NOTE TO USERS

Compression of long-term EEG using power spectral density

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ABSTRACT

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Continuous long-term electroencephalogram (cEEG) has been shown to be extremely valuable in monitoring patients whose brain function may be in jeopardy, particularly in the neurological intensive care unit (NICU). Since cEEG monitoring can last from days to weeks, the amount of data generated can become unwieldy and methods that can help in the review process are necessary. Recently, a technique that compresses several hours of cEEG has been presented. The compressed summary includes a graph showing the temporal evolution of the different patterns in the cEEG along with their representative samples presented in the traditional EEG display format. This technique is based on segmentation and classification using a set of features called the *generic* features consisting of the amplitude, frequency, and frequency-weighted energy. Because the generic features used in this method are not always optimal, our aim in this thesis is to incorporate an alternative feature set in the above cEEG compression method. Specifically, in this thesis we propose a set of features based on power spectral density, referred to as the *spectral* features. Different methods are proposed to classify the segments that are parameterized with these features. We also propose a method, referred to as the *histogram* technique, to find the required initial seeds for the *k-means* clustering algorithm used to classify the segments. The performance of the existing classification scheme and the proposed classification methods are evaluated using sleep EEG on an epoch-to-epoch basis. For this purpose, we use two matrices namely, the *epoch cluster-sleep stage* matrix and the *agreement* matrix. Based on eight full-night sleep EEG records, our results indicate that the average classification is improved by six percent with the use of the *spectral* features over that with the *generic* features. Furthermore, the average classification performance is improved by approximately one percent with the proposed *histogram* technique compared

to that with the technique used in the literature. We also present the application of the compressed cEEG results for an eighteen-hour NICU cEEG recording of a patient in *status epilepticus*. The compressed results show that the *spectral* features can identify certain changes in the given NICU cEEG recording, which are not identified using the *generic* features. On the basis of our analysis, it can be concluded that the proposed method using the *spectral* features can provide an improved performance over that using the *generic* features.

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Tarun Madan, February 2005

To my loving family...

Contents

List of Figures

List of Tables

List of Algorithms

List of Symbols

A	:	Average absolute amplitude.
E	:	Mean of Frequency weighted energy.
f	:	Dominant rhythm.
$G_{NLEO}(n)$	:	Segmentation criterion generated using the NLEO.
ICD_X	:	Average of the inter-cluster distances associated with Cluster X.
K_f	:	Final number of initial seeds required for classification based on the iterative k-means clustering algorithm.
K_i	:	Number of feature vectors from which K_f initial seeds for k-means algorithm are calculated.
K_t	:	Number of equally spaced feature vectors from which K_i feature vectors are selected.
L	:	Length of window to calculate the threshold required for selection of segment boundaries.
P	:	Power spectral density.
P_i	:	Power in i^{th} bands, where i belongs to $delta(\delta)$, $theta(\theta)$, $alpha(\alpha)$, $sigma(\sigma)$, $beta1(\beta_1)$, $beta2(\beta_2)$.
P_T	:	Sum of the absolute powers in the six frequency bands.
r	:	Subscript to identify the relative powers in the different frequency bands.

$_S$	:	Subscript to define the features or feature vector that parameterize Segment S.
S_Y	:	Representative segment of Cluster Y.
S_Y^{20}	:	20-second long representative epoch of Cluster Y.
$X(f)$	:	FFT of $x(n)$, a channel of EEG in a given segment.
^{1,2}		Superscript to identify the features that parameterize Channels 1 and 2.

List of Abbreviations

AR	:	Auto regressive.
cEEG	:	Continuous long-term EEG.
CSA	:	Compressed Spectral Array.
DWT	:	Discrete Wavelet Transform.
EEG	:	Electroencephalogram.
EKG	:	Electrokardiogram.
EMG	:	Electromyogram.
EOG	:	Electrooculogram.
FFT	:	Fast Fourier Transform.
FV	:	Feature Vector.
FWE	:	Frequency Weighted Energy.
ICA	:	Independent Component Analysis.
ICD	:	Inter-cluster distance.
NICU	:	Neurological Intensive Care Unit.
NLEO	:	Teager's Non Linear Energy Operator.
R & K	:	Rechtschaffen and Kales.

Chapter 1

INTRODUCTION

Electroencephalogram can provide a generalized view of the complex neurological activities inside the brain. Applications such as sleep staging and epilepsy monitoring require the recording of the electroencephalogram (EEG) for durations extending from a few minutes to a few hours or even days, generating a huge set of data. In neurological intensive care units, the long-term EEG can provide information about the ensuing abnormalities well in advance of clinical manifestations, thus providing a window of time during which corrective action can be taken, before irreversible brain damage can occur.

Visual analysis of the EEG by a reviewer requires a lot of time and the analysis depends to a great extent on the reviewer's expertise and experience. Thus, the visual analysis of the EEG is subjective. Further, it is not feasible to manually keep a continuous vigil on long-term EEG for changes. These limitations cause the neurologists to refrain from the frequent usage of long-term continuous EEG recording. To encourage the usage of long-term EEG monitoring by the clinicians, we need to develop computer-based systems that can present the long-term EEG in a simplified compressed format.

In this chapter, we discuss the basics of the EEG and the requirement of computer-based methods to compress continuous long-term EEG. A brief overview of the literature related to various computer-based methods for the compression of long-term EEG is also provided.

1.1 THE ELECTROENCEPHALOGRAM

An EEG is a recording of the electric potentials generated by nerve cells in the brain and is measured using electrodes that are placed either intracranially or extracranially. The recorded signals reflect the potential differences between the two electrodes, caused by the flow of ionic currents through the tissue surrounding the electrically active brain cells. An EEG recording consists of various channels and each channel represents the amplified potential difference between the two electrodes. The potential difference is primarily recorded in two formats : (1) *Referential or Monopolar* and (2) *Bipolar*. The *referential* recording determines the potential differences with respect to a single common electrode and hence, makes it possible to compare the amplitude of the signals recorded at the different electrodes. A *bipolar* recording determines the potential differences between the pairs of electrodes and is useful in noise environments as it nullifies the effect of noise. A block diagram representation of a two-channel EEG recording in *referential* and *bipolar* formats is shown in Figure 1.1. The placement or configuration of the channels in the EEG record is termed *montage*. Figure 1.2 shows a sample from the EEG, recorded in *bipolar* format.

EEG waveform has various patterns that differ in frequency, amplitude or duration of occurrence. Every waveform is a result of an activity in the brain and can be considered as a pattern. A pattern may be short-lasting or may occur for a sustained duration of time. Typical examples of transient or short-lasting activity are sleep spindles (bursts of EEG activity of 12-14 Hz waves lasting 0.5-1.5 seconds with amplitudes generally less than $50\mu V$) or K-complexes (EEG activity with a frequency less than 0.5 Hz and duration less than 0.5 second). The patterns occurring for sustained duration constitute the background activity.

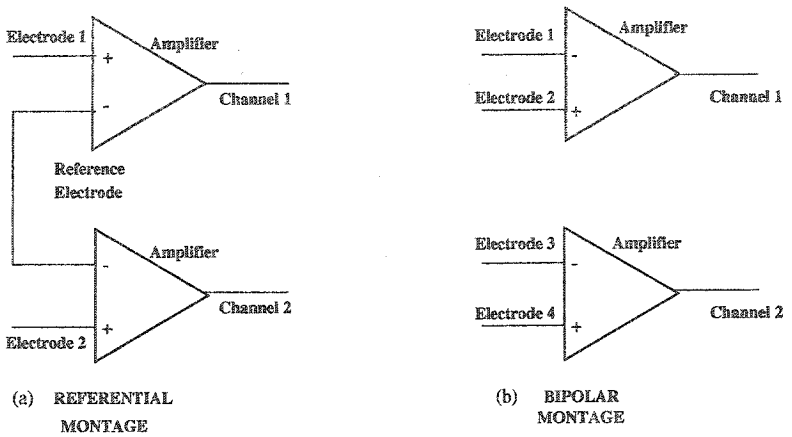


Figure 1.1: Block diagram of a two channel EEG recording in Referential and Bipolar formats. (a) Referential montage (b) Bipolar montage

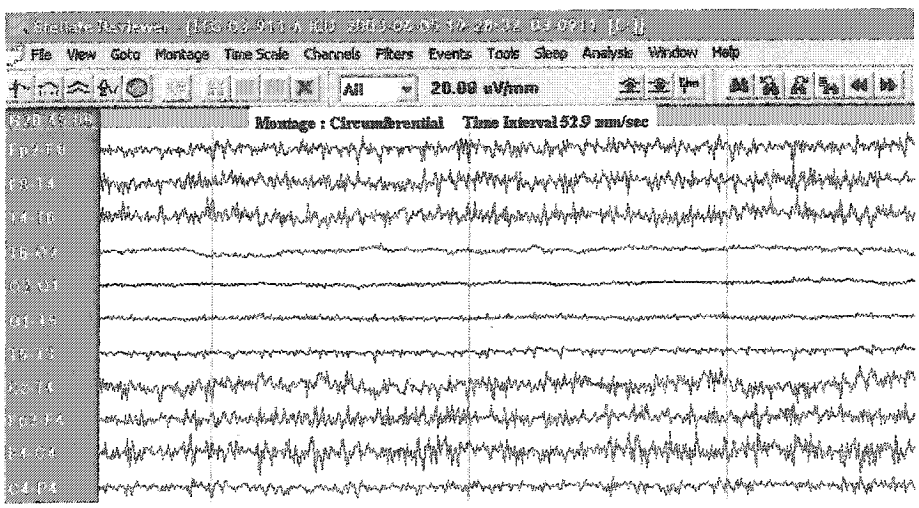


Figure 1.2: Sample of bipolar EEG recording in the circumferential montage.

During sleep, the brain goes through different states repeatedly. Each state is represented by an EEG pattern that is sustained in time. These different states of the brain present an example of background activity. Typically, short-lasting patterns occurring continuously can also be considered as a background activity. For example, continuous seizure activity can be considered as a background activity. In applications such as sleep staging or epilepsy monitoring in neurological intensive care unit (NICU) or monitoring the effect of medication, the EEG is generally categorized in the frequency range 0.1Hz to 35Hz. The most commonly used frequency bands are shown in Table 1.1.

Table 1.1: Classical Bands of EEG

SPECTRAL BAND	FREQUENCY (HZ)
Delta (δ)	0.25-4
Theta (θ)	4-8
Alpha (α)	8-12
Sigma (σ)	12-15
Beta1 (β_1)	15-24
Beta2 (β_2)	24-36

1.2 CONTINUOUS LONG-TERM MONITORING OF EEG

The EEG allows the reviewers to map electrical impulses across the cortex and observe changes over time. It can show the state of the brain during sleep, wakefulness, sedation or epileptic activity because of the characteristic EEG patterns associated with these states. The duration of the EEG recording varies with the pathology in question. It can be either short (approximately 30 minutes [2]) or of a longer duration that can span weeks. The continuous long-term EEG (cEEG) monitoring is typically used to study the epileptic activity like spikes and seizures for pre-surgical evaluation, and provides information in localizing the regions of the brain that generate epileptic activity [3]. Certain biological cycles such as those of sleep or fluctuations in dominant frequencies of EEG, may be readily detected with cEEG monitoring.

Further, EEG can play a vital role in patient management. For example, by using the appropriate electrode placements and montages, the EEG abnormalities detected at the scalp can provide useful inferences about the disease localization [4]. The cEEG monitoring in the NICU can provide information about the ensuing brain abnormalities well in advance of clinical manifestations, thus providing a window of time in which corrective action can be taken prior to any irreversible brain damage [3, 5]. For example, in case of cerebral ischemia, the EEG becomes suppressed with a decline in the cerebral blood flow well ahead of irreversible brain tissue injury, i.e., EEG becomes substantially suppressed in amplitude with a decline in cerebral blood flow ranging from 2 to 30 ml/100g/min [6]. Since reversible damage occurs at flows of 10-12 ml/100g/min [6], changes in the EEG can provide early indication of the cerebral ischemia.

Quantitative analysis of cEEG can also give some useful information about the changes in the brain. For example, quantitative cEEG shows that the variability of the power in the *alpha* (8-12 Hz) band declines in conjunction with vasospasm[1] and later returns to excellent or good variability as the blood flow velocities return to normal. In the study given in [7], it has been observed that for over 70% patients considered, the variability in the *alpha* band monitored using cEEG predicted vasospasm before the commonly used *transcranial doppler ultrasound* did.

For the patients in NICU, the cEEG can play an important role in analyzing the effect of treatment on the brain. Patients in NICU may be therapeutically paralyzed and serial neurologic examination (clinical examinations) even when performed conscientiously are discontinuous and may miss important evolving changes in the patient's condition. On the other hand, the cEEG monitoring being continuous can provide information on the evolving changes in the brain in response to the treatment. For patients in deep coma, the study of the changes in the EEG activity may be the only change noted with stable clinical findings [8].

[1] Vasospasm is a narrowing of the cerebral arteries, which reduce the blood flow to the brain.

1.3 Manual Review of EEG

Presently, in most laboratories the EEG is reviewed manually. The reviewer visually examines the EEG, section by section or page by page, and using the rules for the pathology in question makes judgment about the recording. For example, to identify the different states of the brain in sleep, the reviewer examines the EEG in 20-second epochs along with other signals like electrooculogram (EOG), electromyogram (EMG), electrokardiogram (EKG) and scores it with a sleep stage as defined by internationally accepted Rechtschaffen and Kales (R&K) sleep classification rules [9]. Visual analysis requires an enormous amount of time by the reviewer. Also, the rules defined for reviewing are not based on strict quantitative measures and thus, even under the best circumstances, the analysis by expert personnel is subjective. The analysis of the same EEG by different reviewers may be in discord. For example, the comparison of visual scoring of two healthy subjects in 10 sleep laboratories in Japan showed an average inter-scorer agreement of only 67-75.3% [10].

1.4 Compression of cEEG

As discussed in the previous sections, the cEEG monitoring in NICU can provide vital information about the patient and can even allow for corrective actions to be taken before irreversible brain damage can occur. Also, cEEG monitoring can play an important role in various applications like postoperative progress and monitoring the progress of patients with head injury or stroke [11, 12, 13]. Since the cEEG monitoring generates extensive data, cEEG review requires an enormous amount of neurologist's time. Further, the analysis depends on his expertise and experience. Also, it is not feasible to manually keep a continuous vigil on the cEEG for changes. There is always a possibility of missing the onset of abnormalities by the staff. These limitations restrain the clinicians from the frequent use of cEEG monitoring for diagnostic purposes.

To encourage the clinicians to use the cEEG monitoring, we need to provide tools that can assist them in the analysis of the cEEG with minimal effort and still obtain similar or improved degree of diagnosis over manual analysis. We need to develop computer-based systems, which can aid in assessing the cEEG and present the information in a simple compressed format. Such techniques for the compression of the cEEG do not aim to replace the manual analysis, but rather to supplement the review process by providing a bird's eye view of the functionality of the brain. The compressed results, if presented in a format that can be easily understood by the NICU staff (typically non-EEG specialists with little or no knowledge of EEG), can help the NICU staff to identify possible evolving structural abnormalities. Such compression techniques can search for patterns with relative changes and do not require any *a priori* information about the data in question. This enables in the detection of evolving patterns or states of the brain that are not easily recognized during the initial manual analysis.

Various computer-based techniques for the compression of cEEG have been proposed in the literature [1, 14, 15, 16, 18]. A simple method to analyze and present the cEEG is the trend analysis [14]. Depending on the brain pathology to be monitored, the features for the segments of the EEG are calculated. The temporal profile of these features gives an indication of the variation in the EEG. Labar *et al.* [14] has shown that the trend analysis of the total power or alpha ratio reveals changes with *subarachnoid hemorrhage* prior to clinical manifestations. Bickford *et al.* [15] introduced the *compressed spectral array* (CSA) that represents the results of sequential power spectral density estimates of digitized EEG over time in an array format, i.e., the power spectrum is calculated using the fixed length EEG segments and displayed in a waterfall-type of graph. Bricolo *et al.* [8] used the CSA in the long-term continuous monitoring of comatose patients to obtain a temporal profile of the brain states of the patients.

Another technique followed for the compression divides the cEEG into quasi-stationary segments. These segments are then evaluated for their characteristic features and accordingly

grouped together using the various clustering methods. In the process, the segments with artifacts are removed. One such method was proposed by Creutzfeldt *et al.* [16] using adaptive segmentation based on the autocorrelation method [17]. The segments formed are clustered in a feature space spanned by the mean frequency and logarithm of the power in the segments. Local maxima are identified as clusters. A temporal profile of different clusters along with the frequency and amplitude of spectral peak of the representative segments are presented to the reviewer. As reported by the authors [16], certain background EEG recordings considered in the study were represented by a number of clusters that are not optimal compared to the actual patterns in the EEGs. Also, it is mentioned that for long-term EEG monitoring, the performance of the method can degrade because of the absence of clear maxima or minima.

A method for the compression of the cEEG, which is similar to the method given by Creutzfeldt *et al.* [16] was suggested by Vladimir *et al.* [18]. The EEG is divided into segments using adaptive segmentation based on the autocorrelation function [17]. Each segment is parameterized by a set of features: average amplitude, variability of the segment amplitude, the maximum positive and negative values in the segment, and amplitudes in *delta*, *theta*, *alpha*, and *beta* spectral bands. Depending on these features, segments are clustered into different groups using fuzzy-c means clustering algorithm [19]. Each cluster is color coded, i.e., all the segments of a single cluster are assigned the same color, but different from the segments of the other clusters. The color coding allows the different EEG patterns to be identified easily from the graphical presentation. This approach has the drawback that the segmentation is performed for individual channels resulting in segments that are not time locked (i.e., the segment boundaries are not synchronized across all channels). Thus, at a given time instant the corresponding segment in the various channels may not represent the same type of pattern or cluster, increasing the complexity in reviewing. The number of fuzzy clusters is also fixed initially and these may or may not differentiate all the patterns present in the data set. Moreover, the segmentation criterion used does not

perform well for the cEEG [20].

The methods described above [14, 15, 16, 18] generally require training and experience for proper interpretation of the compressed cEEG. None of these techniques have been clinically accepted. A few years ago, Agarwal *et al.* [1] suggested a new method for the compression of the cEEG. It relies on the observation that the background activity in the cEEG usually consists of different patterns that are recurrent, and summarizes the cEEG recording using a simple bar chart with different colors. The temporal profile of the colors depicts the temporal profile of the different EEG patterns that may be present. Based on Teager's non-linear energy operator (NLEO) [38], a simultaneous multi-channel segmentation procedure was used in [1]. The segments are characterized by three features (referred to as the *generic* features) - amplitude, dominant rhythm, and frequency-weighted energy. Segments with similar features are grouped into clusters using an iterative method based on the *k-means* clustering algorithm. The results of compression are displayed as a color-coded temporal profile bar-graph. Along with the temporal profile, a representative sample of actual-EEG for each pattern type is provided. Since the reviewer is already experienced in reading the actual-EEG, the use of the actual-EEG epochs in the compressed results simplifies the review process. Thus, minimal training is required for identifying the relative changes.

1.5 Scope of Thesis

The method proposed by Agarwal *et al.* in [1] for the compression of the cEEG uses the *generic* features - amplitude, frequency-weighted energy, and dominant rhythm to parameterize the segments for compression. These features have only limited information about the amplitude and frequency of the signal. During manual analysis of the EEG, the EEGer (EEGer is a person who interprets the EEG) requires a good understanding of the frequency and amplitude of the signal. Moreover, the complete spectral content of the

signal is inherently used by the reviewer for reviewing. Hence, we expect the features based on a wider information about the frequencies of the EEG to provide a better description of the segments and to give improved compression results. We propose to replace the *generic* features with features based on the power spectral density, henceforth, referred to as the *spectral* features, as the basic descriptors of the segment in the compression framework proposed by Agarwal *et al.*

The classification algorithm proposed in [1] was designed based on the *generic* features and thus, may not work optimally with the proposed *spectral* features. Hence, we propose a new technique for the classification of the segments using the *spectral* features. We also propose a generalized histogram-based technique, henceforth referred to as the *histogram* technique, to replace the the technique given in [1], henceforth referred to as the *temporal* technique used to calculate the initial seeds[2] required for the *k-means* clustering algorithm.

In order to compare the performance of the *spectral* features and the *generic* features in the compression framework, we evaluate them in terms of their ability to form homogeneous clusters that can provide clinically meaningful information. A methodology is designed to compare the clusters formed with the different manually determined states of the brain during sleep. For this purpose, we use two matrices, viz, the *epoch cluster-sleep stage* matrix and the *agreement* matrix.

1.6 Outline of Thesis

In Chapter 2, we first give a description of a some techniques existing in the literature for the various blocks in the compression framework, viz, segmentation, artifact rejection, feature extraction and classification. The second part of this chapter explains in detail the method presented by Agarwal *et al.* [1] for the compression of the long-term EEG. We describe the techniques used for multi-channel segmentation, rejection of the segments contaminated

[2]The *k-means* clustering algorithm requires a set of data points, which is used as the centroids of the probable clusters present in the data set under consideration. These data points are called as initial seeds.

with artifacts, calculation of the *generic* features to parameterize the segments, classification of the segments based on the iterative *k-means* clustering algorithm, and display of the compressed results.

In Chapter 3, we propose a method for the compression of the cEEG, which is similar to the method by Agarwal *et al.* given in [1]. We propose to use the *spectral* features to replace the *generic* features used in [1]. Different classification methods are proposed to cluster the segments which are parameterized using the *spectral* features. *Histogram* technique is proposed to calculate the initial seeds for the *k-means* clustering . In the second part of this chapter, we explain the methodology followed to compare the performance of the different compression methods using two matrices, namely, the *epoch cluster-sleep stage* matrix and the *agreement* matrix.

Chapter 4 discusses the performance of the method presented in [1] using the *generic* features and the proposed method using the *spectral* features for the compression of the cEEG. We explain the advantages of the proposed method using the compressed cEEG results of eight different full-night sleep EEG recordings. In Chapter 5, we present an application of the compressed cEEG with the neurological intensive care cEEG recording of a patient in *status epilepticus*. A comparison between the onset and offset of the various patterns as shown by the compressed cEEG and the clinical information provided by the physician is given in this chapter. Finally, in Chapter 6 we give a summary of the contributions in this thesis and provide guidelines for some future work in the area.

Chapter 2

BACKGROUND

The technique for the compression of the cEEG consists of four basic blocks - segmentation, feature extraction, artifact rejection and classification. In this chapter, we first present a brief overview of the literature related to the different blocks in the compression technique. Since our work is based on the methodology followed by Agarwal *et al.* [1] for the compression of the cEEG, we explain it in detail in the last section of this chapter.

The goal of the cEEG compression techniques is to present a summary of the cEEG to assist the review process. It provides a bird's eye view of the different activities during the cEEG monitoring, which otherwise can take enormous amount of time for review. Further, it allows the reviewer to easily identify the relative changes in the cEEG. A block diagram for the compression of the cEEG is shown in Figure 2.1.

The first block is *Segmentation*. EEG is assumed to be composed of stationary segments of variable length. For example, a single EEG record might have slow waves of small duration, rhythmic bursts (like seizures, spindles, and k-complexes) or ongoing patterns that differ in duration (like transition from wakefulness with eyes closed to wakefulness with eyes open). EEG is analyzed in stationary segments where it appears to be unchanging. The segments are created by drawing boundaries at time instants corresponding to the changes in amplitude and/or frequency content of the signal.

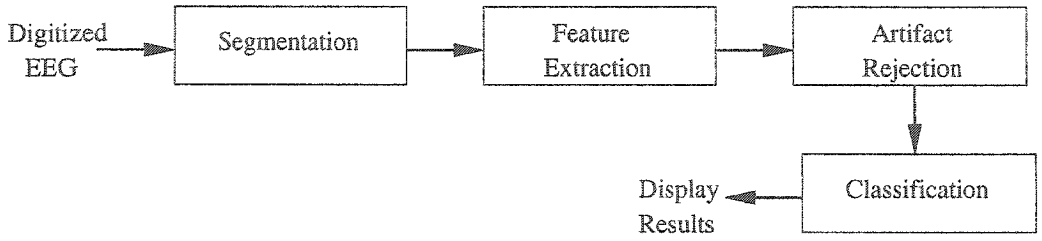


Figure 2.1: Block diagram for the compression of cEEG

During the manual review, the reviewer analyzes the EEG on the basis of its features like frequency, amplitude and duration of the different patterns. He/she accordingly differentiates between the normal and abnormal EEG activity. In accordance to this, a set of features is selected to parameterize each EEG segment. This is the role of the second block in the compression technique - the *Feature Extraction* block in Figure 2.1. The selection of these features is dependant on the application in question. For example, monitoring during drug titration, the power in the *alpha* band or the power in the different frequency bands may be relevant, whereas in epilepsy monitoring the power in the different frequency bands, information about the duration, amplitude and frequency may be needed.

EEG is presumed to represent only the cerebral activity, but it also includes other electrical activities that are not of cerebral origin. These signals are undesirable and are considered to be artifacts. The presence of these artifacts can severely degrade the performance of the compression method and thus, must be removed. Hence, the need for the third block - the *Artifact Rejection* block in Figure 2.1.

The fourth block in Figure 2.1 is called *Classification*. By using the features that parameterize each segment, segments with similar features are grouped together. This allows the identification of the different patterns present in the data set and can be used to provide a temporal view of the occurrence of each pattern in the data. Finally, the summary of the temporal profile of the different patterns in the data set is presented to the reviewer.

In the following sections we provide an overview of the different techniques available in the literature for each of the blocks in Figure 2.1.

2.1 SEGMENTATION

As mentioned earlier, the EEG is divided into quasi-stationary segments by drawing boundaries at time instants corresponding to the changes in the amplitude and/or frequency content of the signal. There are two basic types of segmentation techniques available - *fixed point* and *adaptive*. In the *fixed-point* technique, the data is divided into fixed length segments, whereas in the *adaptive* segmentation, the segments are created when there is a change in the EEG pattern. The *adaptive* segmentation results in variable length segments.

In the literature, various methods have been suggested for the *adaptive* segmentation of the EEG. Most of the methods are based on a common scheme - features are extracted from an initial reference section of the EEG and continuously compared with those of the subsequent EEG (i.e., the EEG in a sliding test window). A segment boundary is declared, if this difference exceeds a predefined threshold. Once the segment has been established, the reference window is placed just adjacent to the segment boundary and entire process starts again. Figure 2.2 shows the commonly used segmentation procedure. The EEGs in the reference and the sliding windows are compared to detect the boundaries for segmentation.

