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利 用 腦 電 波 訊 號 之 循 環 交 替 模 式 偵 測

Detection of Cyclic Alternating Pattern
in Electroencephalographic Signals

研 究 生：李健銘

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中 華 民 國 一 百 年 八 月

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A Thesis

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摘　　要

　　本論文之目的在發展睡眠腦電波之循環交替模式偵測演算法，並利用分類器進行改善 A-phase 之子模式分類準確度。而現代人生活中，睡眠品質的重要性節節提高，但睡眠品質主要利用宏觀結構之睡眠階段來作為判斷依據。微觀結構部分，醫學文獻指出睡眠中循環交替模式與 A-phase 之子模式可用於判斷睡眠品質。但由於人工判讀循環交替模式費時費力且較主觀，所以尚未大量應用在臨床上。本研究結合過去方法之優點，利用相對性的功率譜數值作為腦波睡眠正規化特徵，並計算最適當循環交替模式長度，以發展改良型長度變化模板式演算法來進行睡眠循環交替模式之偵測。在本演算法中，比較相對性的功率譜數值與閾值來判斷循環交替模式中的 A-phase 之存在與否和長度，而在判斷出 A-phase 之後，利用循環交替模式之標準評比方式決定出單一睡眠循環與睡眠循環序列。在 A-phase 之子模式分類中則結合相關 Carlo Navona 等學者在 2002 年所提出之方法、碎型維度與 k 最近鄰居法分類器以提升分類準確度。

　　首先我們利用二位有失眠疾病的受測者的睡眠腦波作為腦電波特徵的測試資料，此兩位受試者循環交替模式之偵測準確度為 66%，A-phase 之子模式分類準確度為 67%。並藉由和 Barcaro 演算法做比較，驗證本演算法結合改良型長度變化模板式演算法與閾值之優越性。接著我們利用 147 位呼吸中止指數大於五的呼吸中止症受試者與 41 位呼吸中止指數小於五的無呼吸中止症受試者睡眠腦波作為腦電波特徵的測試資料。在不同的年齡層中，計算循環交替模式率的結果，呼吸中止症的受測者顯著高於無呼吸中止症的受測者。且在重度呼吸中止症受試者之循環交替模式率會有顯著提升。可驗證我們所設計的睡眠循環交替模式演算法能夠偵測到可信賴的循環交替模式率。

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Abstract

The purpose of this study is to develop a cyclic alternating pattern (CAP) detection algorithm based on EEG signal and to improve the classification accuracy of the A-phase subtypes. In the past study, sleep-related researches have been a lot, in which there is a large part of the analysis on the quality of sleep. But most of researches are applied for macrostructure analysis of sleep stage. Sleep medical literature has demonstrated that microstructure such as CAP and A-phase subtypes can be used in the analysis of quality of sleep. However, because of CAP has been noticed for sleep quality analysis in recent years and its intensive labor requirement, there are very few studies for the microstructure of CAP. Our study has inherited advantages of previous methods. It employed the descriptor of power spectrum, because the descriptor of power spectrum can provide a normalized measure. It also made use of the improved variable length template to detect the most suitable A-phase length of CAP detection algorithm. In order to decide A-phases' length and existence, our method made use of descriptor to compare with threshold. After the detection of A-phase, it is used for determining CAP cycle and CAP sequence by CAP scoring rule. In the classification of A-phase subtypes, our method has attempted to enhance classification accuracy by using Navona classification method, fractal dimension, and k-NN classifier.

In our experiment, we applied sleep EEG features of two insomnia subject's brain waves as the testing data. The accuracy of the proposed method is 65% in the CAP detection and 70.30% in A1, 24.4% in A2, and 65.4% in A3 in the classification of A-phase of subtypes. The proposed method combines variable length template method and EXIST/LENGTH thresholds method. Compared to Barcaro method, the proposed method is superior because of its usage of variable length template. We also used sleep EEG of 147 obstructive sleep apnea syndrome (OSAS) subjects and 41 non-OSAS subjects as the testing data. The CAP rates of 188 OSAS patients obtained by the proposed method are higher than those of non-OSAS subjects, which is consistent to the literature. For the severe OSAS subjects, the CAP detection results show increased values of CAP rates.

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Chapter 1

Introduction

In this chapter we briefly describe the motivation of the proposed work at the first section. In Section 1.2, we introduce sleep EEG from the definitions of sleep and the methods of sleep quality examination. In Section 1.3 we describe the development of automated cyclic alternating pattern (CAP). In Section 1.4 we give a brief introduction to CAP A-phase subtype. Finally in Section 1.5 presents the overview of the thesis.

1.1 Motivation

Sleep plays an important role in our life. On the average, people spend one-third of their life times sleeping. Therefore, sleep quality is essential for good quality of life. The sleep quality will bring people a lot of advantages, such as increased concentration, increased physical activity, increased ability of body cell requirement, and lowering blood pressure. The poor quality of sleep may lead to the lack of concentration, fatigue, high blood pressure, stress increases, and other negative affective states. Nowadays, varies types of sleep disorders such as narcolepsy [18], obstacle sleep apnea, and insomnia, may result in poor sleep quality.

In the past study, sleep-related research have been a lot, in which there is a large part of the analysis on the quality of sleep. Many researches used polysomnography (PSG) to record sleep signals and utilized subjective self-report such as Pittsburgh sleep quality index (PSQI) for analysis. Because we also need objective analysis of sleep quality, human sleep Electroencephalography (EEG) scored by PSG could be used to analyze the quality of sleep. There are two parts of sleep quality analysis used sleep EEG. One is sleep staging of macrostructure, the other is arousal and CAP of microstructure. We plan to develop an algorithm for accurate CAP classification of the micro-organization of human sleep Electroencephalography (EEG) without human intervention.

1.2 Sleep Quality Analysis

1.2.1 Polysomnography

During sleep, the physiological signals can be comprehensive recorded by polysomnography (PSG). PSG can examine the dynamic structure of sleep. The PSG monitors many physiological signals such as electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG), blood pressure, respiratory efforts, oxygen saturation (SaO2), and so on during sleep. The computer-based PSG system involves sensors, amplifiers, filters, analog-digital converters and computer with peripheral devices. The PSG could use EEG, EOG, and EMG to automatically analyze sleep stages and use EEG to automatically analyze CAP, then provide sleep stage report and CAP report. The PSG system also could use respiration, snoring, and oxygen saturation values for analyzing sleep related breathing disorders and other parameters such as body temperature, ECG, and blood pressure have their own usefulness in sleep research. Although most PSG system has the function of sleep scoring and CAP detection, most sleep specialist would rather score manually and the PSG system report is used for reference. Due to sleep scoring system is unreliable; PSG system is only for signal acquisition. Now in Taiwan, many hospitals set up sleep center. In sleep center, they have professional devices and suitable environments for sleep data recording. These two reason is needed for reducing noise while signal recording.

1.2.2 Sleep EEG

Sleep is a complex behavioral and physiological process. In the sleep EEG, the signal for the analysis of sleep is divided into two major categories of macrostructure and microstructure. Macrostructure of sleep has some parameters, such as total sleep time, time in bed, sleep efficiency, sleep latency, wake after sleep onset, sleep stages, rapid eye movement latency. Macrostructure part is the analysis of sleep stages. Sleep signals are used to analyze sleep stages according to R & K procedure. The sleep signal is divided every 20s or 30s as an epoch of sleep stage classification. In sleep, it can be divided into two states which are rapid eye movement (REM) and non-rapid eye movement (NREM). REM sleep

is defined by EEG activation, muscle atonia, and episodic bursts of rapid eye movements. Conventionally, NREM sleep is subdivided into four stages, which are stage 1, 2, 3, and 4. Usually, stage 1 and 2 sleep are referred as light sleep; Stage 3 and 4 are combined as slow-wave-sleep (SWS). Stage 3 and 4 are also called deep sleep [7]. Within sleep, brain activity is mainly divided into four rhythms [12]. According to different frequencies, it can divided into delta wave (<4 Hz), theta wave (4-8 Hz), alpha wave (8-12 Hz), and beta wave (>13 Hz). Beta waves have higher frequency than other rhythms. Alpha waves occur during relaxed state such as eyes closing, so it appears regular rhythms with higher amplitude than beta waves. Generally, theta waves have greater amplitude and slower frequency than alpha waves. Delta waves are the highest amplitude and the slowest EEG rhythms. Theta waves and delta waves become more and more obvious in the EEG background activities during deep sleep. Microstructure part is divided into two types of arousal and CAP. Arousal represents the fragmentation of sleep and sleep signal is applied to arousal analysis which calculates the number of occurrences of sleep arousal. Another is that the direction of this study, Cyclic alternating pattern (CAP). CAP is a defense mechanism of sleep, because CAP likes a sentinel in accordance with the same physical condition at certain times to certain frequencies or the length of time to do some physical state monitoring. If CAP sequences appear frequently, it indicates the sleep state is tight, sleep phenomenon is not stable and the sleep quality is poor. However, If CAP sequences appear infrequently, there are health problems that may not be dealt with timely. Therefore, CAP is very important indicator in sleep quality analysis.

1.2.3 Macrostructure : sleep stage and Rechtschaffen and Kales rules

In the last 4 decades, the standard of classification of the single sleep stages, which is proposed by Rechtschaffen and Kales in 1968 [13], has been widely used. The standard of the single sleep stage classification which is proposed by Rechtschaffen and Kales (R&K) paradigm is based on the electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG). In EEG, it is the minimum requirement of central leads of EEG such as C3-A2 and C4-A1 and occipital leads such as O2-A1 and O1-A2 are additionally recorded. Two EOG leads are placed at the outer corners of the eyes to detect

vertical and horizontal eye movements. In order to monitor the variation of voltage between the mental and submental areas, EMG leads are placed in the two areas. The entire sleep recording is divided into epochs with the standardized length of 20 sec or 30 sec. According to the characteristics of EEG signal, sleep staging process can divided into six stages: Stage W, Stage 1, 2, 3, 4, and REM. The characteristics of EEG signals and corresponding sleep stages defined are described in the following list [8]. The EEG pattern is also presented with such characteristic waveform as vertex sharp wave, spindles, sawtooth wave, and K-complexes as shown in Figure 1.1. These EEG patterns may appear in different sleep stages.

(a) vertex sharp wave   (b) spindle   (c) sawtooth
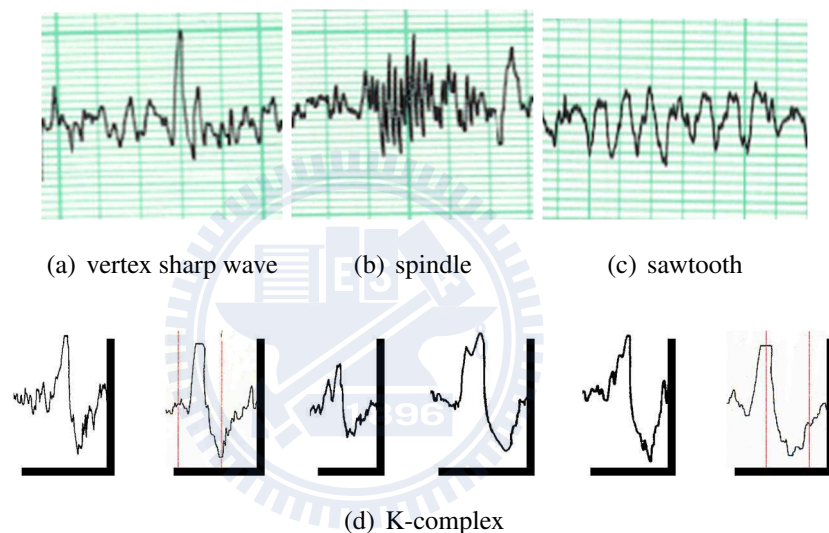
(d) K-complex

Figure 1.1: (a) vertex sharp wave; (b) spindle wave; (c) sawtooth wave; (d) K-complex wave

- **Stage W (Wakefulness):** The EEG contains alpha activity with low voltage or not and mixed frequency activity.

- **Stage 1:** Stage 1 is the beginning of the sleep cycle. it is characterized by the low voltage and mixed frequency of EEG signal. Stage 1 can be considered the transition between wakefulness and other sleep stages. In Stage 1, the alpha wave is less than 50% in overall epoch and the slow wave with sharp negative voltage which is called vertex sharp wave may appear in the EEG.

Table 1.1: Outline of sleep scoring standard according to R&K standard

Stage		EEG	EOG	EMG
Wakefulness		**Eyes Closed:** rhythmic alpha (8-13 cps); prominent in occipital; attenuates with attention; **Eyes open:** relatively low voltage, mixed frequency	Voluntary control; REMs or none; blinks; SEMs when drowsy	Tonic activity, relatively high; voluntary movement
NREM	**Stage1**	1.Relatively low voltage, mixed frequency; 2.May be theta (3-7 cps) activity with greater amplitude 3.Vertex sharp waves; 4.Synchronous high-voltage theta bursts in children	SEMs	Tonic activity, may be slight decrease from waking
	Stage2	**Background:** relatively low voltage, mixed frequency; **Sleep spindles:** waxing, waning, 12-14 cps (>0.5sec); **K complex:** negative sharp wave followed immediately by slower positive component (>0.5sec); spindles may ride on KCs; KCs maximal in vertex; spontaneous or in response to sound	Occasionally SEMs near sleep onset	Tonic activity, low level
	Stage3	20%-50% high amplitude (>75 uV), slow frequency (<2cps); maximal in frontal	None, picks up EEG	Tonic suppression; phasic twitches
	Stage4	>50% high amplitude, slow frequency	None, picks up EEG	Tonic activity, low level
REM		Relatively low voltage, mixed frequency	Phasic REMs	Tonic suppression; phasic twitches

Adopted from Principles and Practice of Sleep Medicine, 2nd Ed. W.B. SAUNDERS company, which is modified from Rechtschaffen A, Kales A (eds): A Manual of Standardized Terminology: Techniques and Scoring System for Sleep Stages of Human Subjects. Los Angeles, UCLA Brain Information Service/Brain Research Institute, 1968.

- **Stage 2:** Stage 2 is the second stage of sleep and appears of high-voltage slow wave activities. The brain begins to appear sleep spindles and K complexes. Sleep spindle wave is an EEG oscillations of 12-15 Hz. K-complex wave is a high-amplitude biphasic wave which begins with a sharp positive voltage wave and the following as a negative deflection slow wave. In Stage 2, body temperature begins to decrease and heart rate starts to slow.

- **Stage 3:** In Stage 3, moderate amount of slow delta waves begin to emerge. The slow delta waves of EEG activity occupy between 20% and 50% of an epoch.

- **Stage 4:** Stage 4 contains more than 50% slow delta waves of an epoch.

- **Stage REM:** In most human adults, Stage REM accounts for 20%25% of total sleep time. Stage REM is defined by a relatively low voltage, mixed frequency EEG. In Stage REM state, it may appear sawtooth wave, which is looks like a sawtooth.
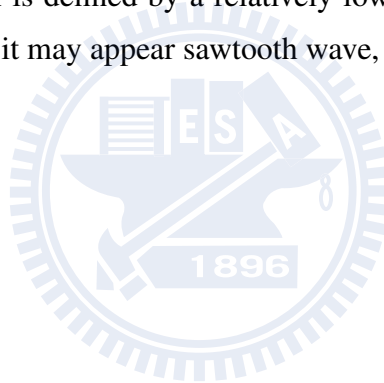
Table 1.2: Arousals and CAP (difference)

	Arousals	**Cyclic Alternating Pattern(CAP)**
Organization	Single events	Rhythm
EEG features	Theta, alpha and/or frequencies bigger than 16 Hz but not spindles	Both fast (arousals) and slow frequences (K-complexes, delta bursts)
Physiological distribution	NREM and REM sleep	Only in NREM stages
Measurement	Only event counting	Event counting/timing/ratio
Age-related evolution	Linear increase	u-shaped profile
Physiological significance	Sleep fragmentation	Sleep instability

(Figure source:Origin and Significance of the Cyclic Alternating Pattern (CAP), Sleep Medicine Reviews,Mario Giovanni Terzano and Liborio Parrino, 2000.)

1.2.4   Microstructure : Arousal and CAP

In the sleep microstructure analysis, we introduce above that contains CAP and arousal. In this section, we will introduce these two kinds of EEG phenomena of sleep microstructure of their characteristics and their differences and similarities. The EEG phenomena of sleep microstructure are an important research to attempt to overcome the limitations of the macrostructure. In sleep analysis, CAP plays an important role on the investigation of sleep instability and arousal quantification is a significant indicator of sleep fragmentation. In this field, we also unsure whether arousals and CAP A-phase are primary cerebral phenomena or evoked responses to activating peripheral events [17]. Both studies have some differences and similarities we present in the Table 1.2 and Table 1.3 [17].

1.3   Cyclic Alternating Pattern

A clinical meaning of CAP is that a number of sleep disorders can be qualified as relating either to the A-phase or to the B-phase [16]. CAP is an index to determine the quality of sleeping and as a marker of arousal instability. CAP can appear spontaneously in non-REM sleep, but it can occur also in association with identifiable sleep pathophysiologies

Table 1.3: Arousals and CAP (overlaps and similarities)

During NREM sleep (in particular during stages 1 and 2), the majority of arousals(87.4%) occur within a CAP sequence, and they always coincide with A-phase
During NREM sleep, most arousals (90%) are preceded by a phasic slow wave activity, in accordance with the feature continuity (progressive desynchronization from A1 to A3) that links the three A-phase subtypes
Both arousals and CAP A-phase (especially subtypes A2 and A3) can be accompanied by activation of muscle tone and cardiorespiratory rate
The post-arousal period and phase B of CAP exert a powerful attenuating effect upon muscle tone and neurovegetative activities
Increased amounts of arousals and of CAP rate both reflect a condition of disturbed sleep

(Figure source:Origin and Significance of the Cyclic Alternating Pattern (CAP), Sleep Medicine Reviews,Mario Giovanni Terzano and Liborio Parrino, 2000.)

(e.g. sleep-disordered breathing and periodic leg movement activity) [1]. CAP occurs not only at drowsiness and light sleep, but in all NREM stages. The CAP sequence, originally conceptualized as an arousal phenomenon, has evolved theoretically to encompass both the process of sleep maintenance and sleep instability. When falling into sleep, information is exchanged among many parts of brain during consciousness, and the frequency of information exchanging reduces, while the exchanges won't disappear. During sleep, EEG would show the waves with higher frequency and amplitude, which calls "micro-arousal". This kind of micro-arousal is to detect whether our body has problem or not. That is why we say CAP likes the sentinel. CAP time and CAP rate can be used to evaluate the sleep efficiency. CAP time can be calculated throughout total NREM sleep and within the single NREM stages. CAP rate is defined by the ratio of CAP time to sleep time. By detecting the rate of CAP which can be measured in NREM sleep (the ratio of CAP time to NREM stage time) and in the single NREM stages (the ratio of CAP time to a given NREM stage to the total duration), the higher the CAP rate the poorer sleep quality. Many factors may affect the CAP rate. For example, CAP rate is increased by perturbing conditions and decreased by hypnotic medication. But the strongest factor is age. Some previous researches show that CAP rate shows a u-shape evolution along the life span (teenagers: mean 43.4%;
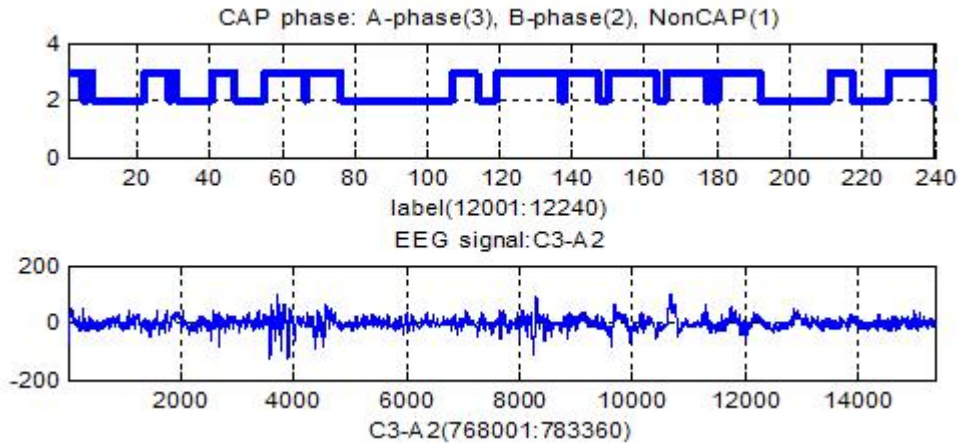
Figure 1.2: CAP sequence and EEG signal C3-A2

young adults: 31.9%; middle aged: 37.5%; elderly: 55.3% [17]) in human sleep. We can observe micro cyclical alternation of sleep by a diagram which is called sleep capsnogram. As shown in Figure 1.2, it appears different CAP phases following with different time in sleep process.

The CAP subtype classification extends the current American Sleep Disorders Association (ASDA) definitions to include a periodicity dimension and a possible marker of pre-arousal activation regarding CAP to be an arousal process [15] [2]. These typically transient events such as EEG bursts with high-amplitude, delta-like wave or K-complex sequence are considered to reflect a possible arousal process. According some sleep phenomena with sleep instability, CAP A-phase can classify as the type of slow wave activity (subtypes A1 of CAP) marks the brains attempt to preserve sleep and subtypes A2 and A3 of CAP with the high-amplitude, slow activity to perform that sleep becomes too unstable or the preservation attempt fails.

CAP analysis is not a method to replace sleep staging or arousal scoring. But CAP analysis is a quantitative sleep analysis and provides a tool to use in our quest to look at human sleep.
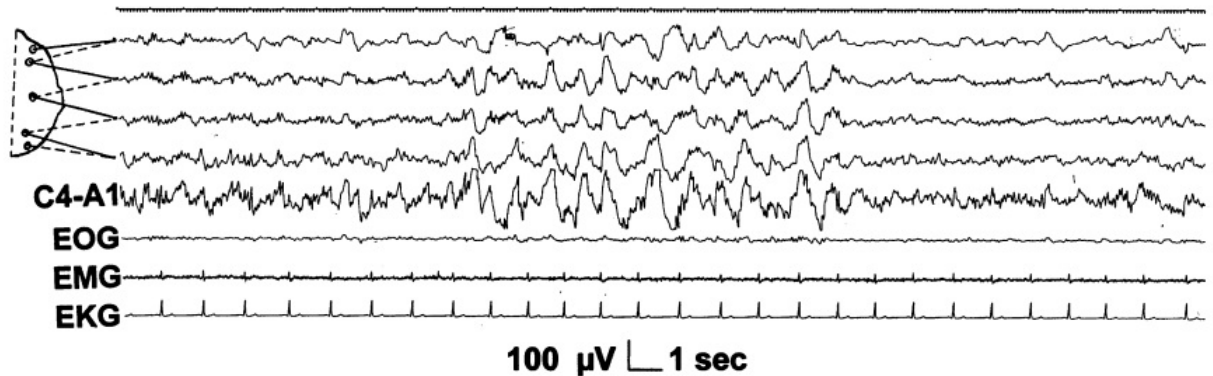
Figure 1.3: Delta burst. Top 4 channels is Bioplolar parasagittal EEG derivation of the right side : FP2F4 , F4C4 , C4P4 , P4O2; C4A1: C4 connects to left ear (A1); EOG: Electrooculogram; EMG: Electromyogram; EKG: Electrocardiogram. (Figure source: Sleep Medicine 3, Consensus Report, Mario Giovanni Terzano et al.: Atlas, rules, and recording techniques for the scoring of cyclic alternating pattern (CAP) in human sleep, p 187-199, 2002)

1.3.1 CAP A-phase EEG events

In this section, we introduce CAP A-phase EEG events. A-phase can be composed of rhythms with slower and higher-voltage, rhythms with faster and lower-voltage, or by mixed patterns including both. They may include: delta bursts, vertex sharp transients, K-complex sequences with or without spindles, polyphasic bursts, K-alpha, intermittent alpha, and EEG arousals [15].

