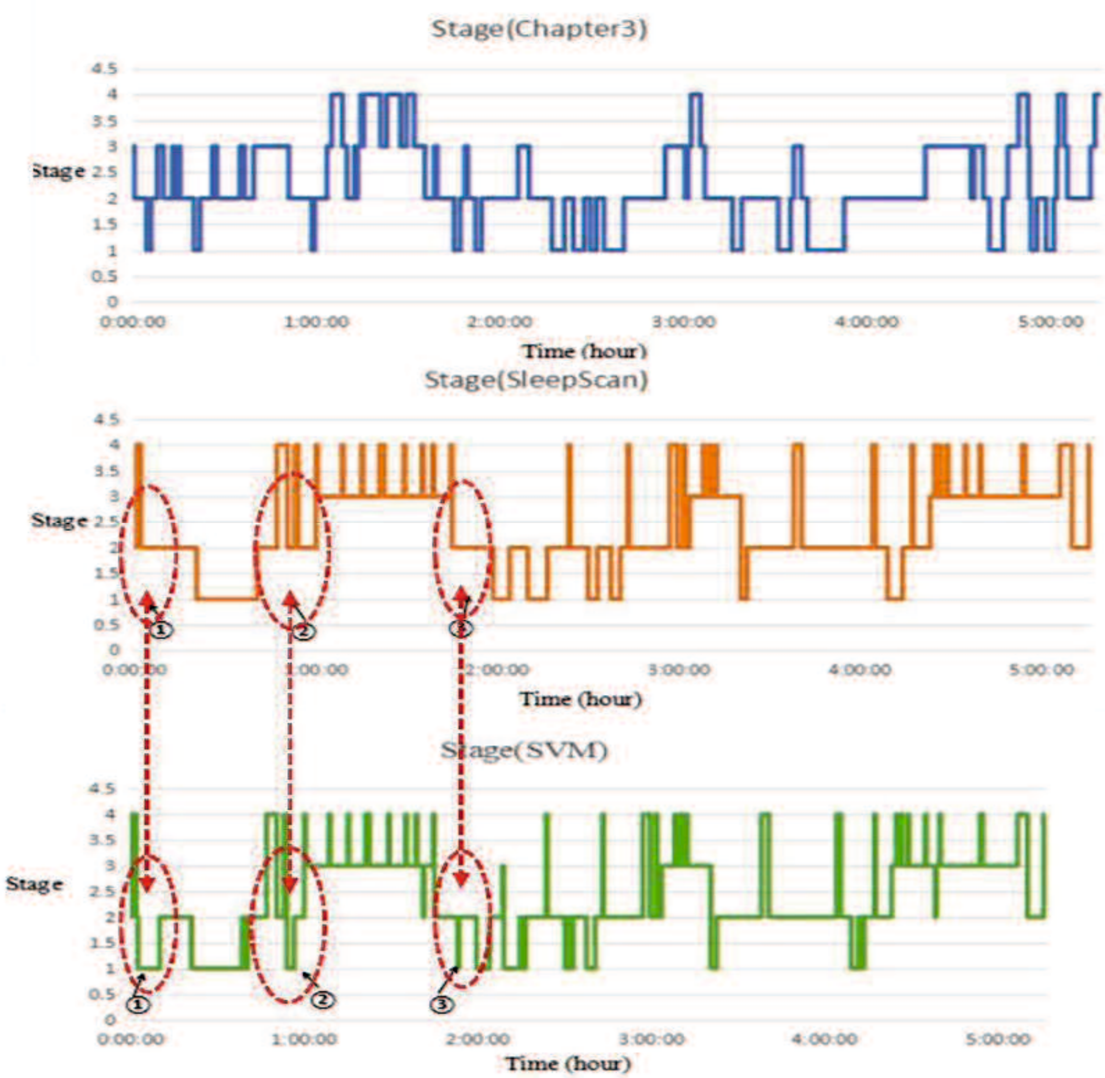


Fig. 6. All-night sleep stage evaluated by Chapter 3 algorithm, SVM and measured by SleepScan (date 1109).

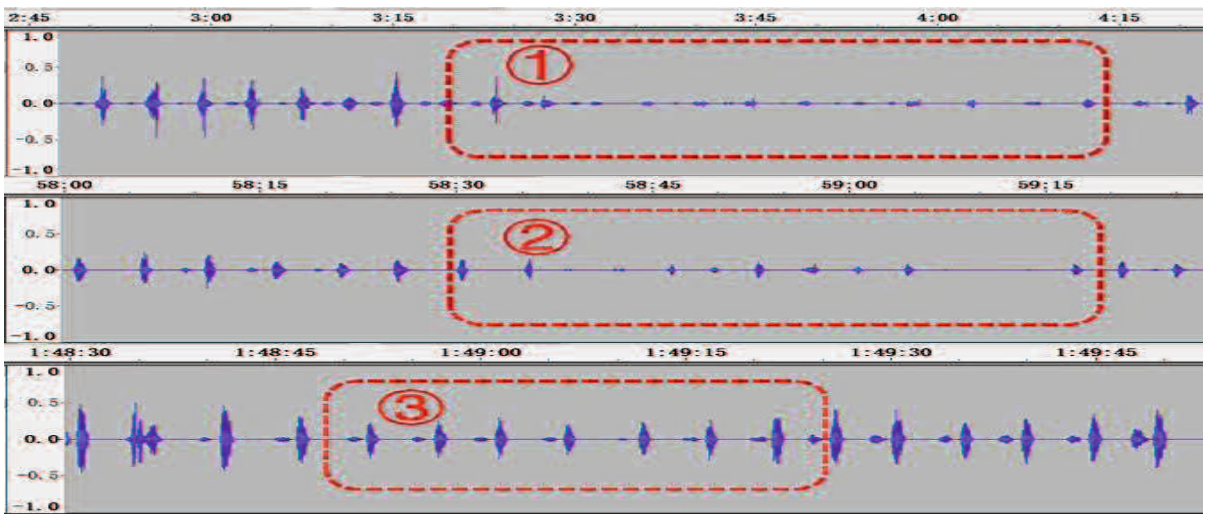


Fig. 7. ① ② ③ breath sound signal and estimated sleeping condition (we could find that the ① ② ③ sleep stage are deep) (date 1109).

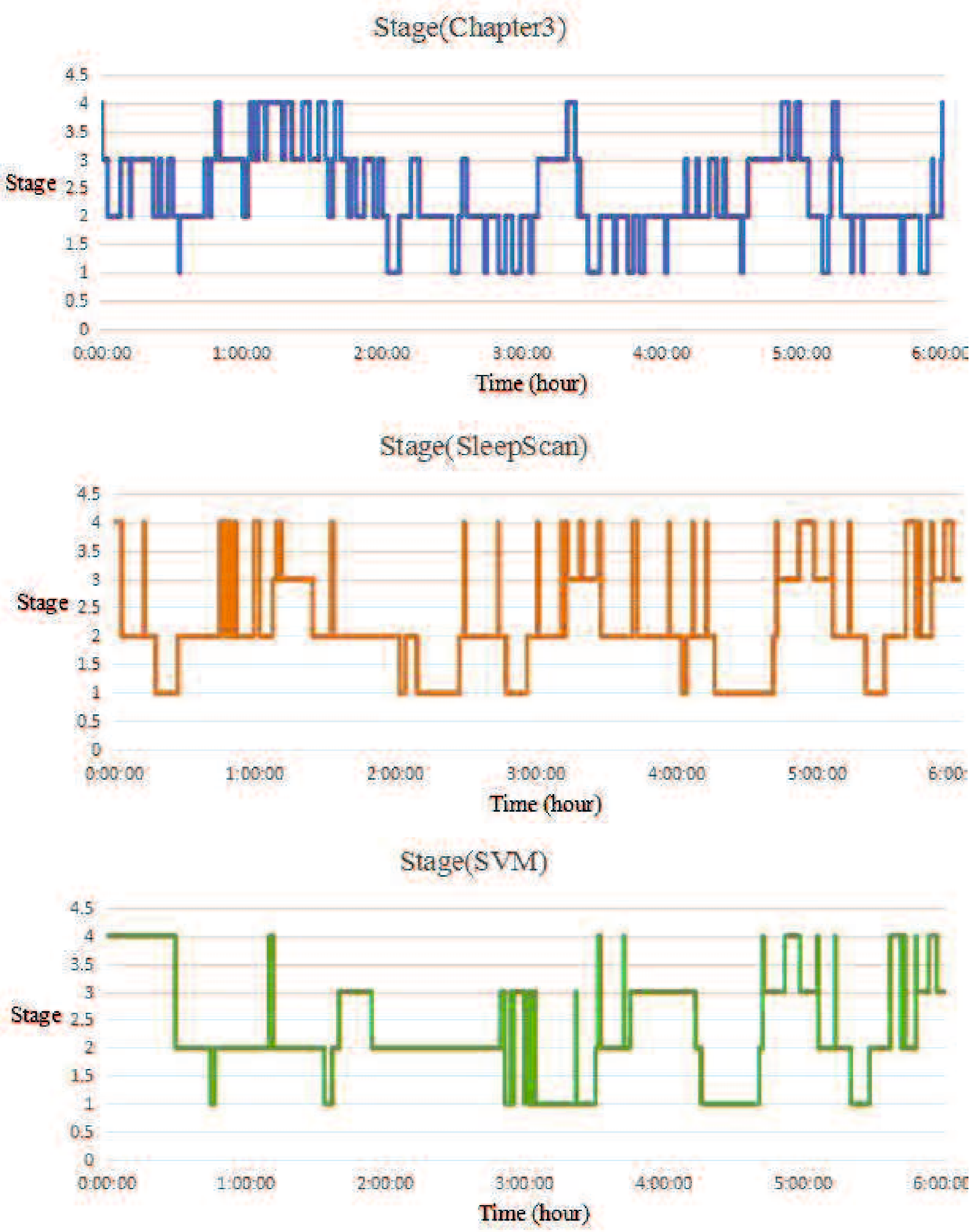


Fig. 8. All-night sleep stage evaluated by Chapter 3 algorithm, SVM and measured by SleepScan (date 1112).

