12-1983

Automated Pattern Recognition of EEG Epileptic Waves

Toshiteru Homma
Clemson University, homma@yamagata1.org

12-1983

Automated Pattern Recognition of EEG Epileptic Waves

Toshiteru Homma
Clemson University

December 13, 1983

To the Graduate School:

Herewith is submitted a thesis written by Toshiteru Homma entitled "Automated Pattern Recognition of EEG Epileptic Waves." I recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Bioengineering.

[redacted]
Thesis Advisor

We have reviewed this thesis
and recommend its acceptance:

[redacted]

[redacted]

Accepted for the Graduate School:

[redacted]

AUTOMATED PATTERN RECOGNITION OF EEG EPILEPTIC WAVES

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Master of Science
Bioengineering

---

by

Toshiteru Homma

December 1983

ABSTRACT

This project developed an automated EEG analysis system for detecting epileptic waves, in particular, spikes and sharp waves (SSWs), in the electroencephalograph (EEG) of epileptic patients.

The EEG data used in this project were obtained from an epileptic patient and scored by an electroencephalographer. They were one-channel depth recordings of some 1 cm deep in the temporal lobe and had a total period of 17.5 minutes.

The system's desired features were real-time operation, microcomputer applicability, ability to reject artifacts, and self-adjustments to intra- and inter-individual EEG variances. Also, it was expected to give some quantitative and objective way of describing and evaluating the epileptic waves.

The system applied a pattern recognition scheme, where the pattern recognition procedures of preprocessing, segmentation, parameterization, and classification were established on the basis of the reviews of traditional and automated EEG analyses.

In the preprocessing procedure, the digitized EEG data were filtered by a simple low-pass filter. In the segmentation procedure, the preprocessed data were further filtered by another simple low-pass filter, and segmented into half-wave segments at each turning point. In the parameterization procedure, two consecutive half-waves of the preprocessed data constituted a wave which brought forth wave parameters, and then the parameters of 18 waves around each wave

(core-wave) were incorporated into an event. Two parameterization methods were tested: in Method A, the wave parameters were an amplitude, two slopes at the extremum of the wave and a duration between the current and the next extremum; in Method T, the wave parameter was a template-matching value where three measures of mean absolute error, mean square error, and correlation coefficient were tested. In the classification procedure, the data consisting of the events were classified by a classifier consisting of classification functions. The stepwise linear discriminant analysis program (BMDP7M) used a set of supervised training data, which was labeled according to the EEG scores of the electroencephalographer, to (1) select a subset of parameters in an event statistically, and (2) calculate the coefficients of Bayes linear classification functions. Two types of canonical classification functions with absolute measure and with square measure were also tested in an example. Three PRE (proportionate reduction in error) measures were used to evaluate the classification results.

Experiments were performed using the Clemson University IBM370/3033 computer system to verify the feasibility of the proposed system and to test its performance. All programs were written in FORTRAN.

The BMDP7M program reasonably selected parameters in and around the core-wave. An overall significance level of 5% provided a means of stopping the stepwise parameter selection at a proper step.

Partial results of classification are as follows. A Bayes classifier in Method A, which included 14 parameters, classified 76 SSW out of 80 correctly, and misclassified 40 background events out of 12,589 as SSW and 1 artifact out of 3 as SSW. The Bayes classifiers with mean absolute error and with mean square error in Method T performed slightly inferior to those in Method A. As an example, a Bayes classifier in Method T with mean absolute error, which included 24 parameters, correctly classified 73 SSW out of 80 and all 3 artifacts, and misclassified 50 background events as SSW. The Bayes classifiers with correlation coefficient in Method T were not successful. The canonical classifiers with 2 or 3 canonical variables were nearly as successful as the classifiers in Method A. As an example, a canonical classifier with absolute measure correctly classified 75 SSW out of 80 and 1 artifacts out of 3, and misclassified 63 background events as SSW. Method A seemed to be more advantageous than Method T in performance and in computation except in rejecting artifacts.

Results showed that classifiers derived from 72 sec. of training data which contained 9 SSW could maintain good performance using all the data. This indicates a good potential of the system's self-adjustability to intra-individual EEG variance. Providing a training data set for each patient should account for inter-individual EEG variance.

The system was consistent in morphologically detecting the waveform(s) labeled in the supervised training data for BMDP7M. It was found that the background events misclassified as SSW were very similar in morphology to the SSW in the training data. The system seemed to contribute to quantitative and objective description and evaluation of SSW. As a prospect, standardization of parameters was indicated as improving performance and establishing standard criteria of SSW.

The FORTRAN programs were converted to an assembly program for a microcomputer with Intel8086 and 8087, and it was found that the system can be real-time operating on this microcomputer with a help of a host computer to calculate coefficients of a classifier.

ACKNOWLEDGEMENTS

I would like to express my sincere thanks to all who have helped me keep on going and finish this thesis.

Dr. Edward M. O'Brien, my major advisor, has consistently advised me and persistently supported the project. Throughout the number of meetings with me, he has never failed to encourage me. Dr. Fertac H. Bilge and Dr. John N. Gowdy in the thesis committee have reviewed the thesis and given valuable comments and suggestions. Dr. Dennis B. Smith and Mr. John S. Henke in the Veterans Administration Hospital, Augusta, Georgia, have initially introduced to me the idea of this project and sent me the EEG data in the hospital. The communication with them has greatly benefited the project. Dr. Manohar G. Bijlani, as one of my friends, has shown me his expertise on the usage of the TSO computer terminals and on his SCRIPTI macro program, which formated this text printout. I am thankful to the staff in the Clemson University Computer Center, who have friendly given me useful information and good services.

Should any errors be found in this thesis, however, I am solely responsible for them. The data and the programs used may be obtained by contacting the department or the author.

Finally, I would like to say, "Thanks!", again, to all of my colleagues and friends, my parents, and my sister, without whose warm-hearted encouragements and supports I could never ever get through this work.

TABLE OF CONTENTS

Table of Contents (Cont'd.)

Table of Contents (Cont'd.)

LIST OF TABLES

List of Tables (Cont'd.)

LIST OF FIGURES

List of Figures (Cont'd.)

Page

CHAPTER 1

INTRODUCTION

The electroencephalogram (EEG) is a record of brain electrical activity from electrodes placed usually on the scalp or occasionally under the scalp. Depending on whether the activity occurs with or without some external stimulus, the EEG is classified into one of the two types, the evoked EEG or the spontaneous EEG, respectively. This research is mainly concerned with the spontaneous EEG.

Historically reviewed, the electrical activity of the brain was first observed in 1874, by Caton, an Englishman, who used rabbits and monkeys. However, it was not until 1924, half a century later, when a German psychiatrist, Hans Berger, for the first time, recorded the human electrical activity from electrodes on the scalp (Berger 1929). He discovered the correlation between the electrical activity of the cortex and psychic functions (Gibbs & Gibbs 1951). Although there was skepticism concerning the significance of the EEG, the EEG measurement has now become one of the most indispensable tools in clinical and research environments for making diagnosis or understanding the functions of the brain.

The traditional EEG analysis is visual inspection of strip chart recording by electroencephalographers, who are well-trained in finding clinically significant information in EEG. It requires a lot of labor and off-line (non-real time) processing. In addition, the analysis criteria are generally based on the experience of electroencephalographers, and are very qualitative.

Rapid developments of analog and digital data processors in recent years have made automated EEG analysis by computer systems within reach. As galvanometers contributed to the pioneering research, and elaborate electrodes and electronic amplifiers did to the clinical applications, the data processors will have innovative effects on the research and clinical aspects of the EEG. The data processors are expected to achieve the automated EEG analyses in order to (1) reduce, substitute, or improve the work of electroencephalographers, (2) accomplish on-line processing, (3) give quantitative or objective criteria to various types of EEG activities corresponding to their clinical significance.

There are, however, some obstacles hindering the automation. The main difficulty for computers to imitate electroencephalographers arises from the lack of quantitative and logical descriptions of specific EEG activities because computers deal with numbers and logic. It may be easy to make some decision making system with a computer, but the decision should correspond to some clinically significant activities. Consideration of intra- and inter-individual variation, or rejection of various kinds of artifacts are other examples difficult to be dealt with by computer analysis, whereas these are easier tasks for electroencephalographers.

Although there has not been a single complete method generally applicable to all occasions, some methods of limited success have been reported. Excellent reviews about a number of attempts for automated analysis are presented in the papers by Barlow (1979) and Gevins (1980).

One of the approaches to the automated EEG analysis has arisen from pattern recognition. A number of pattern recognition algorithms have been proposed to overcome the difficulties and to accomplish work equivalent to electroencephalographers'.

The objective of this project is, along the course of pattern recognition, to find a suitable method for a system of detecting certain waveforms of EEG, in particular, spikes and sharp waves(SSW). SSW[1] is a major type of interictal epileptiform transients. These epileptiform transients are the most characteristic interictal EEG features of epileptogenic disorders (Frost 1979), and consist essentially of SSW (Gotman 1980).

The features of the implemented system are desired to be

(1) real-time operating,

(2) microcomputer applicable,

(3) able to reject artifacts,

(4) free from adjusting to intra- and inter-individual variances,

(5) contributing to quantitative description of epileptic waves.

The pattern recognition procedure can be divided into the following series of procedures:

(1) preprocessing, whereby the data is prepared for computer analysis;

(2) segmentation, whereby the data is segmented;

(3) parameterization, whereby the data is parameterized;

(4) classification, whereby the data is classified so that the desired waveforms are detected.

---

1. SSW may refer to a single wave, waves, a type of waves, or a group of waves. Which one of the objects the word SSW in the text means will be evident from the context. SSWs may be used to imply the noun is plural.

Based on these sequential procedures, the following methods have been designed to achieve the objective of this project, realizing the desired features of the system. Turning points (or peaks) are used for segmentation. Two methods are tested in parameterization: a set of amplitude, slopes, and duration is used in one method, and a set of template matching values in the other method. The classifier for the detection of epileptic transient waves is derived from a stepwise linear discriminant analysis (SLDA) program during a supervised training period, which allows the system to adjust to the patient's particular waveforms. The discrimination of artifacts is also tried. Although the algorithms have been programmed in FORTRAN and tested on the Clemson University IBM370/3033 computer, the real-time microcomputer application has been taken into account in the choice of algorithms. All the algorithms are free from manual setting of thresholds or coefficients of parameters. Providing a supervised training data for the discriminant analysis is available, the classifier can be free from adjusting to inter-individual variance. It is possible to avoid adjusting to intra-individual variance by standardizing the parameters used for classifying the epileptic waves and/or adding a self-learning ability to the classifier. However, the standardization of parameters and the development of the self-learning classifier were not investigated in this project.

The main structure of this thesis follows. Chapter 2 provides for some background information of EEG, the traditional EEG reporting, and the EEG of epileptics. Chapter 3 reviews the relative literature for automated EEG analysis, focusing on the procedures of pattern recognition. Chapter 4 shows the implemented system's analysis procedures. Chapter 5 describes experimental design and results. Chapter 6 summarizes and discusses the results and the implemented system's significance, and also demonstrates the prospects for improvements and applications of the system. Conclusion follows in Chapter 7. Appendices contain lists of programs, mathematical expressions of the discriminant analysis program, output samples, etc.

CHAPTER 2

EEG AND ITS TRADITIONAL REPORTING

This chapter briefly reviews the EEG as neurophysiological phenomena, the characteristics and significance of the EEG, the traditional EEG reporting, and the EEG of epileptics.

EEG Characteristics

Answering "what is the origin of the EEG?", Thatcher and John (1977, pp. 1-41) made the following summary:

> The primary contribution to EEG comes from summated synaptic potentials arising on the dendrites and soma of neurons. The other contributions come from after potentials associated with axon spikes and possible neural intrinsic oscillations. In addition, the glia cells contribute to DC steady potentials, and the extracellular space[1] passes the current generated by the activation of synaptic ensembles. Also the extracellular medium shows (1) an electrical characteristic of a passive low-pass filter for transient waves and (2) a characteristic of nonhomogeneous medium for slow waves. As a consequence of the point (2), some nonlinear propagation of electrical signals will occur through the medium.

Adey (1973) pointed out the information handling in cerebral neurons includes not only fiber conduction and synaptic activation, but also dendrodendric conduction, neuronal-neuroglial interactions across the intercellular spaces, and the sensing of weak stimuli such as weak electric (and perhaps magnetic) fields and minute amount of chemical substances (drugs, hormones and neurohumors).

---

1. It is occupied by branching mucopolysaccharides and glycosaccharides.

Gevins et al.(1975a) suggested that the electrical potentials of EEG are generated by pyramidal cells in the cerebral cortex, which are triggered by rhythmic discharges from thalamic nuclei. They also mentioned that as the electrical potentials are conducted through the cerebrospinal fluid, the skull, and the scalp, they are diffused and attenuated. Then, the scalp activity can be considered as the spatial average of the cortical activity over a limited area (see Pfurtscheller and Cooper 1975).

As seen in Fig.2.1, the cerebral cortex region is a densely packed assembly of neural elements (Kooi 1971, p. 40), and has six distinct layers. Each cortical neuron is connected to approximately 600 other neurons, conservatively speaking, most of which are in close proximity of the cell, and the density of cortical synapses is estimated to be between 7,000 and 13,000 synapses per neuron (Cragg 1967, see Thatcher and John 1977, p.41). It is then indicated that the information processing in the brain is largely statistical in nature (Thatcher and John 1977, pp. 41-52).

At this point, it is obvious that interpreting the EEG is not an easy task. Because (1) there are a multiple of generating sources of the EEG probably interacting with each other, (2) the true physiological information has a statistical nature itself, and (3) it has been nonlinearly diffused and attenuated through the transmission process.

Furthermore, the subject's physical and mental conditions also affect the EEG. Gibbs and Gibbs (1951, p.78) summarized these conditions as follows:

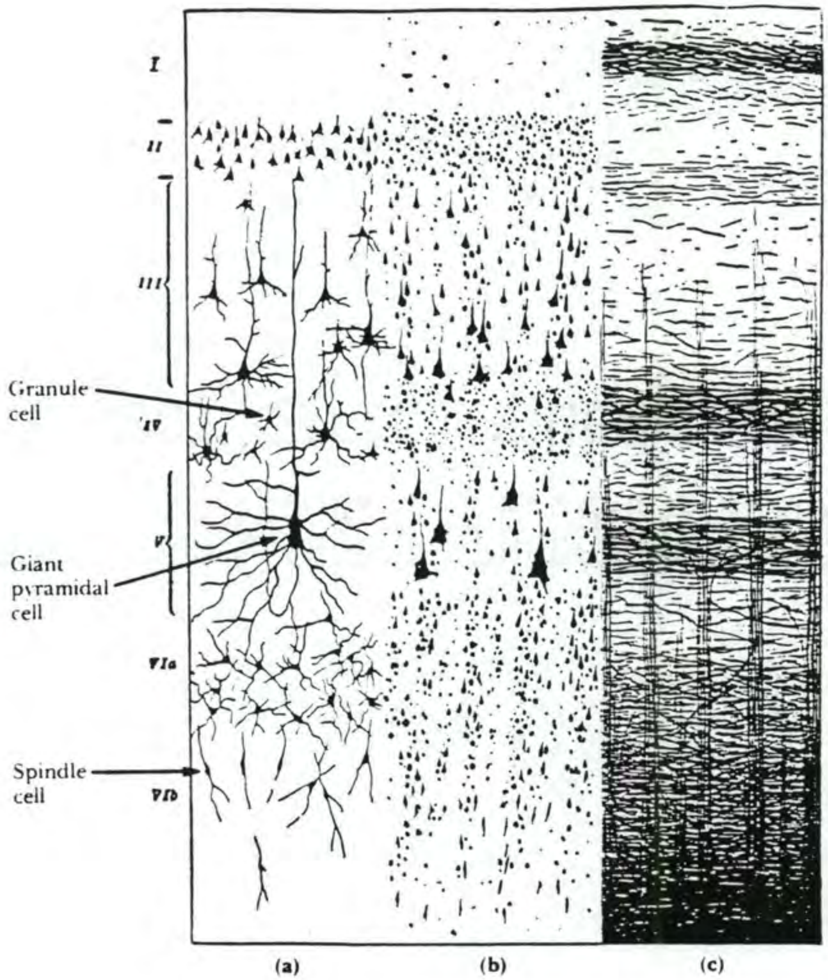


Figure 2.1 Structure of the Cerebral Cortex. Results obtained using different specific histological stains specific for cell bodies, dendritic and axonal processes, and myelin sheath are shown in (a) Golgi stain, (b) Nissl cellular stain, and (c) myelin sheath stain. The six layers of the cortex area are also demonstrated: I=molecular layer, II=external granular layer, III=external pyramidal layer, IV=internal granular layer, V=large or giant pyramidal layer (ganglionic layer), VI=fusiform layer. (Copied from Webster 1978, p.194.)

(1) brain metabolism,

(2) age,

(3) the level of consciousness,

(4) the clinical symptomatology of epilepsy and related brain disorder,

(5) the pharmacological action of stimulants, sedatives, and anti-epileptic substances.

Because of these and possibly some other variables, Gevins(1979) suggested that especially tight experimental designs are necessary. In the paper, he proposed the methodological criteria on neurophysiologic basis, sample of population, experimental design, recording conditions, data selection, and data standardization.

In addition, there are instrument related factors affecting the EEG recording. The recorded EEG differs depending on the type, sites, and arrangement of electrodes used.

The types of electrodes commonly used are scalp, sphenoidal, nasopharyngeal, electrocorticographic, and intracerebral electrodes. Each of these is developed for a specific type of recording. The scalp recording is non-invasive and the most popular. The sphenoidal and nasopharyngeal electrode recordings are useful for investigating temporal lobe epilepsy. The electrocorticographic recording (electrocorticogram: ECoG) is directly from the surface of the cortex, and the intracerebral recording, also called depth recording, is from the depth of the cortex. The latter two recordings are principally for surgical treatments and need a very careful setting and a team of experienced staff. In the case of patients with intractable epilepsy being considered for surgical intervention, these recordings are of use (Wyler and Ward 1981).

The scalp electrode placed a few centimeter apart from the others does not add useful EEG information, but the electrocortical or intracerebral electrode placed even a few millimeter apart from the others can show a significant difference.

Either a monopolar (referential) or a bipolar arrangement of electrodes combination is used. The monopolar recording is more popular because it gives a more comprehensible and graphic view of voltage condition (Gibbs and Gibbs 1951, p. 48), although it is more susceptible to artifacts. The common reference obtained by connecting the ears is relatively more advantageous than other references (Kooi 1971, p. 30).

Traditional EEG Reporting

In the traditional EEG reporting, the EEG reporter controls the above mentioned conditions as much as possible, and sorts the major features into the following sequence for the description of the EEG record (Cooper at al. 1969, p. 117):

(1) the most persistent rhythm,

(2) other rhythmic features,

(3) discrete features of relatively long duration,

(4) discrete features of relatively short duration,

(5) the activity remaining,

(6) artifacts.

Each of the above features is described in terms of some or all of the following parameters:

(1) amplitude,

(2) frequency or period,

(3) waveform,

(4) location or spatial distribution,

(5) incidence or temporal variability,

(6) responsiveness to stimuli.

Yeager (1972) summarized the traditional method of analysis and interpretation of human EEG records in a four-step procedure:

(1) initial record scan, noting electrode montage (arrangement), time and amplification scales, and the age and condition of the subject;

(2) the secondary record scan, closely examining wave patterns characteristic of the dominant background, and noting the presence of transients or paroxysmal activity;

(3) tertiary scan, determining the causes of variation from area to area and over time;

(4) categorical summary of all features of the tracing that may be relevant to interpretation.

Interestingly and importantly electroencephalographers frequently can not conclude whether or not a spike-like waveform is abnormal if only 1 or 2 min. of record is shown to them as the sole basis of decision (Smith 1974). An attempt is then made to relate those observations to known conditions of the subject (see Gevins and Yeager 1975).

It is convenient to classify the activity into the stationary and the transient activities. The stationary activity can be grouped by the following frequency bands, which are conventionally used and relating to some symptomatic phenomena:

(1) delta band : 0.5 - 3 cycles/second,

(2) theta band : 4 - 7 cycles/second,

(3) alpha band : 8 - 13 cycles/second,

(4) beta band : 14 - 30 cycles/second.

Since the definition of the frequency here is the number of complete cycles of a rhythm in one second, it should not be confused with the frequency used in physics or electrical engineering, which is based on a sinusoidal wave. In fact, the waves of the stationary activity are commonly deviated from a sinusoidal wave. And there is a possibility that more than one activity, which have different frequency bands, are superimposed on the record.

The transient activity includes spike, sharp, vertex sharp, and lambda waves, and these waves may form a complex such as a spike and wave complex, or a poly-spike and wave complex (Storm van Leeuwen et al. 1966). The transient waves can be superimposed on the stationary waves. A spike wave is defined as a wave distinguished from background activity and having a duration of 1/12 second or less, and likewise a sharp wave as a wave distinguished from background activity, with a duration of more than 1/12 second and less than 1/5 second (Storm van Leeuwen at al. 1966). These definitions seem insufficient to practically apply without other supplemental information or experience, especially when automated analysis is to be accomplished, as mentioned by Barlow (1980).

The voltage picked up at the electrode, which is in the order of microvolts, are input to a preamplifier and then to a main amplifier. In the beginning years of the EEG research, galvanometers were used, but now, very reliable electronic amplifiers are commercially available. Usually a band-pass filter of 0.5 Hz - 70 Hz is used to eliminate DC shifts and high frequency noises. The output from the main amplifier is an input to a strip chart recorder for visual inspection. It should be noted that the DC shift and the high frequency components eliminated in the filtering may have had some significance. In fact, DC shifts relate to the subject's condition and transient waves have frequency components higher than 70 Hz. The filtering is thus mostly contributing to the adequate input for the recorder, thereby avoiding noisy or saturated output.

Although the filtering reduces DC shifts and high frequency noises, artifacts still remains on the EEG record usually. The physiological and instrumental artifacts (see Kooi 1971, Appendix II) contained in the EEG record must be distinguished.

The result of the EEG report can be significant in making diagnosis, prognosis, and treatment of various diseases or disorders[1] ; monitoring the level of sleep or depth of anesthesia; or advancing research in neurophysiology, psychophysiology, or psychopharmacology (Gevins 1975).

Abnormal EEG : Epilepsy

To make the report of the EEG consistent and objective, it is important to establish clear-cut criteria for normal and abnormal EEG. But the criteria has not been completely established in either case because of the lack of the carefully controlled subject's data, the intra-

---

1. epilepsy, cerebral tumors, and other abnormal conditions including cerebral trauma and thrombosis, developmental abnormalities, infectious diseases, and metabolic and endocrine disorders.

and inter-individual variations in the record, the lack of the systematic understanding of the diseases or disorders, etc..

Kooi (1971, p. 93) mentioned that the abnormal EEG is divided into two types depending on whether it is paroxysmal or not. Paroxysm is defined here as a series of waves, appearing and disappearing, and having a different amplitude, frequency, or form than the basic pattern. The epileptogenic type of abnormality is a part of the paroxysmal type of abnormality, and called a specific paroxysmal type. The epileptogenic type of abnormality is briefly described in the next paragraph since the detection of epileptic transients is the main objective of this project.

According to Dictionary of Epilepsy (Gastaut 1973), "epilepsy is a chronic brain disorder of various etiologies characterized by recurrent seizures due to excessive discharge of cerebral neurons, associated with a variety of clinical and laboratory manifestations." It afflicts about 1 % of the American population and about 7% suffer at least one convulsion in a lifetime (O'Leary and Goldberg 1976). There are various types of epilepsies, some of which can not be distinguished by clinical symptomatic data, but can be distinguished by electroencephalographic data, and vice versa. Because of this, Gibbs and Gibbs (1952, p. 10) suggested that the clinical data and the electroencephalographic data must supplement each other and lead to the understanding of epilepsy.

In the recording of epileptic EEG, sleep condition is generally better than wake condition mainly because of the less artifacts caused by the patients' movements and physiological activities. Also, the temporal regions are more prone to epileptogenic activity. Gevins et al.

(1975b) included, in the test heuristics of their system, that surface negative polarity for monopolar montages or location of phase reversals for bipolar montages is more likely associated with transient waves. Gotman (1980) retained, in his transient wave detection system, only spike or sharp waves which have negative peaks because these are most commonly encountered.

In addition to a normal scalp EEG recording, other EEG recordings such as depth recordings or ECoG are considered to be taken depending on the patients condition. Furthermore it is desirable to record various motor and autonomic phenomena[1] in conjunction with the EEG. These recordings are also useful for checking various artifacts in the EEG recording. In the detection of spike or sharp waves, spiky nonepileptogenic normal activities must be properly distinguished as well as backgrounds and artifacts.

Recently the magnetoencephalogram (MEG), the measurement of brain magnetic fields, on the scalp has been realized with an unshielded environment by using a superconducting quantum interference device (SQUID, S.H.E. Corporation, San Diego, Calif.) and a second derivative flux transporter (gradiometer) (Barbanera et al. 1981, and Williamson and Kaufman 1981). The MEG has just begun to reveal its values, and will have a substantial role in clinical and laboratory research, complementing the information which is not available otherwise. This information and the others such as computer tomographies may be integrated to make diagnoses or to unravel the mechanisms of the brain system.

---

1. electromyogram (EMG), electrooculogram (EOG), electrodermogram (EDG), pneumogram, plethysmogram, barogram, etc. (Gastaut and Broughton 1972, pp. 11-18).

Since this project is concerned with the interictal EEG, the significance of the interictal EEG is mentioned in the following. Interictal epileptic activity in human EEG consists essentially of spikes and sharp waves (Gotman 1980), and the morphology of interictal activity in the EEG is used as a diagnostic tool. But its relationship to the possible focus of seizure activity is still not completely known (Gotman and Gloor 1976). Angeleri et al. (1981) mentioned the pattern of spike activation during slow sleep stages fairly correspond to computerized tomography findings of focal lesions and high frequency of seizures. Ayala et al. (1973) suggested some changes of feedback systems in the cortex is relating to a possible mechanism for the generation of the interictal epileptic spike. Lieb et al. (1981) conducted a multivariate analysis to see to what characteristics of interictal and ictal EEG correlates to the surgical outcome of the patients who had anterior temporal lobectomy. They reported that the interictal and ictal EEG characteristics can independently predict surgical outcome at levels significantly better than chance, and ictal and interictal EEG data contain non-redundant information for making such prediction.

The relevant interictal EEG variables included:

(1) various types of bilaterally synchronous surface/deep spikes,

(2) diffuse background slow waves,

(3) sharp waves,

(4) the presence of multiple independent deep spike patterns.

Therefore, the detection of interictal spike waves, sharp waves and slow waves seems important to constitute satisfiable diagnosis.

CHAPTER 3

REVIEW OF AUTOMATED EEG ANALYSIS

Introduction

As described in Chapter 2, the EEG contains significant information in clinical practice and research. The aim of EEG analysis is to extract this information. In this sense, the analysis is considered signal processing. Therefore, the attempts of automated EEG analysis are to establish signal processing systems to reduce, substitute or improve the work of electroencephalographers.

This chapter reviews selected previous research concerning automated EEG analysis from the viewpoint of signal processing. Since surveying is not the objective of this chapter, the literature in the following paragraphs of this chapter are the papers selected as examples or credentials in the course of explanation.

Basic Categories of Analysis Method

The analysis methods are categorized by (1) whether the analysis is primarily in the time domain or the frequency domain, and (2) whether the analysis primarily concerns the stationary signals or the non-stationary signals (Barlow 1980). Accordingly, the four basic categories are listed as follows:

(1) time-domain, stationary signal analysis method,

(2) time-domain, non-stationary signal analysis method,

(3) frequency-domain, stationary signal analysis method,

(4) frequency-domain, non-stationary signal analysis method.

In this paper, a signal is considered stationary when its properties (e.g. mean, variance or covariance) are invariant to a shift in time (see Zetterberg 1977). A signal is non-stationary when it is not stationary. Periodical waves such as alpha or beta waves are stationary, and transient waves such as spikes or sharp waves are non-stationary, for example.

Transformation into Frequency Domain

The EEG is originally in the time domain and needs a transformation to be in the frequency domain. In certain cases, the signal characteristics are more clearly expressed when the signal is transformed into the frequency domain from the time domain. Actually one can regard this transform as a change of a viewpoint because the inverse transform can reconstruct the original data in the time domain completely, provided that the sampling theorem is not violated in the operation. Some transform algorithms have been proposed for EEG analysis: a Fourier transform (based on sine and cosine functions), a Walsh transform (based on Walsh functions), a Haar transform (based on Haar functions).

The drawbacks of these transforms are generally pointed out as follows: (1) the original data to be transformed are assumed stationary, which is not always the case in EEG, and (2) a vast number of arithmetic operations is necessary.

The first point is an indigenous fate of frequency analysis, but can be less affective by having short period segments so that during the period a pseudo-stationarity is guaranteed. Overlapping the segments helps to detect the change of stationary parameters.

The second point was remarkably improved by the introduction of the fast Fourier transform (FFT) (Cooley and Tukey 1965), which reduced the number of operations significantly. As a matter of fact, the FFT made the Fourier transform applicable to practical situations. The concept of the FFT algorithm was applied to the Walsh and the Haar transforms, thereby introducing the fast Walsh transform (FWT) and the fast Haar transform (FHT). The calculation time in FWT or FHT is much less than that in FFT because Walsh and Haar functions are much simpler than sine or cosine functions. The Walsh transform was criticized as being unsuitable for EEG analysis because it neither matches the Fourier transform, nor represents the physiological characteristics of EEG (Dumermuth 1977), but the recent paper by Larsen and Lai (1980) has demonstrated that the Walsh transform is not only much faster than the Fourier transform but also can have comparable results (in the power spectrum) to the results of the Fourier transform.

If the purpose is only to estimate the power spectrum, there is another way that calculates the autocorrelation function and transforms it into the frequency domain. This method gives more flexibility and accuracy in estimating the power spectra, but more calculations are required.

When an autoregressive or an autoregressive moving-average model is used, the power spectra is directly derived from the coefficients of the model (Gersch 1970). Unfortunately, it is not a simple calculation to evaluate the values of model coefficients.

Some of the frequency domain analysis methods have proved to be effective when dealing with stationary waves. But the drawbacks mentioned above, i.e., (1) the assumption of stationarity and (2) computational complexity, make the application awkward. This project seeks a real-time method to detect transient waves, which are non-stationary. Therefore, time-domain, non-stationary analysis methods will be emphasized in the following descriptions. However, the frequency-domain, non-stationary analysis will be also mentioned if it has some advantage in interpreting EEG, and a possibility of real-time implementation.

Multichannel Inputs

There have been a number of systems proposed for multichannel EEG analysis (e.g., Walter and Shipton 1951, Shaw and Roth 1955, Remond 1969, Gersch and Goddard 1970, Lopes da Silva et al. 1977, Lehmann 1977, Gotman et al. 1978, Giese and Bourne 1979, Sidman and Smith 1980, Romani et al. 1982). The multichannel analysis is particularly necessary to determine a possible epileptic focus, which is one of the primary goals of the automated EEG analysis (Gevins 1975a).

A method to localize the neural generators of scalp recorded evoked components in three dimension was presented by Kavanagh et al. (1976, 1978). It assumed the head is a homogeneous conducting sphere, the suspected source of surface data is simulated by a single current dipole, and the site of a dipole is located by minimizing the square error between the theoretical and empirical evoked potentials at the scalp (see Sidman and Smith 1980).

Romani et al. (1982) applied the MEG method (see the section of Abnormal EEG: Epilepsy in Chapter 2) for a tonotopic mapping in three dimension, identifying the locations of the source of the evoked magnetic fields, assuming these fields are caused by current dipoles. Applying the same method for a mapping of interictal spikes, Barth et al. (1982) localized the intracortical sources producing epileptiform discharges. The major advantages of the MEG may be summarized as (1) the MEG is completely non-invasive since the probes even do not touch the subject, (2) it gives sharper spatial localization of the cortical activities than EEG. The disadvantages may be that the instrument is expensive and large.

Although this project analyzes only a single channel EEG data, the single channel analysis system could be readily extended to a multichannel analysis system as needed.

Conventionally the 16 channel recording with the electrode locations of the International 10-20 system is standard on the scalp EEG. The number of channels is increased when necessary. Especially in ECoG recording, more electrodes are often placed. Furthermore, Gevins (1980b) recently suggested that the increase in the number of electrodes is useful in the restoration of spatial information, and had a plan to implement a scalp array of 60 electrodes. In the field of ECG research, Boineau and his team (1980) have already made a successful research using an array of 64 electrodes attached onto the dog heart.

Because of the restriction of processing time and storage capacity for a real-time microcomputer system, the required operation is expected to be as simple as possible. At the same time, however, the development of data processing algorithms and devices should be updated because it makes more complicated operation feasible in a shorter time. For example, as one of the recent developments, the high-speed data acquisition subsystem proposed by Lake (1982) can operate at acquisition rate up to 500,000 samples/sec.

Pattern Recognition Procedures

Although the objective of analysis can be as abstract as making distinction between the subject's psychic normality and abnormality, evaluating the effects of pharmacological or surgical treatments, etc.[1] , this review concentrates on describing the detection methods of certain types of EEG waveforms. Thereby, the concept of pattern recognition is appropriately introduced to describe these methods. In fact, a major part of the traditional EEG reporting is a pattern recognition done by humans (see Cox et al. 1972).

Generally the analysis procedure for pattern recognition can be divided into the following four parts:

(1) preprocessing,

(2) segmentation[2] ,

(3) parameterization,

(4) classification.

---

1. John et al. (1977) presented an approach called "neurometrics" dealing with these types of information. Kulikowski (1980) reviewed artificial intelligence methods applied to medical consultation.

2. If segmentation is not particularly designed, each data point may be considered a segment.

The following sections discuss these procedures, the evaluation of system's performance, and the artifact rejection. The evaluation and the artifact rejection are discussed because it is necessary to know how to evaluate the system's performance, and how to deal with the artifact rejection.

Preprocessing

Preprocessing converts an original EEG to an acceptable data for analysis, including amplification, analog filtering, analog to digital (A/D) conversion and digital filtering if necessary. Because the EEG on the scalp ranges from ± 1 μV to ± 500 μV, preamplifiers are usually needed, which are then connected to main amplifiers. Thousands of times amplification are needed as a total, which are easily achieved by commercial electronic amplifiers.

Miscellaneous kinds of noises can also be present and must be dealt with. Near DC voltage shifts and high frequency noises can be diminished by a band-pass analog filter which normally has its frequency range of 0.5 to 70 Hz, assuming the original EEG does not have significant frequency components out of the range. If the noise has frequency components within this range, those remain and will have to be managed in the following analysis procedures. Unfortunately, many of the artifacts, whether instrumental or physiological, remain a whole or a part after the filtering. The noise from the electric power source of 60 Hz can be efficiently eliminated by a 60 Hz analog notch filter, but with a risk of distorting the original EEG, especially the phase information.

In traditional EEG reporting, the output from the main amplifier is recorded on a strip chart recorder for a visual inspection, but in automated EEG analysis the main amplifier output is used as an input to a main analysis system. When digital processors are used for the main analysis, A/D conversion is necessary. More than 9 bits of conversion are recommended to represent an EEG signal sufficiently (Harner and Ostergren 1976, MacGillivray 1977). It is important to note that the sampling rate must be at least twice as high as the high cut-off frequency so that no aliasing might occur. In practice, since the attenuation of the band-pass filter is not perfect, the rate of more than twice the cut-off frequency is recommended because the higher the sampling rate is, the less is the probability of aliasing (see Oppenheim and Schafer 1975, p. 28). Usually the sampling rate is around 200 samples/second.

Digital filters may be implemented in the system to reduce a round-off effect in digitization or to further reduce the noises. The 60 Hz power noise may be eliminated more properly by a certain digital filter than by an analog notch filter. Among various types of digital filter implementaton, Lynn's fast digital filters (Lynn 1977) seem convenient for real-time applications.

Segmentation

In processing the data for pattern recognition, the data is segmented so that a set of parameters can be derived from each segment, transforming a serial signal into a point process (Burger 1980). The procedure is also considered as a data reduction.

Segmentation is basically divided into two types: (1) fixed and (2) adaptive segmentations.

In the fixed segmentation, the length of a segment is previously decided by researchers. The length is usually between a few seconds and a few tens of seconds (see Isaksson et al. 1981) in the detection of stationary activity, assuming the EEG is stationary during the period. Though it is simple to implement, there is an obvious defect in the assumption. The EEG is not always stationary. There will be a transient period from one stationarity to another stationarity, or there may be some transient EEG waves such as spikes or sharp waves included. In these cases, the characteristics of the segments derived from the same data can differ greatly depending on where the data is cut. For example, as shown in Fig. 3.1, the segment SB(1) contains a combined part of the segments SA(1) and SA(2), which makes the characteristics averaged, or a segment SB(2) contains only half of a spike wave, which ruins the characteristics of the spike wave. However, when the change of stationary state is very slow, fixed segmentation has led to several successful results in such cases as the sleep stage analysis (e.g. Larsen and Walter 1970). Once the stationarity is assured, frequency analysis methods are useful.

In the adaptive segmentation, the length of a segment is not fixed, but adjusted as the segmentation algorithm orders. An advantage of adaptive segmentation is that it is possible to adjust the length of a segment to include a portion which has only one pattern or a uniform characteristic. In Fig.3.1, for example, each of the segments SC(1) to SC(4) only contain one pattern evaluated visually. It can be

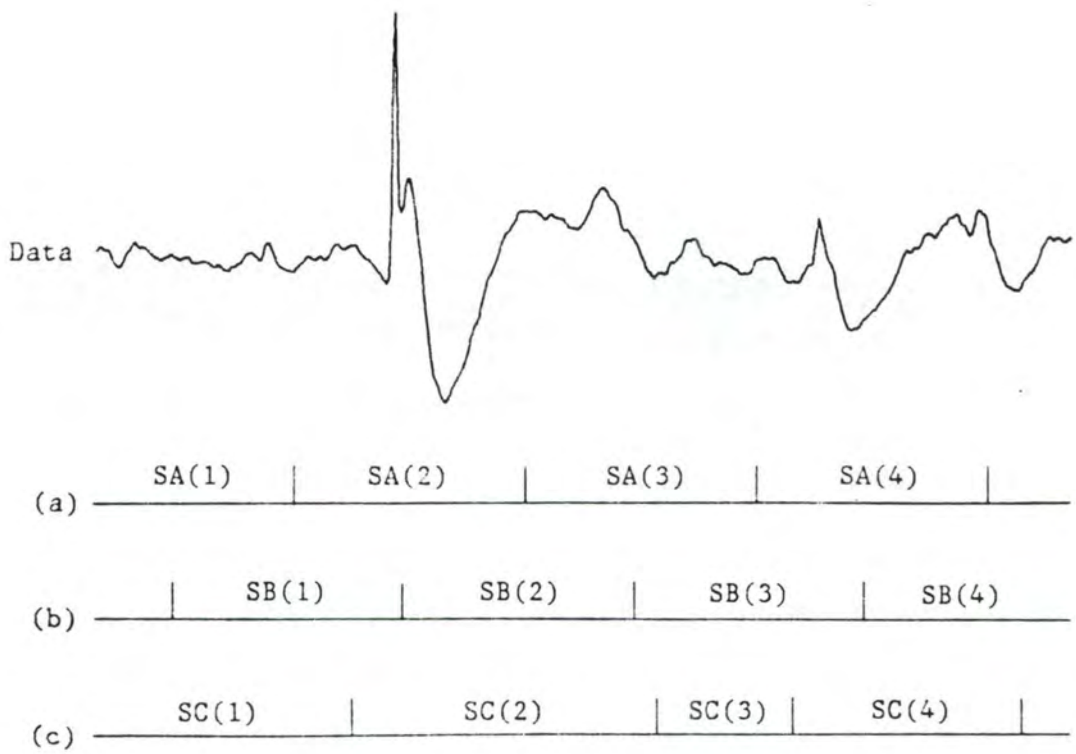


Figure 3.1 Examples of Segmentation. (a) and (b) : fixed length segmentation. (c) : possible adaptive segmentation.

especially suitable for transient wave detection. The following paragraphs of this section consider the adaptive segmentation methods.

Baseline crossing segmentation is one of the earliest adaptive segmentations offered to the EEG automated analysis. It segments the data whenever the baseline is crossed by the data, its first derivative or its second derivative (Barlow 1980), the first two of which are called zero-crossing algorithm (or period detection algorithm) and extrema algorithm (or peak detection algorithm), respectively. The baseline crossing of the second derivative has not been commonly used for segmentation. Burch (1959) stated in his review that the baseline cross establishes each period or the basic unit of information which in turn is used to gate additional information.

Because of its simple implementation, this algorithm was very suitable for real-time systems. The zero-crossing algorithm was applied to real-time systems by Legewie and Probst (1969), Carrie (1972b), Smith et al. (1975), Keane (1978), and Salb (1980), for example. There are, however, two major drawbacks in the zero-crossing algorithm: (1) when low and high frequency waves are superimposed, the algorithm tends to neglect the higher frequency components; (2) when contaminated by noises, insignificant segments appear. The first point is improved when the baseline crossing of the first or the second derivative is used because differential operation has a nature close to high-pass filtering.

A number of researchers applied extrema algorithm (or peak detection algorithm), which is the baseline crossing of the first derivative, to their analysis systems as reviewed in the following paragraphs.

Gevins et al. (1975a) used a simple low-pass digital filter at 20 Hz to eliminate the high frequency noises at the expense of distorting the original waveforms of the EEG. Fridman (1982) used a digital filter in the frequency domain to detect the peaks of a certain type of evoked potentials.

Leader et al. (1967) attempted to remove insignificant segments caused by noises, whereby introducing a concept of relative and absolute extrema (maximum and minimum). Turning points are named relative extrema. By setting up two pre-set thresholds and three conditions, the absolute extrema are derived from a series of relative extrema so as to neglect noisy fluctuations of the data.

Gotman and Gloor (1976) designed a similar way to eliminate the insignificant segments caused by noise. The data is segmented at the extrema first, and a series of segments are merged into a sequence through the algorithm which needs some logic operations and a previous set-up of two thresholds. A wave is defined by some combination of segments or sequences. Remond and Renault (1972) had proposed a similar idea.

Horowitz (1977) suggested that the use of a piecewise polynomial approximation is more advantageous than others in peak detection, and proposed a new syntactic approach to segmentation by using a piecewise linear approximation. In its practical consideration, however, three tolerance constants concerning the duration, the slope and the amplitude of the data in a segment were to be set up previously.

Burger (1980) in his comparative study of zero-crossing algorithm and extrema algorithm, demonstrated that the extrema algorithm is better adapted to the analysis of transient phenomena whereas the zero-crossing algorithm is better adapted to the analysis of background activities. The paper also showed the extrema algorithm can be faster than the zero-crossing algorithm in processing by a computer although the number of segments is usually larger in the extrema algorithm. The baseline of the both algorithms were a moving average of the data. In the extrema algorithm of the paper, the parameters needed to be previously fixed were (1) a threshold for eliminating waves of small amplitude, (2) the order of the moving average filter, and (3) the amplitude factor which relates to peak recognition. It was pointed out that the moving average filter used caused a phase shift between the signal and the baseline, and the use of a linear phase non-recursive filter proposed by Goldberg (1971) was recommended. Computationally, however, an equivalent Lynn's fast digital filter is more efficient at the expense of increase of necessary storage capacity (Lynn 1977). Malik (1980) showed an application of the Lynn's filters to a microcomputer system.

Abenstein and Tompkins (1982) presented a new data reduction algorithm for ECG arrhythmia analysis, in which the turning point algorithm (extrema algorithm) and the Amplitude-Zone-Time-Epoch-Coding algorithm (Cox et al. 1968) are incorporated. Reconstruction of data is also an important aspect of signal processing as discussed by Abenstein and Tompkins (1982).

Dumpala (1982) presented a simple peak detection algorithm based on a three-point "sliding" window, which needed amplitude, slope and duration thresholds.

Horowits (1981) attempted to incorporate a zero-crossing and a peak detection algorithm to restore both the low and high frequency components of superimposed waves. Palem (1982) also combined both algorithms. But they did not use them for adaptive segmentation.

In the system proposed by Frost (1979), an event begins when the second derivative exceeds a threshold which is calculated using a running average of the previous second derivatives. These algorithms mentioned in the above paragraphs are all oriented for real-time operation.

The paper by De Vries (1981) shows an example of hardware realization where analog filters and Schmitt triggers are used for checking the timing of spike waves.

It must be noted that the thresholds or constants manually set up in the algorithms bring some subjective decisions by researchers, thereby hampering the full automation and the versatility of the system.

An adaptive segmentation proposed by Bodenstein and Praetorious (1977) is conceptually different from the algorithms mentioned so far. An autoregressive model, which has a structure of all pole recursive filters, is fitted to a fixed-length, pseudo-stationary portion of the EEG (i.e. Wiener filtering), and when the discrepancy between the model at the beginning of the segment and the current model becomes bigger than a threshold, an epoch is made and a new model is set up. The threshold can be derived using a χ-square test.

Duquesnoy (1976) also introduced a similar segmentation method using a modified Kalman filter. These algorithms seem closer to the ideal algorithm which distinguishes the non-stationary EEG from the stationary EEG because it is important both in theory and in practice to distinguish non-stationary portions of data from stationary ones. This type of algorithms seems promising. However, the drawback is that it needs a longer computation time, which will be overcome by a development of a more efficient algorithm and/or faster processing computer.

Summarizing the adaptable segmentation algorithms mentioned above in the perspective of this project:

(1) the use of extrema is better than that of zero-crossing for the segmentation of transient EEG;

(2) the use of parametric models by Wiener or Kalman filters seems promising, but needs more improvements in the algorithms and the processing speed of the computer;

(3) the thresholds or constants manually set in the algorithms hamper the full automation and the versatility of the system.

Parameterization

A number of parameters have been utilized in the automated EEG analysis. These and other possible parameters are shown in Table 3.1. Definitions of specific parameters are different from one paper to another even if they are in a same type. The choice of parameter types depends on the objective of analysis and the preference of the analysts. One or more of the parameters may be chosen in an event. Importantly the calculation time and the number of parameters must be minimized for real-time operation whereas the detection system itself must maintain an acceptable performance.

Table 3.1 Types of Time-domain Parameters in Automated EEG Analysis.

Types of parameters	Examples
Morphological parameters	duration (period, interval) amplitude slope (first derivative) curvature (sharpness, second derivative)
Statistical parameters	moments (mean, variance, etc.) Hjorth's parameters (activity, mobility, and complexity) skewness, kurtosis, and other statistics from from chi-square-test, F-test, and Student's t-test, etc.
Template matching parameters	mean absolute error mean square error correlation coefficient Tauberian approximation
Parameters of models	Models: AR, ARMA, polynomial, etc.
Parameters from filtered values	Filters: fixed linear filters (low-,high-, and (band-pass filters; AR and ARMA filters) adjustive linear filters (Wiener or Kalman filters, etc.)

Parameters Derived in Time Domain

Morphological Parameters

Saltzberg and Burch (1971) showed that the average frequency baseline crossings of the data, its first derivative and its second derivative per unit time were proven to correspond to the second, the fourth and the sixth spectral moment, respectively. They showed the following formula stands generally:

$$(N_n)^2 \simeq \int_0^\infty \omega^{2n} P(\omega) d\omega$$

where N_n: average number of zero crossings per second of the n-th derivative, ω: angular frequency, and $P(\omega)$: normalized power spectral density.

These parameters seem suitable for a stationary EEG analysis as a simplified spectral analysis (Barlow 1980). For the non-stationary EEG analysis, however, the durations between the crossings are better parameters.

Usually the duration of a segment or consecutive two segments is used as a parameter when data is segmented by one of the baseline crossings. However, this sole parameter seems not to retain enough information to distinguish non-stationary waves from stationary waves, because there are so many background waves which have the same durations as the transient waves. It is suggestive that the definition of spike or sharp waves in traditional EEG reporting (Storm van Leeuwen et al. 1966) indicates not only the ranges of duration, but the distinguished features from background waves as well. Thus, other features than duration are sought.

Period-amplitude analysis added a peak-to-peak amplitude along with the duration to retain the characteristics of waves more precisely, as shown in Fig.3.2(a) (Legewie and Probst 1969, Smith 1975 and Harner and Ostergren 1974).

Carrie (1972a) introduced three amplitudes at a half, a fourth and an eighth wave durations. Each amplitude is divided by the moving average of similar measurements from a pre-set number of preceding consecutive waves. This idea to incorporate the property of the preceding waves is important in distinguishing spikes and sharp waves from others. This operation is expected to reduce the intra-individual variability. Also, features transformed into dimensionless standard scores can reduce the inter-individual variability (Gevins 1980a). Frost (1979) used a similar approach, but excluded the period of transient waves and artifacts from calculating the moving average in order to stabilize the moving average.

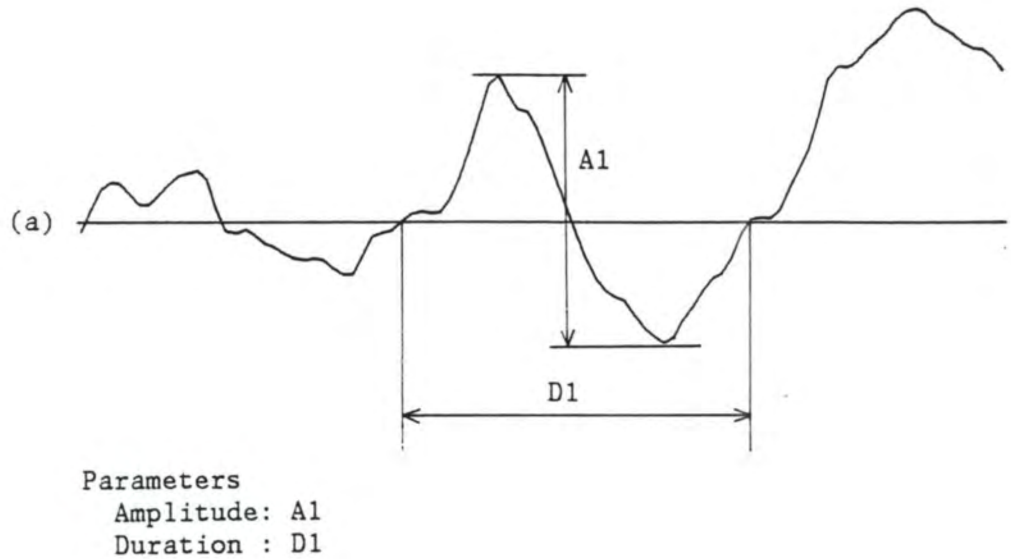
Saltzberg et al. (1967) introduced a curvature of the data as a parameter which is derived as a second derivative, and shows a sharpness of the signal. Carrie (1972b), and Gevins (1975a) also used a curvature as a parameter, which was divided by the moving average of the preceding curvatures. As the names of spikes and sharp waves indicate, sharpness seems to become a prominent parameter.

As to the calculation of curvature, simple arithmetic operations are substituted for differentiations. Birkemeier et al. (1978) derived curvature using a coefficient of a quadratic approximation formula. It is noteworthy that they demonstrated the curvature of the filtered data as determined by an autoregressive filter is more distinctive than the

curvature of the data in the classification between the transient and the background waves. Gevins et al. (1975a) presented a complex formulation of curvature. Although there may be some merit of the formula, the complex operations, which would be time-consuming, distracts from the application to real-time operating systems.
The peak angle of a wave proposed by Hill and Townsend (1973) and Smith (1973) also shows a sharpness of a wave. They calculated the peak angle, for example, by fitting a pair of straight lines to four data points on either side of the peak, and calculating the angle of the lines.

Bickford (1974) used slopes and amplitudes of up and down strokes (half-waves) of a full-wave as parameters. Actually a curvature is a difference of two slopes before and after the measuring point of time. Gotman (1980), beside the above four parameters, used two durations of the up and down strokes, and attempted to measure the asymmetry between the two strokes. The property of asymmetry is one of the most characteristic aspect of spikes and sharp waves.