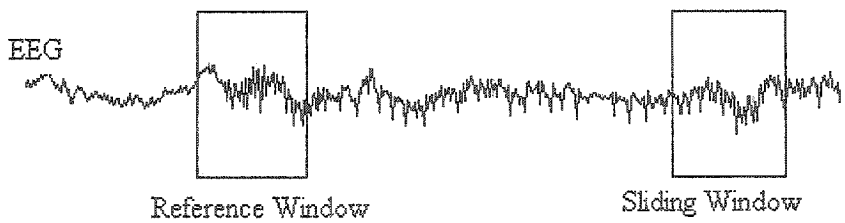


Figure 2.2: Commonly used segmentation technique

2.1.1 PARAMETRIC MODEL

An *adaptive* segmentation method based on an autoregressive filter was suggested by Bondenstein *et al.* [21]. The EEG in the moving test window is passed through an

eighth-order autoregressive filter, whose coefficients $[a_R(0), \ldots a_R(p)]^T$ are determined from the auto-correlation function of the EEG in the reference window. The prediction error $e(t)$, gives an estimate of the difference between the spectral content of the two windows :

$$e(t) = \sum_{k=0}^{p} a_R(k) s(t-k)$$

where $s(t)$ is the EEG in the test window. The spectral error measure $d(t)$, is given by

$$d(t) = \left[\frac{r_e(0,L)}{r_e(0,t)} - 1\right]^2 + 2.\left\{\sum_{k=0}^{p}\left[\frac{r_e(k,t)}{r_e(0,t)}\right]^2\right\}$$

where

$$r_e(k,t) = \sum_{i=t-L+1}^{t-k} e(i)e(i+k)$$

When $d(t)$ exceeds the predetermined threshold, a signal boundary is placed at the centre of current test window.

Michael and Houchin [17] suggested calculating the autocorrelation function of the EEGs in the reference and the temporal sliding windows. Differences in the spectral power were determined from the zero lag point of the two autocorrelation functions. The distance measure $d(t)$ based on autocorrelation is calculated from the normalized measures based on the energy difference and spectral distance. If d_o is the threshold value of the distance measure, then $d(t) > d_o$ indicates a segment boundary.

2.1.2 Generalized Likelihood Ratio

A segmentation algorithm based on generalized likelihood ratio test was proposed by Appel and Brandt [22]. In this method, prediction error quantities in three windows - reference window (growing till a boundary is detected), test window of fixed length L, and a pooled window formed by concatenation of the two windows are calculated. From these values, the distance measure $d_1(t)$ is calculated. Assuming a normal distribution of the EEG, $d_1(t)$ is

the generalized log-likelihood-ratio test statistics. If $d_1(t)$ crosses the threshold, a segment boundary is created at that instant.

This method requires larger number of numerical computations compared to the methods based on parametric models. Also, when applied in a scenario of multi-channel EEG segmentation, it results in non-synchronous segment boundaries across the different channels.

2.2 ARTIFACT REJECTION

As mentioned earlier, the EEG is presumed to represent only the cerebral activity, but may have unavoidable signals, which are considered as artifacts. The artifacts may be *physiological* or *non-physiological*. The *physiological* artifacts are signals originating from the patient, but from sources other than brain. These can include EKG, EOG, muscle contractions of neck, forehead, blinking, coughing, and swallowing. The *non-physiological* artifacts originate from the electrodes or switch contacts of other devices or external signals such as the 60 Hz interference. Moreover, any pattern or signal not needed for a given application is considered as an artifact. The brain signal of interest for background cEEG monitoring consists of patterns that occur for sustained durations and the presence of transients like spikes or seizures can also be considered to be artifacts.

In the computer-based cEEG analysis that are based on classification algorithms, it is extremely important to remove the segments with artifacts, which otherwise can severely degrade the performance of the classification methods. There always exists a trade-off between the performance of the computer-based system and the scheme for artifact removal. If the artifact rejection strategies are made very stringent, we are bound to lose a significant amount of the vital data. On the other hand, it can degrade the performance of the system by allowing the artifacts to contaminate the vital data. The selection of the technique for the automated artifact removal is based on the application in question. In the literature, various techniques for automatic detection and elimination of the EEG artifacts have been

presented. Some of the techniques are discussed in the following subsections.

2.2.1 Frequency and Amplitude

The electromyogram (EMG) activity is the electrical activity of the muscle fibers. It is typically a high frequency activity. Thus, a low pass filter with a cut-off frequency around $15\,Hz$ can make the artifact contaminated EEG segments free of the EMG artifacts [23, 24]. In an application of seizure detection, a low-pass filter of $25\,Hz$ was used to eliminate the artifact due to the EMG [25]; it was argued that during the contractions of the scalp muscles, most of the energy of EMG activity is above $15 - 20\,Hz$. The rhythmic activity of the seizures typically has a fundamental frequency lower than $25\,Hz$. Therefore, the total elimination of activity above $25\,Hz$ would eliminate most of the EMG activity with a minimal risk of eliminating rhythmic cerebral activity.

For normal healthy subjects, the EEG amplitude is typically in the range of $20-100\,\mu V$, whereas the EKG has an amplitude in the order of mV. The relative high energy of the EKG may have a pronounced effect on the EEG. Many techniques have been described in the literature to remove this artifact. Nakamura *et al.* [26] has proposed the segmentation of the EKG-contaminated EEG synchronously with respect to the R-peaks of the EKG. The average across the segments, when subtracted from the raw series, results in a clean-EEG.

2.2.2 Neural Networks

Concept based on neural network has been used for the separation of artifact contaminated segments and the EEG segments. The network learns a certain mapping from the set of realization examples, which can later be used to classify the segments. For example, Ahn *et al.* [27] have suggested a multi-layer perceptron-based classifier to separate the artifact contaminated segments. It consists of three layers: an input layer, a hidden layer and an output layer. The learning data set is classified into three classes: good quality, middle quality and artifact. Depending on the input segment, the network assigns it to one of

the three classes. The performance of the network is determined by several factors, like error allowance in the learning process, values assigned to the target layer, training data set, and threshold applied in the decision rule. Since neural network based techniques require *a priori* information about the different classes that are possible with the training set, they cannot be used in the computer-based EEG analysis methods that have no *a priori* information available about the data in question.

2.2.3 Independent Component Analysis

Tzyy *et al.* [28] proposed an approach based on *independent component analysis* (ICA) for the artifact rejection in the EEG. The ICA approach assumes a linear mixing of the signals from statistically independent sources at the sensors and uses spatial filters to recover these sources. Sources such as the brain, heart, and eye movement generators are assumed to be independent. Hence, using ICA it is possible to separate the activities from these sources. ICA resolves the recorded EEG into various components and by visual examination, the components corresponding to artifacts are identified and excluded in the reconstruction of the signal. The resulting reconstructed EEG is free of the artifacts. The major disadvantage with ICA is that it requires visual inspection of the components in order to select the artifact components to be removed. This requires time and thus, is not a feasible technique to be used for the artifact rejection in the computer-based EEG analysis methods.

2.3 Features

The selection of features for the classification of segments is based on the application in question. Some of the features used in the analysis of the EEG for different applications are summarized in the following subsections.

2.3.1 PARAMETRIC MODEL

Autoregressive (AR) parameters are used for spectral estimation. AR models have been demonstrated to successfully model the EEG. Thus, the coefficients of the AR model can serve as features to parameterize the segments. The use of the AR model was exemplified by Tsoi *et al.* [30]. They used the coefficients of the 8^{th} order AR model, computed using the Yule-Walker equations, to differentiate between the different psychiatric disorders. In another application, to monitor the depth of anesthesia, AR coefficients of the EEG segments (2 seconds duration) were used as features to construct a classification scheme [31]. The basic drawback with the AR model is that it requires *a priori* information about the data set to select the appropriate order of the AR model, and this is not always available. Further, in the cEEG monitoring the computation of the AR model for each segment will result in high computational complexity.

2.3.2 HJORTH PARAMETERS

In 1970, Hjorth [32] introduced three parameters to describe the EEG in the time domain. The first parameter m_1 is the mean power representing the activity of the signal s. The second parameter m_2 called the mobility is an estimate of the frequency and the third parameter m_3 gives an estimate of the bandwidth of the signal. The three parameter are defined as

$$m_1 = \sigma_s^2$$

$$m_2 = \frac{\sigma_s}{\sigma_d}$$

$$m_3 = \frac{\sigma_{dd}}{\sigma_s * m_2}$$

where σ_s^2 is the variance of the signal s, σ_d the standard deviation of first derivative of the signal, and σ_{dd} the standard deviation of the second derivative of the signal. Since the calculation of the Hjorth parameters is based on the variance of the data, the computational cost of this method is less compared to the other methods.

Vourkas *et al.* [33] used the Hjorth parameters as features to discriminate between

three mental tasks - baseline (epochs with eyes closed), math 1 (addition and subtraction with dictation under eyes closed) and math 2 (repetitive simple subtraction). In another application involving epileptic seizures, Wu and Gotman [34] used the Hjorth parameters along with other features for segmentation and classification of the EEG.

2.3.3 WAVELET TRANSFORMATION

During EEG analysis, the reviewer is interested in the temporal profile of the frequency content of the EEG. Wavelet provides the joint time-frequency information of the data set. In *discrete wavelet transform* (DWT), the signal is decomposed using a series of high and low pass filters. The original signal is divided into high and low bands and the low frequency signal is again divided into high and low bands. The number of times this is performed is known as the level of decomposition. The output of the low pass filter is known as *approximation* and that of the output of high pass filter as *detail*. The approximation and detail components provide information about the signal in different bands. The definition of each band is dependent on the level of decomposition and the sampling rate of the EEG signal.

In brain tumor diagnosis, for classifying the region of the brain with lesions, Karameh *et al.* [35] expanded the EEG signal using wavelets. It was proposed that the absolute mean and the number of zero-crossings of the approximation and details at different levels can be used as characteristics features for the brain tumor diagnosis. In another application, Stephane *et al.* [36] used the Daubechies wavelet for decomposition and concluded that by comparing the probability distribution function of the wavelet coefficients of the detail band (32Hz - 64 Hz) before and after the administration of the drug, the hypnotic state of the anesthetized person can be assessed.

2.4 CLASSIFICATION

Classification refers to the process of separating the data set into different groups based on certain features. The key property to evaluate the performance of a classification technique is its ability to form homogeneous groups, i.e., all the members in the respective group should have similar features but different from the other groups.

The clustering techniques can be divided into two types; *hierarchical* and *partitional*. *Hierarchical* clustering arranges the data into nested sequence of groups, whereas *partitional* clustering generates partitions of data in order to recover the different groups that may be present in the data set [37].

The *k-means* algorithm is a *partitional* clustering method ([37] and the references therein). In *k-means*, the data points are assigned or partitioned into one of the K clusters so that the degree of association (generally euclidean distance) of a member with respect to the cluster centroid is minimized, while the distance between any pair of cluster centroids is maximized. The *k-means* algorithm is an iterative procedure. It starts with an initial partition of the data points by assigning them to their nearest possible cluster. The centroids of the initial set of probable clusters are termed as *initial seed* points. The initial seed points can be the first K data points or K points determined from a matrix defined by the data set. Subsequently, with each iteration, the data points are reassigned to a cluster such that the degree of association between the members and the cluster centroid is minimized. For each iteration, the centroids of the clusters formed in the previous iteration are used as the seed points.

The computer-based EEG analysis system classifies the segments of the EEG such that each group represents one type of the brain activity. The results of the classification can later be used to formulate a clinically-relevant evaluation.

2.5 A Recent Method for Compression of cEEG

The recent method for the compression of the cEEG used by Agarwal *et al.* in [1] is based on the idea that the background cEEG has patterns which are sustained in time and repetitive in nature. It involves 4 basic steps: *segmentation*, *feature extraction*, *classification*, and *display* of results. The non-stationary EEG is first broken down into segments by adaptive segmentation based on the Teager's non linear energy operator (NLEO) [38]. Each segment is parameterized with the *generic* features: amplitude, frequency and frequency weighted energy. The segments with similar features are grouped into various clusters using an iterative method based on the *k-means* clustering algorithm [39]. The artifact contaminated segments are removed by applying the artifact or outlier removal methods at several stages. Figure 2.3 shows the block diagram representation of the method given in [1]. The details of the different blocks are provided in following subsections.

2.5.1 Segmentation

During the review of the EEG, the neurologist is interested in the onsets and offsets of the various rhythms in the EEG. The metrics based on the frequency and the amplitude are typically used to quantify the rhythms. Thus, a measure that varies with the changes in the frequency and amplitude of the EEG can be used for *adaptive* segmentation. Since the output of Teager's NLEO [38] is a function of the frequency and/or the amplitude, the method used in [1] uses this operator for multi-channel *adaptive* segmentation [20]. Details of the NLEO can be found in Appendix A. The output of the NLEO is termed *frequency weighted energy* (FWE). Algorithm 2.1 describes the overall segmentation procedure used in [1]. A sliding temporal window of a predefined length as shown in Figure 2.4 is used to detect the segment boundaries. At the time instant when the difference between the sums of the FWEs in the left and right halves of the window is greater than an adaptive threshold, a segment boundary is defined.

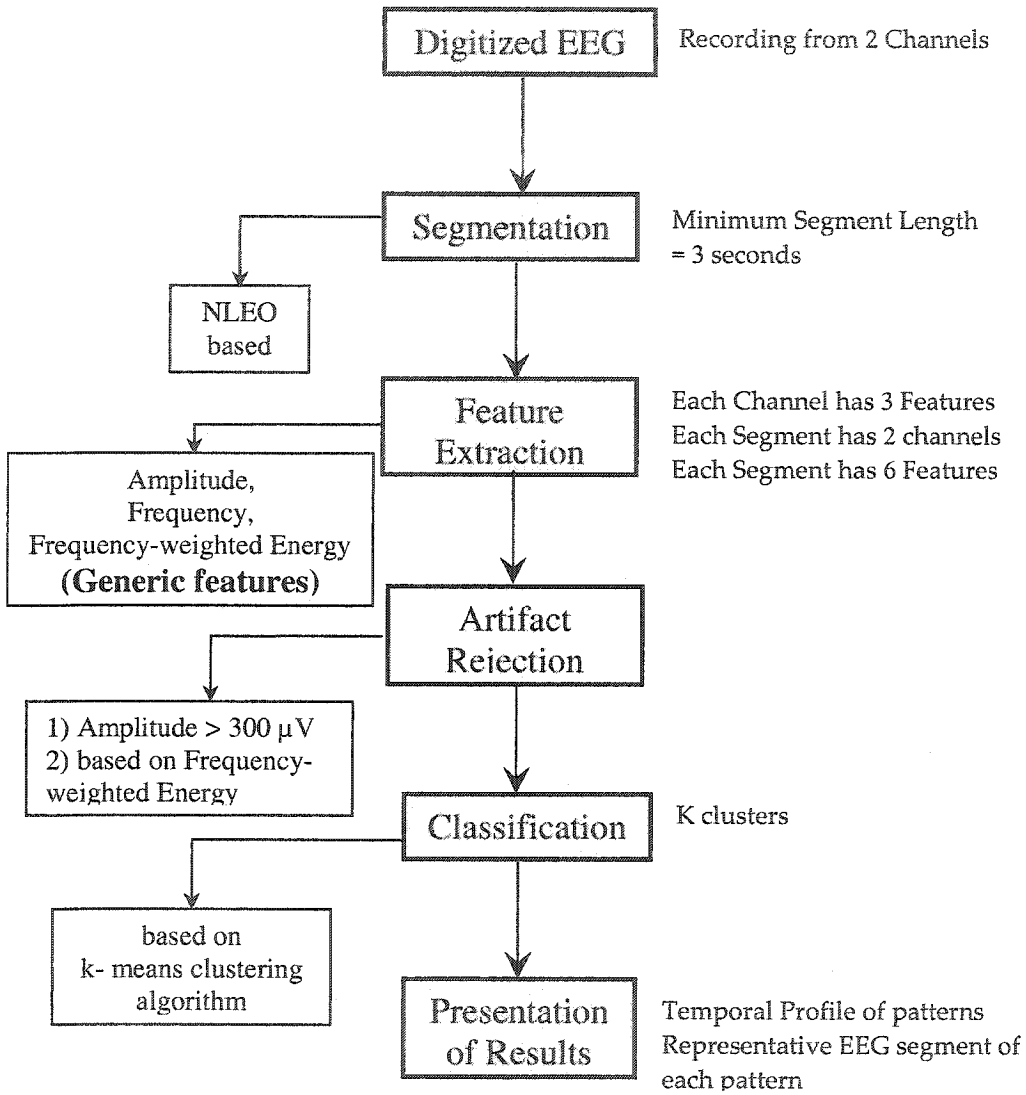


Figure 2.3: Block diagram for the compression of the cEEG as suggested by Agarwal *et al.* [1]

ALGORITHM 2.1: MULTI-CHANNEL SEGMENTATION BASED ON NLEO

STEP I: Consider a channel from the given duration of EEG, $x(n)$, and calculate the FWE defined as

$$FWE = \Psi[x(n)] = x(n-1)x(n-2) - x(n)x(n-3)$$

STEP II: The segment boundaries are detected by sliding a temporal window over $\Psi[x(n)]$. At any time instant n, the window has 2N samples, N samples to the left and N samples to the right of instant n. The sum of the FWEs in the left half of the window is subtracted from that in the right half of the window to generate the segmentation criterion, $G_{NLEO}(n)$:

$$G_{NLEO}(n) = \left| \sum_{m=n-N+1}^{n} \Psi(m) - \sum_{m=n+1}^{n+N} \Psi(m) \right|$$

STEP III: Repeat Steps I and II, for all the P channels under consideration.

STEP IV: Add the G_{NLEO} values of all the P channels.

$$G_{NLEO}^{T} = G_{NLEO}^{1} + ...G_{NLEO}^{P}$$

STEP V: To remove the spurious peaks in the segmentation criterion, a threshold based on window length L is applied.

$$T(n) = max(G_{NLEO}^{T}(n - \tfrac{L}{2} : n + \tfrac{L}{2}) \qquad n = \tfrac{L}{2}, (\tfrac{L}{2} + 1), ...$$

STEP VI: The time instant of the local maxima of $G(n)$ is used to find the segment boundary, where

$$G(n) = \left\{ \begin{array}{cc} G_{NLEO}(n) & if\ G_{NLEO}^{T}(n) \geq T(n) \\ 0 & if\ G_{NLEO}^{T}(n) < T(n) \end{array} \right\}$$

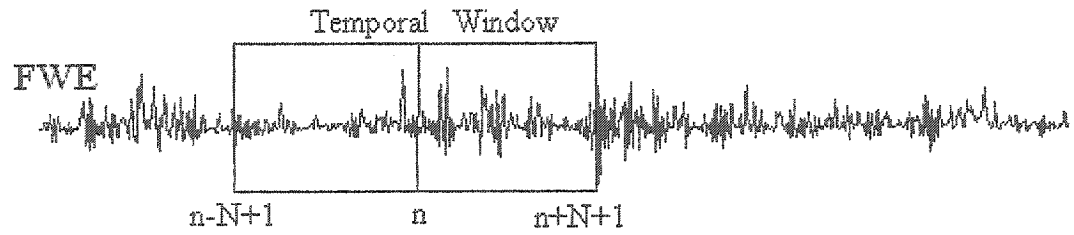


Figure 2.4: Placement of temporal window for the generation of the segmentation criterion for segmentation based on the NLEO. At any instant n, there are N samples on the either side of the instant n.

Figure 2.5 shows the different stages of the method. An example of Channel 1 EEG to be segmented is shown in part (a). The corresponding FWE is shown in part (b). The sum of the FWEs in the left half of the window is subtracted from that in the right half of the window to generate the segmentation criterion, $G^1_{NLEO}(n)$, as shown in part (c).

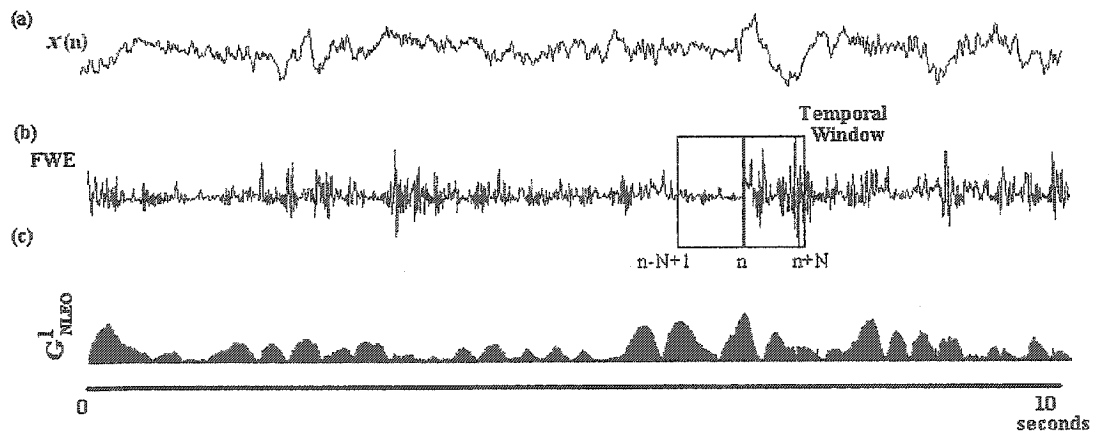


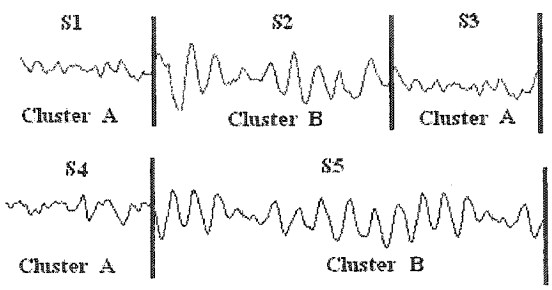
Figure 2.5: Different stages of process for segmentation using the NLEO. (a) Example of Channel 1 EEG to be segmented. (b) Corresponding FWE (c) Segmentation Criterion (G^1_{NLEO}): difference between the FWEs in the right and the left halves of the temporal window.

The performance of the segmentation method is dependent on two main parameters, namely, the temporal window length (2N samples) and the window length L used to calculate the threshold. The temporal window length is chosen depending on the application of the resulting segments. It must be long enough such that a rational measure of the FWE can be obtained, while being short enough to represent the shortest segment expected. There exists a trade-off between a good measure of energy and the expected minimum segment length. If the window length is chosen too small, then the subtle changes in the EEG generates segment boundaries; on the other hand, if the temporal window length is made to include a large number of samples, then the segmentation becomes coarse. The window length L chosen for the calculation of the threshold T determines the sensitivity of the method. By increasing L, the threshold becomes coarse and the number of segments are reduced, and vice-versa.

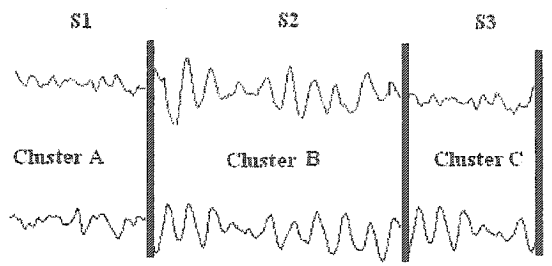
It was argued by Agarwal *et al.* in [20] that the segmentation based on the NLEO is more effective compared to the segmentation based on the parametric models [17, 21] (see Section 2.1 for details) and requires a significantly reduced numerical calculation.

Moreover, the technique in [1] is applicable to multi-channel segmentation. If the EEG recording has more than one channel and each channel is segmented independently using the segmentation criterion from the respective channel, the non-synchronized segment boundaries are created across different channels. This will make it more complex to study the patterns that exist in the different channels. The multi-channel segmentation uses the segmentation criterion from all the channels. It results in synchronous segment boundaries across all channels. Since during the clinical review, all the channels are reviewed simultaneously, multi-channel segmentation may yield groups that are clinically more relevant compared to the groups formed with single-channel segmentation. Figure 2.6(a) shows the results of segmentation when the segmentation criterion from each channel is used independently to create the segment boundaries in the respective channel. The classification based on the characteristic features of the respective segments yields the

clusters labeled above the traces. Segment S1 and S3 of Channel 1 have features similar to those for Segment S4 of Channel 2. Hence, these segments belong to Cluster A. Similarly, Segments S2 and S5 belongs to Cluster B. During multi-channel segmentation, the segmentation criterion from both the channels are used simultaneously. The resulting segment boundaries are shown in Figure 2.6(b). The multi-channel segmentation creates synchronous segment boundaries across both the channels, which allows the features from both the channels of Segment S3 to be considered simultaneously. Although the activity in Channel 1 of S3 is similar to that of activity in S1 and activity in Channel 2 of S3 is similar to that in S2, but when both the channels are considered together, S3 represents a new activity that belongs to a new Cluster C.



(a)



(b)

Figure 2.6: Classification of the segments (a) when the segmentation criterion from each channel is used independently, and (b) when the segmentation criterion from all the channels is used collectively (multi-channel segmentation).

The background activity during the cEEG monitoring is assumed to be stationary for least 3 seconds [20]. Thus, the minimum length of a segment was selected as 3 seconds. The temporal window length of 2.5 seconds (i.e., 1.25 seconds on each side of each time instant) and a length L of 1.5 seconds have been used in [1]. To increase the speed of segmentation procedure, the sliding temporal window is moved in steps of 5 samples along the signal.

2.5.2 ARTIFACT REMOVAL

The strategies used in artifact removal are multi-staged and implemented at various points in the complete compression method.

Since in general signals with amplitude greater than $300\mu V$ are not considered to be of cerebral origin [1], any segment with a maximum absolute amplitude greater than $300\mu V$ is considered as artifact and neglected from further analysis.

EEG can sometimes be contaminated by EMG. A segment contaminated with EMG is expected to have a high energy compared to an EMG-free segment. Segments with relative high energy can be considered to be artifact contaminated. To find these segments, an adaptive artifact rejection method based on the output of the NLEO was suggested by Agarwal *et al.* [1]. For different segments in each channel, the histogram of the FWE, feature is constructed. It is argued that most of the segments will not be contaminated with EMG and therefore, will represent the dominant mode in the histogram. However, due to the relatively large energy of the EMG compared to that of the EEG, the segments contaminated with EMG will lie at the high end of the histogram. Removal of the segments corresponding to high energy can yield an effective artifact removal strategy. The procedure is defined in Algorithm 2.2.

ALGORITHM 2.2: ARTIFACT REJECTION IN EACH CHANNEL

STEP I: Determine the histogram for the FWEs of all the segments using 100 equally spaced bins.

STEP II: Set i =1 (i= 1 to 10)

STEP II*a*:

Set *range* =1

Find the number of segments (M) with FWE in the bins - (100-*range**5 : 100).

If $M < N(i)$, *range* = *range* + 1

Goto STEP II*a*. (for *range* = 1 to 20)

If $M \geq N(i)$, *range* = *range* - 1

The segments in bins (100-*range**5 : 100) can be neglected as artifacts.

STEP II*b*:

Goto STEP II*a*, $i = i+1$

The threshold for the number of segments to be rejected is adaptive and depends on the data set. For each channel, it varies with iteration i . The threshold is calculated as:

$$N(i) = \{0.005 * (1 - (i-1) * 0.1) * (number\ of\ segments) + 0.5\}$$

Figure 2.7 shows the histogram of the FWE of a single channel for all the segments in a data set. The density of the values in the left side of the histogram corresponds to the FWE of the EMG-free segments, whereas the points towards the right side marked 'outliers' depicts the high FWE of the likely EMG-contaminated segments and therefore are removed.