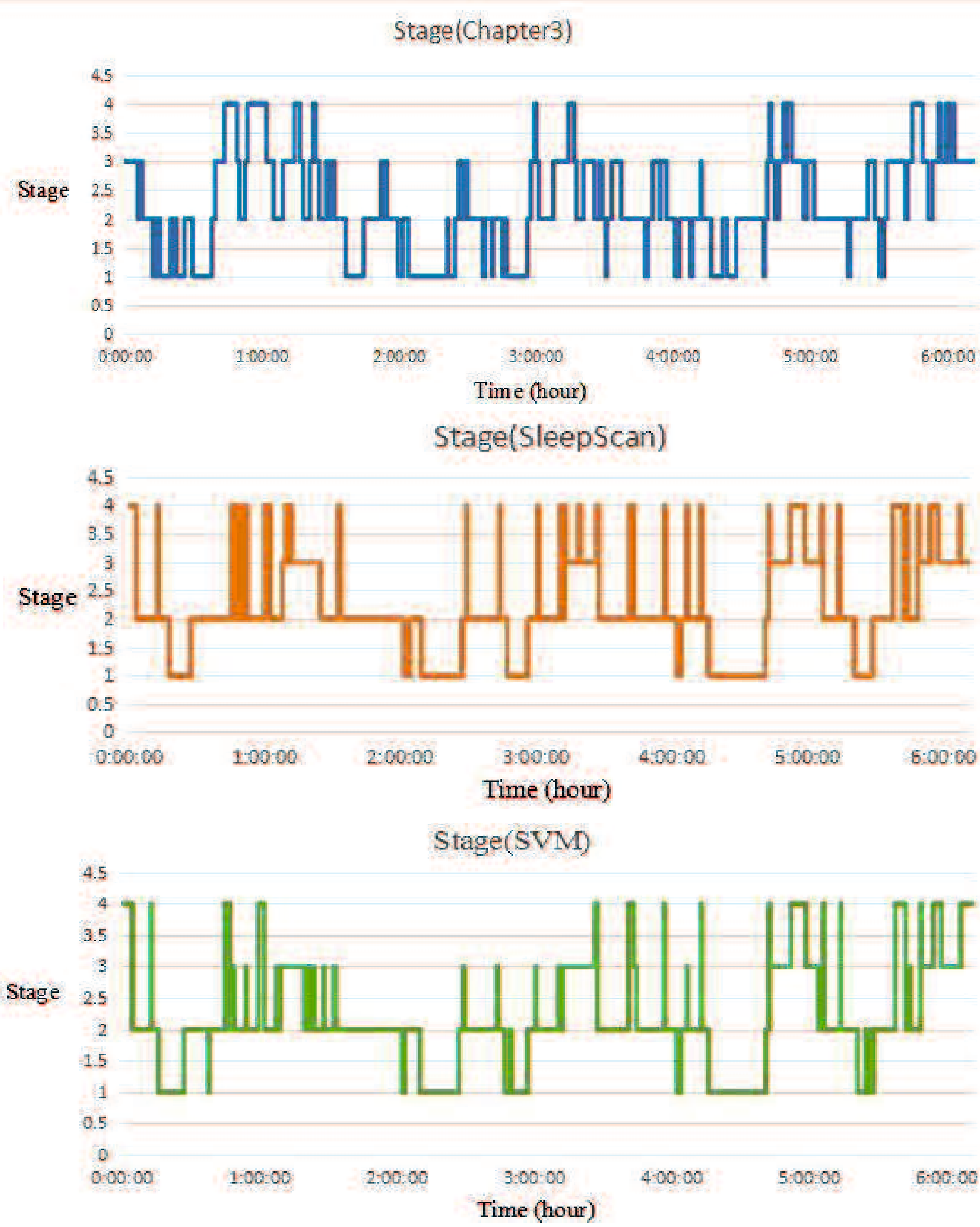


Fig. 9. All-night sleep stage evaluated by Chapter 3 algorithm, SVM and measured by SleepScan (date 1113).

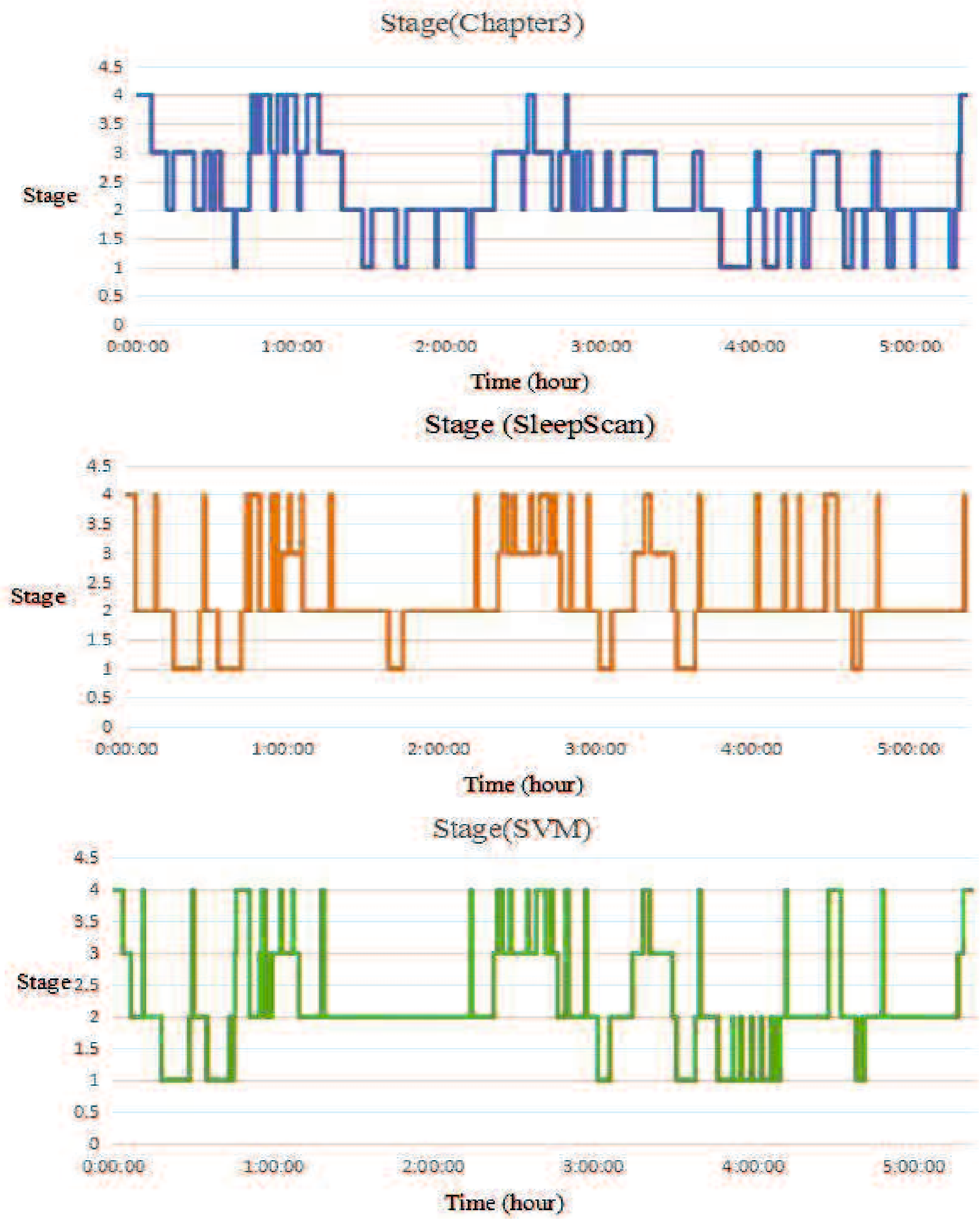


Fig. 10. All-night sleep stage evaluated by Chapter 3 algorithm, SVM and measured by SleepScan (date 1114).

4.4 Discussion

The features extracted by different methods were subject to the SVM-RFE ranking method. This operation had mainly goal which is determining the most important features, extracted from the breath sound signal, for sleep stages classification. The ranking showed that the set of 6 features presented in Table 15. The reliability mean value of our algorithm obtained for the set of 6 features are presented in Table 14. Our results show that the SVM model classifies the majority of stages with high sensitivity. In addition, the results shown in the Table 14 are divided into four stage: Deep representing deep sleep (Se=87.3%), Shallow representing shallow sleep (Se=82.7%) and REM representing rapid eye movement (Se=94.2%); Wake have Se is 93.4%. The positive predictivity P+ are 81.8%, 83.7%, 92.8%, 96.9%, corresponding to Deep, Shallow, REM, Wake, respectively. Then it appears that our classifier is better to be used with subjects. Fig. 5-Fig. 10 are the predicting sleep stages used SVM classifier, results of measured by SleepScan and sleep scoring based on Chapter 3 algorithm since results are moderately good. The curves of SVM predicting are close to the curves measured by SleepScan, the vast majority of parts are coincidence. This means that the support vector machine classifier system could predict sleep stages accurately. Compared Fig. 3 and Fig. 4, Fig. 6 and Fig. 7, we can conclude SVM classifier algorithm may be more accurately for all-night sleeping condition monitoring than SleepScan. Broadly speaking, sleep stages are mostly confused with adjacent elements in the matrix. This could be explained by the fact that sleep is a continuous process with stronger similarities among certain pairs of consecutively occurring stages (Wake and REM, or Shallow and Deep). Furthermore, because of this similarity, the transition between some of these adjacent stages may be harder to distinguish.