More elaborate morphological features have been proposed to make the description of waves more precise. Gotman and Gloor (1976) presented features including a pseudo-duration as shown in Fig.3.2(b). Each amplitude and curvature are divided by the averages of Ktonas et al.(1981) added inflection points and a duration between the points as shown in Fig.3.2(c). In the system implemented by Frost (1979), the parameters are two durations, two amplitudes, a curvature and a surface area as shown in Fig.3.2(d). The study of Steinberg (1962) showed an extensive parameterization of this type in automated ECG analysis.



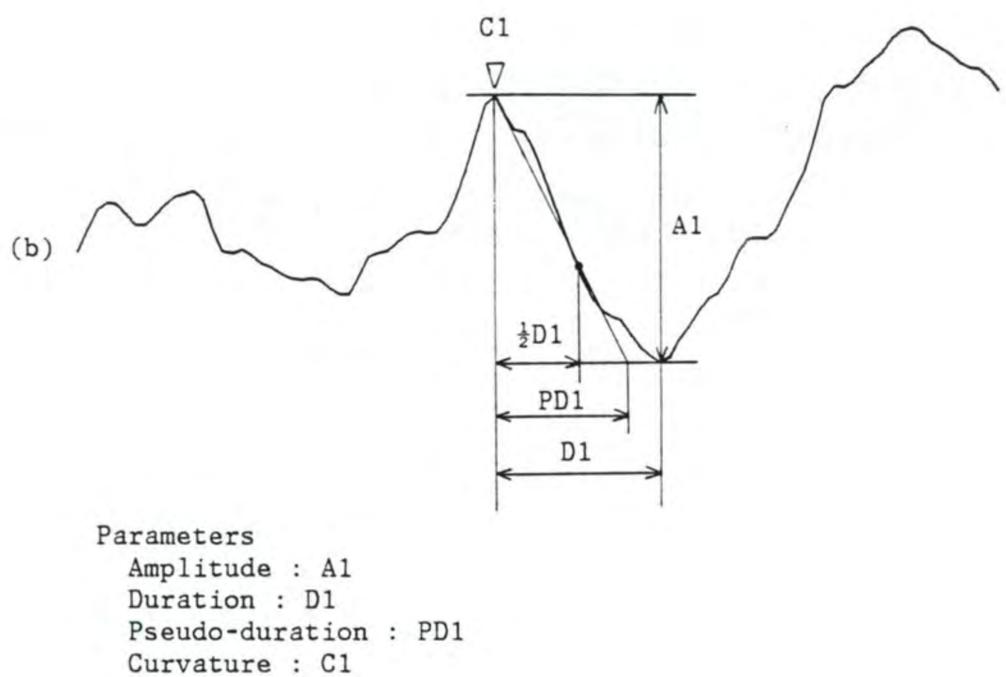
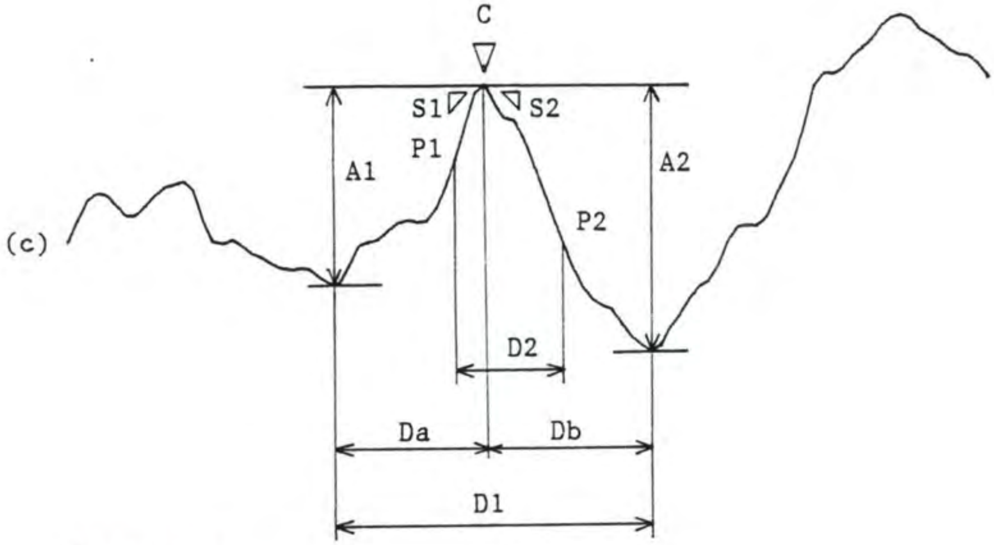
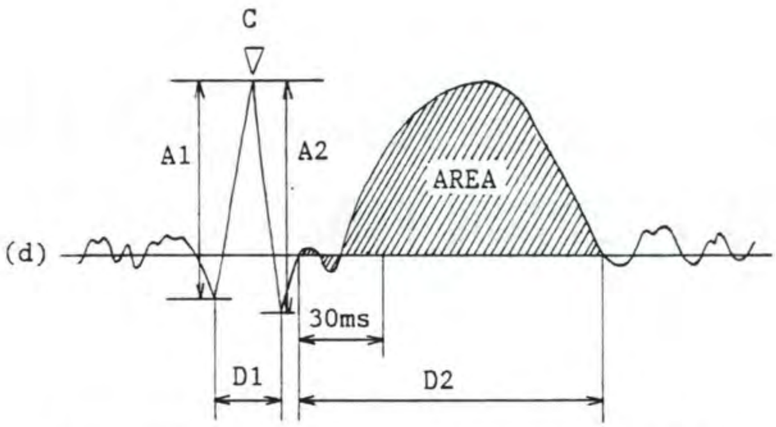


Figure 3.2 Designs of Morphological Parameters.



Parameters
  Amplitude: A1, A2
  Duration : D1, D2, Da, Db
  Slope   : S1, S2
  Curvature: C



Parameters
  Amplitude: A1, A2
  Duration : D1, D2
  Curvature: C
  Area   : AREA

Sequential logics

1. $C > 2C' + K$
   where $C' = C_0 + (C - C'_0)F$,
   F, K: constants.
2. $36 < D1 < 100$ (msec.).
3. $\min(A1,A2) > 10$ (μV) and
   $\max(A1,A2) > 20$ (μV).
4. AREA > 10 (μV•sec.)
   AREA > 20•D2 (μV•sec).

Figure 3.2 (Cont'd.)

The "iterative time-domain approach" by Matejcek and Schenk (1972; see also Schenk 1976) is an elaborate procedure and suitable for real-time operation, but lacks in physical and theoretical correspondence. The first step in this analysis is the estimation of the slower underlying component, which is the average of the maxima and the minima of the vectorized envelope of the signal. The second step iterates the procedure using the result of the preceding step. After a certain number of steps, superimposed components of the signal are obtained as a result. Parameters of a duration and an amplitude are derived primarily based on quarter-waves and half-waves. The idea to include the parameters of the waves around the referred wave as parameters of the referred wave is interesting, and is one of the hints to derive a concept of "events" in this project as mentioned in the last section of this Chapter and explained in Chapter 4.

Statistical Parameters

It seems reasonable to use statistical parameters because they characterize some aspects of data, although there are not many papers which applied them to automated EEG analysis. Luder et al. (1976) demonstrated the use of various statistics for the detection of EEG transients, their ultimate goal of the research being to develop statistical measures for classifying specific types of EEG transients. Bronzino et al. (1980) also pointed out the importance of statistical parameters. Salb (1980) used a value of absolute integral in each wave. Advantages in using these types of parameters are that many of them are normalized, and confidence levels may be obtained if a certain distribution of each parameter is supposed. Salb (1980) used a sum of absolute value of amplitude in full-wave as a parameter. Guedes de Oliveira and Lopes da Silva (1980) proposed a statistic for χ-square test in evaluating a correlation of spike events between channels.

Hjorth (1970) proposed the following three parameters:

(1) activity $\sigma_0{}^2$,

(2) mobility σ_1/σ_0 ,

(3) complexity $(\sigma_2/\sigma_1)/(\sigma_1/\sigma_0)$,

where σ_i is i-th moment. In the time domain, the activity can be conceived as the variance, the mobility as the relative average slope measure, and the complexity as the deviation from sine shapes. In the frequency domain, the activity, mobility and complexity have been proved to be equal to the zeroth, the second and the fourth spectral moments. In the paper by Hjorth (1973), the definition of complexity was changed as

$$C_n=(\sigma_{n+1}{}^2/\sigma_n{}^2 - \sigma_n{}^2/\sigma_{n-1}{}^2)^{\frac{1}{2}}$$

where C_n is called the n-th complexity. The autocorrelation function was shown to be expressed by the moments as follows:

$$R(\tau)=1-(\tau^2/2!)(\sigma_1/\sigma_0)^2+(\tau^4/4!)(\sigma_1/\sigma_0)^2(\sigma_2/\sigma_1)^2$$
$$-(\tau^6/6!)(\sigma_1/\sigma_0)^2(\sigma_2/\sigma_1)^2(\sigma_3/\sigma_2)^2+\ldots \quad .$$

Wyper et al. (1975), Denoth (1975), and Matthis et al. (1981) used the parameters and had unsuccessful results. However, Matejcek and Devos (1976) reported that they were sufficiently sensitive to objectify the time course of action of psychoactive drugs, to monitor changes in vigilance, and to quantify drug effects on the sleep-wakefullness cycle.

Bergland and Hjorth (1973), Depoortere et al. (1973) and Devos et al. (1975) also showed the applications of the parameters.

Template Matching Parameters

Given a template representing a pattern, data is compared to it via some algorithm which results in a measure of similarity or dissimilarity to the template. Barlow and Dubinsky (1976) demonstrated a spike detection method by using a template, which was chosen visually as a typical spike event. A correlation coefficient was the measure of similarity in the paper. A mean absolute error and a mean square error, for example, are also potent to application, especially when computational efficiency is considered.

A visual choice of a template seems to be an obstacle to automated EEG analysis. A mathematical procedure in constituting a template and its length will have to be established.

In order to eliminate background waves from a template of a transient event, inverse frequency filtering was suggested by Saltzberg et al. (1971) and Zetterberg (1973). An attempt by Saltzberg et al. (1971) to make a template used a depth spike as a trigger of a scalp transient. It is interesting in the Saltzberg's paper that the background waves were more appropriately approximated by a 1/f function in the frequency domain than a constant function (i.e. a white noise). It coincides with the description that the higher the frequency gets, the lower the amplitude gets in background EEG (Gevins 1975a).

Widrow (1973) proposed the flexible template, "rubber masks", capable of changing their shapes to fit natural data. Multi-templates can be used (Pfurtscheller and Fischer 1978). The method of waveform extraction based on Tauberian approximation (De Figueiredo and Hu 1982) may be considered as a more general template matching method.

Parameters of Models

When a parametric EEG model is introduced, the parameters of the model characterize the EEG waves. In time series data, autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models are popularly used, where a certain type of stationary EEG waveforms is modeled as an output of a digital linear filter to a Gaussian white noise input. The coefficients of the filter are used as parameters. Several applications of the models to the EEG analysis have been presented (e.g., Fenwick et al. 1969, Zetterberg 1969, Barlow and Solokov 1975, and Bodenstein and Praetorious 1977). Other than a choice of the type of model, the orders of the filter must be chosen. The optimal choice of the filter orders has been proposed by several researchers (see Isaksson et al. 1981, Kashyap 1982, and Cadzow 1982). An iterative nature of optimization to obtain values of the parameters has been a major computational disadvantage. Cadzow (1982) presented a new method which is non-iterative and computationally more economical. These models are attractive because they are (1) theoretically sound and simple, (2) usually efficient in data reduction, and (3) directly applicable to the spectral density estimate.

However, if transient waves are to be modeled, the statistical nature of the models, such as the use of a white noise and the assumption of a stationary input, makes these models inadequate. Then, instead of modeling transient waves, the prediction error which is a deviation from the stationarity was taken as a measure of the non-stationarity of the input, which indicates transient waves. The prediction error may be obtained by an inverse filtering (Lopes da Silva et al. 1977).

We have seen these AR and ARMA models have some advantages and disadvantages as well in the transient EEG analysis. Isaksson et al. (1981) said analysis of epilepsy will require new and more refined models of an EEG. Whereas AR and ARMA models are linear models, there are non-linear models available, which usually require more complicated computations.

Instead of modeling the morphological nature of EEG waves, there are attempts to formulate process models based on physiological knowledge of the brain function (see Moser et al. 1980, Isaksson et al. 1981, p. 459). This type of modeling is interesting because good parameters should be physiologically or clinically interpretable as well as being derived by simple algorithms and being capable of distinguishing spikes and sharp waves, artifacts, background waves, etc.

Parameters from Filtered Data

Proper filtering may facilitate revealing a characteristic of the EEG waves. Analog filters are well-developed, inexpensive, and work in real-time. But there are some limitation in realization because of some physical properties of the parts. Digital filters are rapidly being developed, which have some advantages over analog ones. For example, linear phase filters are realized easily. In addition, non-linear filters such as Wiener or Kalman filters can be implemented rather easily in digital systems. These filters can be either fixed or adaptive, the latter being preferred in the EEG analysis because of the ability to learn the property of the data and to adjust to the slow change of it. They have been used in radar detection, seismic rhythm detection (Chen 1982), ECG wave analysis (Eisenstein and Vaccaro 1982), or EEG wave analysis (Saltzberg et al. 1971, Lopes da Silva et al. 1977, Isaksson and Wennberg 1976).

Widrow et al. (1975) presented several types of adaptive filters for noise cancelling and their applications. The coefficients of a model may be used as parameters of stationary waves, and the error between the filter output and the data as a parameter of non-stationary waves. The adaptive filters studied by Chen (1982) were developed to detect seismic rhythms, but seem readily applicable to a real-time spike EEG analysis as well.

In sleep analysis, Bar-On and Andreassen (1981) recently reported a fast 16 bit microprocessor (Intel 8086) system which performs the analysis of 8 channel (including EOG and EMG envelope recording), where inverse filtering is used to detect non-stationary and stationary events. The system included clustering and/or classifying of the events and still operated at 10 times real-time.

Parameters Derived in Frequency Domain

The data transformed into the frequency domain has a complex number at each frequency, which carries the amplitude and phase information. Commonly the EEG analysis in the frequency domain only considers the power spectrum which comprise of the square of the amplitude, neglecting the phase information. Once the power spectrum is obtained, the data is represented as a series of real numbers versus frequency in a two dimensional space. Thereby, the methods to derive the parameters in the time domain can be adopted directly to the data in the frequency domain.

Morphological parameters of peaks, powers and bandwidths of α, β, γ and θ frequency bands are typical in the EEG analysis in the frequency domain. The use of cepstra suggested by Saltzberg (1976) was aimed at detecting spike waves. The cepstrum of a function f(t) is defined as the inverse Fourier transform of the logarithm of the Fourier Transform of f(t). Others are not directly concerned with spikes and sharp wave detection (see Matthis 1981 and Dumermuth 1977 for the slope parameter; Kunkel et al. 1976 for other morphological parameters; Zetterberg 1977 for higher spectra moments). However, frequency characteristics may serve as a media for inverse filtering, or as an aid to eliminate artifacts. Furthermore, if segmentation is done properly so that only one pattern is included in one event, the parameters listed in the figure might become distinctive features in spike detection.

The longer computation time is again a disadvantage. The applications of FWT or FHT may be interesting. Bishop et al. (1970), for example, proposed the use of Haar transform to parameterize the data. The computation time was greatly reduced, but more extensive investigations are needed to evaluate the method.

The Concept of Events

By the procedures discussed so far, a set of parameters is obtained in each segment. However, this set of parameters may not be sufficient to characterize the waveform (an epileptic waveform, for example) when the segment does not contain the whole part of the waveform. In fact, as noticed by the way electroencephalographers mark the events of spikes and sharp waves shown in Fig. 4.1, for example, an event seems to consist of more than one wave.

The syntactic approach by Remond (1969) and the way of parameterization offered by Schenk (1976) has led to the concept of an "event", which includes one or more segments, in this project as explained in Chapter 4. Then, a set of parameters in each event will be forwarded to the procedure of the classification.

Classification

After getting a set of parameters in each event, the analysis proceeds to the classification stage. Each event is classified into one of certain groups such as spikes and sharp waves, artifacts, and background waves.

The description in this section reviews the classification methods in the previous papers of automated EEG analysis, proceeding from a simple classification to more sophisticated methods. Then, it is suggested that the analysis requires a more general approach rather than ad hoc approaches. The classification method of linear discriminant analysis, especially stepwise linear discriminant analysis is further explained because this method is used for classification in this project.

Thresholds

One of the simplest way of classification is the use of thresholds. Single threshold is used in the papers by Bickford (1959), Saltzberg

(1967), Carrie (1972b), Hill and Townsend (1973), and Barlow and Dubinsky (1976), for example. Although high percentage of correct spike detection is reported in some of these papers, mostly the data used are pre-selected, only a particular type of spike is detected, or the thresholds are adjusted manually to optimal values.

The search for the supplemental information to detect transient events resulted in an increase in the number of parameters. And also the logical criteria for the use of classification process were developed. Kaiser (1976) set up a criterion of duration for an after-spike wave in addition to an amplitude threshold. Smith (1974) implemented the logical criteria with using operational amplifiers and TTL logic circuits. Leader (1967) specified thirteen patterns of EEG by using thresholds and critical ranges of parameters, and their logical descriptions. An extensive example of this type of classification is seen in the paper of Steinberg (1962) in ECG application, which used 17 morphological parameters and more than twenty steps of their logical description. Similarly, Frost (1979), in his real-time, microcomputer system, used five parameters and the sequential logical criteria for the parameters. This type of classification, which uses several parameters and their logical criteria to classify EEG events, was reported to be reasonably successful. But the problems are (1) the thresholds or critical range of parameters were manually set up, and (2) the choice of the logical criteria also relied on the experiences of researchers.

Several attempts were concerned with overcoming the first point (see Gotman 1980, p. 551, and Ktonas et al. 1981), as well as establishing quantitative criteria for spike and sharp events. Means and variances of the parameters, such as duration, amplitude, slope and curvature, were calculated as hoped to be norms for spikes and sharp waves. The results indicated the only one parameter is not good enough, but several of them are needed to correctly distinguish the spike or sharp events (Ktonas et al. 1981, p. 242). From a critical viewpoint, (1) other statistics than means and variances could be presented, and (2) there is no way to check the aspect of inter-relations between parameters out of means and variances.

Linear Combination of Parameters

As the analysis method gets more elaborated, it became necessary to consider the inter-relation between parameters as well as their individual values.

Actually, the studies of morphological asymmetry of spikes or sharp waves (see Gotman 1980, p. 551) have shown that differences of two parameters are also distinctive parameters, for example. Harner and Ostergren (1974, 1976) displayed the half-wave events on a bivariate screen. Gotman and Gloor (1976), instead of specifying a threshold or a range of each parameter, assigned a region to each group in a two dimensional space where a combination of two parameters is considered. Also, in the second stage of classification, a combination of four parameters is used to finally detect spike events. In the classification schemes by Birkemeier et al. (1978) and Bodenstein and Praetorious (1977), the consideration of a combination of two parameters in a two-dimensional space is shown with success. Therefore it seems reasonable to extend the idea to considering a combination of parameters in a multi-dimensional space.

Discriminant Analysis

Now the problem is how to assign a region of each group in the multi-dimensional space. It appears to be too much work to do it manually because of so many combinations of parameters and the difficulty to visualize the image of multi-dimensional space. The methods in discriminant analysis can solve the problem according to their criteria for discriminating or classifying the events. They offer classification rules automatically through mathematical procedures. In practice, the following points are also concerned with the procedure of classification: (1) what parameters should be selected for use in the classification? (parameter selection), (2) how well does the classifier perform? (performance of the classifier), and (3) how robust is the classifier to departure from the assumption that made? (robustness of the classifier) (see Lachenbruch 1975, p.1). The points (2) and (3) can be stated as how to evaluate the classifiers. (evaluation of the classifier). The following topics are discussed in this section: (1) selection of parameters, (2) classifiers, (3) packaged programs available to select parameters and/or to calculate classifiers, and (4) evaluation of a classifier.

Selection of Parameters

Not all the parameters may be distinctive in classifying the events into one of the specified groups. The inclusion of irrelevant parameters can cause a marked reduction in the effectiveness of the discriminant analysis techniques (Hawkins 1976). Thus it is desirable to select only significantly relevant parameters for classification. The methods of selecting parameters include (1) selection criterion, (2) way of selection, and (3) stopping criterion. The selection criterion gives a measure of how much the parameters contribute to the classification. The way of selection is how the method proceeds in finding a "best" subset of parameters in calculating a classifier. The stopping criterion is how to stop the selection procedure.

Classifiers

In general, there are a lot of types of classifiers. These may be categorized (see Remond and Renault 1972, Chen 1973, Sklansky 1973, and Fu 1977) by whether a classifier is

(1) deterministic or statistical in derivation,

(2) supervised or unsupervised in derivation,

(3) parameteric or nonparametric,

(4) linear or nonlinear,

(5) single- or multi-layered,

(6) syntactic or non-syntactic.

It is beyond the scope of this paper to describe these methods generally. This section focusses on the type of the classifiers that are parametric, linear, single-layered, non-syntactic, and derived on the basis of a statistical criterion and a supervised dataset. The procedure for deriving these classifiers is called a linear discriminant analysis. These classifiers are simple, popular, and appears to be a natural extension of the attempts mentioned above because they offer linear classifiers which include linear combinations of parameters.

Three approaches of linear discriminant analysis are described in Appendix B. They are Bayes, Fisher's, and canonical approaches. The classifier by Bayes approach assumes the multinormality and the equal covariance of each group population in the data. Although this approach has an advantage to be able to include the cost coefficients, the coefficients are supposed to be equal in order to have a simple linear classifier. There is no assumption of distribution in deriving a classifier by Fisher's approach. But the classifier is optimal for two group problems if each group is normally distributed, and has the same covariance and prior probability. Other than a trivial constant, the classifier of Fisher's approach is the same as the classifier of Bayes approach for two groups from the multivariate normal distribution with the same covariance. The classifiers of Bayes and Fisher's approaches for more than two groups will be similar if the group means are nearly colinear. In canonical approach, the classifier will have better ability to discriminate the events than the Fisher's classifier at the expense of more calculation needed. The robustness of the linear classification to the deviation from the optimal condition is discussed by Lachenbruch (1975, pp. 41-50).

Fukunaga (1972, pp. 118-119) suggested that even a nonlinear classifier can be interpreted as a linear classifier in a functional space where the functions $g_j(\mathbf{x})$'s are variables instead of $\mathbf{x}$'s in the original space. This method can be used if the structures of the functions $g_j(\mathbf{x})$'s are known beforehand.

The study by Larsen and Walter (1970) is interesting in that they introduced a way to implement a quadratic discriminant classifier by using a linear discriminant method and also introduced a multi-stage linear discriminant classifier.

Although there have been few papers adopting the linear discriminant analyses to detect transient events, quite a number of papers have applied them in sleep stage scoring, drug effect detection, or psychological pattern classification, for example, all of which are dealing with stationary EEG events (see Gevins 1980a).

Packaged Programs

There are several programs established for selecting parameters and deriving a classification rule. Habbema and Hermans (1977) compared some characteristics of the five programs shown in Table 3.2. Among them, the programs in BMD (Dixon 1967,1969 and 1974), BMDP (Dixon 1975) and SPSS (Nie 1975) are stepwise linear discriminant analysis (SLDA) programs. They are put in the center of the following discussion because one of the SLDA programs, called BMDP7M (Dixon 1975), was primarily used for classification in this project.

The SLDA programs have been popularly used for classification (Larsen and Walter 1970, Martin et al. 1972, Jenden et al. 1972, Bowling and Bourne 1978). They used the established programs such as BMD07M in BMD 1974) or the SLDA program in SPSS. Gevins (1980a) gave an excellent survey on the papers that applied SLDA to the EEG analysis.

The SLDA programs select a set of parameters useful for classification, and calculate a classifier of Bayes approach. The programs in BMD and BMDP also have a feature to calculate canonical variables, which may be used for calculating a classifier of Fisher's approach or canonical approach. The data set used for calculating the classifier are called a training data set, and the classifier is applied to the data sets, called testing data sets, for classification.

Table 3.2 Comparison of Some Characteristics of the Five Selection Programs BMD07M, DISCRIM ALLOC-1, SPSS and BMDP7M. (Copied from Habbema and Hermans 1977, p. 489.)

	BMD07M/SPSS/ BMDP7M	DISCRIM	ALLOC-1
Distributional assumptions	Multinormal, equal covariance	Multinormal, equal covariance	Direct density estimation by kernel functions
Selection Criterion	Maximal value of F-statistic and three related criteria(BMDP7M only F-criterion)	Minimal value of U-statistic	Maximal correct classification rate
Way of selection	Stepwise	All subsets	Stepwise
Way of posterior probablity estimation	Resubstitution (BMDP7M also leaving-one-out)	Resubstitution	Leaving-one-out
Stop criterion	Threshold value for F-statistic	Reduction in U-statistic	Threshold on increase of correct classification rate
Loss-function	No	No	Yes

The SLDA programs are computationally more efficient than others in deriving a classifier and assigning a new event to a group by the classifier. But the SLDA programs may be criticized in the following points (Habbema and Hermans 1977; see Table 3.2):

(1) the distributional assumption of multinormal and equal covariance is too restrictive;

(2) the variable selection criterion of F-statistics does not yield better classification percentages in the case of more than two groups, compared to the case of two groups;

(3) the stepwise procedure does not take into account that a combination of some variables may better separate the groups;

(4) the F-statistic do not give the overall significance level, resulting in the lack of valid stopping rules.

The program DISCRIM (McCabe 1975) improved the defect of the point (3) by checking all the subsets, but increased the computation time. The U-statistic is equivalent to the F-statistic for variable selection. They are essentially for testing equality of the group mean vectors under the assumption of multivariate normality with equal covariance matrices (Habbema and Hermans 1977). The program ALLOC-1 (Habbema et al. 1974) chose the selection criterion of classification percentages using Parzen estimate to estimate the probability density functions (Habbema, Hermans and Van den Broek 1974). The performance is good, and does not assume any distributions of data. However, the computation time is long. The modified stepwise procedure proposed by Farer and Dunn (1979), which discards half the number of variables from the analysis according to a t-test, seems to be an improvement. Recently Habbema and Gelpke (1981) offered a program called INDEP-SELECT, which is similar to ALLOC-1 in principle, but has a choice of more flexible criteria and takes less computation time. McKay and Campbell (1982a,b) suggested to use all subset selection using classification percentage criterion. Lachenbruch (1975, pp. 73-78) also discussed some criteria of selecting parameters. Noteworthy is the second criteria in BMD07M (Dixon 1974), which may be better in performance than F-statistic criterion in the case of more than two groups. But this option is omitted in BMDP7M (Dixon 1975).

As to where to stop the stepwise procedure, the conservative simultaneous testing procedure proposed by Hawkins (1976) seems readily useful for the SLDA (see McKay and Campbell 1982a, p.12).

Adjustments of Classifiers

The classifier derived during the training data is applied to the other data (the testing data). As far as the data property of each group stays same, the performance in the testing data is expected to be as good as in the training data. But the properties may change gradually. Also the training data set may not have been quite appropriate. In that case, an adjustment of the classifier would be recommemd. One way to solve the problem is to make the system interactive with a supervisor, and another is to make the system have an unsupervised learning ability so that the system itself adjust the classifier to the change of the properties. Usually an unsupervised learning system's performance is not as good as a supervised learning system in a limited data, but also the system's algorithm becomes more complicated and costly. Therefore, a combination of the both seems to be reasonable, that is, the system derives a classifier during a training period, and have an ability to adjust the classifier to changes of data property. Also it is desirable for the system to have an option to interact with a supervisor.

Hill and Townsend (1973) implemented a simple unsupervised system for detecting spike waves. Saridis and Gootee (1982) applied a learning linear classifier (Fukunaga 1972, pp. 196-217) in the EMG pattern classification, which improved the performance of a linear classifier considerably.

Artifact Rejection

The artifacts are either physiological or instrumental, and have morphology and mode of appearance like real EEG components such as spikes and sharp waves (Gotman and Gloor 1976). Whereas the electroencephalographers can recognize artifacts with their experience, the automated EEG analysis has to have some quantitative or logical criteria for artifact rejection. Some of the artifacts may be discarded while the analysis proceeds to detecting specific waveforms. Since it is not enough usually, many systems added some special procedure for artifact rejection.

For the artifacts caused by gross body motion, EMG or instrumental source, Gevins (1975a) proposed a special artifact rejection scheme which compares intensity at specified frequencies with a threshold determined during an artifact-free calibration period. The threshold can be corrected by an electroencephalographer.

The system offered by Salb (1980) rejected the portion of data as artifacts when, in the 1 second running window, the amplitude totals in the wavebands of less than 30 msec. and more than 100 msec. exceed the artifact threshold calculated during a calibration period. Gotman and Gloor (1976) presented an auxiliary processing design for rejecting three major artifacts; muscle activity, rapid eye blinks and onset sharp alpha activity. The data of 1/3 sec. before and after the time being analyzed are considered to be an artifact (1) if these periods include a large number of high amplitude, or a sharp decline of the autocorrelation function for muscle activity; (2) if they have a positive wave of longer than 150 msec. in homogeneous contralateral frontal channels for eye blinks; (3) if the correlation functions of (a) 1/3 sec. of data centered at the apex of a given wave over a lag of 60 msec., and (b) 1/3 sec. of data centered at 100 msec. before and after the apex over a lag of 60 msec. have more than 60% for onset of alpha activity. These three methods were reported to have rejected muscle activity and onset of alpha artifacts perfectly, and eye blinks incompletely when asymmetry between right and left recording occurs.

The adaptive noise cancelling techniques (Widrow et al. 1975) may serve as a good artifact rejector. Johnson et al. (1979), after noting the limitation of linear filter in reducing muscle artifact because of the EEG and muscle artifacts have overlapped frequency property, proposed a Kalman type nonlinear filter that can eliminate muscle artifacts on the EEG.

If the other recordings such as EOG, EMG, ECG are available, they can contribute to the artifact rejection.

Evaluation

After classification, it is important to know how good the performance is. Because there has not been a perfect machine to correctly classify the EEG events, the standard is usually set to the classification of experienced electroencephalographers. In this case, the classification results are evaluated in comparison with the results of electroencephalographers using the same data. There are some measures available to evaluate the success of classification. Hilderbrand et al. (1977), for example, proposed this type of measures. As mentioned in Introduction, however, the identification of EEG events by electroencephalographers tends to be qialitative and subjective. Therefore, when the results of the classification or identification of EEG events by electroencephlographers are used as the standard to evaluate the classification results by computers, it is important to know how credible and significant the standard classification being used is. The following paragraphs discuss the topic.

In the classifications of sleep stage analysis, the discrepancy among electroencephalographers seems not significant. For example, Martin et al. (1972) reported that 89 percent of agreement between 3 judges based on the sleep EEG and EOG data. The evaluation of evoked potentials does not have this problem because each event is labeled with a designated stimulus. However, in the classification of EEG transient events, the disagreements between electroencephalographers seem substantially big. Gevins et al. (1975a) reported that when five electroencephalographers marked the spike and sharp waves of EEG, only 11 percent of all marked spikes and sharp waves were marked by all the electroencephalographers and only about 30 percent were marked by at least three electroencephalographers.

Gotman et al. (1978) explained that the low percentages of agreement were obtained in the Gevins' study because the marking of every transient wave is not part of the traditional EEG interpretation. Considering that identifying individual spikes or sharp waves is not the purpose of the EEG interpretation, he proposed "structural reports", which show the level of the epileptic subject's interictal activity on each recording channel and the relation between channels. The reports primarily contribute to identifying a patient's epileptic foci. When the structural reports were used for interpretation, the agreement between electroencephalographers was improved to 72 percent using the paper records (84 percent using the computer displayed data). Between the computer and human analyses, Gotman and Gloor (1978) reported the correlation of about 60% in the structural reports, suggesting that the evaluation is more reliable when a cumulative data for diagnosis is used than when individual spikes or sharp waves are used.

To interprete a complex fluctuation of the rate of occurrence of epileptiform events with time, Saltzberg et al. (1981) found that the curvature of the cumulative distribution of these events with time indicates a diagnostically significant characteristic of the event profile. That is, the curvature may be considered a measure of seizure risk, which provides a basis for early prediction of the efficasy of medication[1]. This fact reveals that the trend of the temporal cumulative distribution of the events is more essential than the times of occurrence of the individual events.

These facts about the structural report (spatial distribution) and the cumulative distribution over time (temporal distribution) imply that the evaluation will be more significant diagnostically when these spatial

---

1. As to the prediction of epileptic seizures, there are other approaches (see Viglione 1973 and Rogowski et al. 1981).

and temporal distributions of the epileptic events are considered rather than when the individual events are considered. In this sense, the detection of the individual epileptic events, which is the main purpose of this project, is not the last step, but one of the early steps toward the goal of making comprehensive diagnosis for epileptic patients.

CHAPTER 4

ANALYSIS PROCEDURES

The analysis procedures to detect spikes and sharp waves(SSW) are explained in this chapter.

The algorithms for the procedures were chosen so that the system adopting the algorithms may be:

(1) real-time operating,

(2) microcomputer applicable,

(3) able to reject artifacts,

(4) free from adjusting to intra- and inter-individual variances,

(5) contributing to quantitative description of SSWs.

In search of suitable algorithms, the programs were written in FORTRAN on the Clemson University IBM370/3033 computer system, and tested using the EEG data stored on a digital magnetic tape as described in the following section.

The first section deals with the data source and the processing before the computer analysis. The second section explains the algorithms for the computer analysis procedures. The third section illustrates the program flowcharts that combine the algorithms, and explain the programs used in the experiments.

Data Source and Processing Before Computer Analysis

The EEG data of an epileptic patient was obtained from the Neurology Laboratory in the V. A. Hospital, Augusta, Georgia. The data was originally eight channel recording from stereotaxically implanted depth electrodes (see Smith et al. 1983) as seen in Fig.4.1. The arrangement of electrodes was monopolar with linked ear reference. The data recorded on the second channel from the top in Fig.4.1 was used for analysis. It was recorded from the temporal lobe at a depth of 1 cm.

Fig.4.2 illustrates the data processing from recording the EEG to storing the data in a digital magnetic tape. The voltage between the electrode and the reference was amplified and filtered by the EEG recording machine (Grass Model 8-16D). The analog filters were the 60 Hz notch filter and the band-pass filter with cutoff frequencies of 1 and 70 Hz. The output from the machine was stored on analog FM tape. It was the inputs for both a strip chart recorder and an auxiliary amplifier. The auxiliary amplifier gave a proper voltage range for the 10 bit A/D converter.

The A/D conversion was controlled by the PDP11 computer in the Neurology Laboratory. The sampling rate was 200 samples/second, and the calibration was 0.37 μV/digital unit. The output data from the amplifier was converted by the A/D converter to the digital data for about 72 seconds, which made up a file on the digital magnetic tape. The next file was made for the same period after about an interval of 20 seconds because of the filing procedure of the computer. As a total, 15 files were stored on the digital magnetic tape, making up 15 data sets for experiments. The digital magnetic tape was copied to another digital magnetic tape installed at the Clemson University Computer Center.

Figure 4.1 An Example of the EEG Data Recorded on a Strip Chart Recorder. * : SSW marked by the electroencephalographer.

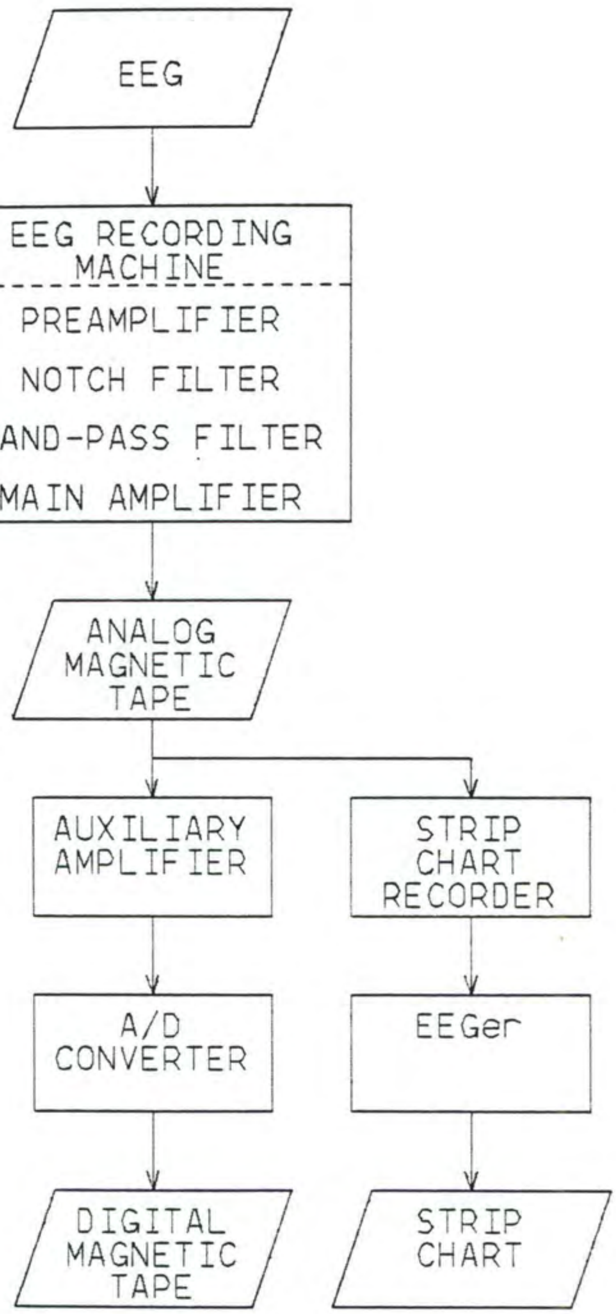


Figure 4.2 Data Processing before Computer Analysis.

The SSWs on the data were marked by an electroencepalographer (a neurologist) in the laboratory on the output of the strip chart recorder as seen in Fig.4.1. While marking these waves, the electroencephalographer was asked to look at only the channel used for computer analysis. The electroencephalographer marked 80 SSWs in 15 data sets. The SSWs[1] in the first five and the seventh data sets are shown in Fig.4.3 (a)-(f) with an averaged SSW and the standard deviation in each data set. Some of SSWs were distinctly different in shape as seen these figures. Then, two subtypes of SSW were introduced: SSWA and SSWB. There was one SSWB event in each of the first three data sets as indicated in Fig.4.3 (a)-(c). These data sets were used as training data sets. These subtypes of SSW were labeled and used only in the training data sets when two SSW types were specified in experiments (see Design of Experiments in Chapter 5). The electroencephalographer also marked 10 doubious SSWs, which he suspected as SSWs, but could not qualify his criteria for SSW. The portions of doubious SSWs are displayed in Fig.4.3(g).

Each data set but the 15th data set consisted of 14,336 integer values, that is, equivalently 71.68 sec. of recording. The 15th data set contained 9,024 values. As a total, there were 209,728 integer values in the 15 data sets, equivalently about 17.5 min. of recording, which excludes the elapsed time between data sets during filing.

Using a computer graphic display, the author identified the sites corresponding to the sites of the SSWs and doubious SSWs marked on the strip chart. Then the wave including the peak of each SSW or

---

1. They are filtered by a three point Hanning filter as will be explained in the later section.

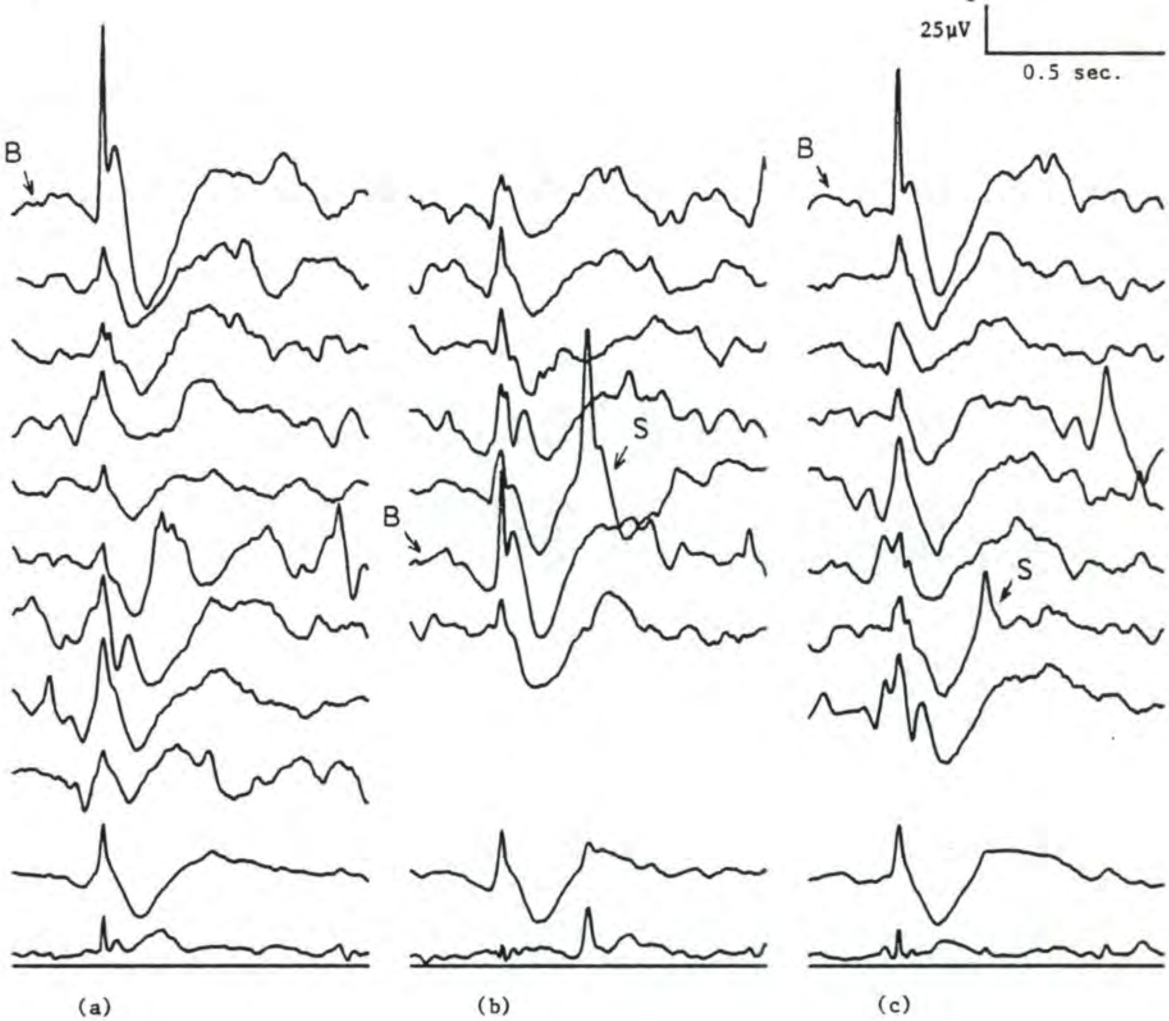


Figure 4.3 Examples of SSWs, Doubious SSWs, Successive SSWs and Artifacts. (a)-(f): SSWs in the data sets DATA01,02,03,04,05 and 07, respectively. (g):doubious SSWs, (h): successive SSWs, (i) artifacts. The second lowest and the lowest graphs in each of (a)-(i) are the averaged SSW and the standard deviation, respectively. The graphs marked by an arrow and a letter B are of SSWB. The graphs marked by an arrow and a letter S include successive SSWs.

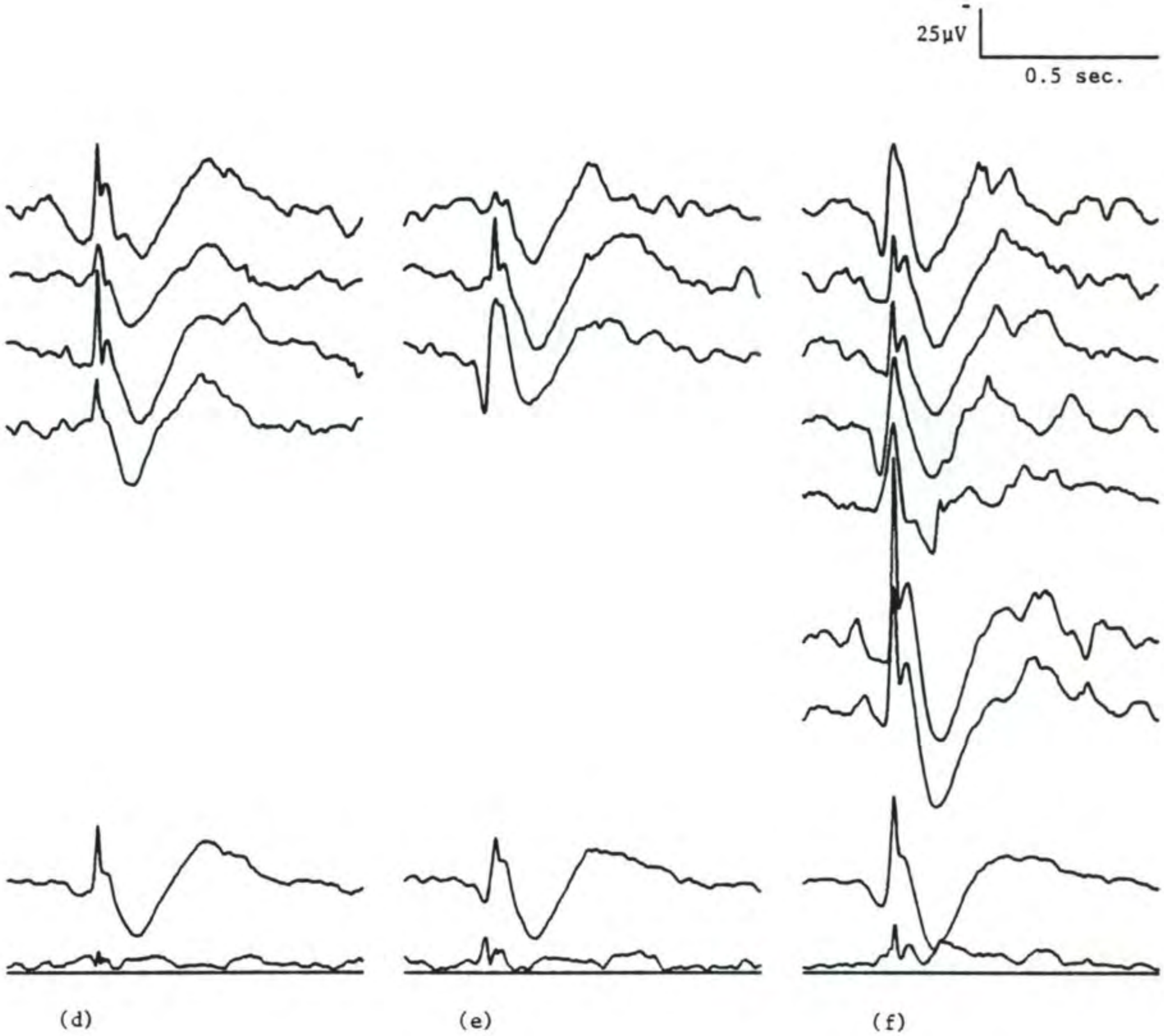


Figure 4.3 (Cont'd.)

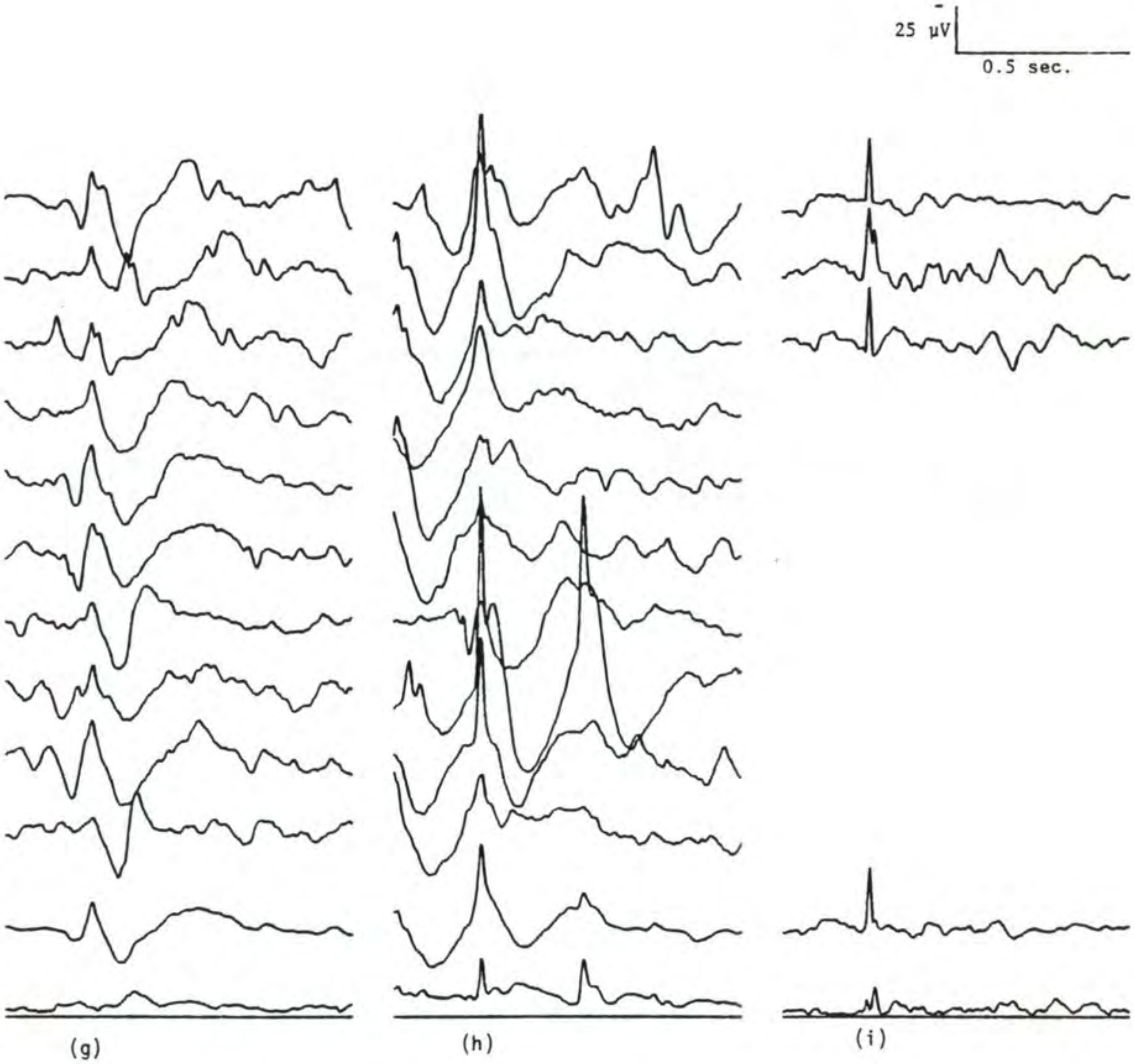


Figure 4.3 (Cont'd.)

doubious SSW was named "SSW" or "doubious SSW", respectively. In some occasions, there was a sharp peak right after a SSW. These waves were named "successive SSW", the portions of which are shown in Fig.4.3(h). There were 15 successive SSWs labeled by the author in the 15 data sets. The artifacts were not marked by the electroencephalographer, but marked by the author. There were 3 artifacts identified by the author, and named "artifact". They are shown in Fig.4.3(i). The rest of the events are named "background", the number of which totaled more than 12,500 in the 15 data sets.

Algorithms for the Computer Analysis Procedures

The block diagram of the computer analysis procedures is shown in Fig.4.4. A brief explanation follows. The EEG data stored in the digital magnetic tape is read sequentially by the computer first. The first data set is a training data set and the rest are testing data. In a training data set, SSWs and artifacts are marked by a supervisor. The data proceeds to the procedures of preprocessing, segmentation, and parameterization, and is now called parameterized data. If the current data is in a training data set, the parameterized data are used for discriminant analysis. The discriminant analysis gives a classifier for classification. If desired, some statistical properties of the training data set may be obtained in this analysis procedure. If the current data is in a testing data set, the parameterized data are classified by the classifier obtained by the discriminant analysis into one of the groups of SSWs, background waves, and/or artifacts. In the following paragraphs, the algorithms for each procedure are explained.