Delta bursts

The EEG delta burst is a wave with frequency range from 0.5 to 4 Hz and with at least 1/3 higher average amplitude than the background signal activity.

Vertex sharp transients

Vertex sharp transients are EEG potentials which has variable amplitude (up to 250 mV) and length of time between 50 ms to 200 ms. Sequences of vertex sharp transients are composed at least two repetitive potentials lasting at least 2 s.

100 μV ∟ 1 sec
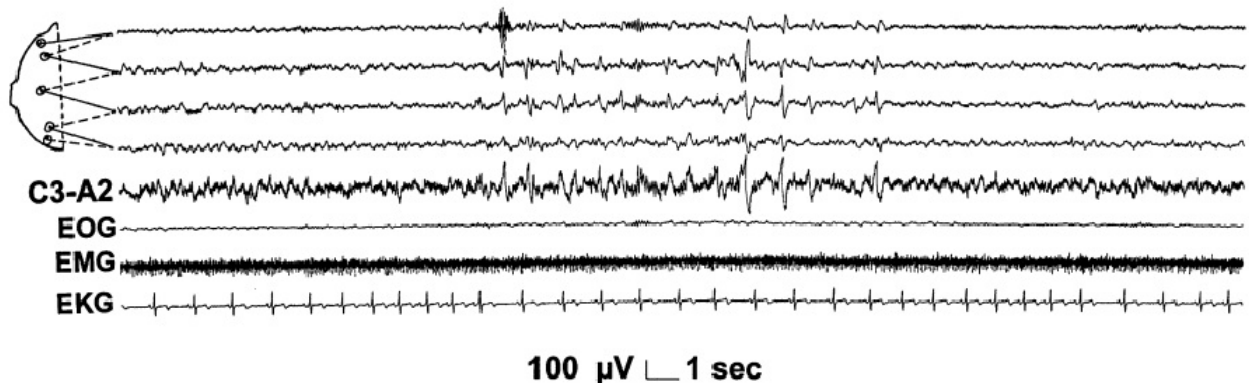
Figure 1.4: Sequence of vertex sharp transients. Top 4 channels: Bipolar parasagittal EEG derivation on the left side : P3O1 , F7T3 , T3T5 , FzCz; C3A2: C3 connected to right ear (A2). (Figure source: Sleep Medicine 3, Consensus Report, Mario Giovanni Terzano et al.: Atlas, rules, and recording techniques for the scoring of cyclic alternating pattern (CAP) in human sleep, p 187-199, 2002)

K-complex sequences with or without spindles

K-complex sequences is composed at least two consecutive K-complexes. Each K-complex presents a biphasic pattern or triphasic pattern consisting of a rapid negative component and a slower positive wave. The K-complex may be mixed with or followed by a sleep spindle. The length of time of a single K-complex is between 0.5 to 2 s; therefore, K-complex sequence duration is more than 2 s.

Polyphasic bursts

Polyphasic bursts consist of high-voltage delta waves and intermixed with theta, alpha, or beta waves. Polyphasic bursts can include at least two delta peaks.

K-alpha

K-alpha is composed of a K-complex and the following as an alpha (8-13 Hz) burst. The overall duration of K-alpha is at least 2 s.

100 μV ∟ 1 sec
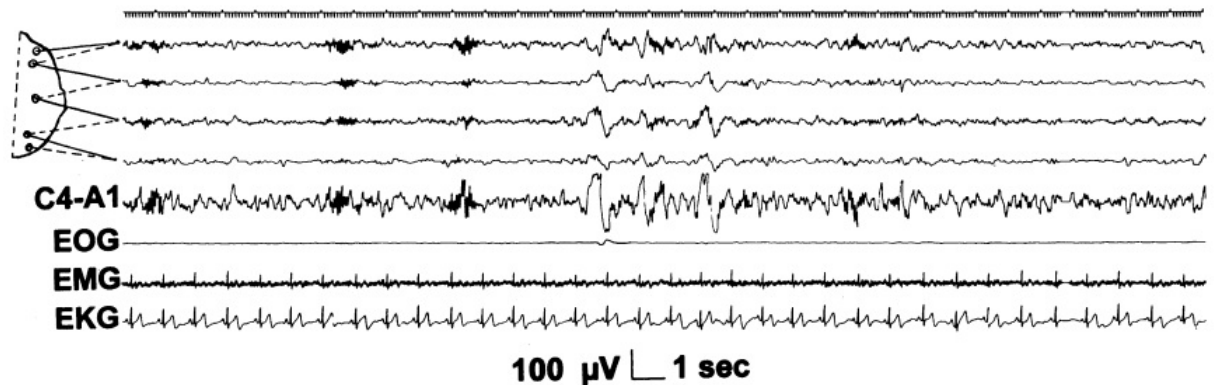
Figure 1.5: K-complexes sequences associated with spindles. Top 5 channels: EEG derivation as in Figure 1.3 (Figure source: Sleep Medicine 3, Consensus Report, Mario Giovanni Terzano et al.: Atlas, rules, and recording techniques for the scoring of cyclic alternating pattern (CAP) in human sleep, p 187-199, 2002).

Intermittent alpha

At sleep onset, the alpha rhythm field tends to spread forward, then it fragments into intermittent sequences in sleep stage 1. When sleep progresses, it disappears. Before it vanishes, the EEG activity of Alpha may also increase in amplitude and decrease in frequency.

EEG arousals

EEG arousals could interrupt sleep continuity shortly and the duration of EEG arousals is more than 3 s. It is a phenomenon that are sudden frequency shifts to faster rhythms such as theta, alpha, beta, but not spindles.

1.3.2 Scoring Rules for CAP or non-CAP

From previous researches, we can list systematically with CAP scoring rules [15].

Requirements for scoring a CAP sequence

1. A CAP cycle consists of an A-phase and followed by a B-phase.

Figure 1.6: Polyphasic burst in stage 2 sleep. Top 5 channels: EEG derivation as in Figure 1.3 (Figure source: Sleep Medicine 3, Consensus Report, Mario Giovanni Terzano et al.: Atlas, rules, and recording techniques for the scoring of cyclic alternating pattern (CAP) in human sleep, p 187-199, 2002).

2. Each CAP sequence is composed of at least two CAP cycles.

Onset and termination of a CAP sequence

3. All CAP sequences start with a A-phase and end with a B-phase.

Non-CAP

4. If the CAP sequence disappear more than 60 s, This period of time is scored non-CAP.

5. An isolated A-phase means that is preceded or followed by another A-phase but the duration between them is more than 60 s. An isolated A-phase is scored non-CAP.

6. The A-phase in the end of the CAP sequence is scored as non-CAP.

7. B-phase with duration between 2 s and 60 s is the signal between two A-phases.

Minimal criteria for the detection of a CAP sequence

8. CAP sequences have no upper limits on overall duration and on the number of CAP cycles.

Figure 1.7: K-alpha complex in stage 2 sleep. Top 5 channels: EEG derivation as in Figure 1.4 (Figure source: Sleep Medicine 3, Consensus Report, Mario Giovanni Terzano et al.: Atlas, rules, and recording techniques for the scoring of cyclic alternating pattern (CAP) in human sleep, p 187-199, 2002).

Stage shifts

9. CAP sequence is scored in non-REM sleep and CAP sequence scoring can extend across adjacent sleep stages so it is not interrupted by a sleep stage shift.

Temporal limits

10. Each phase of CAP is between 2 s and 60 s in duration.

11. If the B-phase between two A-phases less than 2 s, the two A-phases are scored an A-phase.

12. If the B-phase between two A-phases longer than 60 s, the two A-phases is scored two different CAP sequences.

Amplitude limits

13. A-phase is the repetitive element represented by the recurring EEG feature. The A-phases phasic activities is at least 1/3 higher average amplitude than the background signal activity.
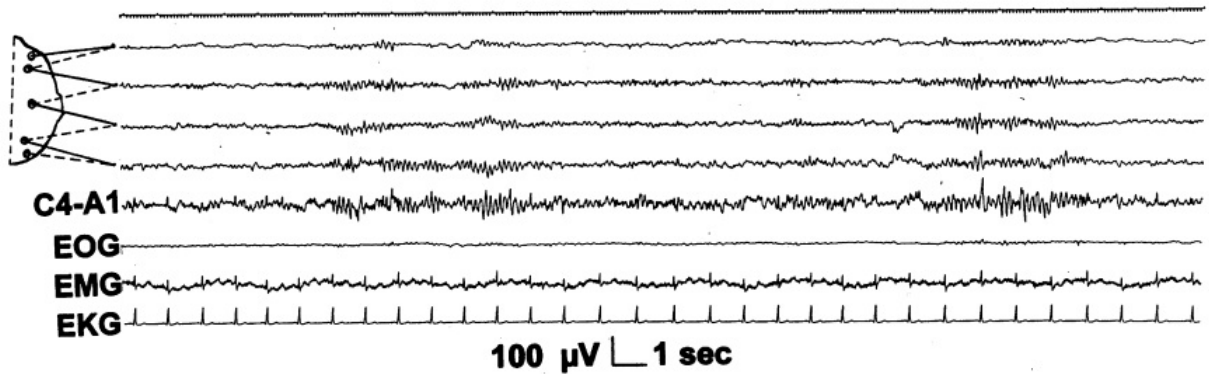
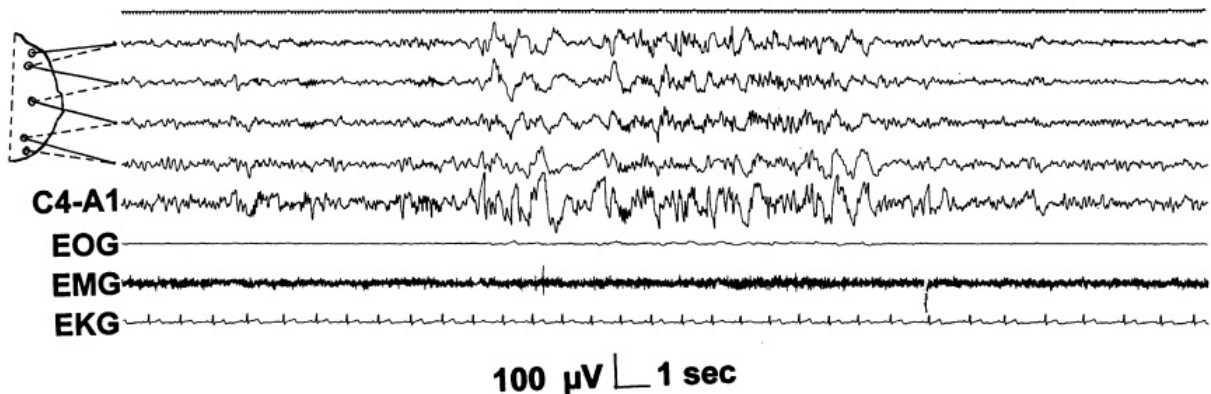Figure 1.8: Intermittent alpha rhythm in stage 1 sleep. Top 5 channels: EEG derivation as in Figure 1.3 (Figure source: Sleep Medicine 3, Consensus Report, Mario Giovanni Terzano et al.: Atlas, rules, and recording techniques for the scoring of cyclic alternating pattern (CAP) in human sleep, p 187-199, 2002).

14. B-phase is a background signal. Phase B is used to separate the A-phase.

1.4   Subtypes of A-phase

CAP A-phase involves different degrees from EEG activities, muscle tone and neurovegetative responses, so A-phase can be classified into three subtypes. There are A1, A2, and A3. The three subtypes classification is based on the percentage of EEG synchrony and EEG desynchrony in the all A-phase duration. EEG synchrony is the reciprocal proportion of high-voltage slow waves and EEG desynchrony is low-amplitude fast rhythms. The following are three subtypes description. [15]

subtypes A1: In subtypes A1, this A phase primary with EEG synchrony patterns involves intermittent alpha rhythm in stage 1, sequences of K-complexes or delta bursts in the other NREM stages, vertex sharp transients, and polyphasic bursts. Subtypes A1 with EEG desynchrony activity is below 20% of all A-phase duration.

subtypes A2: In subtypes A2, this A-phase mixes with EEG desynchrony patterns and slow high-voltage waves such as K-complexes with alpha and beta activities, K-alpha and arousals with slow wave synchronization. Subtypes A2 with EEG desynchrony activity is
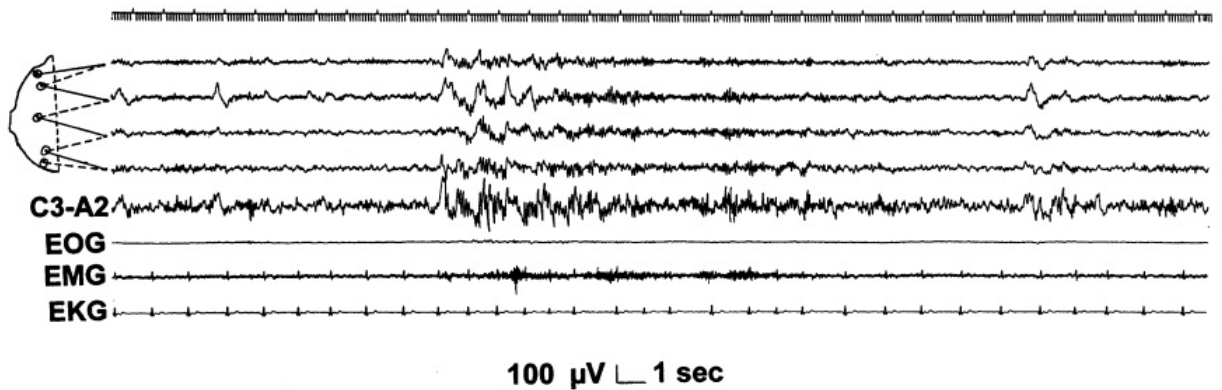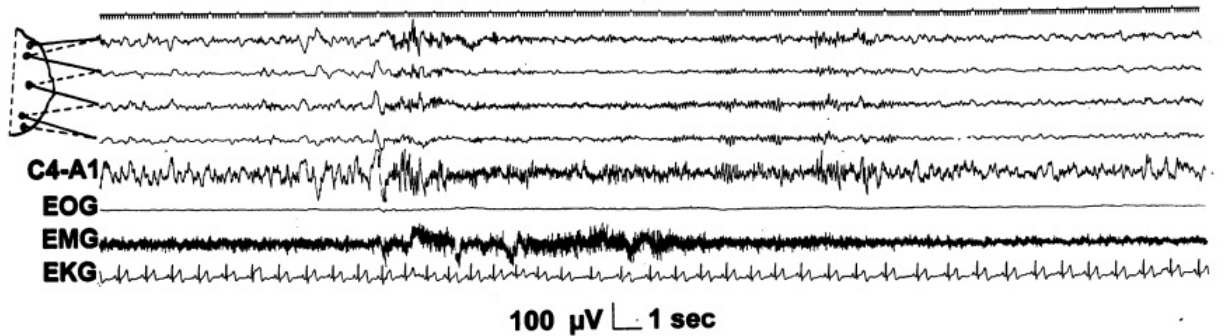
Figure 1.9: Arousal preceded and followed by sleep. Top 5 channels: EEG derivation as in Figure 1.3 (Figure source: Sleep Medicine 3, Consensus Report, Mario Giovanni Terzano et al.: Atlas, rules, and recording techniques for the scoring of cyclic alternating pattern (CAP) in human sleep, p 187-199, 2002).

20-50% of all A-phase duration.

subtypes A3: In subtypes A3, this A phase with desynchronized EEG patterns involves transient activation phases, EEG arousals, K-alpha, and polyphasic bursts. The A3 subtypes is primary with rapid low-voltage rhythms and with over 50% EEG desynchrony activity of all A-phase duration.

Generally, the number of subtypes A1 is more than subtypes A2 and subtypes A3. Because subtypes A1 has different patterns with A2 and A3, A1 is easier distinguished in A-phase than A2 or A3.

1.5   Thesis overview

In this chapter we introduce the purpose of this study at first, and second we introduce analysis system sleep quality as PSG and sleep quality analysis as macrostructure and microstructure. Finally, we introduce about CAP and A-phase subtypes. In Chapter 2, we introduce the automated CAP detection method in the past and the proposed method of modified CAP detection algorithm. In the beginning, we introduce several related work of CAP detection algorithm. By all related work, we talk about two kinds of features used in CAP detection and a new feature to subtypes A-phase classification, and we also mention

about two kinds of methods to detect A-phase. We may analysis the advantages and drawbacks of these algorithms, and extract their useful parts as reference method for our work. Then, we provide the methods of our proposed CAP detection algorithm system. It contains four sessions as data preprocessing, feature extraction, A-phase detector and context decision. In Chapter 3, we will present the experimental results. There are two parts of our experiments: the first part is the CAP detection testing with subjects and the second part is the A-phase subtypes classification. In these two parts, the efficacy will present in the results. In Chapter 4, we summarize our work with the results and explain some possible problems of our method. In Chapter 5 we conclude this work and mention future works for extended research.
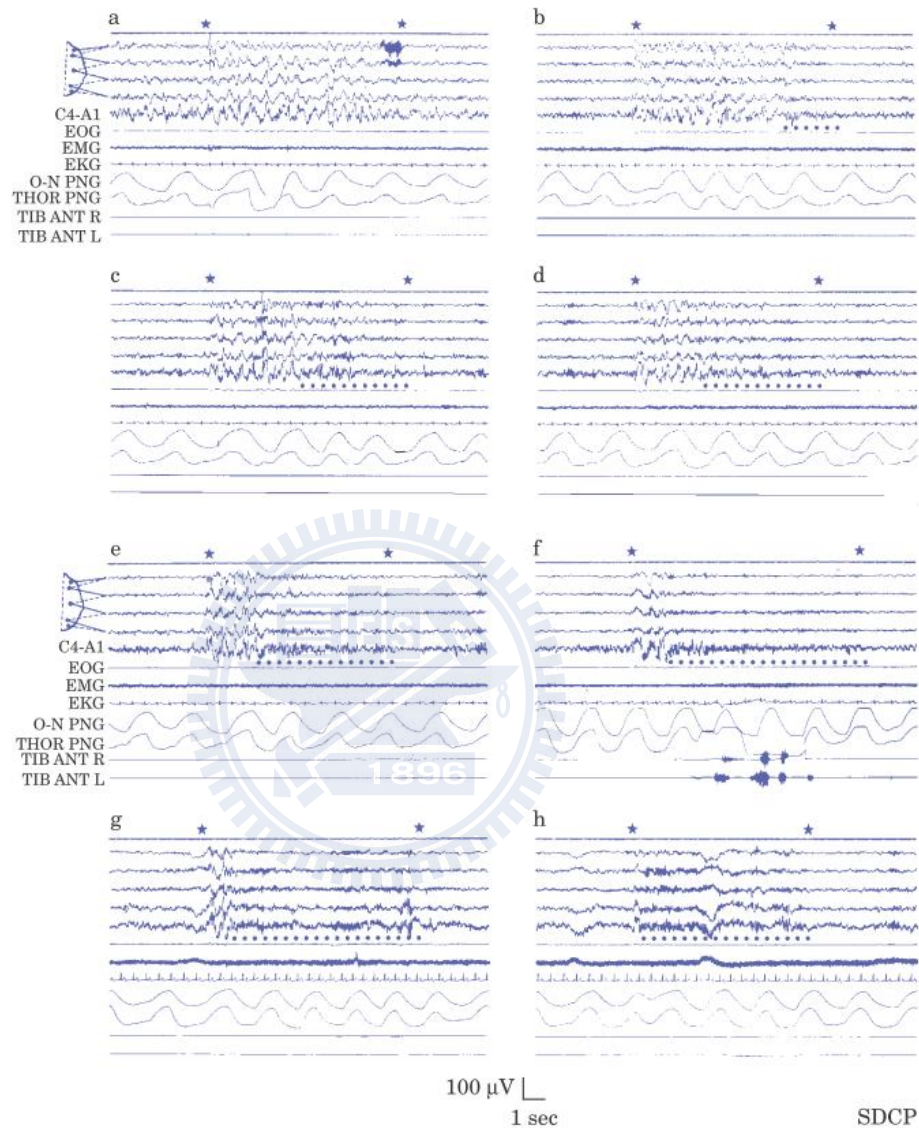
Figure 1.10: These samples are separated to represent the A-phase subtypes of CAP. Sample a and b are subtypes A1; sample c and d are subtypes A2; sample e, f, g, and h are subtypes A3. (Figure source:Origin and Significance of the Cyclic Alternating Pattern (CAP), Sleep Medicine Reviews,Mario Giovanni Terzano and Liborio Parrino, 2000).

Chapter 2

Automated Detection Algorithm for Cyclic Alternating Pattern

2.1 Introduction to automated cyclic alternating pattern detection

In the last 3 decades, the EEG phenomena of sleep microstructure such as arousal and CAP have been extensively explored with the attempt to overcome the limitations of the R & K procedure. In earlier study, an automatic detection system of CAP sequences was proposed by Rosa et al. [14]. The system has three parts: The feature extraction part is an EEG generation model-based maximum likelihood estimator. The detector part is a variable length template matched filter, which adjusts template length to decide A-phase length in order to decide CAP A-phase and non-A-phase. The classification criteria part is a context decision system, which is rule-based on a consensus report by Terzano et al. [15]. Another automatic method was based on the computation of seven descriptors to recognition and classification of the A-phase proposed by Umberto Barcaro et al. [1]. In order to compute these descriptors, it used two suitable thresholds and simple criteria for logical discrimination [1]. It is also to define a unified method for the auto recognition and quantitative description of EEG phasic events of sleep microstructure occurring during NREM sleep, particularly arousals, A-phase subtypes of cyclic alternating pattern, and spindles. The conclusion is that visually defined events can be reliably identified by means of automatic recognition. Then, an automatic method for the recognition and classification of the A-phases of the cyclic alternating pattern was proposed by Navona et al. [9]. This method is based on five descriptors computed from different frequency band of EEG signals and for the recognition and classification with a simple procedure with the mathematical and computational points of view. Recently, some features were proposed on the relation with EEG complexity measures, such as fractal dimension (FD), sample entropy, and Hjorth parameter [5] [6]. These studies suggest that features may assist in the detection of sleep dynamic structures.