4.5 Summary

A sleep stages classifier by SVM was developed. A set of features were extracted from breath sound. All-night breath sound signals were used to extract 6 features in order to built sleep stages database and were applied in an SVM training and classification system for sleep stages predicting. An SVM-RFE feature selection method was applied for features ranking. The method was tested using the proposed database. Results showed that the mean value of breath period is most important in 6 features. Indeed, good classification efficiency was reported for the best set of 6 features. In addition, sleep stages values were accurately estimated for both sets. Finally, results proved that it is possible using our sleep stages database to predict sleep stages based on support vector machine classifier system.

4.6 References

[1] Rechtschaffen A, Kales A, editors. A manual of standardized terminology, techniques and scoring system for sleep stages of human subject. Washington, DC: US Government Printing Office, National Institute of Health Publication; 1968.

[2] Iber C, Ancoli-Israel I, Chesson AL, Quan SF. The AASM manual for the scoring of sleep and associated events: rules, terminology, and technical specification. American Academy of Sleep Medicine; 2007

[3] Agarwal R, Gotman J. Digital tools in polysomnography. J Clin Neurophysiol 2002;19(April (2)):136–43.

[4] Berthomier C, Drouot X, Herman-Stoïca M, Berthomier P, Prado J, Djibril, et al. Automatic analysis of single-channel sleep EEG: validation in healthy individuals. Sleep 2007;30:1587–95.

[5] Huang C-S, Lin C-L, Ko L-W, Liu S-Y, Su T-P, Lin C-T. Knowledge-based identification of sleep stages based on two forehead electroencephalogram channels. Front Neurosci 2014(September):8.

[6] Fraiwan L, Lweesy K, Khasawneh N, Fraiwan M, Wenz H, Dickhaus H. Classification of sleep stages using multi-wavelet time frequency entropy and LDA methods. Inf Med 2010;49.

[7] Grozinger M, Fell J, Roschke J. Neural net classification of REM sleep based on spectral measures as compared to nonlinear measures. Biol Cybern 2001;85:335–41

[8] Kerkeni N, Ben Cheikh R, Bedoui MH, Alexandre Dogui M. Sleep stages classification by hierarchical artificial neural networks. IRBM 2012;33:35–40.

[9] Ronzhina M, Janousek ˇ O, Kolárová ˇ J, Nováková M, Honzík P, Provazník I. Sleep scoring using artificial neural networks. Sleep Med Rev 2012;16(June (3)):251–63.

[10] Krakovska A, Kristina M. Automatic sleep scoring. A search for an optimal combination of measures. Artif Intell Med 2011; 53:25–33.

[11] Shing-Tai P, Chih-En K, Jian-Hong Z, Sheng-Fu L. A transition-constrained discrete hidden Markov model for automatic sleep staging. BioMed Eng Online 2012:11–52.

[12] Koley B, Dey D. An ensemble system for automatic sleep stage classification using single channel EEG signal. Comp Biol Med 2012; 42:1186–95.

[13] C. Cortes and V. Vapnik, Support-Vector Networks, Machine Learning 1995; 20(3): 273-297.

[14] C. J.C. Burges, A tutorial on support vector machines for pattern recognition, Data Mining and Knowledge Discovery 1998; 2(2): 121-167.

[15] S. Choi, Detection of valvular heart disorders using wavelet packet decomposition and support vector machine, Expert Systems with Applications 2008; 35(4): 1679-1687.

[16] S. R. Gunn, Support vector machines for classification and regression. Technical Report, Image Speech and Intelligent Systems Research Group, University of Southampton, 1997.

[17] K-Q. Shen, C-J. Ong, X-P. Li and E.P.V. Wilder-Smith, Feature selection via sensitivity analysis of SVM probabilistic outputs, Machine Learning 2008; 70(1): 1-20.

[18] I. Guyon, J. Weston, S. Barnhill and V. Vapnick, Gene selection for cancer classification using support vector machines, Machine Learning 2002; 46(1-3): 389-422.

[19] Reyes-Ortiz, J. L., Oneto, L., Albert, Parra, X., and Anguita, D. Transition-aware human activity recognition using smartphones. Neurocomputing 2016; 171(C), 754-767.

[20] J. Sim and C.C. Wright, The kappa statistic in reliability studies: use, interpretation, and sample size requirements, Physical Therapy 2005; 85(3): 257-268.

[21] MH Bonnet, Effect of 64 hours of sleep deprivation upon sleep in geriatric normals and insomniacs. Neurobiology of Aging 1986; **7**(2): pp. 89-96.

[22] A.C. Cheng, J.F. Black and K.L. Buising, Respiratory rate: The neglected vital sign, Medical Journal of Australia 2008; 189(9): 531-532.

[23] W. Cassel, T. Ploch, B. Griefahn, T. Speicher, A. Loh, T. Penzel, U. Koehler and S. Canisius, Disturbed sleep in obstructive sleep apnea expressed in a single index of sleep disturbance (SDI), Somnologie 2008; 12(2): 158-164.

[24] J.W. Shin, Y.R. Yoon, J.C. Principe, Evaluation of body movement during sleep by thermopile using wavelet and neuro-fuzzy, Conf. Proc. IEEE Eng. Med. Biol. Soc., 2003, pp. 2406–2407.

[25] Chazal, P. D., Fox, N., O'Hare, E., Heneghan, C., Zaffaroni, A., Boyle, P, Sleep/wake measurement using a non-contact biomotion sensor, Journal of Sleep Research. 20(2) (2011) 356-66.

[26] V.N. Vapnik, Statistical Learning Theory, Wiley, New York, 1998.

[27] Lei, B., Rahman, S. A., Song, I. Content-based classification of breath sound with enhanced features. Neurocomputing 141 (2014) (4) 139-147.

[28] Chang Ch, Lin Ch, LIBSVM: A Library for Support Vector Machines. Department of Computer Science and Information Engineering. (2003) National Taiwan University.

[29] Yu S, Li P, Lin H, Rohani, E, Support Vector Machine Based Detection of Drowsiness Using Minimum EEG Features, International Conference on Social Computing, IEEE Computer Society 2013; Vol.10, pp.827-835.

[30] Lajnef T, Chaibi S, Ruby P, et al. Learning machines and sleeping brains: Automatic sleep stage classification using decision-tree multi-class support vector machines[J]. Journal of Neuroscience Methods 2015; 250:94-105.

Chapter 5

Apnea detection using breath sound signals

5.1 Introduction

Sleep apnea syndrome (SAS) is a common sleep disorder with high prevalence of 4% in adult men and 2% in adult women [1]. SAS subjects experience daytime sleepiness, tiredness, low concentration and impaired learning, hence are prone to motor vehicle and work place accidents. Moreover, undiagnosed and untreated SAS can relate to hypertension, myocardial infarction, cardiovascular dysfunction and stroke. The detection of apnea events in a night recordings is a wide field of research and the methods involved are complex. In general, this task is done by the processing of the respiration signal since the apnea (absence of respiration for long period) appear in the recording of respiration [2].

Nowadays, Polysomnography (PSG) is a standard testing procedure to diagnose OSA. Complete PSG includes the monitoring of the breath airflow, respiratory movement, oxygen saturation (SpO2), body position, electroencephalography (EEG), electromyography (EMG), electrooculography (EOG), and electrocardiography (ECG). Nevertheless, the whole PSG process is complex, expensive and time consuming procedure due to the need of many physiologic variables using multiple sensors that needs to be attached to the patients [3].

According to the American Academy of Sleep Medicine (AASM), the Apnea Index (AI) is used to describe the number of complete and partial apnea events per hour of sleep and it is calculated to assess OSA syndrome severity. OSA severity is usually determined as follows: AHI 5-15 indicates mild, 15-30 indicates moderate and over 30 indicates severe OSA syndrome. Therefore, patients are diagnosed with OSA if they have five or more apnea events per hour of sleep during a full night sleep period [4].

However, new simplified diagnostic methods and continuous screening of OSA is needed, in order to have a major benefit of the treatment on OSA outcomes. In this work, an alternative method to the expensive PSG visual scoring method, which is commonly used today to assess a patient's sleep quality, is provided.

At present, much of the current apnea research is being done on providing portable devices that monitor those process of apnea during the day. The device could act as an inexpensive and convenient way for doctors to diagnose SA patients and as a means for collecting data on apnea sufferers to determine the severity of the condition once diagnosed. More specifically, this may help in the initial assessment of patients with suspected OSA in order to prioritize patients. Patients with utmost need of treatment will go through complete PSG recordings within a sensible time frame; meanwhile those who are free of apnea symptoms will avoid the cumbersome procedure [5].

Many portable monitor devices already exist in the market. ApneaLinkTM Plus Home Sleep Apnea Test Device is one of the carriage able in home sleep test diagnostic devices that records up to four channels of information: respiratory effort, pulse, oxygen saturation and nasal flow. The patient can sleep normally while ApneaLinkTM Plus monitors his/her sleep, checking breathing patterns and the amount of oxygen in his/her blood and recording possible apneas or other breathing abnormalities [6]. Also, SleepStripTM may be a simple and effective tool for OSA diagnostic strategy. This device has to be worn for a minimum of five hours of sleep, and the actual device is placed on the individual's face where the two flow sensors (oral and nasal thermistors) are placed in just below the nose and above the upper lip to capture the breath of individual patient. For all samples combined, sensitivity and specificity values ranges from 80-86% and 57-86% respectively [7]. WM ARES is a home sleep test device that records heart rate, airflow, respiratory effort and oxygen saturation [8]. When the patient wakes up in the morning, after removing the tube from the nose and the tape and sensor from the finger, he/she returns the device to the clinician for analysis. The device contains a detailed record of the patient's personal sleep patterns, which can be downloaded, analyzed and processed in the clinician's computer. The clinician will then identify if the person is suffering from sleep apnea.