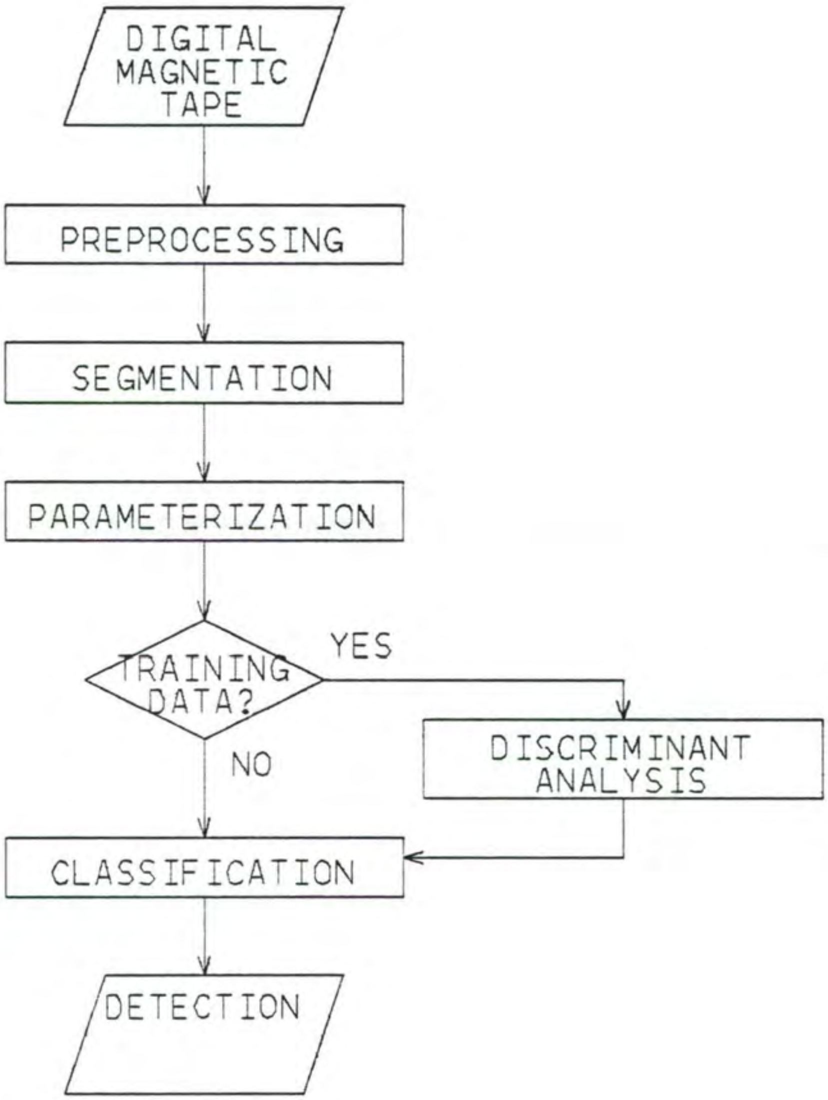


Figure 4.4 Analysis Procedure.

Preprocessing

A simple three point Hanning filter

$$y(n)=(1/4)x(n-2)+(1/2)x(n-1)+(1/4)x(n) \qquad (4.1)$$

was chosen to further reduce high frequency noise and the round-off effect of digitization. This filter is especially suitable for microcomputer application because the coeficients of the filter are only 1/2 and 1/4, which need one and two bits right shifts respectively in microcomputing. The z-transform of the formula (4.1) is

$$Y(z)=(1/4)z^{-2}X(z)+(1/2)z^{-1}X(z)+(1/4)X(z) \quad . \qquad (4.2)$$

The filter's frequency characteristics are obtained by replacing $\exp(2\pi jf/f_s)$ for z in the formula (4.1) where f is a frequency (Hz), and f_s is the sampling frequency 200 Hz (see Fig 4.5). The data obtained after this low-pass filtering is called the "basic data" and will be used as the basic data for analysis.

Segmentation

Segmentation is a procedure to give a basis for parameterization. Among various algorithms of segmentation, the discussion of segmentation in Chapter 3 and the consideration for real-time operation led to applying an extrema algorithm for the segmentation in this project. However, the use of values manually set up, such as tolerance constants or thresholds (see Segmentation in Chapter 3), were avoided as much as possible, so that the algorithm would be simpler than the previously proposed algorithms, and require as little subjective decisions by researchers as possible.

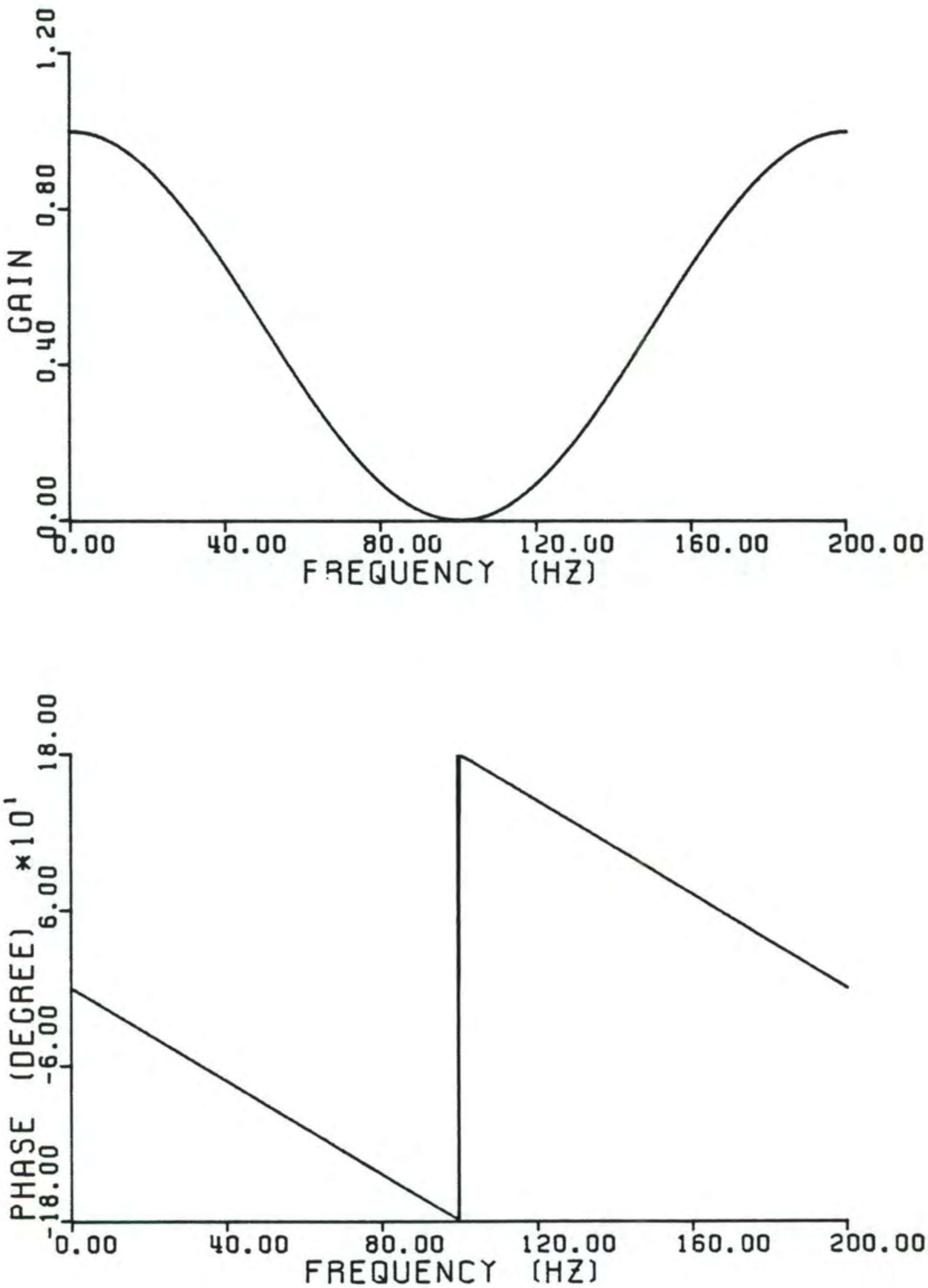
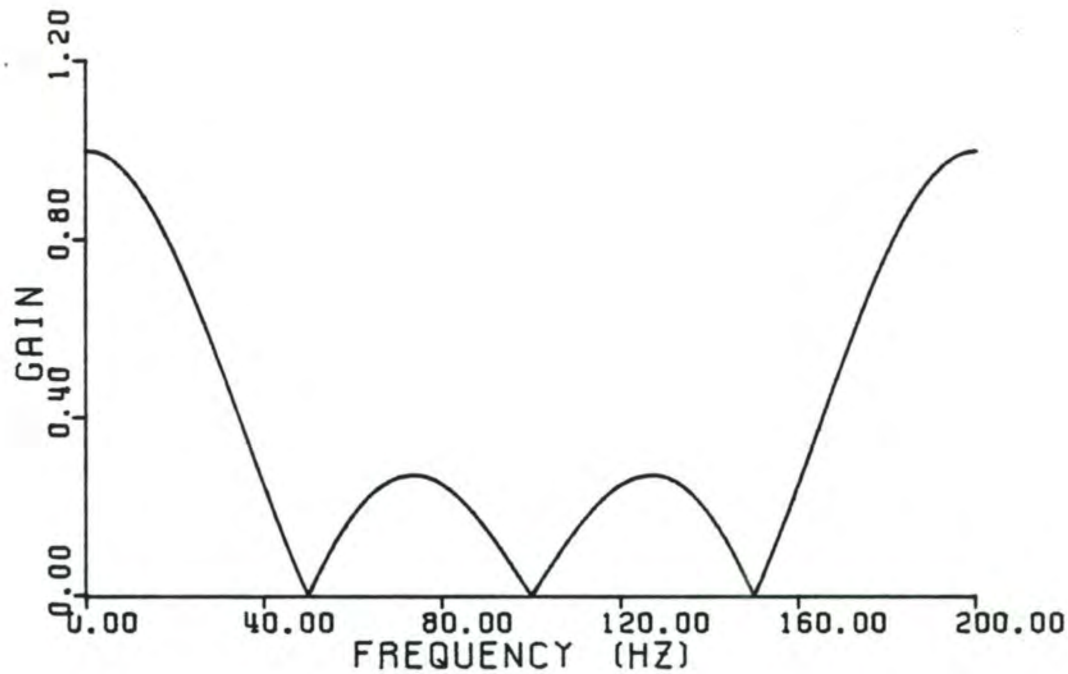


Figure 4.5 Frequency Characteristics of the Filter in Preprocessing.



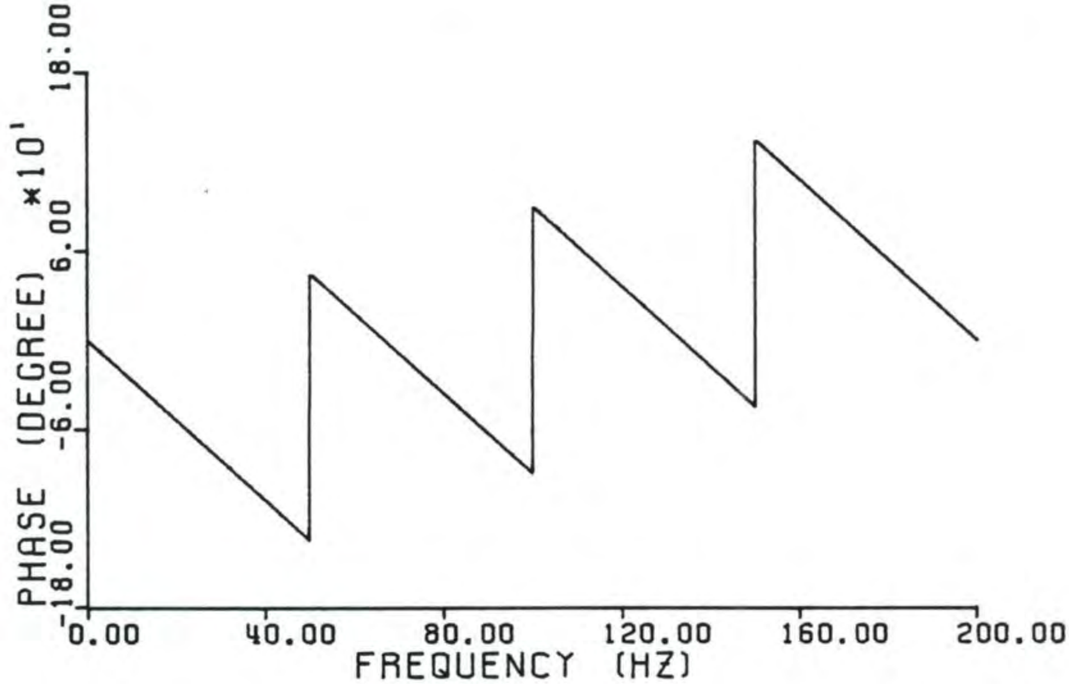


Figure 4.6 Frequency Characteristics of the Filter in Segmentation.

First the basic data is filtered by a simple low-pass filter below to suppress small amplitude fluctuation of the data:

$$y(n)=y(n-1)+x(n)-x(n-m) \tag{4.3}$$

which is one of the fast digital filters proposed by Lynn (1977). This filter has a cutoff frequency f_s/m, a linear phase characteristic, and a delay of $(m-1)/(2f_s)$ seconds. The value m is chosen so that the filter will at once suppress insignificant fluctuation of the data, and retain the extrema of SSWs and artifacts to a certain extent. The filter's initial conditions were set to zero. The order of the filter, m, is chosen to be an odd number preferably so that interpolation is not necessary to adjust the delay caused by filtering. However, the order m=4 was appropriate to meet the cutoff frequency 50Hz, considering the duration of a SSW is longer than 20 msec.. In this case, m is an even number and has a delay of $1.5/f_s$. The delay was rounded up to $2/f_s$ from the correct value of $1.5/f_s$. This does not cause any significant discrepancy in the following procedures, and does not affect the values of wave parameters at all. The frequency characteristics of the filter is shown in Fig.4.6, which was obtained by using the z-transform of the filter

$$Y(z)=z^{-1}Y(z)+X(z)-z^{-4}X(z) \tag{4.4}$$

and replacing z for $\exp(2\pi jf/f_s)$ where f is a frequency (Hz), and f_s is the sampling frequency 200 Hz.

Fig.4.7 shows how the basic data is segmented. The graph (a) of the figure is an example of the original data, and the graph (b) is the basic data after preprocessing by a Hanning filter. The data after the low-pass filtering is shown in the graph (c). The time delay caused by the filter is adjusted. The extrema marker in the graph (d) has a non-zero value when the low-pass filtered data (c) has an extremum (a peak or a trough), and zero otherwise. The non-zero value is +1 when the low-pass filtered data (c) has a peak at the time, and -1 when the data has a trough at the time.

A "segment" is defined as the portion of the basic data between one extremum and the next. Note the graph (c) is used for segmentation only and not for other purposes. There are two types of segments accordingly: one being a down-stroke and another an up-stroke. These segments are also called "half-waves." A "wave" consists of two consecutive segments. One type of wave has two peaks at the edges of the wave and one trough inbetween ("trough wave"), and another type has two troughs at the edges and one peak inbetween ("peak wave"). By the definition, a wave has one and only one significant extremum between the edges. Fig.4.8(b) shows the waves corresponding to the data in Fig.4.8(a). In the graph(b) of Fig.4.8, W(I) represents the portion of the I-th wave in the data set, W(I-1) the portion of the (I-1)-th wave, etc. Adjacent waves are partially overlaped as seen in the graph (b).

Parameterization

One or more parameters are derived from each wave. There are two methods tested in this project, although there are others as mentioned in Parameterization, Chapter 3. In one method, called Method A, some morphological parameters are derived. And in another,

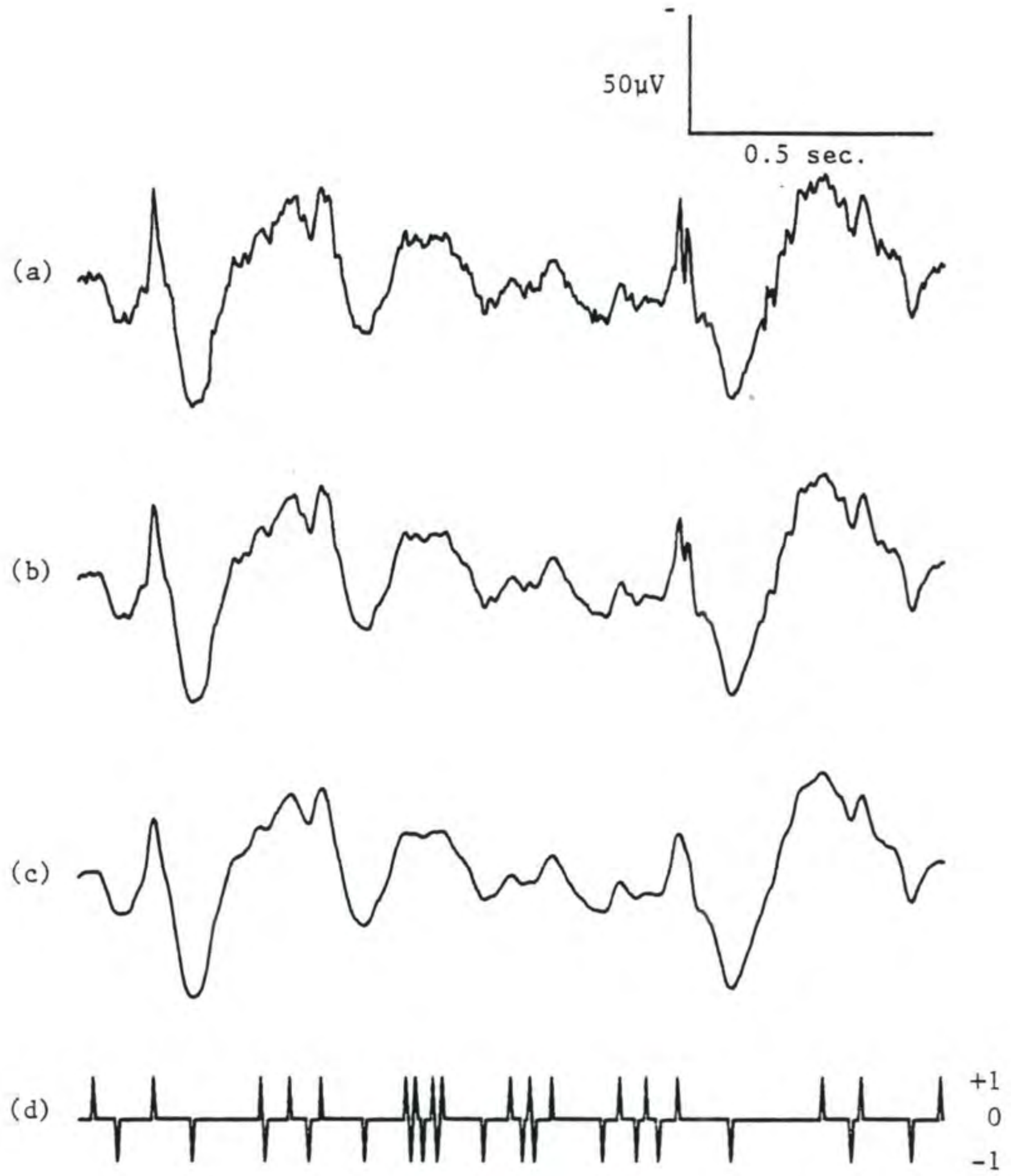


Figure 4.7 Segmentation Procedure. (a) Original data, (b) Basic data, (c) Low-pass-filtered data, and (d) Extrema marker.

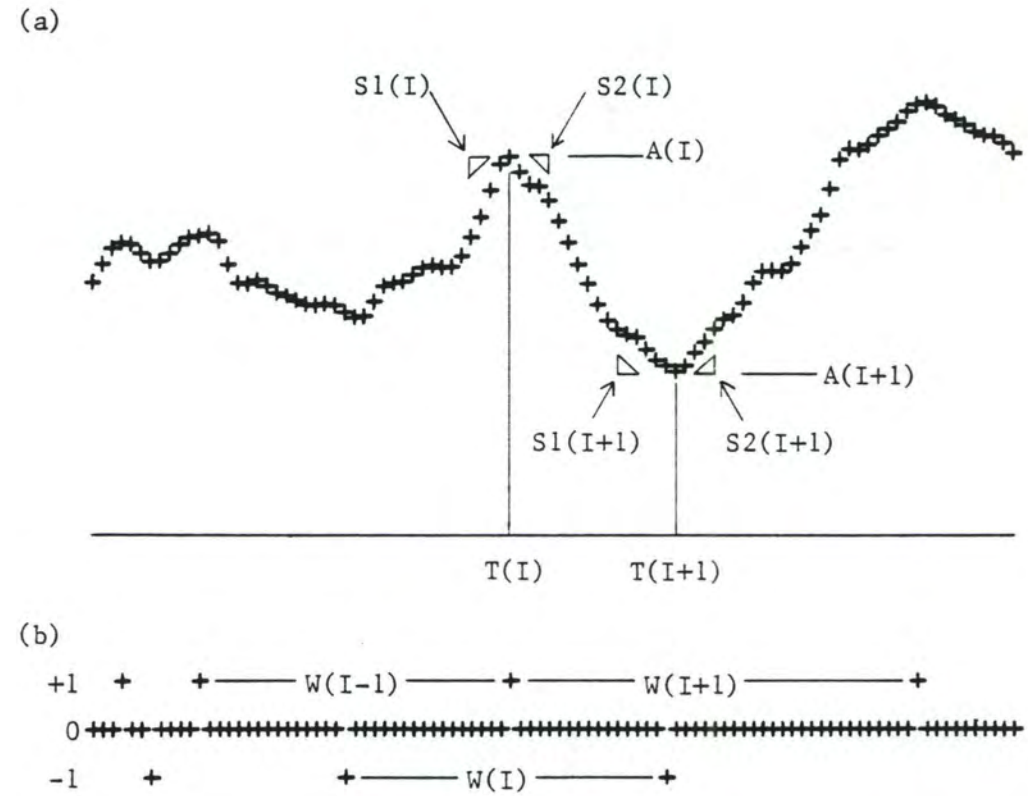


Figure 4.8 Parameterization Procedure. (a) Basic data and (b) Extrema marker and waves.

called Method T, a parameter is derived by template matching. After describing the two methods, an "event", which extends the category of waves, is defined.

Method A

In each wave, the time of the extremum of the wave, the amplitude at this time, and the slopes before and after this time are measured, using the basic data. In Fig.4.8, the I-th wave W(I) has the time T(I), the amplitude A(I), and the slopes S1(I) and S2(I). S1(I) and S2(I) are calculated as follows:

$$S1(I)=(A(I)-A_1(I))/N_1 \text{ and}$$
$$S2(I)=(A_2(I)-A(I))/N_2$$

where $A_1(I)$ and $A_2(I)$ are the amplitudes at the times of $T(I)-TD*N_1$ and $T(I)+TD*N_2$, respectively. TD is the sampling period, and N_1 and N_2 are constant numbers. Likewise W(I+1) has T(I+1), A(I+1), S1(I+1) and S2(I+1). Then, the four parameters of the I-th wave W(I) are defined as follows:

(1) the duration[1] DU(I)=T(I+1)-T(I) ,

(2) the amplitude[1] AM(I)=A(I+1)-A(I) ,

(3) the slope before the extremum S1(I) ,

(4) the slope after the extremum S2(I) .

1. These parameters could be defined as DU(I)=T(I)-T(I-1) and AM(I)= A(I)-A(I-1), so that a future wave W(I+1), supposing W(I) is the current wave, is not needed.

Method T

In Method T, template matching is adopted in deriving parameters. The scheme of making a template in this project is introduced and the three measures of similarity or dissimilarity that are tested in this project are explained.

Making a Template

To avoid relying on researchers' subjective decisions in making a template as much as possible, the following procedure was established, thereby the shape and the length of a template being decided.

First the sharp peaks of the SSWs marked by the electroencephalographer in a training data set are aligned as shown in the graph (a) of Fig.4.9. These aligned SSWs are averaged, and the averaged SSW shown in the graph (b) becomes the shape of a template. The graph (c) shows the standard deviation in averaging. The length of a template is decided by using a confidence level of a T-test, which gives a statistical value of how far the averaged value is deviated from a mean. The score of the T-test was obtained by the subroutine TTEST in the packaged programs of SSP[1] , using the option 1, where the hypothesis is that the mean of the population is equal to a given mean. The confidence level was calculated by the function PROBT in SAS[2] program package.

---

1. See System/360 Scientific Subroutine Package (360A-CM-03X) Version III Programmer's Manual. IBM Corp.

2. Statistical Analysis System. See SAS User's Guide: Basics 1982 Edition. SAS Institute Inc.

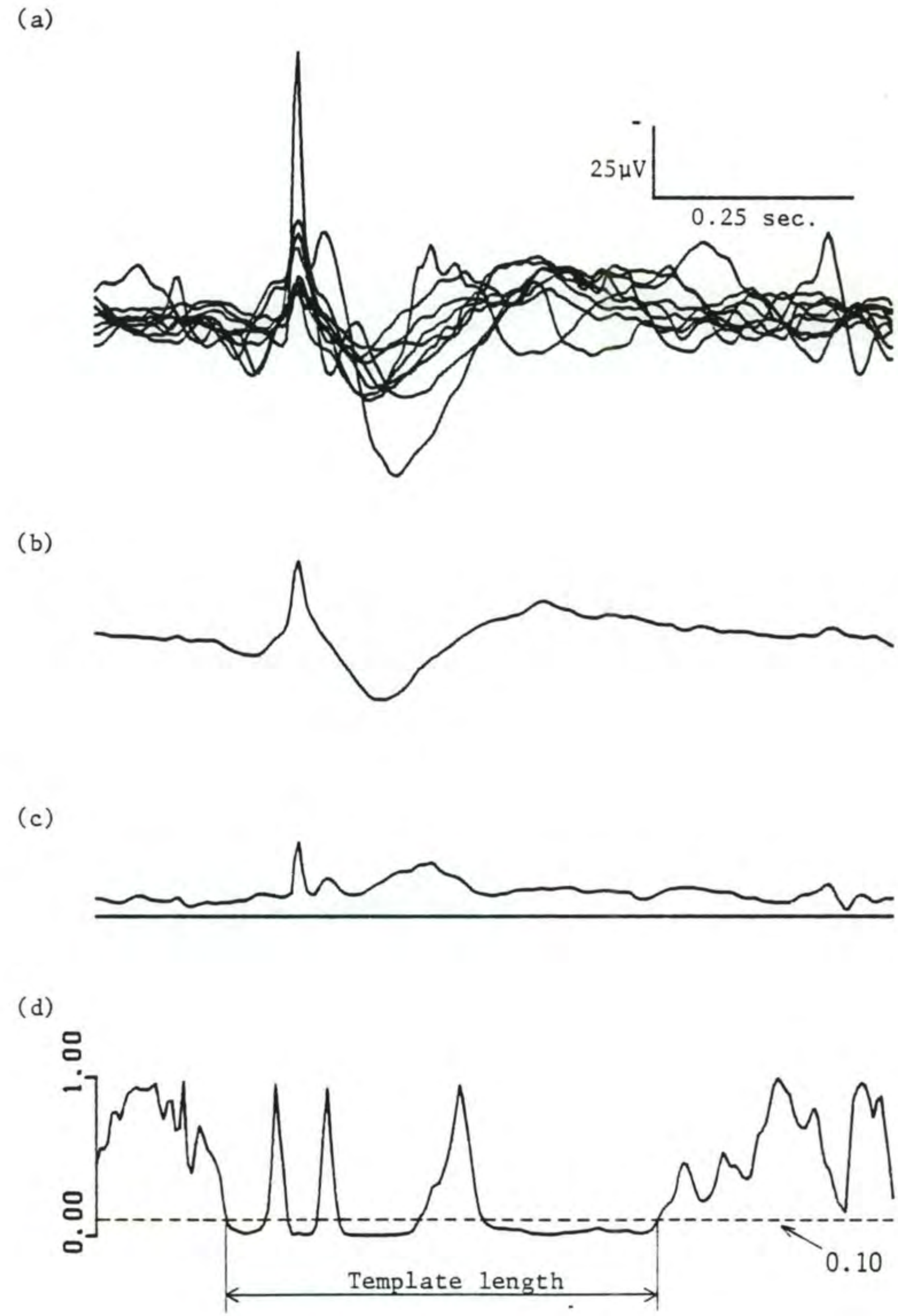


Figure 4.9 Procedure of Making a Template. (a) SSWs in a training data set, (b) Averaged SSW, (c) Standard deviation and (d) Confidence level of T-test.

The procedure follows. The data was an ensemble of several SSW portions. Each portion was 9 second long, and had a peak of SSW at the center of it. The 3 second middle portion was used for the T-test, and the rest were used for getting the mean for the T-test. To calculate the mean, the averaged data, a center part of which is shown in the graph (b) of Fig.4.9, was averaged excluding the middle 3 second portion. The graph (d) of Fig.4.9 shows the confidence level and the length of the template when a threshold level 10% was applied.

It is important to exclude redundant portions as much as possible so that only a significant or distinctive portion is compared in template matching. Although the length of a template could be decided by visual inspection, it again comprises researchers' subjective decision. The procedure established in this project at least gives an objective way of selecting the length except for the necessity of choosing a threshold of the confidence level.

Template Matching

As shown in Fig.4.10, the value of template matching in the I-th wave W(I) is needed only when the peak of the I-th wave, A(I), is aligned with the peak of the template, AT. Then, the template matching value becomes a parameter in the wave. Furthermore, only peak waves are considered as possible SSW candidates. Because the SSWs marked were all peak waves in the obtained data sets, and peak waves, which have electrically negative peaks, are said to be more characteristic of epileptic waves as mentioned in Chapter 2. Thus, in Fig.4.10, V(I-2), V(I) and V(I+2) are parameters of the waves W(I-2), W(I) and W(I+2) respectively, for example. The parameters V(I-1) and

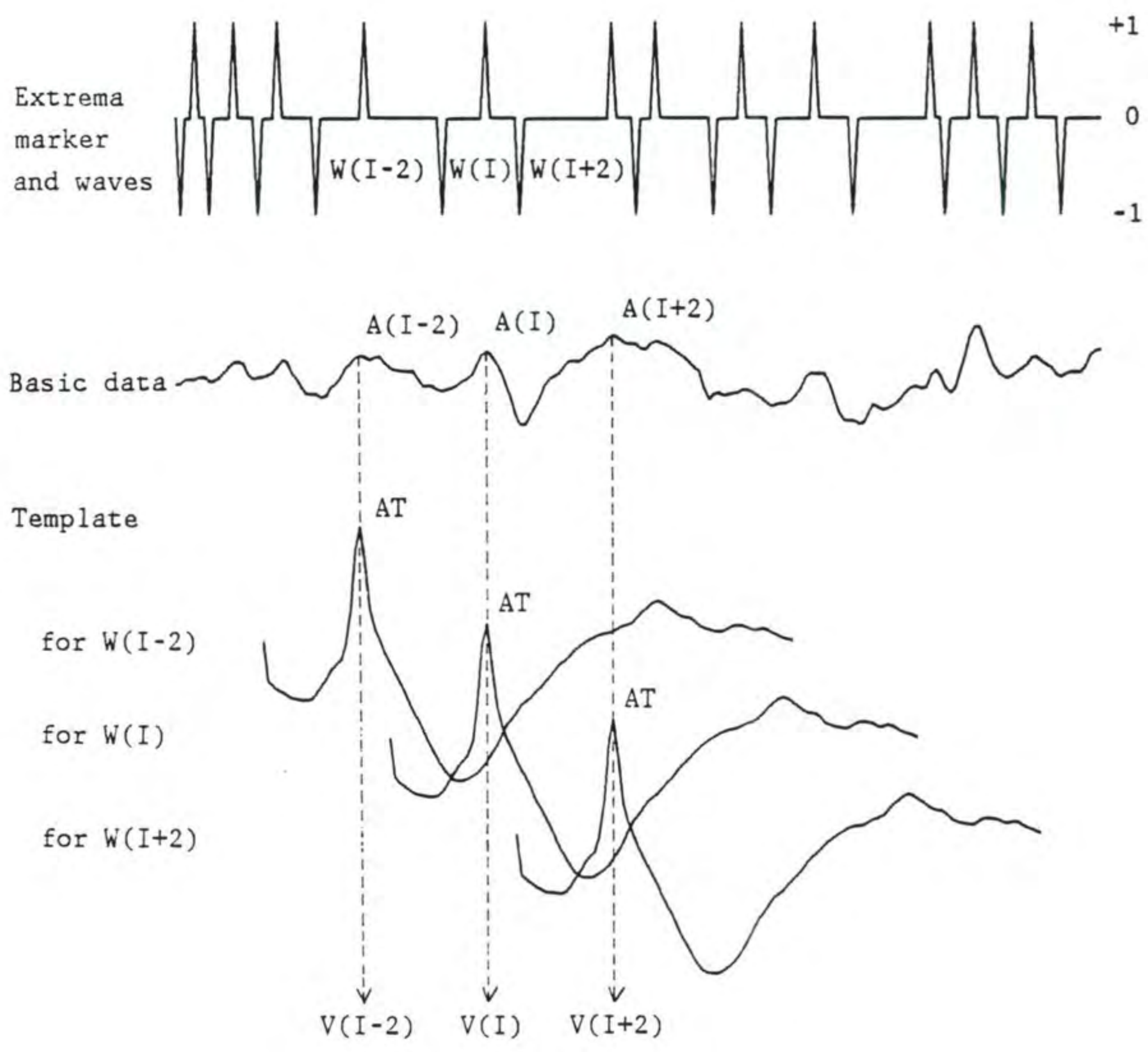


Figure 4.10 Template Matching Calculation Scheme.

$V(I+1)$ of the waves $W(I-1)$ and $W(I+1)$, respectively, are not shown in the graph, but used for analysis.

Three measures were tested in this project: (1) mean absolute error, (2) mean square error, and (3) correlation coefficient. Hence, the parameter of the I-th wave in Method T is calculated by one of the following formulas:

$$Va(I)= \frac{1}{N} \sum_{i=1}^{N} |a_I(i)-at_I(i)|$$

$$Vs(I)= \frac{1}{N} \sum_{i=1}^{N} \{a_I(i)^2-at_I(i)^2\}$$

$$Vc(I)= \{\sum_{i=1}^{N} a_I(i)at_I(i) - \frac{1}{N} \sum_{i=1}^{N} a_I(i) \sum_{i=1}^{N} at_I(i)\}$$

$$\bullet[\{\sum_{i=1}^{N} a_I(i)^2- \frac{1}{N}\{\sum_{i=1}^{N} a_I(i)\}^2\}\{\sum_{i=1}^{N} at_I(i)^2- \frac{1}{N}\{\sum_{i=1}^{N} at_I(i)\}^2\}]^{-\frac{1}{2}}$$

where Va, Vs and Vc are measures of mean absolute error, mean square error, and correlation coefficient, respectively. Fig.4.11 shows the notation used in the formulas above. NT1 is the point at the peak of the SSW template.

Definition of an Event

Considering that the morphological features of a SSW may spread beyond one wave segment, it is reasonable to introduce a concept of an "event", which covers more than one wave. This concept is hinted at by the concept of a "sequence" proposed by Remond (1969) and the method of parameterization presented by Schenk (1976) (see The Concept of Events, Parameterization in Chapter 3).

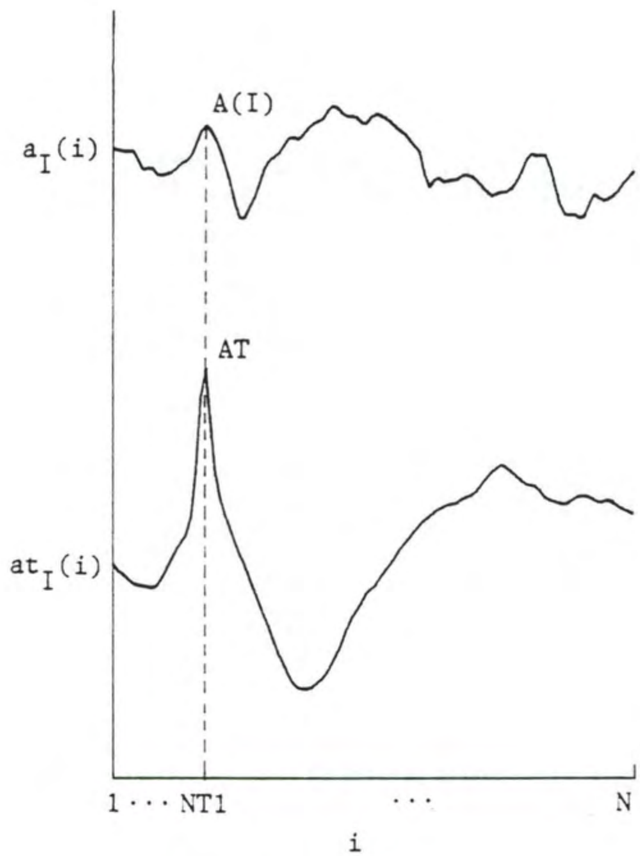


Figure 4.11 Template Matching.

An "event" consists of a set of parameters of one or more waves. For example, the I-th event E(I) in Fig.4.12 includes the waves W(I-4), W(I-3), W(I-2), W(I-1), W(I), W(I+1), W(I+2) and W(I+3). In general, the I-th event E(I) contains the parameters of the waves {W(J), J=N1,N1+1,...,I,I+1,...,N2; N1≤I≤N2}. When an event includes M=N2-N1+1 waves, the number of parameters in an event is 4M in Method A, and M in Method T. It may not seem to be necessary in Method T because the templates already covers the main portion of SSW. However, by including more than one template matching values in an event as candidate parameters for classification, it leaves a possibility to find more than one template matching parameters useful for classification.

The following notation for those parameters in an event is suitable: Suppose E(I) includes the waves $W_1(I)$, $W_2(I)$,..., and $W_M(I)$, whereby $W_{M1}(I)$=W(I). The M1-th wave $W_{M1}(I)$ in an event is then called a "core wave" because it is the wave being investigated for the detection of SSW, and, if necessary, artifacts. Each $W_N(I)$, N=1,...,M has parameters: $AM_N(I)$, $S1_N(I)$, $S2_N(I)$ and $DU_N(I)$ for Method A; $Va_N(I)$, $Vs_N(I)$ or $Vc_N(I)$ for Method T.

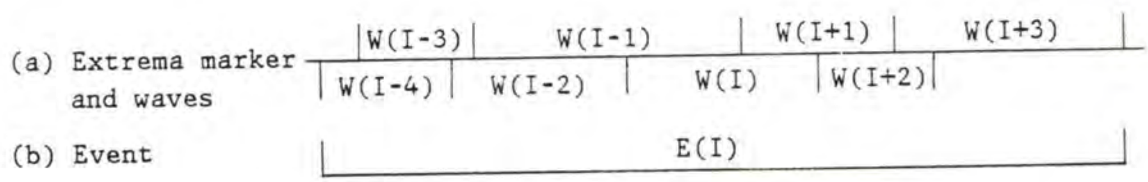


Figure 4.12 Example of an Event.

Classification

The stepwise linear discriminant analysis program in Biomedical Computer Programs, called BMDP7M (Dixon 1975), was chosen to deal with both the selection of the parameters and the calculation of the classification functions. The input of the program is the parameterized data of a training data set. Each event in the data is labeled as one of the groups by a supervisor.

In selecting the "best" set of parameters, the program uses a stepwise procedure, which selects one parameter at a step, and the univariate F-ratio as the criterion of selection. As already mentioned in Chapter 3, there are some criticisms of the selection procedure. One of the criticisms is the lack of the overall significance levels. The levels proposed by Hawkins (1976) were tried to incorporate the overall significance levels in this project. The other points criticized still remained. Computationally, though, the procedure is more economical than most others. Another advantage is the popularity of the BMDP program, which is available in a number of institutes. The univariate F-ratio and the estimation of the overall significance levels are described in Appendix A. The mathematical procedure of the program is found in Appendix C.

Three types of linear classifiers are described in Appendix B. The BMDP7M program calculates the linear classifier by Bayes approach. The program also calculates the canonical variables, by which the classifier derived by canonical approach may be constructed. The mathematical procedures are described in Appendix C. It must be noted that the canonical variables in the program are derived using the specified contrasts, and are standardized. The data usually do not conform to the assumption of multivariate normality and equal covariance in the Bayes classifier. The classifier by canonical approach does not assume the multivariate normality, but assumes equal covariance. Also, the prior probabilities are not needed in the calculation, which is an advantage. Fisher's approach may be considered as a special case of the canonical approach. The Bayes classifiers are tested in this project mainly because they are used by the BMDP7M program. The canonical classifiers are also tested using one example. It is interesting to compare the performances of both classifiers.

Evaluation of Classification Results

First the measures to estimate the success of classification are derived. Then, the reconstruction of original data in Method A is described as a means of investigating the properties of individual events.

Measures of Classification Success

PRE (proportionate reduction in error) approach are used instead of using raw percentages of correct classification, which are poor measures. The following development of the measures is based on the description of the PRE measures by Hilderbrand et al. (1977, pp.36-79). PRE measures make a comparison of error rates and permit operational interpretation. Because the detection of SSW events is the main purpose, the classification table is simplified to such a 2 by 2 table as follows. First, the labels of events are simplified as SSW_{orig} and Non-SSW_{orig} where SSW_{orig} is for SSW events and Non-SSW_{orig} is for the others. Likewise the specified groups on a classifier are simplified as SSW_{clas} and Non-SSW_{clas}. These simplified results in a 2x2 classification table. The numbers of events in the table are divided by the total number of events. Hence, the classification table is converted to the table as shown in Table 4.1. In Table 4.1, P_{ss} is the probability of classifying the original SSW (SSW_{orig}) to the group SSW (SSW_{clas}), for example. $P_{n.clas}=P_{sn}+P_{nn}$ and $P_{s.orig}=P_{ss}+P_{sn}$, and the like. The measures are P1, P2 and P3, corresponding to the logics Non-SSW_{clas} => Non-SSW_{orig}, SSW_{clas} => SSW_{orig}, and SSW_{clas} <=> SSW_{orig}, respectively. Herein a logic X => Y refers to the sentence of "X tends to be a sufficient condition for Y," and a logic X <=> Y is equivalent to a logic X=> Y and Y => X. Then, the error cells corresponding to the measures P1, P2, and P3 are the cells of P_{sn}, P_{ns}, and P_{sn} plus P_{ns}, respectively. The definitions of these measures are given below:

$$P1 = 1 - P_{sn}/(P_{s.orig} \bullet P_{n.clas}) \quad ,$$

$$P2 = 1 - P_{ns}/(P_{n.orig} \bullet P_{s.clas}) \quad ,$$

$$P3 = 1 - (P_{sn} + P_{ns})/(P_{s.orig} \bullet P_{n.clas} + P_{n.clas} \bullet P_{s.clas}) \quad .$$

Table 4.1 Simplified Classification Table Configuration.

	SSW_{clas}	Non-SSW_{clas}	
SSW_{orig}	P_{ss}	P_{sn}	$P_{s.orig}$
Non-SSW_{orig}	P_{ns}	P_{nn}	$P_{n.orig}$
	$P_{s.clas}$	$P_{n.clas}$	1.00

Let us suppose a prediction that predicts the original events given the knowledge of classification result. By evaluating the prediction success, we can know how successful the classification is. Let a logic X => Y be one of the logics corresponding to P1, P2 and P3. The value r, $0<r<1$, of the measure with the logic X => Y indicates that 100*r% reduction in error is achieved by applying the logic given knowledge of the classification result over that expected when the prediction is applied to randomly selected events whose groups are not known by classification. The value of r is 1 if and only if the prediction is perfect, and is zero if and only if the classification result and the original assignment is statistically independent. The measure goes below zero if the prediction is worse than the prediction that gives the value zero.

Once a SSW is missed, there will be no way to recover it, whereas even if background events are included in the detected SSWs, they can be eliminated by processing further. For this reason, it is more important in practical application for the detection system not to miss possible SSWs than not to miss possible backgrounds. Therefore, the measure P1 should be more considered than the measure P2 in practical application of the detection system. The measure P3 is a weighted average measure between the measures P1 and P2. When both the background and SSW misclassifications are considered, the measure P3 will be appropriate.

Reconstruction of Original Data

In Method A, the original data can be reconstructed. The data reconstruction may contribute to reducing the data to be stored stored for later analysis and giving an insight for how the original data is parameterized.

At the level of wave data where the data is converted to wave parameters, the original data sequence can be reconstructed using the wave parameters, AM(.), S1(.), S2(.) and DU(.), on condition that the initial time and amplitude are known. From a set of wave parameters in a wave W(I) including the check value ICK1, which is 1 or -1, the following three pairs of amplitude and time are derived: $(A_1,T_1),(A_2,T_2)$, and (A_3,T_3) where

$$A_1=A(I+1)=A(I)+AM(I), \quad T_1=T(I+1)=T(I)+DU(I),$$
$$A_2=A(I)+S1(I)*(N-1)/2*ICK1, \quad T_2=T(I)-TD*(N-1)/2,$$
$$A_3=A(I)-S2(I)*(N-1)/2*ICK1, \quad T_3=T(I)+TD*(N-1)/2,$$

where N is the number in the subroutine GETD to calculate the slopes, and TD is the sampling period. At the level of event data where the data is converted to event parameters, a portion of original data covering the waves in an event can be reconstructed from a set of parameters in one event. Since a set of parameters in one event consists of several sets of wave parameters, the event portion is reconstructed in the same way as described above. An example of event reconstruction is shown in Fig.4.13. The event included 18 waves and had the core-wave at the 10-th wave. Because the initial amplitude is assumed to be zero, the DC component of the reconstructed data can not be known. But it is not a loss of information for analysis because the DC components are insignificant in dealing with transient waves such as SSW.

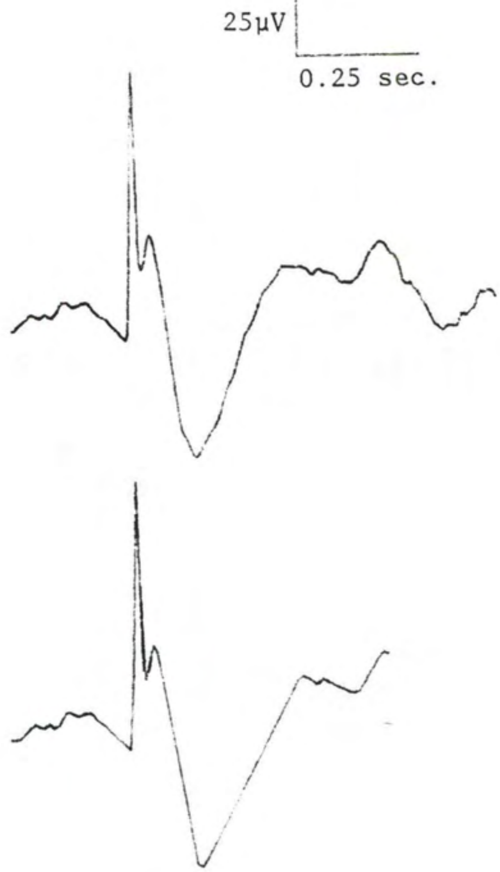


Figure 4.13 An Example of a Portion of Original Data and the Corresponding Reconstructed Data.

Programming

This section demonstrates how the procedures mentioned above make up one whole analysis sequence.

Flowcharts

The diagrams in Fig.4.14 and Fig.4.15 show the basic program flowcharts for Method A and Method T, respectively. The subprograms and subroutines are shown in Fig.4.16. However, these program flowcharts are written only to aid understanding, and therefore include some redundant parts. Also, there will be modification in practical programming according to experimental design. The following paragraphs explain the program flowcharts for Method A, and for Method T. The notations of input parameters are as follows.

N	:	number in getting the slopes of basic data Y(.) by the subroutine GETD.
NW	:	number in getting the slopes of the filtered data YL(.) by the subroutine GETD.
L'	:	order of the linear filter. L=L'+1 is used in the subroutine GETL2.
NT	:	total number of points in a template.
NT1	:	number of the point where the peak of a template is put in a wave.
TD	:	sampling period in seconds.
M	:	number of waves included in one event.
M1	:	number of the wave where the core-wave is put in an event.
NC	:	number of groups to be classified.
NV	:	number of variables selected.

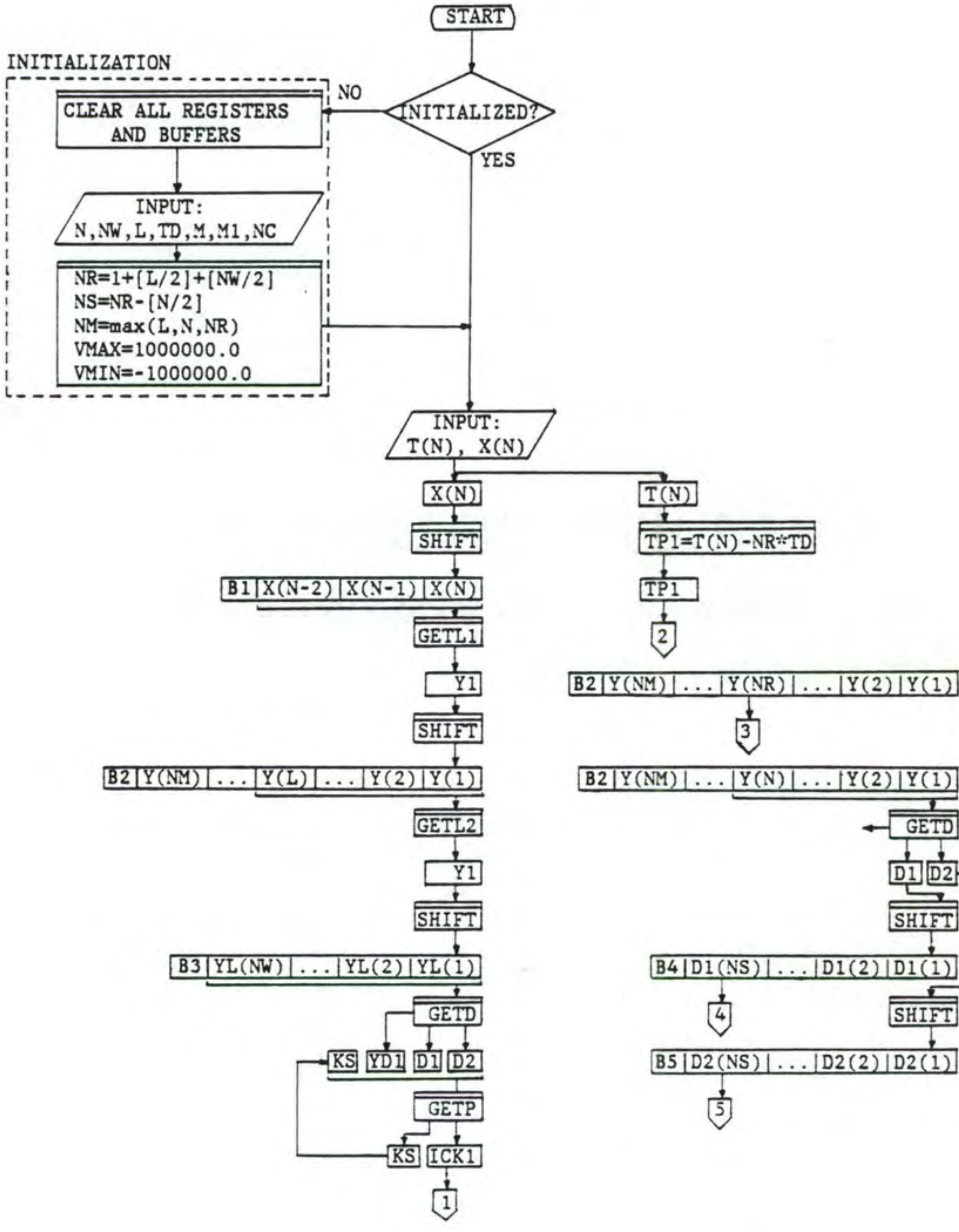


Figure 4.14 Program Flowchart: Method A.