Framework of CAPS
classification

General structure of the CAPS detector
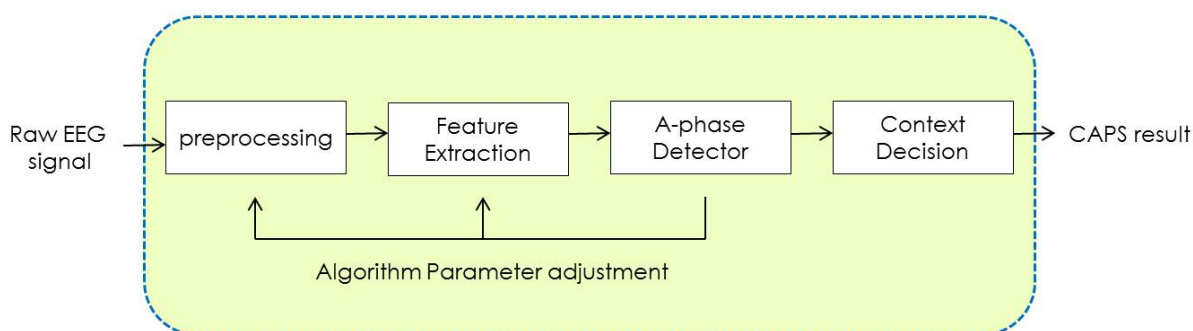
Figure 2.1: Framework of cyclic alternating pattern sequence classification

2.2 Survey of automated cyclic alternating pattern methods

Generally, the CAP detection algorithm has a flow chart shown in Figure 2.1. This flow chart includes preprocessing, feature extraction, A-phase detector, and context decision. The automated CAP A-phase subtypes classification with another flow chart that involves preprocessing, feature extraction, and classification. The differences with the CAP detection algorithm are the selection of feature sets and the A-phase detector method. We can get some information about how to combine different feature sets and A-phase detector methods. In automated CAP A-phase subtypes classification, some features were mentioned in previous studies, so we tried to use this information to improve accuracy.

2.2.1 Feature extraction method

In the literature, there are two different EEG feature extraction methods in CAP detection algorithm. There are gains and short-long term ratios. The following is the parameters and descriptions of the two feature extraction methods. After these two features, we intro-
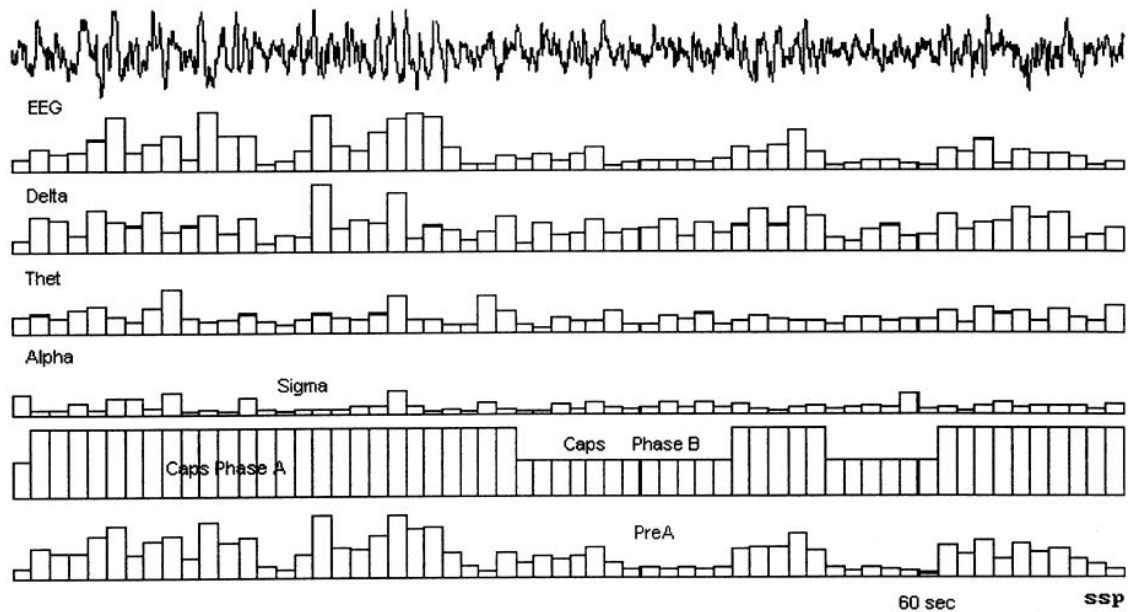
Figure 2.2: An CAP automatic classification result with the duration of 60 s. The top row id the EEG CA-A1 channel. The following 4 rows are the estimated gains of delta band, theta band, alpha band, and sigma band. The sixth row represents CAPS detection result. The hight level is A-phase. The middle level is B-phase. The zero level is NCAPS. The bottom row is the weighted combination of the estimated gains.) (Figure source: Clinical Neurophysiology, A.C. Rosa et al.: Automatic detection of cyclic alternating pattern (CAP) sequences in sleep: preliminary results, p 585-592, 1999)

duce one kind of EEG features used in sleep microstructure analysis.

Gains

The sleep EEG process is described by an EEG generation model with physiological background [4]. The necessary features set for CAP detection algorithm are obtained by estimating the gains shown in Figure 2.2. There are separated four components (delta, theta, alpha, and beta). For each component, a vector of gains was computed every 0.5 or 1 s, so we can get delta, theta, alpha, and sigma activities.

Short-long term ratios

Short-long term ratios is also called descriptor. The computation of the descriptors has three parts.

The first part is to separate five bands by a digital band-pass filter into different frequency of original EEG signals, there are delta (0.75-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), sigma (12-15 Hz), and beta (15-25 Hz).

In the second part, two amplitude averages are computed every 0.5 or 1 s. One is short interval with 2 s and the other is long interval with 64 s. The length of shorter interval is taken two reasons into account: it should be short to provide microstructure information for CAP detection algorithm and long enough to ensure Fourier transform correctness. The long interval value is considered for macrostructure information.

In the third part, the descriptors for each band are computed according the following formula:

$$ShortAverage_i = \frac{1}{2k} \sum_{t=i-k}^{i+k} \widetilde{x}_i(t) \tag{2.1}$$

where k denoted the number of sample points of 1 s interval and i denoted each point of time. So we compute short average at 2 s interval.

$$LongAverage_i = \frac{1}{64k} \sum_{t=i-32k}^{i+32k} \widetilde{x}_i(t) \tag{2.2}$$

where k denoted the number of sample points of 1 s interval and i denoted each point of time. So we compute long average at 64 s interval.

In the third part, the descriptors for each band are computed according the following formula:

$$descriptor_i = \frac{ShortAverage_i - LongAverage_i}{LongAverage_i} \tag{2.3}$$
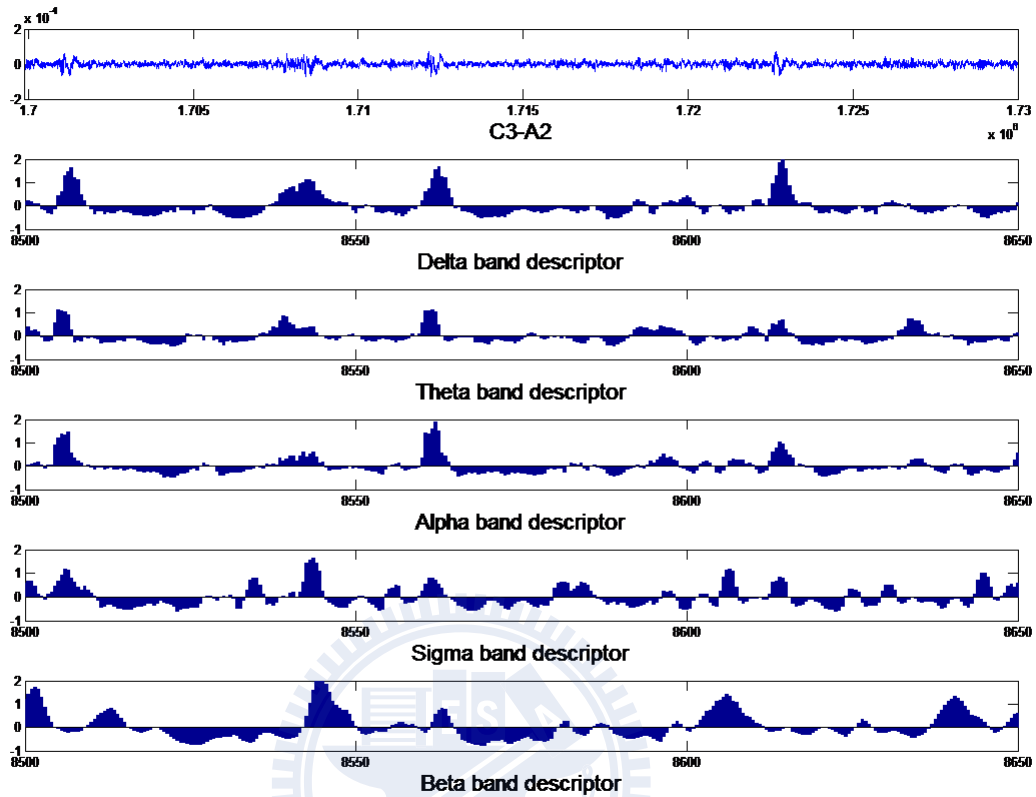
Figure 2.3: The rows from top to bottom are EEG signal C3-A2 channel, delta band descriptor, theta band descriptor, alpha band descriptor, sigma band descriptor, and beta band descriptor.

Fractal dimension

In fractal geometry, fractal dimension (FD) is a statistical quantity. The fractal dimension gives an indication of how completely a fractal appears to fill space. Fractal dimension used in sleep microstructure was proposed by Chouvarda in 2010 [3]. This work explores the relationship between EEG complexity measures such as fractal dimension and sample entropy, sleep macrostructure structure such as sleep stages, and sleep microstructure structure such as A-phase activation of CAP. FD has the relationship with the transitions between light and deep sleep. Finally, A-phase subtypes A1, A2, and A3 has progressively
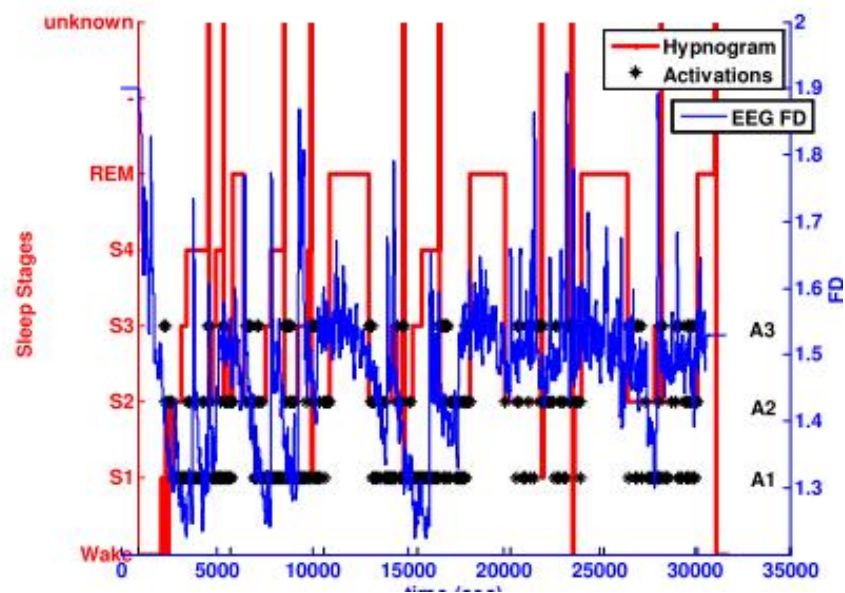
Figure 2.4: This figre represents FD in solid blue line, Sleep Stages in dotted red line, and A-phases with subtypes in black dots. A-phase subtypes A1, A2, and A3 has progressively increased its FD values. (Figure source: Annual International Conference of the IEEE EMBS, I. Chouvarda et al.: EEG Complexity during Sleep: on the effect of micro and macro sleep structure , 2010)

increased its FD values. It is shown in Figure 2.4. FD values of show a progressively increase

In the time domain analysis, it is hard to present the signal variability between the different of A-phase or non-A-phase since scoring is based on the analysis of EEG power spectrum. But fractal dimension is an EEG complexity measure which can be used to estimate EEG signal variability. Fractal dimension analysis is frequently used in biomedical signal processing including EEG analysis. The two types of approaches are used in the applications of FD, those are time domain and phase space domain. Previous methods estimate the FD in the time domain or original waveform domain. We compare three algorithm proposed by Rosana in 2001 [5], Higuchi's algorithm, Katz's algorithm and Petrosian's algorithm. In the IEEG signal, the Katz's algorithm is the most consistent method for distinguishing ability of epileptic states. It is relative insensitivity to noise. Higuchi's method is a better accurate estimation of FD than other algorithms. But in synthetic data,

Higuchi's method is relative sensitivity to noise. Petrosian's method performance depends on the type of signal used. Petrosian's method becomes less suitable in some cases for analog signal analysis. This method used in synthetic data has high sensitivity to noise. Our study focuses on experimental signals derived from EEG, its results are widely applicable to any type of signal. We use Higuchi's method to calculate fractal dimension because Higuchi's algorithm provides the most accurate estimates of the FD. The algorithm implements with the following criteria. First, consider *s(1), s(2), ..., s(N)* the EEG sleep time sequence signal to be analyzed. s_n^k is constructed as *k* new time series

$$s_n^k = \{s(n), s(n+k), s(n+2k), ..., x(n+\lfloor \frac{N-n}{k} \rfloor k)\} \text{ ,for } n = 1, 2, ..., k \qquad (2.4)$$

Where *n* is initial time value and *k* shows the time interval between points. Second, The average length $L_n(k)$ is computed as

$$L_n(k) = \frac{\sum_{i=1}^{\lfloor \frac{N-n}{k} \rfloor} |s(n+ik) - s(n+(i-1)k)|(n-1)}{\lfloor \frac{N-m}{k} \rfloor k}$$

(2.5)

For each time series s_n^k

Where *N* is the overall length of data *s* and $(N-1)\lfloor \frac{N-n}{k} \rfloor k$ is used to normalize. Third, all time series has the same scale *k* to compute average length, so the mean of the *k* length $L_n(k)$ for $n = 1, ..., k$. This procedure run for each *k* from *1* to k_{max}. For each *k*, the sum of average length *L(k)* is

$$L(k) = \sum_{t=1}^{k} L_n(k) \qquad (2.6)$$

L(k) is the total average length for scale *k*. *L(k)* is proportional to k^{-D}. Then *D* means the fractal dimension by Higuchi's method. In the curve of $\ln(L(k))$ versus $\ln(1/k)$, we can estimate the FD with the slope of the least squares linear best fit.

2.2.2 Detection methods

In the literature, two major detection methods are length template matched filter and threshold decision for detect A-phase from EEG signals. We plan to construct an A-phase detector using previous method advantages.

Variable length template matched filter

The A-phase detection method was proposed by A.C. Rosa in 1999 [14]. It is called adaptive matched filter which can detect CAP A-phases and B-phase candidates. The structure of this filter is shown in Figure 2.5. The A-phase detector is a filter using template matched method and threshold decision to decide A-phase. First, a sliding unit amplitude square pulse (2 s duration) is convoluted by feature values. Compare with a threshold, if the convolution value is larger than threshold, then repeating the convolution with the square pulse by increasing pulse length 1 s which means variable pulse. At last, the convolution process stops when the convolution value is smaller than threshold. Finally, the length of the square pulse is the length of candidate A-phase and all non-A-phases are candidate B phase.

EXIST/LENGTH threshold decision

Another algorithm for A-phase detection method was proposed in 2002 and 2004. The A-phase detection method use two thresholds and two conditions to recognize and classify the microstructure events and characteristic during sleep, a exist threshold (equal to 1) and a length threshold (equal to 0). The two conditions have a small different setting, by [9], The candidate A-phase condition is at least one descriptor in one of all components above the length threshold for all the points and the A-phase condition is at least one point in delta or the theta descriptor above the recognition threshold in the candidate A-phase. But in [1], except the two conditions are mentioned above, this research gives a restriction to candidate A-phase. The limits of the length of A-phase is that all of these bands' descriptor of the first two consecutive points at the left and the first two consecutive points at the right below the length threshold. The example is shown in Figure 2.6.
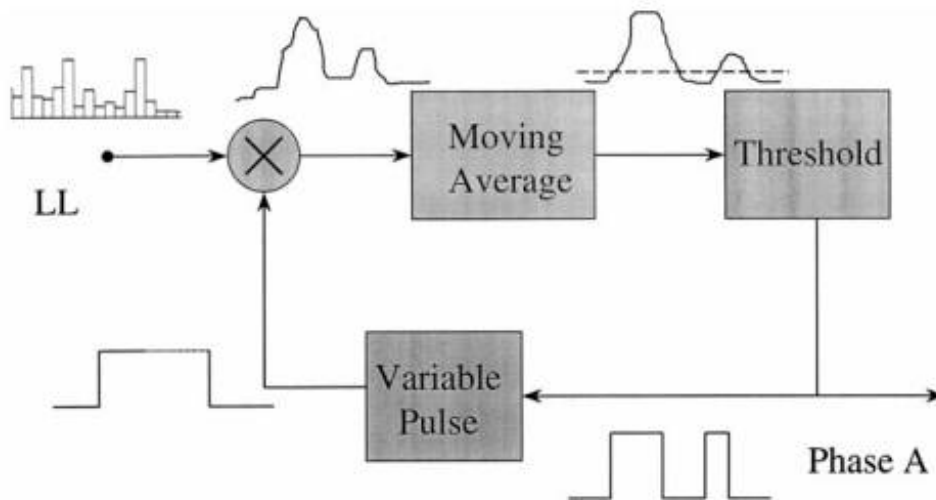
Figure 2.5: "The implementation structure of the matched filter. The feature input (LL) is windowed (multiplied) by the output of the variable pulse (zero or one) which is controlled by the threshold output (A-phase). The moving average of windowed feature is the input of the threshold block. The whole process is equivalent to a unit amplitude variable length square pulse template filter." (Figure source: Clinical Neurophysiology, A.C. Rosa et al.: Automatic detection of cyclic alternating pattern (CAP) sequences in sleep: preliminary results, p 585-592, 1999)

2.2.3   Discussion of previous method

After reviewing related researches for automated CAP detection method, we prefer to adopt the method of short-long term ratios and template length filter method.

We choose short-long term ratios because it has some advantages better than each component's gain. The features of short-long term ratios are considered the EEG signals relationship between short-term variability and long-term variability. Short-long term ratios method is very simple from the mathematical and computational points of view, which provides a strong and significant data reduction from the original EEG signal. These descriptors are an extension of powerful macrostructure descriptors, some of which are commonly applied to the quantitative analysis of sleep EEG. The method appears extensible to other microstructure phenomena different from the CAP.

The variable length template can vary template length to cover features near the time

to fit template, so the A-phase detect is not only decided by a single threshold but also considered nearby features. Because CAP is a periodic EEG activity of non-REM sleep that is distinguished from background EEG activity, the variable length template is an efficiency method to achieve this condition.

Therefore, we need to calculate a set of features from EEG single channel which correspond with the descriptor of short-long term ratios. After that, implement the modify version template length filter to detect A-phase. The proposed automated CAP detection system will test by 2 subjects to verify its reliability and efficacy. Afterwards we also calculate CAP rate and capsnogram to verify it reliability again.

2.3 The proposed method

The procedure of CAP detection algorithm can be divided into four main steps: (1) EEG preprocessing, (2) feature extraction, (3) A-phase detector, and (4) context decision. The flow chart of CAP A-phase subtypes has three steps: (1) feature extraction, (2) classifier-based classification, and (3) rule-based classification. First, EEG raw data is recorded from PSG, then preprocessing for noise removal. Second, some features of the preprocessed EEG signals are extracted. We use seven bands of band power and Hjorth parameter activity to calculate their descriptors and to compute fractal dimension for A-phase detection and subtypes classification. In A-phase detector, we propose an automated method which can adjust parameters and make some extension to detect A-phase. In context decision, we choose some parameters set as same as previous researches. In subtypes classification, we choose k-nearest neighborhood (k-NN) algorithm.

2.3.1 Signal preprocessing

At first, we use the raw EEG signal which is C3-A2 channel, and the sampling frequency is 128 Hz. Then, the continuous time EEG signal are segmented with every 0.5-second interval. We choose the segment length of 0.5 seconds because earlier studies considered about the microstructure and decided a suitable time length. For instance, an 8 hour records will divide into 57600 segments.

2.3.2   Feature extraction

The purpose of our work is to implement CAP detection algorithm. The accuracy of the CAP detection algorithm is the essential consideration. In our method, we only use a single channel of EEG signal for CAP sequence detection, so feature sets which can represent the difference between A-phase and non-A-phase is an important consideration. For this reason, the feature extraction method is an important factor of CAP detection algorithm. Two feature extraction methods are mentioned in Section 2.3.2.

Owing to the specific features of CAP detection algorithm in frequency bands defined in CAP consensus report, we extract the feature sets in the frequency domain. We divide the frequency band into seven sub-bands between 0.5 Hz and 45 Hz. In addition, we also divide the δ band into lower and higher band. The δ band is 0.5-4 Hz. The band is divided into $delta$ (0.5-2.5 Hz) and $delta$ (2.5-4 Hz) ; The θ band is 48 Hz; The α band is 8-12 Hz; The σ band is 12-15 Hz; The β band is 15-25 Hz. Besides, the total band is defined with the range of 0.5-45 Hz. The EEG signal is filtered by using the butterworth filter and the bandwidth of each frequency bands is defined above. These eight frequency bands is shown in Table 2.1.

Table 2.1: Eight frequency bands with its frequency range respectively

Frequency band	Range (Hz)
1. Total band	0.5-45
2. Delta band	0.5-4
3. Lower delta band	0.5-2.5
4. Higher delta band	2.5-4
5. Theta band	4-8
6. Alpha band	8-12
7. Sigma band	12-15
8. Beta band	15-25

Short-long term ratios

After the frequency band is separated as we mentioned above. The computation of the descriptors has two parts. First, we compute two amplitude averages each *0.5* s. One is short interval with *2.5* s as formula 2.7 and the other is long interval with *64.5* s as formula 2.8. The short interval value is considered two reasons: it should be short to provide microstructure information for CAP detection algorithm and long enough to ensure Fourier transform correctness. The long interval value is considered for macrostructure information.

$$ShortAverage_i = \frac{1}{5} \sum_{t=i-2}^{i+2} \widetilde{x}_i(t) \tag{2.7}$$

where *i* denoted each point of time and the band power is average each *0.5* s. So we compute short average between *-2* to *2* that depends on the band power average length.

$$LongAverage_i = \frac{1}{129} \sum_{t=i-64}^{i+64} \widetilde{x}_i(t) \tag{2.8}$$

where *i* denoted each point of time and the band power which average each *0.5* s. So we compute long average between *-64* to *64* that depends on the band power average length.