In [9], a new screening test for OSA is implemented on a Personal Digital Assistant (PDA) platform to perform the test at home during the patient's nightly rest. The Bluetooth ECG sensor, made by Corscience [10] is integrated into this platform, and the algorithm running on the PDA calculates an index that quantifies the magnitude of the heart beats rate variability power spectrum alterations. After the patient's first night using the device at home, the collection of test results are transmitted directly from the PDA to the hospital via the internet either by a WiFi connection, or by GPRS/UMTS connection. Once the healthcare staffs have evaluated the results, they will notify the patient whether the collected test results are conclusive or not. If the results are conclusive the patient should return the device. If needed; however, the patient may be asked to repeat the test again to collect additional data the following night. However, there is a loss of efficiency in the use of the wireless network because normal ECGs are also sent, which implies a high cost.

The portable device hardware design of an FPGA for home preliminary screening of SA syndromes in [11] stores a combination of three signals data of three sensors, namely the nasal air flow and the thorax and abdomen effort signals of overnight sleep on a Secure Digital card. Later, the sleep specialist at the clinic uses an algorithm for the evaluation and detection of SA. The device is relatively inexpensive and simple to use to diagnose more cases of SA. Habul et al. [12] developed a diagnostic device for initial test at home that measures three vital signals, namely the respiratory rate measurement, the oxygen concentration in blood and chest oscillations. The system architecture is divided into 5 parts, the micro-controller, the external communications, data storage, power management, and signal conditioning part. The data will be transmitted wireless and stored on the storage device. After the patient has finished sleeping, the next morning he or she can bring the data received on the storage device to a clinic's office, where the physician can interpret the data and determine what the patient's condition is. However, the device will reduce the cost for the patient because the patient does not have to pay for an overnight stay at the sleep center [13].

In using vision based analysis to diagnose OSA in [14], there has been effective use of two

SONY infrared camcorders (DCR-HC-30E) that work together in order to capture 10 video clips from three different angles. General body movement is continuously monitored and updated in a 2D breathing activity template. After collection of video data, offline analysis is used to detect abnormal breathing and to facilitate diagnosis of OSA. Furthermore, after a careful meta-analysis of literature for twenty-five various tools and devices used to screen and detect SA by Ross et al. [15], it is discovered that only two of these are done at home, all others are performed under supervision in the sleep laboratory. The results show sensitivity values ranging from 78-100% and specificity values ranging from 62-100%. However, the related issues such as reliability, compliance, prices and safety, equipment failure rates are largely ignored.

A simple method of detection would be the calculation of the breath cycle. The value of breath cycle will be very long in the case of apnea occurrence. However, the quality of the breath signal is not always good which make it difficult to detect accurately the breath cycles. Then, some researchers proposed to use the ECG signal, sometimes combined to the respiration signal to detect apnea episodes [16]. In this chapter, we are presenting much simpler method to detect apnea episodes. This method is not sensitive to the noise and bad quality of the breath signal. Then, results can be accurate using the breath signal. In the following explanation and tests of the mentioned method are shown.

5.2 Methods

Arterial oxygen saturation (SpO2) measured by pulse oximetry can be useful in OSA diagnosis as clinical experience indicates that an apneic event is frequently accompanied by a fall in the SpO2 signal (oxygen desaturation) [17]. Several studies assess multivariate analysis of the usefulness of SpO2 in OSA diagnosis [18-22]. In the present studies, the researchers provide complementary information with combined different physiological signals, in order to obtain additional information to that provided by classical methods to evaluate sleep quality and detect apnea. In some studies, breath sound and SpO2 data have been bridged to analyze sleep data. As the blood oxygen saturation falls during apnea, the resultant increase in heart rate and blood pressure causes stress and potential injury to the parts of the cardiovascular system [23]. In [24], the authors analyze various feature sets and a combination of classifiers based on the arterial oxygen saturation signal measured by pulse oximetry (SpO2) and breath sound. Then, based on aforementioned chapter, we proposed the method to evaluate sleep quality, so, if we can get a strong correlation between breath characteristic parameter with SpO2, OSA could detect only using breath signal. For the sake of connection of SpO2 with breath characteristic parameter, we took the experiment to monitor all-night SpO2 from subjects in sleeping conditions and different physical situations. The pulse oximeter results is detected by Nonin WristOx2 is shown in Fig.1. The Nonin WristOx2 3150 is one of the most versatile wrist oximeters that has unmatched performance and provides the best value for the money. It works on the proven PureSAT SpO2 technology made by Nonin Medical. This SpO2 pulse oximeter can be used with a wide range of patients in a variety of settings from home to hospital. Some of the popular applications include cardio-ambulatory monitoring, remote wireless monitoring and overnight studies. It is also a wireless Bluetooth oximeter, which means you don't have to deal with wires and can transmit downloads securely to a Bluetooth PC. This oximeter is highly versatile and reliable in providing the most accurate readings for blood oxygen saturation and pulse rate. It comes with 270 hours of patient recording and 100 meters range for transferring data [25].

Fig. 1. Nonin WristOx2(Model7500).

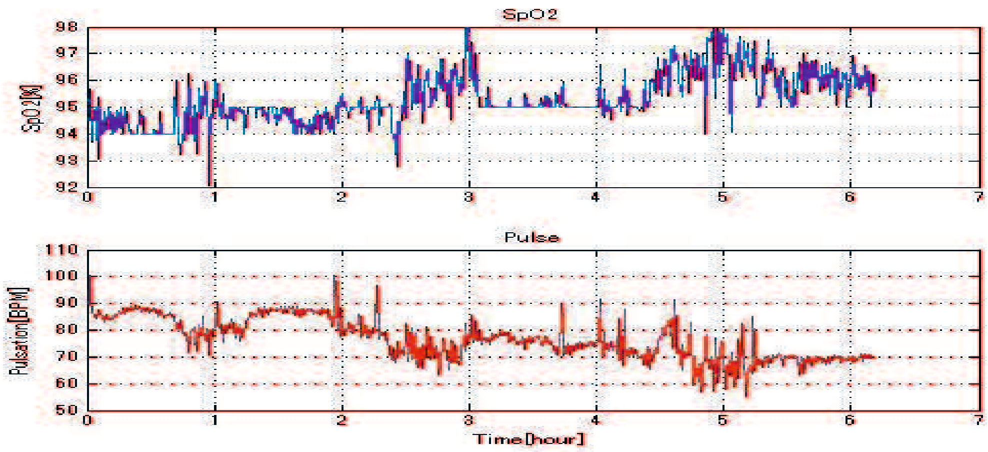
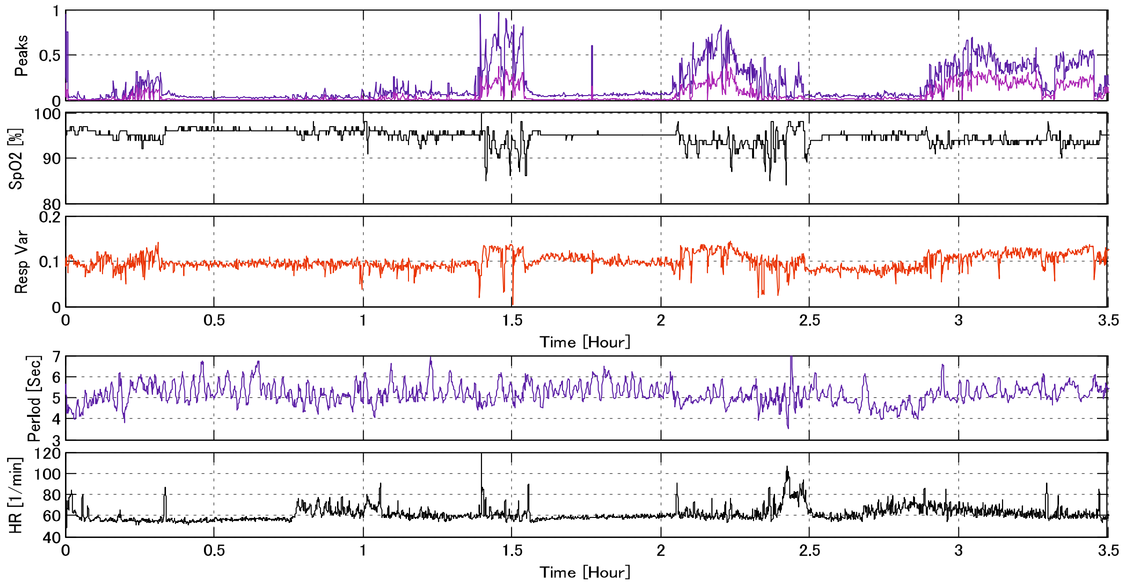
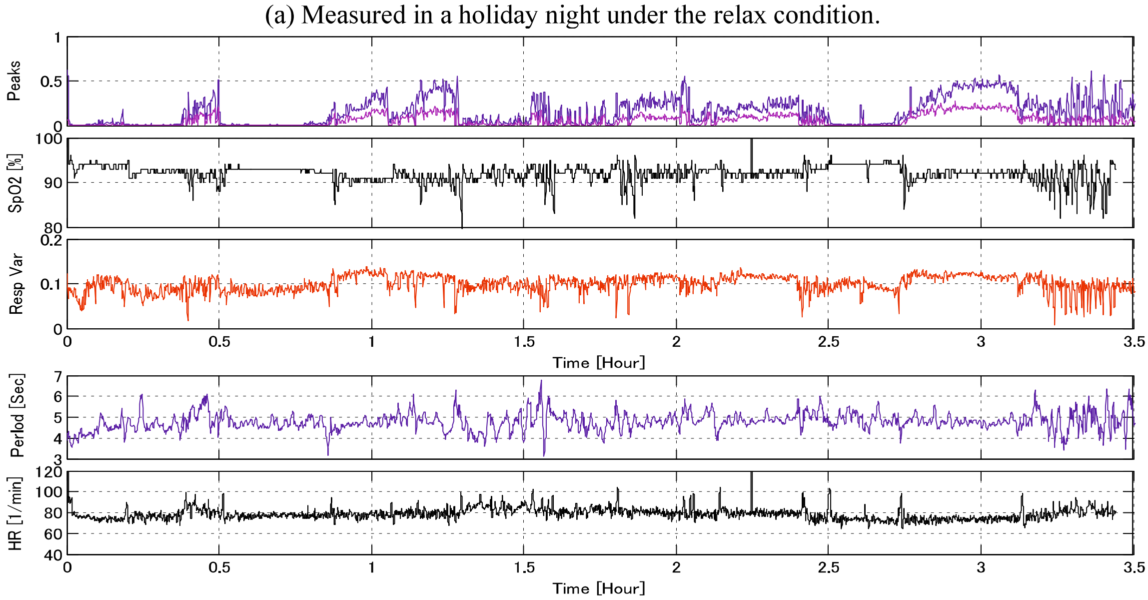


Fig. 2. Example of SpO2 and Pulse measured by NONIN Wrist Ox2 in all-night.