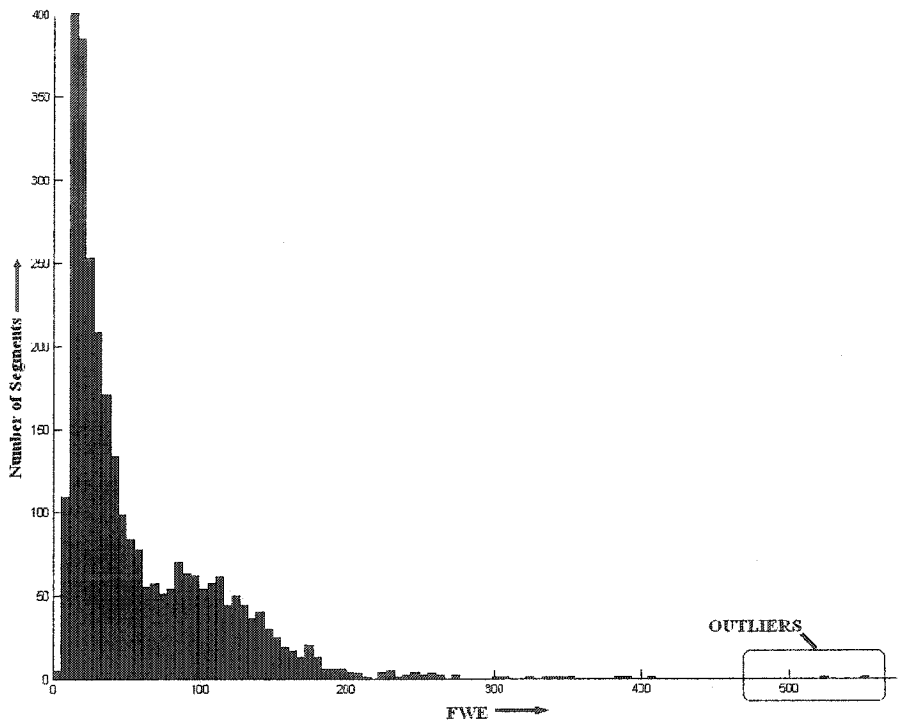


Figure 2.7: An example showing the distribution of the FWE of all the segments in Channel F3, subject A. The FWE values away from the majority (towards the right of the distribution and marked 'outliers') represents the high FWE of the likely EMG-contaminated segments that are removed.

2.5.3 Features

Generic Features

Amplitude and frequency are inherently used during visual examination of the EEG. Hence, the *generic* features, namely, measure of the amplitude, measure of the dominant rhythm, and measure of the energy have been used in [1] to parameterize each segment. The average

of the absolute amplitude has been used as a measure of the amplitude of the segment. Based on a second order autoregressive model, a measure to estimate the dominant rhythm of each segment has been used. The pole frequency of the second order AR model that best models the segment was used as an estimate of the dominant rhythm. In the cases where more than one rhythm may be present, the second order AR model represents a compromise of the two rhythms. Energy, the third feature, was calculated from the output of the NLEO [38]. Since the output of the NLEO, termed as *FWE*, varies with the change in the frequency or amplitude of the signal, it was reasoned that the FWE can be considered to provide a combined measure for the frequency and amplitude of the EEG (refer to Appendix A for details). The mean of the FWE of each segment was used as a measure of the energy.

2.5.4 CLASSIFICATION

The classification technique as suggested in [1] is a three stage procedure, which revolves around iterative clustering. Figure 2.8 shows the three stages of the complete classification technique. In the first stage, the features of each segment are scaled such that all features span the same range of feature space. The scaled features are used to define vectors, termed *feature vector*s, that parameterize each segment. The feature vectors are used to classify the segments using the *k-means* clustering algorithm. The *k-means* clustering requires an initial selection of a set of points to be used as the centroids of the clusters around which the clustering is performed. The points are called as the *initial seeds* and are determined in the second stage. Initially a set of K_i feature vectors greater than the required K_f initial seeds are chosen. With these K_i feature vectors as the initial seeds, the *k-means* clustering is performed. The resulting clusters are merged until K_f, clusters are left. Subsequently, the centroids of the clusters formed in the previous step are used as the K_f initial seeds for final *k-means* clustering in the third stage.

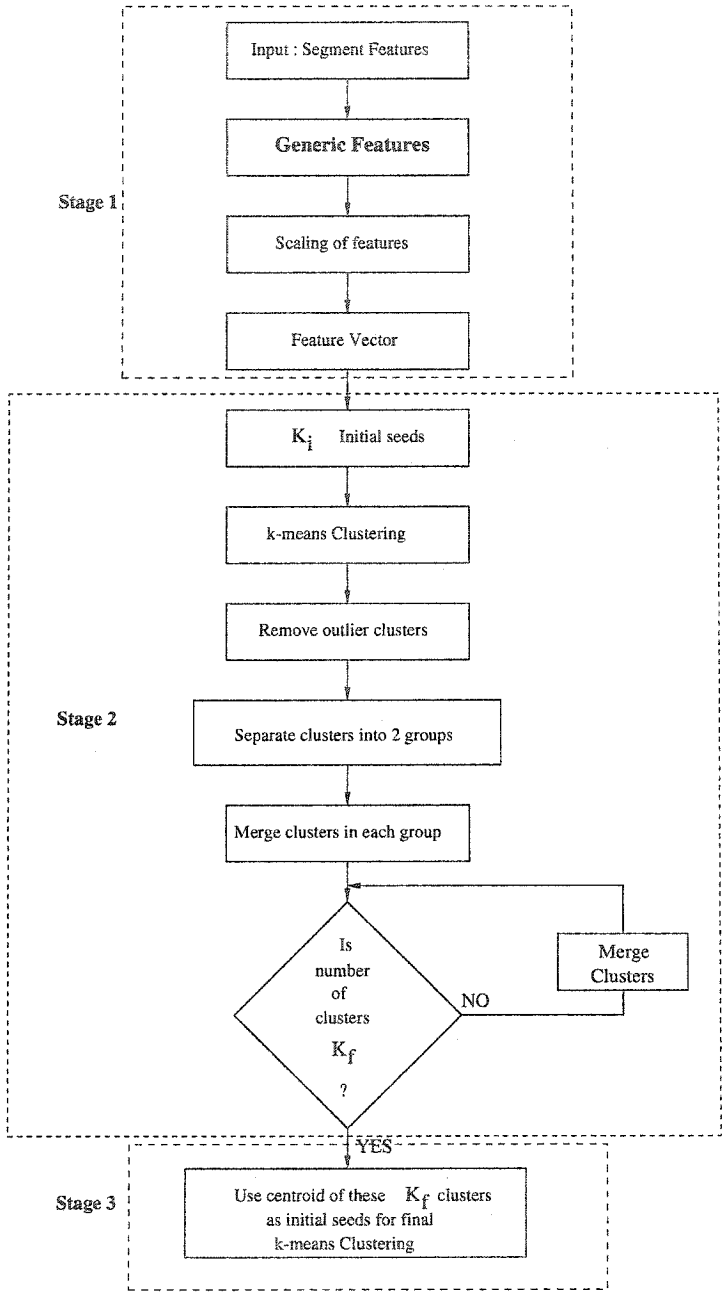


Figure 2.8: The figure shows the classification procedure. It consists of three stages - In first stage, the feature vector of each segment are conditioned to be used as data points with the *k-means* clustering. In second stage, the K_f initial seeds are determined using the set of K_i seeds points. Finally in third stage, using the K_f initial seeds, the final *k-means* clustering is performed.

FEATURE VECTOR

Each channel in a segment is parameterized by the *generic* features (set of 3 features) and each segment is defined by a $1 \times 3P$ feature vector, where P is the number of channels in the segment.

Let Segment S consists of two channels, the first channel defined by features $\{A_s^1, f_s^1, E_s^1\}$ and the second by $\{A_s^2, f_s^2, E_s^2\}$, where A, f, and E are the average absolute amplitude, dominant rhythm, and FWE, respectively. Then, S is parameterized by the feature vector, $FV_s = \{A_s^1, f_s^1, E_s^1, \ A_s^2, f_s^2, E_s^2\}$ such that s represents Segment S and the superscripts 1 and 2 represents the channel numbers of Segment S.

SCALING

The *generic* features consist of a set of features that represent amplitude, frequency and energy of the EEG signal. These features span different ranges of the feature space. For example, amplitude can be in the range $0 - 300\,\mu V$ and frequency in the range $0 - 30\,Hz$. The *k-means* clustering algorithm assigns each feature vector (or data point) to the different clusters depending on the euclidean distance between the feature vector and the centroids of the clusters around which clustering is performed. The euclidean distance weighs each feature equally. If the absolute values of the features in a feature vector are not in the same range, the resulting euclidean distance will be dominated by the feature(s) with the higher range of values. In these cases, the clustering would be based mostly on the information from the feature(s) with the higher values and the feature(s) with lower range of values become insignificant. This can degrade the performance of the classification technique. Hence, it is required to have a scaling method to bring all the features in to the same range. It was proposed in [1] to scale the individual features as explained in Algorithm 2.3. The feature vectors with the scaled features are used as the data points during classification.

ALGORITHM 2.3:SCALING OF GENERIC FEATURES

STEP I:	Consider a feature F_i, and find its maximum in the complete data set, Max_i. i = 1, 2,3. $Max_i = maximum\,(F_{ij})$, j = 1 ... number of segments.
STEP II:	Calculate $MaxAll = maximum(Max_i)$
STEP III:	Scaled feature, $F'_{ij} = (MaxAll/Max_i) \times F_{ij}$

INITIAL SEEDS

To determine the initial seeds, a methodology, henceforth referred to as the *temporal* technique was used in [1]. In this technique, first a large number of feature vectors K_t ($K_t \gg K_i$) are selected from all the K_t feature vectors at equally spaced time intervals in the cEEG recording. It is argued in [1] that for the cEEG recording with the repeating patterns, the feature vectors spaced in the time can provide a good sampling of the various EEG types present in the data set. Next, the K_t feature vectors are iteratively merged until the K_i feature vectors are left. A description of the merging process is explained later in this section. With the K_i feature vectors as the initial seeds, the *k-means* clustering is performed. Since for the background cEEG monitoring the short duration patterns are not of significant interest, any cluster with members fewer than the prespecified number are considered to represent the short duration patterns in the EEG and therefore rejected from further analysis. The remaining clusters are divided into two groups depending on their average *inter-cluster distance* (ICD) (see Figure 2.9), where ICD is defined as the euclidean distance between the centroids of the two clusters. This is done to isolate the clusters that are far away from the majority of the clusters and to reduce the effect of any outlying cluster in the cluster merging process. The clusters are merged iteratively until the

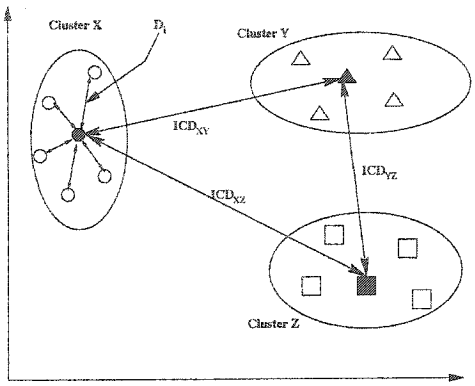


Figure 2.9: A set of three clusters - X, Y and Z is shown. The **bold** dot in each cluster represents the centroid of the respective cluster. ICD_{XY} represents the distance between the centroids of cluster X and cluster Y and D_i represents the distance between the i^{th} segment and the centroid of the cluster to which it belongs.

required number of K_f ($K_f < K_i$) clusters remain. With the centroids of these K_f clusters as the initial seeds, the final *k-means* clustering is performed. The complete procedure for the classification is described in Algorithm 2.4.

CLUSTER MERGING

To explain the technique used in [1] to merge two clusters, we consider two clusters, viz, Cluster X and Cluster Y. Let the centroid of Cluster X have a feature vector $FV_X = \{A_X^1, f_X^1, E_X^1, A_X^2, f_X^2, E_X^2\}$ and that of Cluster Y be the feature vector $FV_Y = \{A_Y^1, f_Y^1, E_Y^1, A_Y^2, f_Y^2, E_Y^2\}$. Let ICD_{XY} be the euclidean distance between the centroids of clusters X and Y, and $\overline{ICD_g}$ be the average of the inter-cluster distances between all unique pair of centroids,

$$\overline{ICD_g} = average\,\{ICD_{12} + ICD_{13} + ... + ICD_{XY}\} \qquad X, Y = 1\,to\,N,\ X \neq Y$$

where N is the number of clusters and ICD_{XY} is the euclidean distance between the centroids of the two clusters.

ALGORITHM 2.4: CLASSIFICATION BASED ON ITERATIVE K-MEANS CLUSTERING ALGORITHM

STEP I: Calculate K_i initial seeds for clustering.

STEP II: Cluster using *k-means* algorithm.

STEP III: Clusters with member elements less than 0.5% of the total number of segments in the data set are marked as artifacts and are not considered in further analysis

STEP IV: For each cluster, say X, calculate the average of the inter-cluster distances ICD_X:

$ICD_X = \frac{ICD_{X1}+ICD_{X2}+....+ICD_{XY}}{K_i-1}$, X, Y = 1 to K_i, X $\neq$ Y

ICD_{XY}= euclidean distance between the centroids of Cluster X and Cluster Y.

STEP V: Divide the clusters into two groups

Group 1: Clusters with $ICD_X < \overline{ICD} + 2\,\sigma_{ICD}$

Group 2: Clusters with $ICD_X > \overline{ICD} + 2\,\sigma_{ICD}$

where $\overline{ICD} = average\,\{ICD_1 + ... + ICD_2 + ... + ICD_X\}$

$\sigma_{ICD} = standard\,deviation\,\{ICD_1 + ... + ICD_X\}$

X = 1 to K_i

STEP VI: In each of the two groups formed, merge the clusters.

STEP VII: If the number of clusters in both the groups combined is greater than the required K_f clusters, the clusters are iteratively merged until the required K_f clusters are left.

STEP VIII: Use the centroids of these new clusters as the initial seeds to perform the final *k-means* clustering.

If the distance $ICD_{XY} < T_{merge}\overline{ICD_g}$, then the clusters X and Y are merged and the resulting Cluster Z has the centroid with the feature vector given as

$$\left\{\frac{A_X^1 + A_Y^1}{2}, \frac{f_X^1 + f_Y^1}{2}, \ldots, \frac{E_X^2 + E_Y^2}{2}\right\}$$

where T_{merge} is a constant used to define the percentage of the average distance $\overline{ICD_g}$ to be used as the threshold to decide the degree of similarity between clusters. T_{merge}= 0.4 was experimentally determined to be adequate in [1].

2.5.5 DISPLAY

An EEG analysis method is effective only if it can present the information to the clinicians in a clinically relevant manner. In [1], a temporal profile of the different clusters in a compressed format is provided to the reviewer to assist him during the EEG analysis. The different clusters are color coded to represent the various pattern types. By examining the temporal evolution of the different patterns types, the neurologist can get a bird's eye view of the evolution of the various patterns for a full-night recording. For example, in sleep analysis the temporal profile of the different colors can provide information about the transition of the brain through the different states of sleep and their duration of occurrence in the night. Any abnormality will result in a distribution of colors different from the expected ones and can be easily identified by the reviewer. Figure 2.10 shows a compressed temporal profile for a 60-minute EEG block. Each color represents a different type of activity and white represents the occurrence of artifacts.

CLUSTER REPRESENTATION

The key advantage of the method in [1] is the ability of the reviewer to understand the results with no specialized training. This is due to the fact that along with the temporal profile of the patterns in the cEEG, a representative segment of the actual-EEG recording

of each cluster is also provided to the reviewer. These representative segments provide an indication of the members in the respective cluster and can be considered as a legend for reading the different patterns in the temporal profile.

In a cluster, the centroid is minimum euclidean distance apart from all the members and can provide the best example of the activity in its members. Since the method for classification described in Algorithm 2.4 merges the clusters or segments at different stages, it is possible that the centroid of a cluster will not represent feature vector of any specific segment. To overcome this limitation, the segment with its feature vector nearest to the centroid and with a predefined minimum length is selected as the representative segment. The steps followed are shown in Algorithm 2.5. The minimum length of the representative segment should be significant for later visual analysis by the reviewer. For example, in sleep analysis the representative segment should be 20 seconds long, so that during the analysis of the compressed cEEG by the reviewer, the representative segment of the different clusters could be associated with the sleep stages (as most sleep laboratories use 20 second epochs to mark sleep stages). For background cEEG monitoring in the NICU, any epoch of duration of less than three seconds may not be clinically relevant [1]. Thus, the minimum length of the representative segment can be chosen to be three seconds as done in [1]. Figure 2.10 shows three different representative segments.

2.6 SUMMARY

The method for the compression of the cEEG has four major blocks, namely, segmentation, artifact rejection, feature extraction, and classification. In first part of this chapter, we provided an overview of the different techniques in the literature for these different blocks. In second part of this chapter, we presented the method given in [1] for the compression of the cEEG recording. The techniques used in [1] for the multi-channel segmentation, artifact rejection, and the classification of the EEG segments parameterized with the *generic*

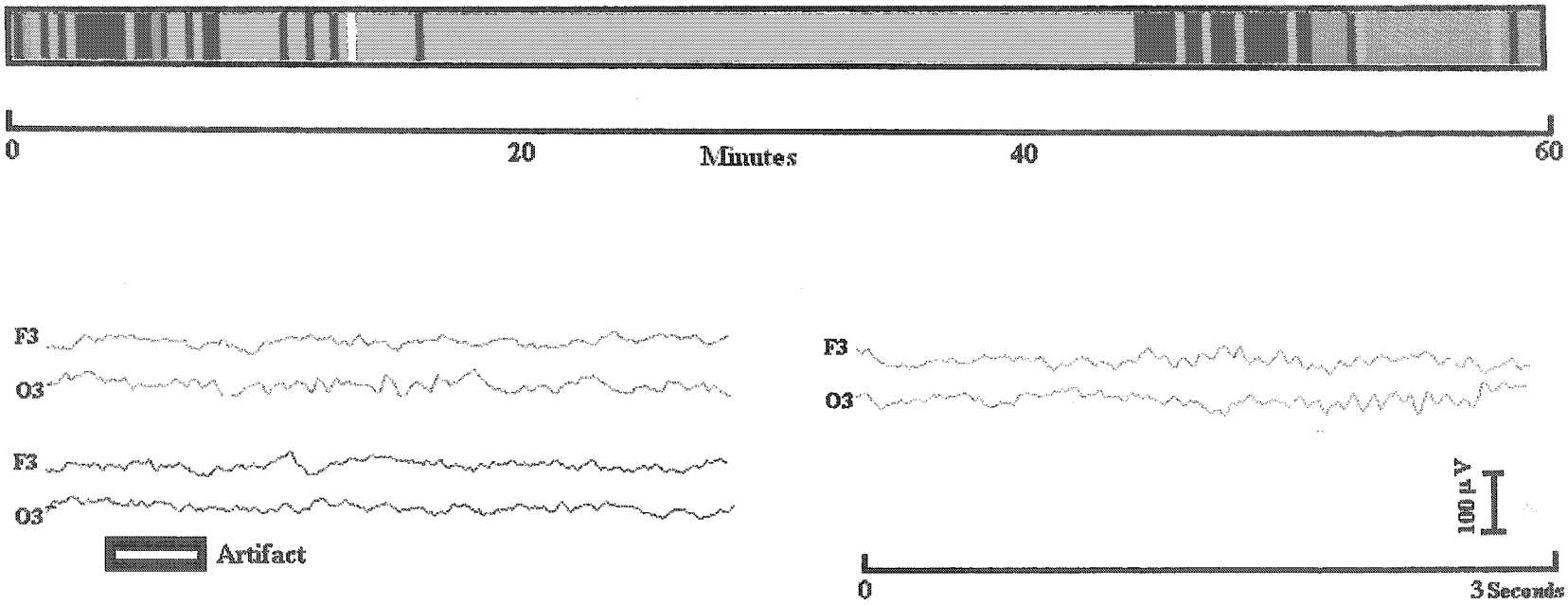


Figure 2.10: Compressed results for a 60-minute cEEG block. Each color shows a type of activity. Temporal profile of different colors indicates the onset and offset of the respective activity. The representative EEG segments for each cluster are also shown.

ALGORITHM 2.5: TO FIND THE REPRESENTATIVE SEGMENT FOR EACH CLUSTER

STEP I:	Calculate the intra-cluster distance D_i, between all the members and the centroid of the respective cluster. i = 1 to n, where n is the number of segments in the respective cluster.
STEP II:	Calculate the mean of D_i $(\overline{D})$ and the standard deviation of D_i (σ_D)
STEP III:	Find the segment having the minimum euclidean distance d between its feature vector and the centroid. The segment should have a length greater than the predefined minimum length. $\{\overline{D} - \sigma_D \leqslant d \leqslant \overline{D} + \sigma_D\}$(refer Figure 2.11).
STEP IV:	If no segment with the minimum predefined length is found, than the segment nearest to the centroid is selected.

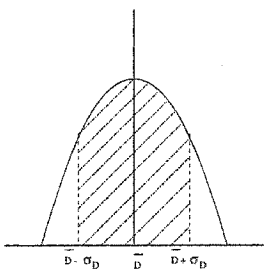


Figure 2.11: The distribution of the intra-cluster distance, D, for the respective cluster. $\overline{D}$ and σ_D represents the mean and the standard deviation of the D .

features were explained. Also, an example of the compressed results for a 60 minutes cEEG recording, using the method given in [1], was provided.

Chapter 3

PROPOSED METHOD

In Chapter 2, we described the computer-based method of Agarwal *et al.* [1] for the compression of the background cEEG. We observed that the *generic* features provide a limited information about the EEG. Hence, if we can replace the *generic* features with features that provide a more detailed information about the EEG, then we may be able to achieve a better classification of the EEG segments resulting in improved compression.

In this chapter, we present a method for the compression of the cEEG. Figure 3.1 shows the block diagram of the proposed method for the compression of the cEEG. The basic blocks of the method are similar to those used in the compression method of [1]. We replace the *generic* features with a set of new features, referred to as the *spectral* features. As the *spectral* features differ from the *generic* features, it is necessary to modify the classification technique given in [1]. Different classification methods are proposed to classify the segments parameterized with the *spectral* features. We compare the proposed compression methods against the compression method given in [1, 6] using the background cEEG recording for sleep application. For this purpose, two matrices, namely, the *epoch cluster-sleep stage* matrix and the *agreement* matrix are used.

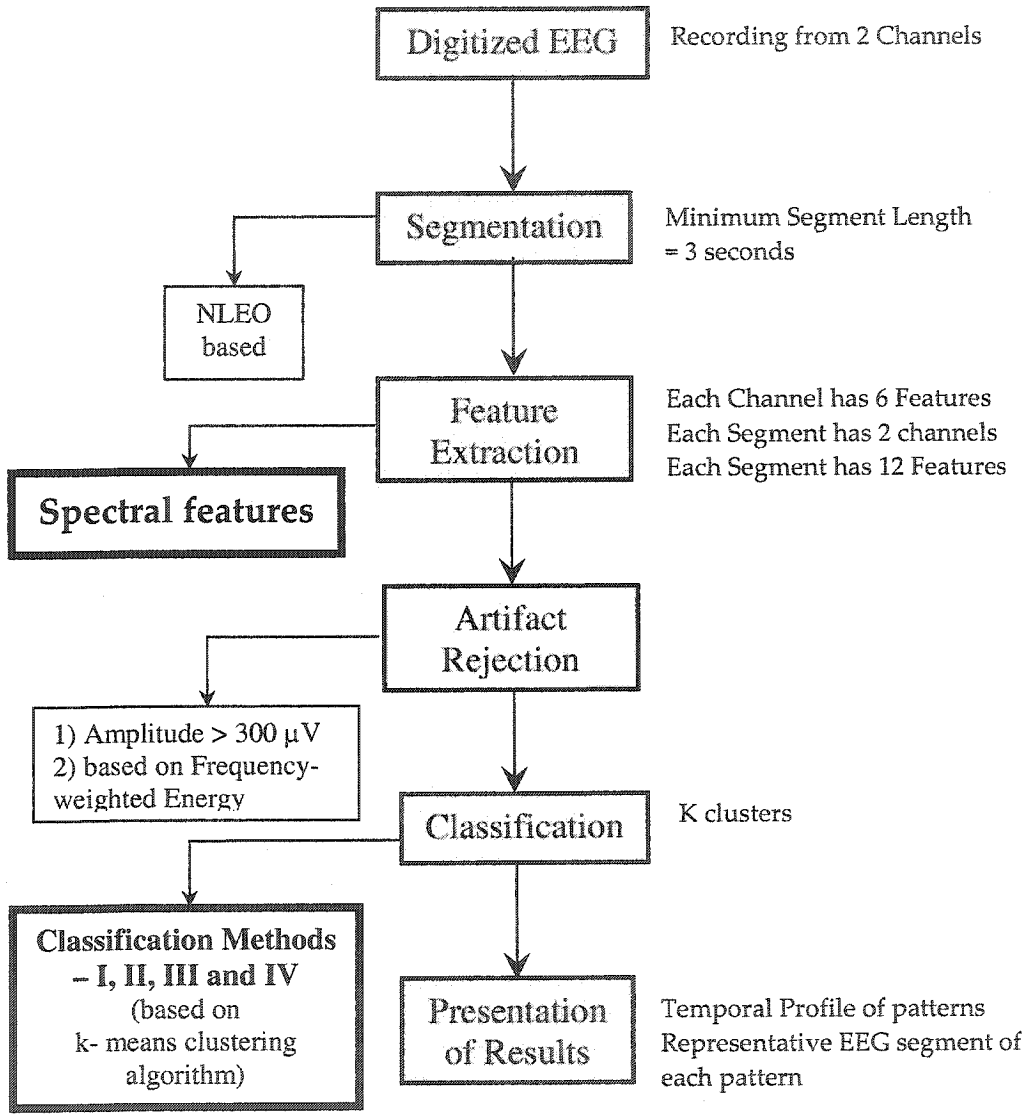


Figure 3.1: Block diagram of the proposed method for compression of the cEEG.

3.1 FEATURES

The measures used to calculate the *generic* features in [1] provide limited information about the signal characteristics. In day-to-day practice, the rules used by the reviewer to classify the different types of the EEG patterns are based on the information about the frequency and amplitude variations of the EEG segment. For most applications, the EEG is analyzed based on its spectral information across various frequency bands. In the literature, features based on spectral composition have been extensively used as descriptors of the EEG for many applications [40, 41, 42].

During sleep, the brain cycles through several repetitive states that can be readily mapped to different patterns in the cEEG. Hence, the features used to differentiate the EEG patterns during sleep may be used to parameterize the cEEG segments. The R&K sleep classification rules [9] use information about the power spectral distribution as well as other information to differentiate the different patterns in the sleep EEG. For example, the EEG of an alert person with eyes closed will have high *alpha* activity $(7 - 11\,Hz)$ and *beta* activity $(15\,Hz\,or\,more)$ compared to deep sleep that has dominant *delta* activity $(0.25-3\,Hz)$. The use of spectral analysis for classifying different states of the brain during sleep has been exemplified by various researchers. Johnsen *et al.* [43] have used spectral analysis to characterize the visually selected epochs from different sleep stages. Larsen *et al.* [44] evaluated these features with multiple regression and multiple discriminant analysis and concluded that spectral analysis can be used to classify the sleep EEG. Osvaldo *et al.* [45] used the power in *delta* and *alpha* bands along with the EMG and the EOG for analysis and automatic classification of sleep stages.