In the second part, the descriptors for each band are computed according the following formula :

$$descriptor_i = \frac{ShortAverage_i - LongAverage_i}{LongAverage_i} \tag{2.9}$$

Because the descriptor provides a relatively measured between the short interval signal instantaneous and background signals variation.

Fractal dimension

In the time domain analysis, it is hard to present the signal variability between the different of A-phase or non-A-phase since scoring is based on the analysis of EEG power spectrum. But fractal dimension is an EEG complexity measure which can be used to estimate EEG signal variability. The proposed method computes one fractal dimension

value each 0.5 s to provide a stable result and use Higuchi's algorithm to compute fractal dimension value. Higuchi's algorithm provides the most accurate estimates of the FD. The Higuchi's algorithm was implemented with the k value we select.

Hjorth parameter

The feature of Hjorth parameters is used to detect A-phase. The Hjorth parameter describes the signal characteristics in terms of activity (variance (VAR) of signal), mobility (a measure of mean frequency), and complexity (a measure of the deviation from sine shape). The activity values are used in the proposed method and calculate in *500* ms time window without overlapping. We compute two activity average values each *0.5* s of the short interval with 2 s and long interval with 64 s, then calculate descriptor as formula 2.9.

2.3.3   A-phase detector

We plan to construct an A-phase detector. The A-phase detector determines the period of time of the A-phase for all night sleep. In the A-phase detector, we combine two methods that are the variable length template and the EXIST/LENGTH thresholds because we plan to inherit the two methods advantages and to avoid their disadvantages. The variable length template method for CAP detection was proposed in 1999 and the EXIST/LENGTH thresholds method for CAP detection was proposed in 2004. Using the variable length template method to detect A-phase is a more reasonable method than the EXIST/LENGTH thresholds method. Because the EXIST/LENGTH thresholds method determines short-long term ratios of each time point and compares short-long term ratios with the EXIST/LENGTH thresholds to decide A-phase or not, the EXIST/LENGTH thresholds method could not make adjustments according to features near the time. The variable length template method could solve the problem. The variable length template can vary template length to cover features near the time to fit template. In the previous A-phase detectors, the EXIST/LENGTH thresholds method used two thresholds (EXIST/LENGTH) is better than the variable length template method used one threshold. In the definition of A-phase, the length of A-phase is decided by all band descriptors. But the exist of A-phase is decided by delta band particularly. The proposed A-phase detector uses two thresholds

to decide the length and the exist of A-phase separately.

The method is considered about the different situation. First, the EXIST/LENGTH thresholds should be adjust because the physiological state is different for each subject. Different subject has different sleep EEG signal structure, so the two thresholds are needed to change case by case. Second, the band is also selected because of different sleep EEG signal structure. The detecting steps are shown below and the structure of this filter is shown in Figure 2.7.

Step1. Choose start point of EEG signals which segment every 0.5 s.

Step2. Initial a 2 s sliding unit square pulse to be template.

Step3. Decide what band descriptors we want to use for detecting A-phase.

Step4. Calculate convolution value between template and descriptor values for every band descriptors we use, if one of convolution values is larger than length threshold, then repeating the convolution with the square pulse by increasing pulse length 0.5 s. if not, then sliding the pulse window right 0.5 s.

Step5. stop the convolution process when the convolution value is smaller than threshold. the feature values convoluted by square pulse are candidate A-phase.

Step6. Compare every feature values of candidate A-phase. If one of the candidate A-phase descriptors of every bands larger than exist threshold, the candidate A-phase is called A-phase. The non-A-phase is candidate B-phase.

Step7. We repeat the A-phase detection procedure until all night EEG signals are checked.

2.3.4   Context decision

In this part, we mention about CAP scoring method used to detect CAP sequence and divide non-A-phase into B-phase and non-CAP. CAP scoring is defined by the context decision method considered by previous studies, so we use the same requirements. First, we examine the CAP sequence epoch by epoch. If the epoch's stage is NREM, then we

continue next step. If not, we consider this epoch is non-CAP. Second, we should find onset of a CAP sequence and calculate CAP cycle which correspond with temporal limits. Each phase of CAP is between 2 s and 60 s. Thus, we can divide non-A-phase into B-phase and non-CAP. Third, we also consider that if the B-phase between two A-phases less than 2 s, the two A-phases are scored an A-phase; CAP sequences have no upper limits on overall duration and on the number of CAP cycles; The CAP sequence is composed of at least two CAP cycles. Fourth, we must find out the non-CAP which contains three parts: 1) If the CAP sequence disappear for longer than 60 s, This period of time is scored non-CAP. 2) An isolated A-phase, which preceded or followed by another A-phase but separated by more than 60 s, is scored non-CAP. 3) The A-phase in the end of the CAP sequence is scored as non-CAP. When all epoch is calculated completely, we can calculate CAP parameter such as CAP rate, average length of CAP sequences to identify the performance of CAP detection algorithm. We follow these rules to develop our algorithm which is shown in Figure 2.8.

2.3.5   Classification of A-phase subtypes

In the classification of A-phase subtypes, we plan to combine previous classification method which was proposed in 2002 and k-NN (k-nearest-neighborhood) classifier to improve the classification accuracy. In fact, the sub-phase of the A-phase classification method proposed in 2002 was based on their classification criteria of A-phase. The recognition of an A-phase is required that either the delta or the theta descriptor overcomes the threshold. In addition, the recognition of a sub-phase of the A-phase is considered about different bands descriptor which overcomes the recognition threshold. The theta, alpha and beta descriptors are considered for the recognition of the sub-phase. The recognition of the sub-phase should be suffced that one of the three descriptor overcomes the threshold. If no sub-phase is recognized, then the A-phase is an A1-phase. If a sub-phase is recognized, then the A-phase is an A2-phase or A3-phase. Then the classification of A2-phase and A3-phase is based on tail. The tail is the portion of the A-phase with low values of the delta descriptor. If the tail is shorter than two-fifths of the A-phase length, it is an A2-phase. Otherwise it is an A3-phase. The classification procedure is show in Figure 2.9.

The k-nearest neighbor algorithm (k-NN) is a classified method. This method distinguishes objects based on closest training examples in the feature sets. In the k-nearest neighbor algorithm, an object is classified by neighbors' voting. The k value means how many nearest neighbors we choose. If k = *1*, then the object is classified to the class as same as the nearest neighbor of the object.

The proposed method which is shown in Figure 2.10 is based on the k-NN classifier and the criteria mentioned above. Before the classification of sub-phase, the proposed method detects some A-phases. First, the proposed method computes fractal dimension values and time dimension values of each A-phase. The fractal dimension values are calculated each 0.5 second and then average all fractal dimension values of entire A-phase. Second, the k-NN classifier is used to classify A1-phase and non-A1-phase by the features of fractal dimension values and time dimension values. Third, delta band descriptor should be calculated for the proposed method. Finally, it is used in the proposed method of the criteria to classify A2-phase and A3-phase with the tail. If the tail is shorter than two-fifths of the A-phase length, it is an A2-phase. Otherwise it is an A3-phase.
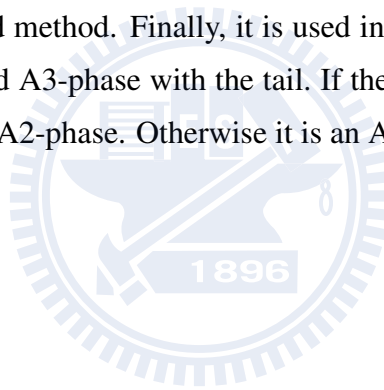
Figure 2.6: The top curve represents the F4-C4 channel with the duration of 20 seconds. The other rows show the descriptors of seven frequency bands. These bands from top to bottom are delta, lower delta, higher delta, theta, alpha, sigma, and beta. These descriptors are sampled every 0.5 s. (Figure source: Sleep Medicine 5 Original article, Umberto Barcaro et al.: A general automatic method for the analysis of NREM sleep microstructure, p 567-576, 2004)
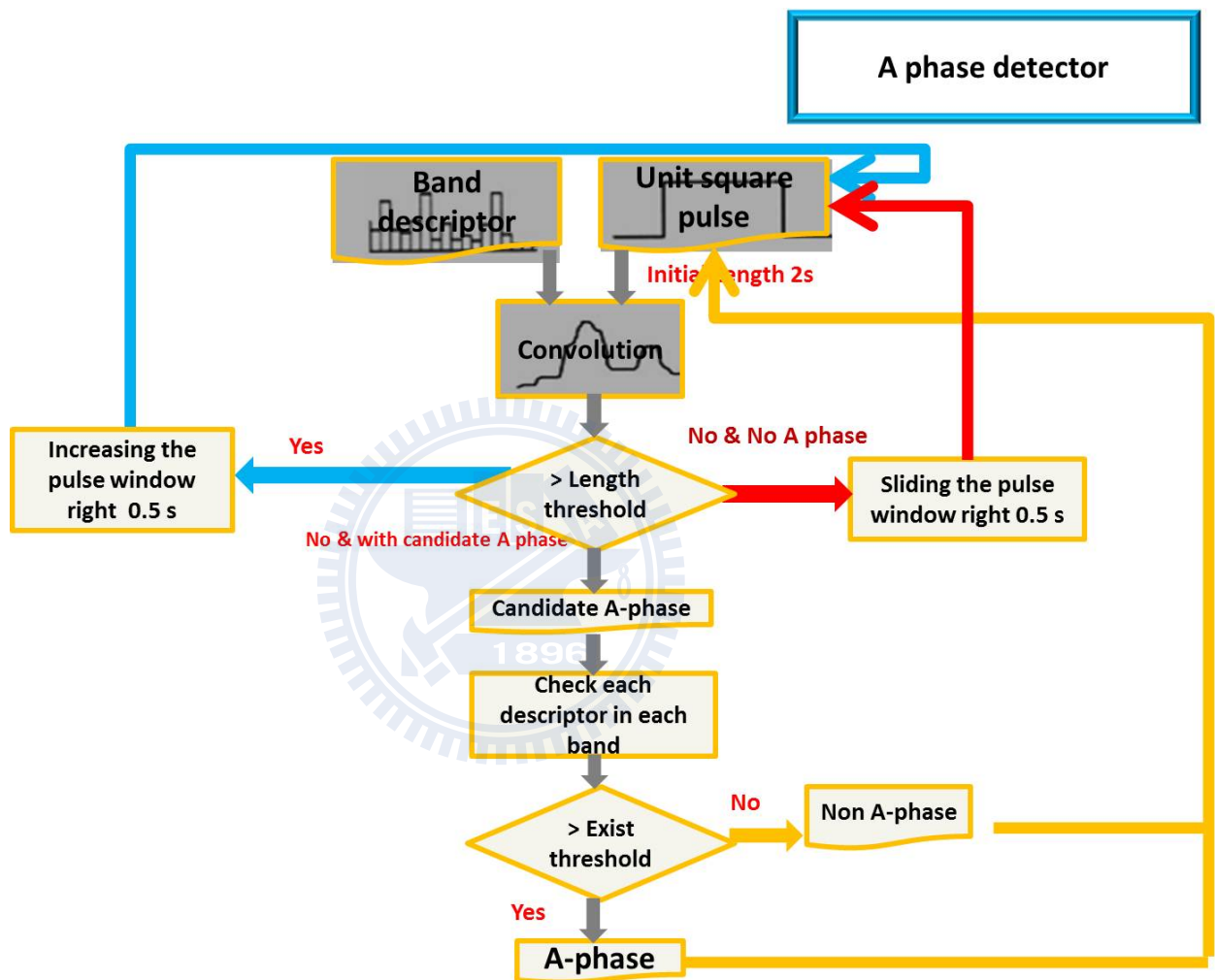
Figure 2.7: The A-phase detector of the proposed method

Figure 2.8: The context decision procedure of the proposed method.
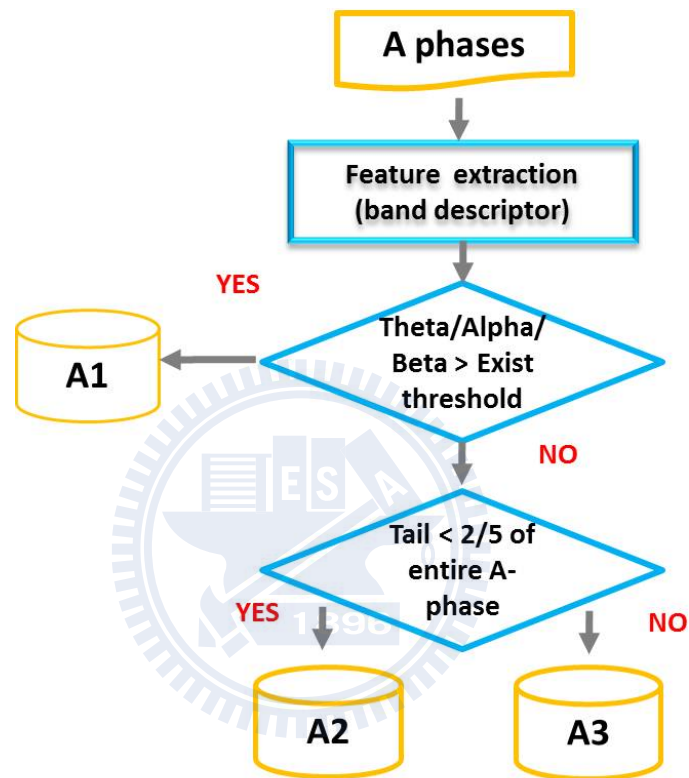
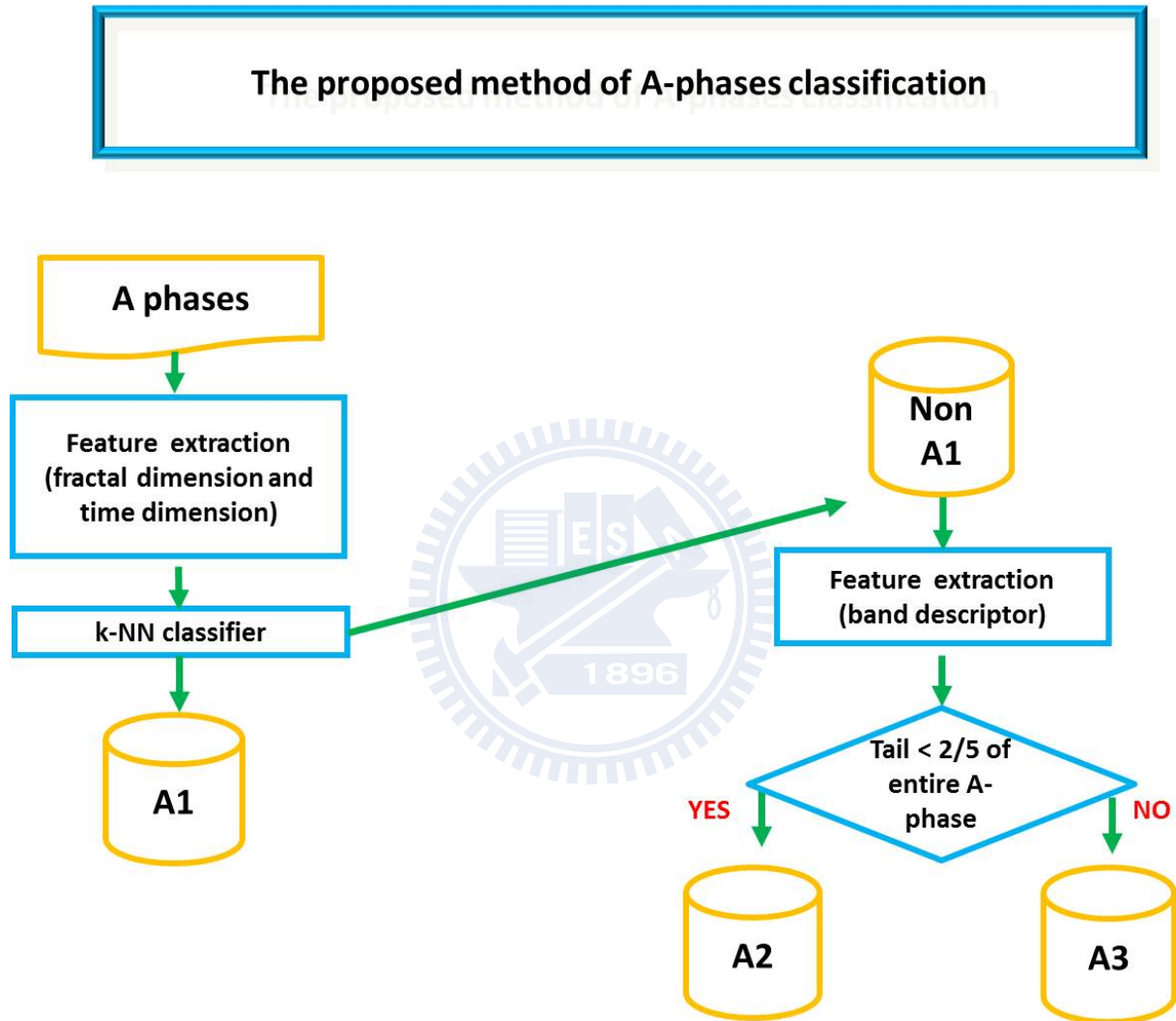Figure 2.9: The A-phase subtypes classification method used in the previous study.

Figure 2.10: The proposed A-phase subtypes classification method which is combined with the k-NN classification method and A-phase classifier.

Chapter 3

Experiments

Table 3.1: Subjects Information

Subjects Information	**Subject1**	**Subject2**	
Age	33	43	
Gender	Female	Male	
Isonomia	1 year	20 years	
Drug	No	Yes	()
Feature Sample Points	46860	55980	
Height(m)	1.71	1.71	
Weight(kg)	59.0	65.0	
BMI	20.2	22.2	

3.1 CAP detection analysis

3.1.1 Data preparation

Subject

In the first part of experiment, the experimental data were acquired in the BGA sleep center in Taichung, Taiwan. There are 188 records which are classified by apnea-hypopnea index (AHI). If the AHI is smaller than 5, the subject is classified as non obstructive sleep apnea syndrome (non-OSAS) subject. If the AHI is larger than 5, the subject is classified as OSAS subject. In the OSAS subjects, there are also classified as mild OSAS (5<AHI<15), moderate OSAS (15<AHI<30), and severe OSAS (AHI>30). These records contain 41 non-OSAS subjects, 51 mild OSAS subjects, 47 moderate OSAS subjects, and 49 severe OSAS subjects. In the second part of experiment, the experimental data were acquired from the sleep center of Tzu-Chi Hospital in Taichung, Taiwan. There are 2 records from 1 male and 1 female. The subjects information table is shown in Table 3.1.

Records

In the first part of experiment, the sleep data were collected by $EMBLA\ Sandman$ system. In the second part of experiment, the sleep data were collected by $EMBLA\ RemLogic^{TM}$ system. These data include four EEG channels (C3/A2, C4/A1, O1/A2, and

O2/A1), EMG, EOG, EKG, SpO2, airflow, and sleep position. These records were saved as a TXT (Text File Format) file. Each subject has one nocturnal sleep records approximately six to seven hours. As reported in [6], EEG data of channel C3-A2 and channel C4-A1 are basically the same in terms of physiological phenomenon. Therefore we arbitrarily choose C3-A2 channel for CAP detection in our work.

These experimental data had been previously scored by sleep Registered Polysomnographic Technologists (RPSGT) and RemLogic system CAP report. These result was assumed as ground truth for comparison with the results of the proposed CAP detection algorithm. We also implemented the CAP detection method proposed by Umberto Barcaro et al. in 2004. We used the previous results to compare with the our results. We analyzed CAP A-phase and A-phase subtypes to explain the proposed CAP detection algorithm advantage and disadvantage with previous method and ground truth. Furthermore, we compared the detection results in different parameters set.

3.1.2   Experimental results of OSAS subjects

In the first part of experiment, the data set include 188 subjects. In [11], it mentioned that the CAP rates of OSAS subjects are significantly higher than those of non-OSAS subjects and CAP analysis shows increased values of CAP rate in severe OSAS. Our experimental results have same conclusions. The CAP rates of 188 OSAS patients obtained by the proposed method are higher than those of non-OSAS subjects, which is consistent to the literature. It is shown in Figure 3.1 and Figure 3.2.

3.1.3   Experimental results of Insomnia subjects

In the second part of experiment, the data set include 2 subjects. These two data set were scored by sleep Registered Polysomnographic Technologists and RemLogic system as our ground truth comparing with results from our method. For the CAP sequences analysis, we classified CAP phases into three classes: A-phase, B-phase, and non-CAP. For the CAP A-phase analysis, we classified CAP phases into two classes: A-phase and non A-phase.
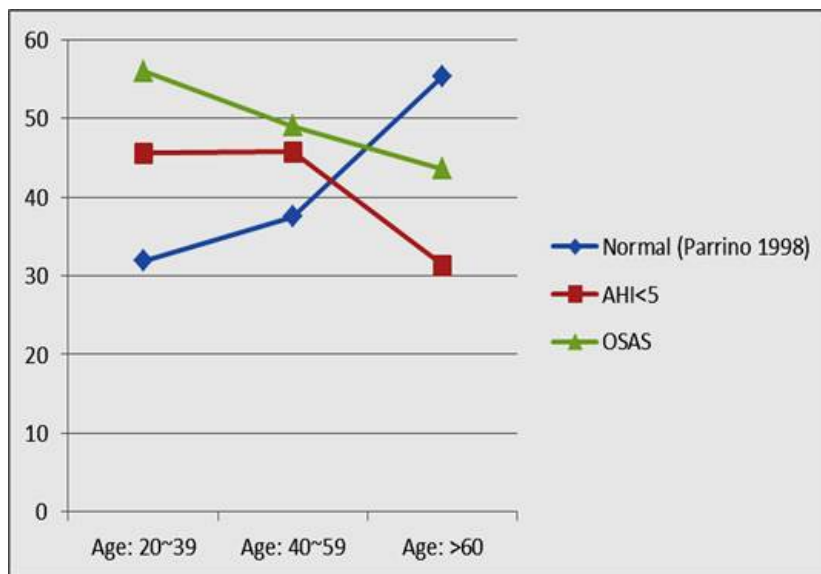
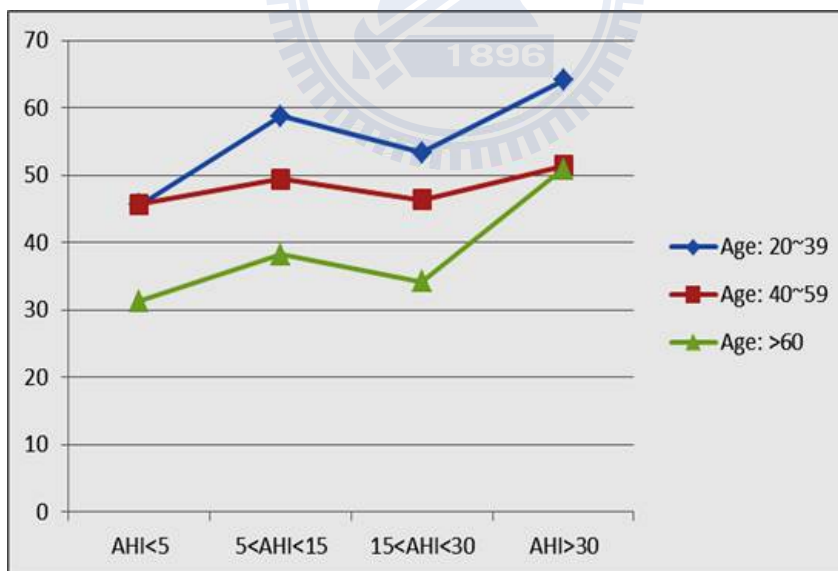Figure 3.1: The CAP rates of OSAS and non-OSAS subjects in different age groups.