Fig. 2 is shown example of SpO2 and Pulse measured by Ox2 in all-night. Fig. 3 is the comparison of breath sound analysis results with the pulse oximeter results (NONIN Wrist Ox2). It indicate that 1) SpO2 and RespVar have strong correlation which means the respiration variation can be used to estimate the arterial oxygen saturation. When SpO2 decrease, RespVar also decrease, the heart rate become fast. Furthermore, it indicate apnea when RespVar is lower than a threshold value; 2) After drinking, the heart rate and breath both become faster than measured in a holiday night under the relax condition. We can find RespVar in the period 3:00-3:30 after drinking, RespVar is strong variance which it's represent apnea.



(a) Measured in a holiday night under the relax condition.



(b) Measured after drinking a large amount of alcohol.

Fig. 3. Comparison of breath sound analysis results with the pulse oximeter results(NONIN Wrist Ox2).

5.3 Apnea detection algorithm

Due to SpO2 and RespVar which is proposed in Fig. 3 have strong correlation, then we found the difference between the respiration variation and the moving average of the respiration variation. If the difference is smaller than the threshold value, it is determined that there is apnea. The schematic of simple SAS detecting algorithm is shown in Fig. 4.

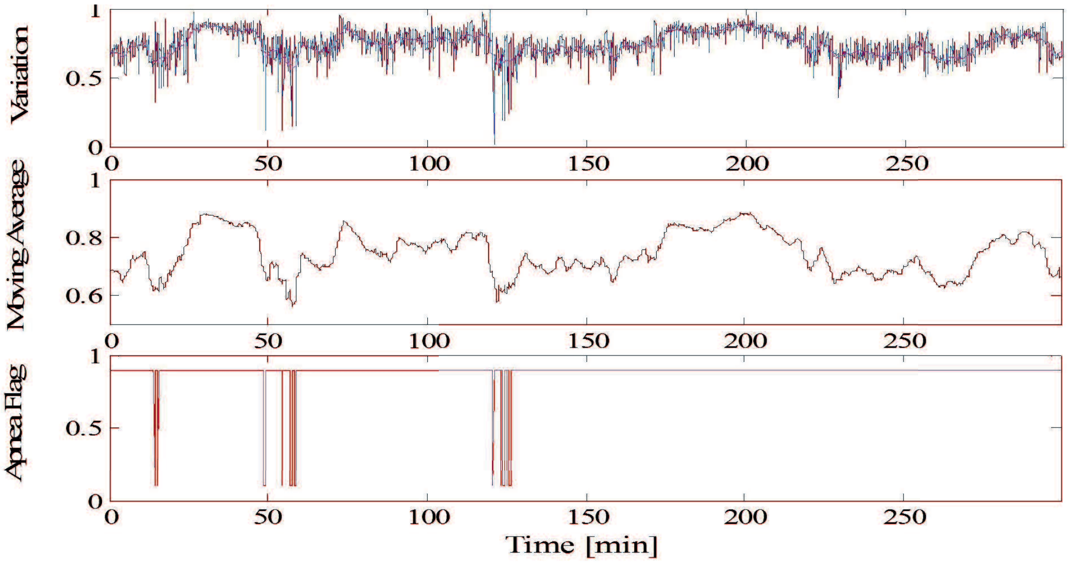


Fig. 4. Simple SAS detecting algorithm.

5.4 Experiments

Four days all-night apnea detecting results by the simple calculation algorithm are shown in Fig. 4 - 7, detected apnea are 19, 19, 13, 13, respectively. Apnea detecting results by breath sound waveform are shown in Fig. 8- 11, detected apnea are 18, 19, 13, 17, corresponding to the Fig. 4 - 7. The results showed that the Apnea Index (AI) values obtained from the our method are close to the fact have a good efficiency and accuracy.

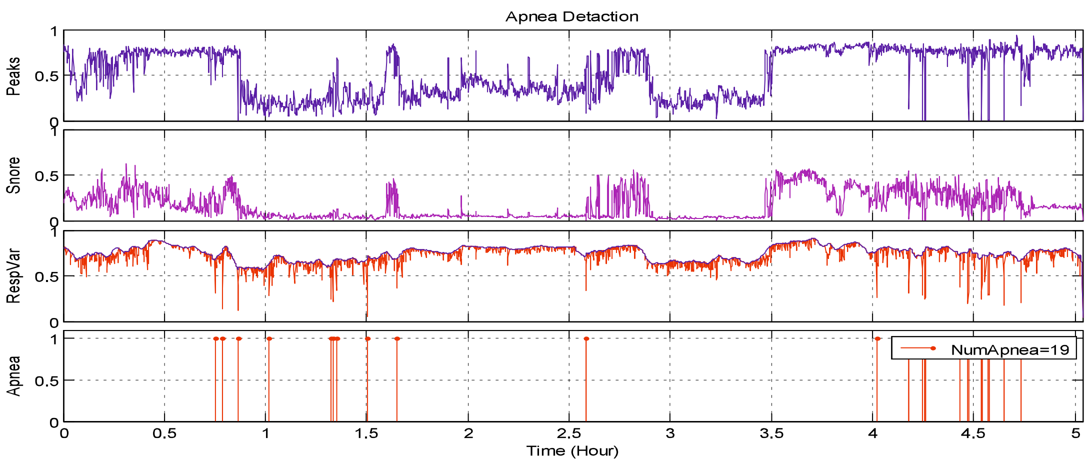


Fig. 4. Apnea detecting results by the simple calculation algorithm (Apnea=19, data 1107).

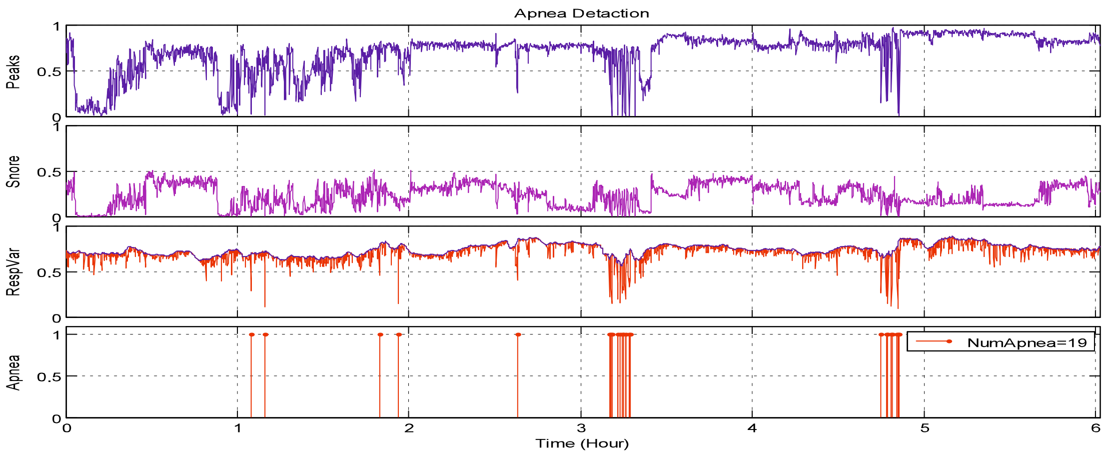


Fig. 5. Apnea detecting results by the simple calculation algorithm (Apnea=19, data 1112).

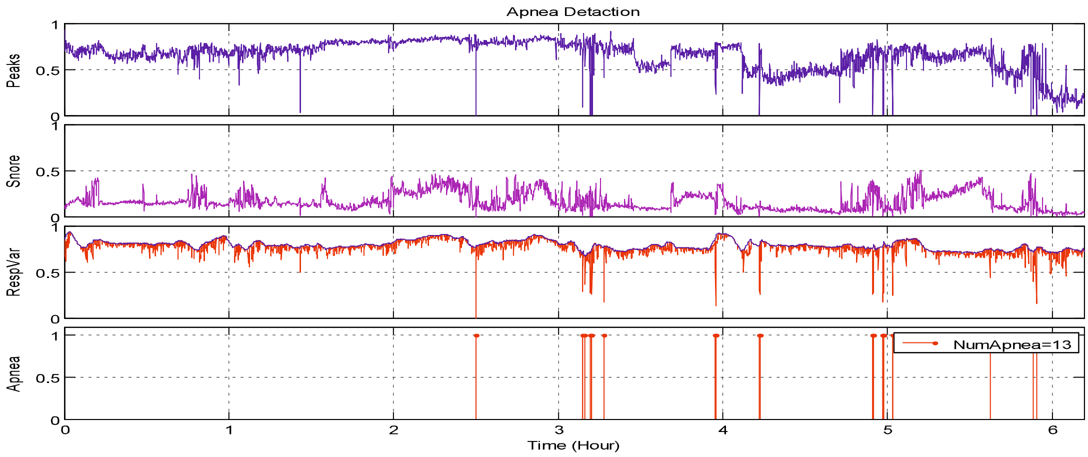


Fig. 6. Apnea detecting results by the simple calculation algorithm (Apnea=13, data 1113).