We propose to use the features based on the power spectral distribution to parameterize the segments for the compression technique. Since the *spectral* features cover information in a wider frequency range, we expect them to provide a better differentiation among the cEEG segments. Hence, an improvement in the compression results is expected.

CALCULATION OF SPECTRAL FEATURES

To calculate the *spectral* features, the spectral content of the EEG is divided into different frequency bands. Table 3.1 shows the definitions of the different frequency-bands used. We calculate the *spectral* features for each channel of each segment independently using the fast Fourier transform (FFT).

Table 3.1: Frequency bands to calculate the *spectral* features

SPECTRAL BAND	FREQUENCY (HZ)
Delta (δ)	0.25-4
Theta (θ)	4.25-8
Alpha (α)	8.25-12
Sigma (σ)	12.25-15
Beta1 (β_1)	15.25-24
Beta2 (β_2)	24.25-36

The power spectral density, P, is calculated as:

$$P = \frac{1}{N'} X(f) X^*(f)$$

where $X(f)$is the FFT of $x(n)$, a channel of the EEG in a given segment, and $X^*(f)$ represents the complex conjugate of the $X(f)$. The signal $x(n)$ is zero padded to obtain the length N', which is equal or greater than the length of the signal $x(n)$ and is a power of two.

The power in each band is defined as:

$$P_i = P(f_L : f_H)$$

where f_L and f_H define the frequency range of the i^{th} band in Table 3.1, $i = \{\delta, \theta, \alpha, \sigma, \beta_1, \beta_2\}$. Hence, each channel of each segment is defined by a set of six features - $\{P_\delta, P_\theta, P_\alpha, P_\sigma, P_{\beta_1}, P_{\beta_2}\}$

3.2 CLASSIFICATION

FEATURE VECTOR

Each channel in a segment is parameterized by the *spectral* features as defined in the previous section. Each segment is parameterized by a vector, termed *feature vector* (FV), formed by concatenating the features from all the channels in the segment.

Let Segment S consists of two channels 1 and 2 such that Channel 1 is defined by the features $\left\{P_{\delta}^{1}, P_{\theta}^{1}, P_{\alpha}^{1}, P_{\sigma}^{1}, P_{\beta_1}^{1}, P_{\beta_2}^{1}\right\}$ and Channel 2 by $\left\{P_{\delta}^{2}, P_{\theta}^{2}, P_{\alpha}^{2}, P_{\sigma}^{2}, P_{\beta_1}^{2}, P_{\beta_2}^{2}\right\}$. Then, S is parameterized by the feature vector FV_s as

$$FV_s = \left\{P_{\delta}^{1}, P_{\theta}^{1}, P_{\alpha}^{1}, P_{\sigma}^{1}, P_{\beta_1}^{1}, P_{\beta_2}^{1}, P_{\delta}^{2}, P_{\theta}^{2}, P_{\alpha}^{2}, P_{\sigma}^{2}, P_{\beta_1}^{2}, P_{\beta_2}^{2}\right\}$$

The feature vectors that parameterize the different segments are used as the data points in the classification stage.

PROPOSED CLASSIFICATION METHODS

In the following subsections, we present different methods to classify the segments that are parameterized using the *spectral* features.

3.2.1 METHOD I

To evaluate the performance of the *spectral* features against the *generic* features in the method of [1], we implement the classification method given in [1] (see Algorithm 2.4) using the *spectral* features. Based on the *spectral* features, the block diagram of the classification technique given in [1] is shown in Figure 3.2 and henceforth, is referred to as *Method* I. Since the absolute power in each frequency band can span different ranges, we use the scaling method as given in [1] (see Algorithm 2.3) to scale the power in each band across all the segments to a single range.

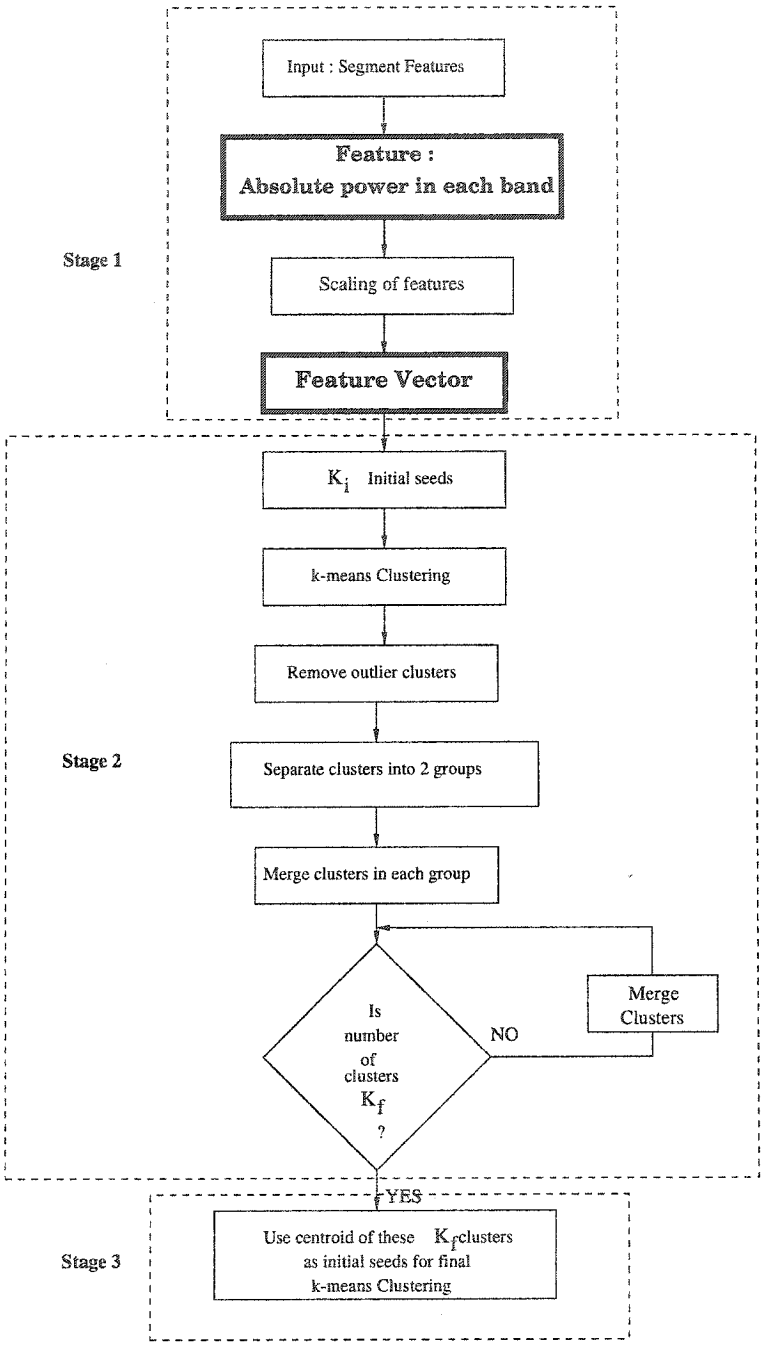


Figure 3.2: Block diagram for *Method* I

3.2.2 METHOD II

We propose a new classification technique, referred to as *Method* II, which is similar to *Method* I except that the scaling of the features is not required [46].

Figure 3.3 shows the block diagram for *Method* II. It is the same as *Method* I except that the feature vector that parameterize each segment is now defined using the relative power in each band. The relative power is defined as the ratio of the absolute power in each band (*delta, theta, alpha, sigma, beta*1 and *beta*2) to the sum of the absolute powers in the six bands of the segment under consideration.

Consider Channel 1 of Segment S with the *spectral* features $\{P_\delta^1, P_\theta^1, P_\alpha^1, P_\sigma^1, P_{\beta_1}^1, P_{\beta_2}^1\}$. Then the features based on the relative power that describe Channel 1 are defined as :

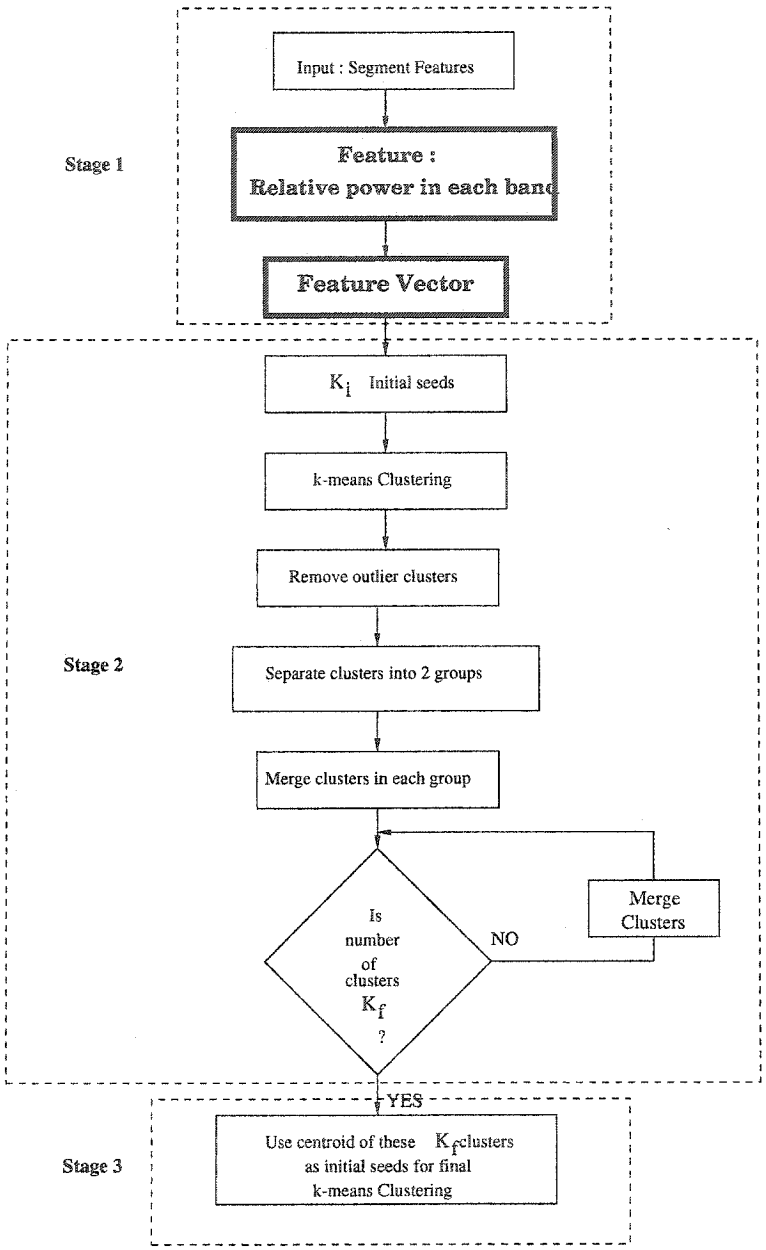
$$P_r^1 = \frac{1}{P_T}\{P_\delta^1, P_\theta^1, P_\alpha^1, P_\sigma^1, P_{\beta_1}^1, P_{\beta_2}^1\}$$

where $P_T = P_\delta^1 + P_\theta^1 + P_\alpha^1 + P_\sigma^1 + P_{\beta_1}^1 + P_{\beta_2}^1$.

3.2.3 METHOD III

An analysis of the temporal profile of the relative powers shows that the relative power in the *delta* band is the highest compared to the other five bands. For example, Figure 3.4 shows the temporal profile of the relative powers in the different frequency bands for a 90-minute sleep EEG. We observe that the relative power in the *delta* band represents around 80-90% of the total power in each segment, whereas the relative powers in other five bands collectively represent the remaining 10-20% of the total power. During the *k-means* clustering, the unequal distribution of the relative powers can lead to biased euclidean distance[1], which can degrade the performance of *Method* II.

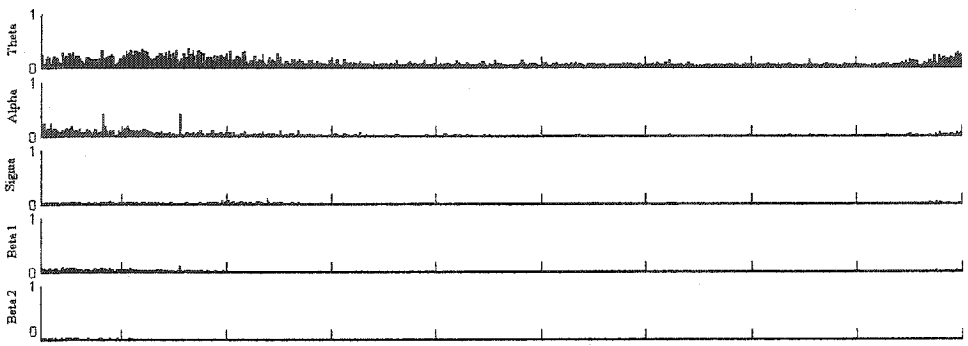
[1]For details on the biased euclidean distance and its effect on classification, refer to Section 2.5.4.



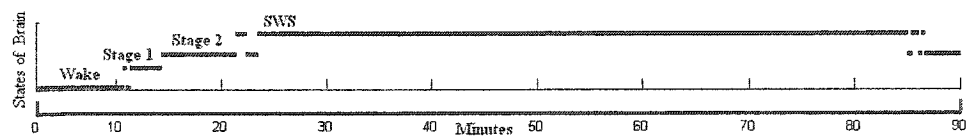
(a)

Figure 3.3: Block diagram for *Method* II.

(a)



(b)



(c)

Figure 3.4: The temporal profile of the relative powers during a 90-minute cEEG recording (a) the relative power in the *delta* band (b) the relative powers in other frequency bands (c) Different states of the brain during sleep.

To overcome this limitation we modify *Method* II and propose a new method, henceforth referred to as *Method* III. Figure 3.5 shows the block diagram of this method. First using only the absolute power in the *delta* band, all the segments are grouped into three clusters. The cluster having the highest power in the *delta* band is separated and the remaining segments are classified using *Method* II.

The cluster with the highest average power in the *delta* band is separated, if and only if, the three clusters satisfy the following conditions:

Condition 1: None of the clusters should have more than 85% of the total number of the segments.

Condition 2: Cluster with the highest average power should have more than 5% of the total number of the segments.

Condition 1 assures that a single cluster does not have a significant number of the segments. Otherwise, it means that only one pattern exists in the data and the classification technique has not been able to separate the different patterns, and hence, the classification has failed. Such a scenario can be possible for a given data set, if there are not sufficient number of segments with absolute power in the *delta* band different from the majority of the segments. Based on the empirical calculations, eighty-five percent is determined as a sufficient number to judge the failure of the classification technique.

Condition 2 checks whether the cluster having the highest average power in the *delta* band has sufficient number of members to represent a different pattern that could be easily recognized in the compressed temporal profile. If the cluster has less than 5% of the total number of segments, then it is possible that the corresponding cluster has segments that may represents a transient activity that may be randomly spread across the complete cEEG recording. Since the transient activities are not considered during the background cEEG monitoring, the cluster having less than 5% of the total number of segments is not considered to have any clinically relevant information.

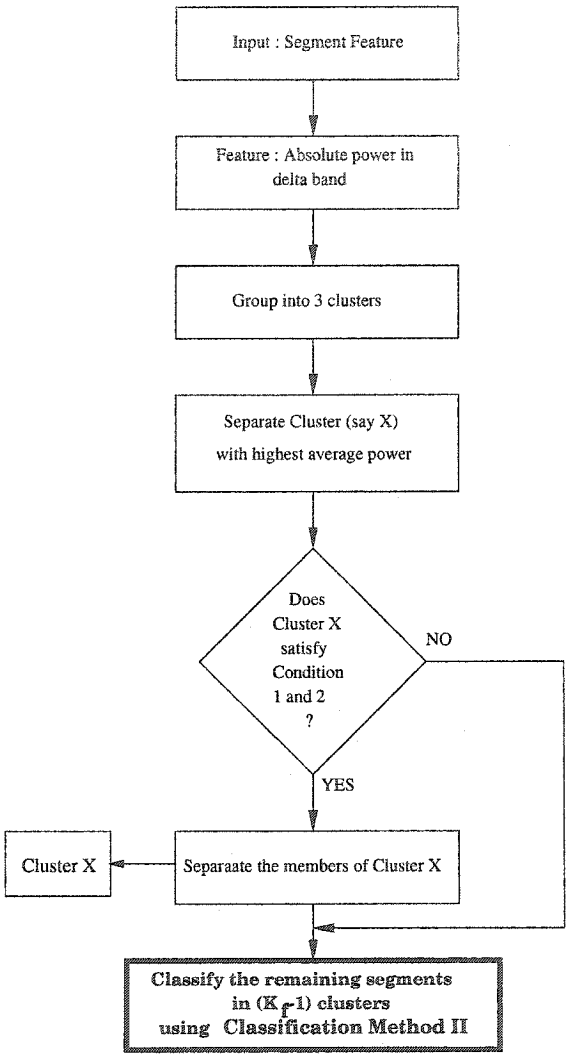


Figure 3.5: Block diagram for *Method* III.

Further, it is exemplified from the fact that a six-hour sleep recording with average segment length of 3 seconds, results in approximately 7200 segments. Five percent of 7200 segments representing 18 minutes or 54 20-second epochs.

For the 90-minute block of the sleep EEG shown in Figure 3.4, the temporal profile of the absolute power in the *delta* band is shown in Figure 3.6. Based on the absolute power in the *delta* band it is expected that if the cluster with the highest power in the *delta* band is removed, then the classification of the remaining segments may improve. For the remaining segments, the temporal profile of the relative powers is shown in Figure 3.7.

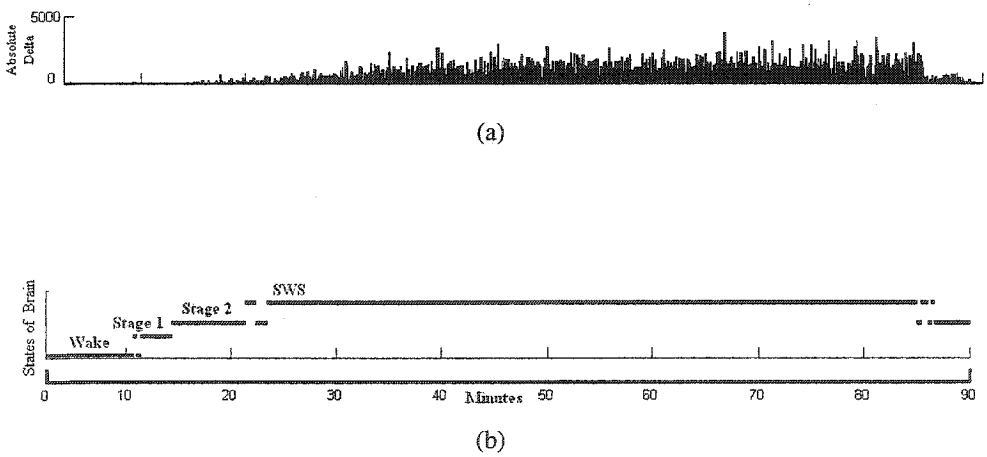
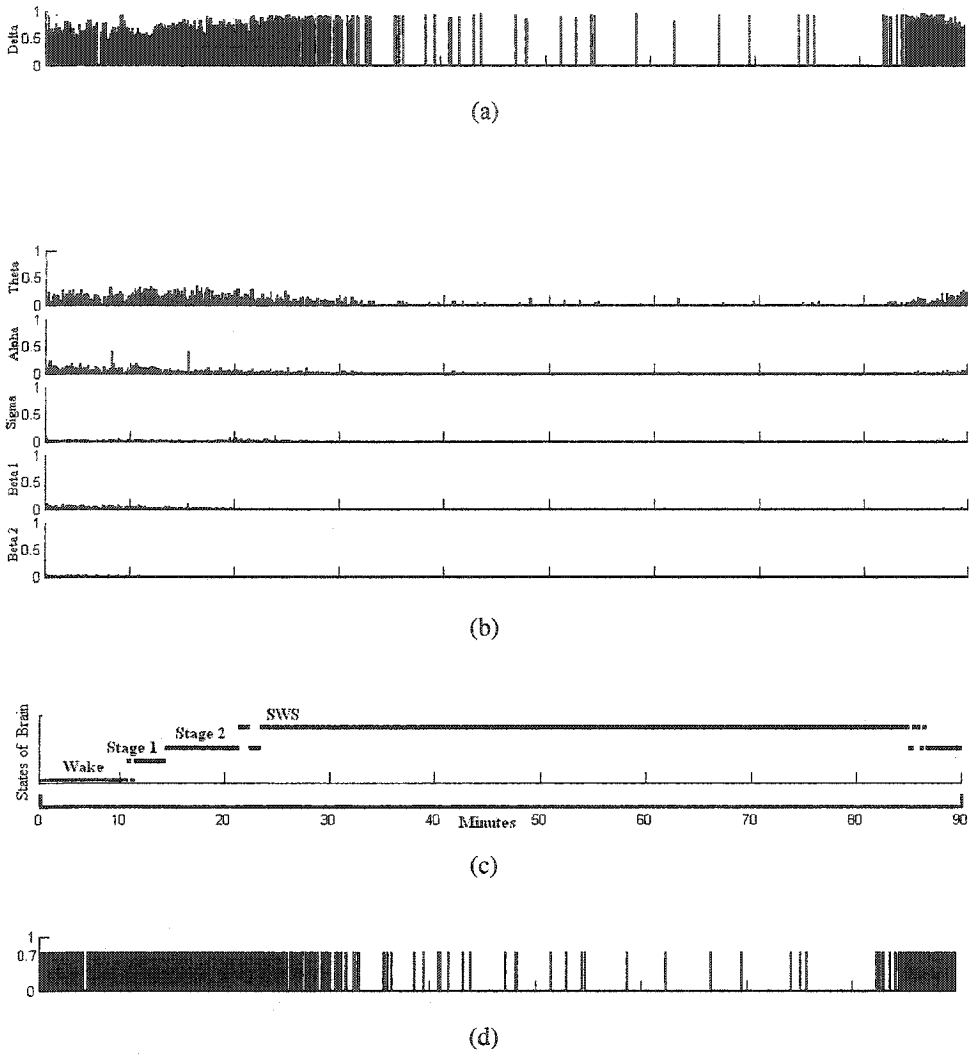


Figure 3.6: (a) Temporal profile of the absolute power in the *delta* band for a 90-minute cEEG. The temporal profile of the relative powers for the same cEEG block was shown in Figure 3.4. (b) Different states of the brain during sleep.



(a)

(b)

(c)

(d)

Figure 3.7: Temporal profile of the relative power for the segments that remain after the cluster of segments with the highest absolute power in the *delta* band has been removed. (a) Temporal profile of the relative power in the *delta* band (b) Temporal profile of the relative powers in other bands. Zero in (a) and (b) indicates that the segments had high power in the *delta* band and have been removed. (c) Different states of the brain during sleep. (d) Zero indicates those segments that had high power in the *delta* band and were removed, whereas 0.7 represents the segments that remain for further classification.

3.2.4 METHOD IV

It can be noted from Figure 3.7 that although the segments with high absolute power in the *delta* band has been initially removed, the remaining segments can still have sufficiently high relative power in the *delta* band (almost 70%-80% of the total power in the segment). This unequal distribution can still yield biased euclidean distance, which may degrade the performance of the classification technique. For the remaining segments, if the absolute power in *delta* band is assumed to be zero, the distribution of powers in the other frequency bands may become more relevant and may lead to better classification of the segments. Hence, we propose a new method, referred to as *Method* IV. A block diagram for *Method* IV is shown in Figure 3.8. First, the segments with high absolute power in the *delta* band are removed as suggested in *Method* III. Next, for the remaining segments the absolute power in the *delta* band is set to zero. Each segment is now parameterized by the relative powers in only five frequency bands - $\{P_\theta, P_\alpha, P_\sigma, P_{\beta_1}, P_{\beta_2}\}$.

Consider a single channel, say 1, of Segment S with the *spectral* features as $\{0, P^1_\theta, P^1_\alpha, P^1_\sigma, P^1_{\beta_1}, P^1_{\beta_2}\}$; then, the features based on the relative powers that describe Channel K_1 are calculated as

$$\frac{1}{P_T}\{0,\ P^1_\theta,\ P^1_\alpha,\ P^1_\sigma,\ P^1_{\beta_1},\ P^1_{\beta_2}\}$$

where P_T, total power of the five bands in the segment = $P^1_\theta + P^1_\alpha + P^1_\sigma + P^1_{\beta_1} + P^1_{\beta_2}$ and 0 represents the absolute power in the *delta* band.

Figure 3.9 shows the temporal profile of the relative powers for the segments that remain after the cluster with the highest average power in the *delta* band has been removed. Figure 3.9(b) shows the temporal profile of the relative powers in bands with the *delta* band excluded from the remaining segments. It can be noted that the distribution of the relative powers in Figure 3.9(b) is more clearly discernible compared to that in Figure 3.7(b).

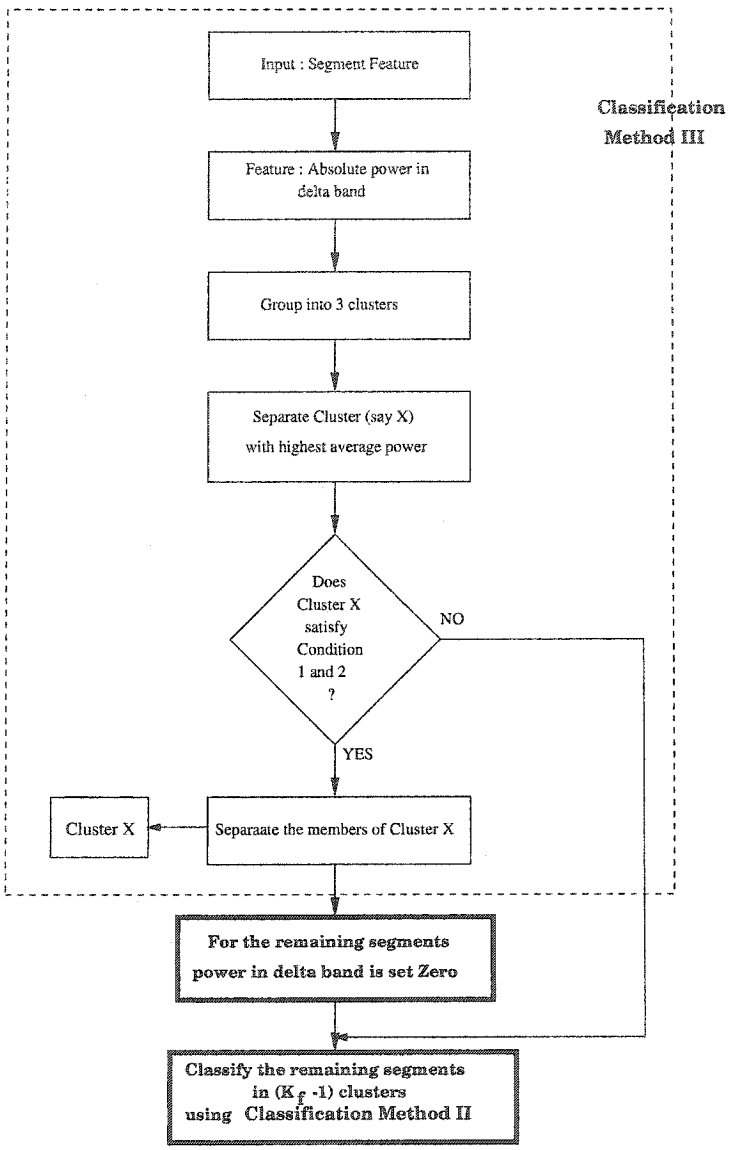


Figure 3.8: Block diagram for *Method* IV.