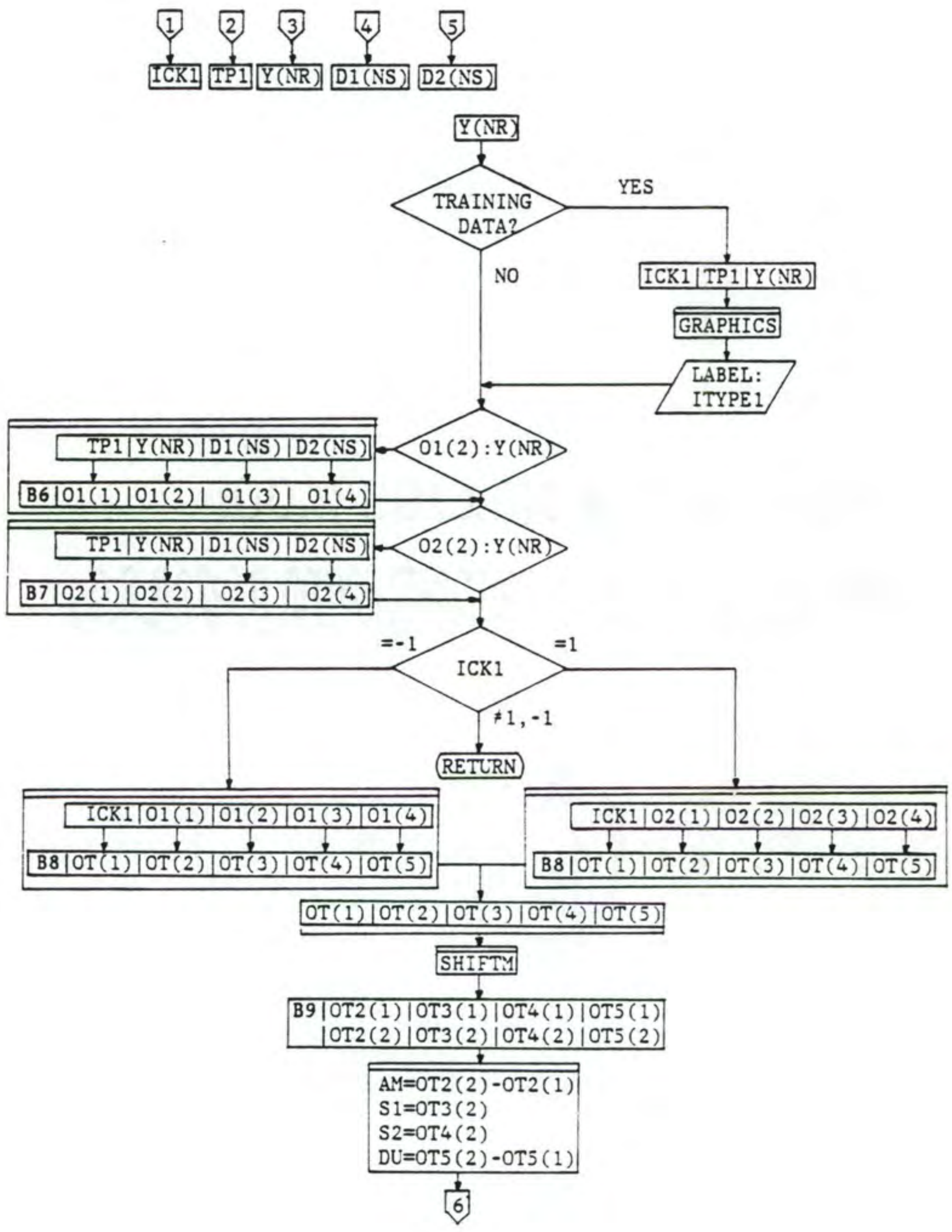


Figure 4.14 (Cont'd.)

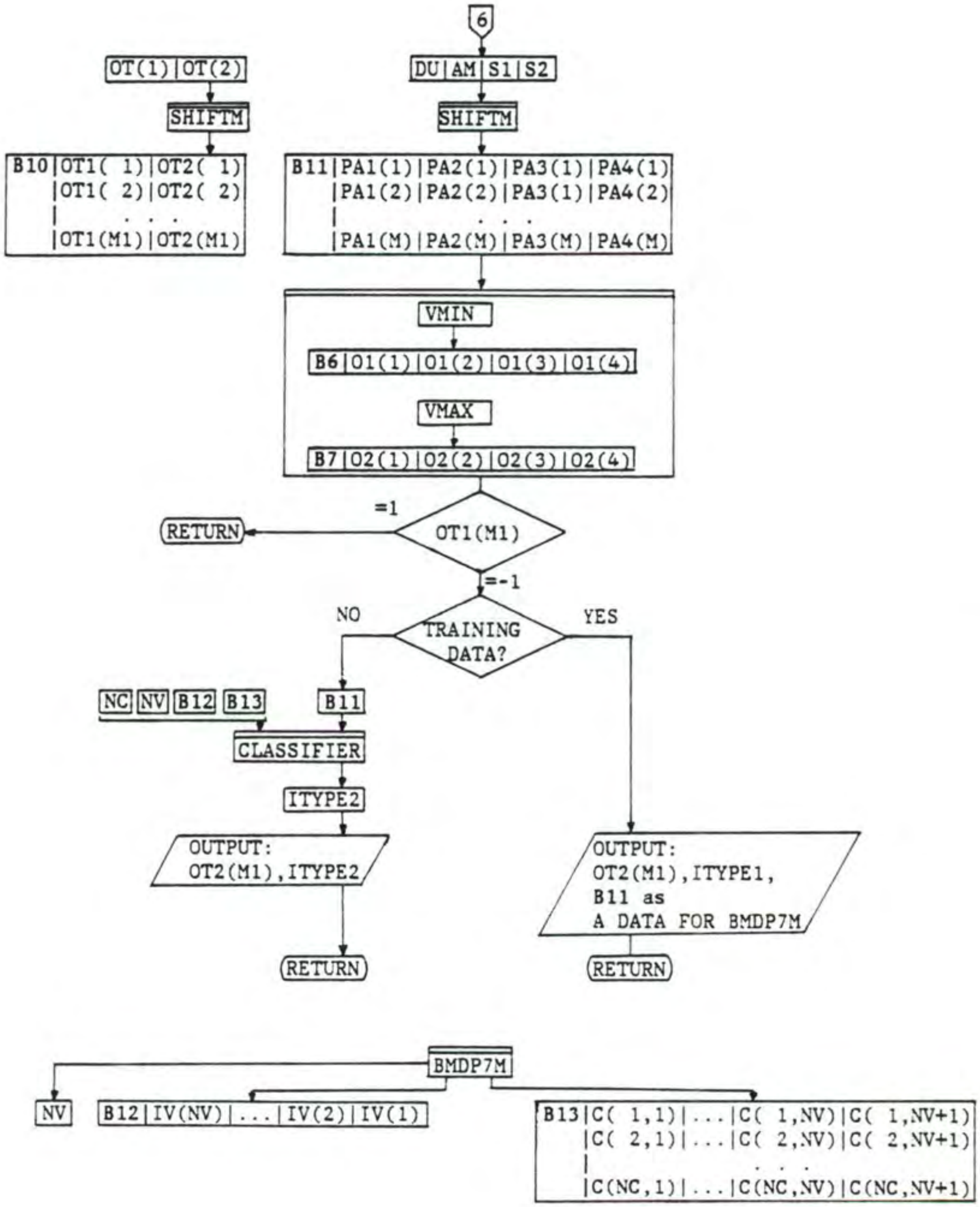


Figure 4.14 (Cont'd.)

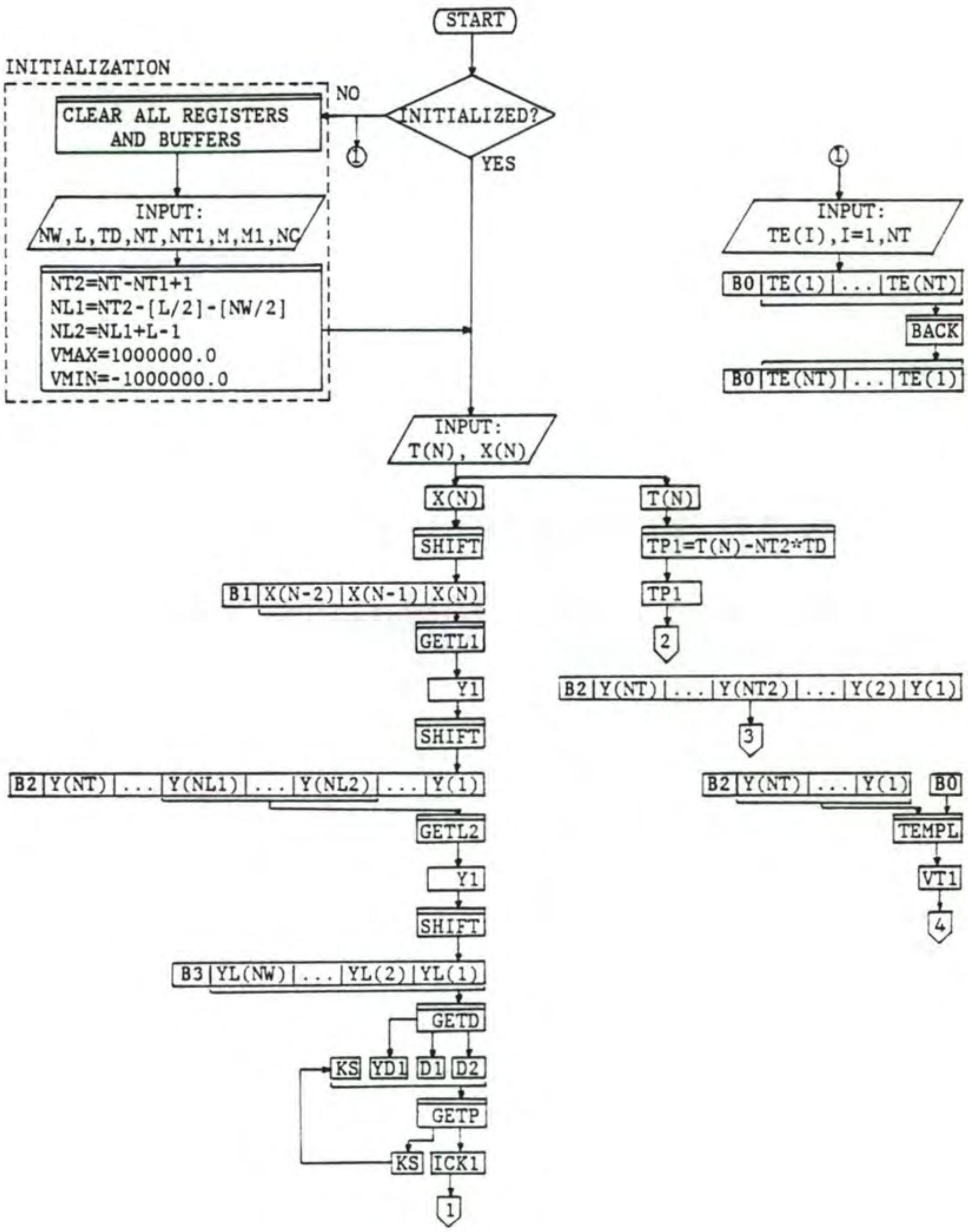


Figure 4.15 Program Flowchart: Method T.

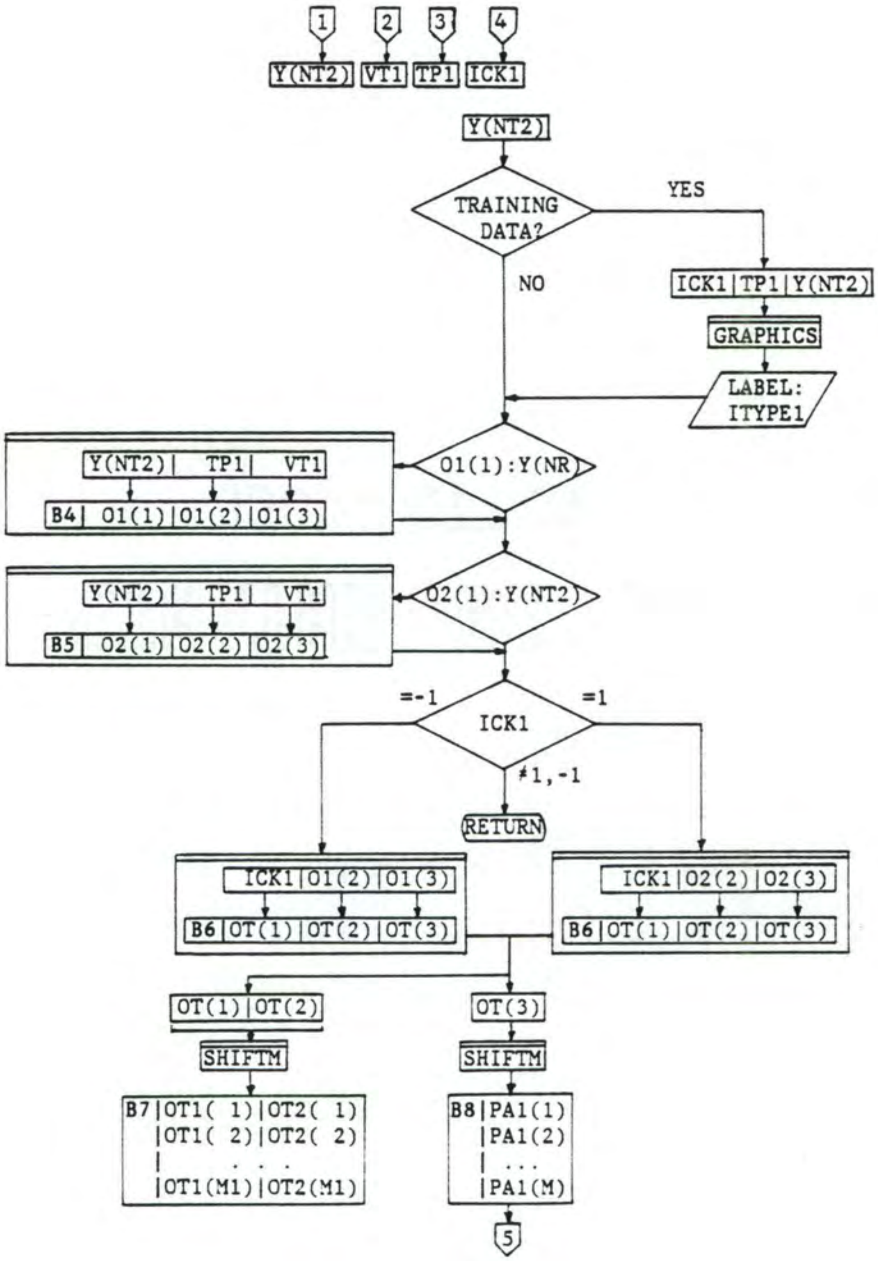


Figure 4.15 (Cont'd.)

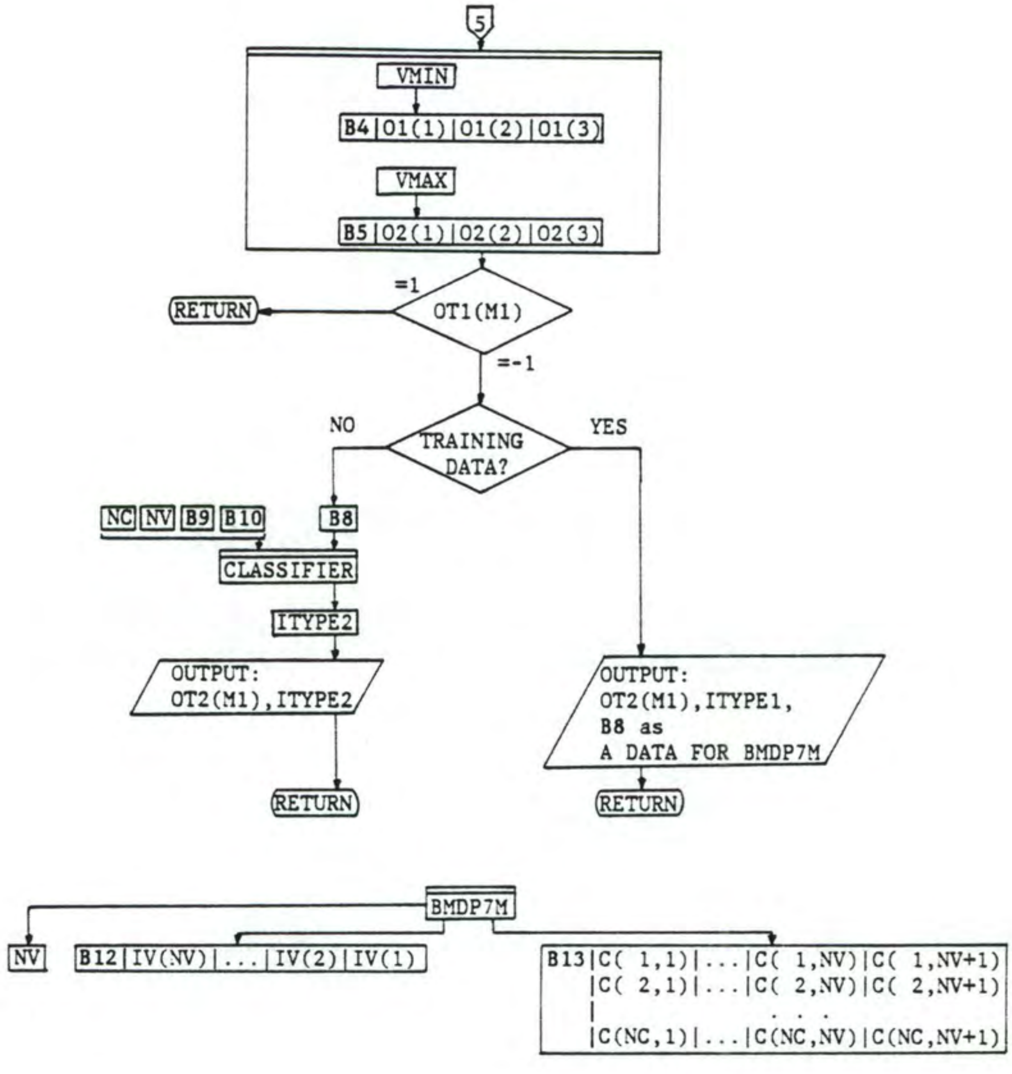


Figure 4.15 (Cont'd.)

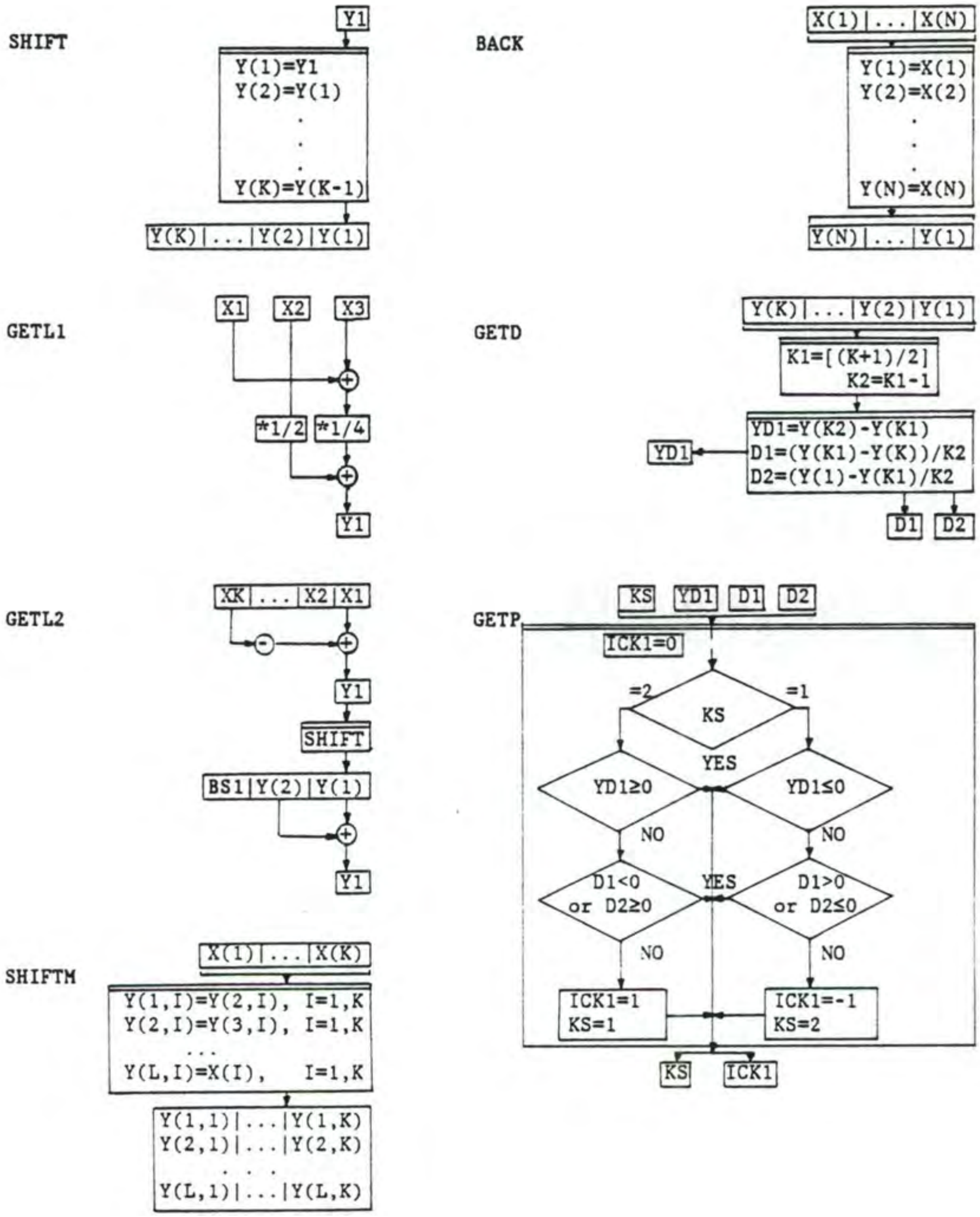


Figure 4.16 Program Flowchart: Subprograms and Subroutines.

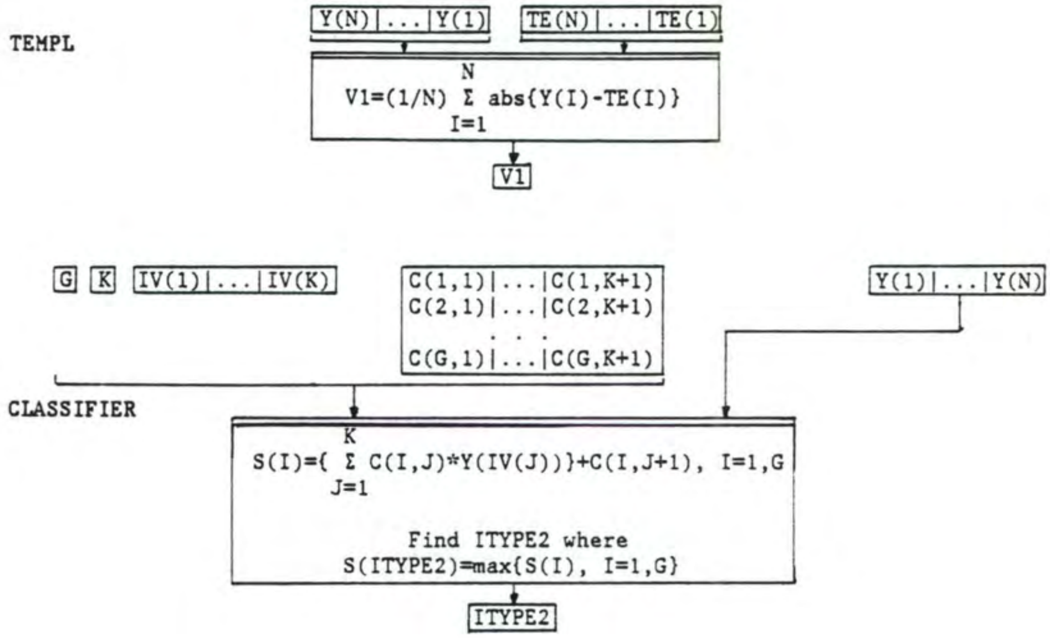


Figure 4.16 (Cont'd.)

After Initialization, the program gets ready to accept sequential data. Suppose a data point X(N) from an A/D converter is input to the program at time T(N). The following describes the process to deal with the data X(N) and T(N). When a RETURN is encountered, the program is ready to accept another pair of data. X(n) is stored in a link buffer **B1** by the subroutine SHIFT. The stored data in **B1** is low-pass-filtered by a three point Hanning filter using the subroutine GETL1. The filtered value Y1 is stored in a link buffer **B2**. The data in **B2** is further low-pass-filtered using the subroutine GETL2, and stored in a link buffer **B3**. Using the outputs from the subroutine GETD, the subroutine GETP outputs ICK1 for checking the extrema of the data: ICK1=1 if an extremum is detected in a convex wave, ICK1=-1 if in a concave wave, and ICK=0 otherwise. Because the time delay to get the value ICK1, which is the largest time delay, is NR times the sampling period TD, the data Y(NR) at time TP1 is corresponding to the timing of ICK1. The slopes S1 and S2 are calculated using the subroutine GETD, and stored in a link buffer **B4** and **B5**. S1(NS) and S2(NS) are corresponding to the timing of ICK1.

If the current data is in a training data set, the data of ICK1,TP1, and Y(NR) are used for a supervisor to label each wave with one of the groups. The next stage of the program is to check the maximum and minimum values of the amplitude Y(NR) in one wave. If the current value of Y(NR) is larger than the stored maximum O1(2) or smaller than the stored minimum O2(2), the stored values in buffers **B6** and **B7** are replaced by the new values as shown.

If ICK1 is not zero, it means it is a checkpoint for a wave. If ICK1 is -1, the last wave is a peak wave, and the values in **B6** are stored in a buffer **B8** with the value ICK1. If ICK1=1, the last wave is a trough wave, and the values in **B7** are stored in a buffer **B8** with the value ICK1. Using the values stored in **B8**, the parameters of a wave are calculated. To do so, a multi-link buffer **B9** is installed using the subroutine SHIFTM. The amplitude AM, slopes S1 and S2, and duration DU in the wave are calculated as shown.

To complete the parameterization, a set of parameters of an event is organized by using SHIFTM. One event contains M waves and the M1-th wave in an event is the wave being examined, which is called a "core-wave". The multi-link buffer **B10** contains the set of parameters in the event. After parameterization is finished, the values O1(2) and O2(2) are replaced by VMIN and VMAX, respectively, to get ready for the next wave. In this project, as mentioned before, only peak (convex) waves are considered to be of interest for SSW detection. Therefore, events that have concave core-waves are discarded.

The program now proceeds to the classification stage. If the data is in a training data set, the values in an event shown in the flowchart become data for the BMDP7M program. Supposing that all the events have been labeled by a supervisor, the BMDP7M program outputs the classification functions (stored in **B13**), NV, and an array IV(.) (stored in **B12**). These values are necessary as an input for the classifier later.

If the data is not in a training data set, the data is input to the classifier. By this time, the classifier is supposed to have the values of the number of groups, NC, the number of parameters used, NV, the identification numbers of parameters used, IV(.) in B12, and the coefficients of classification functions C(.,.).

In Method T, there are some differences in the program flowchart. In Initialization, the number of points in a template NT and its peak point NT1 are included whereas N is not needed. The time delay corresponding to the checkpoint of ICK1 is decided to be NT2 times the sampling period TD. Some values relating to time delay is accordingly changed, the lengths of buffers are different, and also the use of location of buffers is different. Instead of calculating the slopes in Method A, the template matching value VT1 is calculated.

Most of the subroutines include only simple operations. The subroutine SHIFT and SHIFTM can be time consuming when the number of data to be shifted is large. However, if a pointer or a pointer-like variable is implemented to update the current element of a buffer, the time of executing the subroutine would not depend on the number of data to be shifted, but only depend on the manupilation to locate the element. Then, these routines are not necessarily time consuming. The subroutine GETD is just a simple way of calculating the first derivatives before and after the center of the data. The subroutine GETP incorporates a sort of double check system to detect an extremum. That is, the data is once checked by YD1, and then checked again by D1 and D2. The purpose of this routine is to detect all the candidates for extrema and to discard insignificant extrema. The TEMPL subroutine in Fig.4.16 inputs arrays of data and a template, and calculates a template matching value using one of the three algorithms mentioned earlier. In the flowchart, the mean absolute measure algorithm is shown as an example.

Programs for Experiments

Appendix D shows the lists of the programs for the experiments in Chapter 5. The selection of parameters and the calculation of classification functions are done by the BMDP7M program. The other programs are written with FORTRAN. These programs basically follow the program flowcharts, but they differ in the following points:

(1) The event identification parameters IFILE for the data set file number, and IEVENT for the event number in the file are used as well as the time parameter TP1.

(2) The type parameter ITYPE1 in testing data sets, which shows the decision of a supervisor about what group each event belongs to, will not be provided in practical application, but was provided to evaluate the results later in this project.

(3) The program flowchart in either Method was divided into three programs as shown in Appendix D. The intermediate lists of the data served as secondary and tertiary data, and were convenient when changing some conditions of experiments.

(4) The program for making up summary tables of classification performance was added.

The instructions for running the programs are provided in Appendix E. Appendix F shows examples of the program outputs.

CHAPTER 5

EXPERIMENTS AND RESULTS

The main purpose of the experiments was to verify the feasibility of the proposed analysis procedures in SSW detection and to evaluate their performance under various experimental conditions.

Design of Experiments

Table 5.1 shows the design of experiments. The main conditions of concern in designing the experiments were as follows:

(1) to retract or not the adjacent events to SSWs in training data sets,

(2) the number of training data sets to be used,

(3) the number of specified groups (e.g. background, SSW, artifact),

(4) the number of parameters used in classification.

The adjacent events to a SSW event mentioned above were the background events that were within the range of 15 events before and after the SSW event. By retracting these adjacent events from the training data sets for the BMDP7M program, the background events that contain SSW waves in the waves constituting the events were eliminated from the discriminant analysis in the program. In addition, the effects of prior probability and the performance of the canonical classification functions were examined in supplemental experiments.

The conditions common to all experiments were as follows:

(1) the sampling period, TD=5 msec;

(2) the number in getting the slopes of the basic data, N=5;

(3) the number in getting the slopes of the filtered data, NW=5;

Table 5.1 Design of Experiments. (a) Method A and (b) Method T.

(a)

Name of experiment		A12	A13	A14	A12R	A13R	A14R	A22R	A23R	A24R	A32R	A33R	A34R
Types	Backgrounds	G1	G1	G1	G1	G1	G1	G1	G1	G1	G1	G1	G1
	SSWA	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2
	SSWB	G2	G2	G3	G2	G2	G3	G2	G2	G3	G2	G2	G3
	Successive SSW	G1	G1	G1	NU	NU	NU	NU	NU	NU	NU	NU	NU
	Doubious SSW	G1	G1	G1	NU	NU	NU	NU	NU	NU	NU	NU	NU
	Adjacents to SSW	G1	G1	G1	NU	NU	NU	NU	NU	NU	NU	NU	NU
	Artifacts	G1	G3	G4	G1	G3	G4	G1	G3	G4	G1	G3	G4
Prior probability	G1	.99	.98	.97	.99	.98	.97	.99	.98	.97	.99	.98	.97
	G2	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
	G3		.01	.01		.01	.01		.01	.01		.01	.01
	G4			.01			.01			.01			.01

NU: not used in BMDP7M. G1, G2, G3 and G4: specified groups.

(b)

Name of experiment		T•12	T•12R	T•13R	T•22R	T•23R	T•32R	T•33R
Template(s) used		TE1	TE1	TE1A TE1B	TE2	TE2A TE2B	TE3	TE3A TE3B
Types	Backgrounds	G1	G1	G1	G1	G1	G1	G1
	SSWA	G2	G2	G2	G2	G2	G2	G2
	SSWB	G2	G2	G3	G2	G3	G2	G3
	Successive SSW	G1	NU	NU	NU	NU	NU	NU
	Doubious SSW	G1	NU	NU	NU	NU	NU	NU
	Adjacents to SSW	G1	NU	NU	NU	NU	NU	NU
	Artifacts	G1	G1	G1	G1	G1	G1	G1
Prior probability	G1	.99	.99	.98	.99	.98	.99	.98
	G2	.01	.01	.01	.01	.01	.01	.01
	G3			.01		.01		.01

T• : TA, TS and TC in Method T.
NU: not used in BMDP7M. G1, G2, G3 and G4: specified groups.
TE1, TE2 and TE3: templates based on SSW in Data01, Data01&02, and Data01&02&03, respectively.
TE1A,TE2A and TE3A: templates based on SSWA in Data01, Data01&02, and Data01&02&03, respectively.
TE1B,TE2B and TE3B: templates based on SSWB in Data01, Data01&02, and Data01&02&03, respectively.

(4) the order of the low-pass filter, $L'=L-1=4$ (L appearing in the subroutine GETL2);

(5) the number of waves included in one event, M=19;

(6) the number of the wave where the core-wave is placed in an event, M1=10;

(7) the options in BMDP7M: METHOD=1, TOL=0.005, BLANK=ZERO, F-to-enter =4.000, F-to-remove =3.996.

There is a nomenclature for the names of the experiments. For example, the experiment A23R means that it was done with Method A, two training data sets, three specified groups, and the retraction of the adjacent events to the SSW events. In general, the first one or two alphabetical character(s) refer(s) to the method. That is, A is for Method A, and TA, TS or TC are for Method T, indicating that the measure used is of absolute mean error, square mean error or correlation coefficient, respectively. The names of Method TA, Method TS and Method TC may be used when the measure of template matching needs to be specified. The first numerical character refers to the number of training data sets used, and the next numerical character is for the number of specified groups. The successive SSW, the doubious SSW and the adjacent events to SSW were not used in executing the BMDP7M program when the experiments had a letter R, for retraction, added at the end of the name. Furthermore, A23R.S03 refers to the classifier obtained by the experiment A23R at the step 3. Generally, one period, the letter S, and a step number are added to the experiment to express the classifier obtained at that step.

The templates were derived as explained in Chapter 4. They were named as described at the bottom of Table 5.1(b). That is, TE stands for template, the following number is for the number of data sets used in averaging, and either A or B were added if either SSWA or SSWB were separately averaged, respectively.

The names of parameters have the following nomenclature: the first two alphanumeric characters show the type of the parameter, and the following number is for the wave number of an event. The types of parameters are AM, S1, S2 and DU in Method A, and VM, VA and VB in Method T. The parameter types AM, S1, S2 and DU are of amplitude, slopes and duration in Method A, as described in Chapter 4. The parameter types VM, VA and VB are derived from all averaged SSW templates (TE1, TE2 or TE3), averaged SSWA templates (TE1A, TE2A or TE3A), and averaged SSWB templates (TE1B, TE2B or TE3B), respectively. For example, S211 means this parameter is of type S2 in the 11th wave of an event.

For convenience, the groups are called as follows. In the experiments of two groups, G1 and G2 are called BCK and SSW, respectively. In the experiments of three groups in Method A, G1, G2 and G3 are called BCK, SSW and ART, respectively. In the experiments of three groups in Method T, G1, G2 and G3 are called BCK, SSWA and SSWB, respectively. In the experiments of four groups, G1, G2, G3 and G4 are called BCK, SSWA, SSWB and ART, respectively. In the experiments with three groups in Method T, two templates were used: one for SSWA and another for SSWB.

The templates used in the experiments in Method T are shown in Fig 5.1. The effects of changing the number of parameters in classification functions will be demonstrated using examples of the experimental results.

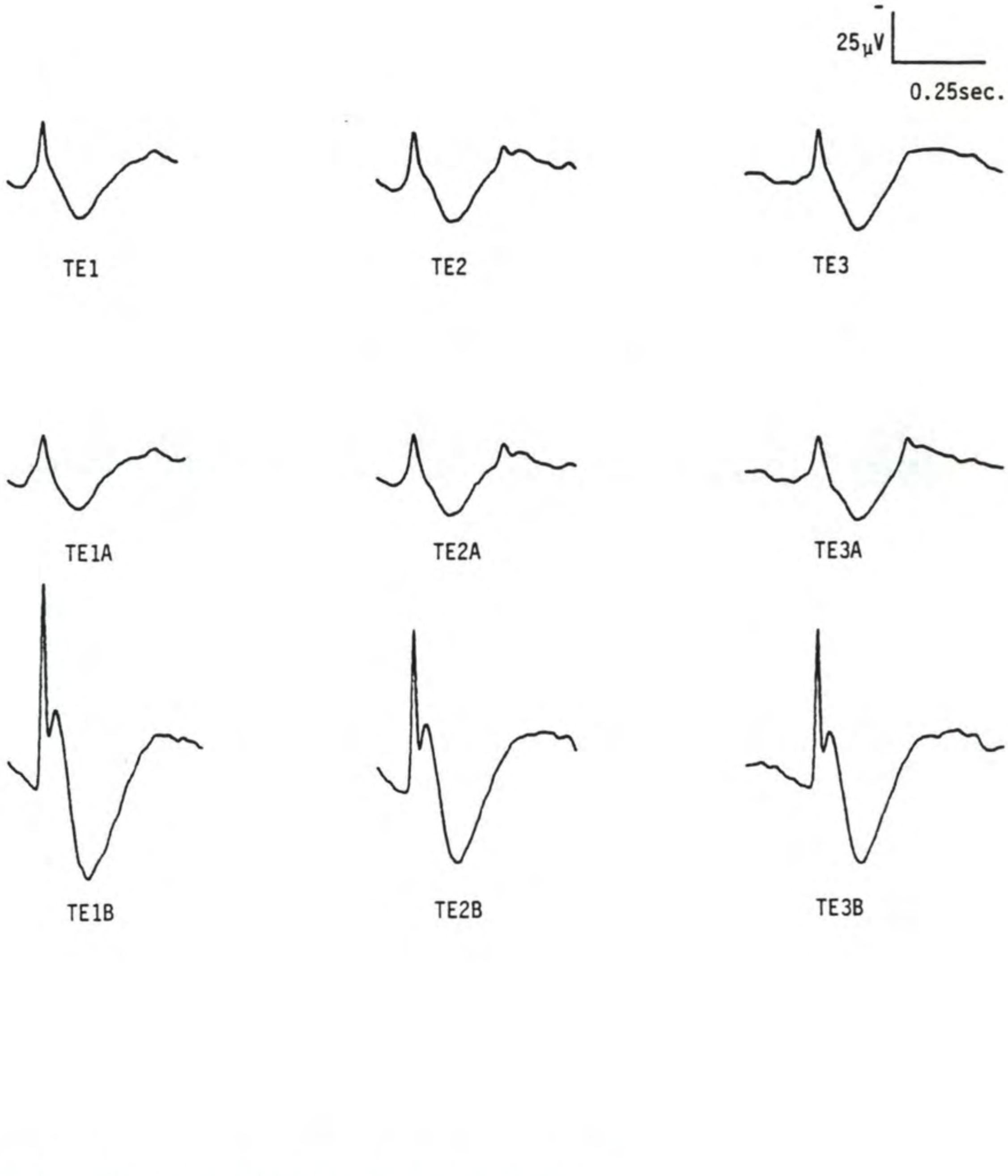


Figure 5.1 Templates Used in Experiments.

The supplemental experiments were designed as variations of the experiment A14R so that they could be compared with each other. The classifier A14R.S14 in the experiment A14R performed well as will be shown in the result section, and was chosen as an example for comparison. First the prior probabilities were changed from the probabilities in the experiment A14R to equal probabilities for all groups (i.e. 0.25 for each group). The classifier obtained at the step 14 was named A14R.PRI, where PRI indicated the change of prior probabilities. Second the coefficients of canonical variables at the step 14 of the experiment A14R were used for classification by the canonical classifiers described in Appendix B. The classifier A14R.CA1 was obtained by substituting the coefficients of the first canonical variable in the canonical classification functions (B.4), which have an absolute measure. The classifier A14R.CA2 and A14R.CA3 were obtained likewise by making use of the first two and the first three canonical variables, respectively. When the canonical classification functions (B.3), which have a square measure, were used, the classifiers were named A14R.CS1, A14R.CS2 and A14R.CS3, likewise.

Results of Experiments

Each experiment can be divided into two major stages: a training stage and a testing stage. In the training stage, the results were obtained in the training period. The data were processed through the preprocessing, segmentation, parameterization. Then, the parameterized data, which were labeled by a supervisor, were used as the input for the BMDP7M program to select parameters and to calculate classification functions. In the testing stage, the parameterized data were input to the classification functions, which classify each event in the data. The results are obtained in the testing period. Unlike in a real situation of application, the events in all the data sets were labeled as belonging to the groups assigned by a supervisor for the purpose of evaluating the performance of classification. The assignment of an event to a group by the supervisor was based on the marks provided by the electroencephalographer. The types of events used at the testing stage were background, SSW, doubious SSW and artifacts, each of which were named BCK, SSW, DBS and ART, respectively. The successive SSWs were included in BCK.

First the results of the experiments designed in Table 5.1 in the training stage are shown. Second the results of the experiments at the testing stage, using chosen classifiers obtained in the training stage, are demonstrated as well as the results of the supplemental experiments.

Training Stage

This section deals with the results obtained in the training period. The topics are (1) F-values in selecting parameters, (2) significance levels of the F-values, (3) selected parameters, and (4) classification of events in training data sets.

F-values

The BMDP7M program calculated the F-value of each parameter at the step 0. If the highest value is greater than the F-to-enter threshold fixed previously, the parameter that had the F-value is selected to be entered into classification functions. The program calculated the F-to-enter and F-to-remove values at each step using the parameters remaining and then those already entered, respectively. If the lowest value of F-to-remove is less than the F-to-remove threshold, the parameter is removed from the classification functions. If the highest value of F-to-enter is greater than the F-to-enter threshold, the parameter is entered. The program stops its stepwise selection process when there is no parameters to be removed or entered. The F-to-enter threshold 4.000 and the F-to-remove threshold 3.996 were the default values of the program, and used in the experiments.

It was desirable to set up significance levels for entering and removing a parameter, and to stop the process of stepwise selection when none of the parameters pass the threshold F-values corresponding to the significance levels. However, the significance levels derived directly from the partial F-values such as F-to-enter and F-to-remove values proved to be inappropriate when the overall significance levels were considered as discussed in Classification, Chapter 4. In this project, the criteria proposed by Hawkins(1976), which are concerned with the overall significance levels, are applied. To use F-values for stopping the selection process of the program with previously specified significance levels for removing and entering a parameter, the F-value thresholds have to vary depending on the degree of freedom. Since the BMDP7M program did not allow the treatment of the F-value thresholds as variables, the program was run with a low F-to-enter threshold, 4.0 in this case, so that the application of significance levels was possible later. The significance level for forward selection of parameters was only used for stopping the selection process. There were some parameters removed, but the significance level for backward selection was not considered.

Table 5.2 shows the F-values in the experiments along with the total number of events of the experiments and the degree of freedom at the step 0 where no parameter is entered yet. The F-value with an asterisk(*) are the lowest F-to-remove value at the step and lower than the threshold. The other F-values are the highest F-to-enter values at the steps. The corresponding parameters are removed or entered accordingly.

Significance Levels

The overall significance level corresponding to the F-value in Table 5.2 except for the F-to-remove value were calculated at each step of the experiments. The degree of freedom at the step N is (NG-1,N0-N) where NG is the number of specified groups and N0 is the value at the step 0 as given in Table 5.2. At the step 0, no parameter is entered yet. The F-value and the degree of freedom were the input for the function PROBF in SAS . The output of the function PROBF was multiplied by p-q to get the overall significance level at the step, where p is the total number of parameters, and q is the number of entered parameters.

Table 5.3 shows the values calculated by the above procedure. When the F-value is a F-to-remove value, the space was left blank. If the calculated significance level is larger than 1.0000, it was set to 1.0000. These significance levels will be compared with the specified significance level of 0.05 (5%) in deciding how many parameters to be chosen on the basis of the F-statistics as described in Classification,

Table 5.2 Total Number of Events and F-values in Each Experiment Obtained by the BMDP7M Program. The F-values are F-to-enter values without an asterisk(*). The values with an asterisk are F-to-remove values.

(a)

Experiment	A12	A13	A14	A12R	A13R	A14R	A22R	A23R	A24R	A32R	A33R	A34R
Total events	869	869	869	754	754	754	1533	1533	1533	2315	2315	2315
D.F.(Step 0)	(1, 867)	(2, 866)	(3, 865)	(1, 752)	(2, 751)	(3, 750)	(1,1531)	(2,1530)	(3,1529)	(1,2313)	(2,2312)	(3,2311)
Step 0	332.2068	286.6284	2053.6960	503.0417	280.6001	2281.2437	718.5803	569.0181	1866.0574	1196.2317	727.4553	2744.8948
1	94.9393	107.2782	123.7371	79.8122	96.4140	154.0647	224.8755	112.3664	189.2494	358.6106	216.2695	256.8110
2	27.2441	72.8492	90.4859	25.4073	132.4352	94.8171	57.1281	91.4256	151.9346	112.2137	80.9411	205.7081
3	27.7894	26.0959	102.3978	22.8705	39.9949	128.1999	41.5437	33.0185	137.8786	40.5284	74.4926	202.4707
4	27.2593	17.9897	33.2937	30.8181	22.9769	60.1030	18.4727	29.1389	71.8664	45.3905	53.2419	139.2093
5	19.2857	17.8945	29.0563	26.2126	21.7085	22.3614	18.1317	35.3088	40.0402	32.8467	51.4313	34.3144
6	21.2808	23.7276	22.0773	18.3466	9.9582	11.0834	19.7399	35.1737	34.9052	20.8924	30.6114	34.5142
7	15.8192	9.0731	10.7497	8.6019	8.3668	9.0783	12.3684	8.3828	13.2057	14.1209	20.3764	17.4199
8	7.8873	13.9496	17.5169	8.1816	7.8528	7.9261	11.4613	6.7219	8.0626	11.6572	8.4760	18.4278
9	4.8555	8.4447	5.8200	7.9021	15.2639	7.4137	9.7700	5.9356	7.6190	28.6985	7.1819	11.5212
10	8.6429	6.1989	5.4713	7.1930	7.1279	7.3646	21.3505	5.5910	6.0253	10.5094	7.3951	5.7223
11	8.4973	4.4533	4.0999	5.6103	7.0494	6.7859	8.0481	4.9645	5.3733	9.8594	5.8053	5.5246
12	0.2155*	3.810	4.7253	4.6323	7.0473	6.6062	7.4300	5.7205	4.3228	8.6328	5.4584	5.6077
13	6.4646		3.860	3.360	5.1107	10.7254	5.5663	4.2881	3.931	8.3220	4.4782	5.2904
14	6.8387				4.8346	4.1497	8.9726	11.4230		8.0815	4.5990	4.6652
15	7.6215				3.384	4.1407	4.1349	5.8558		5.9763	4.1063	8.5607
16	7.0968					3.933	4.3157	1.3328*		5.8533	10.7216	4.2913
17	5.7259						7.3998	7.5224		4.9398	4.8534	4.2245
18	4.5830						3.8623*	5.3416		4.5831	5.1171	2.0331
19	3.962						3.862	4.1722		4.3864	4.0259	4.3747
20								3.462		4.7562	3.996	3.560
21										4.6492		
22										4.7302		
23										2.3181*		
24										7.5181		
25										6.0844		
26										3.702		

Table 5.2 (Cont'd.)

(b)

Experiment	TA12	TA13	TA12R	TA13R	TA22R	TA23R	TA32R	TA33R
Total events	869	869	754	754	1534	1535	2316	2314
D.F.(Step 0)	(1, 867)	(2, 866)	(1, 752)	(2, 751)	(1,1532)	(2,1532)	(1,2314)	(2,2311)
Step 0	75.3752	106.9703	174.2312	192.6546	259.0857	207.1542	367.5471	357.6621
1	37.2151	236.8616	126.5170	379.6348	117.4324	342.5320	365.2883	561.7683
2	129.4189	71.0625	84.0540	97.1776	81.7050	170.6888	217.8502	432.9473
3	87.8159	34.2451	118.4827	46.9201	62.3250	57.3928	185.7416	98.7383
4	21.0660	39.6294	73.4356	40.9096	63.8304	36.5338	90.9151	44.8034
5	12.8070	20.2413	43.4703	32.7046	72.2087	27.0843	66.3010	46.1760
6	15.7104	21.0428	31.0074	27.2298	153.3399	32.5668	44.8866	39.7603
7	5.0866	13.4923	0.3728*	26.8622	18.7073	28.7111	46.2709	38.9169
8	4.9693	12.5802	15.2483	33.2498	16.5600	24.2158	28.1054	34.6402
9	4.1821	15.9067	11.4779	27.1382	4.2295	22.8332	6.6980	14.5344
10	2.779	13.1513	6.9875	24.9303	4.3037	19.2504	4.2561	14.5116
11		24.9987	3.385	19.9874	3.755	17.8126	3.305	20.0295
12		12.7659		26.5580		11.9120		15.3727
13		18.0122		15.3396		8.4100		13.5426
14		1.8791*		7.2964		2.3033*		12.0033
15		9.6028		6.2262		8.6563		11.6609
16		7.4493		5.8207		8.9778		11.4731
17		5.7809		4.9322		7.4463		8.9150
18		4.0187		6.1282		10.2476		7.7926
19		3.231		5.2144		9.2967		9.5269
20				5.0849		8.8985		3.879
21				3.634		6.6583		
22						5.9863		
23						10.4883		
24						4.5167		
25						0.5371*		
26						4.4569		
27						6.1205		
28						3.633		

Table 5.2 (Cont'd.)

(c)

Experiment	TS12	TS13	TS12R	TS13R	TS22R	TS23R	TS32R	TS33R
Total events	869	869	754	754	1534	1535	2316	2314
D.F.(Step 0)	(1, 867)	(2, 866)	(1, 752)	(2, 751)	(1,1532)	(2,1532)	(1,2314)	(2,2311)
Step 0	74.2316	112.1874	276.5737	753.5984	482.6201	491.5710	689.0740	754.0552
1	145.7913	135.4994	199.7837	321.2424	106.3738	182.9321	341.2004	214.3188
2	230.4652	89.0148	118.8083	160.1512	166.9775	95.9628	114.3392	186.0036
3	39.0350	49.6228	155.9000	74.4946	139.9987	75.8831	361.0032	117.4837
4	20.2932	31.4597	29.9599	70.7892	39.0752	64.0897	109.2924	197.6682
5	9.2639	19.9235	26.9727	65.1627	28.6825	56.6849	57.8761	88.1681
6	9.9683	21.2614	6.9878	43.0751	14.9067	44.2013	34.5944	51.2295
7	4.7979	2.3305*	5.6789	36.7492	14.9755	57.1699	17.7264	40.6395
8	6.2415	18.6004	0.0774*	33.9888	9.4631	43.0366	16.8303	60.6094
9	2.429	18.7692	4.1599	29.5452	7.7227	23.4998	10.9317	58.5765
10		125.0564	6.4206	47.3061	6.9178	23.5388	4.1111	19.5927
11		33.3593	3.019	22.9105	3.996	18.8555	3.729	15.8663
12		32.2558		19.4409		16.2252		14.2425
13		19.1535		33.1527		15.2468		11.2152
14		18.9007		31.6848		13.5257		9.8500
15		25.0923		13.7461		10.9589		11.2514
16		19.6803		8.8986		8.4563		12.7928
17		17.9728		27.7731		12.5331		8.1362
18		0.0966*		11.7320		2.6382*		8.2540
19		22.2538		7.1073		10.7162		0.6724*
20		20.5651		7.2143		8.8668		7.4667
21		7.7162		5.8702		14.6737		0.5598*
22		4.7282		3.4997*		8.6611		6.2115
23		3.1605*		4.8987		5.4700		2.1255*
24		5.5628		4.4522		21.3581		12.3935
25		4.4597		7.1840		1.5387*		4.8897
26		3.997		7.0636		8.5114		4.6680
27				4.0071		8.9123		19.8824
28				0.5657		6.1265		3.8459*
29				2.688		4.5609		9.3155
30						3.986		11.6777
31								11.9672
32								7.3305
33								25.3731
34								4.5501
35								5.7178
36								2.7118*

Table 5.2 (Cont'd.)