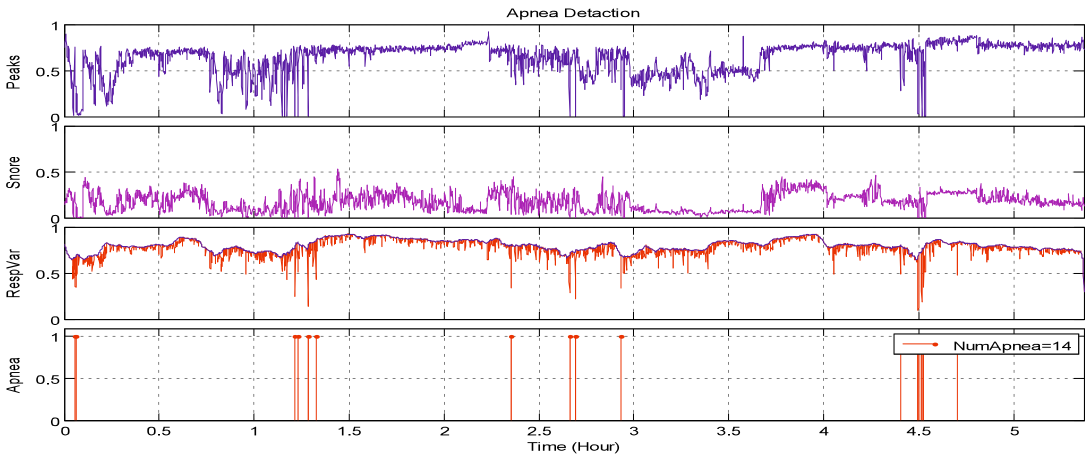


Fig. 7. Apnea detecting results by the simple calculation algorithm (Apnea=13, data 1114).

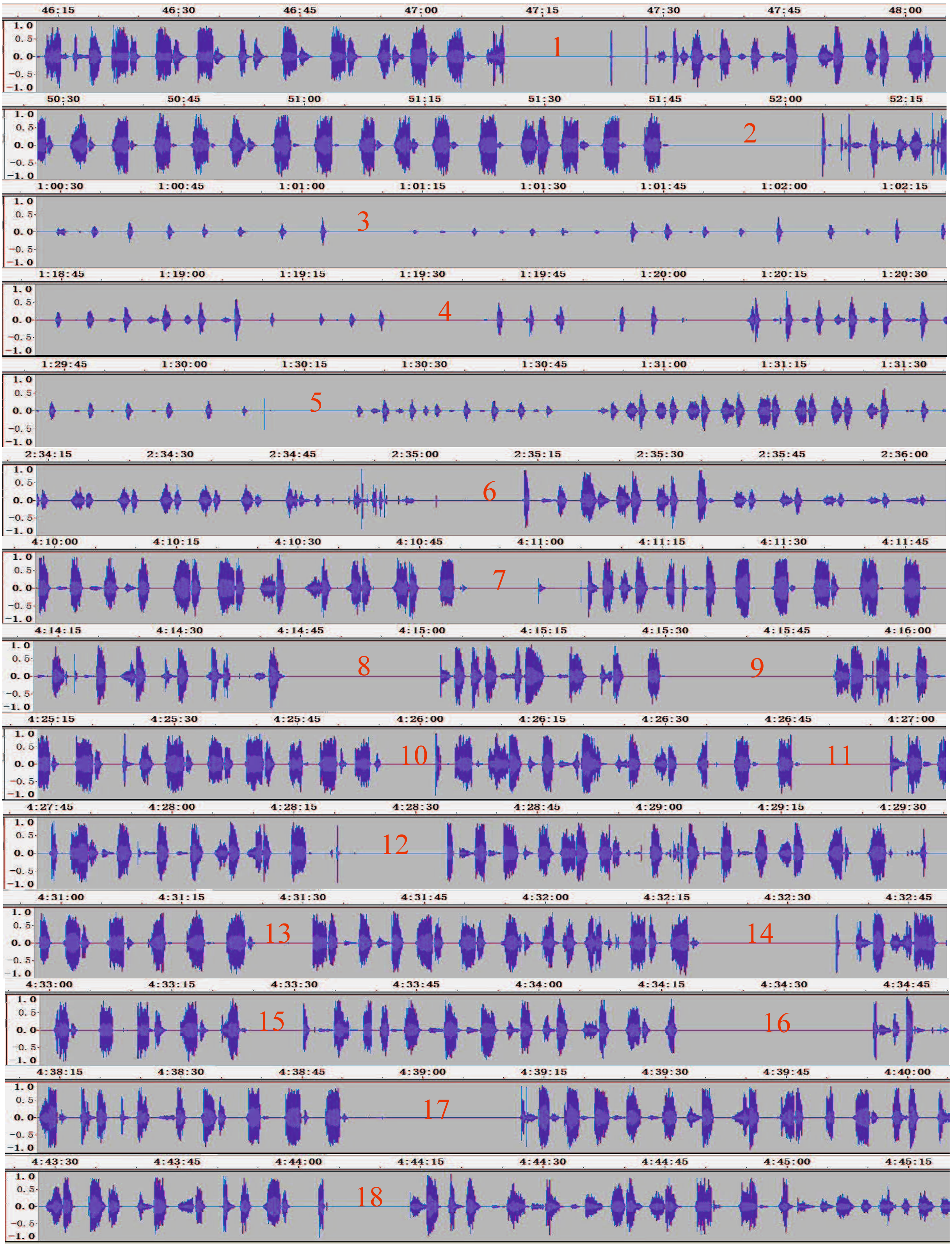


Fig. 8. Apnea detecting results by breath sound waveform (Apnea=18, data 1107).

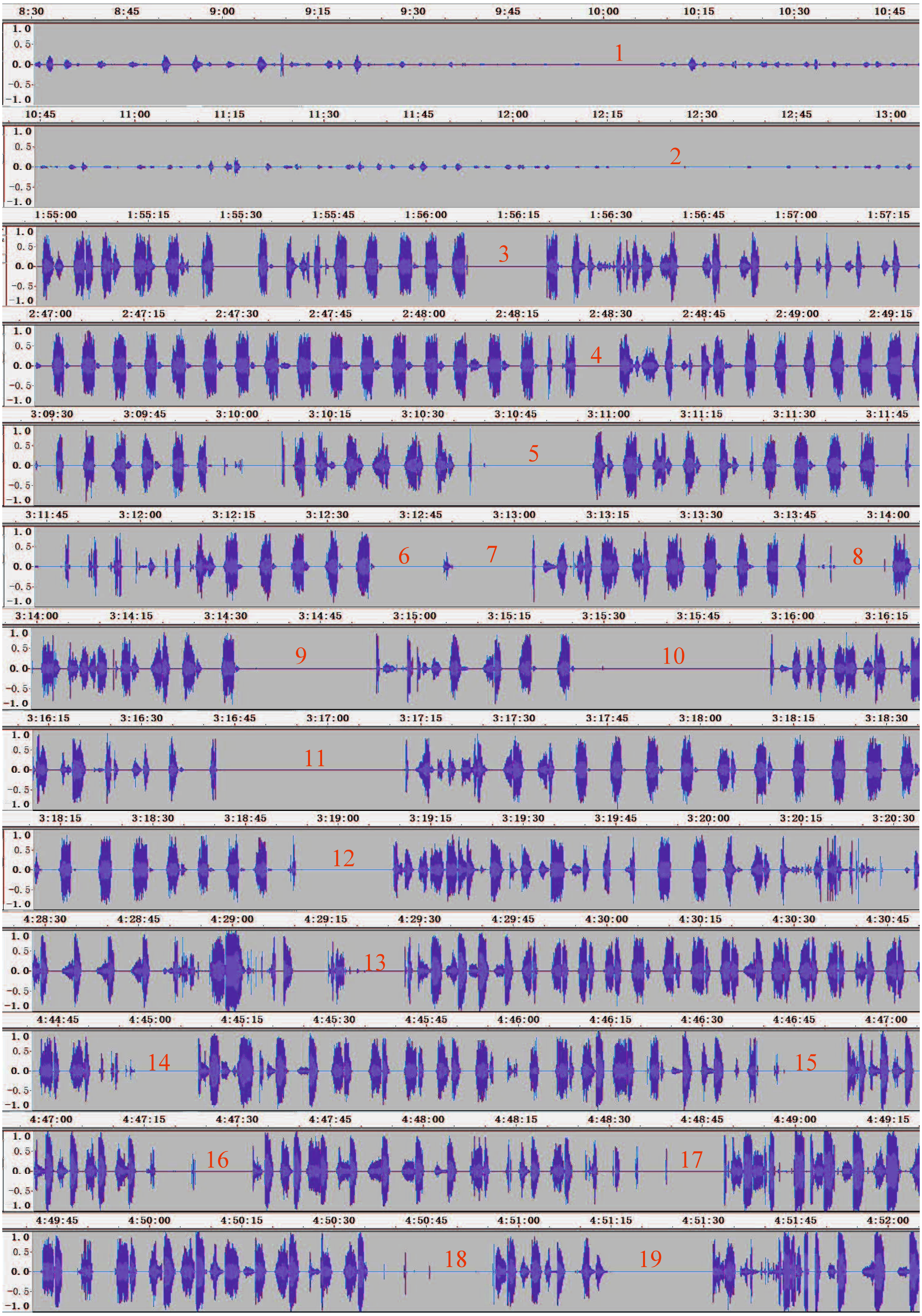


Fig. 9. Apnea detecting results by breath sound waveform (Apnea=19, data 1112).