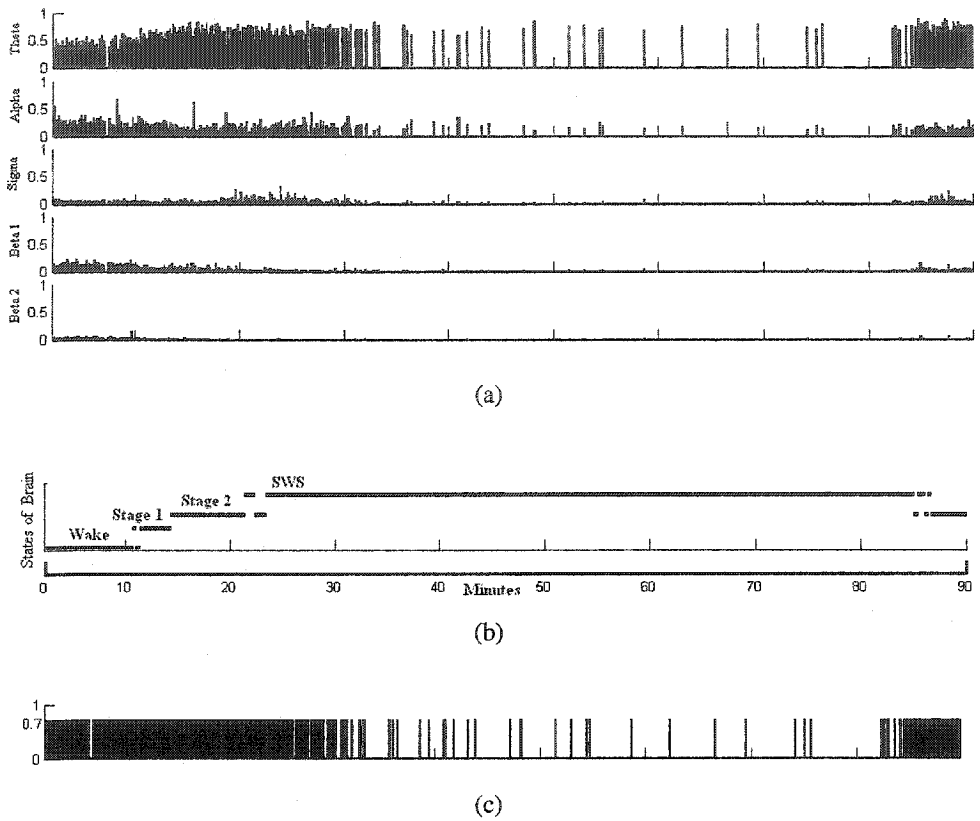


Figure 3.9: Temporal profile of the relative powers across the segments that remain after the segments with the highest absolute power in the *delta* band have been removed. The power in *delta* band is set as zero. (a) The relative powers in other frequency bands (b) Different states of the brain during sleep. (c) Zero indicates that the segment belongs to the cluster, which had highest average power in the *delta* band and was removed, whereas 0.7 represents the segments that remained for further classification.

3.2.5 Initial Seeds using Histogram Technique

A key factor in the success of the *k-means* clustering algorithm is the selection of the seed points for the initial cluster centroids. In the method of Agarwal *et al.* [1], a *temporal* technique to select the initial seeds (see Section 2.5.4 for details) was suggested. It is based on the observation that the different patterns in the background cEEG are repetitive and exist for sustained periods of time. Further, if the feature vectors at equally spaced time intervals are selected, there exists a high probability of achieving a reasonable representation of the various pattern types by the initial seeds. Also, it was suggested that nine initial seeds be used for clustering the complete data set. Since the cEEG recording varies with each patient and their status during the recording, it may not be reasonable to assume the patterns to be repetitive. The nine initial seeds may not be sufficient in number. To overcome this limitation, we propose a new *histogram* technique for the calculation of the initial seeds. It determines the possible variations in the data set using a histogram of the feature vectors. By using a histogram, the data set is classified into several groups such that each group represents a subset of the data and all the groups collectively cover complete data. The centre point or centroid of each group gives an idea about the variations in the data set. Based on the idea of a histogram, we propose to find the groups present in the data set, and the centroids of these groups can be used as the initial seeds. With the proposed method, the number of the initial seeds is adaptive and determined by the data set under consideration. The proposed *histogram* technique is a two-stage procedure as given in Algorithm 3.1. First, all the feature vectors are divided into K groups (K is a number higher than the expected number of groups in the data set). Each group is termed as a *bin*. The presence of transients in the data set may result in *bins* with very few members. Since the centroids of the *bins* are to be used as the initial seeds, *bins* with a fewer members may degrade the classification of the cEEG segments. Hence, *bins* with members less than an adaptive threshold are merged with those having members greater than the median of bin count.

ALGORITHM 3.1 CALCULATION OF THE INITIAL SEEDS USING THE HISTOGRAM TECHNIQUE

STEP I: Choose a feature vector,

$$FV_s = \left\{ P_\delta^1, P_\theta^1, P_\alpha^1, P_\sigma^1, P_{\beta_1}^1, P_{\beta_2}^1, P_\delta^2, P_\theta^2, P_\alpha^2, P_\sigma^2, P_{\beta_1}^2, P_{\beta_2}^2 \right\}$$

STEP II: Find all those segments that have their feature vectors in the range $\left\{ P_\delta^1 \pm 0.1, ..., P_{\beta_2}^2 \pm 0.1 \right\}$.

STEP III: From the remaining segments, repeat Steps I and II, until all the segments are assigned to a *bin* or K *bins* have been created.

If some segments have not been assigned to any of the K *bins*, then these segments are assigned iteratively to the *bin* that has minimum euclidean distance between its centroid and the feature vector representing the segment.

STEP IV: In ascending order of the number of members, consider the *bins* with members that collectively add up to 1% of the total number of the segments in the given data set. These *bins* are considered to represent segments contaminated with artifacts and are not considered in further steps.

STEP V: Let N_i be the number of the segments in the i^{th} *bin*, then $\rho_N = median(N_i)$, $i = 1$ to n, where n is the number of bins.

STEP VI: Any *bin* with members less than ρ_N is merged with the nearest bin having members greater than ρ_N .

STEP VII: For each of the remaining *bins*, calculate the mean of the feature vectors describing its members and consider them as the required initial seeds.

3.3 PERFORMANCE EVALUATION

We evaluate the performance of the proposed classification methods and the method given in [1] for the compression of the cEEG in terms of their ability to form homogeneous clusters, i.e., each cluster should have segments that have similar EEG activity. Since there exists no standards to define the patterns or types of activities present in the cEEG, we use sleep EEG and compare our results against the different states of the brain during sleep. The different states of the brain can be mapped to the repetitive patterns in the cEEG. Each state can be considered to contain segments of the EEG with similar activity. Hence, the clusters formed during compression of the cEEG can be assessed for homogeneity with respect to these states. Moreover, since the states of the brain have been classified manually based on the well accepted R&K sleep classification rules [9], our comparison is against an accepted standard. To explain the methodology followed in evaluating the performance using the sleep EEG, we provide a brief overview about sleep.

FUNDAMENTALS OF SLEEP

Sleep is a non-uniform biological state that can be divided broadly into two types, REM (*rapid eye movement*) and NREM (*non-rapid eye movement*). NREM can be further classified into four stages viz. Stage 1, Stage 2, Stage 3 and Stage 4 (refer to Table 3.2). The classification of these stages is based on the recordings of the EEG, EMG and EOG. Normal healthy sleep is composed of these stages that cycle every 60-90 minutes. Each cycle is characterized by a sequence of sleep stages starting with light sleep, followed by deep sleep, and rapid eye movement. The sleep EEG recording is called as polysomnogram (PSG). A PSG is divided into epochs of 10, 20 or 30 seconds depending on the preference of the sleep laboratory. These epochs are manually scored by the sleep technologist into one of six stages {Stage 1, Stage 2, Stage 3, Stage 4, Stage REM, Stage Wake} according to the R&K [9] sleep classification rules. The resulting time profile of the different stages is termed the hypnogram, and is presented to the clinician for diagnostic purposes.

Table 3.2: Features of different sleep stages

Light sleep ↓ Deep sleep	SLEEP STAGE	FREQUENCY	CHARACTERISTICS
	STAGE 1 (Non REM)	alpha, theta	transition between wake and sleep. composed mostly of high amplitude and low frequency *theta*. burst of *alpha* activity representing drowsiness.
	STAGE 2 (Non REM)	theta, k-complexes, Spindles	Spindles - 12-14 Hz waves lasting 0.5-1.5 sec, amplitude 50μV. k-complexes - frequency less than 0.5 Hz and duration less than 0.5 sec. mostly *theta* activity.
	STAGE 3 (Non REM)	delta, theta	20 - 50% of the epoch consists of *delta* waves.
	STAGE 4 (Non REM)	delta, theta	more than 50% of the epoch consists of *delta* waves.
	REM	beta	high frequency *beta*, similar to Wake. associated with atonia, muscle activity, eye movement.
	WAKE	beta, alpha	muscle activity, eye movement. *beta* activity is associated with eyes open. *alpha* activity is associated with eyes closed.

A single epoch may have patterns that resemble more than one stage or part of the epoch may belong to one stage while another part may belong to another stage. But the R& K sleep classification rules assigns only one stage to each epoch based on the *maximum of epoch* rule, i.e., the stage that occurs for maximum duration in the epoch is assigned to that epoch [47, 48]. Sleep is a continuum and transition from one stage to another cannot be clearly identified. The exact time of change in the sleep stage is highly subjective and gives scope for discrepancy between two different scorers for a single sleep file.

CLASSIFICATION BASED ON EPOCHS

We use the sleep EEG to evaluate the performance of our method. Most sleep laboratories analyze the sleep EEG in 20-second epochs. Hence, we need to translate the classification information based on variable-length segments to conventional fixed-size epochs of 20 seconds. This is done by assigning a cluster number to each 20-second epoch such that the corresponding cluster number has its members occupying a majority of the 20-second epoch. For example, consider two epochs as shown in Figure 3.10. The first epoch has four segments - S_A belongs to cluster $C1$ having length 3 seconds, S_B belongs to cluster $C2$ and 7 seconds long, S_C belongs to cluster $C1$ and length 5 seconds, and S_D belongs to cluster $C1$and length 5 seconds. The first epoch is assigned to cluster $C2$ as the S_B and S_D collectively span majority of the epoch (12 seconds out of 20 seconds). Similarly, the second epoch is assigned to cluster $C1$.

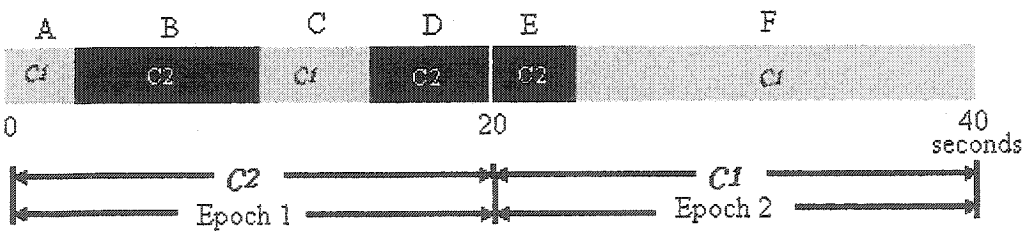


Figure 3.10: Conversion of clustering information based on variable length segments to clustering based on 20-second epochs.

If in an epoch, two or more clusters span equal time duration, then the epoch is assigned to the cluster number that was assigned to the immediate preceding epoch. The resulting clusters of epochs represents the different patterns of activities that exist in the recording.

3.3.1 Qualitative Analysis

To have a qualitative assessment of our results, we compare the temporal profile of patterns obtained using computer-based compression method over the manually-scored hypnogram. We compare the onset and offset of the clusters in the compressed results with the onset and offset of the sleep stages as marked by the reviewer. A cluster is considered as homogeneous, if the occurrence of the respective cluster mostly correlates with the occurrence of a single sleep stage.

We use the classification information based on 20-second epochs as discussed in the previous section. The data set is clustered into eight clusters. Six clusters account for the six sleep stages as defined by the R&K sleep classification rules. Since during the course of the night certain epochs can have varying spectral content within the same stage or can be contaminated, we consider two additional clusters to account for these epochs [39]. For example, Figure 3.11 shows the temporal profile of the cluster of the epochs representing different EEG patterns on an hour-by-hour basis as determined using the computer-based method. These are labeled 'C' on the left of the horizontal bar. Each color represents a cluster of the segments with similar EEG activity. As a reference, the manually scored hypnogram is also provided. It is labeled as 'M' on the left of the horizontal bar. Here, each color represents a sleep stage. The comparison of temporal profile and hypnogram suggests a high degree of correlation between the onset and offset of the different activities found by the computer-assisted method and the manual staging as marked by the reviewer. The clusters created appear to be homogeneous as each cluster matches a single sleep stage. For example, the segments represented by the green color map mostly to Stage 1, whereas the segments represented by red map mostly to Stage Wake.

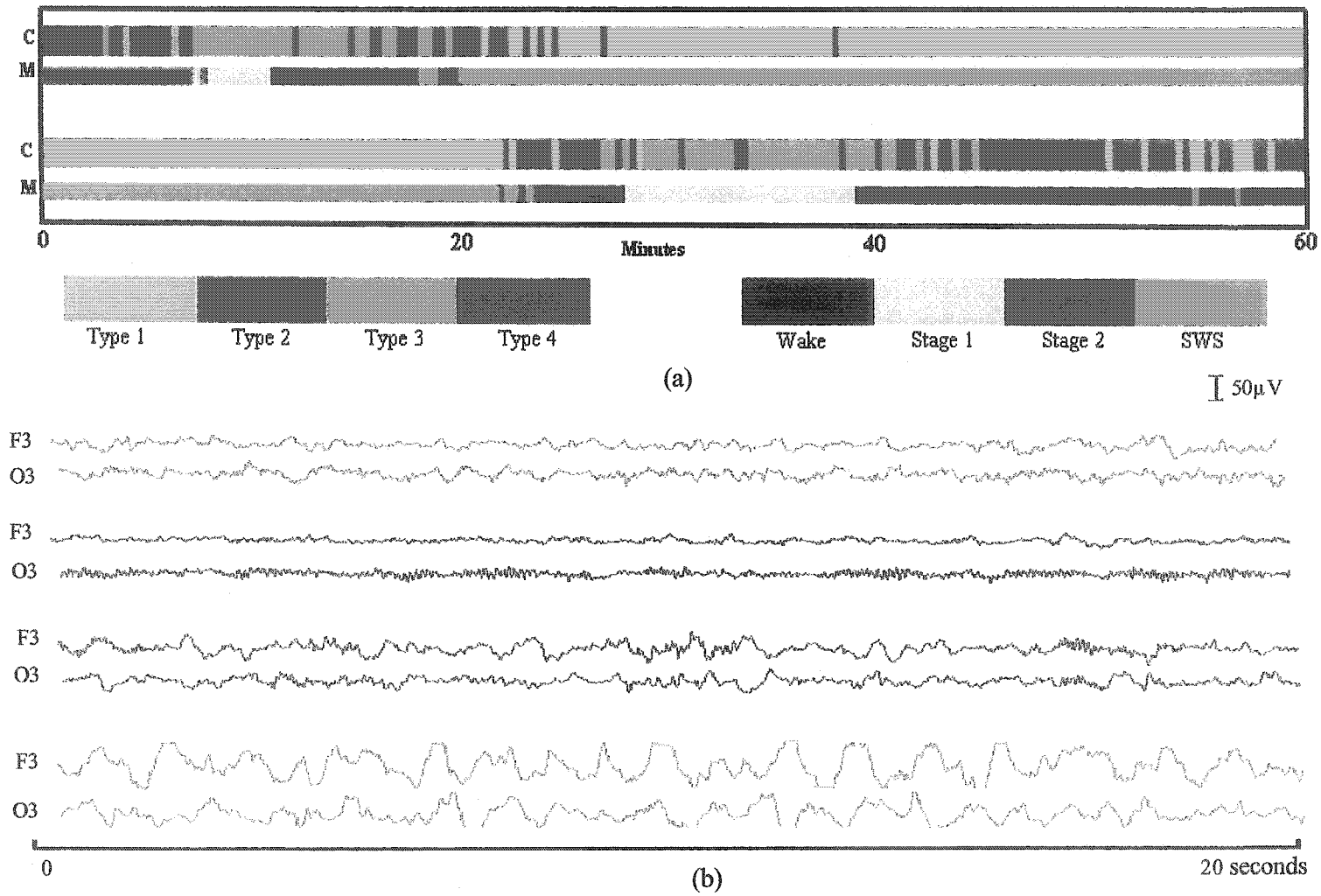


Figure 3.11: Qualitative assessment of the compressed results. (a) Figure shows temporal profile of the patterns obtained with computer-based classification labeled 'C'. As a reference, the manual staging as marked by reviewer is also provided. This is labeled 'M'. Each horizontal bar represent one hour of recording. The different colors in horizontal bars labeled 'C' represents different patterns, whereas the different colors in horizontal bars labeled 'M' represents the different sleep stages. (b) It shows the representative epochs for each cluster.

CLUSTER REPRESENTATION

The method in [1] provides the reviewer the representative segments of the actual-EEG for each pattern type along with the temporal profile of the different patterns. Since the sleep EEG is classified manually using 20-second epochs, the representative segment should be of 20-second duration. The algorithm used in [1] finds the representative segments based on the variable length segments (see Algorithm 2.5). We modify Algorithm 2.5 to find a representative epoch for each cluster using the clustering based on 20-second epochs.

Let us assume S_Y to be the representative segment for Cluster Y determined using Algorithm 2.5. Let S_Y^{20} be the desired representative epoch for Cluster Y. Using the clustering information based on 20-second epochs, we search for an epoch that is assigned to Cluster Y and contains S_Y. If yes, that epoch is selected as S_Y^{20}; otherwise, we search for an another epoch that is assigned to Cluster Y and has the segment having the minimum euclidean distance from S_Y.

Figure 3.11 shows the representative epochs for each cluster. For example, the cluster with cyan color mostly matches to SWS[2], which has slow activity mostly in the *delta* band. The representative epoch with cyan color shows the slow activity similar to SWS.

3.3.2 QUANTITATIVE ANALYSIS

To have a quantitative assessment of the ability of the computer-based compression method to create homogeneous clusters, we use two matrices, namely, the *epoch cluster-sleep stage* matrix and the *agreement* matrix. The *epoch cluster-sleep stage* matrix maps the epochs in each cluster to the manually scored epochs and allows the labeling of each cluster as one of the sleep stages. The overall agreement between the epochs belonging to the computer-based classification and the manually classified epochs is evaluated using the *agreement* matrix.

[2]Since Stage 3 and Stage 4 have similar spectral properties, for the purpose of evaluation they are combined as *slow wave sleep* (SWS).

EPOCH CLUSTER-SLEEP STAGE MATRIX

To compute the *epoch cluster-sleep stage* matrix, we use the classification information based on the 20-second epochs as discussed earlier. We consider each cluster of epochs formed by the computer-based classification and compare the epochs to the corresponding manually-staged epochs. Each row in the *epoch cluster-sleep stage* matrix represents a single cluster of epochs. The entries in a given row provides the information about the number of epochs that match the different sleep stages. Subsequently, each cluster is assigned a sleep stage. The assignment of a sleep stage to each cluster is based on a match of the majority of the epochs in the cluster to the manually-staged hypnogram. For example, if a cluster has a majority of its epochs matching Stage X of the manual hypnogram, then all the members of the cluster are classified as belonging to Stage X. For the case where a cluster has identical number of maximum epochs matching two or more sleep stages, then the cluster is assigned a stage that occurs first in the sequence - {Stage Wake, Stage 1, Stage 2, SWS, Stage REM}.

For a cluster to be homogeneous, it should have a majority of its epochs assigned to a single sleep stage in the *epoch cluster-sleep stage* matrix. However, in certain cases a cluster can be considered homogeneous even if its epochs matched to multiple sleep stages. It is feasible that the multiple sleep stages have similar spectral composition and some additional information like the EOG or EMG is needed to distinguish between them. For example, the epochs of Stage 2 and Stage REM can often have similar spectral composition and may require additional information about the EOG to differentiate between them.

An example of the *epoch cluster-sleep stage* matrix for subject C is shown in Table 3.3. The ***bold-italics*** cells represent the manually marked sleep stage that majority of the epochs from each cluster matched. For cluster C1, out of total 13 epochs, 10 epochs map to Stage Wake, 1 to Stage 1, and 2 to Stage REM. Since C1 has a majority of its epochs mapping to Stage Wake, all epochs in this cluster are assigned to Stage Wake.

Table 3.3: Epoch Cluster-Sleep Stage matrix for subject C

	Stage Wake	Stage 1	Stage 2	SWS	Stage REM	Stage Assigned
C1	***10***	1	0	0	2	WAKE
C2	1	1	20	0	***95***	STAGE REM
C3	6	1	12	0	***43***	STAGE REM
C4	7	4	***131***	4	19	STAGE 2
C5	0	6	52	3	***53***	STAGE REM
C6	0	2	***67***	6	0	STAGE 2
C7	5	7	***136***	57	2	STAGE 2
C8	1	1	78	***213***	2	SWS

AGREEMENT MATRIX

The *agreement* matrix is based on the *epoch cluster-sleep stage* matrix. In the *epoch cluster-sleep stage* matrix, clusters assigned the same stage are summed together to compute the *agreement* matrix. Each row of the *agreement* matrix shows the epoch distribution of each sleep stage determined by the computer-based classification across the different manually-classified sleep stages. The sum of the diagonal epochs of the matrix divided by the total number of epochs gives the overall agreement.

Based on the *epoch cluster-sleep stage* matrix for subject C as given in Table 3.3, the *agreement* matrix for subject C is shown in Table 3.4. Epochs of clusters C2, C3 and C5 were summed together to form the row *Stage REM* in *agreement* matrix. The row Stage REM shows that among the 293 epochs marked Stage REM by the computer-based classification, only 191 epochs map the manually-classified epochs of Stage REM. Overall agreement between the computer-based and manual classifications is 71.2% for this sleep record.

Each sleep stage is assumed to be distinct and should form a homogeneous cluster. The overall agreement calculated from the *agreement* matrix provides a measure of similarity between the computer-based and manual classifications of the epochs to the various sleep stages.

Table 3.4: Agreement matrix*for subject C

Manual / Auto	Stage Wake	Stage 1	Stage 2	SWS	Stage REM
Stage Wake	***10***	1	0	0	2
Stage 1	0	0	0	0	0
Stage 2	12	13	***334***	67	21
SWS	1	1	78	***213***	2
Stage REM	7	8	84	3	***191***

*based on the *epoch cluster-sleep stage* matrix for subject C, Table 3.3

Hence, the overall agreement can be considered a metric to measure the homogeneity of the clusters formed. A higher overall agreement indicates that an increased number of epochs were assigned the same sleep stage during the computer-based and manual classifications. Thus, higher overall agreement depicts that the clusters formed are comparatively more homogeneous.

3.4 SUMMARY

In this chapter, we have presented a new method for the compression of the cEEG, which is essentially modification of the method used by Agarwal *et al.* in [1]. To parameterize the segment we have used a set of features based on power spectral density, termed as the *spectral* features as opposed to the *generic* features used in [1]. Different classification techniques were presented to cluster the segments parameterized with the *spectral* features. We also proposed a methodology to compare the performance of the proposed method for the compression of the cEEG and the method given in [1]. Two matrices namely, the *epoch cluster-sleep stage* and the *agreement* matrix were discussed.

In the following chapter, we present the results with the proposed method for compression using the different classification schemes - *Methods* I, II, III and IV. We compare these

results with those obtained with the method given in [1]. We also present the performance of these different methods with the initial seeds calculated using the *temporal* technique and the *histogram* technique.

Chapter 4

Results And Discussion

In Chapter 2, the classification scheme first presented by Agarwal *et al.* [1] to cluster the segments based on the *generic* features was discussed. Based on the *spectral* features, we then proposed four classification schemes *Methods* I, II, III and IV to cluster the cEEG segments (see Chapter 3). In this chapter, we will discuss the performance of each of these methods along with that of Agarwal *et al.* by assessing the overall agreement between the computer-based classifications and the manual classification by an EEG expert. The overall agreement is calculated using the *agreement* matrix introduced in Section 3.3. Also, we evaluate and compare the performance of each of the classification methods with the initial seeds for the *k-means* clustering algorithm being selected using the original *temporal* technique and the proposed *histogram* technique. The results for the compression of sleep cEEG recording using the *generic* features as well as the *spectral* features are discussed.

For the comparison, we use the full-night sleep EEG records of eight different subjects, recorded with a sampling rate of 128 Hz using the software developed by Stellate Systems, Montreal, Canada. No prior information about the sleep patterns of the subjects was used in the data selection. There were only two constraints for the selection of the data set. First, the recording must include one of each of the frontal and occipital channels on the same side (either right or left) of the brain. Second, recordings must have been previously staged

using the R&K sleep classification rules [9].

4.1 Performance of Classification Methods

In this section, we study the performance of the different classification methods proposed in this thesis as well as the original method described in [1] which uses the *generic* features to parameterize the EEG segments. The four classification methods uses the *spectral* features. This study is carried out first by utilizing the *temporal* technique and next by using the *histogram* technique to select the initial seeds required for the *k-means* clustering algorithm.

4.1.1 Initial seeds selected using the Temporal technique

As mentioned in Section 3.2.5, the performance of the *k-means* clustering algorithm depends on the selection of the initial seeds used in the clustering. It is expected that a robust selection of the initial seeds will yield a reasonable classification of the segments. In the method given in [1], the initial seeds are selected using the *temporal* technique (see Section 2.5.4). This technique is based on the idea that in applications with recurrent patterns such as in full-night cEEG recording, where cycling sleep stages is a normal occurrence, the initial seeds selected from the equally spaced feature vectors are likely to provide a reasonable sampling of the variations present in the data set. We first use the *temporal* technique to select the initial seeds and study the performance of the various classification methods.