(c cont'd)

Experiment	TS12	TS13	TS12R	TS13R	TS22R	TS23R	TS32R	TS33R
37								4.4228
38								19.9751
39								3.3976*
40								4.9129
41								6.0784
42								0.2459*
43								5.6442
44								2.954

(d)

Experiment	TC12	TC13	TC12R	TC13R	TC22R	TC23R	TC32R	TC33R
Total events	869	869	754	754	1534	1535	2316	2314
D.F.(Step 0)	(1, 867)	(2, 866)	(1, 752)	(2, 751)	(1,1532)	(2,1532)	(1,2314)	(2,2311)
Step 0	49.6754	25.4830	48.5161	24.8020	87.7814	43.7527	171.7223	87.2210
1	17.0363	10.8647	17.4619	10.9806	14.7450	12.2931	60.9299	33.5482
2	13.6088	9.0860	14.6835	8.5102	18.0678	10.1963	15.9149	14.7723
3	4.9677	13.5646	4.5608	14.2648	5.9671	6.5581	8.2670	12.6210
4	4.0303	1.8049*	3.771	1.6065*	3.815	14.4468	5.1153	14.4163
5	2.539	5.6916		6.7697		1.2343*	5.7385	14.6289
6		5.4959		5.7326		13.8858	1.510	19.6730
7		4.2218		9.8848		8.2220		10.4095
8		7.1063		3.218		3.4229*		3.4453*
9		4.2562				22.0995		14.0977
10		8.4149				4.1251		1.4919*
11		3.337				7.0165		8.9758
12						4.4765		7.1885
13						5.3138		5.9044
14						5.1158		9.4052
15						0.0210*		5.4792
16						4.8835		7.1147
17						3.951		5.3934
18								2.897

Table 5.3 Overall Significance Levels Derived from F-values in Table 5.2. The steps for removal of a parameter were left blank.

(a)

Experiment	A12	A13	A14	A12R	A13R	A14R	A22R	A23R	A24R	A32R	A33R	A34R
Step 0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0001	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0012	0.0	0.0	0.0	0.0	0.0
5	0.0008	0.0	0.0	0.0	0.0	0.0	0.0015	0.0	0.0	0.0	0.0	0.0
6	0.0003	0.0	0.0	0.0014	0.0036	0.0	0.0006	0.0	0.0	0.0003	0.0	0.0
7	0.0049	0.0082	0.0	0.2250	0.0166	0.0004	0.0292	0.0156	0.0	0.0114	0.0	0.0
8	0.3258	0.0001	0.0	0.2784	0.0270	0.0021	0.0466	0.0794	0.0016	0.0416	0.0138	0.0
9	1.0000	0.0147	0.0387	0.3193	0.0	0.0043	0.1139	0.1704	0.0029	0.0	0.0490	0.0
10	0.2090	0.1317	0.0620	0.4639	0.0532	0.0045	0.0003	0.2361	0.0276	0.0747	0.0390	0.0417
11	0.2226	0.7266	0.4068	1.0000	0.0566	0.0099	0.2815	0.4328	0.0679	0.1044	0.1864	0.0542
12		1.0000	0.1689	1.0000	0.0558	0.0125	0.3893	0.2009	0.2891	0.2001	0.2589	0.0474
13	0.6820		0.5469	1.0000	0.3686	0.0	1.0000	0.8200	0.4889	0.2332	0.6757	0.0728
14	0.5446				0.4758	0.3634	0.1615	0.0007		0.2617	0.5890	0.1720
15	0.3476				1.0000	0.3616	1.0000	0.1669		0.8307	0.9456	0.0007
16	0.4563					0.4723	1.0000			0.8750	0.0013	0.2797
17	0.9651						0.3629	0.0320		1.0000	0.4335	0.3014
18	1.0000							0.2732		1.0000	0.3273	1.0000
19	1.0000						1.0000	0.8578		1.0000	0.9526	0.2446
20								1.0000		1.0000	0.9629	0.7414
21										1.0000		
22										1.0000		
23												
24										0.3078		
25										0.6718		
26										1.0000		

Table 5.3 (Cont'd.)

(b)

Experiment	TA12	TA13	TA12R	TA13R	TA22R	TA23R	TA32R	TA33R
Step 0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0001	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0051	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0010	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	0.2923	0.0001		0.0	0.0002	0.0	0.0	0.0
8	0.2866	0.0001	0.0013	0.0	0.0005	0.0	0.0	0.0
9	0.4116	0.0	0.0089	0.0	0.3990	0.0	0.0971	0.0
10	0.8629	0.0001	0.0922	0.0	0.3438	0.0	0.3530	0.0
11		0.0	0.6619	0.0	0.4227	0.0	0.5536	0.0
12		0.0001		0.0		0.0002		0.0
13		0.0		0.0		0.0058		0.0
14				0.0175				0.0002
15		0.0019		0.0479		0.0046		0.0002
16		0.0149		0.0683		0.0032		0.0002
17		0.0738		0.1565		0.0139		0.0029
18		0.4030		0.0459		0.0008		0.0085
19		0.8401		0.1072		0.0020		0.0014
20				0.1154		0.0029		0.3745
21				0.4571		0.0251		
22						0.0463		
23						0.0005		
24						0.1772		
25								
26						0.1880		
27						0.0338		
28						0.3734		

Table 5.3 (Cont'd.)

(c)

Experiment	TS12	TS13	TS12R	TS13R	TS22R	TS23R	TS32R	TS33R
Step 0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0001	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0337	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0214	0.0	0.1089	0.0	0.0015	0.0	0.0	0.0
7	0.3451		0.2090	0.0	0.0014	0.0	0.0003	0.0
8	0.1393	0.0		0.0	0.0235	0.0	0.0005	0.0
9	1.0000	0.0	0.5009	0.0	0.0552	0.0	0.0096	0.0
10		0.0	0.1263	0.0	0.0776	0.0	0.3845	0.0
11		0.0	0.8271	0.0	0.3663	0.0	0.4288	0.0
12		0.0		0.0		0.0		0.0
13		0.0		0.0		0.0		0.0004
14		0.0		0.0		0.0		0.0013
15		0.0		0.0		0.0004		0.0003
16		0.0		0.0033		0.0049		0.0001
17		0.0		0.0		0.0001		0.0063
18				0.0002				0.0054
19		0.0		0.0167		0.0005		
20		0.0		0.0142		0.0030		0.0117
21		0.0100		0.0503		0.0		
22		0.1815				0.0033		0.0408
23				0.1310		0.0730		
24		0.0796		0.1915		0.0		0.0001
25		0.2249		0.0122				0.1444
26		0.3369		0.0128		0.0034		0.1706
27				0.2417		0.0021		0.0
28				1.0000		0.0313		
29				0.8930		0.1378		0.0016
30						0.2252		0.0001
31								0.0001
32								0.0094
33								0.0
34								0.1279
35								0.0367
36								
37								0.1331
38								0.0
39								

Table 5.3 (Cont'd.)

(c cont'd)

Experiment	TS12	TS13	TS12R	TS13R	TS22R	TS23R	TS32R	TS33R
40								0.0743
41								0.0210
42								
43								0.0323
44								0.4186

(d)

Experiment	TC12	TC13	TC12R	TC13R	TC22R	TC23R	TC32R	TC33R
Step 0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0007	0.0008	0.0006	0.0007	0.0023	0.0002	0.0	0.0
2	0.0041	0.0045	0.0023	0.0080	0.0004	0.0014	0.0012	0.0
3	0.4173	0.0001	0.5286	0.0	0.2350	0.0511	0.0652	0.0001
4	0.6750		0.7879		0.7647	0.0	0.3571	0.0
5	1.0000	0.1226		0.0427			0.2335	0.0
6		0.1445		0.1150		0.0	1.0000	0.0
7		0.4942		0.0019		0.0093		0.0010
8		0.0278		1.0000				
9		0.4488				0.0		0.0
10		0.0072				0.5230		
11		1.0000				0.0287		0.0041
12						0.3457		0.0232
13						0.1454		0.0803
14						0.1709		0.0024
15								0.1141
16						0.2153		0.0216
17						0.5247		0.1151
18								1.0000

Chapter 5. The specified significance level could be larger to include more number of parameters or smaller to include less number of parameters. The value of 5% was chosen just as a moderate value.

Selected Parameters

Table 5.4 shows the parameters selected to be entered or removed at the steps of the experiments according to the F-values. The removed parameters are marked with an asterisk(*). The parameter types VM, VA and VB are of template matching as described in Design of Experiments, Chapter 5. One of the three template matching measures in Method TA, TS, or TC was used to calculate the value of VM, or VA and VB. A parameter was selected at the step it appears in Table 5.4, and entered into the classification functions at the next step if the F-value qualifies the threshold test.

Classification

The BMDP7M program applies the classification functions at each step to classify the events in the training data sets, and outputs the classification table. The classification tables at all the steps in the experiments are listed in Table G-1 in Appendix G together with the three PRE measures explained in Classification, Chapter 4.

To demonstrate and compare the performances of the experiments in the training data sets, the classifier at the step that first exceeded the 5% significance level in Table 5.4 was chosen in each experiment as a representative of the experiment. The classifier representing the experiment may not have the best classification result among all the classifiers of the experiment necessarily. However, choosing the

Table 5.4 Parameters Selected at the Steps in the Experiments by the BMDP7M Program. The parameters without an asterisk(*) are selected at the step to be entered. The parameters with an asterisk are selected at the step to be removed.

(a)

Experiment	A12	A13	A14	A12R	A13R	A14R	A22R	A23R	A24R	A32R	A33R	A34R
Step 0	AM10	S210	S210	AM10	AM10	S210	S210	S210	S110	AM10	S210	S210
1	S210	S111	S110	DU10	S210	S110	AM10	AM10	S111	DU10	AM10	S110
2	S28	AM10	S111	S111	S111	AM10	DU10	S111	S210	S110	S111	AM10
3	DU10	S29	AM10	AM9	DU10	S111	AM14	DU10	AM10	S114	DU10	S111
4	S111	S110	DU10	DU9	S29	DU10	S110	S110	DU10	S111	S110	DU10
5	AM9	S28	S29	AM11	S110	S29	S111	S29	S29	AM11	S29	S29
6	DU9	DU10	S28	AM1	AM11	AM12	S114	S114	S114	S210	S114	S114
7	DU11	AM9	AM9	S211	AM1	AM11	AM2	AM14	AM12	S211	AM11	AM12
8	AM8	DU9	DU9	AM14	AM9	DU12	AM11	AM2	AM14	AM9	AM13	AM11
9	AM11	DU11	AM5	S210	DU9	S113	AM9	AM11	DU12	DU9	DU12	DU12
10	AM12	AM5	DU11	DU1	AM12	S212	DU9	AM13	AM2	DU12	S211	AM18
11	S211	DU5	AM14	S115	DU12	AM1	S112	S112	AM11	DU13	AM2	S113
12	DU11*	AM12	AM12	DU12	S212	AM9	S212	S212	AM18	AM15	S213	AM8
13	AM13		AM11	AM9	DU1	DU9	S115	AM9	AM9	AM8	AM18	AM14
14	AM1				S211	AM17	DU14	DU9		AM2	AM15	AM9
15	S22				AM15	S211	DU2	AM12		S16	AM9	DU9
16	DU1					DU1	S117	AM14*		S14	DU9	S211
17	S16						AM16	DU12		S28	AM12	AM13
18	S29						DU2 *	AM15		S112	AM8	AM14*
19	S114						DU2	AM8		S27	DU14	AM15
20								S115		S113	S14	AM2
21										DU14		
22										AM13		
23										DU13*		
24										S213		
25										S115		
26										AM12		

Table 5.4 (Cont'd.)

(b)

Experiment	TA12	TA13	TA12R	TA13R	TA22R	TA23R	TA32R	TA33R
Svep 0	VM6	VB10	VM6	VB10	VM6	VB10	VM13	VB10
1	VM10	VA11	VM11	VA11	VM13	VA11	VM6	VA11
2	VM11	VA10	VM10	VA10	VM1	VA10	VM10	VA10
3	VM8	VA9	VM8	VA2	VM16	VB9	VM11	VB9
4	VM9	VB8	VM15	VB4	VM8	VA9	VM19	VA9
5	VM16	VA12	VM1	VB13	VM10	VB8	VM1	VB8
6	VM12	VB2	VM5	VA5	VM11	VA8	VM16	VB14
7	VM1	VA8	VM6 *	VA8	VM4	VA2	VM8	VB11
8	VM7	VB11	VM9	VB11	VM18	VB4	VM4	VA8
9	VM14	VB12	VM18	VB16	VM9	VA13	VM15	VA13
10	VM5	VA15	VM4	VA12	VM17	VB11	VM9	VB12
11		VB13	VM16	VB8	VM7	VA12	VM18	VA12
12		VB4		VB9		VB16		VA5
13		VA2		VA15		VB13		VB7
14		VB2 *		VB12		VA13*		VA15
15		VB16		VA1		VB7		VA6
16		VB9		VB5		VB6		VA14
17		VA14		VA17		VA15		VA1
18		VA5		VA13		VB14		VA19
19		VB14		VA4		VA14		VB19
20				VA9		VB18		VB1
21				VB1		VA1		
22						VA17		
23						VB15		
24						VA13		
25						VB13*		
26						VA5		
27						VB5		
28						VB19		

Table 5.4 (Cont'd.)

(c)

Experiment	TS12	TS13	TS12R	TS13R	TS22R	TS23R	TS32R	TS33R
Step 0	VM8	VA8	VM6	VA8	VM6	VA8	VM6	VA6
1	VM10	VB10	VM11	VA4	VM11	VA2	VM13	VB6
2	VM11	VB11	VM10	VB11	VM10	VB8	VM10	VA8
3	VM12	VB12	VM9	VA2	VM8	VB11	VM11	VB11
4	VM9	VB2	VM16	VB10	VM1	VB10	VM9	VB10
5	VM16	VA12	VM8	VB6	VM15	VB7	VM1	VA14
6	VM14	VB8	VM12	VA12	VM18	VA7	VM15	VA2
7	VM2	VA8 *	VM5	VB1	VM7	VB9	VM4	VA9
8	VM13	VB9	VM6 *	VA1	VM9	VA12	VM8	VA10
9	VM17	VB13	VM1	V14	VM13	VA10	VM7	VB8
10		VA14	VM2	VA15	VM12	VB14	VM12	VB7
11		VB14	VM15	VB16	VM17	VA15	VM19	VB2
12		VB15		VA9		VA4		VB5
13		VA13		VB8		VB12		VB9
14		VA16		VA10		VB2		VA15
15		VB4		VA6		VA16		VB14
16		VA11		VA14		VB1		VA11
17		VA2		VA13		VA1		VB1
18		VB2 *		VB12		VB2 *		VA1
19		VA8		VB19		VA3		VB2 *
20		VA10		VB17		VB18		VA7
21		VA6		VB15		VA17		VA8 *
22		VA9		VA15*		VB2		VB4
23		VB9 *		VB9		VA14		VB6 *
24		VA5		VB4		VB15		VB3
25		VB6		VA3		VA15*		VA5
26		VB1		VB3		VB19		VB16
27				VB18		VA13		VA17
28				VB19*		VA19		VA5 *
29				VA15		VB13		VB18
30						VA9		VB19
31								VA19
32								VA12
33								VB12
34								VA16
35								VB15
36								VA15*
37								VB13
38								VA13
39								VA14*
40								VA15

Table 5.4 (Cont'd.)

(c cont'd)

Experiment	TS12	TS13	TS12R	TS13R	TS22R	TS23R	TS32R	TS33R
Step41								VB17
42								VA17*
43								VA18
44								VA5

(d)

Experiment	TC12	TC13	TC12R	TC13R	TC22R	TC23R	TC32R	TC33R
Step 0	VM10	VA10	VM10	VA10	VM10	VA10	VM10	VA10
1	VM11	VA11	VM11	VA11	VM11	VA11	VM11	VA11
2	VM8	VB12	VM8	VB12	VM8	VB8	VM12	VB12
3	VM13	VA12	VM13	VA12	VM19	VB12	VM8	VA12
4	VM7	VA11*	VM7	VA11*	VM7	VA12	VM7	VA14
5	VM16	VB11		VA14		VA11*	VM6	VB14
6		VA14		VB14		VA14	VM5	VA16
7		VA8		VA15		VB14		VB11
8		VA11		VB11		VB8 *		VA11*
9		VB14				VB15		VB10
10		VA15				VB8		VA10*
11		VA9				VA9		VA9
12						VB11		VA11
13						VA11		VA18
14						VB10		VB16
15						VA10*		VB8
16						VB13		VB7
17						VB7		VA10
18								VA19

representatives according to a significance level gives a statistical background on the property of chosen classifiers, and prevents to a certain extent a haphazard choice of the classifier caused by incomplete or peculiar training data sets. The classification results of these classifiers are shown in Table 5.5.

Table 5.6 presents the step numbers of the chosen classifiers. The following points may be noticed as to these step numbers.

(1) A tendency of increase in the step number when the number of specified groups are increased. This tendency is slight in Method A, and strong in Method T.

(2) The increase of the number of training data sets seems not to affect the step numbers.

(3) Method TC had notably less step numbers than others.

(4) The retraction of the adjacent events did not affect the number of the step chosen for the 5% significance level.

The number of the step is the same as the number of parameters included in the classification functions if there is no removal of parameters before that step. In Method A, there was no removal of parameters before the steps in Table 5.5, then the step number of the classifier of Method A in Table 5.5 is exactly same as the number of parameters in the classification functions obtained at the step. In Method T, there were some removals before the step chosen in Table 5.5.

Table 5.7 shows the frequency of appearance of each parameter in the chosen classifiers in Table 5.5. The parameters in Method A is heavily concentrated on the core-wave parameters (AM10, S110, S210 and DU10). The frequencies of the parameters in the ninth, tenth and eleventh waves total over 75% of the total of the frequencies in all the

Table 5.5 Classification in Training Data Sets by the Classifiers Chosen at the 5% Significance Level.

(a)

Classifier	PRE			BCK ->		SSW ->	
	P1	P2	P3	BCK	SSW	BCK	SSW
A12 .S 8	1.000	0.899	0.947	859	1	0	9
A12R .S 7	1.000	0.899	0.947	744	1	0	9
A22R .S 9	0.811	0.865	0.837	1515	2	3	13
A32R .S10	0.916	0.845	0.879	2287	4	2	22
TA12 .S 7	0.888	0.798	0.840	858	2	1	8
TS12 .S 7	0.888	0.798	0.840	858	2	1	8
TC12 .S 3	0.550	0.449	0.494	854	6	4	5
TA12R.S10	0.776	1.000	0.874	745	0	2	7
TS12R.S 6	0.888	1.000	0.941	745	0	1	8
TC12R.S 3	0.549	0.448	0.493	739	6	4	5
TA22R.S 9	0.810	0.762	0.786	1514	4	3	13
TS22R.S 9	0.748	0.798	0.772	1515	3	4	12
TC22R.S 3	0.429	0.311	0.361	1503	15	9	7
TA32R.S 9	0.874	0.806	0.838	2287	5	3	21
TS32R.S10	0.832	0.832	0.832	2288	4	4	20
TC32R.S 3	0.575	0.311	0.404	2262	30	10	14

(b)

CLASSIFIER	PRE			BCK ->			SSW ->			ART ->		
	P1	P2	P3	BCK	SSW	ART	BCK	SSW	ART	BCK	SSW	ART
A13 .S10	0.888	1.000	0.941	859	0	0	1	8	0	0	0	1
A13R .S10	1.000	1.000	1.000	744	0	0	0	9	0	0	0	1
A23R .S 8	0.874	0.933	0.902	1515	1	0	1	14	1	0	0	1
A33R .S11	0.790	0.824	0.807	2286	4	0	4	19	1	0	0	1

Table 5.5 (Cont'd.)

(c)

CLASSIFIER	PRE			BCK ->			SSWA ->			SSWB ->		
	P1	P2	P3	BCK	SSWA	SSWB	BCK	SSWA	SSWB	BCK	SSWA	SSWB
TA13 .S17	0.888	0.798	0.840	858	2	0	1	7	0	0	0	1
TS13 .S22	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TC13 .S 5	0.662	0.456	0.540	853	6	1	3	5	0	0	0	1
TA13R.S16	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TS13R.S21	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TC13R.S 6	0.774	0.494	0.603	738	5	2	2	5	1	0	0	1
TA23R.S24	0.810	0.719	0.762	1514	5	0	3	11	0	0	0	2
TS23R.S23	0.873	0.734	0.798	1514	5	0	2	12	0	0	0	2
TC23R.S 3	0.619	0.411	0.494	1505	13	1	6	7	1	0	0	2
TA33R.S20	0.916	0.756	0.828	2283	7	0	2	19	0	0	0	3
TS33R.S25	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TC33R.S13	0.788	0.426	0.553	2265	20	5	5	14	2	0	0	3

(d)

CLASSIFIER	PRE			BCK ->				SSWA ->				SSWB ->				ART ->			
	P1	P2	P3	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART
A14 .S10	1.000	0.747	0.855	856	3	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S14	1.000	1.000	1.000	744	0	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A24R .S11	1.000	0.759	0.863	1511	5	0	0	0	14	0	0	0	0	2	0	0	0	0	1
A34R .S11	0.958	0.791	0.866	2284	6	0	0	1	20	0	0	0	0	3	0	0	0	0	1

Table 5.6 Step Numbers of Classifiers Chosen at the 5% Significance Level. * : rounded integer.

Method	Groups	Step number		
		min.	max.	average*
A	2	8	10	9
	3	8	11	10
	4	10	14	12
TA	2	7	10	9
	3	16	24	19
TS	2	6	10	8
	3	21	25	23
TC	2	3	3	3
	3	3	13	7

Table 5.7 Frequency of Entered Parameters in the Classifiers Chosen at the 5% Significance Level.

No.	AM	S1	S2	DU	VM	VA	VB
1	3				5	6	2
2	2					7	1
3						1	1
4					3	2	5
5	1				1	2	1
6					6	4	2
7					3	2	4
8			3		11	7	9
9	7		8	7	6	6	7
10	12	10	11	12	12	11	9
11	7	12	2	3	12	8	9
12	3		1	3	3	10	9
13	1	1			4	3	4
14	3	6			1	7	7
15					3	7	2
16					5	3	4
17						2	1
18	1				3		2
19	–	–	–	–	1	1	2
Total number	40	29	25	25	79	89	81
Number of experiments	12				12	12	
Average number	3.3	2.4	2.1	2.1	6.6	6.8	7.4
Average number in an experiment	9.9				6.6	14.2	

waves. The parameters in Method T is more scattered away from the core-wave parameters than those in Method A. The frequencies of the parameters in the ninth, tenth and eleventh waves total less than 40% in Method T. The top 5 parameters in popularity according to Table 5.7 are AM10, S111, DU10, S210 and S110 in Method A. The first 3 parameters were entered in all the chosen classifiers, and selected within the first 6 steps. The top 5 parameters were selected, if selected, within the first 6 steps except for the experiment A12R where S210 was selected at the step 9. The top 5 parameters in popularity in Method T with 2 groups was VM10, VM11, VM8, VM9 and VM6. The top 6 in Method T with 3 groups were VA10, VA12, VB8, VB10, VB11 and VB12. The parameters VM10, VM11 and VM8 were selected within the first 6 steps except for TA32R and TS32R where VM8 was selected at the steps 7 and 8, respectively. The parameters VA10, VA12 and VB8 were selected from the steps ranging up to 18 if selected.

In the following, the classification results in Method A and Method T are described in detail.

Method A

From the classification results in Method A shown in Table G-1, the following may be pointed out.

At least during the first few steps, the performance of each experiment improved except for the experiments A13, A14 and A13R, which attained perfect classification in terms of the measures P1 or P2 at the very first step. It must be noted that the experiments with 4 groups consistently excelled the others in the value of the measure P1 because the measure P1 refers to the correct classification of SSW and is more important in practical application than the measure P2 as explained in Classification, Chapter 4.

As the number of step increases, the performance of each experiment reaches, at a certain step, its best in terms of one of the performance measures concerned. Take, for example, the measure P3 to evaluate the performance. The classifiers at these best steps of experiments performed very well, that is, the largest number of misclassification events was 2, 4 and 6 when the number of training data sets was 1, 2 and 3, respectively. Especially, the classifications of the best classifiers in the experiments A13, A13R and A14R were perfect.

As the step proceeded further, the performance usually did not change very much, but slightly deteriorated in some experiments. The results of the experiment A23R is a good example to show that the performance improves, comes to the peak, and slightly deteriorates as the number of the parameters in the classifier increases (see Fig.5.2).

The classifiers derived from retracted data gave the same or better performance when compared with the corresponding classifiers without the retraction. It should be noted, though, that the retracted events are not included in the classification.

Concerning the chosen classifiers in Table 5.5, the number of misclassified events increased when the number of training data sets increased. However, the values of the PRE measures did not go down consistently when the number of training data sets increased except in the experiments with 3 groups. No distinct difference was seen in terms of the measure P3 when the number of specified groups changed.

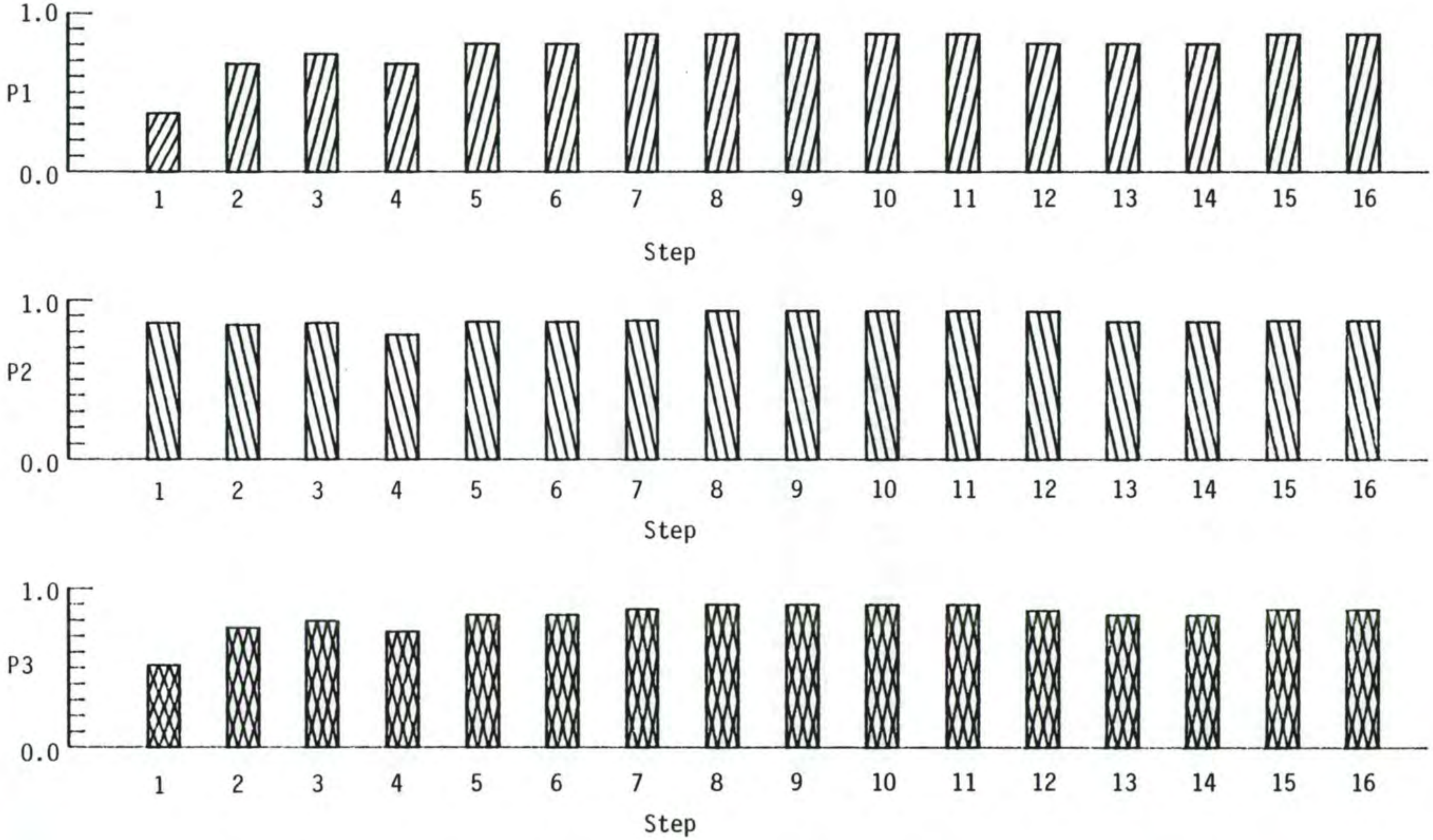


Figure 5.2 Histograms of the PRE Values by the Classifiers of A23R at the Training Stage Shown in Table G.1.

The comparison was made among the classifiers with a sign R in Table 5.5. For example, when only one training data set was used, the classifier with two groups had the lowest value of the measure P3, but had the highest P3 value among the three classifiers being compared with. The PRE values in Method A shown in Table 5.5 are illustrated by histograms in Fig.5.3.

The above observation of the classification results have assured a good potential of success of the classifiers at least in the training data sets. But the effects of the data retraction, changes of training data sets and specified groups have not been clearly observed or conclusive. These effects may become more distinctive when the classifiers are tested with all the data sets at the testing stage.

Method T

First the classifiers of Method TC performed much inferior to the others. The classifiers of Method TA and TS were slightly inferior but comparable to those of Method A. Between Method TA and TS, there was not much consistent difference in performance. Because of the simpler calculation, the classifier of Method TA is preferred if the performance is about the same as that of Method TS. The classifiers of Method TA shown in Table 5.5 will be tested using all the data sets at the testing stage.

From the classifications in Method T shown in Table 5.5(a) and (c), the following may be pointed out:

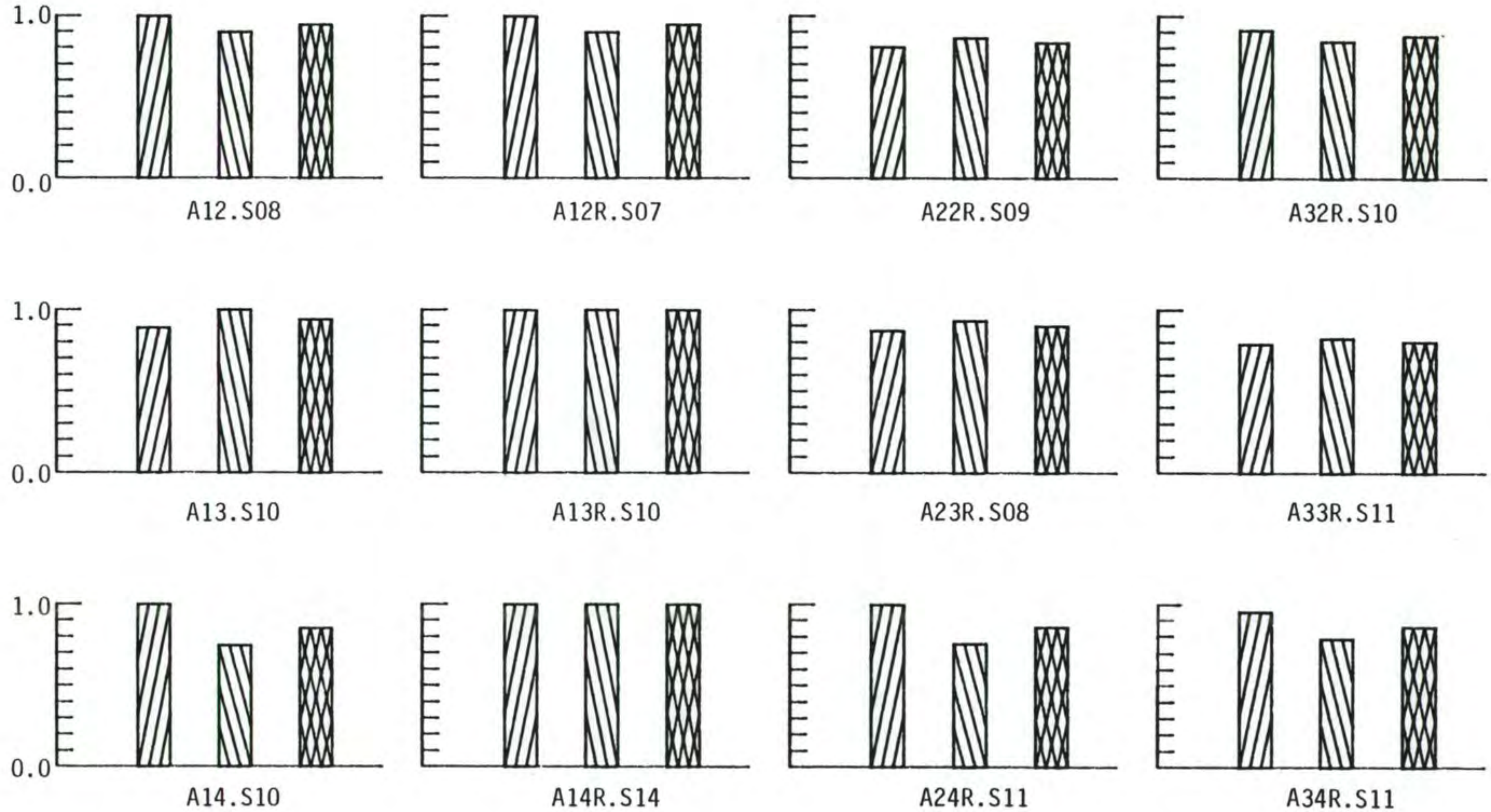


Figure 5.3 Histograms of the PRE Values by the Classifiers of Method A at the Training Stage Shown in Table 5.5. (in one graph, P1: left, P2: middle, P3: right.)

(1) Better classifications were obtained when the retracted training data sets are used.

(2) The effect of changing the number of training data sets seemed not to be consistent or meaningful.

(3) When the number of specified groups changed from 2 to 3, the P1 values of the classifiers with 3 groups were always superior to those of the classifiers with 2 groups; the P2 values of the classifiers with 3 groups were always inferior to those of the classifiers with 2 groups; the P3 values of the classifiers with 3 groups were superior to those with 2 groups except for the experiment TS22R.

The histograms in Fig.5.4 show the values of the PRE measures obtained by the classification in Method T shown in Table 5.5.

Testing Stage

In the testing stage, the classifiers are applied to all the data sets. The results are expected to be more unbiased than those in the training stage, and to reveal the capability of the classifiers in the situation closer to the clinical practice.

Classification

Based on the results in the training stage, the following classifiers were chosen for testing in all the data sets:

(a) the classifiers chosen at the 5% specified significance level in Method A,

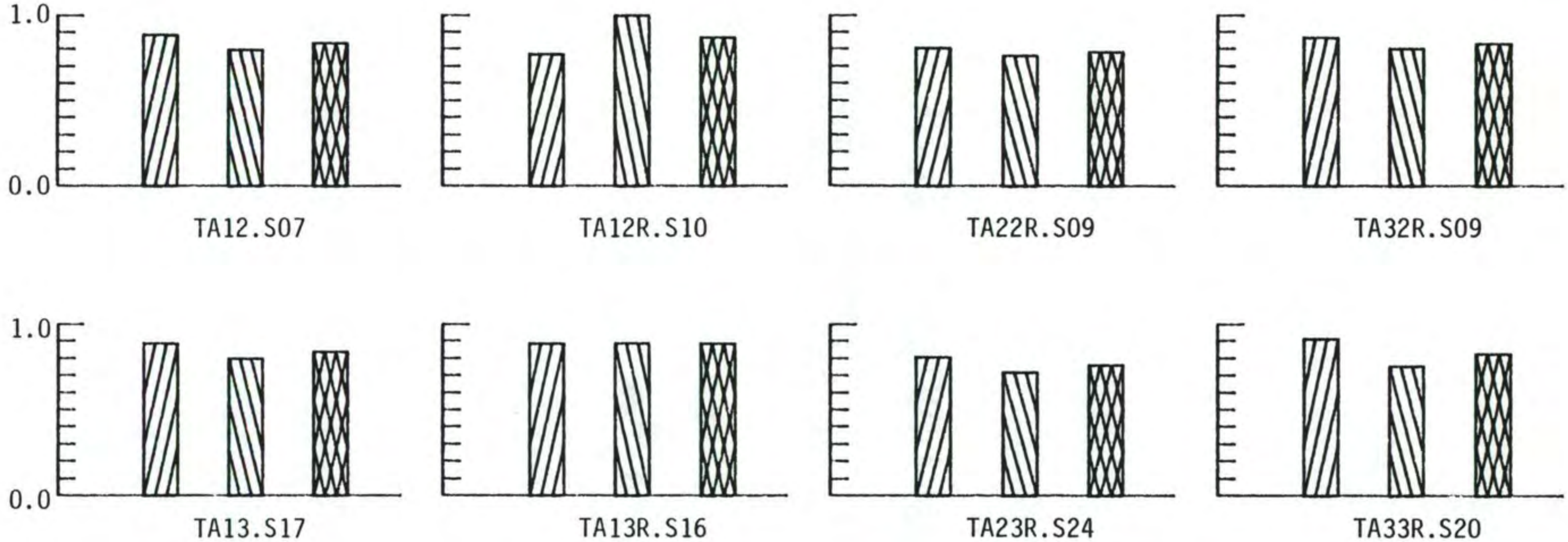
(b) the classifiers chosen at the 5% specified significance level in Method TA.

(c) the classifiers in the experiment A14R at the step 1 through 16,

(d) the classifier in the supplemental experiments.

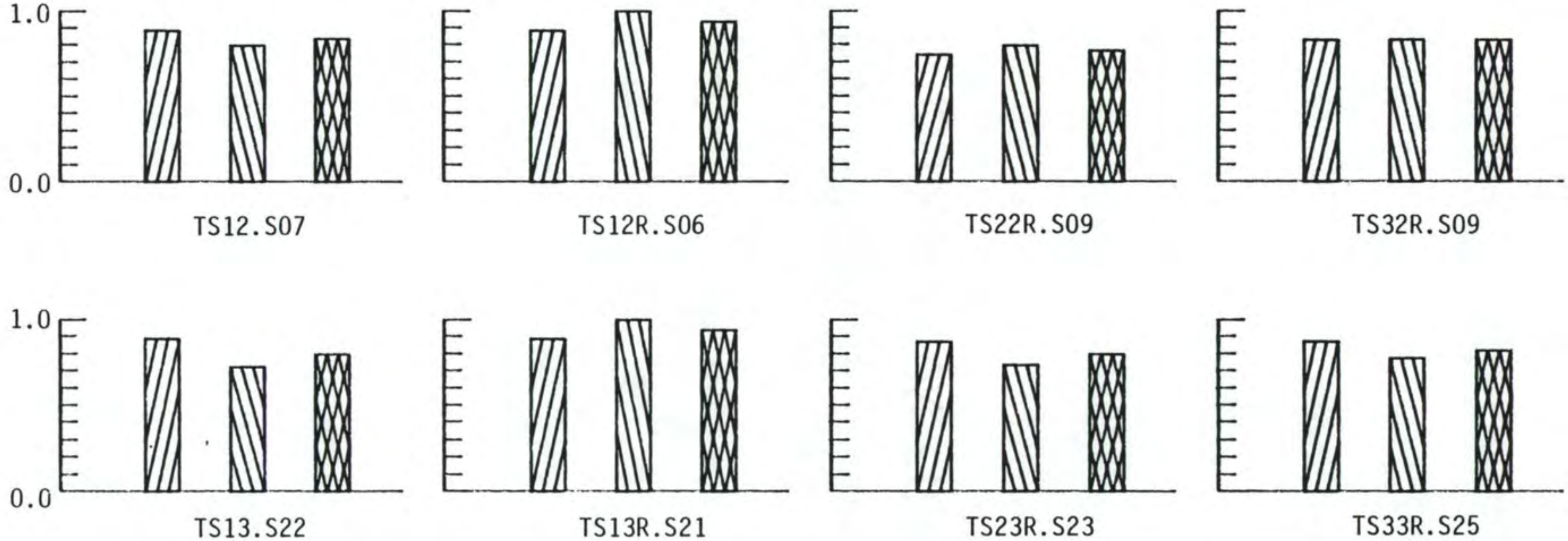
---

1. The total number of background events in all the data sets slightly differed because a few events at the beginning of one or more



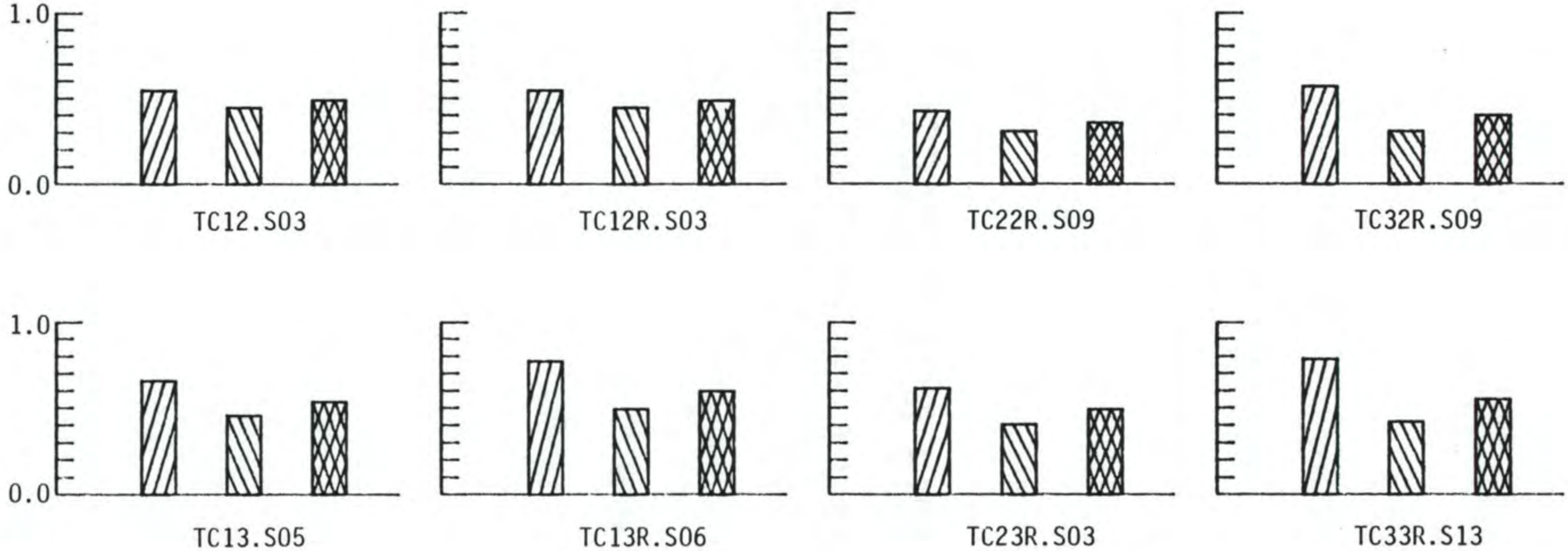
(a)

Figure 5.4 Histograms of the PRE Values by the Classifiers of Method T at the Training Stage Shown in Table 5.5. (a) Method TA, (b) Method TS and (c) Method TC. (in one graph, P1: left, P2: middle, P3: right.)



(b)

Figure 5.4 (Cont'd.)



(c)

Figure 5.4 (Cont'd.)

Table 5.8[1] shows the results of classification by these classifiers. In calculating P1, P2 and P3 of PRE, the DBS events were omitted. Because these events were originally indefinite, and the group these DBS events belong to ought not to affect the evaluation of performance if a group for DBS is not specified.

It was noticed that the classifiers, especially derived from retracted data sets, sometimes detected the event of SSW or ART at the adjacent events to the originally marked event. Let this kind of misclassification call "nearmiss detection" of SSW. Practically, even if the nearmiss detection is treated as correct detection, it will not make the value of this analysis system less. To evaluate the performance of the classifiers with a tolerance for the nearmiss detection, a scheme to correct the classification results in Table 5.8 was introduced as explained in the following.

It is assumed that there is no consecutive SSW or ART events. Suppose the event I is on the test of correction, and the event J is one of the adjacent events to the event I. Table 5.9 is the test table for correction. If any pair of classifications of the event I and the event J in the same row of the table matches, the event I is not counted as a misclassified event, but as a correctly classified event.

Table 5.10 shows the classifications in all the data sets, corrected using the scheme. Four adjacent events were tested to look for correction, that is, J=I-4, I-2, I+2, I+4 in Table 5.9. When SSWA and SSWB appeared, they were simply treated as SSW in Table 5.8.

---

data sets were not included in some of the experiments.

Table 5.8 Original Classification in All the Data Sets by the Classifiers Chosen at the 5% Significance Level.

(a)

CLASSIFIER	PRE			BCK ->			SSW ->			ART ->			DBS ->		
	P1	P2	P3	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART
A12 .S08	0.710	0.556	0.624	12545	43		23	57		1	2		6	4	
A12R.S07	0.671	0.338	0.449	12487	102		26	54		1	2		3	7	
A22R.S09	0.811	0.485	0.607	12527	65		15	65		0	3		5	5	
A32R.S10	0.823	0.482	0.608	12522	67		14	66		0	3		4	6	
A13 .S10	0.610	0.560	0.584	12549	37	3	28	49	3	1	1	1	6	4	0
A13R.S10	0.634	0.398	0.489	12511	75	3	26	51	3	1	1	1	4	6	0
A23R.S08	0.798	0.526	0.634	12533	55	4	12	64	4	0	2	1	6	4	0
A33R.S11	0.747	0.462	0.571	12517	68	4	15	60	5	0	1	2	4	6	0
A14 .S10	0.810	0.482	0.604	12520	67 (66,1)	2	5	65 (58, 7)	10	0	2 (1, 1)	1	2	8 (8, 0)	0
A14R.S14	0.785	0.383	0.514	12488	99 (98,1)	2	7	63 (56, 7)	10	0	1 (1, 0)	2	2	8 (8, 0)	0
A24R.S11	0.861	0.454	0.594	12509	80 (79,1)	3	7	69 (57,12)	4	0	2 (1, 1)	1	5	5 (5, 0)	0
A34R.S11	0.848	0.427	0.568	12499	88 (87,1)	2	8	68 (56,12)	4	0	2 (1, 1)	1	2	8 (8, 0)	0

(b)

CLASSIFIER	PRE			BCK ->			SSW ->			ART ->			DBS ->		
	P1	P2	P3	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART
A14R.S01	0.772	0.394	0.521	12494	93 (92,1)	2	8	62 (57,5)	10	0	1 (1, 0)	2	5	5 (5, 0)	0
A14R.S02	0.785	0.428	0.554	12504	82 (81,1)	3	4	63 (58,5)	13	0	1 (1, 0)	2	4	6 (6, 0)	0
A14R.S03	0.785	0.405	0.535	12496	90 (89,1)	3	5	63 (58,5)	12	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S04	0.798	0.412	0.543	12497	89 (88,1)	3	6	64 (57,7)	10	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S05	0.785	0.408	0.537	12498	89 (88,1)	2	7	63 (56,7)	10	0	1 (1, 0)	2	1	9 (9, 0)	0
A14R.S06	0.785	0.414	0.542	12502	87 (86,1)	3	7	63 (56,7)	10	0	1 (1, 0)	2	1	9 (9, 0)	0
A14R.S07	0.785	0.408	0.537	12497	89 (88,1)	3	7	63 (56,7)	10	0	1 (1, 0)	2	1	9 (9, 0)	0
A14R.S08	0.785	0.395	0.525	12495	94 (93,1)	3	7	63 (56,7)	10	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S09	0.785	0.392	0.523	12491	95 (94,1)	3	7	63 (56,7)	10	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S10	0.785	0.390	0.521	12493	96 (95,1)	3	7	63 (56,7)	10	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S11	0.797	0.377	0.512	12483	103 (102,1)	3	7	64 (56,8)	9	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S12	0.785	0.376	0.508	12487	102 (101,1)	3	8	63 (55,8)	9	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S13	0.772	0.370	0.500	12483	103 (102,1)	3	8	62 (55,7)	10	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S14	0.785	0.383	0.514	12488	99 (98,1)	2	7	63 (56,7)	10	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S15	0.785	0.383	0.514	12488	99 (98,1)	2	7	63 (56,7)	10	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S16	0.785	0.383	0.514	12491	99 (98,1)	2	7	63 (56,7)	10	0	1 (1, 0)	2	2	8 (8, 0)	0

Table 5.8 (Cont'd.)

(c)

CLASSIFIER	PRE			BCK ->			SSW ->			ART ->			DBS ->		
	P1	P2	P3	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART
TA12 .S07	0.647	0.433	0.519	12525	67		28	52		3	0		5	5	
TA12R.S10	0.744	0.188	0.301	12342	250		20	60		3	0		6	4	
TA22R.S09	0.834	0.249	0.384	12395	197		13	67		3	0		4	6	
TA32R.S09	0.885	0.299	0.447	12418	163		9	71		3	0		3	7	
TA13 .S17	0.659	0.462	0.543	12531	61 (60,1)		27	53 (47, 6)		3	0 (0, 0)		5	5 (5, 0)	
TA13R.S16	0.795	0.220	0.344	12371	221 (220,1)		16	64 (56, 8)		3	0 (0, 0)		2	8 (8, 0)	
TA23R.S24	0.898	0.363	0.517	12496	124 (118,6)		8	72 (61,11)		3	0 (0, 0)		3	7 (7, 0)	
TA33R.S20	0.936	0.236	0.376	12344	237 (236,1)		5	75 (61,14)		3	0 (0, 0)		1	9 (9, 0)	

(d)

CLASSIFIER	PRE			BCK ->			SSW ->			ART ->			DBS ->		
	P1	P2	P3	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART
A14R.PRI	0.797	0.348	0.484	12473	117 (116,1)	2	6	64 (57, 7)	10	0	1 (1, 0)	2	1	9 (9, 0)	0
A14R.CA1	0.796	0.240	0.369	12393	196 (195,1)	3	5	64 (58, 6)	11	0	1 (1, 0)	2	4	6 (6, 0)	0
A14R.CA2	0.684	0.353	0.466	12490	99 (98,1)	3	16	55 (47, 8)	9	0	0 (0, 0)	3	3	7 (7, 0)	0
A14R.CA3	0.772	0.336	0.469	12472	118 (117,1)	2	13	62 (51,11)	5	0	2 (1, 1)	1	1	9 (9, 0)	0
A14R.CS1	0.796	0.240	0.369	12393	196 (195,1)	3	5	64 (58, 6)	11	0	1 (1, 0)	2	4	6 (6, 0)	0
A14R.CS2	0.785	0.371	0.504	12485	104 (103,1)	3	6	63 (57, 6)	11	0	1 (1, 0)	2	3	7 (7, 0)	0
A14R.CS3	0.797	0.348	0.484	12473	117 (116,1)	2	6	64 (57, 7)	10	0	1 (1, 0)	2	1	9 (9, 0)	0

Table 5.9 Testing Table for Correction of Classification.

	Event I	Event J		
Classi-fication	BCK->SSW	SSW->BCK,	SSW->SSW,	SSW->ART
	BCK->ART	ART->BCK,	ART->SSW,	ART->ART
	SSW->BCK	BCK->SSW		
	SSW->ART	BCK->SSW		
	ART->BCK	BCK->ART		
	ART->SSW	BCK->ART		

Method A

In Fig.5.5, the shaded bars show the PRE values by the original classification shown in Table 5.8(a), and the white bars added on the top of the shaded bars show the gained PRE values by the corrected classification shown in Table 5.10(a). In the original classification, among the classifiers in Table 5.8(a), the highest P3 value was attained by the classifier A23R.S08, which classified 64 SSWs out of 80 correctly and 57 events were misclassified as SSW. The classifier A24R.S11 had the highest P1 value classified 69 SSW correctly, and misclassified 82 events as SSW. In the corrected classification, among the classifiers in Table 5.10(a), the highest P3 value were attained by the classifier A23R.S08, again, which classified 69 SSW correctly, and misclassified 22 events as SSW. The classifier A34R.S11 had the second highest P3 value, classified 75 SSW correctly, and misclassified 33 events as SSW. The highest P1 value was obtained by the classifier A14R.S14, which classified 76 SSW correctly, and misclassified 41 events as SSW. By the way, in Table 5.10(b), the classifier A14R.S16 had the higher P1 value than A14R.S14, classifying 77 SSW correctly, even though 46 events were misclassified as SSW.