Figure 3.2: The CAP rates of mild OSAS, moderate OSAS, severe OSAS and non-OSAS subjects in different age groups.

Prove context decision

In the beginning, the correctness of context decision is needed to prove, so it is compared that the CAP detection result of the proposed method of A-phase from RemLogic system and the CAP report from RemLogic system in Figure 3.3. In these two results, the CAP rate is about the same and the capsnogram has high similarity except for some single A-phase which is not contained in the CAP sequence but the CAP report from RemLogic system also shows it on CAP report in Figure 3.4 and Figure 3.5.
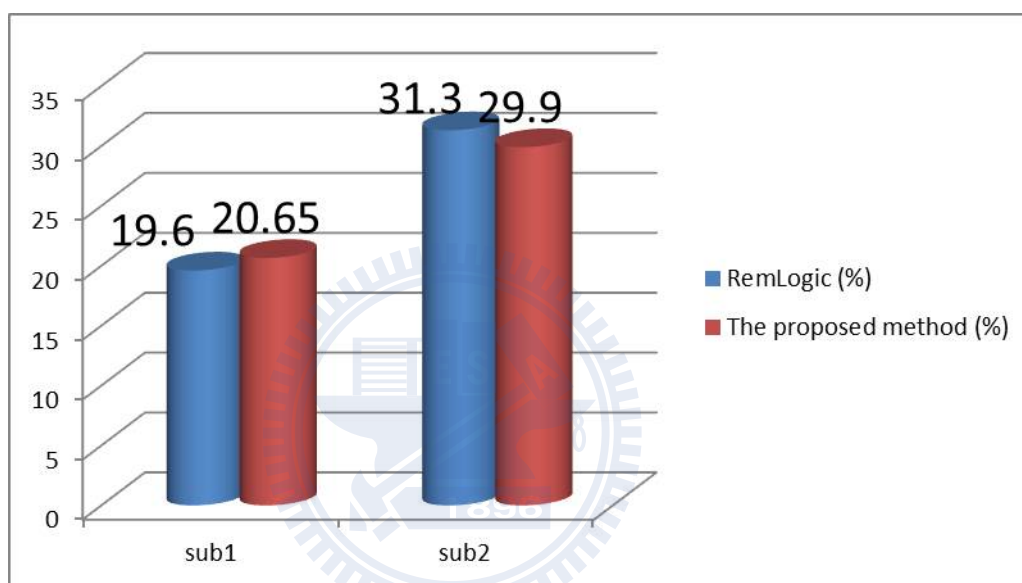

Figure 3.3: CAP rate of two subjects with A-phases of RemLogic result and CAP report. The correctness of context decision is needed to prove, so it is compared that the CAP detection result of the proposed method of A-phase from RemLogic system and the CAP report from RemLogic system.

CAP rate

Table 3.2 shows the u-shape evolution along the life span in human sleep [10]. Table 3.6 shows the results of 2 subjects. This table shows the CAP rate of the proposed method, the previous method proposed by Barcaro et al. in 2004, RemLogic system results in CAP report, and RPSGT manual scoring results. Compare with the U-shape, we can figure out that the last two results are too small to fit the general U-shape.

Figure 3.4: The top field contains hyponogram in first row and RemLogic detection result in second row. The bottom field contains hyponogram in first row, A-phases of RemLogic detection result, and its context decision result in the third row.
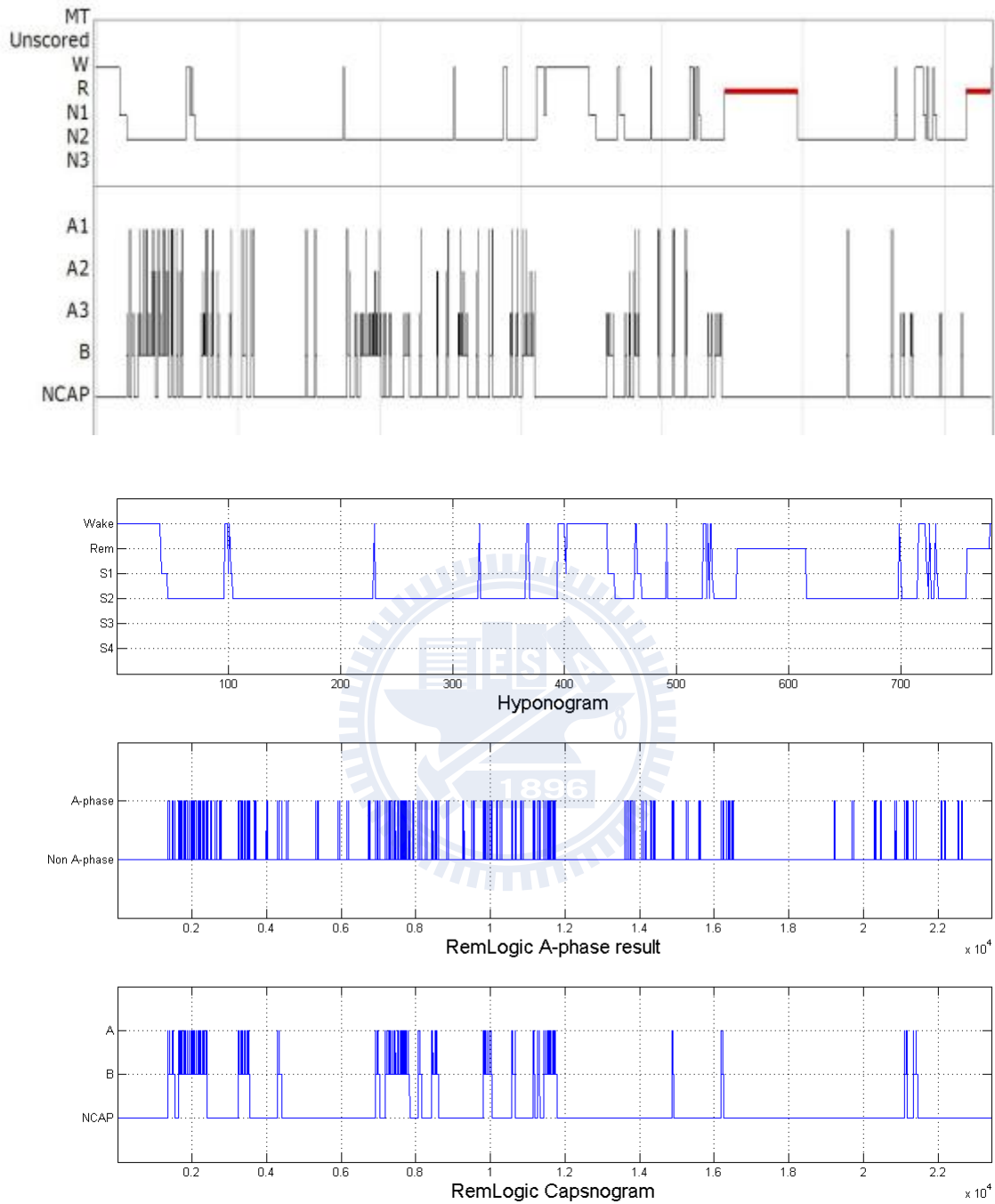
Figure 3.5: The top field contains hyponogram in first row and RemLogic detection result in second row. The bottom field contains hyponogram in first row, A-phases of RemLogic detection result, and its context decision result in the third row.
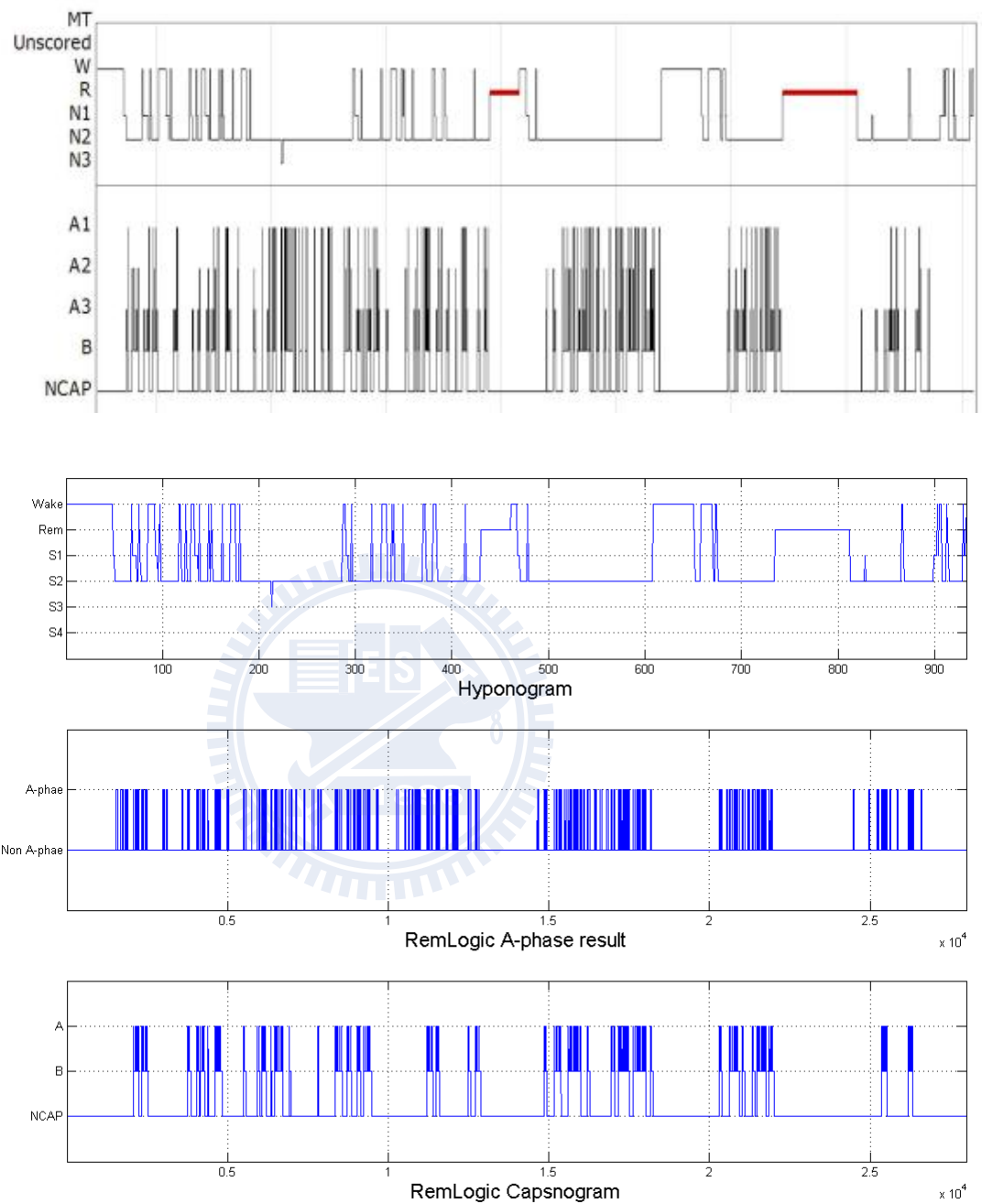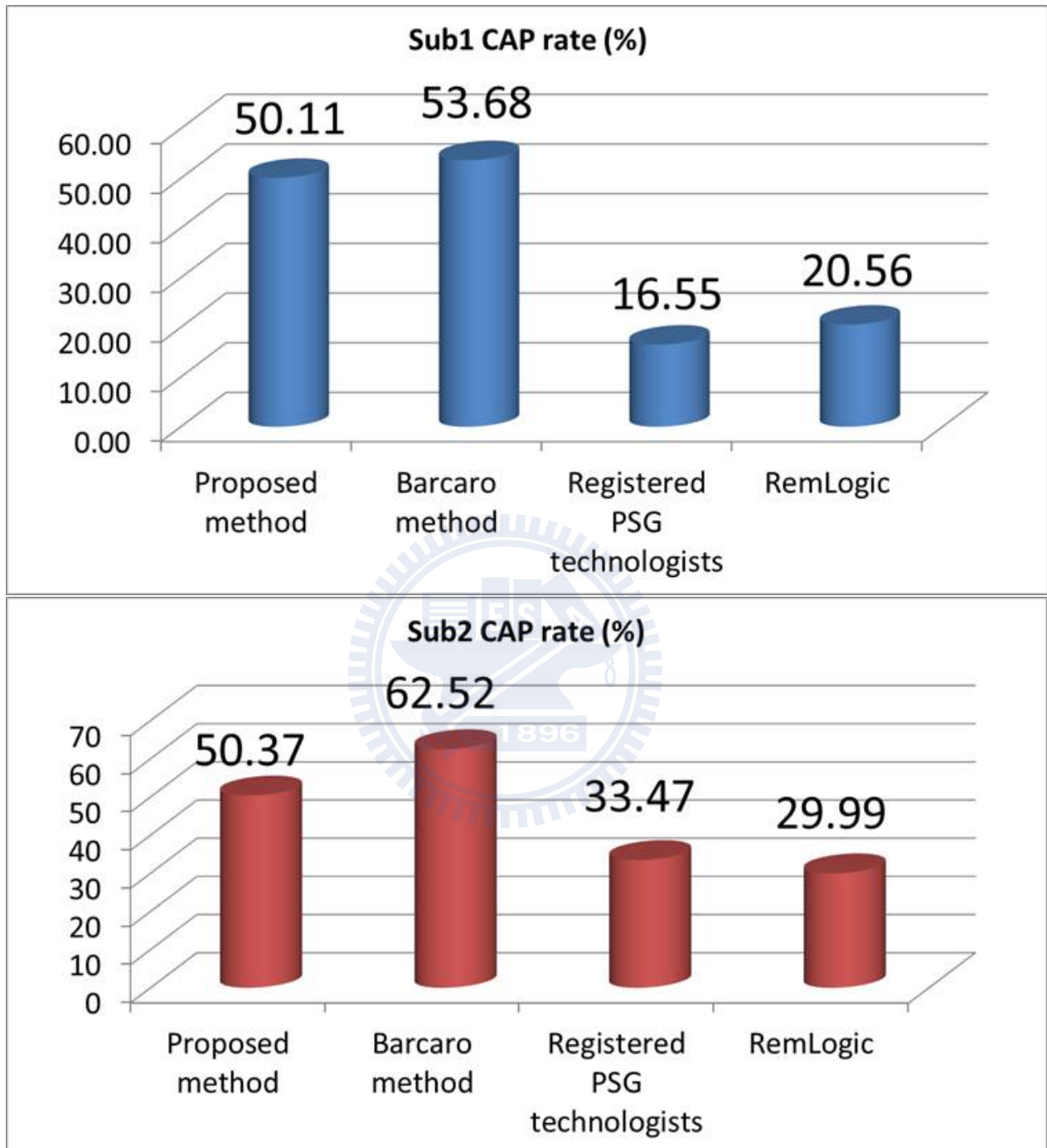
Figure 3.6: CAP rate analysis of two subject. CAP rate of two subject of the proposed method, the previous method proposed by Barcaro et al. in 2004, RemLogic system results in CAP report, and RPSGT manual scoring.

Table 3.2: CAP rate U-shape in the life span and insomnia

Group	CAP rate	Age
Teenagers	43.4%	$10-19$
Young	31.9%	$20-39$
Middle	37.5%	$40-59$
Elderly	55.3%	$>=60$
Isonomia	58.1%	

CAP detection results

First, these data are classified as A-phases and non A-phases by A-phase detector. Second, these data are classified three types of CAP phase as A-phase, B-phase, and NCAP after context decision. The accuracy of the first result is 80.4% to 81.5% and 80.98% in average and the correctness of the proposed automated CAP detection algorithm is 64.6% to 66.9% and 65.8% in average. The values of Figure 3.7 are used to evaluate accuracy of A-phases classification of two subjects. These values contain that accuracy which means that predicted label is same as ground truth, PPV is defined by the ratio of TP and the sum of TP and FP, NPV is defined by the ratio of TN and the sum of TN and FN, Sensitivity is defined by the ratio of TN and the sum of TN and FP, and specificity is defined by the ratio of TP and the sum of TP and FN. These terms are shown as Table 3.3. The values of Figure 3.8 are used to evaluate correctness of CAP sequence classification of two subjects. The total correct detection C (correctness) is defined by the ratio of all true events detected and the sum of total events.

$$C = \frac{TA + TB + TN}{T + TB + F + M + FA + FB + MA + MB} \tag{3.1}$$

The CAPS specificity SP_C is defined by the ratio of all detected true CAPS period and the sum of reference CAPS.

$$SP_C = \frac{TA + TB + F + M}{T + TB + F + M + MA + MB} \tag{3.2}$$

The CAPS sensitivity SE_C is defined by the ratio of all detected true CAPS period and total CAPS detected.

$$SE_C = \frac{TA + TB + F + M}{T + TB + F + M + FA + FB} \tag{3.3}$$

The NCAP specificity SP_{NC} is defined by the ratio of all detected true NCAP period and the sum of reference NCAP.

$$SP_{NC} = \frac{TN}{TN + FA + FB} \tag{3.4}$$

The NCAP sensitivity SE_{NC} is defined by the ratio of all detected true NCAP period and total NCAP detected.

$$SE_{NC} = \frac{TN}{TN + MA + MB} \tag{3.5}$$

These terms are shown as Table 3.4. T, TB and TN mean the correct classification of A-phases, B-phases, and NCAP. F is misclassification of B by A in CAP. M is misclassification of A by B in CAP. In NCAP, FA is false positives A and FB is false positives B. In CAPS, MA is and false negatives A and MB is false negatives B.

Table 3.3: Relationships among terms. Definitions of True positive (TP), False positive (FP), True negative (TN) and False negative (FN)

		Test outcome)	
		negative	**positive**
Condition(ground truth)	**negative**	True Negative (TN)	False Positive (FP)
	positive	False Negative (FN)	True Positive (TP)

Table 3.4: Relationships among terms. Definitions of TA,TB,TN,F,M,FA,FB,MA,MB

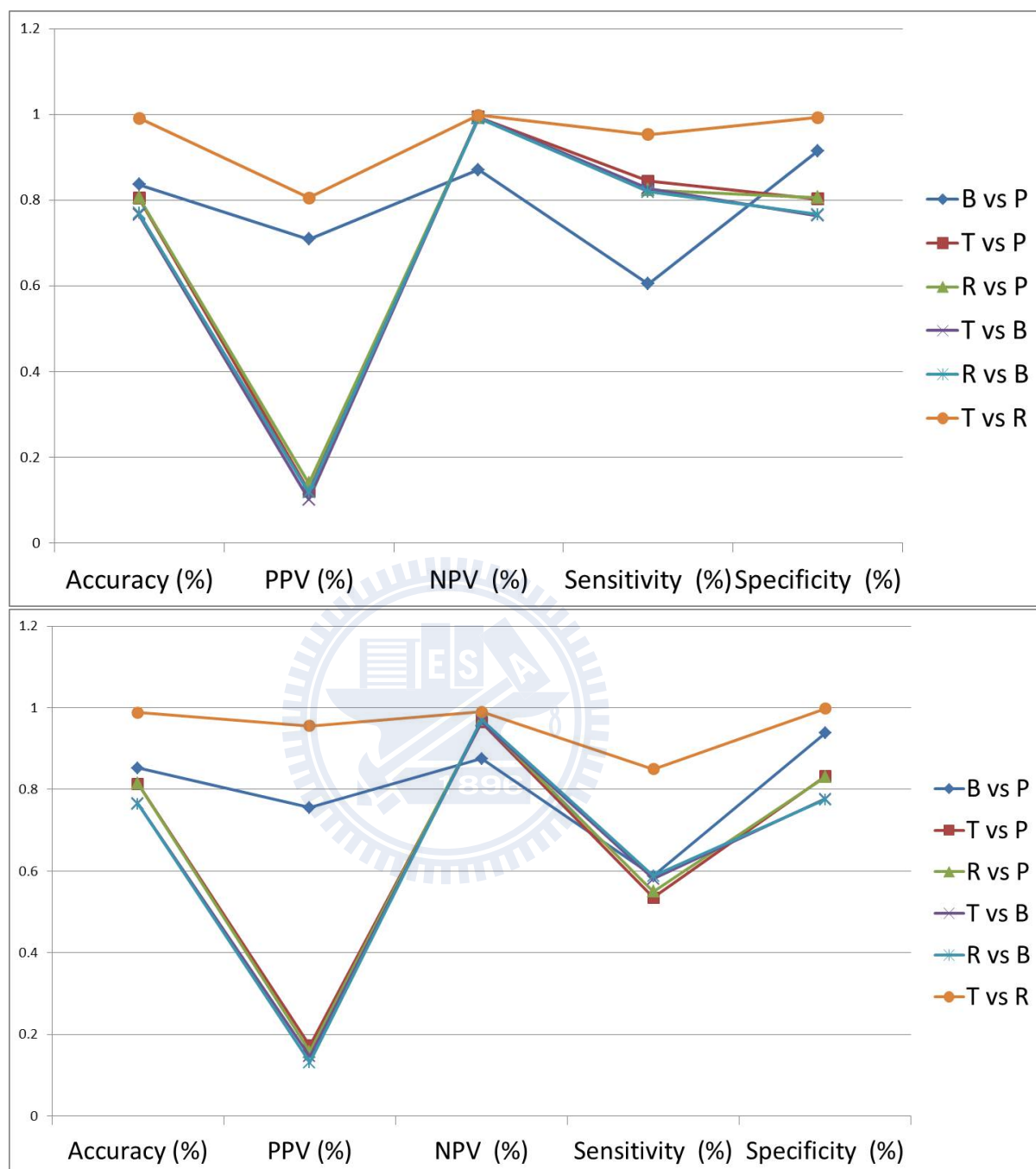|		Test outcome)		
		A-phase	**B-phase**	**NCAP**
	A-phase	TA	M	MA
Condition(ground truth)	**B-phase**	F	TB	MB
	NCAP	FA	FB	TN