Original Classification Method

To compare the performance of the proposed *spectral* features with that of the *generic* features, we implemented the methodology in [1] to cluster the segments of the cEEG based on the *generic* features. For the eight subjects under consideration, the overall agreement between the manual and computer-based classifications on an epoch-to-epoch basis are

Table 4.1: Agreement between the manual and computer-based classifications using the *generic* and *spectral* features

	Generic (Original Method)	Spectral *Method* I	Spectral *Method* II	Spectral *Method* III	Spectral *Method* IV
Subject A	82.3%	73.5%	78.1%	77.9%	71.4%
Subject B	61.5%	67.0%	66.7%	65.7%	69.0%
Subject C	63.2%	62.6%	71.2%	70.6%	70.6%
Subject D	67.5%	70.9%	72.7%	70.7%	71.3%
Subject E	52.8%	53.1%	66.9%	66.9%‡	66.9%‡
Subject F	59.6%	62.0%	66.3%	66.3%	71.0%
Subject G	60.2%	63.6%	67.0%	67.0%‡	67.0%‡
Subject H	68.3%	68.0%	70.3%	67.9%	69.8%
Mean	**64.4%±8.7**	**65.1%±6.3**	**69.9%±4.1**	**69.1%±4.0**	**69.6%±1.8**

‡*Condition* 1 (see Section 3.2.3) was not satisfied and *Method* II was used to classify the segments.

shown in the *Generic* column of Table 4.1. An average overall agreement of 64.4% (±8.7) is observed.

METHOD I

As mentioned in Section 3.2.1, *Method* I is similar to the original classification method presented by Agarwal *et al.* [1], except that the feature vectors for clustering are now based on the absolute power in the different bands that are scaled as in the original method [1]. The overall agreement between the manual and computer-based classifications for the eight subjects are shown in the *Spectral Method* I column of Table 4.1. We observe an average overall agreement of 65.1% (±6.3).

METHOD II

Method II uses the relative power in each of the six frequency bands to define the feature vectors (see Section 3.2.2). The overall agreement between the manual and computer-based classifications using the *spectral* features and *Method* II for the eight subjects are shown in the *Spectral Method* II column of Table 4.1. An average overall agreement of 69.9% (±4.1)

is observed.

METHOD III

As explained in Section 3.2.3, if we observe the temporal profile of the relative power in the different frequency bands, it is found that the relative power in the *delta* band spans almost 80% of the total power in the six bands. The relative power in the *delta* band may mask the information from the other bands and can degrade the performance of *Method* II. To overcome this limitation, we proposed *Method* III. Since the power in the *delta* band is highest compared to the other bands, we separate the cluster with the highest average absolute power in the *delta* band. The remaining segments are classified using *Method* II. The *Spectral Method* III column of Table 4.1 shows the overall agreement as 69.1% ($\pm$4.0) between the manual and computer-based classifications for the eight subjects under consideration.

If we compare the results for subjects E and G in the *Spectral Method* III and *Spectral Method* II columns of Table 4.1, we observe that *Method* III gives the same results as *Method* II. On further analysis of the results with *Method* III, it was found that during the clustering of segments based on only the absolute power in the *delta* band, a single cluster with more than 85% of total number of segments was formed, i.e., the necessary *Condition* 1 (see Section 3.2.3) required to separate the cluster was not satisfied. Thus, the segments with a relatively high power in the *delta* band could not be separated and hence, all the segments were classified using *Method* II. On the visual analysis of the EEGs for subjects E and G, it is observed that these subjects have a majority of epochs belonging to Stage 2 with only a fewer number of epochs belonging to SWS. Since the demarcation between SWS and Stage 2 is highly subjective [49], it is possible that the majority of the epochs belonging to Stage 2 and SWS lie in the same cluster as observed with the results.

METHOD IV

Method IV is similar to *Method* III except that the segments remaining after the segments with high absolute power in the *delta* band have been removed are parameterized using the relative powers in only the five bands - $\{0, P_\theta, P_\alpha, P_\sigma, P_{\beta_1}, P_{\beta_2}\}$ (see Section 3.2.4). The overall agreement between the manual and computer-based classifications using *Method* IV is shown in *Spectral Method* IV column of Table 4.1. As previously explained in connection with *Method* III, the subjects E and G (denoted by ‡) do not satisfy *Condition* 1 and thus, all the segments for these subjects are classified using *Method* II. The average overall agreement is observed as 69.6% ($\pm$1.8)

COMPARISON OF PERFORMANCE

The average overall agreement for the eight subjects under consideration using the *spectral* features and *Method* I parallels that of the original method in [1] based on the *generic* features (see Table 4.1). However, the performance of *Method* I is inferior compared to that of *Methods* II, III and IV (refer Table 4.1). For all the subjects, *Method* I showed a higher ambiguity in the classification of the epochs belonging to Stage 2 and Stage REM compared to *Method* II. For example, Figure 4.1 shows the compressed results for the two hours of cEEG recording for subject C. The horizontal bar labeled 'M' indicates the sleep stages as determined from the manually staged hypnogram and the label 'C' indicates the temporal profile of the clusters obtained using the computer-based classification. Each color represents a particular cluster. Figure 4.1(a) shows the temporal profile of the different clusters using *Method* I and Figure 4.1(b) shows the results using *Method* II. Since the compressed results with *Methods* I and II are calculated independently, the same colors in the Figures 4.1(a) and (b) may represent different activity. On comparing Figures 4.1(a) and (b), we observe that using *Method* I we are not able to differentiate between the epochs from Stage 2 and Stage REM. They are represented by the green color. However, using *Method* II, the epochs from Stage 2 and Stage REM are separated into different clusters.

The epochs from Stage 2 are mostly represented by grey and dark green colors, whereas the epochs from Stage REM are mostly represented by red, light green, and cyan colors.

From the results obtained with our data set, we observe that even though a certain number of segments have high relative power in the *delta* band, the performance of *Method* II is not degraded as initially expected during the development of the various classification methods. For example, the *agreement* matrices for subject C based on *Methods* II, III and IV are shown in Tables 4.2, 4.3 and 4.4, respectively. The overall agreement between the manual and computer-based classifications with *Methods* II, III and IV is found to be 71.2%, 70.6% and 70.6% respectively. If we compare Tables 4.2, 4.3 and 4.4 on a stage-to-stage basis, we observe that the agreement between the computer-based scoring and manual scoring is very similar for all the classification methods.

The feature vectors used with *Methods* II, III and IV are based on the relative power in each of the six frequency bands. The relative power in each band spans the same range $(0, 1)$ and a method to scale the features as required with the *generic* features is not needed.

As mentioned earlier, for subjects E and G, the high power segments in the *delta* band could not be separated as expected by *Methods* III and IV. Therefore, *Method* II was used to classify the complete set of segments. If we exclude subjects E and G in Table 4.1, the average overall agreements for the remaining six subjects using *Methods* II, III and IV are 70.8%, 69.85% and 70.5%, respectively. These results indicate that the performance of *Method* II is marginally better compared to that of *Methods* III and IV. Also, it is noted that there is no added benefit of the initial classification using the power in the *delta* band. Further, from Table 4.1, it can be seen that the performance of *Method* II is approximately 5.5% higher compared to that with the original method in [1] which is based on the *generic* features. Hence, based on our results, *Method* II is seen as the best method to classify the segments of the cEEG that are parameterized with the *spectral* features and is also better compared to the method given in [1] when the initial seeds for the *k-means* clustering algorithm are selected using the *temporal* technique.

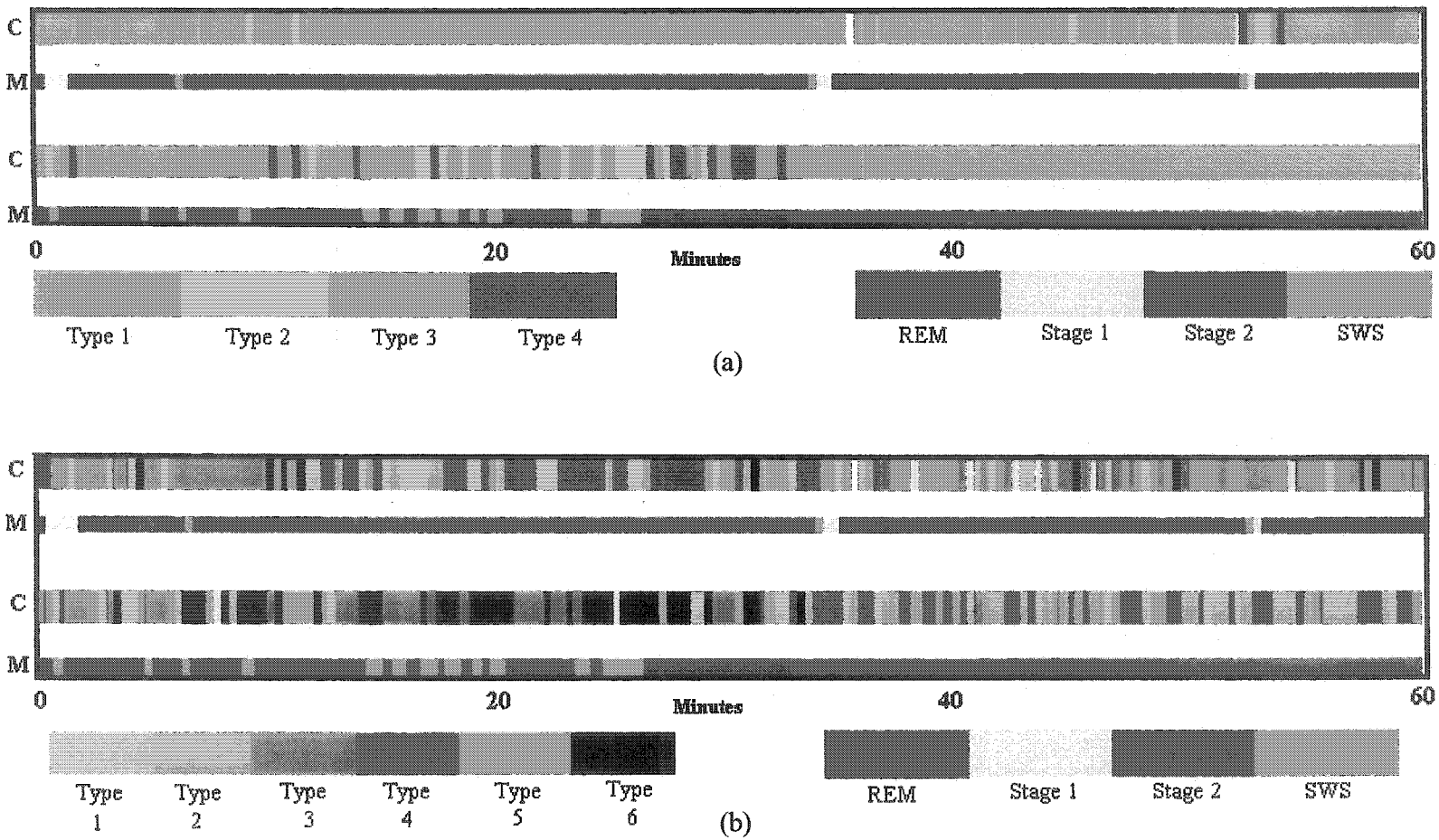


Figure 4.1: Compressed cEEG results for a two-hour block of subject C using (a) *Method* I and (b) *Method* II. The row labeled 'C' shows the temporal profile of the clusters evaluated using the computer-based classification, whereas rows labeled 'M' show the manual Hypnogram. The same colors in (a) and (b) may not necessarily represent similar EEG activity.

Table 4.2: Agreement matrix for subject C based on the *spectral* features and *Method* II

Manual / Auto	Stage Wake	Stage 1	Stage 2	SWS	Stage REM
Stage Wake	***10***	1	0	0	2
Stage 1	0	0	0	0	0
Stage 2	12	13	***334***	67	21
SWS	1	1	78	***213***	2
Stage REM	7	8	84	3	***191***

Table 4.3: Agreement matrix for subject C based on the *spectral* features and *Method* III

Manual / Auto	Stage Wake	Stage 1	Stage 2	SWS	Stage REM
Stage Wake	0	0	0	0	0
Stage 1	0	0	0	0	0
Stage 2	9	10	***322***	49	27
SWS	3	6	109	***232***	2
Stage REM	18	7	65	2	***187***

Table 4.4: Agreement matrix for subject C based on the *spectral* features and *Method* IV

Manual / Auto	Stage Wake	Stage 1	Stage 2	SWS	Stage REM
Stage Wake	***14***	0	4	1	1
Stage 1	0	0	0	0	0
Stage 2	1	2	***308***	63	6
SWS	1	16	128	***217***	6
Stage REM	14	5	56	3	***203***

4.1.2 INITIAL SEEDS SELECTED USING THE HISTOGRAM TECHNIQUE

As mentioned earlier in previous section, the *temporal* technique is based on the idea that for applications with recurrent patterns, the initial seeds selected from the equally spaced feature vectors are likely to provide a reasonable sampling of the variations present in the data set. However, the initial seeds selected from the equally spaced feature vectors may not represent the patterns that do not recur frequently or occur for short durations like the occurrence of seizures in epilepsy monitoring. For example, in the neurological intensive care unit, the cEEG recording of a patient in *status epilepticus* has short bursts of activities occurring randomly but very often. The initial seeds selected with the *temporal* technique may miss these short bursts of activities. To overcome this limitation of the *temporal* technique, we proposed the *histogram* technique (see Section 3.2.5) based on the features of the different patterns and not on the temporal information of the patterns. The initial seeds selected with the *histogram* technique are more likely to represent these short bursts. For example, consider Figure 4.2, which shows a sample of the EEG recording with different patterns: A, B, C, and D. If the initial seeds were selected by taking equidistant samples (thick lines indicate equally-spaced sampling) as in the *temporal* technique, then pattern B might be missed in the samples and not represented in the initial seeds. However, with the *histogram* technique, pattern B would be considered as it has features different from the other patterns.

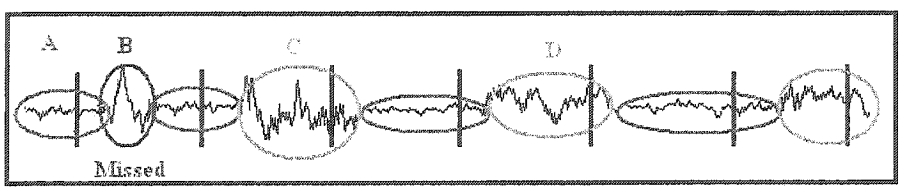


Figure 4.2: Temporal profile of different patterns in a sample EEG recording. Each colour represents a different type of pattern. With the *temporal* technique, pattern B may not be represented in initial seeds but with the *histogram* technique, pattern B will be sampled. The thick lines indicate the equidistant samples of the EEG selected using the *temporal* technique.

The performance of the different classification methods with the initial seeds determined using the *histogram* technique are shown in Table 4.5.

Table 4.5: Agreement between the manual and computer-based classifications using the *generic* and *spectral* features.

	Generic (Original Method)	Spectral *Method* I	Spectral *Method* II	Spectral *Method* III	Spectral *Method* IV
Subject A	83.3%	73.7%	77.7%	77.9%	72.2%
Subject B	61.0%	66.4%	66.7%	65.6%	70.4%
Subject C	65.8%	59.5%	74.0%	70.6%	70.9%
Subject D	67.6%	72.7%	71.9%	70.8%	72.8%
Subject E	52.7%	53.1%	70.2%	70.2%‡	70.2%‡
Subject F	60.2%	62.3%	66.7%	65.4%	70.9%
Subject G	63.5%	66.0%	71.7%	71.7%‡	71.7%‡
Subject H	68.1%	68.1%	70.1%	67.0%	69.0%
Mean	**65.3%±8.8**	**65.2%±6.8**	**71.1%±3.7**	**69.9%±4.1**	**71.0%±1.2**

‡*Condition* 1 was not satisfied and *Method* II was used to classify the segments.

It can be noted from Table 4.5 that the average overall agreement between the manual and computer-based classifications using *Method* II to classify the segments based on the *spectral* features is higher compared to that of *Methods* I, III, and IV. The average agreements for subjects E and G with the initial seeds selected using the *histogram* technique are same for *Methods* II, III, and IV. As explained in the previous section, subjects E and G do not satisfy *Condition* 1, and thus, all the segments are classified using *Method* II. If we exclude subjects E and G in Table 4.5, the average overall agreement for the remaining six subjects using *Methods* II, III and IV are 71.2%, 69.8% and 71%, respectively. These results show that there is no added advantage of the initial classification using the power in the *delta* band. It can also be seen from Table 4.5 that the average overall agreement using *Method* II is almost 6% higher compared to that with the original method given in [1] which is based on the *generic* features. Hence, the results show that *Method* II provides best results among the different methods used to classify the segments based on the *spectral*

features and the method given in [1] which is based on the *generic* features.

4.1.3 COMPARISON OF PERFORMANCE BASED ON THE METHOD OF SELECTION OF INITIAL SEEDS

In this section, we compare the performance of the different classification methods using the initial seeds selected using the *histogram* technique as well as the *temporal* technique. If we compare Tables 4.1 and 4.5, we observe that the average overall agreement of each of the classification methods is improved with the *histogram* technique compared to that with the *temporal* technique. For example, the classification method given in [1] shows an improvement of almost 1% with the *histogram* technique compared to that with the *temporal* technique. Similarly, the average overall agreement for *Method* II used to classify the segments based on the *spectral* features with the initial seeds selected using the *histogram* technique is 71.1%, whereas with the *temporal* technique the average overall agreement is 69.9%.

From the comparison of the average overall agreements for the eight sleep cEEG recording in Tables 4.1 and 4.5, it is observed that irrespective of the method for the selection of the initial seeds for the *k-means* clustering algorithm, *Method* II, which is based on the *spectral* features, provides better classification of the segments compared to *Methods* I, III and IV based on the the *spectral* features and the original method in [1].

In our further study of the proposed method for the compression of the cEEG, we will use *Method* II to classify the segments parameterized with the *spectral* features. Also, for the proposed method as well as the original method given in [1], we will use the *histogram* technique to select the initial seeds for the *k-means* clustering algorithm.

4.2 PERFORMANCE OF THE cEEG METHOD

The method for the compression of the cEEG as given in [1] provides the actual EEG segments as a legend to read the compressed results. Because actual EEG samples are used, these results are easy to understand compared to the results with other compression techniques such as CSA [15] or the trend analysis [14]. As mentioned earlier, the compression method in [1] uses the *generic* features to parameterize the segments of the cEEG, and since the *generic* features provide a limited information about the segments compared to the *spectral* features, it is expected that the *spectral* features can better parameterize the segments and hence, may improve the classification and the overall performance of the EEG compression method. We evaluate the performance of the proposed compression method based on the *spectral* features and the compression method given in [1] which is based on the *generic* features by comparing the patterns as identified by the computer-based methods with the different sleep stages in the manually staged hypnogram on an epoch-to-epoch basis. For this comparison, the two matrices, namely, the *epoch cluster-sleep stage* matrix and the *agreement* matrix, as explained in Section 3.3.2, are used. As mentioned in the previous section, if we compare the columns *Generic* and *Spectral Method* II columns of Table 4.5, we observe that the results using the *generic* features as given in [1] provide an average overall agreement of 65.3% when compared to the manual classification, whereas the proposed method based on the *spectral* features gave a 71.1% agreement. Thus, an improvement of almost 6% is achieved.

The transition between the sleep stages is a continuum and the demarcation between the sleep stages is not clearly defined. The epochs during the transition from one stage to another, such as the transition from Stage 2 to SWS or Stage Wake to Stage 1, may have overlapping or similar features. These transitional epochs can be assigned to either one of the two stages by the scorer depending on his/her preferences. This often lead to discrepancies in the scoring of the same sleep cEEG recording by two different scorers. For example, on an epoch-to-epoch basis the visual scoring of two healthy subjects in

10 different sleep laboratories in Japan showed only 67%-75.3% agreement [10]. Since typically there is only 80%-90% inter-scorer agreement in the manual classification of the same sleep cEEG recording [48], the 71% average overall agreement between the manual classification and our computer-based classification based on the *spectral* features is a significant achievement.

A computer-based method similar to the method for the compression of the cEEG in [1] was presented for the classification of the sleep EEG epochs in [39]. The segments were parameterized using the *generic* features and additional sleep related features like presence of spindles, alpha-slow-wave, presence of eye-movement in the EOG channels. Comparison between the computer-based and manual classifications of the epochs showed an average overall agreement of 61.1% for the twelve different sleep cEEG recordings. If we compare the 61.1% agreement against our results based on only the *spectral* features, we find our results to have a higher average agreement (71.1%) with the manual-classification. Moreover, the use of the *spectral* features together with additional sleep related features are expected to provide an even better classification of the segments and will further enhance the performance of our method.

The overall agreement as calculated from the *agreement* matrix provides a measure to evaluate the similarity between the manual and computer-based classifications. Since each sleep stage is considered to represent epochs that have EEG activities with similar properties, a higher overall agreement can be considered to indicate comparatively more homogeneous clusters. As the average overall agreement obtained with the *spectral* features is higher compared to than with the *generic* features (see Table 4.5), the clusters formed with the *spectral* features can be considered to be more homogeneous.

During our performance analysis of the compression method, we consider a cluster to be homogeneous if majority of its members match with the same sleep stage. Moreover, a cluster with members that match to different sleep stages is consider as homogeneous, if and only if, the epochs of those sleep stages require some information in addition to the

spectral information to differentiate between them. For example, on basis of the R&K sleep classification rules [9], the epochs of Stage 2 and Stage REM can have similar EEG. In certain cases, to differentiate between these epochs it is necessary to use some information in addition to the EEG, such as information about the EOG or the EMG activity. Several computer-based automatic sleep staging methods have shown that on the basis of only the EEG, it is difficult to distinguish the epochs of Stage 1 and Stage REM, and that additional information is required about the EOG and EMG [51]. Similarly, in order to distinguish between certain epochs of Stage 1 and Stage Wake, the EMG information is indispensable [51]. Table 4.6 shows the *epoch cluster-sleep stage* matrix for subject D. Cluster C3 has epochs mapping to Stage 1, Stage 2 and Stage REM. As per the R&K sleep classification rules, the epochs of Stage 1 and Stage 2 can have similar power in the *theta* band or the epochs of Stage 1 and Stage REM have similar power in the *beta* or *alpha* band. Hence, classification based on only the power in the different bands as considered by using the *spectral* features, the epochs belonging to Stage 1, Stage 2, and Stage REM may lie in same cluster. On the other hand, Cluster C3 has a negligible number of epochs that map to SWS because there is generally no overlap in the spectral content of SWS with Stage 1, Stage 2, or Stage REM. Hence, Cluster C3 can be considered to be homogeneous.

Table 4.6: Epoch Cluster-Sleep Stage matrix for subject D based on the *spectral* features

	Stage Wake	Stage 1	Stage 2	SWS	Stage REM	Stage Assigned
C1	2	3	0	0	***9***	Stage REM
C2	4	18	***71***	4	31	Stage 2
C3	1	33	***50***	2	35	Stage 2
C4	***18***	1	0	0	0	Stage Wake
C5	2	8	2	0	***35***	Stage REM
C6	1	15	***157***	13	12	Stage 2
C7	0	3	***160***	71	1	Stage 2
C8	2	2	20	***269***	2	SWS

For the data under consideration, we cluster the segments into eight clusters - six clusters representing the six different sleep stages and two additional redundant clusters. The EEG changes during the course of the night and it is possible that the epochs from the same sleep stage can have different properties at different times during the course of a full-night recording. For example, during the course of the night the epochs assigned to Stage 2 can have dominating K-complexes (the EEG activity with frequency less than 0.5 Hz and duration less than 0.5 sec) or spindles (bursts of the EEG activity with 12-14 Hz and lasts around 0.5 to 1.5 seconds) or dominating *theta* (4-8 Hz) activity or any combination of the three EEG activities. Furthermore, since Stage 2 is a transitional stage from drowsiness (Stage 1 or Stage Wake) to SWS, it is possible that during the course of night different degrees of the *delta* activity can be present. Since these epochs can have different spectral content, based on only the *spectral* features these epochs may fall in different clusters. As expected, our results indicate that we can have more than one cluster representing a single sleep stage. For example, Table 4.6 shows the *epoch cluster-sleep stage* matrix for subject D. Clusters C2, C3, C6 and C7 have majority of the members matching to Stage 2 and thus, are labeled Stage 2. Figure 4.3 presents the representative segments for Clusters C2, C3, C6, and C7. All these four segments have features that are characteristics of Stage 2, but quantitatively these segments are different. The segment in Figure 4.3(a) show a mixture of spindles and *theta* activity, and the representative segment for Cluster C3 in Figure 4.3(b) resembles the *theta* activity. The representative segments of Clusters C6 and C7 in Figures 4.3(c) and 4.3(d) have spindles and K complexes. Since Clusters C6 and C7 represent similar activity, they can be considered to be examples of redundant clusters.

Example: Failure of Generic Features

In our data it was observed that in some of the sleep EEG records, the *spectral* features are able to differentiate between the different stages, which was not possible using the *generic* features. For example, Figures 4.4(a) and 4.4(b) show the compressed results for two hours

of sleep recording of subject E based on the *spectral* and *generic* features, respectively. Each color represents one type of activity and the repetition of colors gives the temporal profile of the different activities. Since the compressed results with the *spectral* and *generic* features were evaluated independently, the same colors in Figures 4.4(a) and 4.4(b) may not necessarily represent similar EEG activity. The horizontal bars marked 'M' show the manual classification.