Table 5.10 Corrected Classification in All the Data Sets by the Classifiers Chosen at the 5% Significance Level.

(a)

CLASSIFIER	PRE			BCK ->			SSW ->			ART ->			DBS ->		
	P1	P2	P3	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART
A12 .S08	0.786	0.661	0.718	12558	30		17	63		1	2		6	4	
A12R.S07	0.937	0.644	0.764	12550	39		5	75		1	2		3	7	
A22R.S09	0.836	0.751	0.792	12573	19		13	67		0	3		5	5	
A32R.S10	0.874	0.671	0.759	12558	31		10	70		0	3		4	6	
A13 .S10	0.673	0.633	0.652	12556	30	3	23	54	3	1	1	1	6	4	0
A13R.S10	0.849	0.645	0.733	12550	36	3	10	68	2	1	1	1	4	6	0
A23R.S08	0.862	0.757	0.806	12568	20	4	11	69	0	0	2	1	6	4	0
A33R.S11	0.874	0.678	0.763	12553	32	4	8	70	2	0	1	2	4	6	0
A14 .S10	0.861	0.558	0.677	12535	52 (52, 0)	2	2	69 (62, 7)	9	0	2 (1, 1)	1	2	8 (8, 0)	0
A14R.S14	0.950	0.647	0.770	12548	40 (40, 0)	1	2	76 (69, 7)	2	0	1 (1, 0)	2	2	8 (8, 0)	0
A24R.S11	0.937	0.650	0.767	12551	38 (38, 0)	3	4	75 (63,12)	1	0	2 (1, 1)	1	5	5 (5, 0)	0
A34R.S11	0.937	0.693	0.796	12557	31 (31, 0)	1	3	75 (63,12)	2	0	2 (1, 1)	1	2	8 (8, 0)	0

(b)

CLASSIFIER	PRE			BCK ->			SSW ->			ART ->			DBS ->		
	P1	P2	P3	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART
A14R.S01	0.848	0.479	0.612	12515	72 (72, 0)	2	6	68 (63, 5)	6	0	1 (1, 0)	2	5	5 (5, 0)	0
A14R.S02	0.848	0.528	0.651	12527	59 (59, 0)	3	3	68 (63, 5)	9	0	1 (1, 0)	2	4	6 (6, 0)	0
A14R.S03	0.937	0.570	0.709	12531	55 (55, 0)	3	2	75 (70, 5)	3	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S04	0.924	0.562	0.699	12530	56 (56, 0)	3	3	74 (67, 7)	3	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S05	0.924	0.580	0.713	12535	52 (52, 0)	2	3	74 (67, 7)	3	0	1 (1, 0)	2	1	9 (9, 0)	0
A14R.S06	0.912	0.577	0.706	12537	52 (52, 0)	3	4	73 (66, 7)	3	0	1 (1, 0)	2	1	9 (9, 0)	0
A14R.S07	0.912	0.577	0.706	12534	52 (52, 0)	3	4	73 (66, 7)	3	0	1 (1, 0)	2	1	9 (9, 0)	0
A14R.S08	0.924	0.575	0.709	12536	53 (53, 0)	3	3	74 (67, 7)	3	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S09	0.924	0.575	0.709	12533	53 (53, 0)	3	3	74 (67, 7)	3	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S10	0.924	0.571	0.706	12535	54 (54, 0)	3	3	74 (67, 7)	3	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S11	0.937	0.579	0.715	12533	53 (53, 0)	3	3	75 (67, 8)	2	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S12	0.937	0.579	0.715	12536	53 (53, 0)	3	3	75 (67, 8)	2	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S13	0.937	0.593	0.726	12536	50 (50, 0)	3	3	75 (68, 7)	2	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S14	0.950	0.647	0.770	12548	40 (40, 0)	1	2	76 (69, 7)	2	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S15	0.950	0.621	0.751	12542	45 (45, 0)	2	2	76 (69, 7)	2	0	1 (1, 0)	2	2	8 (8, 0)	0
A14R.S16	0.962	0.624	0.757	12545	45 (45, 0)	2	1	77 (70, 7)	2	0	1 (1, 0)	2	2	8 (8, 0)	0

Table 5.10 (Cont'd.)

(c)

CLASSIFIER	PRE			BCK ->			SSW ->			ART ->			DBS ->		
	P1	P2	P3	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART
TA12 .S07	0.710	0.562	0.627	12548	44		23	57		3	0		5	5	
TA12R.S10	0.784	0.314	0.448	12457	135		17	63		3	0		6	4	
TA22R.S09	0.848	0.374	0.519	12480	112		12	68		3	0		4	6	
TA32R.S09	0.899	0.405	0.559	12477	104		8	72		3	0		3	7	
TA13 .S17	0.773	0.657	0.711	12560	32 (32,0)		18	62 (56, 6)		3	0 (0, 0)		5	5 (5, 0)	
TA13R.S16	0.886	0.391	0.542	12483	109 (109,0)		9	71 (63, 8)		3	0 (0, 0)		2	8 (8, 0)	
TA23R.S24	0.912	0.591	0.717	12570	50 (45,5)		7	73 (62,11)		3	0 (0, 0)		3	7 (7, 0)	
TA33R.S20	0.949	0.372	0.535	12455	126 (126,0)		4	76 (62,14)		3	0 (0, 0)		1	9 (9, 0)	

(d)

CLASSIFIER	PRE			BCK ->			SSW ->			ART ->			DBS ->		
	P1	P2	P3	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART	BCK	SSW (SSWA, SSWB)	ART
A14R.PRI	0.962	0.559	0.707	12531	59 (59,0)	2	1	77 (70, 7)	2	0	1 (1, 0)	2	1	9 (9, 0)	0
A14R.CA1	0.873	0.297	0.443	12428	161 (161,0)	3	2	70 (64, 6)	8	0	1 (1, 0)	2	4	6 (6, 0)	0
A14R.CA2	0.823	0.557	0.664	12537	52 (52,0)	3	12	66 (58, 8)	2	0	0 (0, 0)	3	3	7 (7, 0)	0
A14R.CA3	0.937	0.533	0.679	12527	63 (63,0)	2	3	75 (64,11)	2	0	2 (1, 1)	1	1	9 (9, 0)	0
A14R.CS1	0.873	0.297	0.443	12428	161 (161,0)	3	2	70 (64, 6)	8	0	1 (1, 0)	2	4	6 (6, 0)	0
A14R.CS2	0.924	0.562	0.699	12533	56 (56,0)	3	4	74 (68, 6)	2	0	1 (1, 0)	2	3	7 (7, 0)	0
A14R.CS3	0.962	0.559	0.707	12531	59 (59,0)	2	1	77 (70, 7)	2	0	1 (1, 0)	2	1	9 (9, 0)	0

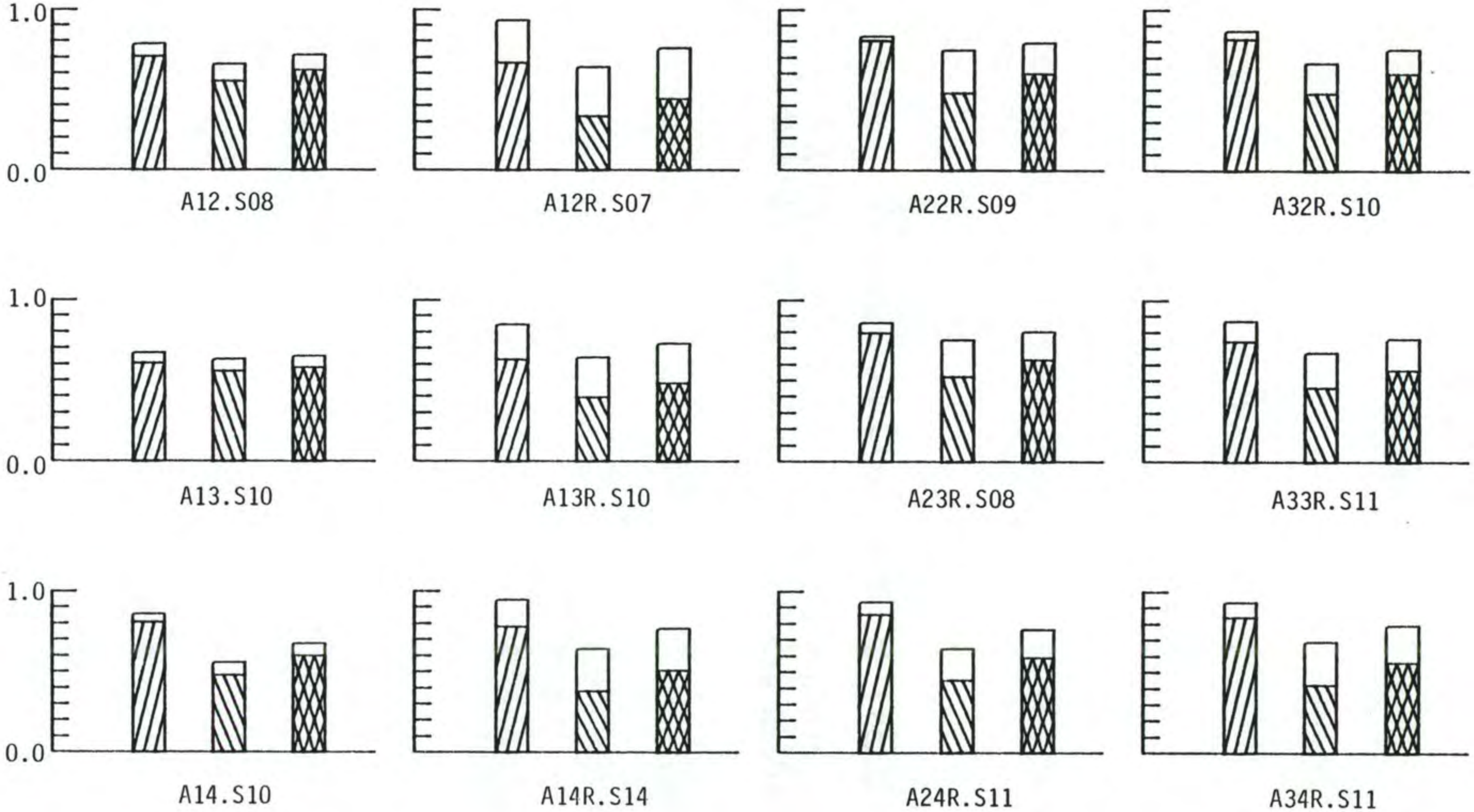


Figure 5.5 Histograms of the PRE Values by the Classifiers of Method A at the Testing Stage Shown in Table 5.8 and 5.10. In one graph, P1: left, P2: middle, P3: right. Bars shaded: Original classification results. Bars total(shaded and white): Corrected classification results.

The classifiers without the retraction of data in training data sets performed better than the classifiers with the retraction in the original classification. However, when the classification was corrected as explained above, the classifiers without the retraction (A12.S08, A13.S10 and A14.S10) did not improve in performance as much as the classifiers with the retraction (A12R.S07, A13R.S10 and A14R.S14).

As for the effects of changing the number of training data sets, the performance was improved considerably in terms of the measure P3 in the classifiers with 2 groups and 3 groups when the number of the training data sets was increased from 1 to 2. However, in general, there was no conclusive or significant observation concerning the change of the number of training data sets.

As for the effects of changing the number of specified groups, the classifiers that have the same number of training data sets were compared with each other. In the original classification, (1) the classifiers with 4 groups always had the highest P1 values and the lowest P2 values, and the classifiers with 3 groups always had the lowest P1 and the highest P2, (2) the classifications with 4 groups appear inferior to others in performance in terms of the measure P3 mainly because more events were misclassified as SSW even though more SSW events were correctly classified. In the corrected classification, (1) the classifiers with 4 groups had not only the highest P1 values, but also the highest P2 and P3 values except for the case of 2 training data sets (A24R.S11), (2) the classifiers A23R.S08 and A22R.S09 misclassified less number of events as SSW than the others, but consistent difference between the classifiers with 2 and 3 groups was not observed.

An example of the effect of changing the number of parameters in a classifier is demonstrated in Fig.5.6, which is based on the PRE values in Table 5.8(c) and 5.10(c). The experiment A14R was taken as the example. In the original classification, the performance was almost the same through the classifiers. In the corrected classification, the performance was improved in terms of all the three measures during the first 3 steps, stayed at almost the same level up to the step 12, and some more improvements were seen after the step 12. As shown in Table G-1, Appendix G, the classifiers in the experiment A14R performed very well in the training data sets, misclassifying only one event from the first step until the step 12, and classified perfectly after the step 12. Comparing the results of classification of A14R at the testing stage with the results in the training stage, the following two points may be mentioned: (1) although the classification in the training data sets was same during the first three steps in the training stage, there were improvements of performance during the first three steps at the testing stage; (2) the improvement at the step 13 in the training stage seemed to coincide with the improvement at the same step in the testing stage. Concerning the point (2), it is not known whether the coincidence occurred by chance, by a possible uniformity of data sets, or something else.

Method T

The histograms in Fig.5.7 shows the results of the PRE values of Method T in Table 5.8(b) and 5.10(b) with the same configuration of the graphs as those in Fig.5.6.

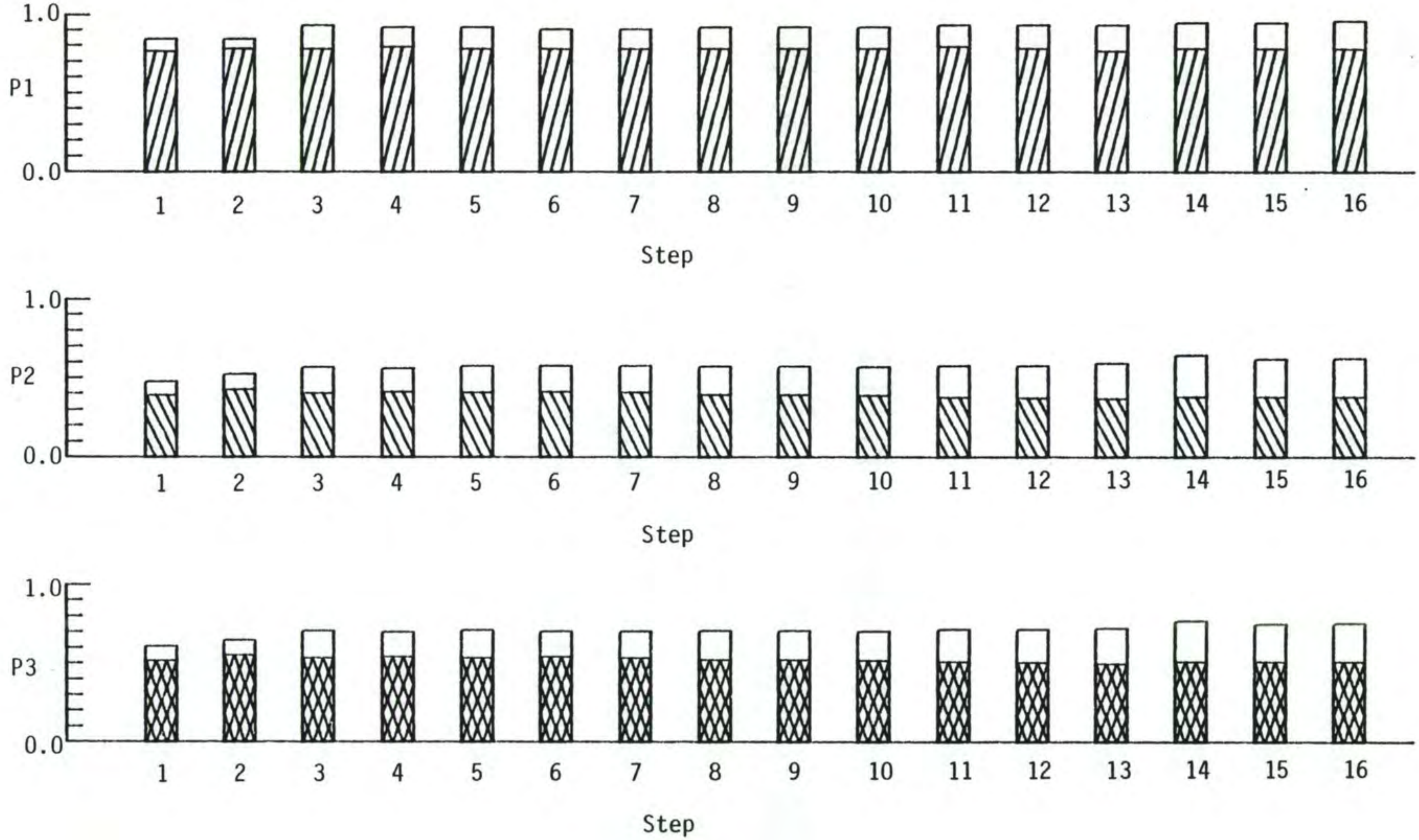


Figure 5.6 Histograms of the PRE Values by the Classifiers of A14R at the Testing Stage. Shown in Table 5.8 and 5.10. Bars shaded: Original classification results. Bars total(shaded and white): Corrected classification results.

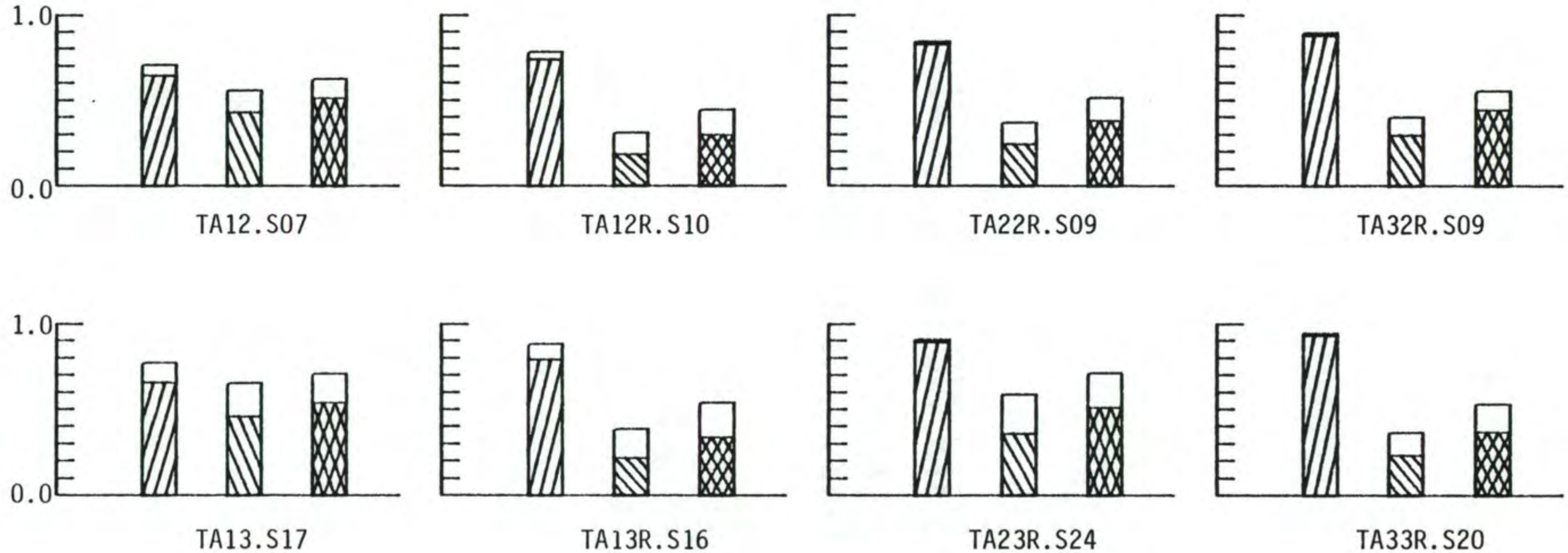


Figure 5.7 Histograms of the PRE Values by the Classifiers of Method TA at the Testing Stage. Shown in Table 5.8 and 5.10. (in one graph, P1: left, P2: middle, P3: right.) Bars shaded: Original classification results. Bars total(shaded and white): Corrected classification results.

In the original classification, the best and the second best performances were given by the classifiers TA13.S17 and TA12.S07, respectively, in terms of the measure P3. In terms of the measure P1, the best and the second best performance was offered by TA33R.S20 and TA23R.S24, respectively. The classifiers TA33R.S20 and TA23R.S24 were very good in detecting SSW (i.e. 75 and 72 SSW detection, respectively), but not good in classifying the non-SSW events correctly (i.e. 124 and 237 events misclassified as SSW, respectively).

In the corrected classification, the best and the second best performances were given by TA23R.S24 and TA13.S17, respectively, in terms of the measure P3, and by TA33R.S20 and TA23R.S24, respectively, in terms of the measure P1. The classifier TA23R.S24 in the corrected classification classified 73 SSW correctly, and misclassified 50 events as SSW. The result was comparable to the results in Method A, but the others were mostly inferior in performance to those in Method A. The correction of classification improved the P2 values, but did not improve the P1 values very much.

There seems to be an advantage in Method T, however, that the classifiers in Method T always classified artifacts as backgrounds, whereas some artifacts were classified as SSW in Method A.

The classifiers with the retracted training data sets always performed better in terms of the measure P1, and worse in terms of the measure P2 and P3 than those without the retraction.

As the number of specified groups increases from 2 to 3, the P1 values always increased, but the P2 values and consequently the P3 values were not consistent in increase. However, there was a tendency that the P2 and P3 values are increasing as the number of training data sets or the number of specified groups increase unless the number of the training data sets is 3.

Classification in Supplemental Experiments

The results of classification in supplemental experiments are shown in Table 5.8(d) and 5.10(d). Fig.5.8 shows the results of the PRE measure in the form of histograms. When the assignment of prior probabilities in the experiment A14R was changed to 0.25 for all the groups, the BMDP7M program selected the same parameters at each step as in the original experiment A14R only with difference of the coefficients of classification functions. Hence, the classifier A14R.PRI have the same parameters as the classifier A14R.S14 with different coefficients of classification functions. The P3 values of A14R.PRI in both the original and corrected classifications were slightly inferior to those of A14R.S14, but the P1 values were better in both of the classifications. The result indicates that an assignment change of prior probabilities seems to have only a minor effect in the classification.

The results of classification by the canonical classifiers indicate the following. The P3 values increased as the number of canonical variables increased. The performance of the canonical classifiers with the absolute measure was slightly inferior to those with the square measure. In both of the classifications, the performances were not as good as those of A14R.S14, but still comparable. Considering that the method of parameter selection which may be more suitable for canonical classifiers (see McKay and Campbell 1982a,b) was not applied, the achievements of these canonical classifiers are remarkable.

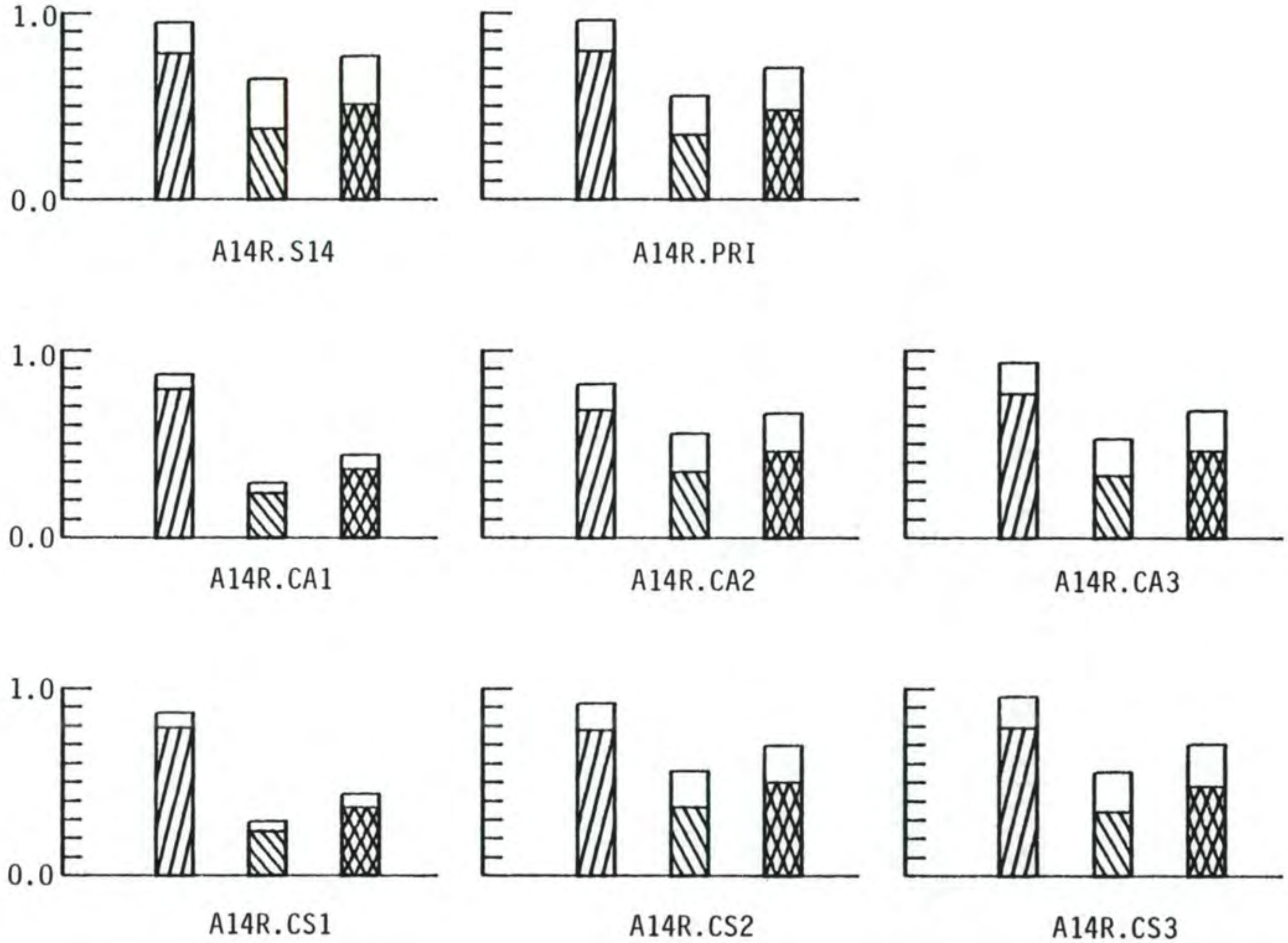


Figure 5.8 Histograms of the PRE Values by the Classifiers in Supplemental Experiments at the Testing Stage Shown in Table 5.8 and 5.10. (in one graph, P1: left, P2: middle, P3: right.)

Analysis of Classified Events

Using some examples in Method A, this section lists and displays the events misclassified or correctly classified, and analyze them.

Event Identification and Posterior Probabilities

Table H-1 in Appendix H shows the list of classified events except correctly classified background events, obtained by the classifier A14R.S14. The list contains, for one event, data set number and event number for event identification, originally assigned event type, predicted (or classified) event type, a check value for correction of classification, time at the peak of core-wave, and posterior probabilities. If CORRECTN is 1, the event has been classified as a correctly classified event in the corrected classification as explained before. The value of TIME is the elapsed time in second starting from the beginning of each file (or data set). The number of EVENT was counted including events with trough (electrically positive) core-waves as well as events with peak core-waves, thereby the neighbouring event to EVENT 385 being numbered as EVENT 383 and EVENT 387 in the list that contains only events with peak core-waves. The posterior probabilities were calculated according to the formula for posterior probabilities in Appendix C.

Morphology of Classified Events

Fig.5.9(a) shows the averaged waveform of each group in the first three data sets: from left to right, the names of groups are BCK, SSWA, SSWB and ART. The numbers of samples of each group in averaging were 25, 21, 3 and 1 for BCK, SSWA, SSWB and ART,

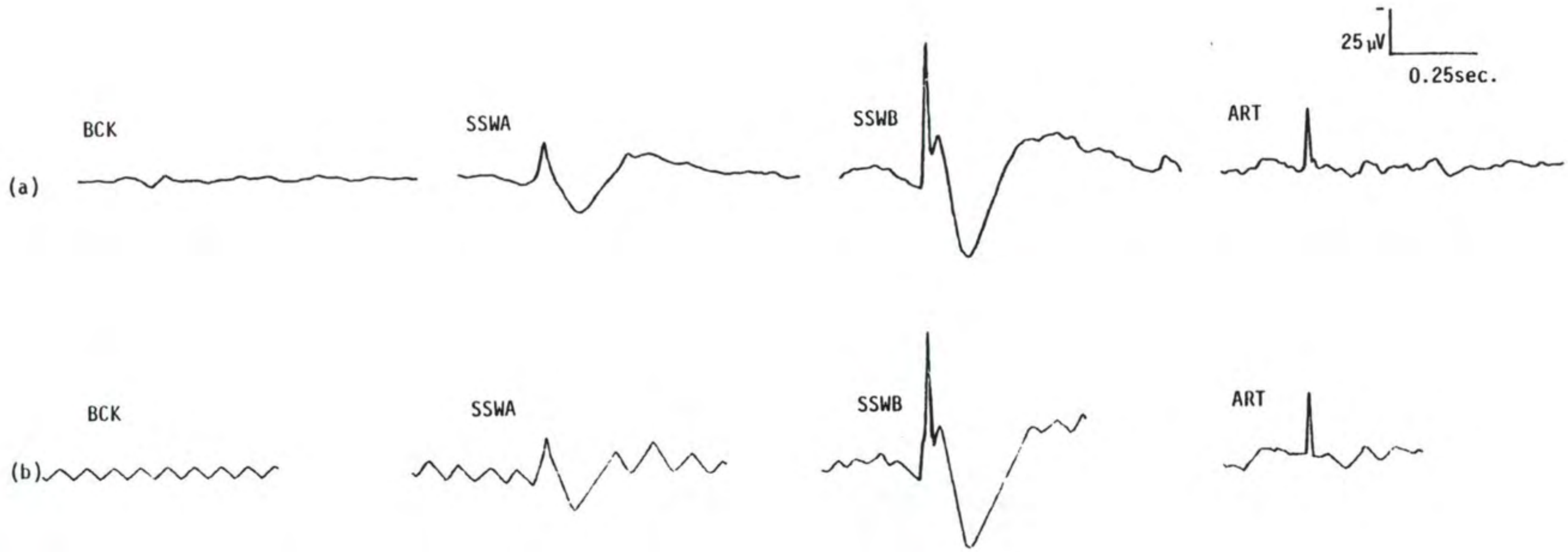


Figure 5.9 Typicl Waveforms and Reconstructed Typical Waveforms.

respectively. Each can be considered a "typical waveform" of a group. In fact, the waveforms of SSWA and SSWB were used as templates in the experiments TA33R, TS33R and TC33R.

As mentioned in Chapter 4, the original data can be reconstructed by using the parameterized data in Method A. When each event parameter is averaged over the events of a group in the data sets, a set of the averaged parameters can be used to reconstruct an "averaged" waveform of the group, or a "reconstructed typical waveform" of the group. Fig.5.9(b) shows these waveforms in the four specified groups. The sampled events in averaging were same as those in the case of Fig.5.9(a) except that all the 2,290 background events in the data sets were used in averaging for BCK[1]. The peak of the core-wave (the 10-th peak) was aligned vertically with the peak of the corresponding typical waveform. The following may be pointed out concerning the figures in Fig.5.9. The reconstructed waveforms covered the characterstic parts of the typical waveforms. An event was restored very well as seen in the case of ART in Fig.5.9(b). However, when averaged, a reconstructed typical waveform was different in shape from the corresponding typical waveform except for the part of the core-wave in general. The reconstructed typical waveform of BCK is a good example in showing the difference. The difference between the waveforms of SSW is interesting. The typical waveforms show four distinct types of waveforms, and so do the reconstructed typical waveforms in a different way.

---

1. The data were obtained in the output of the BMDP7M program for the experiment A34R.

Fig.5.10 displays the portion data of misclassified events concerning the SSW detection in the experiments A12R, A13R and A14R. The graphs in the first and second rows from the top show the results from A12R; the graphs in the third and fourth rows for A13R; the graphs in the fifth and sixth for A14R. The graphs in the first, the second, the third and the fourth columns in Fig.5.10 show the misclassified events of SSW->BCK, BCK->SSW, ART->SSW (ART->SSWA in A14R) and SSW->ART, respectively. An averaged waveform was added right below each superimposed display of misclassified events. Fig.5.11 displays the same events in the same order, but the graphs were reconstructed from the event data in Method A. Some wildly large waves seen in the second column of Fig.5.10 were the successive waves defined in Design of Experiments, Chapter 4. They were labeled as BCK, but could have been labeled as SSW. The corresponding waveforms are also found in Fig.5.11.

It is interesting that the averaged waveforms in the second column of Fig.5.11 seem to show the same morphological characteristics as the typical waveform of SSW in Fig.5.9(a). The difference seems to be only the magnitude of the wave after the core-wave. Fig.5.12(a) shows the superimposed graph of the typical waveform of SSWA in Fig.5.9(a) and the averaged waveform of BCK->SSWA misclassification in Fig.5.10. Fig.5.12(b) shows the superimposed graph of the reconstructed typical waveform in Fig.5.9(b) and the averaged waveform of BCK->SSWA misclassification in Fig.5.11.

The graphs of A12R and A13R in the first column have a common feature of waveforms, that is, a small bump right after the core-wave.

Figure 5.10 Portions of Misclassified Data.

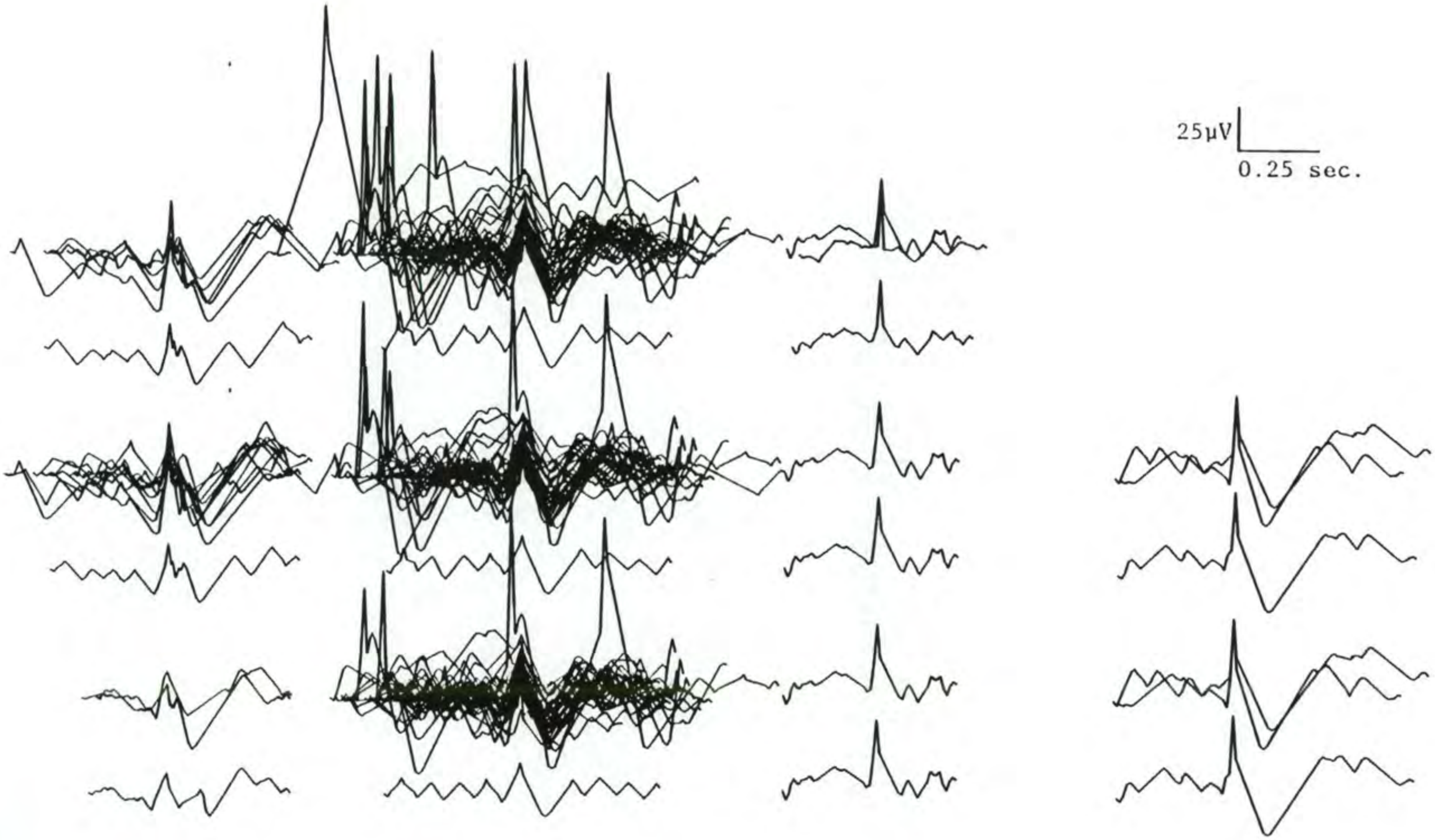


Figure 5.11 Reconstructed Portions of Misclassified Data.

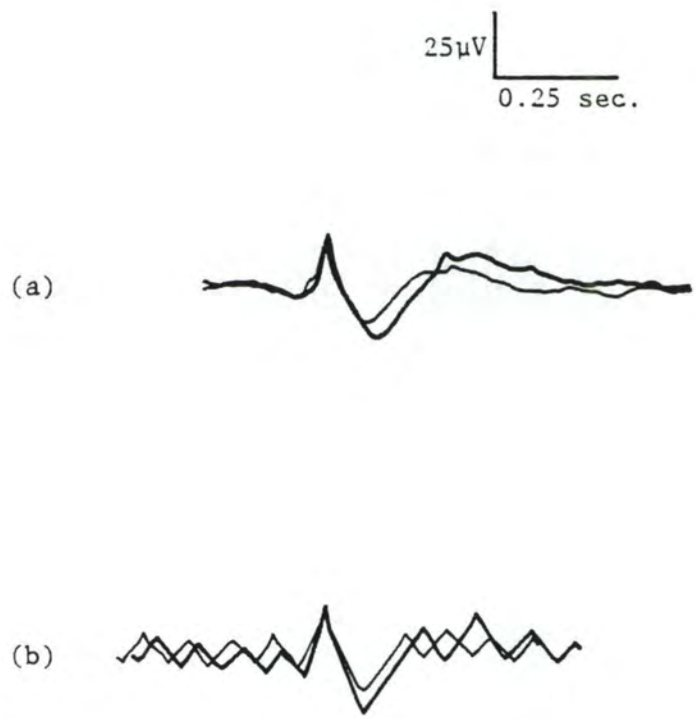


Figure 5.12 Comparison of a Typical Waveform of SSWA and an Averaged Waveform of BCK->SSWA Misclassification. Thick lines: Typical waveforms. Thin lines: Averaged waveforms of BCK->SSWA misclassification. (a) Basic data. (b) Reconstructed data.

It was more distinctively noticed in Fig.5.11. Obviously the classifiers were susceptible to the bump after the sharp peak, and misclassified these bumped SSWs as BCK. This was improved in the classifier of A14R, where it missed only two SSWs of untypical shapes.

It was not clearly seen why one or two artifacts were misclassified as SSW. Even though the morphological features of the artifacts seemed quite different for SSW, some of them were classified as SSW. On the other hand, two SSW events were misclassified as ART despite the similar morphological features to SSW. It must be noted that only one artifact sample was available in the training data sets. So, the poor performance of artifact classification may be improved if more artifact samples are used in the training data sets.

However, how to explain why some events were misclassified may be a problem when a set of classification functions is used to classify events. That is a question of how to visualize the behavior of a classifier. For example, canonical variables can be used for it, thereby showing the corresponding point to an event in the coordinate of canonical variables. As shown in Table 5.10(d), two canonical variables can serve the purpose, resulting in a plane coordinate. Fig.5.13 shows an example of it using the output of the BMDP7M program. The origin is the mean of all events, and the scale is standardized as described in Appendix C. If the point of an event is closer to the mean point of a group, the event is closer to the typical event of the group.

As a caution in Fig.5.11, the method of reconstruction caused some noticable jerky portions, especially in the first column of Fig.5.11. This occurred because of the method of averaging. These jerks of the

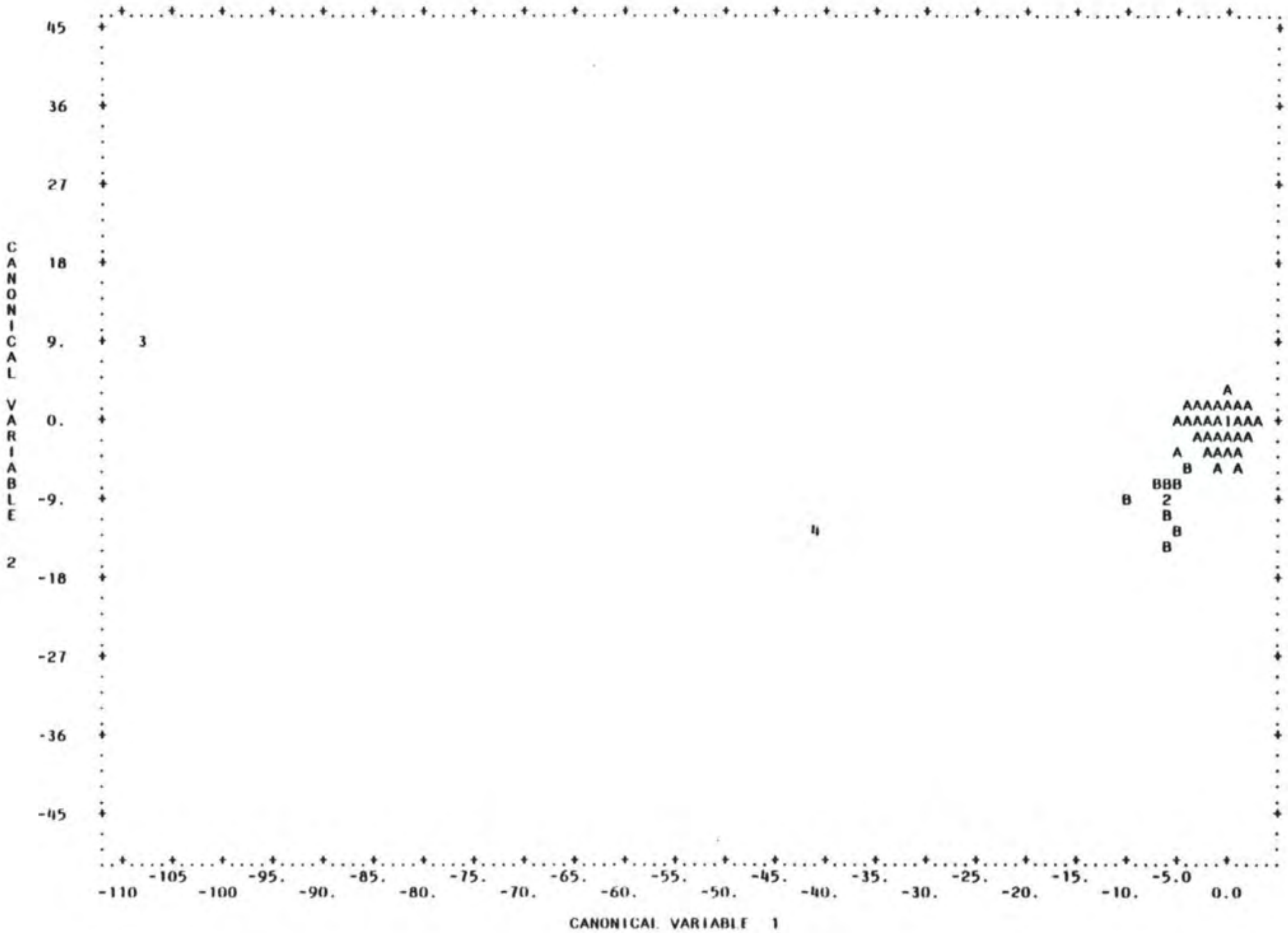


Figure 5.13 An Example of Canonical Bivariate Graph. A, B, C, and D for events of the groups of BCK, SSWA, SSWB, and ART, respectively. 1, 2, 3, and 4 are for the means of the events in BCK, SSWA, SSWB, and ART, respectively.

graphs can be smoothed out easily. Also, the whole reconstructed waveform can be more natural if, for example, one of spline interpolation techniques is appropriately applied.

CHAPTER 6

SUMMARY, DISCUSSION AND PROSPECT

This chapter summarizes and discusses the results of the experiments, and the concept and design of the proposed system. The prospective improvements and applications of the proposed system are also suggested.

Experimental Results

Based on the experimental results in Chapter 5, this section organizes them and sees to their significance.

Parameter Selection

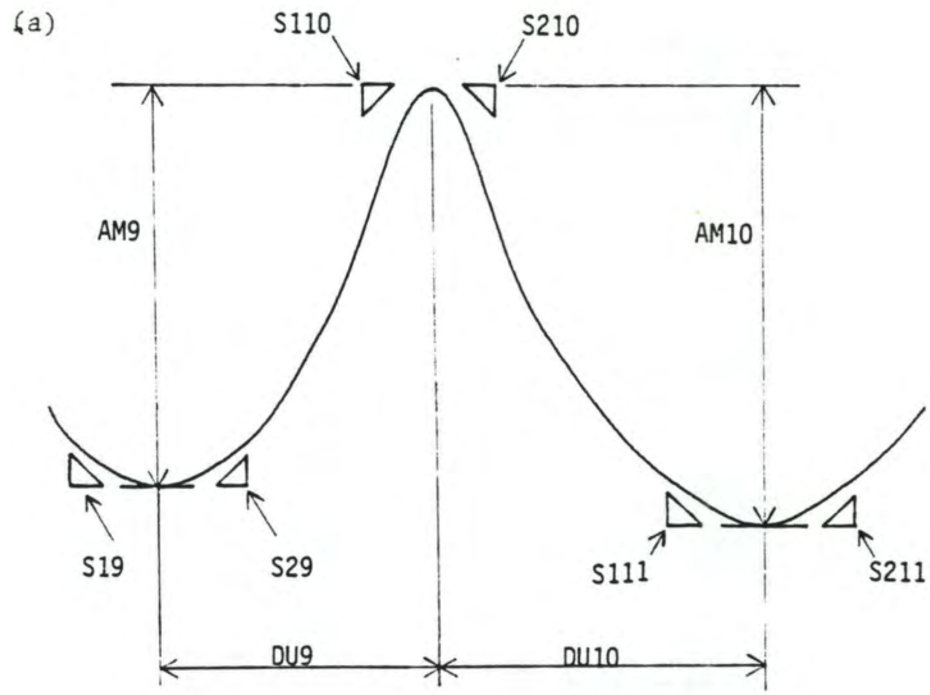
The overall significance level proposed by Hawkins(1976) was applied to choose the step of the BMDP7M program where an appropriate classifier to represent the experiment is obtained. As Hawkins stated, the overall significance level is conservative in selecting parameters. With the modest value of 5% for the overall significance level, the average number of selected parameters was about 10 in Method A. In Method T, the average number was about 7 and 14 with 2 and 3 groups, respectively.

The overall significance level of 5% to choose a representing classifier from each experiment seems to be moderate to get a "matured" classifier of an experiment, but a smaller value of the significance level seems not to damage the performance too much. Therefore, if having a less number of parameters in a classifier is more crucial than having slightly better performance, a smaller value of the significance level could be used.

These parameters are statistically significant in terms of F-values, and derived from more than one wave in an event. The parameters in the core-wave were selected most popularly and mostly in the early steps. The second most popular parameters derived from the two waves adjacent to the core-wave. The results have proved that they contribute very much to improve the classification performance. This tendency is very reasonable because the core-wave is visually most characteristic of SSW and is aligned to constitute a set of event parameters.

Very recently, Oliveira et al. (1983) ranked the parameters to detect SSW using Mahalanobis distance between epileptiform and non-epileptiform waves. Some of the parameters in his paper correspond to those of Method A in this paper as shown in Fig.6.1, although they are standardized by standard deviations. The parameters of Method A are ranked based on Fig.5.6, and the ranks are compared with the ranks of the parameters presented by Oliveira et al. (1983) in Table 6.1. The top 5 parameters by Oliveira et al. corresponded to the top 5 parameters of Method A.

The other parameters of Method A are selected from the waves more remote to the core-wave. They contributed to the improvement, but to the less extent than those parameters mentioned above. Then, it may be suggested, as far as the proposed analysis system is concerned, that the most distinguishable and coherent characteristic of SSW is in the core-wave area, but the surrounding waves also can have



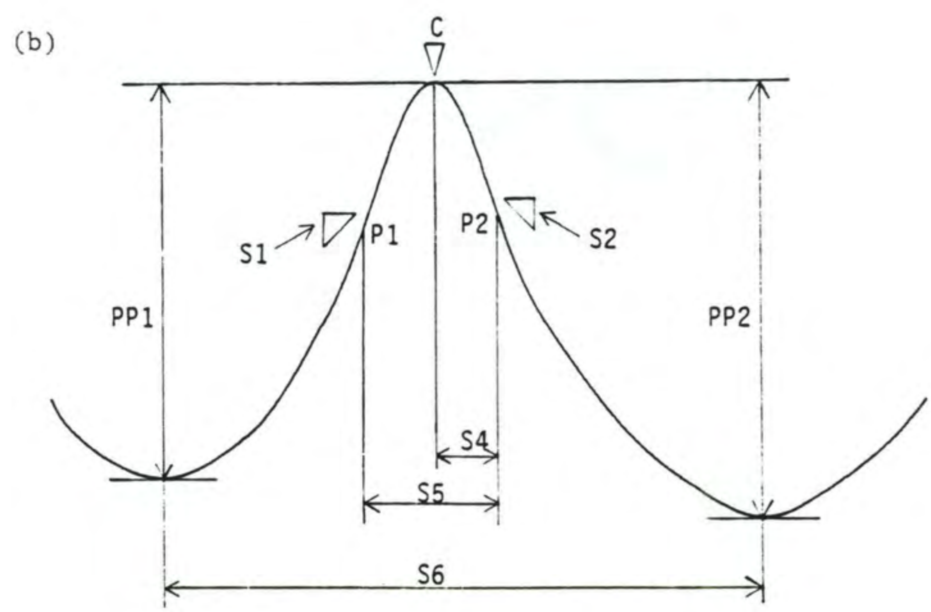


Figure 6.1 Schematic EEG Wave and its Parameters by Oliveira et al. (1983) in Comparison with Those in This Project. (a) Parameters of Method A around a core-wave in this project. (b) Parameters presented in the paper by Oliveira et al. (1983). P1 and P2 are inflection points.

Table 6.1 Ranks of Parameters in Comparison with Those by Oliveira et al. (1983). σ, σ_1, and σ_2: standard deviations of the data, the first derivative, and the second derivative, respectively.

In the paper by Oliveira et al.		Relation between parameters	In this paper	
Parameter	Rank		Parameter	Rank
$\|CM\|(=\|C\|/\sigma_2)$	1	C≈S210-S110	S210	2
			S110	3
$\|M2\|(=\|S2\|/\sigma_1)$	2	S2<min(S210,S111)	S210	2
			S111	1
$\|M1\|(=\|S1\|/\sigma_1)$	3	S1>max(S29,S110)	S29	4
			S110	3
$\|PP2m\|(=\|PP2\|/\sigma)$	4	PP2=AM10	AM10	1
S6	5	S6=DU9+DU10	DU9	5
			DU10	1
S4	6			
S5	7			
$\|PP1m\|(=\|PP1\|/\sigma)$	8	PP1=AM9	AM9	5

a role in characterizing SSW even if the contribution is minor. However, there may be another characteristic part of SSW that has not been unraveled by the parameters of the system.