Figure 3.7: It is used to evaluate accuracy of A-phases classification of two subjects. P means the proposed method result. B means the method proposed by Barcaro et al. in 2004. R means RemLogic system automatic scoring. T means the RPSGT visual scoring. The top figure is Subject1 result and the bottom figure is Subject2 result. Accuracy means that predicted label is same as ground truth, PPV is defined by the ratio of TP and the sum of TP and FP, NPV is defined by the ratio of TN and the sum of TN and FN, Sensitivity is defined by the ratio of TN and the sum of TN and FP, and specificity is defined by the ratio of TP and the sum of TP and FN.
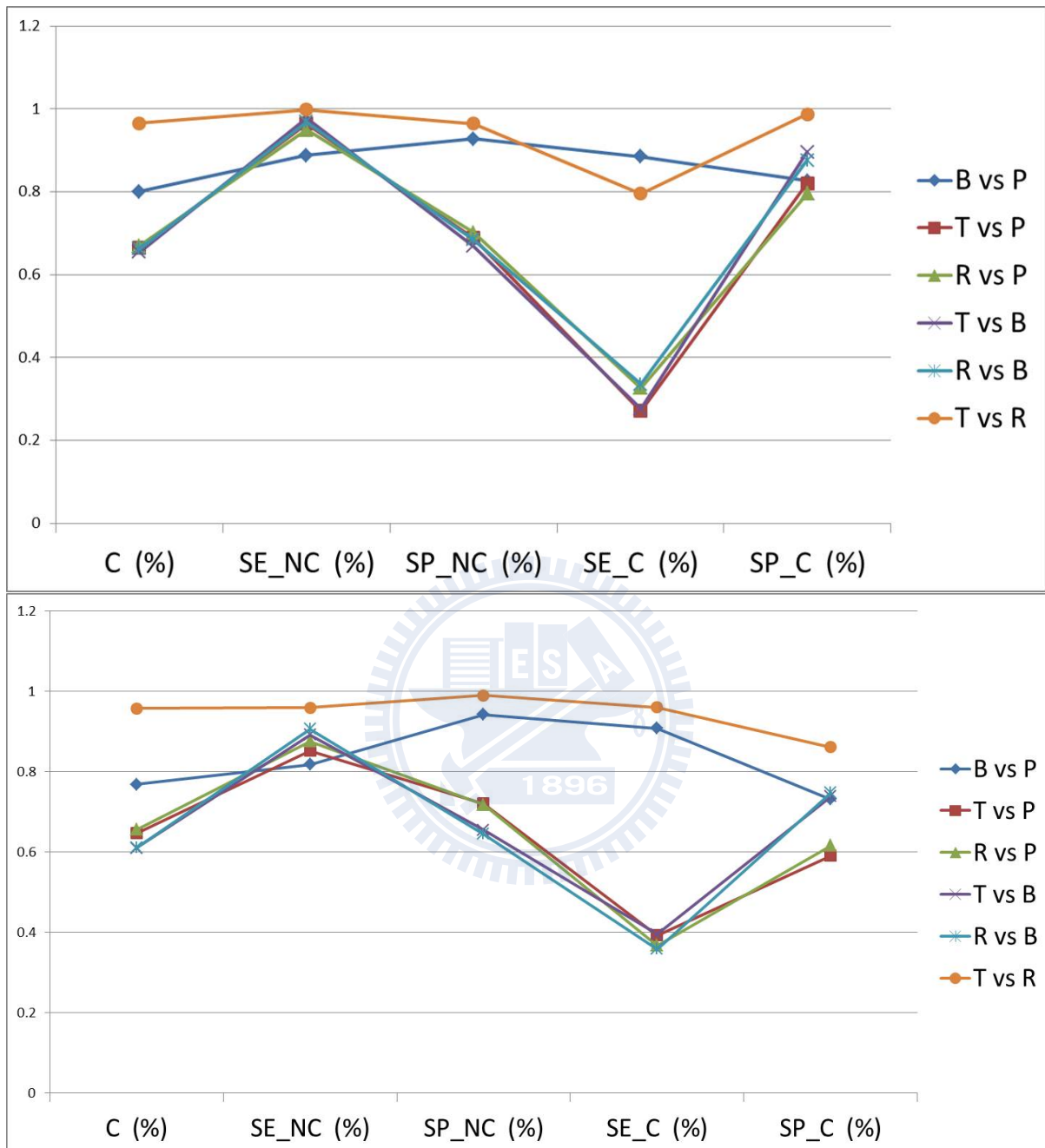
Figure 3.8: It is used to evaluate correctness of CAP sequence classification of two subjects. P means the proposed method result. B means the method proposed by Barcaro et al. in 2004. R means RemLogic system automatic scoring. T means the RPSGT visual scoring. The top figure is Subject1 result and the bottom figure is Subject2 result. The definition of total correct detection C, the CAPS sensitivity SC, the CAPS sensitivity SC, the NCAP sensitivity SNC, and the NCAP sensitivity SNC are mentioned above.

CAP capsnogram

Figure 3.9 and Figure 3.10 show the capsnogram of the sleep structure of two subjects. In Figure 3.9, the first field is Subject1 and the second field is Subject2. It shows all night sleep. The top row shows hyponogram of sleep stage, the fourth row and the fifth row represents the results of manual scoring and RemLogic system automates scoring which we assumed as the ground truth, the third row is the results of implement of previous method proposed by Barcaro et al. in 2004, and the second row is the results of automated scoring by our system. In Figure 3.10, the first field is Subject1 and the following two fields are Subject2. It shows part of all night sleep. The top row shows automated detection result of A-phase, the fourth row and the fifth row represents the results of manual scoring and RemLogic system automates scoring which we assumed as the ground truth, the third row is the results of implement of previous method proposed by Barcaro et al. in 2004, and the second row is the results of automated scoring by our system. The bottom row shows EEG signal in C3-A2 channel. In Figure 3.10, it is found that the proposed method can detect A-phase in every moment which EEG signal satisfy the conditions, but the automated detection of RemLogic system and the manual scoring by RPSGT may loss some A-phase. On the other hand, there are some A-phases and non A-phases too long to fit the CAP scoring rule which is removed by the proposed method.

Figure 3.11 shows the variable length template method's advantage of the proposed method, compared to Barcaro method. In Barcaro method, A-phase ends when all band descriptors are smaller than the length threshold. Candidate A-phase means that the average power in one of these bands is larger than background average power in the definition of A-phase. The proposed method can increase template length to cover the following features in a short period time to fit template. In the proposed method, A-phase contains the period in which all band descriptors are smaller than the length threshold but the average power in one of these bands is larger than background average power at some point in this period. The proposed method combines variable length template method and EXIST/LENGTH thresholds method. Compared to the Barcaro method, the proposed method is superior because of its usage of variable length template.
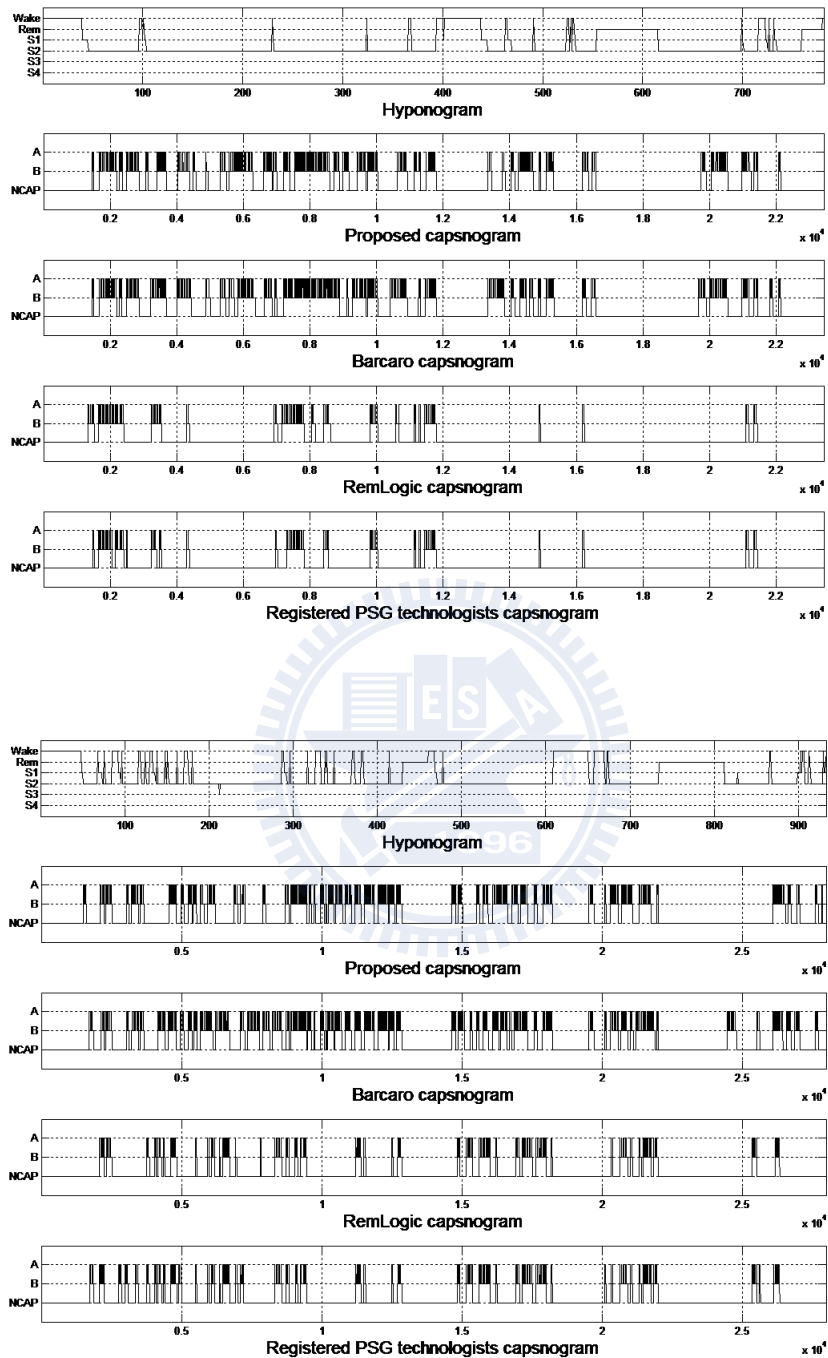
Figure 3.9: The capsnogram of the sleep structure of two subjects in all night sleep.
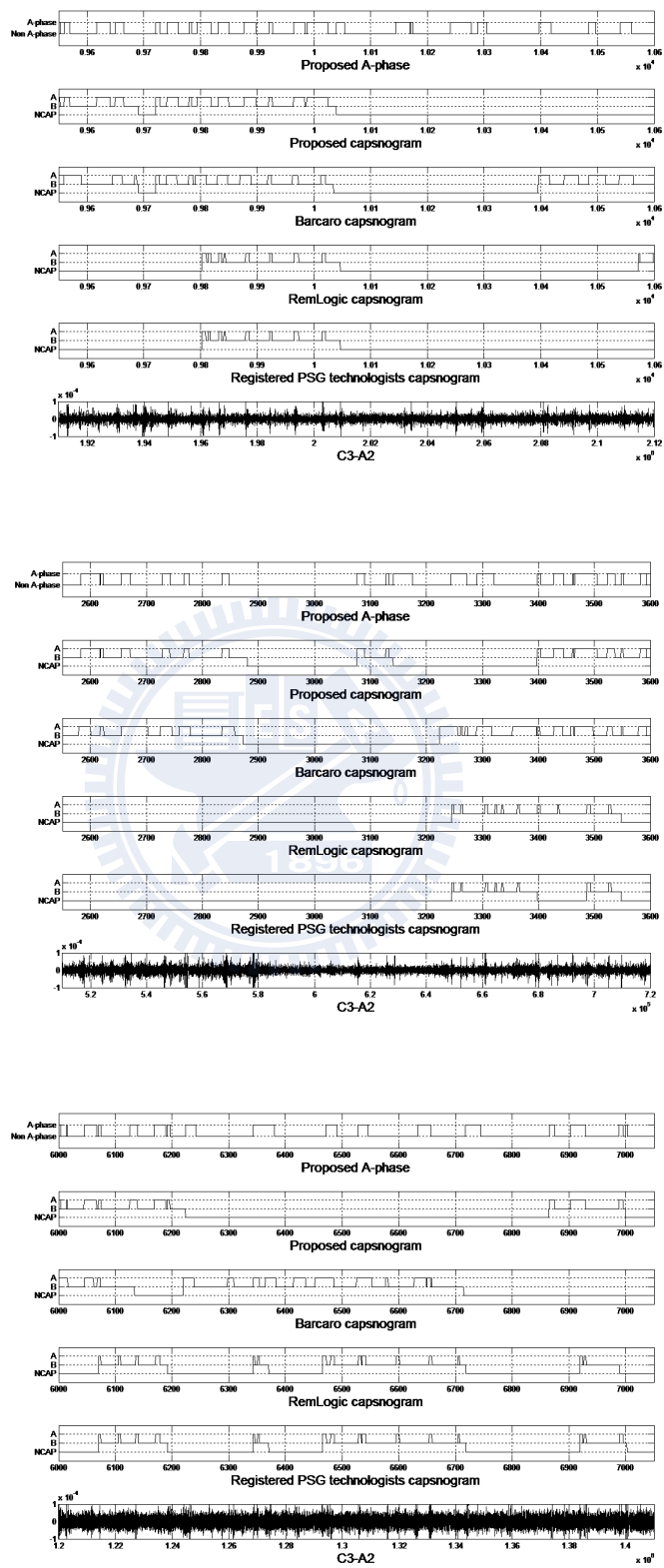
Figure 3.10: The capsnogram of the sleep structure of two subjects in part of night sleep.

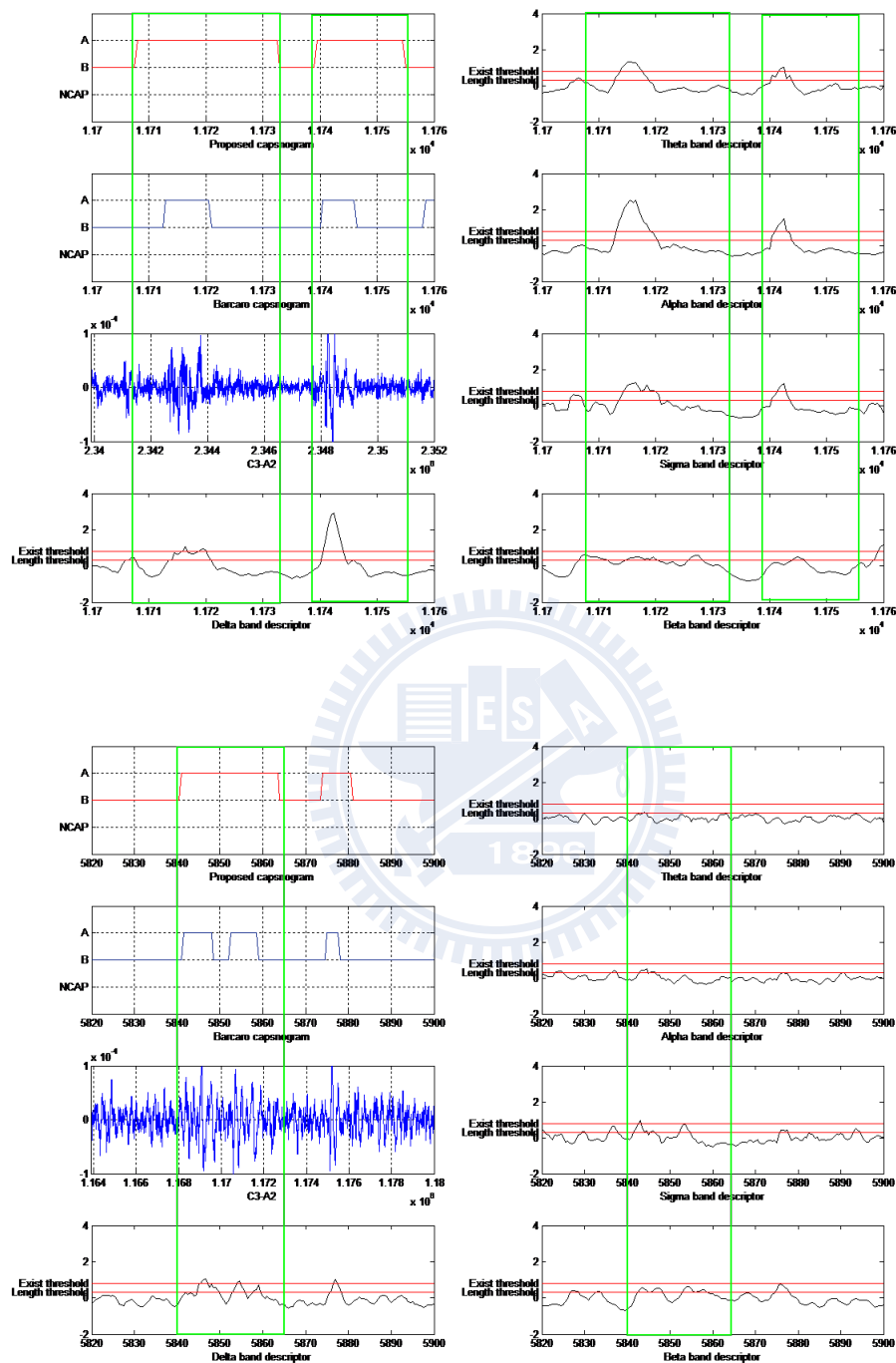Figure 3.11: Compared to the Barcaro method, the proposed method is superior because of its usage of variable length template. The left column from top to bottom is the proposed method capsnogram, Barcaro method capsnogram, EEG signal of C3-A2 channel, and delta band descriptor. The right column from top to bottom is theta band descriptor, alpha band descriptor, sigma band descriptor, and beta band descriptor.

Table 3.5: Ground truth

Ground Truth	Subject1 RemLogic	Subject1 Registered PSG technologists	Subject2 RemLogic	Subject2 Registered PSG technologists
A1	95	58	139	152
A2	41	24	53	53
A3	60	84	105	122
ALL	196	166	297	327

Table 3.6: Accuracy of Subtypes of the proposed method

Reference	Subject1 RemLogic	Subject1 Registered PSG technologists	Subject2 RemLogic	Subject2 Registered PSG technologists
A1	65.5%	77.9%	73.0%	64.8%
A2	16.7%	41.5%	17.0%	22.6%
A3	75.0%	68.3%	63.9%	54.3%

Show the accuracy of the proposed subtypes classified method which use RemLogic system scoring and RPSGT manual scoring as reference.

3.2 A-phase subtypes classification analysis

3.2.1 Materials

The experimental data were acquired from the sleep center of Tzu-Chi Hospital in Taichung, Taiwan. There are 2 records from 1 male and 1 female. The ground truth table is shown in Table 3.5.

3.2.2 Experimental results

In the classification of A-phases subtypes, Figure 3.12 shows the distribution of A-phase subtypes of RemLogic system scoring result. The following Table 3.6 presents the accuracy of the proposed subtypes classified method which uses RemLogic system scoring and RPSGT manual scoring as reference. The classified accuracy of subtypes is 65.5% to 77.9% in subtypes A1, 16.7% to 41.5% in subtypes A2, and 54.3% to 75% in subtypes A3.
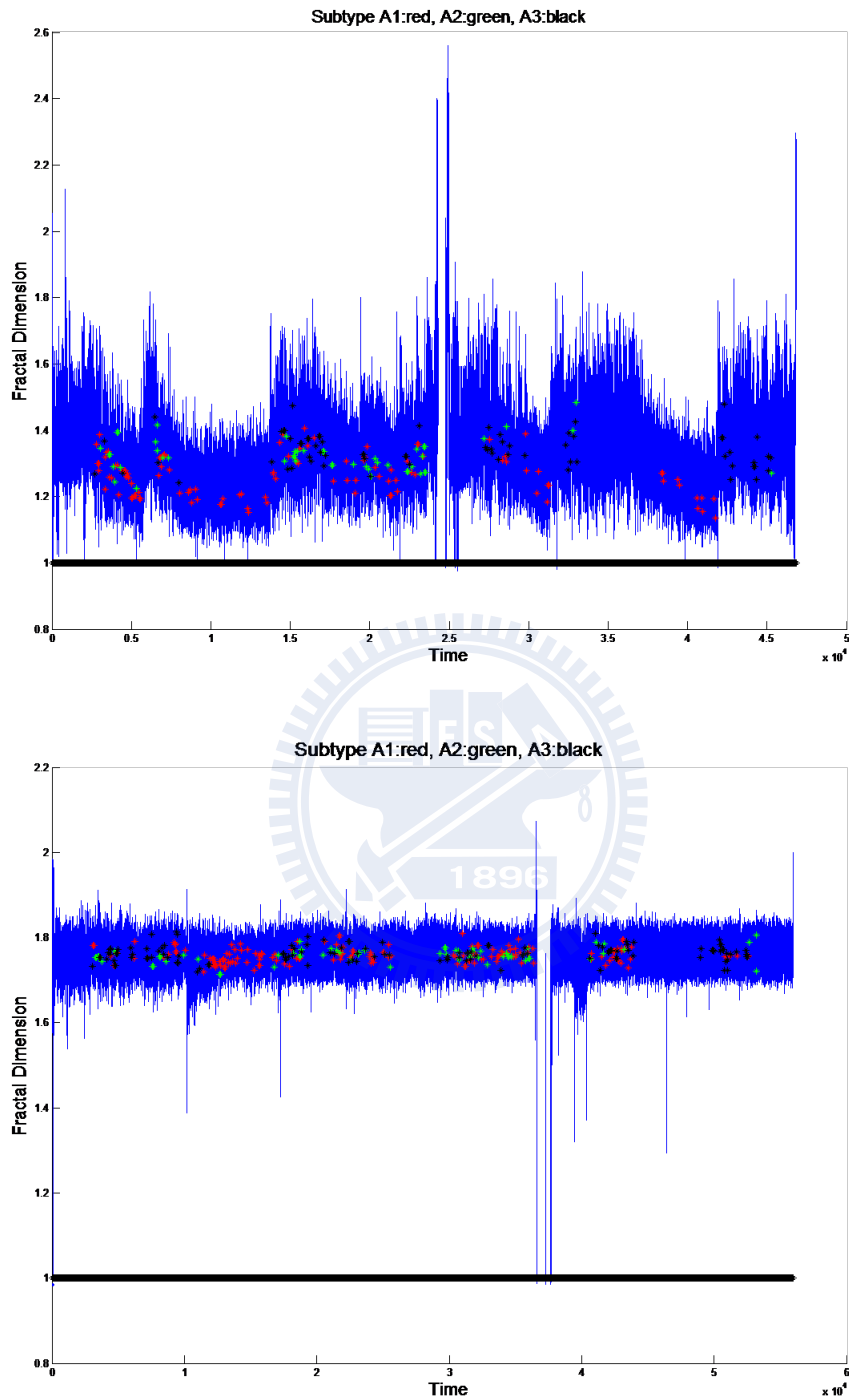
Figure 3.12: The row dimension means times of all night and the column dimension means fractal dimension value. The blue line is fractal dimension by Higuchi's method and the subtypes of A1, A2, and A3 are presented by red, green, and black point.

Chapter 4

Discussion

4.1   Parameter searching

In our method of A-phases detection, parameter selection is an essential procedure. We have four parameters. They are template, threshold adjustment, forward function, and band selection. The purpose of this section discusses the influence of these parameters on CAP detection. In the subtypes classification method, we discuss the difference in LDA, kNN, previous method proposed by [9], and the proposed method.