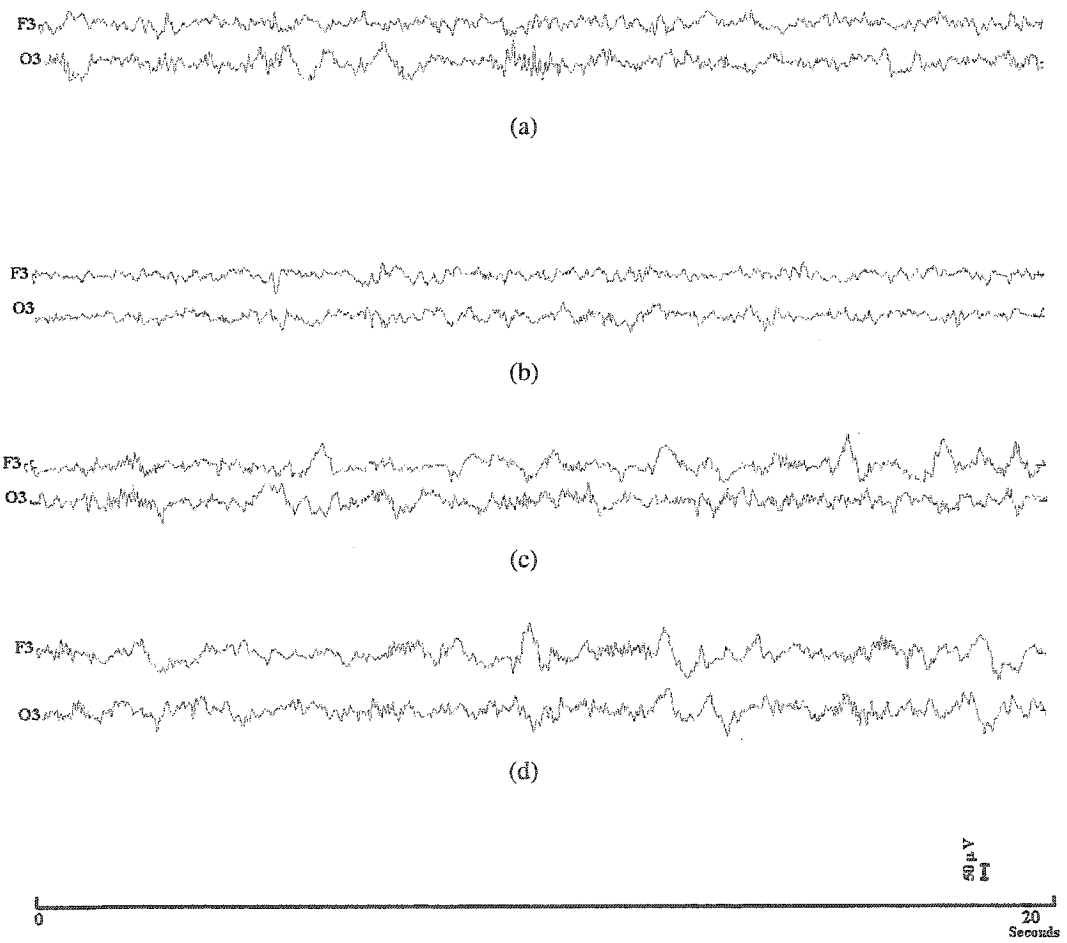


Figure 4.3: The representative segments of Clusters C2, C3, C6 and C7 based on the *epoch cluster-sleep stage* matrix for subject D given in Table 4.6. (a) Cluster C2 (b) Cluster C3 (c) Cluster C6 (d) Cluster C7.

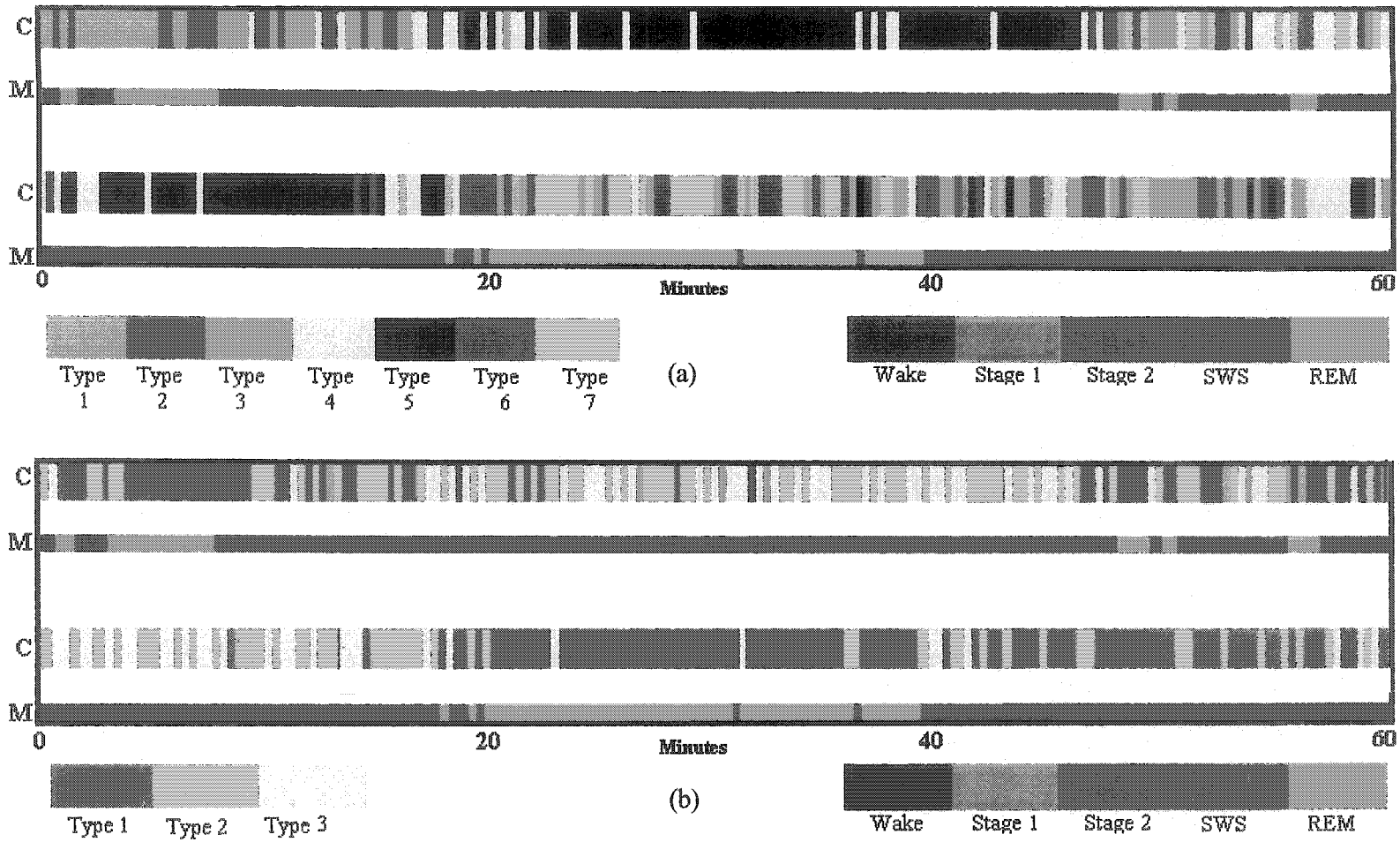


Figure 4.4 Compressed results for a two-hour cEEG recording of subject E. Compressed results when segments are parameterized using (a) the *spectral* features and (b) the *generic* features. Each horizontal bar represents one hour of recording. Each color represents a particular activity. The thin bar labeled 'M' shows the manual Hypnogram. The same colors in (a) and (b) may not necessarily represent similar EEG activity.

On comparing the onset and offset of patterns obtained with the computer-based methods to the manual classification, we observe a better classification using the *spectral* features compared to that using the *generic* features. The *generic* features are not able to classify between the different stages and the epochs from various stages are grouped into a single cluster. For example, the blue color represents epochs from Stage 1, Stage REM and Stage 2 (Figure 4.4(b)), whereas the *spectral* features are able to differentiate between these epochs as different sleep stages. The epochs from Stage REM are represented mostly by cyan color, and pink and yellow colors represents most of the epochs from Stage 2 (Figure 4.4(a)). The *agreement* matrices for subject E, based on the *spectral* and *generic* features are shown respectively in Tables 4.7 and 4.8. By using the *spectral* features, the epochs are clustered into four stages - Stage Wake, Stage 2, SWS and Stage REM (see Table 4.7), whereas based on the *generic* features, the majority of the epochs are grouped as Stage 2 or SWS (see Table 4.8). Further, the classification of the epochs using the *spectral* features is in concordance with the various sleep stages as shown in the hypnogram.

Table 4.7: Agreement matrix for subject E based on the *spectral* features

Manual / Auto	Stage Wake	Stage 1	Stage 2	SWS	Stage REM
Stage Wake	*14*	7	3	0	3
Stage 1	0	0	0	0	0
Stage 2	9	24	*430*	37	118
SWS	1	1	67	*231*	4
Stage REM	2	2	36	3	*75*

Table 4.8: Agreement matrix for subject E based on the *generic* features

Manual / Auto	Stage Wake	Stage 1	Stage 2	SWS	Stage REM
Stage Wake	0	0	0	0	0
Stage 1	0	0	0	0	0
Stage 2	18	33	***495***	203	196
SWS	8	1	41	***68***	4
Stage REM	0	0	0	0	0

4.3 SUMMARY

In this chapter, we first studied the performance of the classification scheme based on the *generic* features given in [1] and *Methods* I, II, III and IV that are based on the *spectral* features, with the initial seeds selected using the *temporal* technique and then, with the *histogram* technique. Our results indicate that the overall average agreement of the different classification methods has improved with the *histogram* technique as compared to the *temporal* technique. Further, it was observed that the performance of *Method* II is better than that of *Methods* I, III and IV, as well as that of the classification scheme given in [1]. Since the average overall agreement using the proposed method based on the *spectral* features shows an improvement of 6% compared to that of the method given in [1] which is based on the *generic* features, it is argued that the clusters formed with the *spectral* features are comparatively more homogeneous than that formed using the *generic* features.

Chapter 5

APPLICATION OF cEEG IN NICU

The compressed cEEG in a neurological intensive care unit (NICU) can assist the reviewer during the visual analysis of the cEEG recording. In this chapter, we apply the proposed compression method to a single eighteen-hour NICU EEG recording of a patient in *status epilepticus*. We correlate the onset and offset of the patterns as determined by the compressed cEEG with the clinical information provided by the physician. We compare the performance of the proposed method for the compression of the cEEG with the method given by Agarwal *et al.* in [1].

5.1 INTRODUCTION

Research in medicine has proved the effectiveness of the EEG in studying the complex behaviour of the brain. The EEG along with the EKG, EOG and EMG constitutes the vital recordings in the neurological intensive care unit (NICU). The cEEG recording in the NICU is generally performed for those patients who have the brain function in jeopardy. The reviewer compares the changes in the EEG at different times to have an insight about the state of the brain at different times and analyze the effect of medication administered to the patient. During the cEEG recording, clinical staff is required to be attentive to be able to take the corrective action as well as identify any abnormality in the EEG for later review

by the neurologist. The manual review of the cEEG recording is complex and requires an enormous amount of time to review. Thus, the onset and offset of the emerging EEG patterns as determined by the compressed cEEG can provide assistance to the reviewer during the visual analysis of the cEEG recording [50].

Epileptic seizure is the result of the electrical disturbance in the brain. Most seizures last for 1-2 minutes, but can last for longer durations. If the seizure recurs multiple times in a short period of time or becomes continuous, the state of the patient is called as *status epilepticus*. During *status epilepticus*, the patient is administered with sedatives like propofol to induce coma in order to suppress the occurrence of the anti-epileptic drug resistant seizures. The seizures may recur as the patient is taken out of the induced coma (i.e, on a reduced medication).

5.2 METHODOLOGY

SUBJECT

We use an eighteen-hour cEEG recording of a subject in *status epilepticus* to demonstrate the application of the compressed cEEG in the NICU. The subject was diagnosed to be in *status epilepticus* and propofol was administered to suppress the long-lasting seizures. During the eighteen-hour recording under consideration, much of the EEG activity was associated with the burst suppression[1]. The subject was induced into coma and during this period, frequent intermittent bursts and 1-3 Hz activity consistent with the electrographic seizures were identified by the physician. During this period, the subject was taken out of coma once (i.e., the propofol was stopped) and within a short period of time, a clinical seizure was observed. Following the clinical seizure, the propofol was again administered to induce coma in order to suppress the seizure.

[1]Typically, the burst suppression activity refers to episodes of the EEG activity with low amplitudes (flattening of EEG) that are interrupted by bursts of mixture of sharp and slow activity. The episodes of the suppression are longer than the bursts of activity.

METHODS FOR THE COMPRESSION OF THE CEEG

We compare the visual findings reported by the physician for the given cEEG recording with the onset and offset of the emerging EEG patterns as identified using the method proposed in this thesis as well as the method given in [1]. To facilitate an easy understanding of the compressed results, we briefly summarize the method given in [1] and the proposed method. The method given in [1] uses a multi-channel adaptive segmentation technique based on Teager's NLEO (see Section 2.5.1). Segments with amplitude greater than $300\mu V$ or with an energy that is higher than that possessed by the majority of the segments are considered as artifacts (see Section 2.5.2). The segments are parameterized with the *generic* features and are classified based on the iterative *k-means* algorithm (see Sections 2.5.3 and 2.5.4).

The proposed method is similar to the method given in [1] except that the segments are parameterized with the *spectral* features. In Chapter 4, we discussed *Methods* I, II, III and IV in terms of their ability to classify the segments parameterized with the *spectral* features. On the basis of our results with the sleep cEEG recordings, we found the performance of *Method* II to be the best among the four proposed classification methods. Hence, in this NICU application we use *Method* II to classify the segments that are parameterized with the *spectral* features.

As discussed in Chapter 4, the performance of the different classification methods improved when the initial seeds calculated using the *histogram* technique were used instead of those calculated using the *temporal* technique. Therefore, we use the *histogram* technique to calculate the initial seeds required for the *k-means* algorithm.

We analyze the complete eighteen-hour cEEG recording in three independent sections of six hours each. The cEEG recording from the right side and the left side of the brain are analyzed independently. For each side, only two channels of the cEEG recording are considered, $FP2$-$T4$and $T4$-$O2$ from the right side and $FP1$-$T3$and $T3$-$O1$ from the left side. Since the physician in his report indicated three types of the EEG activity - burst

suppression, 1-3 Hz slow activity and 4-8 Hz activity, we classify the EEG segments into three clusters.

5.3 Results and Discussion

The proposed method and the method given in [1] differ primarily in the set of features used to parameterize the segment. The ability of each method to distinguish between the different types of the EEG activities can be considered as an adequate measure for the corresponding set of features, namely, the *spectral* and *generic* features to parameterize the segments.

As an overall assessment of the compressed result for the given eighteen hours of the cEEG recording, it is observed that the compressed results with the proposed compression method provide a better classification of the different EEG activities compared to that with the method given in [1]. In the following subsections, we present examples where the proposed method is able to identify the changes in the EEG activity, whereas the method given in [1] failed to identify these changes.

5.3.1 Case 1: First six hours of the cEEG

The compressed results for the six hours (19h:28m:55s - 01h:28m:55s) of the cEEG recording on the right side of the brain are shown in Figures 5.1 and 5.2.

Figure 5.1(a) shows the compressed results using the proposed method. Each horizontal bar represents the compressed results for one hour of the cEEG recording. Each color represents a single cluster of segments. The temporal profile of the different colors show the presence of the different patterns in the cEEG recording. Figure 5.1(b) shows the sample segments of the EEG activity represented by each cluster, which provides a legend to read the temporal profile shown in Figure 5.1(a).

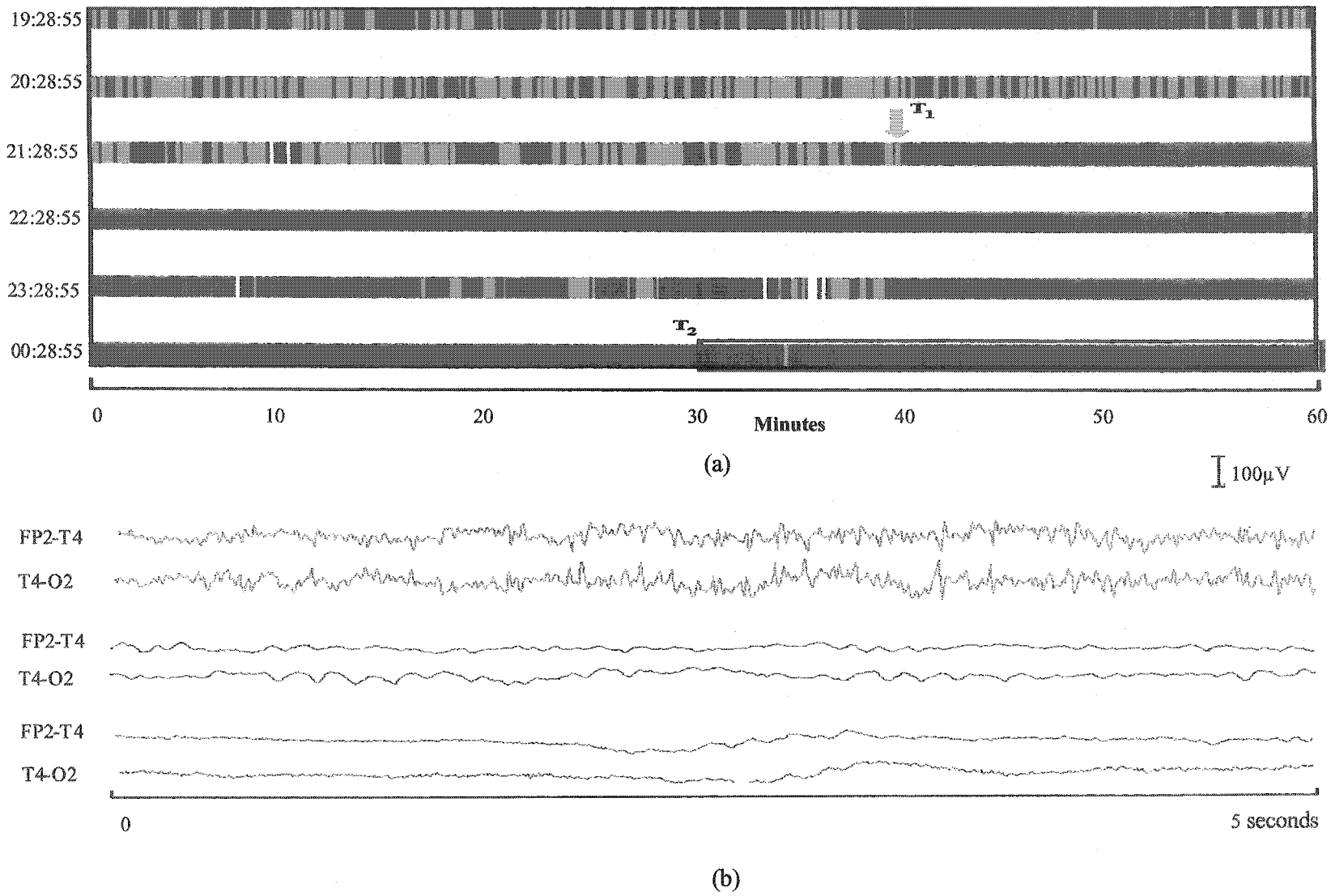


Figure 5.1 (a) Compressed results for the first six hour cEEG recording (19h:28m:55s - 01h:28m:55s) on the right side of the brain using the *spectral* features as proposed in this thesis. (b) Figure shows the representative segments of each cluster.

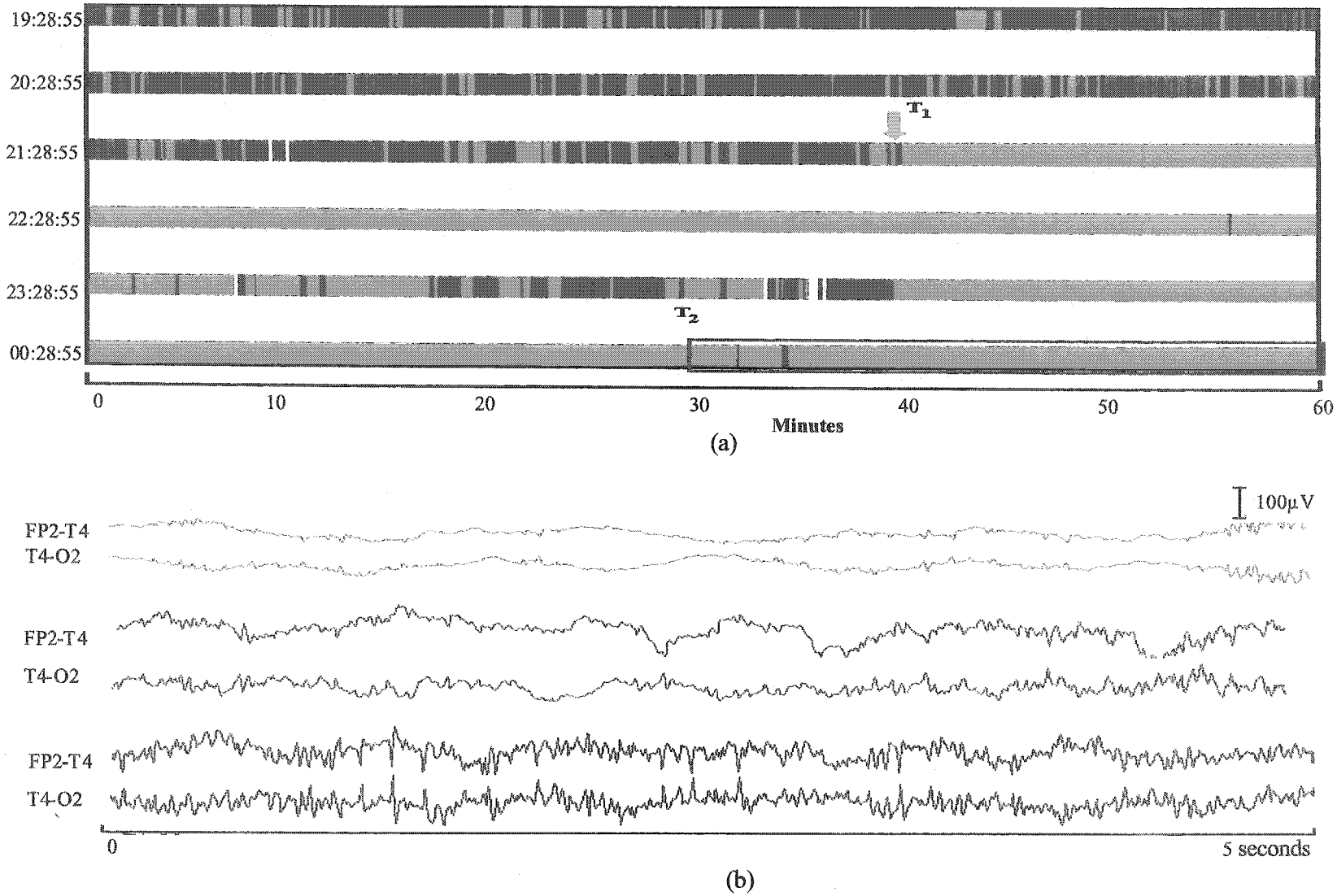


Figure 5.2 (a) Compressed results for the first six-hour cEEG recording (19h:28m:55s - 01h:28m:55s) on the right side of the brain using the *generic* features as given in [1]. (b) Figure shows the representative segments of each cluster.

For example, the EEG activity associated with the segments shown in green color in Figure 5.1(a) is represented by green color EEG in Figure 5.1(b). Figure 5.2 shows the results using the *generic* features as given in [1]. Since the compressed results with the proposed method and the method given in [1] are calculated independently, the segments with same color in Figures 5.1 and 5.2 may not represent similar activity. For example, the segments represented by blue color in Figure 5.1(a) represents burst suppression, whereas the segments with burst suppression in Figure 5.2(a) are shown in green color.

When the compressed results for the six hours of cEEG recording shown in Figures 5.1 and 5.2 are compared to the visual review of the actual cEEG recording, it was observed that the onset and offset of patterns as shown in the compressed results is in accord with the pattern changes in the actual cEEG recording. For example, at the time instant T_1 (11:10 PM) the compressed results show a change in the EEG activity from a mixture of slow and fast activity to burst suppression. This change is found to be in accordance with the changes in the cEEG recording. Further analysis show that the *spectral* features are able to identify the changes in the EEG activity that were not identified using the *generic* features. For example, in Figure 5.1, around 1:00 AM and the duration labeled T_2, we observe a change in the activity from burst suppression represented by blue color to a mixture of burst suppression and 1-3 Hz slow activity represented by blue and red color. However, during the same interval the results using the *generic* features in Figure 5.2 do not show the transition to 1-3 Hz activity. The temporal profile indicates a continued burst suppression activity represented by green color.

5.3.2 CASE 2: Second six hours of the cEEG

As with case I, during the second six hours (01h:28m:55s - 07h:28m:55s) of the cEEG recording on the right side of the brain, we compare the performance of the proposed method with that of the method given in [1]. Figures 5.3 and 5.4 show the results with the *spectral* features as used in the proposed method and the *generic* features as used in [1].

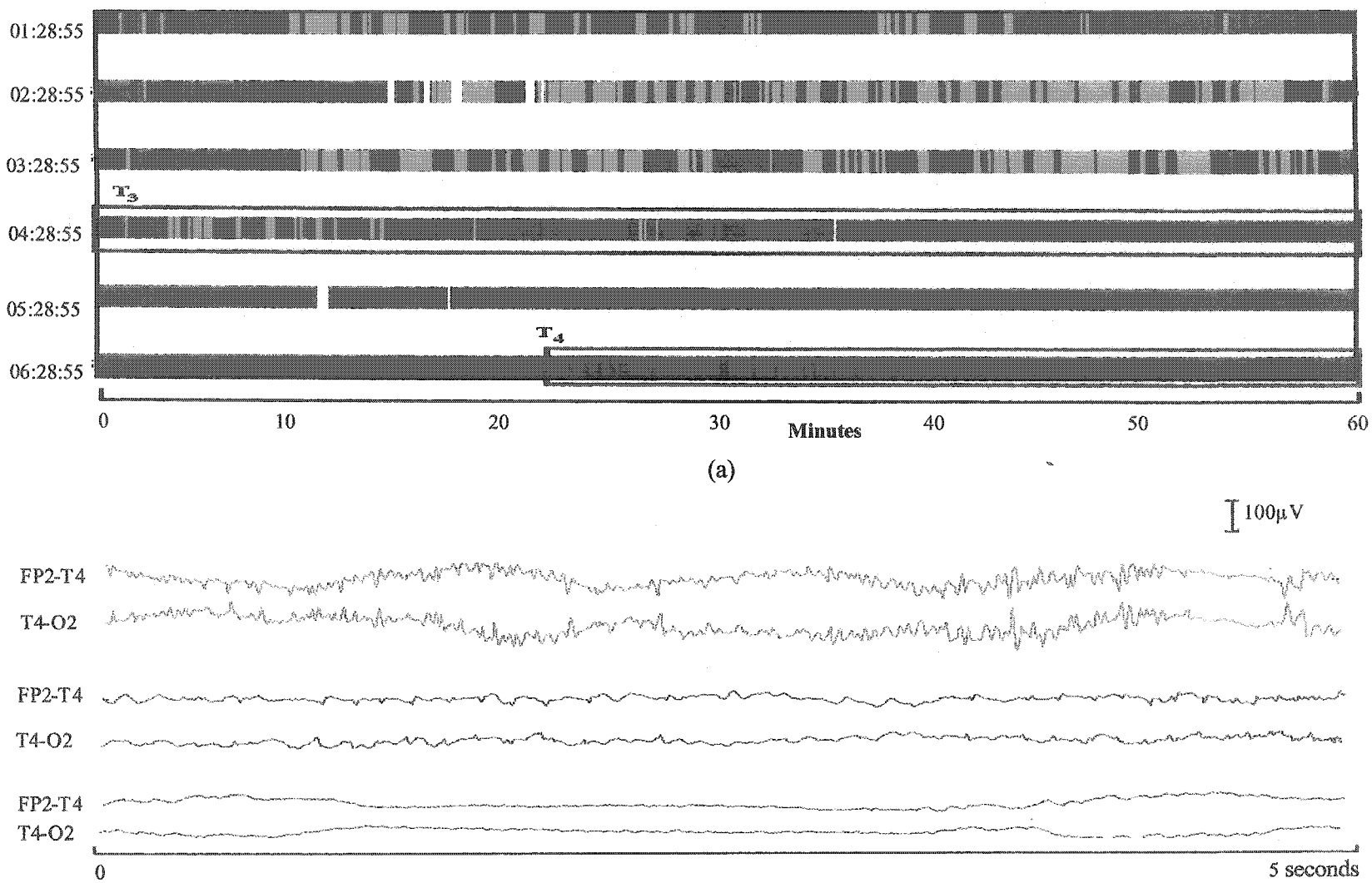


Figure 5.3 (a) Compressed results for the second six-hour cEEG recording (01h:28m:55s - 07h:28m:55s) on the right side of the brain using the method proposed in this thesis. (b) Figure shows the representative segment of each cluster.