It was observed that Method T leads to selecting parameters from broader range of waves in an event than in Method A. It probably reflects the fact that a template usually covers a larger portion of the data than a wave.

It was typically observed as a trend that as the step proceeds in an experiment at the training stage, the classification performance obtained by the classifier at the step improved considerably for a few steps by the inclusion of the parameters from the core-wave area, then keeps on improving slowly by including other parameters until the step begins to enter a parameter that is not significant enough to contribute to the improvement, by which the perfotmance may deteriorate. In an example at the testing stage, the classifiers in the experiment A14R followed the trend in the corrected classification except that the performance did not deteriorate, but improved even at the last few steps. In the original classification at the testing stage, the classification performance of A14R did not change very much through the steps. In this example, it can be considered the performance in the original classification at the testing stage was already very close to the best even at the first step. The same tendency was observed in the classifiers at the training stage. It is not clear why the parameters at the second, the third and the following steps in the experiments A14R did not contribute to the improvement very much, but rather interesting is that the corrected classification improved almost constantly. It means that the parameters entered at the later steps are contributing toward distinguishing the events even if it was not apparent in the classification at the training stage and in the original classification at the testing stage. This and the reverse case can happen when the distribution of events in the training data sets is not same as that at the testing data. Therefore, if there is no wildly deviated events which distort the proper statistical values, the use of a statistical value to choose the best step to stop the selecting procedure is more recommended than the use of classification results. As described in Chapter 3, the F-statistics applied in this project has been criticized as inappropriate, but proved to be useful to a certain extent as the results showed.

Retraction of Adjacent Events to SSW in Training Data Sets

The original classification results obtained by the classifiers chosen at the 5% significance level showed that the retraction of the adjacent events to SSW events in the training data sets just deteriorated the results. However, when the classification results are converted to the corrected classification, the retraction improved the values of the measures P1, P2 and P3 in Method A except for the P2 value of A12R.S07 and the values of the measure P1 in Method T. Therefore, if the nearmiss detection of SSW is not tolerated, the retraction is not recommended. If the nearmiss detection is tolerated, the retraction is recommended in Method A. In Method T, by tolerating the nearmiss, the SSW detection is improved, but more background events may be detected as SSW.

The following seems to explain the above results. By the retraction, the background events did not include the waves of SSW and artifacts in the events. It lessened the variety of background events, thereby making more background events classified as SSW, which resulted in the lower values of the measure P2. But, it turned out that many of those misclassified events of BCK-> SSW, etc. are very close to SSW events, especially in Method A. In addition, the category of SSW was broadened by less variety of background events, thereby resulting in accepting more variety of SSW events.

Number of Training Data Sets

The results did not imply a consistent tendency of classification performance when the number of training data sets was changed. It is naturally anticipated that the longer the training period, the better the classification ability of a classifier. It is probably true statistically, but does not apply to individual cases because each of the training data sets is always somewhat peculiar in its statistical properties. What may be conclusive in the results concerning the number of training data sets is that the classifiers with a training data set of about 72 seconds including 9 SSWs performed fairly well for the testing data of 17.5 minutes, and the performance was not greatly different when the period of the training data set was made twice or triple including 16 and 24 SSWs, respectively. How long the training period should be is still not solved, but the the above results are encouraging because they showed only the training data of 72 seconds with 9 SSWs, which will be reasonably acceptable in clinical situations, could achieve a satisfactory classification.

Number of Specified Groups

There were some points notable in the results at the testing stage as to the effect of changing the number of specified groups. The P1 values of the experiments with 4 groups in Method A and with 3 groups in Method TA were always better than others in each Method both in the original classification and in the corrected classification. However, the P2 and P3 values of these experiments were mostly inferior to those in the other experiments in the original classification. In the corrected classification, the performances of the classifiers with 4 groups in Method A surpassed those with 2 or 3 groups in Method A in all the measures. In Method TA, it did not happen when the number of groups was increased from 2 to 3.

Observing these results, dividing a group SSW into two groups SSWA and SSWB brought (1) a success in terms of improving the detection of SSW events, and (2) a problem of detecting more background events as SSW. A tolerance for the nearmiss SSW detection shown in the correction classification helps solve the problem in Method A. The problem was not solved likewise in Method TA.

When only two groups were specified in Method A, the results were not necessarily worse than the others. Then, if a simpler system is desired, the classifiers with two groups seems to carry the classification task quite satisfactorily. They also have some advantages in classification theories because a classification problem with dichotomy sometimes has special advantageous properties, and has been extensively investigated.

Prior and Posterior Probabilities

The results obtained by the classifier A14R.PRI suggested that the assignment of prior probabilities for the specified groups, which is necessary to calculate the Bayes linear classification functions, is not crucially influential to the classification results. In fact, it is difficult to estimate the true prior probabilities because it may vary depending on the subject and his/her conditions. Although this is only one example, the preliminary implication serves to ease one of the disadvantages in using the Bayes classification functions. It also supports the fact that the results of the experiments will not be changed very drastically by changing the prior probabilities that were approximated and assigned by the author.

Since the assignment of the prior probabilities themselves are not based on a firm principle as mentioned above, the posterior probabilities, although an example was demonstrated in Chapter 5, could not be recognized as accurately conveying a reliable information.

Canonical Classifiers

The results demonstrated that under the condition of one training data set and four specified groups, the ability of the canonical classifiers was very close to that of the Bayes classifiers when more than one canonical variables are used. The second canonical variable contributed to the improvement of performance very much whereas the third did a little. It indicates that the first two canonical variables may suffice for the classification purpose. It is interesting that the canonical classifiers with the absolute measure, which needs much less calculation time by computers, performed almost as well as those with the square measure.

Evaluation of Classification Results

The PRE measures applied for evaluating the classification results were considered to be better than the raw probabilities that can be misleading. The PRE measures were general in concept, simple in the calculation, and versatile in the applications as far as appropriately applied. The three measures P1, P2 and P3 reflected different aspects of the classification results, and offered proper interpretations for the results.

When misclassified events were displayed, it was found that the background events misclassified as SSW have close morphological features to SSW events and almost indistinguishable from SSW morphologically when averaged as shown in Fig.5.12. One possible explanation for it is that the electroencephalographer missed to check them as SSW. Another possible explanation is that he used broader range of data than the portion of data included for an event in order to decide whether an event is SSW or not.

As far as classifying an event morphologically based on a portion of the data for an event, the system worked quite well. But, if background activities around an event to be classified are somehow incorporated in parameters of an event, the results may be improved.

The System's Concept and Design

The objective of implementing an automated EEG analysis system to detect SSWs was circumstantiated by (1) the significance of the EEG, especially the epileptic EEG in the clinical practice and research environment, as revealed in Chapter 2, and (2) the on-going development of modern computers which may reduce, replace, or even improve the work of electroencephalographers by utilizing sophisticated data processing schemes as demonstrated in Chapter 3.

The system to be implemented adopted a pattern recognition scheme. Then, a conceptual structure of the pattern recognition system was established as a sequence of procedures: preprocessing, segmentation, parameterization, and classification. This type of complete conceptual structure for pattern recognition was not explicitly or consciously perceived in most of the reviewed papers on SSW detection in Chapter 3. However, the detection procedures of the systems in the previous papers could be decomposed and reorganized so that each of the procedures in the previous papers may belong to one of the procedures described above. Thus, in Chapter 3, each of the procedure could be independently reviewed.

The scheme for each procedure of the system in this paper was based on the consideration and improvement of the previous systems in the review. Ad hoc approach and manual set-up of the numbers such as thresholds and tolerance ranges were avoided as much as possible. As a result, once a supervised training data is provided in the proposed system, the manual input parameters required before the system runs are not specific to or derived from the particular data. The order of the low-pass digital filter is set assuming the minimum duration of SSW is 20 msec. However, this assumption is not particular to a data set, but generally acceptable. Simple and effective algorithms were preferred so that the system has a chance of real-time operation by a microcomputer.

Structure of Analysis Procedures

In general, the whole procedure of a pattern recognition is divided into feature extraction and classification. In this paper, it was divided into the four procedures which are distinct and essential in a waveform pattern recognition system, as explained in Chapter 4. It is important to carefully examine which algorithm suits best for each procedure to achieve the system objective. Discriminant analysis was applied to select useful parameters and to calculate a classifier at the training stage. When the types and their number of waveforms are not known, a procedure of clustering may be added at the training stage before the discriminant analysis so as to help decide the types and the number of the types systematically and automatically. Clustering algorithms have been developed and available commercially: BMDP1M and BMDPKM in BMDP programs (Dixon 1975), for example.

Preprocessing

The preprocessing in this project included a preamplifier, a band-pass filter of the cutoff frequencies of 1 and 70 Hz, a main amplifier, a 10 bit A/D converter, and a simple three-point, linear-phased, low-pass digital filter. The band-pass filter has been used routinely in clinical situations and were necessary to attenuate the voltages of high frequency noises and artifacts. The A/D converter of 10 bits proved to be capable of representing the EEG data in a digitized form satisfactorily as seen in Fig.4.7. The digital filter was used to further reduce the noises, in particular, the round-off error caused by digitization. It seems not to distort the main waveforms of the EEG, but to reduce unnecessary jitters. It also contributed to making the data look closer to the strip chart recorder output, the pen of which has a frequency response lower than 70 Hz. The filter was very simple in operation, and the result was satisfactory.

Segmentation

Instead of a fixed length segmentation, a zero-crossing segmentation, or others, a turning-point (extrema) segmentation was used because of the advantages described in Chapter 3. A linear-phase, low-pass digital filter was used to prevent from segmenting the data at unnecessary extrema. The segmentation procedure included two subroutines: one for the digital filter and another for detecting turning-points (extrema). The latter subroutine, although simple, had a double-check to detect an extremum so that it does not miss a tuning-point but discard it if not significant. The filter was very simple and proved to be useful. But some redundant extrema on the data still remained as seen in Fig.4.7 for example. One way for the improvement is to use a better filter: for example, another low-pass filter proposed by Lynn (1977),

$$y(n)= 2y(n-1)-y(n-2)+x(n)-2x(n-m)+x(n-2m)$$

has smaller side lobe gains in expense of a slight increase of calculation and memory requirement. Another way for the improvement may be to introduce tolerances or thresholds in duration and/or amplitude of a segment. For example, the data is not segmented at a turning-point unless a certain time (i.e. a duration threshold) has been passed after the last turning-point and/or unless a certain difference of the amplitude between the current and the last amplitude (i.e. an amplitude threshold) is made. These schemes were not incorporated in the proposed system because incorporating these thresholds makes the system less simple and necessary to include additional input parameters which must be given their values by a researcher. However, if necessary, these thresholds can be very easily incorporated in the system by slightly modifying the subroutine for detecting turning-points.

Parameterization

The concept of "wave" is not new, but it must be noted that the "peak wave" and "trough wave" were clearly defined and overlaped in this paper. In deriving parameters in a wave, the use of the basic data (preprocessed data) instead of the low-pass filtered data used for segmentation was another point to be noted. Because the low-pass filtered data is likely to have lost some of the vital information in the EEG, especially the sharpness of SSW.

The concept of "event" in this paper is rather unique, although hinted elsewhere (Gotman and Gloor 1976, Schenk 1976, and Remond 1969), in the sense that it integrated parameters for several waves systematically, and that an event was used as a unit (or case) to be classified.

Among a lot of possible parameters as shown in Table 3.1, a set of morphological parameters in Method A and three types of template matching parameters were tested. They were simple in operations and the meaning of the parameter values could be easily interpreted. In Method A, only four parameters in a wave were used, but other morphological parameters could be included: a curvature, or slopes at inflection points in a core-wave, for example. The subroutine for deriving the slopes was one of the simplest, but could be refined, if necessary, by using a polynomial approximation for example. Method T can be viewed as an extended form of classical template matching, which in a way resembles the Tauberian approximation method.

Advantages of standardization of parameters is discussed in Standardization of Parameters and SSW Criteria, Chapter 6. The ability of reconstruction in Method A can be a big advantage as will be discussed later in Data Reduction Aspects of the System, Chapter 6.

Parameter Selection

Even though the results proved the usefulness of the automatic parameter selection and the classification applied in this project, there are a lot of room for improvements as discussed in Chapter 3. In selecting parameters, although automatic selection of parameters was an advanced idea to the others, (1) the hypotheses of multinormal distribution and equal covariance of each group were probably violated in the data, (2) the F-value for giving priorities to parameters could be misleading if the number of groups was more than two (Habbema and Hermans 1977), and (3) the one-parameter-at-a-time stepwise promotion of parameters into classification functions may not promote a set of parameters which are significant when combined but not so if not combined.

As described in Chapter 3, there are other programs available for automatic selection of parameters. Among them, the program INDEP-SELECT offered by Habbema and Gelpke (1981) seemed to have some attractive features. The parameter selection by canonical analysis as described by McKay and Campbell (1982a,b) was also interesting. In fact, the problem of parameter selection itself can constitute an academic field and is still to be investigated further.

Classifiers

This project tested mainly the Bayes classifiers that used Bayes linear classification functions. The canonical classifiers that used canonical variables were also tested. The Fisher's linear classification function can be considered as a special case of canonical classifiers. These classifiers were simple in calculation, and theoretically clear-cut.

Table 6.2 shows the numbers of multiplications, additions, and absolute operations in calculating a set of classification scores for a classifier: a Bayes classifier, a canonical classifier with absolute measure, or a canonical classifier with square measure. I, J, and K are numbers of groups, entered parameters, and used canonical variables. K≤min(I-1,J) can be supposed (see Dixon 1975).

Table 6.2 Numbers of Multiplications, Additions, and Absolute Operations to Calculate Classifiers

	Classifiers		
	Bayes	Canonical with absolute measure	Canonical with square measure
Multiplication	I*J	J*K	(I+J)*K
Addition	I*J	(J-1)*K+I*(K-1)	(J-1)*K+I*(K-1)
Absolute operation		I*K	

After executing these operations, only finding a group which has either the largest score (in Bayes classifiers) or the smallest score (in canonical classifiers) complete classifying an event. Appendix I demonstrates the comparison of three types of classifiers concerning the number of operations required to calculate a classifier. It showed, within a range of the number of canonical variables from 1 to 3, canonical classifiers with absolute measure need less number of operations in most of the combinations of I and J than Bayes classifiers do except for some cases of the combinations. Canonical classifiers with square measure also has less number of operations than Bayes classifiers do with more exceptional cases than canonical classifier with absolute measure.

The hypotheses for these classifiers seemed tight: normal distributions and equal covariances for Bayes classification; equal covariances for canonical classifiers. These hypotheses have been probably violated in the data of this project. The robustness of the classifiers to the deviations of data property from their ideal situations is to be examined theoretically. Nevertheless, the results have shown good abilities of the classifiers. The hypothesis of equal covariances can be dropped by deriving the Bayes classifier with the covariance of each group if the hypothesis can not be considered acceptable. When two covariances are used, the classification functions become quadratic. Quadratic classification functions may be better in performance, but are more complicated in calculation than linear classification functions. As mentioned in Chapter 3, a number of other types of classifiers has been proposed. The discussion of those other classifiers is beyond the scope of this chapter.

The advantages of canonical classifiers over Bayes classifiers may be summarized as follows:

(1) Prior probabilities are not necessary for calculation.

(2) Number of operations tends to be less in canonical classifiers, especially those with absolute measure, than in Bayes classifiers.

(3) If no more than three canonical variables are used, each event can be mapped on a canonical variate coordinate.

(4) The hypothesis of normal distributions is not necessary.

Canonical classifiers performed a little inferior to Bayes classifiers in an example of this project, but the performance may be improved if a procedure for selecting parameters is changed as suggested by McKay and Campbell (1982a,b).

Feasibility of the Real-time Operation by a Microcomputer

The programs of Method A for the testing stage, written in FORTRAN (see Appendix D), were rewritten in PL/M-86 (Version 2.1)[1] with some modifications of programming. After compiling the PL/M-86 program by the ISIS-II[2] , the object codes in the assembly language were obtained. The main modification was the subroutine for the link buffers. The following two PL/M-86 procedures facilitate a pointer of an array:

---

1. The reference for the programming was PL/M-86 Programming Manual for 8080/8085-Based Development Systems (Intel Corp., 1980).

2. Intel Systems Implementation Supervisor in the operating system for the Intellec and Intellec Series II microcomputer development systems. Intel Corp., Santa Clara, California. 1980.

```
SH_U:PROCEDURE(J,N) INTEGER;
    DECLARE (J,N) INTERGER;
    IF J>=N THEN J=J-N;
    RETURN J;
END SH_U;

SH_D:PROCEDURE(J,N) INTEGER;
    DECLARE (J,N) INTERGER;
    IF J<N THEN J=J+N;
    RETURN J;
END SH_D;
```

The pointer moves up and down within the limit of an array by the procedures SH_U and SH_D, respectively. By keeping track of the current pointer of an array and moving up or down the pointer to address a desired element of an array, an iterative routine of shifting operations appearing in the FORTRAN subroutine SHIFT in Appendix D is avoided. By this pointer usage, the number of operations needed to shift in or out a data has become constant regardless of the length of an array. By assigning the lengths of some arrays multiples of two, some multiplications for addressing in the assembly program could be replaced by bit-shift operations. The classification scores of classification functions was calculated by floating-point operations provided by a co-processor INTEL8087. The lists in the manuals for INTEL8086 provided by INTEL Corp. showed the number of clocks needed for executing each assembly operation. By summating the number of clocks for the operations in the program, the required computation time was estimated. In the following, C is the integer number of clocks needed to execute the program, NC is the integer number of groups, and NV is the integer number of parameters in the classifier. As a result, the summated number of clocks was

C= 7015+901*NC+892*NC*NV.

Suppose $C < 5$ msec./0.2 μsec. = 25000 because a 5 MHz clock is to be used. Then,

$$7015+901*NC+892*NC*NV < 25000.$$

Therefore,

$$NV < (17985 - 901*NC)/892*NC.$$

If NC=2, then NV<9.07, that is, NV≤9.

If NC=3, then NV<5.71, that is, NV≤5.

If NC=4, then NV<4.03, that is, NV≤4.

Thus, the system of Method A for the testing stage can be implemented with a classifier which can include 9, 5 or 4 parameters at most when the number of groups is 2, 3 or 4, respectively. The results in Chapter 5 show that the system can perform saticfactorily with these numbers of entered parameters and specified groups. The operation speed of processors is getting faster and faster these days. Array processors can achieve millions of operations in a second. For example, the array processor AP500 (Analogic Corp.) has a peak MFLOPS (i.e. theoretical maximum millions of floating-point operations per second) of 9, which is decades faster than the INTEL 8087. There are also better processors available currently (see Cohler 1983). This trend will surely spread into the microcomputers. Considering the above fact, the maximum numbers of entered parameters and specified group will be getting larger. Also, multichannel processing by a processor will get easier to be realized with less number of processors.

Data Reduction Aspects of the System

The process of the EEG analysis can be viewed as a data reduction process. The raw EEG contains the significant and insignificant information. The analysis process is to discard the insignificant information, and to make the significant information explicit. The 15 EEG data sets in this project had 209,728 data points when digitized. The data were segmented into 25,384 waves, for example. Since each wave contains 4 parameters in Method A, the number of data points became 101,536, which was about 2 times reduction of data points. If only peak waves (electrically negative) are of interest, the reduction rate is 4. If a better low-pass filter for segmentation is used as discussed in Segmentation, Experimental Results in this chapter, the reduction rate would be larger. As seen by the results of reconstruction in Fig.4.13 and Fig 5.11, these data points were sufficient to keep the major information of the EEG in a different way than the original EEG data. The data were further converted into event parameters, and classified. By the classifier A14R.S14, 125 events out of 12,692 events were classified as SSW, thereby reducing the number of events 102 times. Supposing that each event contains 18x4 parameters in Method A, the 125 events contain 9,000 data points, which can regenerate the detected portions. When comparing the number of 9,000 to the number of the original EEG data, the reduction rate of data points became about 23.

Comparison of SSW and the System in
This Project with Others

Table 6.3 compares some of the averaged parameter values of the events in the three training data sets (see Appendix J for all the averaged parameter values) with an example of the corresponding averaged parameter values in the paper by Ktonas et al. (1981). Fig.6.2 illustrates the parameters defined by Ktonas et al.. The values from the paper by Ktonas et al. are not exactly comparable with those from this project because the recording, the filters, the definitions of the parameters, the algorithms to derive the parameters, etc. are different. For instance, in their system, three bandpass filters with the passbands of 1-70 Hz, 0.25-175 Hz, and 1.5-85 Hz were used; digital differentiators were used and had some bandpass effects; the sampling rate was 1 kHz; the recording was from the scalp; the slopes were the maximum first derivative in the up-stroke half-wave and the minimum first derivative in the down-stroke half-wave. Nevertheless, it seems to be of some interest to compare these values in Table 6.3 to acquire a perspective to the data used in this project.

First, compare SSWA with Sharp waves in Table 6.3. The durations of SSWA and Sharp waves appear to be similar. The amplitudes of SSWA and Sharp waves are very different. (The sign of AM10 is ignored.) But, if Amplitude A and Amplitude B are multiplied by a factor of 0.14, they become close to AM9 and Am10 in the values. Also,

$$AM10/AM9 \simeq (\text{Amplitude B})/(\text{Amplitude A}) \simeq 1.5$$

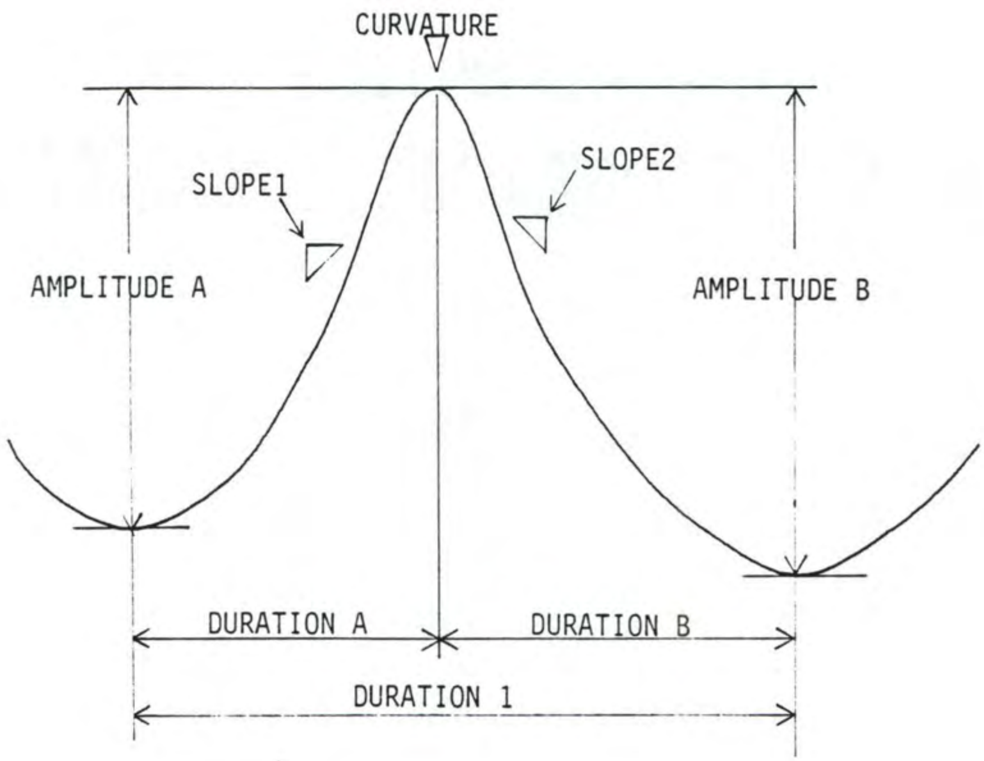


Figure 6.2 Hypothetical EEG Wave and Related Electrographic Parameters. (Partly copied from Ktonas et al. 1981).

Table 6.3 Comparison of Averaged Parameter Values around a Core-wave with Those presented by Ktonas et al. (1981). The values are means with standard deviations in parentheses.

This project					Ktonas et al. (1981)**		
Recording	Depth recording				Recording	Routine scalp recording	
	Referential					Referential & Bipolar	Referential
Type of waves	BCK	SSWA	SSWB	ART	Type of waves	Sharp waves	Spikes
Sample number	2290	21	3	1	Sample number	73	121
D10*(msec)	79.6	121.0	43.3	75.0	Duration 1 (msec)	116.3(25.6)	79.5(27.7)
DU9 (msec)	38.6(23.1)	42.4(18.4)	28.3(14.4)	40.0(0.0)	Duration A (msec)	46.7(16.3)	34.5(22.0)
DU10(msec)	41.0(23.4)	78.6(26.8)	15.0(0.0)	35.0(0.0)	Duration B (msec)	69.6(17.5)	45.0(17.1)
AP9 (μV)	6.7(5.2)	26.7(11.4)	80.4(20.3)	33.3(0.0)	Amplitude A (μV)	198.3(117.6)	140.3(102.5)
AP10(μV)	-6.7(5.0)	-40.5(10.9)	-61.8(16.0)	-35.2(0.0)	Amplitude B (μV)	288.4(152.4)	239.9(138.5)
S110(μV/msec)	0.16(0.11)	0.85(0.39)	5.49(1.64)	3.27(0.0)	Slope 1 (μV/msec)	8.9(5.3)	8.2(4.9)
S210(μV/msec)	-0.15(0.10)	-0.98(0.30)	-5.79(1.85)	-3.45(0.0)	Slope 2 (μV/msec)	8.8(3.5)	10.0(4.4)
C10*(μV/msec)	-0.16	-0.92	-5.64	-3.36	Sharpness (μV/msec)	0.9(0.6)	1.2(0.7)

* D10=DU9+DU10, C10=(S210-S110)/((N-1)/2) where N=5.
** examples taken from Table II in the paper.

where those are of SSWA and Sharp waves. The values of the slopes are vastly different between SSWA and Sharp waves. But this can be explained by the difference in the definition and the calculation of the slopes between the two systems. Interestingly, the sharpness of SSWA turned out to be almost identical to that of Sharp waves in value. Therefore, despite the differences in definition, algorithms, etc. as mentioned above, the SSWA waves are morphologically similar to the Sharp waves except for proportional reduction of the amplitudes. Although the depth recording is expected to be less noisy than the scalp recording, the coefficients of variations (=(standard deviation)/(mean)) were not very different. Secondly, when SSWB is compared with Spikes in Table 6.3, morphological similarity was not found. Interesting is that SSWB waves are much sharper at the peaks than Spikes. It might have been caused by the depth recording. It is noteworthy that morphological difference between SSWA and SSWB is much conspicuous than that between Sharp waves and Spikes.

Frost (1979) presented the results obtained from three patients with focal motor epilepsy. In the epileptic EEG recording, although whether it was referential or bipolar is not clear, the averaged amplitude Af, the Averaged duration Df, and the averaged sharpness Cf were listed on the table of the paper. Each recording lasted 1- to 10-min., had about 100 sharp transient waves detected by his system. A bandpass filter of 0.5-42 Hz was used in preprocessing, and the sampling rate was 250 Hz with 8 bit A/D converter.

There seems to be relations as follows:

$Af \approx AM9+AM10$ and $Cf/2 \approx C10$.

Especially, Cf/2 was derived in the same way C10 was derived. The results presented by Frost showed Af=96±35.9μV and Cf/2= 1.35±0.4μV/msec^2 (for an awake patient), and Af=167±50.0μV, 115.8±44.8μV and Cf/2=2.4±0.6μV/msec^2, 2.0±0.6μV/msec^2 (for two patients of slow wave sleep). Since his system discarded the waves in which the duration is over 100msec., the detected waves is more adequate to be compared with SSWB or Spikes in Table 6.3. Then, the following relations are observed:

AM9+AM10 < Af < (Amplitude A) + (Amplitude B)

C10 > Cf/2 > Sharpness.

Based on the above observations and comparisons, the following points may be speculated.

(1) The SSWA waves possess the morphological property similar to that of "sharp waves" in a scalp recording.

(2) The SSWB waves are much sharper at their peaks than "spikes" in a scalp recording presumably because of the depth recording.

(3) The coefficients of variations of SSWA and SSWB are not much less than those of spikes and sharp waves in a scalp recording. Therefore, the proposed system may be able to attain the same level of success in SSW detection even if the data are obtained from a scalp recording. However, the SSWB waves were much more conspicuous than regular spikes in a scalp recording, and the background waves in the data in this project might have been rather benign.

Table 6.4 compares the materials and methods of this project with those presented in the paper by Oliveira et al. (1983). There are advantages and disadvantages on the both sides as indicated in the table.

It will be necessary for this proposed system to be tested using the data from more than one patient, and to standardize the parameters

Table 6.4 Comparison of Materials and Methods in This Project with Those in the Paper by Oliveira et al. (1983).

	This project		Oliveira et al. (1983)	
Recording	depth, referential		scalp, bipolar	
A/D conversion	10 bits		8 bits	
Number of patients	1		10	A
Length of data	17.5 min.	A	50×10 sec.	
Length of training data	72, 144, or 216 sec.	A	50×5 sec.	
Preprocessing	digital lowpass filter		screening by a curvature threshold	A
Segmentation	lowpass filter. digital extrema detection.	a a	analog differentiators. hybrid zero-crossing detection of data and derivatives.	
Parameterization	4 parameters per wave in Method A. 1 parameter per wave in Method T. multi-wave eventA. no standardization.		8 parameters. standardization by standard deviations.	a A
Parameter selection	discriminant analysis by BDP7M. significance level was applied to select the number.	A A	4 parameters were selected on the basis of ranking by Mahalanobis distance and empirical experience.	
Classification	linear classificaton functions (Bayes or canonical)	A	4 independent thresholds set by using classification results in training data (i.e. minimizing D=SN+SP) and empirical experience.	
Evaluation	1 EEGer. PRE measures.	 A	8 EEGers. SN(sensitivity) and SP(specificity).	a
Artifact rejection	specifying goup ART	a	additional routines specially designed for an EMG complex and an eye movement.	
Real-time processing	feasible		4 channel on-line processing	A
Microcomputer application	feasible		a hybrid microcomputer system with MC6800	A

A: advantageous. a: advantageous possibly.

in some method to seek an adjust-free system from intra- and inter-individual variances. The data screening by a curvature threshold is helpful to reduce the number of events to be classified. Eight morphological (or descriptive) parameters in their system will not be necessary, but a parameter for curvature, which can be included as (S210-S110)/2 in the proposed system, will help improve the performance. It may sound better and more desirable to evaluate the results on the basis of the EEG scores of more than one electroencephalographer. However, it should be emphasized that a detection system should seek either (1) to mimic an electroencephalographer's scoring, or (2) to establish a standard criteria for SSW, which has not been done quantitatively and systematically. It is impossible to fulfill both the points (1) and (2) at once because of a great discrepancy in detecting individual SSWs among electroencephalographers as described in Chapter 3. The benefit of employing several electroencephalographers should be to possibly find some genuine principles consistent and objective among the electroencephalographers' scoring, so that the standard criteria for SSW may be established on the basis of these principles. Once the standard criteria are established this way, the goal of a detection system is to implement a system which classifies events according to the standard criteria. If the standard criteria has not been established, the goal of a detection system would be to be able to imitate the SSW detection of an electroencephalographer as far as he/she is, in some fashion, consistent in detecting SSW. It is conceivable that the system will contribute to checking the consistency of electroencephalographers' scoring and eventually establishing the standard criteria for SSW.

It is encouraging that the proposed system could perform well for the testing data of 17.5 min. long where the training data is only 1/15, 2/15 or 3/15 as long as the testing data. The digital filters used in the proposed system was very simple, fast and linear phase. Analog filters are fast, but usually not linear phase. The multi-wave parameterization was a successful idea. In parameter selection and classification, the proposed system had obvious advantages in automating the procedures and avoiding subjective decisions. The PRE measures applied in this project, i.e. P1, P2 and P3, seem to have more theoretical background and broader applicability than the corresponding measures presented by Oliveira et al. (1983). It is a possible advantage for the proposed system to be able to classify any type of artifacts by labeling the samples in the training data as artifact types. The proposed system has been shown to be realizable as a real-time system and applicable to a microcomputer system with a help from a host computer system during a training period.

Prospective Improvements and Applications of the Proposed System

This section discusses prospects of deriving classifiers sequentially, multichannel analysis, standardization of parameters and SSW criteria. Then, a model system for clinical application of the proposed system is demonstrated as well as possibilities of the applications to other analyses.

Sequential Derivation of Classifiers

If the algorithm for deriving a classifier can accept a sequential input of data, there are some advantages. In the training stage, it saves memory space because only current data is necessary for the calculation. In the testing stage, it can constitute an unsupervised learning system which corrects the classifier in accordance with a gradual change of data property by utilizing the classification results obtained by the classifier itself, or some statistical property of the results. If not used as an unsupervised learning system, it enables a supervisor to alter the characteristic of the classifier gradually and easily by adding the classifier another data for recalculating the classifier. This ability of a classifier, as well as the standardization of parameters may contribute to making the system free from adjusting to intra- and inter-individual variances. Some researchers already applied a learning classifier and obtained good result as described in Adjustments of Classifiers, Chapter 3. Perceptron (Rosenblatt 1962) is a classic example, and LSM algorithm (Kohonen 1979) and ALSM algorithm (Oja and Kuusela 1983) are recent examples among many algorithms of this kind. LSM and ALSM algorithms reportedly had successful results in speech recognition.

Multichannel Analysis System

As explained in Chapter 3, the EEG recording is a multichannel recording, and interchannel relationship must be considered in EEG analysis. One possible and straightforward way of making the proposed system multichannel processing may be the following. From a view-point of pattern recognition, making the recording multichannel means adding another dimension to the pattern to be dealt with. In a single channel analysis, the pattern is spread time-wise. In a multichannel analysis, the pattern is spread both time-wise and channel-wise. When it can be made sure that a single channel analysis detects all the candidates for SSW, the classification of the multichannel analysis is necessary only if a candidate SSW is detected by a single channel analysis. The methods for segmentation and parameterization will be necessary to be modified, and will cause an increased number of event parameters. It must be noted that the increased number of event parameters does not necessarily cause the increase of processing time to make parameterized data if pointers for arrays are utilized in the program as explained in Feasibility of the Real-time Operation by a Microcomputer, Chapter 6.

Standardization of Parameters and SSW Criteria

A parameter may be standardized by the standard deviation (Oliveira et al. 1983) or the moving average (Frost 1979), for example. The standardization of parameters helps (1) incorporate background activities around SSW into parameters as discussed in Evaluation of Classification Results, Chapter 6, and (2) make the system adjust-free from intra- or inter-individual variances.

The parameters in the system could be easily standardized by increasing the lengths of buffers for example, so that standard deviations may be calculated. However, it will increase the calculating time. If a recursive moving average digital filter is used, it may save the buffer space and the calculation time. It seems necessary either to exclude the SSW and artifact portions from calculating the standard deviations or to have a long period of the data for calculating the standard deviations. The system by Frost (1979) implemented the exclusion of the spike portion from calculating the value of moving average.

In the section of Classifiers, Chapter 6, the hypotheses were viewed as obstacles, but if the parameterized data conforming to the hypotheses is considered the ideal, the data can be regarded as "standard data". The standard data may be represented by the covariance and the group means. It is hardly possible to create the ideal data from the real EEG data, but it is possible to do it artificially. That is, the training data sets may be edited, or some idealized waveforms may be created and included, for example. It leads to a possible solution to how to describe the criteria of transient waveforms such as SSW or artifacts in a systematic, quantitative, and objective way. The standard SSW criteria may be represented by the form of a training data set, a parameterized data set, or a set of statistical parameters of the hypotheses such as means and covariances.

A Model System for EEG Analysis

Fig.6.3 presents a possible system configuration for EEG analysis. It could be a general EEG analysis system, but the following paragraphs of the section focuss on the system applied to SSW detection by Method A.

In the training stage, the host computer inputs the training data through the Data Storage Device 1 either off-line or on-line. The training data contain the wave parameters. The Data Storage Device 1 can be a cassette tape drive, a diskette drive, etc. The input parameterized data are reconstructed and displayed on the Display Device along with the ticks of extrema marker. If the reconstructed

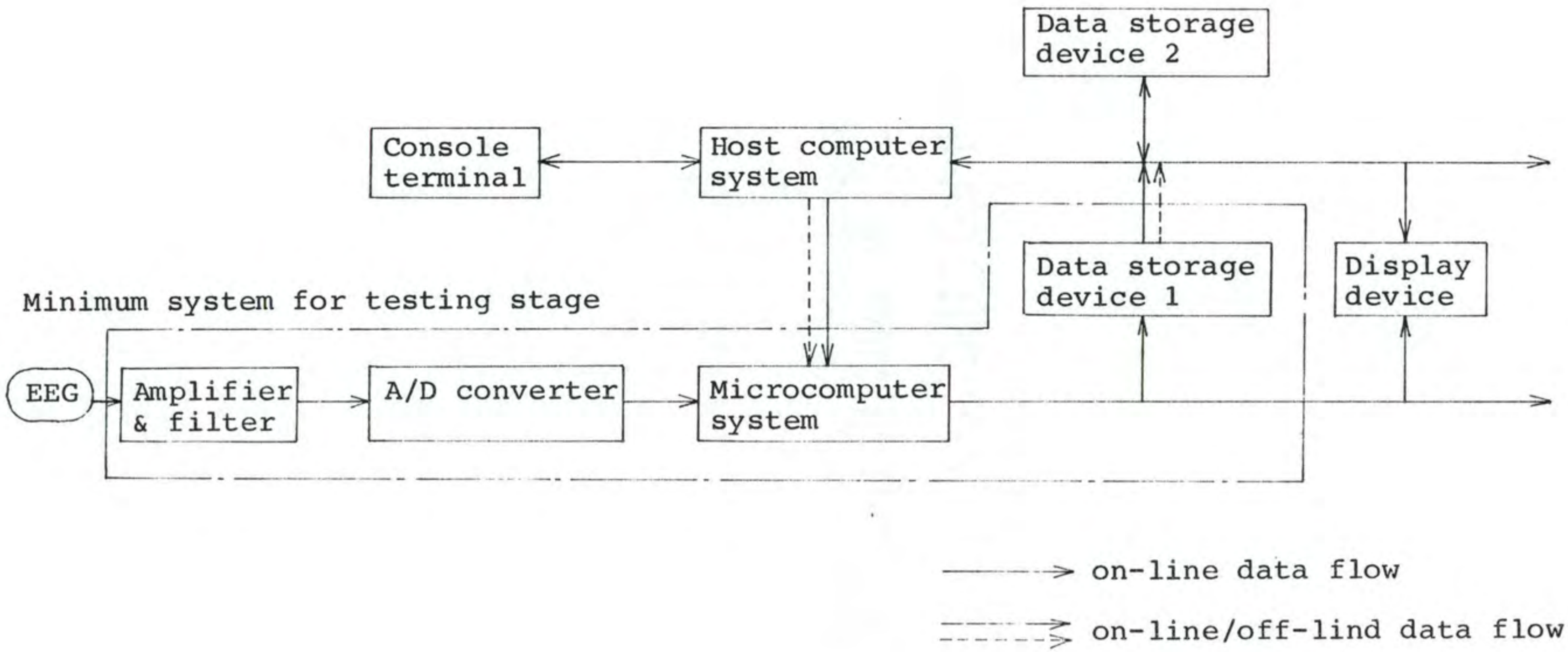


Figure 6.3 A Configuration of a Model System for EEG Analysis.

data display is not satisfactory, the basic data may be displayed instead. A supervisor labels each wave. In reality, only SSW waves and, if necessary, artifact waves have to be labeled because the rest are all considered as background waves. If possible, doubious SSW and successive SSW are recommended to be labeled. There will be various ways to input the labels into the host computer. For example, by numbering the wave sequentially and displaying the wave number on the site of extrema marker corresponding to the wave, the supervisor on the terminal type the wave number in with its label. Events are organized based on the wave parameter data that are already labeled. The event (parameterized) data adopt the labels of the wave corresponding to the core-wave. The event data are then analyzed by a discriminant analysis program such as the BMDP7M program. If there is not enough storage capacity in the Host Computer System, the Storage Device 2 can be temporarily used. The Data Storage Device 2 can be a digital magnetic tape drive, a disk drive, etc. The program selects a subset of event parameters, and provides a classifier. If more than one type of waveforms are specified and the number of types is not known, a cluster analysis may be included before labeling. The microcomputer system stores a program for SSW detection, and then the input parameters necessary to initialize the program including the input parameters for the classifier are transferred from the Host Computer System to the Microcomputer System either on-line or off-line.

Now the system is ready for the testing stage. The Microcomputer System inputs digitized EEG data and processes the data by the program that includes the procedures of preprocessing, segmentation, parameterization, and classification. The result is displayed by the Display Device, and stored by the Data Storage Device 1. Several output forms may be conceivable. For example, the result output may consist of the parameters and time of each event classified as SSW. The wave parameters with the time, wave number and the label obtained by a classifier may be stored by the Data Storage Device 2 and the reconstructed data may be displayed with a mark for the label of the wave after classification. If canonical variable coefficients are calculated, each data point of the events can be displayed on a canonical bivariate plane or in a canonical trivariate space using two or three canonical variables, respectively. The data stored in Data Storage Device 2 may be used for a further analysis such as making diagnosis. The portion of the system in Fig.6.3 referred as Minimum System for Testing Stage can function independently once the program is initialized with the input parameters. It will provide patients with a compact equipment for epileptic EEG monitoring.

Possible Applications to Other Analyses

The proposed system may be applied to other data analyses than the EEG analysis of SSW with proper modifications: seismic signal analysis for modern seismic exploration systems, submarine detection (see Cohler 1983); ECG analysis, especially abnormal ECG classification (e.g. arrhythmia); EP (evoked potential) analysis; speech recognition. Concerning the digital signal processing of EP, Aunon (1983) stated that ensemble averaging remains one of the most used and, at the same time, abused tools in EP research. Then, he presented a system for classifying single event-related potentials using linear and quadratic classification techniques. Feldman (1983) suggested in his recent review an advantage of the arrhythmia detection system that interacts with a supervisor. The system proposed in this paper can be applied to these kinds of systems with some modifications. A difficulty may occur in these applications if (1) a core-wave can not be adequately defined or (2) the order of the waves in an event portion is not regular among events in the same group, for instance. To adjust to the situations, the algorithms for segmentation and parameterization may be modified appropriately.

CHAPTER 7

CONCLUSION

An automated EEG pattern recognition system for epileptic waves was developed in this project.

It was recognized at the beginning of this project that the automation by computers was demanded in clinical and research environments and yet incomplete in spite of many attempts. The problem appeared to be attributed to not only a lack of proper algorithms for computers but also the nature of EEG, its traditional recording, and its evaluation schemes. Chapter 2 served to reveal the nature and significance of EEG and SSW, and the methods of traditional EEG recording. Chapter 3 reviewed the previous researches relating to automated EEG analysis. The review was done from a view point of pattern recognition because the SSW detection was conceived as a pattern recognition. These two chapters benefited in giving broad perspective on this research and developing the analysis procedures of this project.

The analysis procedures of preprocessing, segmentation, parameterization, and classification were established as essential procedures for SSW detection. In the preprocessing, the digitized EEG data was filtered by a simple, linear-phased, low-pass, digital filter. In the segmentation, the preprocessed (basic) data was further filtered by another simple, linear-phased, low-pass, digital filter, and segmented into half-wave segments at each turning point. Because these filters were linear-phased, the delays caused by them could be cancelled by merely shifting the data points. In the parameterization, the data were processed in the following way. (1) Two consecutive half-waves of the basic data constituted a wave. A wave was either a peak wave or a trough wave depending on the polarity of the extremum of the wave. (2) In Method A, each wave brought forth four parameters, i.e., an amplitude and two slopes at the extremum of the wave, and a duration between the current and the next extremum. In Method T, each wave brought forth one parameter per template: one or two templates were used, and the three measures tested for template matching were mean absolute error, mean square error, and correlation coefficient. (3) Furthermore, an event was defined as consisting of a set of parameters for several (18 in the experiments) waves. In the classification, after labeling the events in training data sets using the EEG scores of an electroencephalographer, the BMDP7M program (Dixon 1975) (1) selected a subset of parameters in an event statistically, (2) calculated the coefficients of linear classification functions, and (3) applied the classification functions to classifying the events in testing data sets. The labeling of the events may be helped by making use of a clustering analysis. In selecting the subset of parameters, an overall significance label was used. Either Bayes or canonical classification functions were used. Three PRE measures were introduced for evaluating classification results, and reasonably reflected the different aspects of the classification results.

The experiments were designed to verify the feasibility of the proposed analysis procedures in SSW detection and to evaluate their performance under various experimental conditions in the classification procedure. Also, the corrected classification was introduced, in which a tolerance for the nearmiss SSW detection was allowed. The experiments were done using Method A and Method T (including Method TA, TS, and TC). The experimental conditions changed were the numbers of parameters entered into a classifier, training data sets, and specified groups; the use of retraction of the adjacent events to SSW; the assignment of prior probabilities for Bayes classifiers; and the type of classifiers.

The results showed the following as for the changes of experimental conditions.

(1) The stepwise parameter selection by using F-statistics, although criticized, was useful, and the use of the overall significance level was shown to be reasonable.

(2) The training data set of 72 second long with 9 SSW samples provided good classifiers, and the training data set of longer period with more SSW samples did not attest providing better classifiers.

(3) Assigning two types of SSW events was successful when the nearmiss SSW detection was tolerated in Method A.

(4) The retraction of the adjacent events to SSW in the training data sets improved the performance of classification when Method A was used and the nearmiss SSW detection was tolerated. In the other cases of the experiments, it did not seem to be much helpful.

(5) It was indicated that the assignment of prior probabilities for the Bayes classifiers was not crucially influential to the classification results.

(6) The canonical classifiers with either absolute measure or square measure performed nearly as good as the Bayes classifiers when more than one canonical variable were used.

Method A was more advantageous in calculation than Method T. Also, from the viewpoint of data reduction in the system, the reconstruction capability in Method A was mentioned as a significant advantage. The classifier A14R.S14 is a good example. At the training stage, it classified all the events correctly in the training data set of 72 sec. long with 9 SSW and 1 artifact samples. At the testing stage, the data was 17.5 min. long with 80 SSW and 3 artifact samples. It classified the data, detecting 76 SSWs correctly and misclassifying 40 background events as SSW, giving the P1, P2, and P3 measures the values of 95%, 65%, and 77%, respectively. Interestingly, it was found, using some results in Method A, that when the misclassified background events were averaged, the morphology was very similar to that of SSW.

In Method T, Method TC was unexpectedly poor in performance. Method TA was simpler in calculation than Method TS, and yet provided nearly the same classification success as Method TS. Method T can be considered as advanced template matching because of using multi-values to classify an event. The classifier TA23R.S24, as a good example, detected 73 SSW and misclassified 50 background events in the testing data, giving the P1, P2, and P3 measures the values of 91%, 59%, and 72%, respectively. It was notable that, despite the poor samples of artifacts, Method T was very good in rejecting artifacts whereas Method A failed to be so.

After the programs of the analysis procedures of Method A in the testing stage were modified and converted to a program in an assembly language, the execution time of the program was estimated. It showed that the program, stored in a microcomputer system, can run in real-time with a sufficient number of parameters included in a classifier for classification.

The system developed in this project was shown to be advantageous in many points to most of the previous systems, but will be improved by integrating the points suggested in Chapter 6. Suggested were filter improvement in segmentation, introduction of other types of parameters and standardization of them, use of a better program for parameter selection, investigation of canonical classifiers which seems to be advantageous in many aspects. Some other ideas to improve the detection system such as sequential derivation of classifiers and standard SSW criteria were discussed.

By comparing the data property in this project with others, it was speculated that even though the data from depth recording were used in this project, the system may be applied to the data for scalp recording without losing the quality of performance very much. A model system was presented as an example of the clinical application. The applications to other analyses were also mentioned.

The objective of this project was, as stated in Chapter 1, to develop an automated detection system of epileptic waves in EEG that is real-time operating, microcomputer-applicable, able to reject artifacts, self-adjusting to intra- and inter-individual variances, and contributing to systematic, quantitative and objective description of epileptic waves. The system proved the feasibility of real-time processing and microcomputer-applicability. It seems to contribute to a systematic, quantitative and objective description of SSW. As a prospect, standard criteria of SSW was discussed and standardization of parameters may be contributing to it. As for the ability to reject artifacts, Method T showed a good potential, but Method A did not. However, further investigation is necessary for the artifact rejection in Method A because the number of artifact samples in the data were very poor. Concerning the ability for the system to be free from adjusting to intra-individual variance, the experiments showed that the classifiers obtained with the training data that was one fifteenth of the testing data in length could maintain the performance well in the testing data. However, further investigations are recommended to draw a conclusion, using longer data. As for the inter-individual variance, the results could not be conclusive because the data were not taken from more than one subject. If a training period is allowed for each subject, however, the problem for inter-individual variance dissolves practically. Besides, standardization of parameters and/or a self-learning ability of the system were suggested as prospects for better performance and self-adjustability of intra- and inter-individual variances.

Although this system was developed for SSW detection, it can be used for other types of transient wave analyses with some modification as mentioned in Chapter 6.

APPENDICES

Appendix A

Stepwise Selection of Parameters

The following paragraphs explains the univariate F-ratio criterion for stepwise selection of parameters in multivariate problems.

The Wilk's Lamda Criterion

It is defined as follows (see Kshirsagar 1972, pp. 290-292):

$$\Lambda(n,p,s)= \frac{|A|}{|A+B|}$$

where

$$A \sim W_p(A|n-s|\Sigma),$$

$$B= \sum_{m=1}^{s} z_m z_m',$$

$$z_m \sim N_p(z_m|0|\Sigma) \qquad \text{for } m= 1, 2, \ldots, s.$$

Note: $W_p(D|n|\Sigma)$ indicates that D has the p-variate Wishart distribution with n d.f. (degrees of freedom) and the covariance matrix Σ. $N_p(x|\mu|\Sigma)$ indicates that **x** has p-variate nonsingular normal distribution with the mean vector μ and the (positive definite symmetric) covariance matrix Σ. $\mathbf{z}_m$ is named a contrast vector. This statistic is used to test any hypothesis which is equivalent to

$$H_0\text{: } E(\mathbf{z}_m)=\mathbf{0} \qquad \text{for } m=1, 2, \ldots, s$$

where $E(\mathbf{z}_m)$ indicates the mean of the variable $\mathbf{z}_m$.

Comparing to the criterion $|B|/|A|$, $|A|/|A+B|$ is more suitable on account of its tractability, and its relation to the likelihood ratio criterion.

One-way MANOVA

Let x_{ijk} for $i=1,2,\ldots,g$; $j=1,2,\ldots,n_i$; $k=1,2,\ldots,p$ be the value of the k-th parameter of the j-th event in the group i. Suppose each group has a p-variate nonsingular normal distribution with the same covariance matrix Σ, but different group mean vectors μ_i for $i=1,2,\ldots,g$. The sample group mean vectors for the group i is

$$u_i = \{x_{i.k} \text{ for } k=1,2,\ldots,p;\ x_{i.k} = \frac{1}{n_i} \sum_{j=1}^{n_i} x_{ijk}\} .$$

The corrected sum of squares and sum of products of the sample of the group α is

$$S_\alpha = \{s_{ij\alpha} \text{ for } i,j = 1,2,\ldots,p;\ s_{ij\alpha} = \sum_{r=1}^{n_\alpha} \sum_{k=1}^{n_\alpha} (\delta(r,k) - 1/n_\alpha) x_{ir\alpha} x_{jk\alpha}\}$$

where $\delta(r,k) = \begin{cases} 1 & \text{for } r=k \\ 0 & \text{for } r\neq k \end{cases}$.

Note: $S_\alpha/(n_\alpha-1)$ is an unbiased estimate of the covariance Σ.

It is shown (see Kshirsagar 1972, pp. 60-61) that

$$u_i \sim N_p(u_i | \mu_i | n_i^{-\frac{1}{2}} \Sigma)$$

$$S_i \sim W_p(S_i | n_i - 1 | \Sigma)$$

and u_i and S_i are independently distributed.