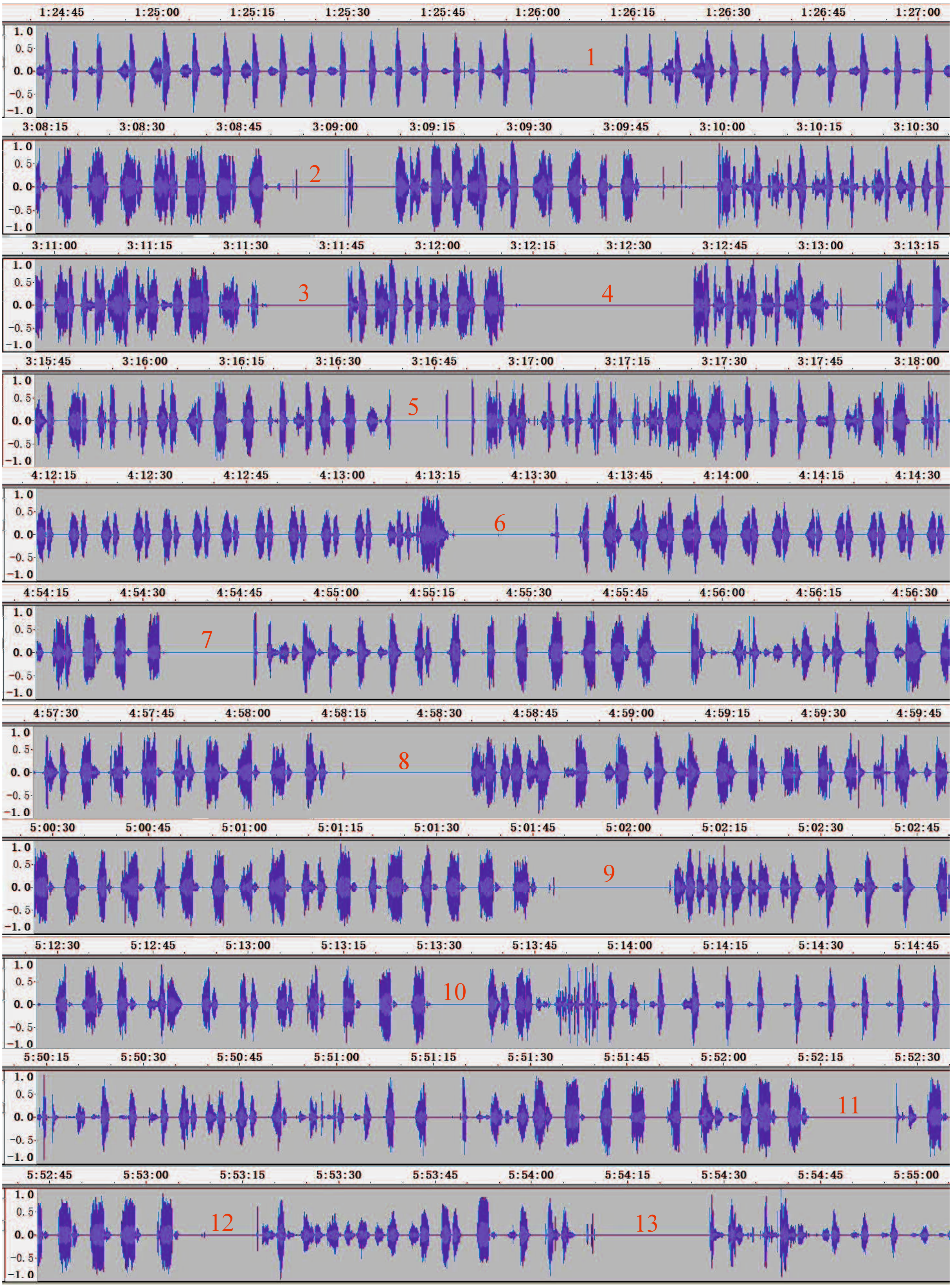


Fig. 10. Apnea detecting results by breath sound waveform (Apnea=13, data 1113).

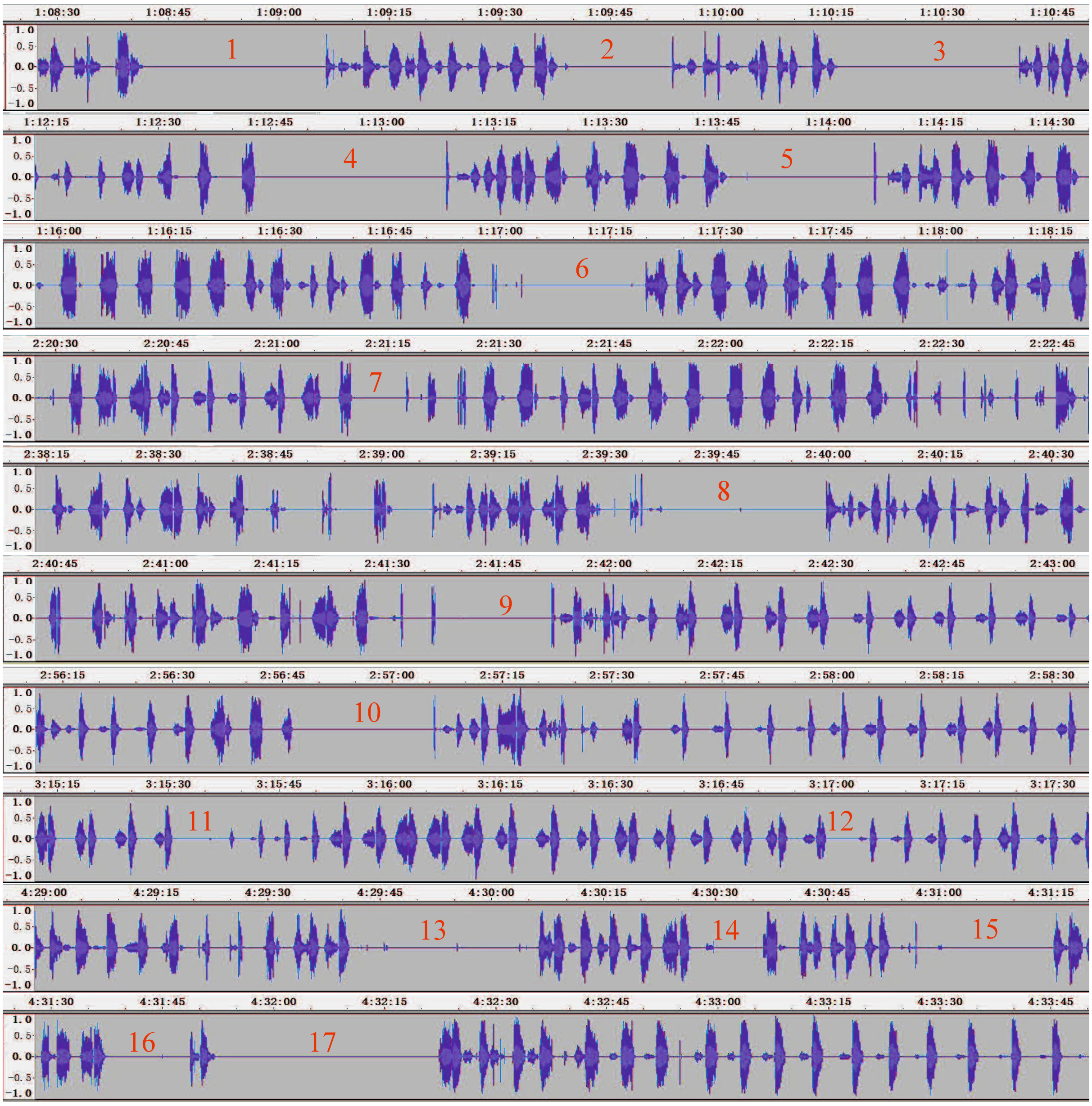


Fig. 11. Apnea detecting results by breath sound waveform (Apnea=17, data 1114).

Due to PSG is very expensive, we only have one night clinic test using PSG. All-night apnea detecting results by the simple calculation algorithm (mounting PSG devices) is shown in Fig. 12, our algorithm detected apnea is 44. The results showed that the AI values obtained from the our method are close to the values obtained using the gold standard PSG results (Apnea=45) have a good efficiency and accuracy.

5.5 Discussion

Health-related events detection system, in particular apnea detection was developed. This new method uses the respiratory variance measures for detecting apnea events. The method was implemented in Matlab 7.1 and it was tested on the sample comparing with the result of PSG. We should notice that this method is very easy to implement and compute and gives online results, which can be very beneficial to physicians and health professionals. In addition, this method is based on processing simple signal (respiration) that makes it an easy tool of health diagnosis.

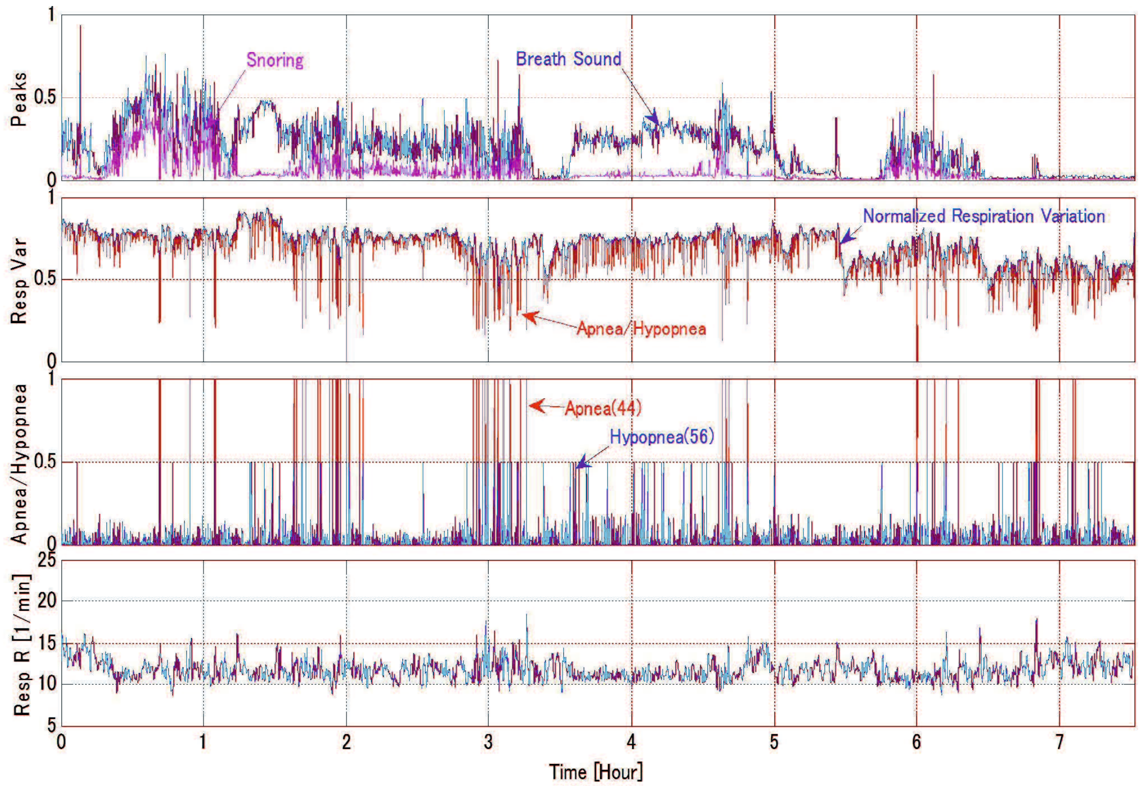


Fig. 12. All-night apnea detecting results by the simple calculation algorithm (Ref. all-night PSG results shows Apnea=45).