4.1.1   Template

The variable length template is a flexible method to adaptive range of time. In Figure 4.1, we plan to investigate the influence of A-phase detection with the variable length template or not. The experimental result without using template method is more similar with ground truth than use that. And in the Figure 4.4 and 4.5, the accuracy of A-phase detection and CAP sequence detection without template is higher than using template. But the results demonstrate that may not adjustment A-phase length if we do not use template. The A-phase length range is 2 second 6 second too short to correspond the previous results with 2 second 60 second.

Figure 4.2 and Figure 4.3 shows the distribution of average descriptor of A-phase and non A-phase. They are the proposed method without using template and the proposed method. The row shows the time dimension and the column shows descriptor mean value in each phase. Compare with the proposed method without using template and the proposed method, the distribution of A-phase and non A-phase of the proposed method converges to a constant respectively.

4.1.2   Threshold adjustment

In the previous methods, the exist threshold (equal to 1) and the length threshold (equal to 0) are used to distinguish A-phase from background signal. But it is different for each subject's physiological state. In our experiment, we set exist threshold to 0.8 and length threshold to 0.3 to compare with previous studies set. This result of accuracy of A-phase detection and CAP detection is shown in Figure 4.4 and Figure 4.5.
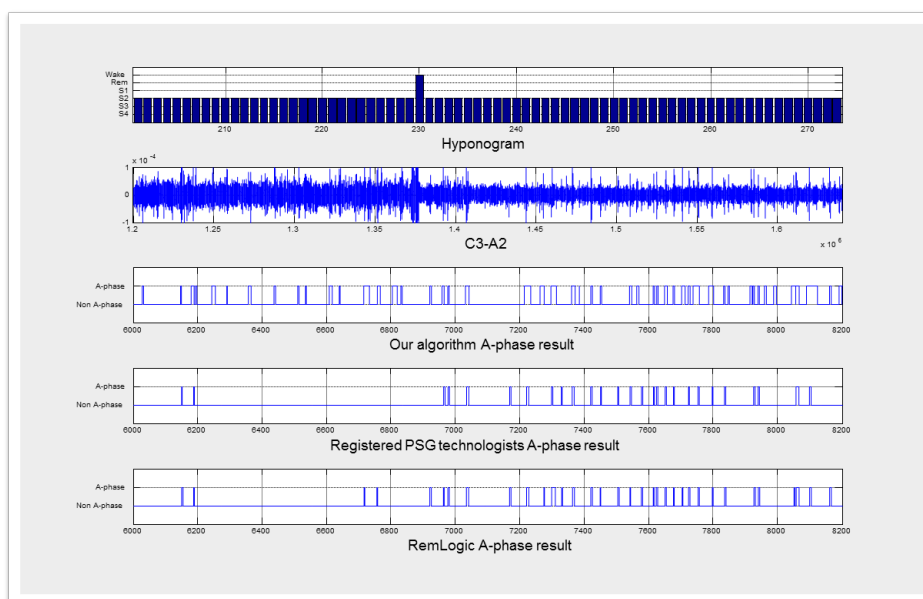
Figure 4.1: The five rows are sleep stage, EEG signal, CAP detection result without template, RPSGT result, and RemLogic system result. The third row shows that the duration of A-phase is reduced to 2 second - 6 second.

4.1.3 Forward function

The forward function is a strategy to overcome that the template method only extends the length to the right. This function is turned on to extend the template to the left for 2 s. We also compare the accuracy for CAP detection in Figure 4.4 and Figure 4.5. The original method detects CAP without using the forward function. Compare with the accuracy with forward function, turning off this function is better. So this function may bring more unnecessary influence than benefit.

4.1.4 Band selection

In the previous studies, the delta band was the most frequency band used in CAP detection. Some studies dropped sigma band for simplicity, due to the secondary or negligible role of this rhythm for CAP detection in normal subjects. In our experiment, we test different band set in exist threshold and length threshold for CAP detection. Figure 4.4 and Figure 4.5 show the result of the accuracy for CAP detection.
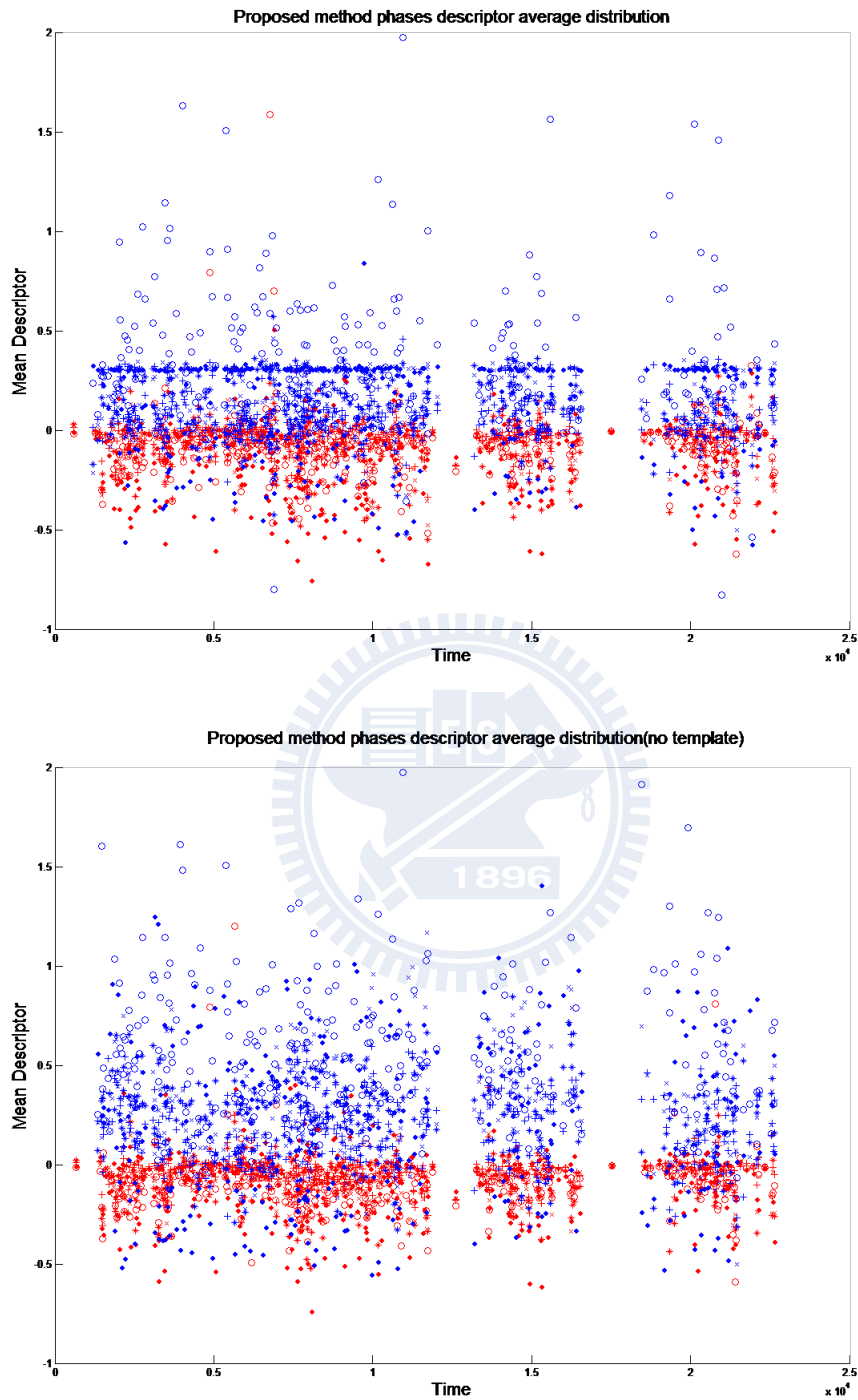
Figure 4.2: The distribution of average descriptor of CAP phases on Subject1. The figure on the top is the proposed method and the figure at the bottom is the proposed method without using template
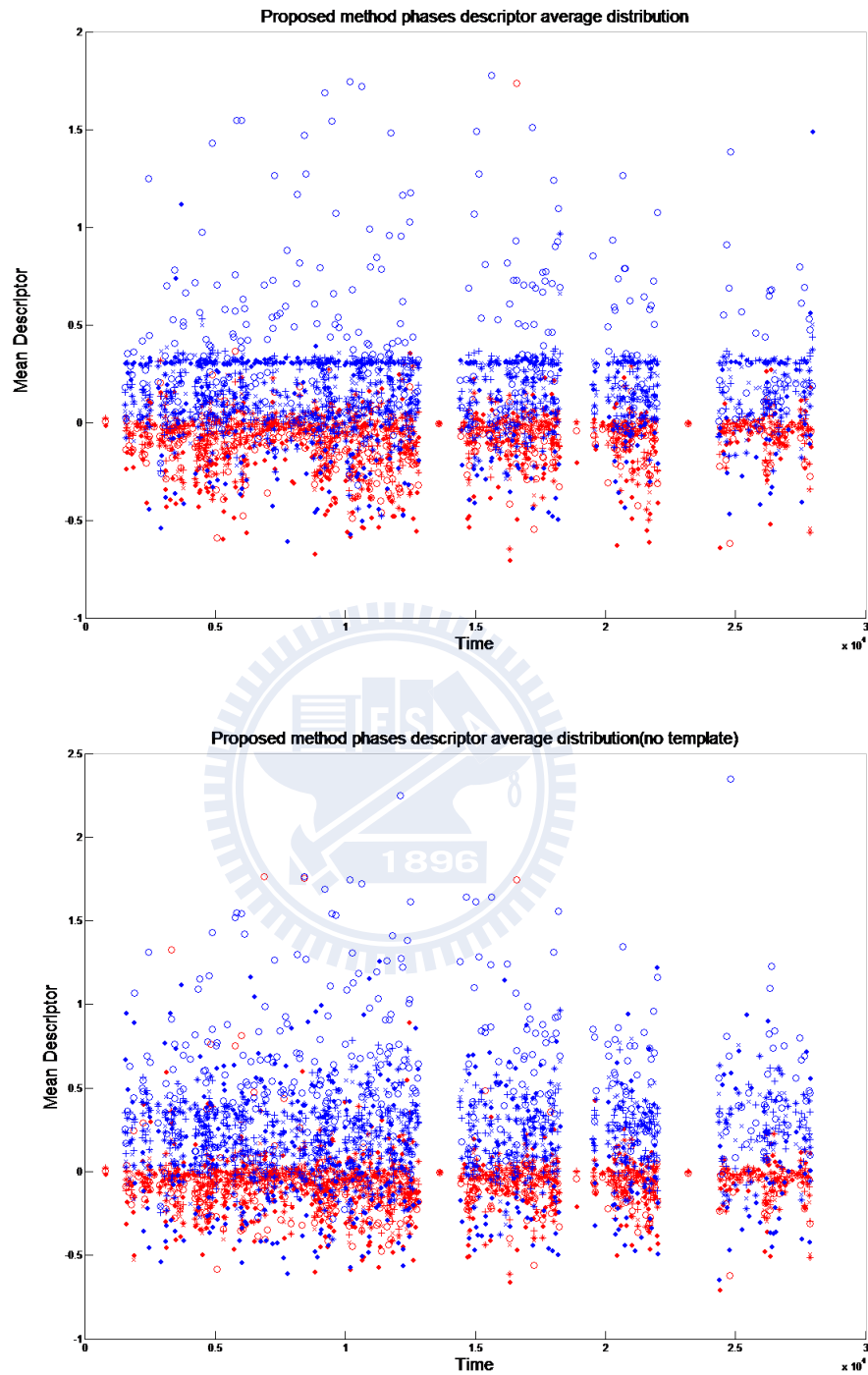
Figure 4.3: The distribution of average descriptor of CAP phases on Subject2. The figure on the top is the proposed method and the figure at the bottom is the proposed method without using template.
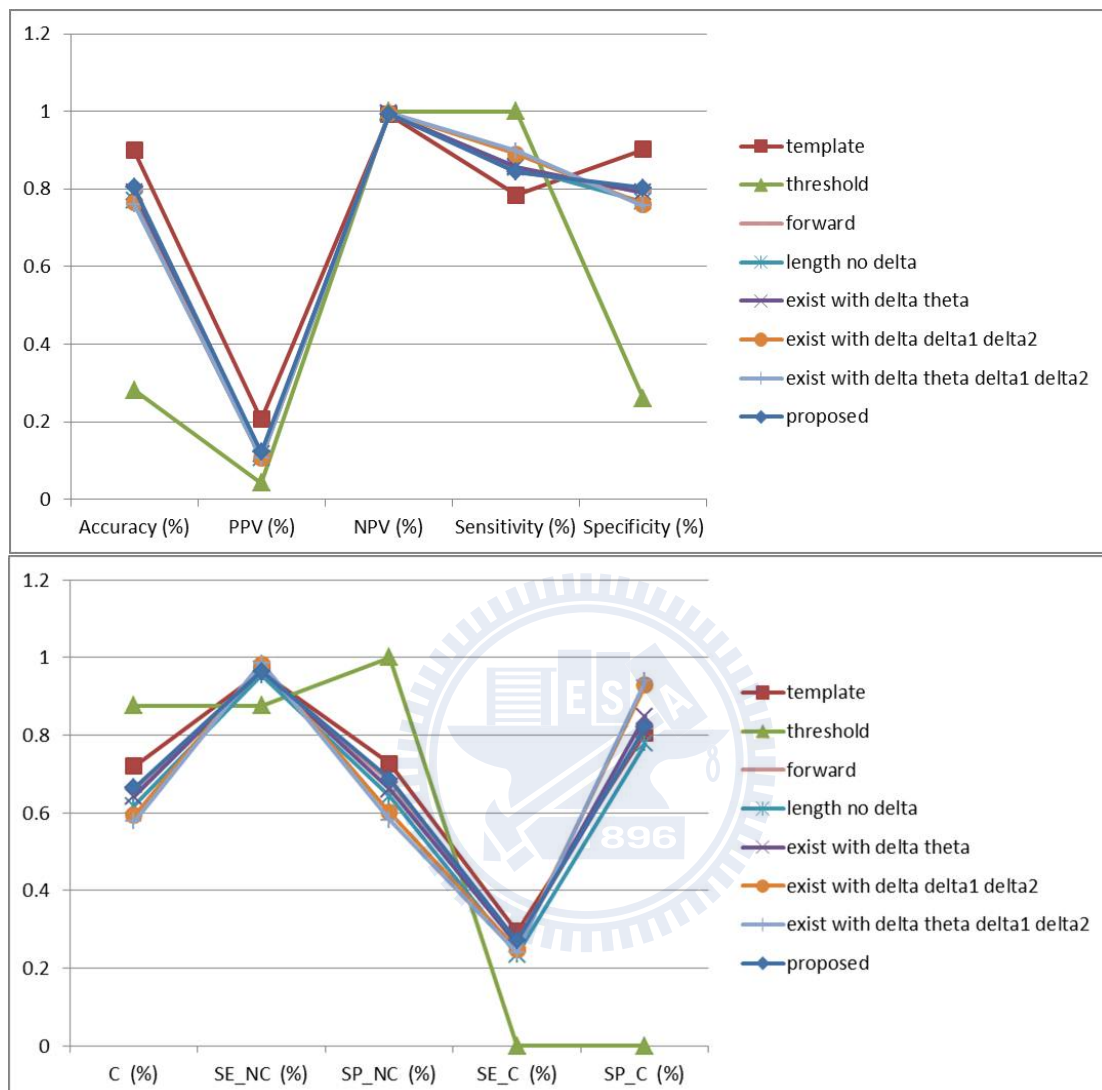
Figure 4.4: Show the Subject1 result which use the proposed result as test and the registered PSG technologists manual scoring as reference. The top figure is A-phase detection result and the bottom figure is CAP sequence detection result. These eight lines from top to down are the proposed method without template, exist threshold set to 1 and length threshold set to 0, the proposed method with forward function, the length band without using delta band, the exist band using delta and theta band, the exist band using delta, higher delta and, lower delta band, the exist band using delta, higher delta, lower delta, and theta band, and the proposed method.
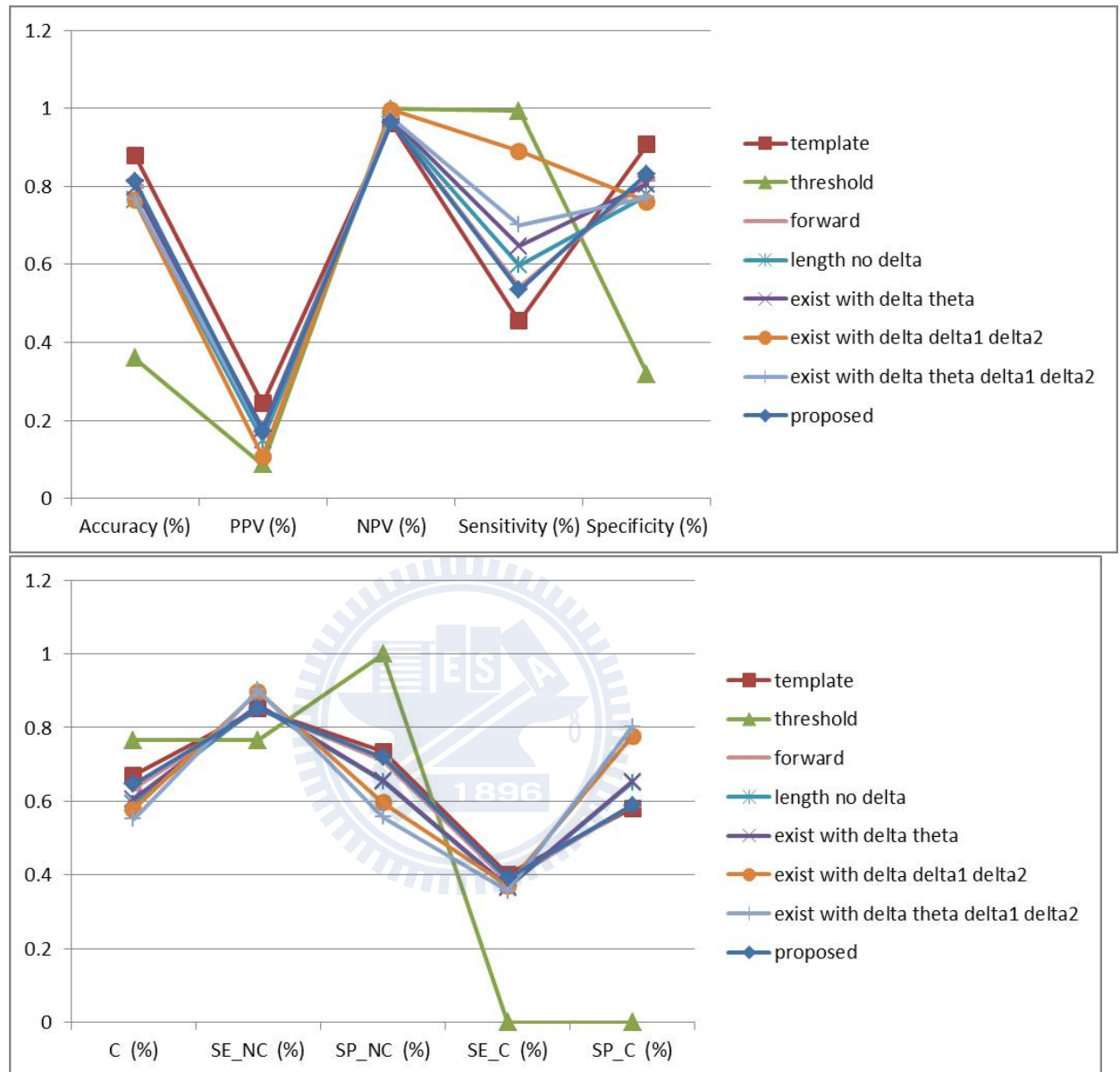
Figure 4.5: Show the Subject2 result which use the proposed result as test and the registered PSG technologists manual scoring as reference. The top figure is A-phase detection result and the bottom figure is CAP sequence detection result. These eight lines from top to down are the proposed method without template, exist threshold set to 1 and length threshold set to 0, the proposed method with forward function, the length band without using delta band, the exist band using delta and theta band, the exist band using delta, higher delta, and lower delta band, the exist band using delta, higher delta, lower delta, and theta band, and the proposed method.

Table 4.1: CAP A-phase detection without vertex sharp wave

	Test non A	Test A
RemLogic non A	41916	8827
RemLogic A	653	921

Table 4.2: CAP A-phase detection with vertex sharp wave

	Test non A	Test A
RemLogic non A	40295	10151
RemLogic A	653	921

4.1.5 Vertex sharp wave

We had developed a vertex sharp wave detection method to improve CAP detection. But it performed negative influence in the A-phase detection. In Table 4.1 and Table 4.2, the confusion matrix of A-phase detection result shows that the true positive in non A-phase is decreasing.