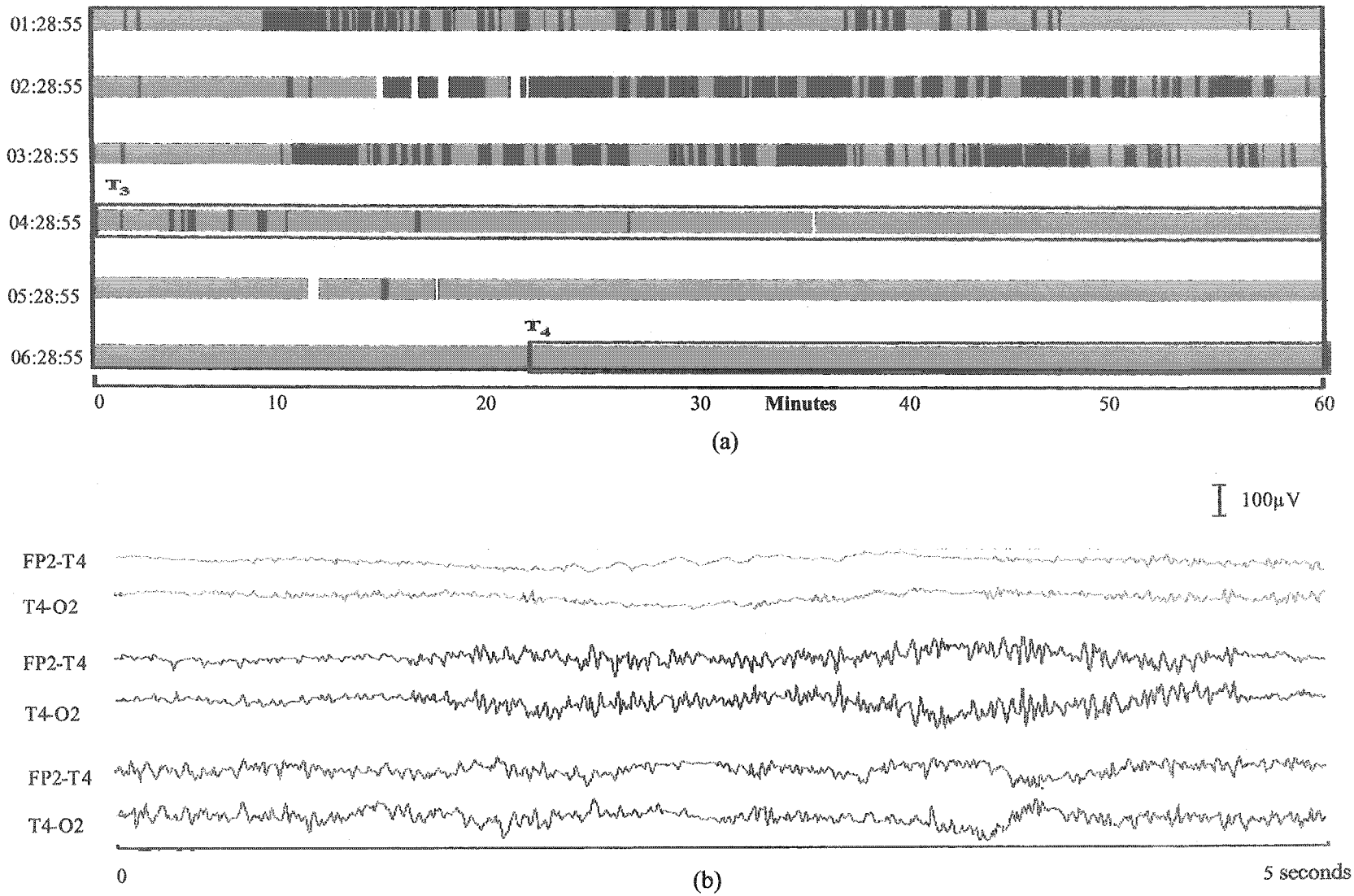


Figure 5.4 (a) Compressed results for the second six-hour cEEG recording (01h:28m:55s - 07h:28m:55s) on the right side of the brain using the method given in [1]. (b) Figure shows the representative segment of each cluster.

On comparing the compressed results in Figures 5.3 and 5.4, it is observed that the *spectral* features are able to classify the segments into three different clusters, whereas the *generic* features classify the segments mostly into two clusters represented by green and blue colors, i.e., the *spectral* features are able to detect a third pattern which is not found using the *generic* features. The onset and offset of the different activities as indicated by the compressed results based on the *spectral* features have a higher agreement with the onset and offset of the patterns in the actual cEEG recording compared to that using the *generic* features. For example, during the time frames marked T_3 and T_4, the *spectral* features as shown in Figure 5.3(a) are able to distinguish between the burst suppression represented by red color and the 1-2 Hz slow activity represented by blue color, whereas the *generic* features in Figure 5.4(a) identify only a single activity that resembles the burst suppression and is represented by green color.

5.3.3 CASE 3: Third six hours of the cEEG

We present the compressed results for the third six hours (07h:28m:55s - 13h:28m:55s) of the cEEG recording on the right side. The clinician had indicated in the EEG report that around 12:00 pm the propofol was stopped and the subject had a clinical seizure around 12:40 pm. Following the clinical seizure, the propofol was restarted.

Figure 5.5 shows the compressed results for the six hours of the cEEG recording using the proposed method and Figure 5.6 shows the results with the method given in [1]. A change in activity around 12:00 pm is indicated in Figure 5.5. The activity shown in blue color and representing a burst suppression has now changed to red color representing 1-3 Hz slow activity. At approximately 12:15 pm, the 1-3 Hz activity represented in red color is followed by the 5-6 Hz activity represented by green color. Since the clinician reported that around 12:15 pm there was a semi-rhythmic build up of 1-3 Hz slow wave activity and the activity progressed to semi-rhythmic 5-6 Hz activity, the changes at approximately 12:15pm in Figure 5.5 are in accord with the findings of the physician.

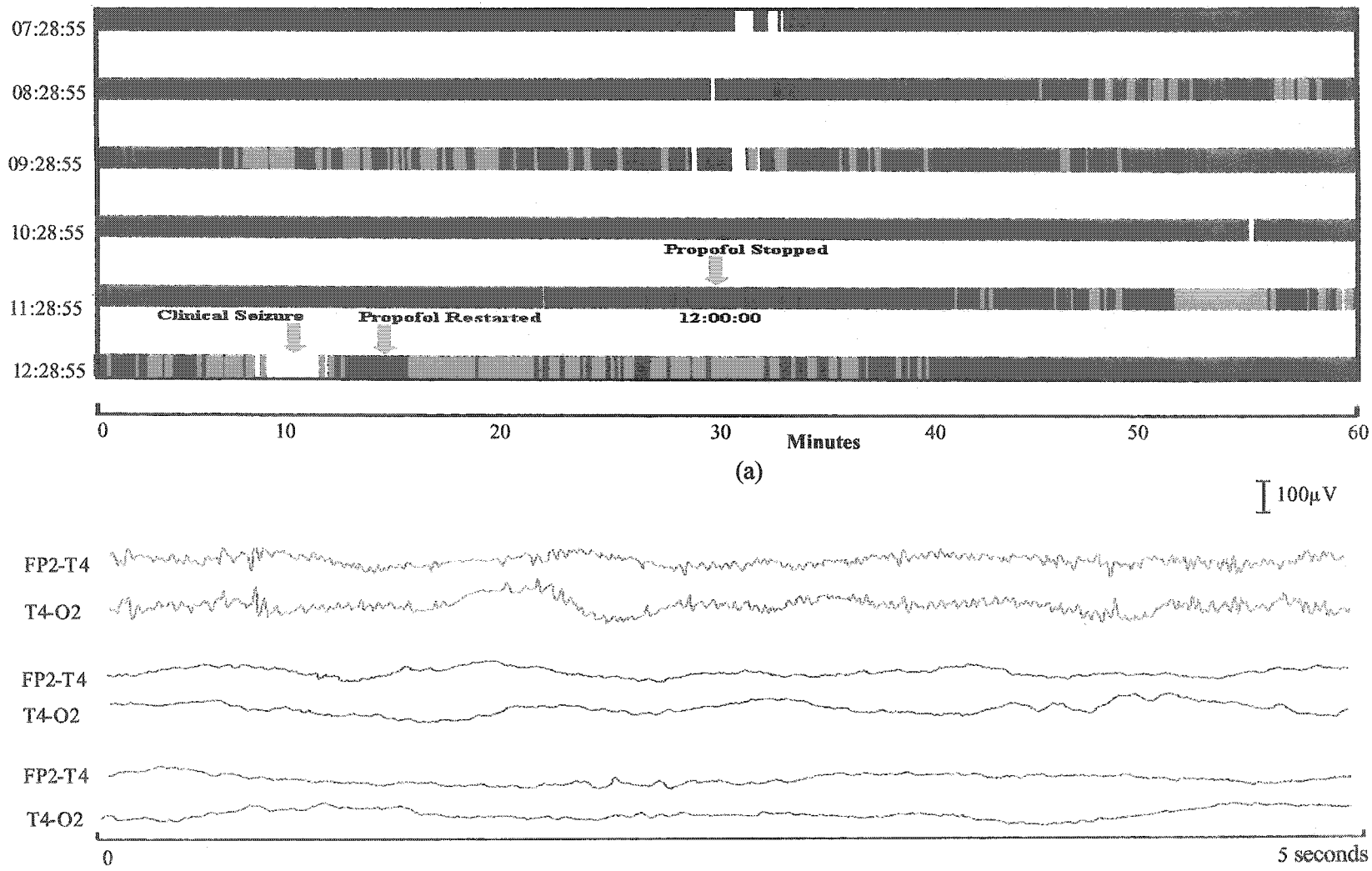


Figure 5.5 (a) Compressed results for the third six-hour block (07h:28m:55s - 13h:28m:55s) on the right side of the brain using the method proposed in this thesis. (b) Representative segment for all the clusters.

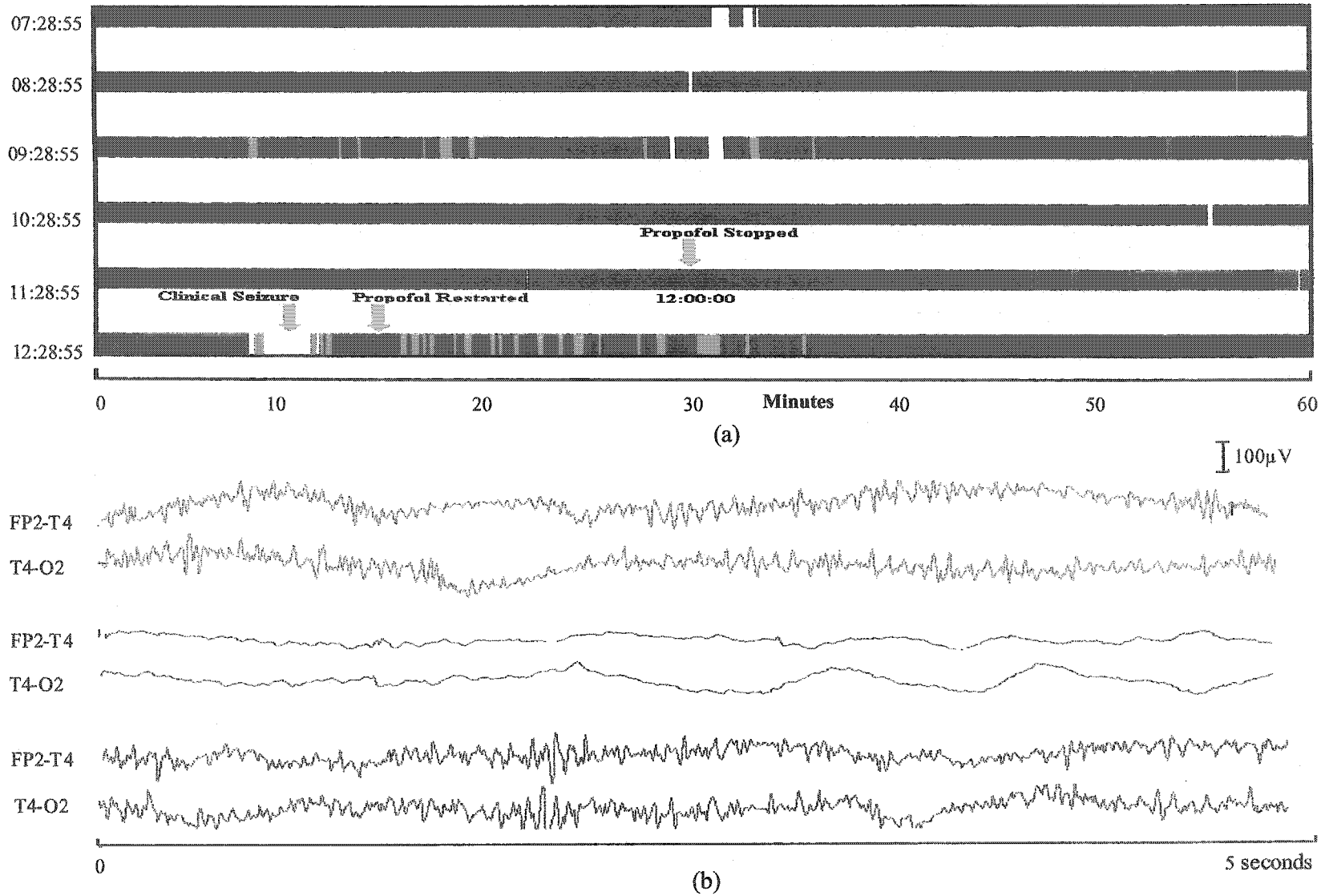


Figure 5.6 (a) Compressed results for the third six-hour block (07h:28m:55s - 13h:28m:55s) on the right side of the brain using the *generic* features as given in [1]. (b) Representative segment for all the clusters.

The results using the method given in [1], presented in Figure 5.6, show no change in the EEG activity at around 12:00 pm and it can be inferred that the *generic* features failed to identify the change in the EEG activity. The clinical seizure is associated with the muscle movement. Since the segments with muscle activity have a high energy and we classify the segments with high energy as artifacts, the clinical seizure has been classified as an artifact by the compression method. Figures 5.5 and 5.6 shows an artifact around 12:40 pm representing a clinical seizure as expected.

5.4 SUMMARY

For the given eighteen-hour cEEG recording, the proposed method for the compression of the cEEG using the *spectral* features yielded a better classification of the segments compared to that given by the *generic* features used in [1]. The compressed results with the *spectral* features parallel the visual classification by the clinician. Hence, on the basis of our results with the given eighteen-hour cEEG recording, it can be concluded that the *spectral* features may provide an improved bird's eye view of the cEEG activity to assist the reviewer during the visual cEEG analysis compared to that using the *generic* features.

Chapter 6

SUMMARY AND FUTURE WORK

This chapter gives a summary of the research contributions reported in this thesis. Some directions for future work are also pointed out.

6.1 Summary

Electroencephalogram (EEG) is the recording of electrical potentials generated by the brain, which can provide a view of the complex cerebral metabolism. EEG is normally used for epilepsy monitoring by detecting transient events like spikes and seizures. Further, the background EEG can provide significant information about the state of the brain prior to clinical manifestations. This allows time for corrective action to be taken before irreversible damage occurs to the brain. The continuous long-term EEG (cEEG) monitoring generates extensive data, which requires an enormous amount of time for the neurologist to analyze. In order to facilitate the analysis of the cEEG recordings and the proper detection of ensuing abnormalities of the brain, automatic analysis techniques are being developed. These are aimed at simplifying the cEEG data into compressed graphical formats to supplement the analysis. Such techniques can help the non-EEG specialists to identify possible evolving structural abnormalities.

Various techniques for compressed EEG have been proposed in the literature, which

generally require training and experience for proper interpretation of the compressed data. Recently, Agarwal *et al.* [1] presented a method of automated cEEG analysis, which relies on the observation that the background activity in cEEG usually consists of different patterns that are recurrent. The compressed display includes the representative samples of each pattern type, presented in the traditional EEG display format, along with a graph showing temporal evolution of the various patterns. As a result, minimal training is required for identifying the relative changes in the cEEG.

In this thesis, we have proposed a method for the compression of the cEEG, which is similar to the method of Agarwal *et al.* [1]. Since the spectral content is inherently used by the EEGer in the manual assessment of the background EEG, we have proposed a set of features based on the spectral content of the EEG, termed *spectral* features, to parameterize the EEG segments instead of the *generic* features consisting of the amplitude, frequency-weighted energy, and dominant rhythm used in [1]. We have proposed four classification *Methods* I, II, III, and IV to classify the segments that are parameterized using the *spectral* features. These methods can be summarized as follows: *Method* I is similar to the classification scheme used in [1], but uses the *spectral* features instead of the *generic* features. In *Method* II, we classify the segments of the EEG based on the relative powers in the different frequency bands. Since the absolute power in the delta band dominates the power in all the other bands, in *Method* III we initially separate the segments with high absolute power in the delta band and then, classify the remaining segments using *Method* II. *Method* IV is similar to *Method* III except that for the remaining segments the power in the *delta* band is not used.

The performance of the *k-means* clustering algorithm depends on the initial seeds used to initialize the algorithm. The method used in [1], termed *temporal* technique can miss the patterns that do not recur frequently or occur for short durations like the occurrence of seizures during epilepsy monitoring. To overcome this limitation, we have proposed a new more generalized method based on the idea of histogram, termed *histogram* technique.

To assess the performance of the method given in [1] and the proposed classification methods, we have used eight full-night sleep EEG recordings. We compare the patterns identified by the computer-based methods and the manual classification on an epoch-to-epoch basis. For the purpose of comparison, we have defined two matrices, namely, the *epoch cluster-sleep stage* and the *agreement* matrix.

The following observations can be drawn from the results presented in Chapter 4:

- For the eight full-night sleep cEEG recordings under consideration, the average overall agreement between the various patterns identified using the computer-based and manual classifications have shown that *Method* II yields results better than *Methods* I, III, and IV, as well as the original method in [1], irrespective of the method used for the selection of the initial seeds required for the k-means clustering algorithm. With the initial seeds selected using the histogram technique, an improvement of almost 6% was observed with the proposed method compared to the method given in [1]. Thus, it can be concluded that the *spectral* features used in the proposed method provide a better classification of the segments compared to the *generic* features used in [1].

- Classification *Method* II does not require the scaling of the *spectral* features as needed with the *generic* features in [1].

- For the various classification methods, the average overall agreement between the computer-based and manual classifications with the initial seeds selected using the proposed *histogram* technique has shown an improvement upto 1% compared to those selected using the *temporal* technique given in [1].

In Chapter 5, we have demonstrated the application of the compressed cEEG in the NICU. The compressed results for an eighteen-hour cEEG recording of a patient in *status epilepticus* have provided the information about the EEG activity to be in accordance with the visual findings reported by the physician. Further, for the given NICU recording, the compressed

results have shown that the proposed method could identify certain changes in the recording that were not identified with the previous method given in [1].

6.2 Future Work

An important aspect of the compression method presented in this thesis is the classification of the cEEG segments. Our results with the sleep EEG have shown that the *spectral* features provide an average agreement of approximately 71% between the computer-based and manual classifications. Since the manual classification is based on the well accepted R&K sleep classification rules [9], the clusters formed with the classification method can be modified by incorporating decision trees, which can automatically label each cluster with a relevant sleep stage [48, 52], i.e., a completely automated sleep staging algorithm can be developed. Also, the method can be developed further to match the patterns associated with the right and the left side of the brain, which could assist the reviewer in judging the symmetries between the left side and the right side using the compressed results.

The *histogram* technique calculates bins, which are adapted to the data set under consideration. Decision rules can be used to merge bins with similar features. Since the number of bins is adapted to the data set, the bins that remain after the merging process can give us an idea of the different types of patterns present in the data set.

The *k-means* clustering algorithm performs a sharp classification, i.e., each data-point is assigned to one of the K clusters, whereas the fuzzy-C means clustering algorithm [19] assigns each data point to several clusters at the same time with different degrees of association. Since the segments of the cEEG can have overlapping properties, the use of fuzzy-C means clustering algorithm in the classification method used by Agarwal *et al.* [1] may improve the performance of the method and can be studied in future.

Appendix A

TEAGER'S NON LINEAR ENERGY OPERATOR

The energy of a sinusoidal signal is dependent on the frequency and the amplitude of the sinusoid. Teager [38] gave a measure of energy, which considers both the frequency and amplitude of the sinusoidal signal. To understand the concepts involved in the algorithm given by Teager in [38], we consider the example of a simple harmonic motion.

SIMPLE HARMONIC MOTION

According to Newton's second law of motion, the equation representing the motion of a mass m suspended from a spring with force constant k is given by

$$\frac{d^2x}{dt^2} + \frac{k}{m}x = 0 \tag{A.1}$$

The solution to the above equation is

$$x(t) = A\cos(\omega t + \Theta) \tag{A.2}$$

where A and ω are the amplitude and frequency of the oscillation, respectively.

The total energy of the above system is given by

$$E = \frac{1}{2}\left(kx^2 + m\left(\frac{dx}{dt}\right)^2\right) \tag{A.3}$$

Substituting (A.2) in (A.3), we obtain

$$E = \frac{1}{2}m\omega^2 A^2$$

Therefore,

$$E \,\alpha\, \omega^2 A^2 \tag{A.4}$$

TEAGER'S ALGORITHM

Consider a signal with samples $x(n)$, such that

$$x(n) = A\cos(\omega n + \Theta) \tag{A.5}$$

where ω is the digital frequency in radians/sec and Θ phase.

Consider three consecutive samples of the signal

$$x(n-1) = A\cos(\omega(n-1) + \Theta)$$
$$x(n) = A\cos(\omega n + \Theta)$$
$$x(n+1) = A\cos(\omega(n+1) + \Theta)$$

Using the trigonometric property, $\cos(\alpha+\beta)\cos(\alpha-\beta) = \frac{1}{2}[\cos(2\alpha)+\cos(2\beta)]$, it can be shown that

$$\begin{aligned} x(n+1)x(n-1) &= \tfrac{A^2}{2}[\cos(2(\omega n+\Theta))+\cos(2\omega)] \\ &= A^2\cos^2(\omega n+\Theta) - A^2\sin^2(\omega) \\ &= x^2(n) - A^2\sin^2(\omega) \end{aligned}$$

The above equation can be written as

$$A^2\sin^2(\omega) = x^2(n) - x(n+1)x(n-1) \tag{A.6}$$

For small values of ω, approximating $\sin(\omega) \cong \omega$ gives

$$A^2\omega^2 = x^2(n) - x(n+1)x(n-1) \tag{A.7}$$

The above expression has unique solution for $\omega \leq \frac{\Pi}{2}$.

Comparing (A.7) and (A.4), it can be shown that (A.7) is the estimate of energy of the sinusoid. Based on (A.7), Teager described the non linear energy operator (NLEO) Ψ as

$$\Psi[x(n)] = x^2(n) - x(n-1)x(n+1) \tag{A.8}$$

The above equation gives the estimate of the energy of the signal based on its amplitude and frequency. Therefore, the output of the equation (A.8) is termed as *frequency weighted energy* (FWE).

In case of a multi-tone signal [20, 38], the output of the NLEO is given by

$$\Psi\left[\sum_{i=1}^{R} A_i\cos(\omega_{in}+\Theta)\right] = \underbrace{\sum_{i=1}^{R} A_i^2\sin^2\omega_i}_{DC} \quad \underbrace{+ f[\omega_i \pm \omega_j]}_{time\ varying} \tag{A.9}$$

$$i = 1, 2...n,\ j \neq i$$

It is to be noted that the above output of the NLEO in (A.9) consists of a DC part representing the FWE and a time varying part corresponding to the cross terms. Taking the time average of (A.9) yields

$$E\left[\Psi\left[\sum_{i=1}^{R} A_i \cos(\omega_{in} + \Theta)\right]\right] = \sum_{i=1}^{R} A_i^2 \sin^2 \omega_i \tag{A.10}$$

If the multi-tone input signal contains a zero-mean additive white Gaussian noise (AWGN), then (A.10) contains an additional noise term as shown

$$E\left[\Psi\left[\sum_{i=1}^{R} A_i \cos(\omega_{in} + \Theta) + w(n)\right]\right] = \sum_{i=1}^{R} A_i^2 \sin^2 \omega_i + \sigma_w^2 \tag{A.11}$$

where $w(n)$ is a AWGN with variance σ_w^2. Since the above equation contains an additional noise term, to avoid erroneous estimation of the energy of the signal using NLEO, a high signal to noise ratio is needed. A more generalized NLEO that is robust to noise is presented by Plotkin and Swamy [53, 54]

$$\Psi[x(n)] = x(n-g)x(n-p) - x(n-q)x(n-s) \qquad g+p = q+s \tag{A.12}$$

Using the above NLEO, the time average of the output of the NLEO for a multi-tone input signal containing a AWGN $w(n)$ is given by [20]

$$\begin{aligned} &E\left[\Psi\left[\Sigma_{i=1}^{R} A_i \cos(\omega_{in} + \Theta) + w(n)\right]\right] \\ &= \sum_{i=1}^{R} A_i^2 \sin\omega_i\left(\tfrac{g-p+q-s}{2}\right) \sin\omega_i\left(\tfrac{q-s-g+p}{2}\right) + \left\{\begin{array}{ll} 0 & g \neq p, q \neq s \\ \sigma_w^2 & g = p, q \neq s \\ \sigma_w^2 & g \neq p, q = s \\ 2\sigma_w^2 & g = p, q = s \end{array}\right\} \end{aligned} \tag{A.13}$$

For $g = 1$, $p = 2$, $q = 0$, $s = 3$, (A.12) becomes

$$\Psi\left[x(n)\right] = x(n-1)x(n-2) - x(n)x(n-3) \tag{A.14}$$

Taking the time average of the output of NLEO in (A.14), it can be shown that [20]

$$E\left[\Psi\left[\sum_{i=1}^{R} A_i \cos(\omega_{in} + \Theta) + w(n)\right]\right] = \sum_{i=1}^{R} A_i^2 \sin^2 \omega_i$$

It is to be noted that the above equation is independent of the noise, and therefore is more robust.

The NLEO output can be used as a measure of the energy of a given signal and is an efficient tool for detecting the instantaneous changes in frequency-dependent energy. For the EEG signal, the frequencies of interest $(0 - 30\,Hz)$ are less than one-fourth of the sampling rate $128\,Hz$, so the output of NLEO as defined in (A.14) can be considered as a measure of the spectral content of the signal.

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