5.6 Summary

In this chapter a simple and efficient method for SAS detection was developed. The method is based on the calculation the difference between the respiration variation and the mean value of the respiration variation. Results showed that the SAS events were detected accurately, which in clinical practice is high enough to reduce the number of patients evaluated by polysomngrahpy (PSG), an expensive and limited diagnostic resource. Moreover, the proposed system operates on single channel measurement of breath signal, that can be taken from a low-cost PC based automated system rather than costly PSG machine. Hence, it is a low cost alternative to PSG based analysis for assessment of SAS. It can also be deployed in the customized hardware or general purpose mobile devices.

5.6 References

[1] T. Young, P.E. Peppard, D.G. Gottlier, Epidemiology of obstructive sleep apnea, a population health perspective, Am. J. Respir. Crit Care Med. 165 (2002) 1217–1239.

[2] D. Baraglia et al.,"Automated sleep scoring and sleep apnea detection in children," in proceedings of SPIE 6039, 2005

[3] P. Chazal, C. Heneghan, and W. Mcnicholas," Multimodal detection of sleep apnoea using electrocardiogram and oximetry signals," Philosophical Transactions of The Royal Society A: Mathematical, Physical and Engineering Sciences, vol. 367, no. 1887, pp. 369-389, 2009.

[4] D. Alvarez, R. Hornero, J. Marcos, F. Campo, and M. Lopez, "Spectral Analysis of Electroencephalogram and Oximetric Signals in Obstructive Sleep Apnea Diagnosis," in Proceedings of the 31st IEEE International Conference on Engineering in Medicine and Biology Society (EMBS 2009), pp. 400-403, Sep. 2009.

[5] H. Khandoker,K. Karmaker, and M. Palaniswami, "Analysis of coherence between Sleep EEG and ECG Signals during and after Obstructive Sleep Apnea Events," In Proceeedings of 30th IEEE International Conference on Engineering in Medicine and Biology Society (EMBS 2008), pp. 3876-3879, 2008

[6] T. Shochat, N. Hadas, M. Kerkhofs, et al., "The SleepStripTM: an apnoea screener for the early detection of sleep apnoea syndrome," European Respiratory Journal, vol. 19, pp. 121-126, 2002.

[7] www.resmed.com. Date retrieved 10/19/2012.

[8] M. Stuart,"Sleep apnea devices: the changing of the guard," START-UP journal, vol. 15, no. 10, pp. 1-8, Oct. 2010.

[9] A. Otero, S. Dapena, P. Felix, J. Presedo, and M. Tarasco, "A Low Cost Screening Test for Obstructive Sleep Apnea that can be Performed at the Patient's Home," In Proceedings of the 6th IEEE International Symposium on Intelligent Signal Processing, pp. 199-204, Aug 2009.

[10] Corscience GmbH & Co. http://www.corscience.es.

[11] K. Al-Ashmount, H. Hamed, and A. Morsy, "FPGA-based Sleep Apnea Screening Device for Home Monitoring," In Proceedings of 28th IEEE International Conference on Engineering in Medicine and Biology Society (EMBS 2006), pp. 5948-5951, 2006.

[12] M. Habul, R. Hallmark, A. Kotlyanskiy, P. Parejk, and R. Kamoua, "Sleep Apnea Diagnosis Device," In Proceedings of 2011 IEEE Long Island conference in Systems, Applications and Technology (LISAT), pp. 1-5, 2011.

[13] C. Wang, A. Ahmed, and A. Hunter, "Vision Analysis in Detecting Abnormal Breathing Activity in application to Diagnosis of Obstructive Sleep Apnoea," In Proceedings of the 28th IEEE International Conference on Engineering in Medicine and Biology Society (EMBS 2006), pp. 4469-4473, 2006.

[14] P. de Chazal, C. Heneghan, E. Sheridan, R. Reilly, P. Nolan and M. O'Malley, Automated processing of the single-lead electrocardiogram for the detection of obstructive sleep apnoea, IEEE Transactions on biomedical engineering 2003; 50(6): 686-696.

[15] S. Ross, I. Sheinhait, H. Katherine, et al., "Systematic review and meta-analysis of the literature regarding the diagnosis of sleep apnea," Sleep Journal, vo. 23, no. 4, pp. 519-532, 2000.

[16] M. Canosa, E. Hernandez, and V. Moret, "Intelligent Diagnosis of Sleep Apnea Syndrome," In IEEE Engineering in Medicine and Biology Magazine., vol. 23, no. 2, pp. 72–81, 2004.

[17] U. Magalang, J. Dmochowski, S. Veeramachaneni, A. Draw, M. Mador, A. ElSolh, and B. Grant, "Prediction of the apnea-hypopnea index from overnight pulse oximetry," Chest, vol. 124, pp. 1694-1701, 2003.

[18] L. Olson, A. Ambrogetti, and S. G. Gyulay, "Prediction of sleep-disordered breathing by unattended overnight oximetry," J. Sleep Res., vol. 8, pp.51-55, 1999.

[19] J. Marcos, R. Hornero, D. Álvarez, F. del Campo, and C. Zamarón, "Assessment of four statistical pattern recognition techniques to assist in obstructive sleep apnoea diagnosis from nocturnal oximetry," Med. Eng. Phys., vol. 31, pp. 971–978, 2009.

[20] J. Marcos, R. Hornero, D. Álvarez, F. del Campo, and M. Aboy, "Automated detection of obstructive sleep apnoea syndrome from oxygen saturation recordings using linear discriminant analysis," Medical & Biological Engineering & Computing, vol. 48, pp. 895–902, 2010.

[21] J. Marcos, R. Hornero, D. Alvarez, F. Campo, and M. Lopez, "Applying Neural Network Classifiers in the Diagnosis of the Obstructive Sleep Apnea Syndrome from Nocturnal Pulse Oximetric Recordings," in Proceedings of the 29th IEEE Annual

International Conference on Engineering in Medicine and Biology Society (IEMBS 2007), pp. 5174–5177, 2007.

[22] T. Micsik, S. Benedek, and Z. Benyo, "A novel Method for the Detection of Apnea and Hypopnea Events in Respiration Signals", IEEE Transactions on Biomedical Engineering, vol. 49, no. 9, pp. 936-942, Sep. 2002.

[23] T. Young, M. Palta, J. Dempsey, J. Skatrud, S. Weber, S. Badr, The occurrence of sleep disordered breathing among middle-aged adults, N. Engl. J. Med. 328 (1993) 1230–1235.

[24] Y Luo, Z Jiang, A simple method for monitoring sleeping conditions by all-night breath sound measurement, Journal of Interdisciplinary Mathematics 2017; 20(1): 307- 317.

[25] Nonin Medical. http://www.nonin.com.

Chapter 6

Conclusions

In this thesis, a study on sleeping condition measurement and evaluation was done. The methods involved are based on the detection and processing of the breath sound signals acquired with a wireless sensor developed in our laboratory in a previous work. As a first step to introduce sleep condition monitoring system which developed in our laboratory.

In a second step the sleep stages discrimination using the breath characteristic parameters for sleeping condition estimation was fulfilled. The results of estimated sleeping condition are compared to the commercial product. The sleeping condition discrimination was fulfilled by a classification method where several features are extracted from the breath characteristic parameters. More precisely, the breath sound signal obtained with the bluetooth sound sensor is prone to high grade noise which necessitated a algorithm to deal with them. It was tested on data sets acquired in our laboratory using the aforementioned sleeping conditions monitoring system. Therefore, sleep efficiency values were accurately estimated for both sets.

Then, built sleeping condition database and use in a support vector machine (SVM) classifier to evaluate and predict sleep state based on sleeping condition database. The results of estimated sleeping condition are compared to the commercial product and the classification efficiency is calculated. Results showed that the mean value of breath period is most important in 6 features. Indeed, good classification efficiency was reported for the best set of 6 features. In addition, sleep stages values were accurately estimated for both sets. Finally, results proved that it is possible using our sleep stages database to predict sleep stages based on support vector machine classifier system.

In a third step, the detection of apnea events in a night recording was performed. Due to SpO2 and RespVar have strong correlation which means the respiration variation can be used to estimate the arterial oxygen saturation. A simple method where the signal obtained with sleeping condition monitoring system is processed by algorithm defined in chapter 3 (respiration variation). The method is based on the calculation the difference between the respiration variation and the mean value of the respiration variation. Results showed that the apnea events were detected accurately.

Finally, results proved that it is possible using our sleeping conditions monitoring system with dedicated processing algorithms to reliably evaluate sleeping condition and apnae.

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