4.2 Hjorth parameter

While we used Hjorth parameter activity as feature rather than band power to perform CAP classification. Figure 4.7 shows the CAP rate of this result on the right column and the proposed method in the left column. Figure 4.8 shows accuracy, sensitivity, PPV, and NPV of CAP A-phase classification results. In the CAP rate, the results of Barcaro method are too high to fit u-shape. In the Figure 4.8, the accuracy of the method with Hjorth parameter activity as feature is lower than the accuracy of the proposed method, that is to say, the using power spectrum as feature is better than using Hjorth parameter activity.
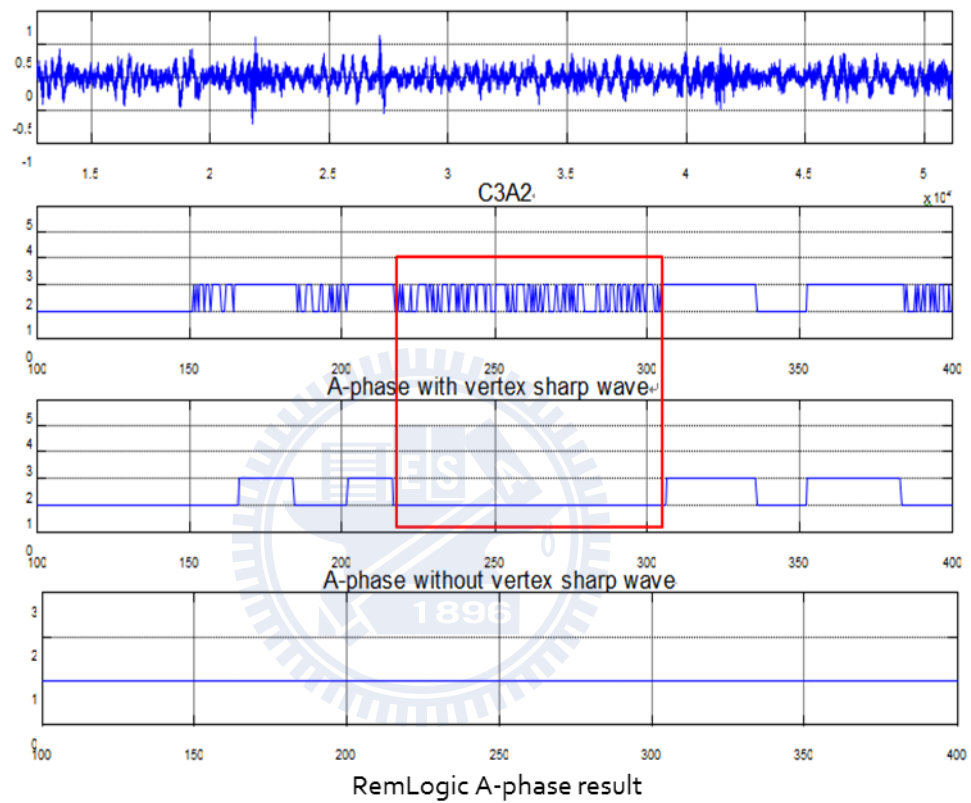
Figure 4.6: The four rows top to down are C3-A2, A-phase detection result with vertex sharp wave, A-phase detection result without vertex sharp wave, and RemLogic system result. This figure shows that the vertex sharp wave detection method may cause some negative influencewith non A-phase true positive value.
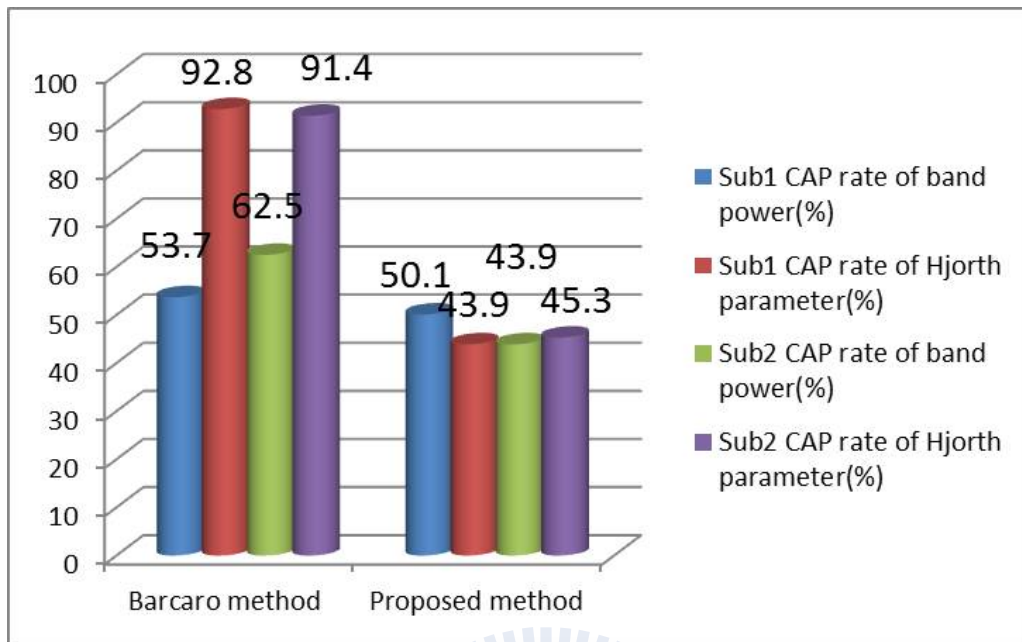
Figure 4.7: Show the CAP rate of two subjects of the proposed method and the method with hjorth parameter activitiy as feature.
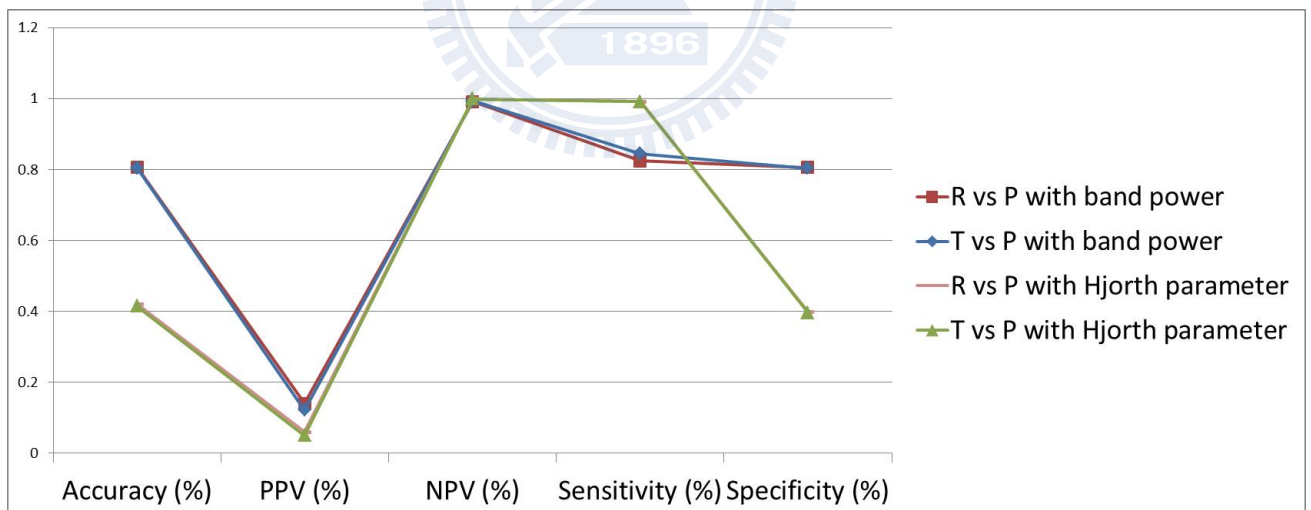

Figure 4.8: Show accuracy, sensitivity, PPV, and NPV of CAP A-phase classification results of two subjects of the proposed method and the method with hjorth parameter activitiy as feature. P means the proposed method result. R means RemLogic system automatic scoring. T means the registered PSG technologists manual scoring.

4.3   Fractal dimension

We can remove part A-phases by adding fractal dimension feature as constrain. At first, we compute one fractal dimension value each 0.5 s. Then we compute short average and long average as the following formula:

$$FD_s(t) = \frac{1}{5} \sum_{t=-2}^{2} \widetilde{FD}_i(t) \tag{4.1}$$

$$FD_l(t) = \frac{1}{61} \sum_{t=-30}^{30} \widetilde{FD}_i(t) \tag{4.2}$$

If the time point is A-phase and the difference between short average and long average is small enough, then it is A-phase. Others are non A-phases. Figure 4.9 shows the CAP rate of the proposed method with fractal dimension as constrain Figure 4.10 shows accuracy, sensitivity, PPV, and NPV of CAP A-phase classification results.
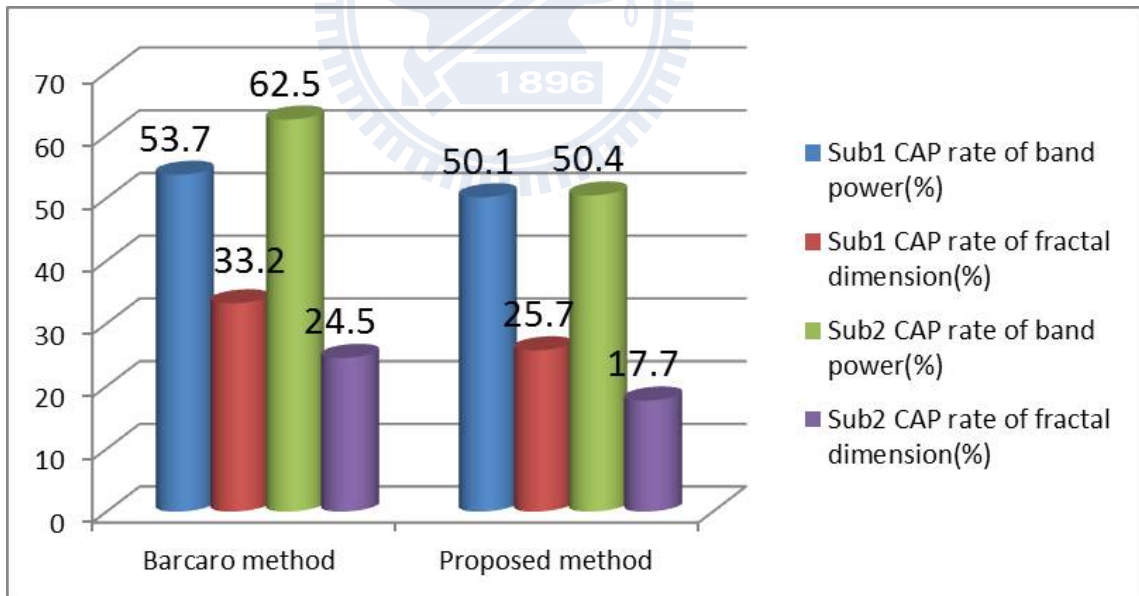

Figure 4.9: Show the CAP rate of the proposed method and he proposed method with fractal dimension as constrain.
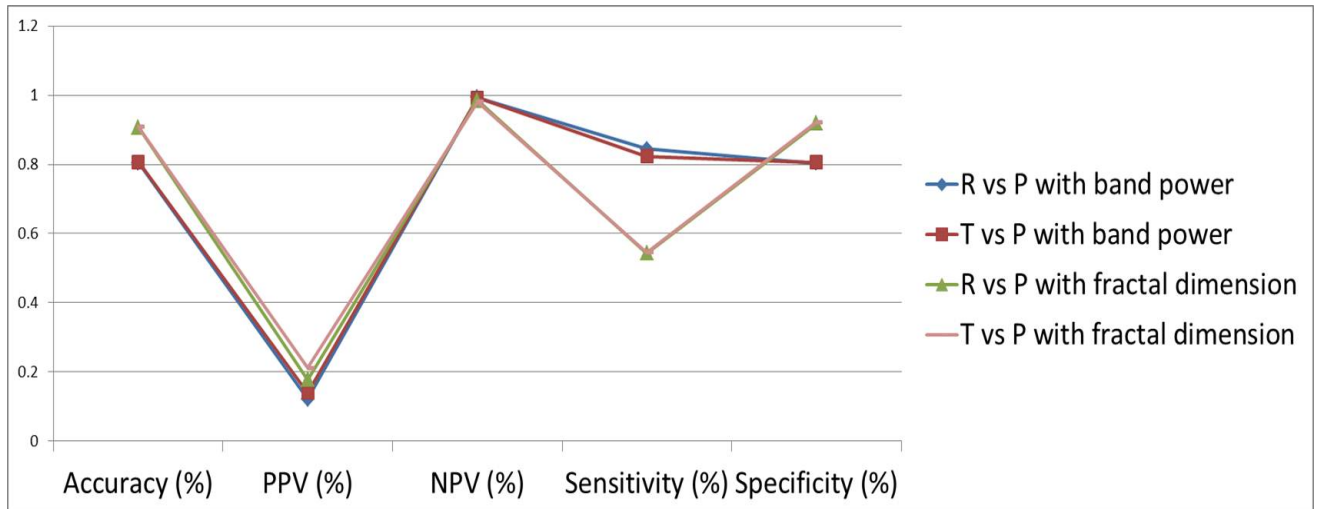
Figure 4.10: Show accuracy, sensitivity, PPV, and NPV of CAP A-phase classification results of two subjects with the proposed method and the proposed method with fractal dimension as constrain. Pr means the proposed method result. R means RemLogic system automatic scoring. T means the registered PSG technologists manual scoring.

4.4 Subtypes

A-phase has three subtypes : A1, A2, and A3. We compare different classifiers efficiency in CAP A-phase subtypes classifications. These classifiers contain LDA, k-NN, Navona method, and the proposed method. The results of the proposed method are more stable than others.

4.5 Problems of automated CAP detection

4.5.1 Reasons for bad classification

From the results of our experiment, the accuracy of CAP detection and subtypes classification achieve 81% and 61% in average with 2 insomnia subjects. Our ground truth is scoring manually by RPSGT and RemLogic system. RPSGT scores visually based on EEG signal and sleep stages. RemLogic system scores automatically with the same data. Since we use only single EEG channel for scoring, the quality of the EEG signal is very

Figure 4.11: Shows the CAP subtypes classification results of Subject1 of two kinds of ground truth in four classify methods which are the proposed method, LDA classifier kNN classifier, and the Navona method.
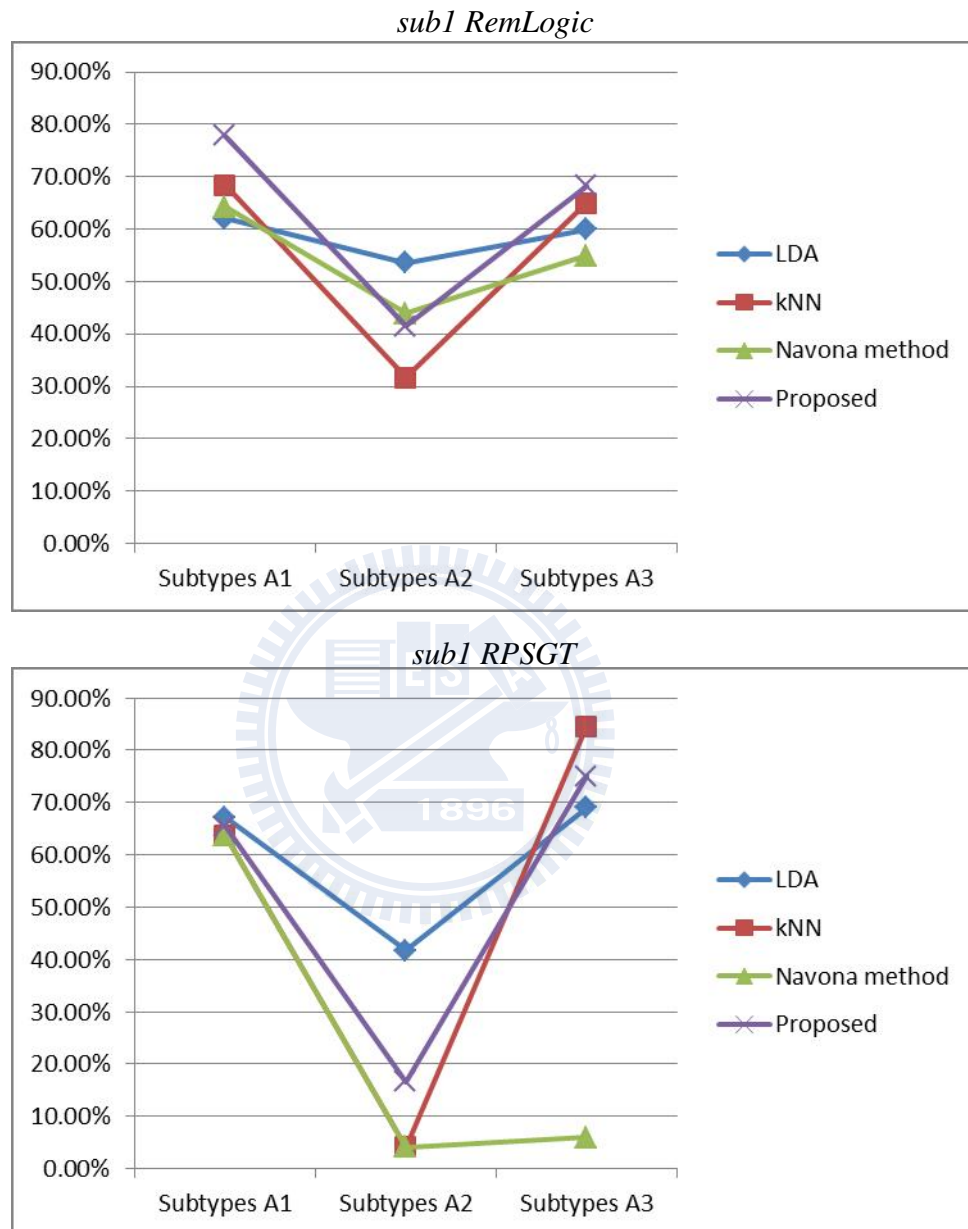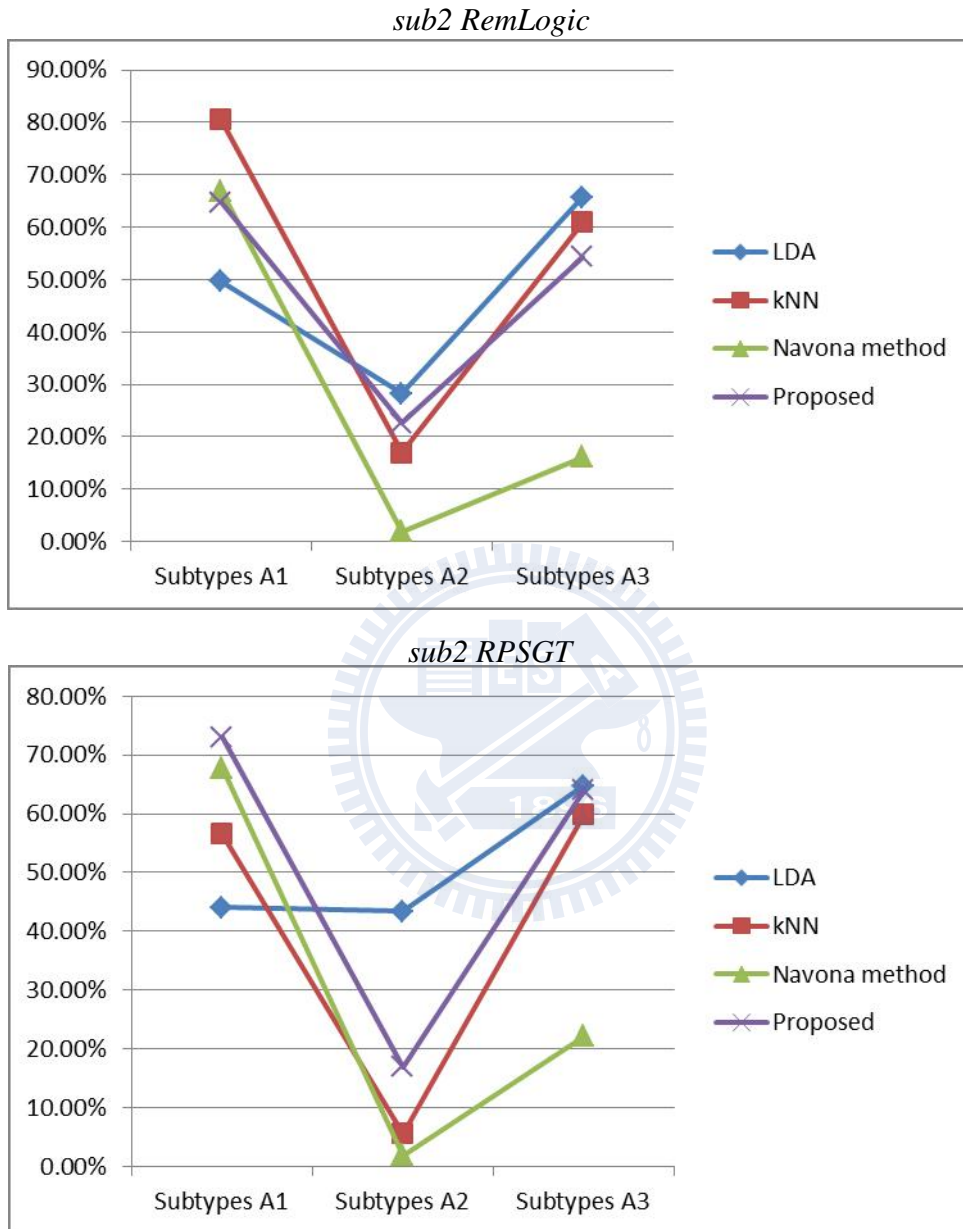
Figure 4.12: Shows the CAP subtypes classification results of Subject2 of two kinds of ground truth in four classify methods which are the proposed method, LDA classifier kNN classifier, and the Navona method.

important. Following are the reasons which will impact the accuracy of classification.

Signal quality

For physiological signal analysis, the analysis result often depends on the signal to noise rate. During the sleep EEG recording, it is inevitable that the signal interferences caused by the body movement. In EEG signal, body movement may affect signal abnormal changing and affect power distribution of the original signal. CAP phases is detected in a short interval and the each time point will affect nearby time points, so body movement may affect scoring result. But it is hard to detect in a suitable way to reject them.

Subjects recording

CAP analysis is a time-consuming effort of the visually scoring process. In Taiwan, there are few CAP professionals. It is a hard process to obtain a lot of CAP scoring results. Although RemLogic system is an automatic CAP detection system, it still has low accuracy problem. Our experimental analysis with 2 subjects is not enough to do statistic process and the 2 subjects are insomnia patients who may appear special situation to impact the accuracy of classification.

Limited information from Inter- scorer reliability

In the literature, inter-scorer agreement is another problem. The CAP detection result agreement between scorers is less than sixty percentages. The special wave detection in CAP such as K-complex is also less than sixty percentages. The low inter-scorer reliability may cause unstable CAP detection results in our study.

Chapter 5

Conclusions and Future Works

5.1 Conclusions

In the last 4 decades, most researches of sleep quality analysis focus on automated sleep staging which has been carried out many excellent researches. The purpose of the system is to develop an automated method to detect CAP. In microstructure, our method may inconclusive because the background researches and development time are not long. It also has no easy solution for us to find enough gold standards. In our experimental results, we have constructed a CAP detection method inherited previous methods advantages at first. The proposed method combines variable length template method and EXIST/LENGTH thresholds method in A-phase detector and short-long term ratios in feature extraction. Compared to the Barcaro method, the proposed method is superior because of its usage of variable length template. Second, we also applied sleep EEG features of 147 obstructive sleep apnea syndrome (OSAS) subject's brain waves and 41 non-OSAS subject's brain waves as the testing data. The CAP rates of 188 OSAS patients obtained by the proposed method are higher than those of non-OSAS subjects, which is consistent to the literature. For the severe OSAS subjects, the CAP detection results show increased values of CAP rate. Third, we suggest that thresholds should be adjusted for each subject because it may has different importance due to subjects are insomnia patients. Fourth, it is proposed that CAP has some typical A-phase EEG events. In our experiment, vertex sharp wave maybe not provide sufficient information to detect A-phases. Fifth, fractal dimension should be able to make A-phases classification stable and improve detection accuracy of CAP.

5.2 Future works

Experiments of normal subjects

In our experiment, we just have applied the proposed method of CAP detection and subtypes of A-phase classification on two insomnia subjects. The CAP rate of standard scoring rules were presented on normal subjects. It is need to discuss and experiment the proposed method on healthy subject so we can record the method efficiency and accuracy. Thus, we may provide a reliable experimental data of CAP detection for neurologists. Neu-

rologists may use these results to analyze the sleep quality. Moreover, we hope more and
more sleep experts who can be invited to provide information of CAP and CAP manual
scoring as gold standard.

Improvement of the proposed algorithm

As we know the characteristics of CAP, we can develop our algorithm to distinguish
different phases of CAP. In the future, we wish the method can be improved by new algo-
rithm instead of combine previous researches advantages. In order to achieve this propose,
it is needed to make an A-phase detection method which contain A-phase distinguishable
ability.

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