Define the pooled sample covariance as

$$A = S_1 + S_2 + \ldots + S_g$$

then $A \sim W_p(A | n-g | \Sigma)$

where $n-g = \sum_{i=1}^{g} (n_i - 1)$ (see Kshirsagar 1972, pp. 73-77).

Suppose a contrast vector

$$\nu_1 = h_{11}\mu_1 + h_{12}\mu_2 + \ldots + h_{1g}\mu_g$$

where $h_{11} + h_{12} + \ldots + h_{1g} = 0$.

The estimate of the contrast vector is

$$v_1 = h_{11}u_1 + h_{12}u_2 + \ldots + h_{1g}u_g \quad .$$

Define

$$z_1 = g_{11}\sqrt{n_1}u_1 + g_{12}\sqrt{n_2}u_2 + \ldots + g_{1g}\sqrt{n_g}u_g$$

where $g_{1i} = \dfrac{h_{1i}}{\sqrt{n_i}}\left(\sum_{j=1}^{g} h_{1j}^2/n_j\right)^{-\frac{1}{2}}$ for j=1,2,...,g.

Then, $\sum_{i=1}^{g} g_{1i}^2 = 1$ and $\sum_{i=1}^{g} g_{1i}(n_i/N)^{\frac{1}{2}} = 0$

where $N = n_1 + n_2 + \ldots + n_g$.

It can be shown (see Kshirsagar 1972, p.369) that

$$z_1 z_1' = \left(\sum_{i=1}^{g} h_{1i}u_i\right)\left(\sum_{i=1}^{g} h_{1i}u_i\right)'\left(\sum_{i=1}^{g} h_{1i}^2/n_i\right)^{-1} \quad .$$

In general, when s contrasts exist,

$$z_m z_m' = (Uh_m)(h_m' N^{-1} h_m)^{-1}(Uh_m)'$$

$$= Uh_m(h_m' N^{-1} h_m)^{-1} h_m' U' \qquad \text{for } m=1,2,\ldots,s$$

where $h_m = [h_{m1}, h_{m2}, \ldots, h_{mg}]'$ g by 1, and

$U = \{u_1 | u_2 | \ldots | u_g\}$ p by g.

Therefore

$$B = \sum_{m=1}^{s} z_m z_m' = UH(H'N^{-1}H)^{-1} H'U'$$

where $H = \{h_1 | h_2 | \ldots | h_s\}$ g by s.

When the test is whether the s contrast vectors ($s \leq g-1$) $z_1, z_2, \ldots, z_s$ are significant for the hypothesis H_0: $E(z_m)=0$ for $m=1,2,\ldots,s$,

$$\frac{|A|}{|A+B|}$$

has the Wilk's $\Lambda(n-(g-1)+s), p, s)$ distribution.

"Pivot" operation is defined as follows: When

$$A= \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

where A_{11} is a q by q matrix. A "pivot" operation on parameters $1,2,\ldots,q$ in A_{11} transforms A to

$$A_{.1} = \begin{bmatrix} A_{11}^{-1} & A_{12}A_{11}^{-1} \\ A_{21}A_{11}^{-1} & A_{22}-A_{21}A_{11}^{-1}A_{12} \end{bmatrix} .$$

The lower right submatrix is the matrix for partial variances and covariances.

Define

$$A_{22.1}= A_{22}- A_{21}A_{11}^{-1} A_{12} \quad . \qquad (A.1)$$

Then $|A|=|A_{.1}|= |A_{11}||A_{22.1}|$ if $|A_{11}| \neq 0$.

Hence $|A|= a_{11}|A_{22.1}|$ when $A_{11}= \{a_{11}\}$.

Now replace $A_{22.1}$ for A.

Let $A_{11}=\{a_{22.1}\}$ where $a_{22.1}$ is the first diagonal element in $A_{22.1}$.

Pivot A with a parameter in A_{11}, and name the matrix $A_{.1,2}$ instead of $A_{.1}$.

Apply the formula (A.1), and name the matrix $A_{22.1,2}$ instead of $A_{22.1}$.

Then $|A_{22.1}|=|A_{.1,2}|=a_{22.1}|A_{22.1,2}|$.

Hence $|A|=a_{11}a_{22.1}|A_{22.1,2}|$.

Likewise $A_{.1,2,3}$ and $A_{22.1,2,3}$ are obtained.

Therefore $A=a_{11}a_{22.1}a_{33.1,2}|A_{22.1,2,3}|$ is shown.

By repeating the similar procedure, it is shown that $A=a_{11}a_{22.1}a_{33.1,2}\cdots a_{pp.1,2,\ldots,p-1}$. Thus, the Wilk's Lamda statistic may be expanded as a product of partial variances (see Hawkins 1976):

$$|A|/|V|=\frac{a_{11}a_{22.1}a_{33.1,2}\cdots a_{pp.1,2,\ldots,p-1}}{v_{11}v_{22.1}v_{33.1,2}\cdots v_{pp.1,2,\ldots,p-1}}=\prod_{i=1}^{p}U_i$$

where $V=A+B$ and $U_i=a_{ii.1,2,\ldots,i-1}/v_{ii.1,2,\ldots,i-1}$.

Suppose that A_j, V_j and B_j are the submatrices consisting of the first j rows and columns of A, V and B. Then

$$|A_j|/|V_j|=(|A_{j-1}|/|V_{j-1}|)\ U_j\ .$$

Therefore, (1) U_j is the statistic for additional information in the j-th parameter, and (2) the optimal subset of any given size j is that for which the ratio $|A_j|/|V_j|$ is maximized. The test ratio for entering the j-th parameter is U_j, and that for removing the j-th parameter entered is $1/U_j$. It is shown (Ellenberg 1973: see Hawkins 1976) that

$$F_i(s,N-g-i+1)=\frac{1-U_i}{U_i}\bullet\frac{N-g-i+1}{s}$$

$$=\frac{v_{ii.1,2,\ldots,i-1}-a_{ii.1,2,\ldots,i-1}}{a_{ii.1,2,\ldots,i-1}}\bullet\frac{N-g-i+1}{s}$$

has a F distribution with s and N-q+1-i degrees of freedom.

F_i is an univariate F-ratio for the i-th parameter. Suppose that the first q parameters, which are placed in the first q rows and columns of the matrix, have been already selected. Use the univariate F-ratio for testing whether the k-th parameter is significant as follows:

(1) select the k-th parameter if the following F-ratio is significant;

$$F_{1k}(s,\ N\text{-}g\text{-}q) = \frac{1-r_1}{r_1} \bullet \frac{N-g-q}{s}$$

where $r_1 = \dfrac{s_{kk.1,2,\ldots,k-1,k+1,\ldots,q}}{v_{kk.1,2,\ldots,k-1,k+1,\ldots,q}}$.

(2) remove the k-th parameter if the following F-ratio is significant.

$$F_{2k}(s,\ N\text{-}g\text{-}q+1) = \frac{1-r_2}{r_1} \bullet \frac{N-g-q+1}{s}$$

where $r_2 = \dfrac{s_{kk.1,2,\ldots,q}}{v_{kk.1,2,\ldots,q}}$.

In the stepwise algorithm, the parameter selected is the most significant of those available and the parameter removed is the least significant of those available. This procedure necessitates the consideration of the simultaneous nature of the testing situation when the significance levels are to be checked. Hawkins (1976) suggested to use the following significance levels when α_e and α_r are predetermined levels for entering and removing a parameter respectively: (1) enter the most significant parameter only if it is significant at the level of $\alpha_e/(p-q)$ when there are q parameters already entered, (2) remove a parameter entered if it is not significant at the level of $\alpha_r/(p-q+1)$.

Appendix B

Classification Functions

Three approaches of linear discriminant analysis are discussed in the following paragraphs. The descriptions are mainly based on the books of Lachenbruch (1975) and Mardia et al. (1979). The problem is to allocate an observation **x** from an unknown origin to one of the groups, which may be formulated as below:

Consider g groups $\Pi_1, \ldots, \Pi_g$, $g \geq 2$.

A classifier is the rule to allocate x to Π_j if $x \in R_j$, $j=1,\ldots,g$

where $\mathbf{x}=\{x_i: x_i\text{'s are parameters of an event}\}$

$$R_i \bigcap R_j = \phi \quad \text{if} \quad i \neq j$$

$$\bigcup R_i = R^p$$

(see Mardia et al. 1979, p. 300).

Bayes Approach

The criterion of goodness of classification in Bayes approach is to minimize the possibilities of misclassification of Π_i into Π_j. Assume the costs of misclassification of an event for Π_i into Π_j are equal, the distributions of groups are multivariate normal, and the covariances of groups are same and estimated by the sample covariance.

The classifier allocates **x** to Π_i if

$$\ln p_i + (x-\tfrac{1}{2}u_i)'S^{-1}u_i = \max_j\{\ln p_j + (x-\tfrac{1}{2}u_j)'S^{-1}u_j\}$$

where p_j: prior probability of group Π_j, u_j: average of **x** in group Π_j, and **S**: sample covariance.

It can be written as

$$a_i'x+ b_i= \max_j\{a_j'x+ b_j\} \tag{B.1}$$

where $a_j=u_j'S^{-1}$ and $b_j= \ln p_j - \frac{1}{2}u_j'S^{-1}u_j$.

Define the functions

$$g_i(x)= \beta_i'x+ \alpha_i \quad \text{for } i=1,2,\ldots,g.$$

They are called the Bayes linear classification functions. Therefore, the classification rule is assign x to a group i if

$$g_i(x)= \max_j\ g_j(x).$$

Fisher's Approach

Fisher suggested to find the linear function a'x which maximize the ratio of the between-groups sample covariance S_b to the within-groups sample covariance S_w. The covariances are assumed to be same. The ratio is given by $a'S_ba/a'S_wa$. The vector a in Fisher's linear discriminant function $g(x)=a'x$ is the eigenvector of $S_w^{-1}S_b$ corresponding to the largest eigenvalue. An event x is allocated to the group whose mean score $a'u_i$ is closest to $a'x$, that is, the classifier allocates x to Π_i if

$$|a'(x-u_i)|= \min_j|a'(x-u_j)| \tag{B.2}$$

or

$$|g(x)-g(u_i)|= \min_j|g(x)-g(u_j)|.$$

Canonical Approach

Generally the number of non-zero eigenvalues of $S_w S_b$ is no more than $k=\min(g-1,q)$ where q is the number of parameters used in classification. The corresponding eigenvectors are a_l, $l=1,\ldots,k$. Instead of using the eigenvector corresponding to the largest eigenvalue as in Fisher's approach, the other eigenvectors are also used for classification in Canonical approach.

The classifier allocates x to Π_i if

$$\sum_{l=1}^{k} \{a_l'(x-u_i)\}^2 = \min_j \sum_{l=1}^{k} \{a_l'(x-u_j)\}^2 \tag{B.3}$$

or

$$\sum_{l=1}^{k} |a_l'(x-u_i)| = \min_j \sum_{l=1}^{k} |a_l'(x-u_j)|. \tag{B.4}$$

This approach is a generalization of Fisher's approach. If the latter formula is used for classification, the classifier includes only linear multiplications and absolute value operations. Define the functions

$$g_i(x) = \sum_{l=1}^{k} |a_l'(x-u_i)|.$$

Then, the equation (B.4) is written as

$$g_i(x) = \min_j g_j(x).$$

Appendix C

BMDP7M

The stepwise linear discriminant analysis program in Biomedical Computer Programs, called BMDP7M (Dixon 1975) was chosen to deal with both the selection of the parameters and the derivation of the classifier. The input of the program is the parameterized data of a training data set. Each event in the data is labeled as one of the groups by a supervisor. The primary objective is to get the output of classification functions, which serves as a classifier. The program output also includes some statistical values, canonical variables, etc.

The following explains the procedure of the program. The description is attributed to the reference manual of BMDP7M (Dixon 1975). The following notations will be used:

p = number of parameters available,

q = number of parameters entered at a given step,

t = total number of groups,

g = number of groups used to define the classification functions,

n = total number of events in the g groups,

n_i = number of events in group i,

x_{ijk} = value of the k-th parameter in the j-th event of group i,

s = number of contrasts,

h_{ki} = coefficient for the group i in the k-th contrast,

p_i = prior probability for group i.

Assume for simplicity the first g of the t groups are used to define the classification functions.

(1) Read the data x_{ijk} $i=1,\dots,t;\ j=1,\dots,n_i;\ k=1,\dots,p$

(2) Compute

the group means $$u_{ik}=\sum_{j=1}^{n_i} x_{ijk}/n_i \qquad i=1,\dots,t;\ k=1,\dots,p$$

the sample covariance $$w_{kl}=\sum_{i=1}^{g}\ \sum_{j=1}^{n_i} (x_{ijk}-u_{ik})(x_{ijl}-u_{il})$$

$$k=1,\dots,p;\ l=1,\dots,p$$

and the matrix $$M=W+U'H'(HN^{-1}H')^{-1}HU$$

where $W=\{w_{rs}\ \ i,j=1,\dots,p\}$, $U=\{u_{ij}\ \ i=1,\dots,g,\ j=1,\dots,p\}$,

$N=\{$the diagonal matrix $[n_1,\dots,n_g]\}$, and

$$H=\{h_{ki}:\ h_{ki}=\begin{cases} 1 & i \le k \\ -i & i = k+1 \\ 0 & \text{otherwise} \end{cases}\}.$$

(3) Assuming for simplicity that the first q parameters, which are selected, are already pivoted on the corresponding diagonal elements, write

$$W=\begin{bmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{bmatrix}$$

$$M=\begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}$$

where W_{11} and M_{11} are q by q, and let

$$A=\begin{bmatrix} W_{11}^{-1} & W_{12}W_{11}^{-1} \\ W_{21}W_{11}^{-1} & W_{22}-W_{21}W_{11}^{-1}W_{12} \end{bmatrix}$$

$$B=\begin{bmatrix} M_{11}^{-1} & M_{12}M_{11}^{-1} \\ M_{21}M_{11}^{-1} & M_{22}-M_{21}M_{11}^{-1}M_{12} \end{bmatrix}$$

Actually the diagonal elements of B are only needed, and are computed from the matrix

$$\begin{bmatrix} A & T \\ T' & C \end{bmatrix}$$

which is defined at step zero to be

$$\begin{bmatrix} W & U \\ U' & 0 \end{bmatrix}$$

and is updated at each step by pivoting or reverse pivoting the diagonal elements of A. The diagonal elements of B are computed using the fact that

$$B=Q'Q+A$$

where $Q=(H(N^{-1}-C)H')^{-\frac{1}{2}}H'T'$.

(4) Compute F value for each parameter.

If the r-th parameter is entered,

$$F_r=\frac{a_{rr}-b_{rr}}{b_{rr}}\cdot\frac{n-g-q+1}{s}$$

with s and (n-g-q+1) degrees of freedom.

If the r-th parameter is not entered,

$$F_r=\frac{b_{rr}-a_{rr}}{a_{rr}}\cdot\frac{n-g-q}{s}$$

with s and (n-g-q) degrees of freedom.

(5) A parameter is removed or added according to the following rules:

Rule 1. If one or more entered parameters are available and have F values less than the F-to-remove threshold, which is set previously in the program, the one with the smallest F value is removed.

Rule 2. If one or more non-entered parameters are available and have F values above the F-to-enter threshold, which is set previously in the program, the one with the highest F value is entered.

(6) If one of the above rules is applied, the program repeats the procedures (2)-(5) except for computing the values previously obtained. If none is applied, the program proceeds to the next procedure.

(7) When the stepping is complete, compute the group classification function coefficients

$$a_i=(n-g)W_{11}^{-1}U_i \quad \text{(q by 1 vector)} \qquad i=1,\dots,g$$

and the corresponding constants

$$b_i=\ln p_i -(1/2)(n-g)U_i'W_{11}\ U_i^{-1} \qquad i=1,\dots,g$$

where p_i is the prior probability for group i.

(8) The classification functions are expressed as follows:

$$s_{ij}=a_i'x_j+b_i \qquad i=1,\dots,g$$

where s_{ij} is called the classification score of the j-th event for the group i, and x_j represents the q-by-1 vector for the set of parameters in the i-th event.

The j-th event is classified into the group i if

$$s_{ij}=\max_k(s_{kj}).$$

The posterior probability that the j-th event belongs to the group i is

$$p_{ij} = \frac{\exp(s_{ij})}{\sum_{k=1}^{g} \exp(s_{kj})} .$$

Appendix D

Programs for Experiments

The data sets of the programs for experiments are listed here as well as the data sets necessary to run the programs. These are examples, and changed according to the experimental conditions. There are other programs for making up classification tables for all the data sets, calculating T-values for template making, displaying the individual event portions, etc., but they are not listed here.

DATA SET NAME = $LOAD

```
PROC 1 DSN
CE .A1B2C3
1 //HOMMAL JOB (0905-6-000-AA-00,:02,2),'BOX 4 HOMMA'
2 //S1 EXEC FTG1CL,PDS='HOMMA.CAL',NAME=&DSN,PLOTTER=SER281I
3 //C.SYSIN DD *
4 /*
5 //
MERGE SUB 3
MERGE &DSN 3
SUB H I
END NO
```

DATA SET NAME = MG

```
C***********************************************************************
C
C PROGRAM MG
C
C***********************************************************************
C THIS PROGRAM DISPLAYS THE BASIC DATA, EXTREMA MARKER. ALSO, IF NEEDED,
C THE LOWPASS-FILTERED DATA, THE SECOND DERIVATIVE OF THE BASIC DATA,
C THE PEAK AMPLITUDE AND THE DURATION OF EACH WAVE CAN BE DISPLAYED.
C THE CORRESPONDING DATA LISTS CAN BE OBTAINED BY UNMASKING THE WRITE
C STATEMENTS FOR FT03F001.
C NOTE : SUBROUTINE SETR(N,V,A) IS IN THE PORT LIBRARY.
C I/O EXAMPLE
C   INPUT  : DATA 01 IN FT07F001
C   OUTPUT : GRAPHIC DISPLAY ON SERVOGOR281 PLOTTER THROUGH IBM3277
C            TERMINAL
C***********************************************************************
C
```

```
C DIMENSIONS
C***DIMENSION II(NG)
      DIMENSION II(2000)
C***DIMENSION Y(3)),YL(MX(L,N)),H(3),YLL(MX(NW,N)),YD(MX(NS1,3))
      DIMENSION Y(3),YL(100),H(3),YLL(20),YD(20)
      DIMENSION D1M(20),D2M(20),OO1(5),OO2(5)
C***DIMENSION XG(NG+2),YG1(*),YG2(*),YG3(*),YG4(*),YG5(*),YG6(*)
      DIMENSION XG(2002),YG1(2002),YG2(2002),YG3(2002),YG4(2002)
      DIMENSION YG5(2002),YG6(2002)
C***DIMENSION YS(NG)
      DIMENSION YS(2000)
      DIMENSION NDY(5),DY1(90),DY2(90),DY3(90),DY4(90),DY5(90),DY6(90)
      DIMENSION DY7(90)
C READ INPUT PARAMETERS
      READ(7,9999) IFILE,NID16,NG,NE,N,NW,L,NH,TD
 9999 FORMAT(8I6,F6.3)
      DATA SX,SY,SY1,SY2,SY3,IPT/5.,5.,1.,1.,1.5,0/
      TID16=TD*FLOAT(NID16)*16.0
C DATA FOR INITIALIZATION
C***DATA Y/3*0./,YL/MX(L,N)*100*0./,YLL/MAX(NW,N)*0./,YD/NS*0./
      DATA Y/3*0.0/,YL/100*0.0/,YLL/20*0.0/,YD/20*0.0/
      DATA D1M,D2M/20*0.,20*0./
      DATA H/0.25,0.50,0.25/
      DATA KS1/1/
C CALCULATION OF DELAY NUMBERS
      L1=L/2
      NR=1+L1+NW/2
      NS=N/2
      NS1=NR-NS
      NDY(1)=-1
      NDY(2)=-1-L1
      NDY(3)=-NR
      NDY(4)=-1-NS
      NDY(5)=0
C NH IS THE COVER RANGE TO STORE ITOP.
      NMIN=0
      DO 5 I1=1,5
      IF(NMIN.GT.NDY(I1)) NMIN=NDY(I1)
    5 CONTINUE
      DO 10 I1=1,5
   10 NDY(I1)=NDY(I1)-NMIN+NH
C INITIAL VALUES FOR DELAY STORAGE
      DATA DY1,DY2,DY3,DY4,DY5,DY6,DY7/90*0.0,90*0.0,90*0.0,90*0.0,
     &90*0.0,90*0.0,90*0.0/
      INDY5=NDY(5)
      DO 15 I1=1,INDY5
      I2=INDY5-I1+1
   15 DY6(I1)=TID16-FLOAT(I2)*TD
C SKIPPING DATA
      CALL IDOL16(NID16)
C NOTE FOR PROGRAM AND DATA USED
C     TED=TD*FLOAT(NE)+TID16
C     WRITE(3,9998) TID16,TED,IFILE,N,NW,L
C9998 FORMAT(1H ,1X,'PROG: DO3'/2X,'DATA: ',F6.3,'-',F6.3,' SEC IN FILE',
```

```
C    &,I3/2X,'PARA: ','N=',I2,', NW=',I2,', L=',I2)
C HEAD LINE OF OUTPUT
C      WRITE(3,9997)
C9997 FORMAT('FILE ','EVENT','IC    ','TYPE ','       TTOP','           A',
C    &'       D1','       D2')
C INITIAL VALUES
      DATA OO1(2),OO2(2)/-1000000.,1000000./
      ITP=1
      YL2=0.0
C BEGINNING OF SEQUENTIAL ANALYSIS
      DO 50 I1=1,NE,NG
C READING OF DATA FOR ONE GRAPH SECTION
      DO 20 I2=1,NG,16
      I3=I2+15
      READ(7,9996) (II(I4),I4=I2,I3)
 9996 FORMAT(1X,16I4)
   20 CONTINUE
C RESET OF ARRAYS
      CALL SETR(NG,0.,YG3)
      CALL SETR(NG,0.,YG5)
      CALL SETR(NG,0.,YG6)
C LOOP FOR ONE GRAPH SECTION
      DO 40 I2=1,NG
      I3=I1+I2-2
        XG(I2)=TD*FLOAT(I3)+TID16
C INPUT SEQUENCE
      Y1=-II(I2)
      CALL SHIFT(Y,Y1,3)
C FILTERING
      CALL GETL(Y,H,3,YL1)
        YG1(I2)=YL1
      CALL SHIFT(YL,YL1,NR)
      YL2=YL2+YL(1)-YL(L)
      YLL1=YL2/FLOAT(L-1)
        YG2(I2)=YLL1
      CALL SHIFT(YLL,YLL1,NW)
C SEGMENTATION BY TURNING POINT
      CALL GETD(YLL,NW,YD1,D1,D2)
      TP1=XG(I2)-FLOAT(NR)*TD
      CALL GETP(YD1,D1,D2,KS1,ICK1)
        IF(ICK1.EQ.0) GO TO 25
        YG3(I2)=ICK1
   25   CONTINUE
C SECOND DERIVATIVE
      CALL GETD(YL,N,YD1,D1,D2)
      YD2=D2-D1
        YG4(I2)=YD2
      CALL SHIFT(D1M,D1,NS1)
      CALL SHIFT(D2M,D2,NS1)
C CHECK OF MAXIMUM AND MINIMUM OF AMPLITUDE IN ONE EVENT
C MAX
      IF(OO1(2).GE.YL(NR)) GO TO 28
      OO1(1)=TP1
      OO1(2)=YL(NR)
```

```
      OO1(3)=D1M(NS1)
      OO1(4)=D2M(NS1)
      ITOP=I2-NR
C MIN
   28 IF(OO2(2).LE.YL(NR)) GO TO 30
      OO2(1)=TP1
      OO2(2)=YL(NR)
      OO2(3)=D1M(NS1)
      OO2(4)=D2M(NS1)
      ITON=I2-NR
   30 CONTINUE
C CHECKING POINT OF AN EVENT
C     IF(ICK1.EQ.0) GO TO 40
C     IF(ICK1.EQ.-1) WRITE(3,9995) IFILE,ITP,ICK1,(OO1(ID1),ID1=1,4)
C     IF(ICK1.EQ.1) WRITE(3,9995) IFILE,ITP,ICK1,(OO2(ID1),ID1=1,4)
C9995 FORMAT(3I5,5X,4F10.3)
C MANIPULATION FOR THE DISPLAY OF MAX AND MIN AMPLITUDE AND SECOND DERIV
      IF(ICK1.EQ.-1) CALL GRMAN(OO1,ITOP,I2,NG,NDY,DY5,DY7,YG5,YG6)
      IF(ICK1.EQ.1) CALL GRMAN(OO2,ITON,I2,NG,NDY,DY5,DY7,YG5,YG6)
C CANCELLATION OF MAXIMUM AND MINIMUM AMPLITUDE OF AN EVENT
      IF(ICK1.EQ.-1) OO1(2)=-1000000.0
      IF(ICK1.EQ.1) OO2(2)=1000000.0
      ITP=ITP+1
   40 CONTINUE
C SHIFTING FOR GRAPHS
      CALL SHIFT1(YG1,YS,NG,DY1,NDY(1))
      CALL SHIFT1(YG2,YS,NG,DY2,NDY(2))
      CALL SHIFT1(YG3,YS,NG,DY3,NDY(3))
      CALL SHIFT1(YG4,YS,NG,DY4,NDY(4))
      CALL SHIFT1(YG5,YS,NG,DY5,NDY(5))
      CALL SHIFT1(YG6,YS,NG,DY7,NDY(5))
      CALL SHIFT1(XG,YS,NG,DY6,NDY(5))
C GRAPHIC DISPLAY
      XI=XG(1)
      XSP=FLOAT(IFIX(TD*FLOAT(NG)/SX*100.+(1./3.)*3.))/100.
      CALL GRAPH1(XG,YG1,NG,0.,SY1,XI,-200.,XSP,300.,SX,SY,00,00,00,IPT)
C     CALL GRAPH1(XG,YG2,NG,0.,SY2,XI,YG1(NG+1),XSP,YG1(NG+2),SX,SY,00,
C    &00,0,IPT)
      CALL GRAPH1(XG,YG3,NG,0.,SY3,XI,   0.,XSP, 0., SX,.5,01,00,1,IPT)
C     CALL GRAPH1(XG,YG4,NG,0.,1.2,XI,   0.,XSP, 0., SX,SY,01,01,0,IPT)
C     CALL GRAPH1(XG,YG5,NG,0.,SY1,XI,YG1(NG+1),XSP,YG1(NG+2),SX,SY,00,
C    &01,0,IPT)
C     CALL GRAPH1(XG,YG6,NG,0.,SY1,XI,YG4(NG+1),XSP,YG4(NG+2),SX,SY,00,
C    &01,1,IPT)
C LISTING UP OF DELAY AND VALUES OF GRAPHS
C     WRITE(3,9994) (NDY(ID1),ID1=1,5)
C9994 FORMAT(1H ,'NDY ',5I5)
C     WRITE(3,9993)
C9993 FORMAT(/1H ,9X,'XG',8X,'YG1',8X,'YG2',8X,'YG3',8X,'YG4',8X,'YG5',
C    &8X,'YG6')
C     WRITE(3,9992) (XG(J),YG1(J),YG2(J),YG3(J),YG4(J),YG5(J),YG6(J),J= G)
C    &1,NG)
C9992 FORMAT(1H ,7(1X,F10.3))
   50 CONTINUE
```

```
      STOP
      END
C*****************************************************************************************
      SUBROUTINE IDOL16(N)
C   N: NUMBER OF DATA CARDS TO BE SKIPPED
      DIMENSION IN(16)
      IF(N.LE.0) RETURN
      DO 10 I1=1,N
      READ(7,9999) (IN(I2),I2=1,16)
 9999 FORMAT(1X,16I4)
   10 CONTINUE
      RETURN
      END
C*****************************************************************************************
      SUBROUTINE GRAPH1(X,Y,N,XO,YO,XI,YI,XSP,YSP,XSZ,YSZ,NSC,NAX,NEN,
     &IPT)
      DIMENSION X(1),Y(1)
      CALL PLOTS
      CALL PLOT(XO,YO,-3)
      IF(NSC.EQ.10.OR.NSC.EQ.11) GO TO 10
      X(N+1)=XI
      X(N+2)=XSP
      GO TO 20
   10 CALL SCALE(X,XSZ,N,1)
   20 CONTINUE
      IF(NSC.EQ.01.OR.NSC.EQ.11) GO TO 30
      Y(N+1)=YI
      Y(N+2)=YSP
      GO TO 40
   30 CALL SCALE(Y,YSZ,N,1)
   40 CONTINUE
      IF(NAX.GE.10) CALL AXIS(0.,0.,'TIME',-4,XSZ,0.,X(N+1),X(N+2))
      IF(NAX.EQ.01.OR.NAX.EQ.11)
     &CALL AXIS(0.,0.,'Y',1,YSZ,90.0,Y(N+1),Y(N+2))
      CALL LINE(X,Y,N,1,IPT,2)
      XEN=XSZ+1.0
      IF(NEN.GE.1) CALL PLOT(XEN,-1.0,999)
      RETURN
      END
C*****************************************************************************************
      SUBROUTINE GRMAN(OO,IT,I2,NG,NDY,DY5,DY7,YG5,YG6)
      DIMENSION OO(1),NDY(1),DY5(1),DY7(1),YG5(1),YG6(1)
      IF(IT.LT.1) IT=IT+NG
      IF(IT.GT.I2) GO TO 10
      YG5(IT)=OO(2)
      YG6(IT)=OO(4)-OO(3)
      GO TO 20
   10 NDY5=NDY(5)-(NG-IT)
      IF(NDY5.GT.NDY(5)) WRITE(3,8899)
 8899 FORMAT(1H ,'WARNING! WARNING! IN SUB. GRMAN.',2X/)
      DY5(NDY5)=OO(2)
      DY7(NDY5)=OO(4)-OO(3)
   20 CONTINUE
      RETURN
```

```
      END
C*****************************************************************************
      SUBROUTINE SHIFT1(Y,YS,N,D,NS)
C******* NS: NUMBER OF SHIFT
C******* D(NS) MUST BE INITIALIZED BEFORE THE FIRST CALL.
      DIMENSION Y(N),YS(N),D(NS)
      N1=N-NS
      DO 10 I1=1,NS
      YS(I1)=D(I1)
      I2=I1+N1
   10 D(I1)=Y(I2)
      DO 20 I1=1,N1
      I2=I1+NS
   20 YS(I2)=Y(I1)
      DO 30 I1=1,N
   30 Y(I1)=YS(I1)
      RETURN
      END
```

DATA SET NAME = $M1A

```
PROC 1 N
CE .X1Y2Z3
//HOMMAM1A JOB (0905-6-000-AA-00,:04,4),'BOX 4 HOMMA',
//         REGION=1024K
//PLEASE EXEC FTG1G,PDS='HOMMA.CAL',NAME=M1A
//G.FT01F001 DD DSN=HOMMA.DATA&N,
//      DCB=(LRECL=80,RECFM=FB,BLKSIZE=4080),
//      DISP=(OLD,KEEP,KEEP),SPACE=(CYL,(1,1),RLSE),
//      UNIT=DISK
//G.FT03F001 DD DSN=HOMMA.LSTA&N,
//      DCB=(LRECL=80,RECFM=FB,BLKSIZE=4080),
//      DISP=(NEW,CATLG,DELETE),SPACE=(CYL,(1,2),RLSE),
//      UNIT=DISK
//
SUB H INFORM
END NO
```

DATA SET NAME = M1A

```
C*****************************************************************************
C
C PROGRAM M1A
C
C*****************************************************************************
C THIS PROGRAM INPUTS DATA FROM A/D CONVERTER AND OUTPUTS A SET OF
C PARAMETERS IN EACH WAVE BY METHOD A.
C I/O EXAMPLE
C   INPUT  : DATA01 IN FT01F001
C   OUTPUT : LST.A01 IN FT03F001
C*****************************************************************************
C
```

```
C DIMENSIONS
C***DIMENSION II(16),Y(3),H(3),YL(MAX(L,N,NR)),YLL(MAX(NW,N))
C***DIMENSION D1M(NS),D2M(NS),OO1(5),OO2(5)
      DIMENSION II(16),Y(3),H(3),YL(20),YLL(20)
      DIMENSION D1M(20),D2M(20),OO1(5),OO2(5)
C INPUT PARAMETERS
      READ(1,9990) IFILE,NE,N,NW,L,TD
 9990 FORMAT(I6,12X,4I6,6X,F6.3)
C INITIAL VALUES
      DATA Y/3*0.0/,YL/20*0.0/.YLL/20*0.0/
      DATA D1M.D2M/20*0.0.20*0.0/
      DATA H/0.25,0.50,0.25/
      DATA KS1/1/
C***DATA OO1(2),OO2(2)/VMIN,VMAX/
      DATA OO1(2),OO2(2)/-1000000.,1000000./
      YL2=0.0
      ITP=1
C CALCULATION OF DELAY NUMBERS
      L1=L/2
      NR=1+L1+NW/2
      NS=NR-N/2
C BEGINNING OF SEQUENTIAL ANALYSIS
      DO 30 I1=1,NE,16
C INPUT DATA
      READ(1,9980) (II(J1),J1=1,16)
 9980 FORMAT(1X,16I4)
      DO 30 I2=1,16
      I3=I1+I2-2
      Y1=-II(I2)
      CALL SHIFT(Y,Y1,3)
C FILTERING
      CALL GETL(Y,H,3,YL1)
      CALL SHIFT(YL,YL1,NR)
      YL2=YL2+YL(1)-YL(L)
      YLL1=YL2/FLOAT(L-1)
      CALL SHIFT(YLL,YLL1,NW)
C CHECKING OF TURNING POINTS
      CALL GETD(YLL,NW,YD1,D1,D2)
      TP1=FLOAT(I3-NR)*TD
      CALL GETP(YD1,D1,D2,KS1,ICK1)
C CALCULATION OF SLOPES
      CALL GETD(YL,N,YD1,D1,D2)
      CALL SHIFT(D1M,D1,NS)
      CALL SHIFT(D2M,D2,NS)
C CHECKING OF MAXIMUM AND MINIMUM OF AMPLITUDE IN ONE WAVE
C MAX
      IF(OO1(2).GE.YL(NR)) GO TO 10
      OO1(1)=TP1
      OO1(2)=YL(NR)
      OO1(3)=D1M(NS)
      OO1(4)=D2M(NS)
      ITOP=I3-NR
C MIN
   10 IF(OO2(2).LE.YL(NR)) GO TO 20
```

```
      OO2(1)=TP1
      OO2(2)=YL(NR)
      OO2(3)=D1M(NS)
      OO2(4)=D2M(NS)
      ITON=I3-NR
   20 CONTINUE
C OUTPUT OF PARAMETERS OF A WAVE
      IF(ICK1.EQ.0) GO TO 30
      IF(ICK1.EQ.-1) WRITE(3,9970) IFILE,ITP,ICK1,(OO1(ID1),ID1=1,4)
      IF(ICK1.EQ.1) WRITE(3,9970) IFILE,ITP,ICK1,(OO2(ID1),ID1=1,4)
 9970 FORMAT(3I5,5X,4F10.3)
C CANCELLATION OF MAXIMUM OR MINIMUM AMPLITUDE OF A WAVE
      IF(ICK1.EQ.-1) OO1(2)=-1000000.0
      IF(ICK1.EQ.1) OO2(2)=1000000.0
      ITP=ITP+1
   30 CONTINUE
      STOP
      END
```

DATA SET NAME = $M1T

```
PROC 3 N K TEMPL
CE .X1Y2Z3
//HOMMAM1T JOB (0905-6-000-AA-00,:06,4),'BOX 4 HOMMA',
//        REGION=1024K
//PLEASE EXEC FTG1G,PDS='HOMMA.CAL',NAME=M1T
//G.FT01F001 DD DSN=HOMMA.DATA&N,
//      DCB=(LRECL=80,RECFM=FB,BLKSIZE=4080),
//      DISP=(OLD,KEEP,KEEP),SPACE=(CYL,(1,1),RLSE),
//      UNIT=DISK
//G.FT07F001 DD DSN=HOMMA.LST&K&N,
//      DCB=(LRECL=133,RECFM=FB,BLKSIZE=4123),
//      DISP=(NEW,CATLG,DELETE),SPACE=(CYL,(1,2),RLSE),
//      UNIT=DISK
//G.FT08F001 DD DSN=HOMMA.&TEMPL,
//      DCB=(LRECL=80,RECFM=FB,BLKSIZE=4080),
//      DISP=(OLD,KEEP,KEEP),SPACE=(TRK,(5,5),RLSE),
//      UNIT=DISK
//
SUB H INFORM
END NO
```

DATA SET NAME = M1T

```
C***************************************************************************
C
C PROGRAM M1T
C
C***************************************************************************
C THIS PROGRAM INPUTS A/D CONVERTED DATA AND OUTPUTS THREE TYPES OF
C PARAMETERS OF EACH WAVE USING THREE MEASURES RESPECTIVELY BY METHOD T.
C I/O EXAMPLE
```

```
C   IF ISEL=1,
C   INPUT  : DATA01 IN FT01F001
C   OUTPUT : LST.T01 IN FT07F001
C   INPUT  : TEMPL1 IN FT08F001
C   IF ISEL=2,
C   INPUT  : DATA01 IN FT01F001
C   OUTPUT : LST.T01 IN FT07F001
C   INPUT  : TEMPLS1 IN FT08F001
C***********************************************************************
C
C DIMENSIONS
C***DIMENSION II(16),Y(3),H(3),YL(NT),YLL(NW),001(),002()
C***DIMENSION TEMP1(NT),TEMP2(NT)
      DIMENSION II(16),Y(3),H(3),YL(300),YLL(20),001(5),002(5)
      DIMENSION TEMP1(300),TEMP2(300)
C INPUT PARAMETERS
      READ(1,9990) IFILE,NE,N,NW,L,TD
 9990 FORMAT(I6,12X,4I6,6X,F6.3)
C INITIAL VALUES
      DATA Y/3*0./,YL/300*0./,YLL/20*0./,H/0.25,0.5,0.25/
C***DATA 001(2),002(2)/VMIN,VMAX/
      DATA 001(2),002(2)/-1000000.,1000000./
      DATA KS1/1/
      YL2=0.0
      ITP=1
C TEMPLATE ARRAY
      READ(8,9980) ISEL,NT,NT1
 9980 FORMAT(I5/2I5)
      CALL SUBM1T(TEMP1,NT)
      IF(ISEL.GT.1) CALL SUBM1T(TEMP2,NT)
      NT2=NT-NT1+1
      NL1=NT2-L/2-NW/2
      NL2=NL1+L-1
C BEGINNING OF SEQUENTIAL ANALYSIS
      DO 60 I1=1,NE,16
C INPUT SEQUENCE
      READ(1,9970) (II(J1),J1=1,16)
 9970 FORMAT(1X,16I4)
      DO 60 I2=1,16
      I3=I1+I2-2
      Y1=-II(I2)
      CALL SHIFT(Y,Y1,3)
C FILTERING
      CALL GETL(Y,H,3,YL1)
      CALL SHIFT(YL,YL1,NT)
      YL2=YL2+YL(NL1)-YL(NL2)
      YLL1=YL2/FLOAT(L-1)
      CALL SHIFT(YLL,YLL1,NW)
C TEMPLATE MATCHING
      IF(001(2).GE.YL(NT2).OR.002(2).LE.YL(NT2)) GO TO 10
      CALL TMABS(YL,TEMP1,NT,CAB1)
      CALL TMSQE(YL,TEMP1,NT,CSQ1)
      CALL TMCOR(YL,TEMP1,NT,COR1)
      IF(ISEL.LE.1) GO TO 10
```

```
      CALL TMABS(YL,TEMP2,NT,CAB2)
      CALL TMSQE(YL,TEMP2,NT,CSQ2)
      CALL TMCOR(YL,TEMP2,NT,COR2)
   10 CONTINUE
C CHECKING OF MAXIMUM AND MINIMUM OF AMPLITUDE IN ONE WAVE
C MAX
      IF(OO1(2).GE.YL(NT2)) GO TO 20
      OO1(1)=TP1
      OO1(2)=YL(NT2)
      OO1(3)=CAB1
      OO1(4)=CSQ1
      OO1(5)=COR1*100.
      IF(ISEL.LE.1) GO TO 20
      OO1(6)=CAB2
      OO1(7)=CSQ2
      OO1(8)=COR2*100.
      ITOP=I3-NR
C MIN
   20 IF(OO2(2).LE.YL(NT2)) GO TO 30
      OO2(1)=TP1
      OO2(2)=YL(NT2)
      OO2(3)=CAB1
      OO2(4)=CSQ1
      OO2(5)=COR1*100.
      IF(ISEL.LE.1) GO TO 30
      OO2(6)=CAB2
      OO2(7)=CSQ2
      OO2(8)=COR2*100.
      ITON=I3-NR
   30 CONTINUE
C CHECKING OF TURNING POINTS
      TP1=FLOAT(I3-NT2)*TD
      CALL GETD(YLL,NW,YD1,D1,D2)
      CALL GETP(YD1,D1,D2,KS1,ICK1)
C CHECKING POINT OF A WAVE
      IF(ICK1.EQ.0) GO TO 60
      IF(ISEL.GT.1) GO TO 40
      IF(ICK1.EQ.-1)
     &WRITE(7,9960) IFILE,ITP,ICK1,OO1(1),(OO1(J1),J1=3,5)
      IF(ICK1.EQ.1)
     &WRITE(7,9960) IFILE,ITP,ICK1,OO2(1),(OO2(J1),J1=3,5)
 9960 FORMAT(3I5,5X,4F13.3)
      GO TO 50
   40 CONTINUE
      IF(ICK1.EQ.-1)
     &WRITE(7,9950) IFILE,ITP,ICK1,OO1(1),(OO1(J1),J1=3,8)
      IF(ICK1.EQ.1)
     &WRITE(7,9950) IFILE,ITP,ICK1,OO2(1),(OO2(J1),J1=3,8)
 9950 FORMAT(3I5,5X,7F13.3)
   50 CONTINUE
C CANCELLATION OF MAXIMUM OR MINIMUM AMPLITUDE OF A WAVE
      IF(ICK1.EQ.-1) OO1(2)=-1000000.0
      IF(ICK1.EQ.1) OO2(2)=1000000.0
   60 CONTINUE
```

```
      STOP
      END
C*******************************************************************************
      SUBROUTINE SUBM1T(TEMP,NT)
      DIMENSION TEMP(1)
      READ(8,9990) (TEMP(ID1),ID1=1,NT)
 9990 FORMAT(8F10.3)
      CALL BACK(TEMP,NT)
      RETURN
      END
```

DATA SET NAME = $M2A

```
PROC 2 LIST LISTM
CE .X1Y2Z3
//HOMMAM2A JOB (0905-6-000-AA-00,:06,4),'BOX 4 HOMMA',
//         REGION=1024K
//PLEASE EXEC FTG1G,PDS='HOMMA.CAL',NAME=M2
//G.FT01F001 DD DSN=HOMMA.&LIST,
//       DCB=(LRECL=80,RECFM=FB,BLKSIZE=4080),
//       DISP=(OLD,KEEP,KEEP),SPACE=(CYL,(1,1),RLSE),
//       UNIT=DISK
//G.FT07F001 DD DSN=HOMMA.&LISTM,
//       DCB=(LRECL=80,RECFM=FB,BLKSIZE=4080),
//       DISP=(NEW,CATLG,DELETE),SPACE=(CYL,(1,2),RLSE),
//       UNIT=DISK
//
SUB H I
END NO
```

DATA SET NAME = $M2T

```
PROC 2 LIST LISTM
CE .X1Y2Z3
//HOMMAM2T JOB (0905-6-000-AA-00,:08,4),'BOX 4 HOMMA',
//         REGION=1024K
//PLEASE EXEC FTG1G,PDS='HOMMA.CAL',NAME=M2
//G.FT01F001 DD DSN=HOMMA.&LIST,
//       DCB=(LRECL=133,RECFM=FB,BLKSIZE=4123),
//       DISP=(OLD,KEEP,KEEP),SPACE=(CYL,(1,1),RLSE),
//       UNIT=DISK
//G.FT07F001 DD DSN=HOMMA.&LISTM,
//       DCB=(LRECL=80,RECFM=FB,BLKSIZE=4080),
//       DISP=(NEW,CATLG,DELETE),SPACE=(CYL,(1,2),RLSE),
//       UNIT=DISK
//
SUB H I
END NO
```

DATA SET NAME = M2

```
C*****************************************************************************
C
C PROGRAM M2
C
C*****************************************************************************
C THIS PROGRAM CREATES A SET OF PARAMETERS IN EACH EVENT FROM M SETS OF
C PARAMTERS IN WAVES WITH A CORE WAVE AT THE M1-TH WAVE OF EACH EVENT.
C I/O EXAMPLE
C   IF ISEL=0,
C   INPUT  : LST.A01 IN FT01F001
C   OUTPUT : LST.A01M IN FT07F001
C   IF ISEL=1,
C   INPUT  : LST.T01 IN FT01F001
C   OUTPUT : LST.T01M IN FT07F001
C   IF ISEL=2,
C   INPUT  : LST.TW01 IN FT01F001
C   OUTPUT : LST.TW01M IN FT07F001
C*****************************************************************************
C
C DIMENSION
C***DIMENSION II(4),YI(4),ID(4,M),PD(4,M)
      DIMENSION II(4),YI(4),ID(4,20),PD(4,20)
C***DIMENSION AM(M),D1(M),D2(M),DU(M),TM*(M)
      DIMENSION AM(20),D1(20),D2(20),DU(20),
     &TM1(20),TM2(20),TM3(20),TM4(20),TM5(20),TM6(20)
C INITIAL VALUES
      DATA ID/80*0/,PD/80*0./
      READ(1,9990) NEVENT,M,M1,ISEL
 9990 FORMAT(4I5)
C BEGIN FROM A WAVE OF ICK=1
      READ(1,9980) ICK
 9980 FORMAT(10X,I5)
      NEVENT=NEVENT-1
      IF(ICK.EQ.-1) GO TO 10
      READ(1,9980) ICK
      NEVENT=NEVENT-1
   10 CONTINUE
C STORE FIRST N-2 LINES OF DATA INTO BUFFERING ARRAYS
      DO 20 I1=3,M
      IF(ISEL.EQ.0) READ(1,9970) (ID(J1,I1),J1=1,4),(PD(J1,I1),J1=1,4)
      IF(ISEL.EQ.1) READ(1,9971) (ID(J1,I1),J1=1,4),(PD(J1,I1),J1=1,3)
      IF(ISEL.EQ.2) READ(1,9972) (ID(J1,I1),J1=1,4),(PD(J1,I1),J1=1,6)
 9970 FORMAT(4I5,4F10.3)
 9971 FORMAT(4I5,3F13.3)
 9972 FORMAT(4I5,6F13.3)
   20 CONTINUE
      IF(ISEL.EQ.0) M2=M-1
      IF(ISEL.NE.0) M2=M
C BEGIN MAIN PART
      DO 40 I1=1,NEVENT,2
C SHIFT DATA INTO BUFFERS
      DO 30 I2=1,2
      IF(ISEL.EQ.0) READ(1,9970,END=50) (II(J1),J1=1,4),(YI(J1),J1=1,4)
      IF(ISEL.EQ.1) READ(1,9971,END=50) (II(J1),J1=1,4),(YI(J1),J1=1,3)
```

```
      IF(ISEL.EQ.2) READ(1,9972,END=50) (II(J1),J1=1,4),(YI(J1),J1=1,6)
      CALL SHFTIM(ID,II,4,M)
      IF(ISEL.EQ.0) CALL SHFTRM(PD,YI,4,M)
      IF(ISEL.EQ.1) CALL SHFTRM(PD,YI,3,M)
      IF(ISEL.EQ.2) CALL SHFTRM(PD,YI,6,M)
   30 CONTINUE
C CALCULATE AND OUTPUT PARAMETERS OF AN EVENT
      IFILE=ID(1,M1)
      IEVENT=ID(2,M1)
      ICHECK=ID(3,M1)
      ITYPE1=ID(4,M1)
      TTOP=PD(1,M1)
      WRITE(7,9960) IFILE,IEVENT,ITYPE1,TTOP
 9960 FORMAT(3I5,F10.3)
      IF(ISEL.EQ.0) CALL SUBM2A(M2,PD)
      IF(ISEL.NE.0) CALL SUBM2T(M2,ISEL,PD)
   40 CONTINUE
   50 CONTINUE
      STOP
      END
C**************************************************************************
      SUBROUTINE SUBM2A(M2,PD)
      DIMENSION PD(4,20)
      DO 10 I1=1,M2
      AM=PD(2,I1+1)-PD(2,I1)
      D1=PD(3,I1)
      D2=PD(4,I1)
      DU=PD(1,I1+1)-PD(1,I1)
   10 WRITE(7,9990) AM,D1,D2,DU
 9990 FORMAT(4F10.3)
      RETURN
      END
C**************************************************************************
      SUBROUTINE SUBM2T(M2,ISEL,PD)
      DIMENSION PD(4,20)
      DO 10 I1=1,M2
      IF(ISEL.EQ.1) WRITE(7,9990) (PD(J1,I1),J1=2,4)
 9990 FORMAT(3F13.3)
      IF(ISEL.EQ.2) WRITE(7,9980) (PD(J1,I1),J1=2,7)
 9980 FORMAT(6F13.3)
   10 CONTINUE
      RETURN
      END
```

DATA SET NAME = $M3

```
PROC 4 FILE1 FILE3 FILE7 FILE8
CE .X1Y2Z3
//HOMMAM3 JOB (0905-6-000-AA-00,:08,4),'BOX 4 HOMMA',
//         REGION=1024K,MSGCLASS=D
//PLEASE EXEC FTG1G,PDS='HOMMA.CAL',NAME=M3
//G.FT01F001 DD DSN='HOMMA.&FILE1',
//      DCB=(LRECL=80,RECFM=FB,BLKSIZE=4080),
```

```
//      DISP=(OLD,KEEP,KEEP),SPACE=(CYL,(1,1),RLSE),
//      UNIT=DISK
//G.FT03F001 DD DSN=HOMMA.&FILE3,
//      DCB=(LRECL=133,RECFM=FBA,BLKSIZE=4123),
//      DISP=(MOD,KEEP,KEEP),SPACE=(CYL,(1,1),RLSE),
//      UNIT=DISK
//G.FT07F001 DD DSN=HOMMA.&FILE7,
//      DCB=(LRECL=133,RECFM=FBA,BLKSIZE=4123),
//      DISP=(OLD,KEEP,KEEP),SPACE=(TRK,(10,10),RLSE),
//      UNIT=DISK
//G.FT08F001 DD DSN=HOMMA.&FILE8,
//      DCB=(LRECL=80,RECFM=FB,BLKSIZE=4080),
//      DISP=(OLD,KEEP,KEEP),SPACE=(TRK,(2,5),RLSE),
//      UNIT=DISK
//
SUB
END NO
```

DATA SET NAME = M3

```
C*****************************************************************************
C
C PROGRAM M3
C
C*****************************************************************************
C PREDICTION BY CLASSIFICATION FUNCTION.
C
C THIS PROGRAM CLASSIFIES A PARAMETRIZED DATA INTO NC GROUPS USING NVT
C PARAMETERS OUT OF NT PARAMETERS IN PARAMETERIZED DATA SET, AND GIVES
C AN ORIGINAL AND A CORRECTED SUMMARY TABLE OF CLASSIFICATION.
C I/O EXAMPLE
C   INPUT  : LST.A01M IN FT01F001
C   OUTPUT : OUT.A13RS05.DAT01 IN FT03F001
C   INPUT  : CLF.A13RS05 IN FT07F001
C   INPUT  : PAR.M3.A13R IN FT08f001
C*****************************************************************************
C
      DIMENSION IV(50),C(4,50),IX(4),X(100),IP(4),S(4),IM(4,4)
      DIMENSION IZ(7,101),TIMEX(100),LR(4),LC(4)
      DATA IM/16*0/,I4/0/,X/5*0./
      DATA IZ(2,101),IZ(5,101),IZ(7,101)/10,10,10/
      DATA MCA/2H A/,MCTA/2HTA/,MCTS/2HTS/,MCTC/2HTC/
C MAIN
      READ(7,9990) NC,NV
 9990 FORMAT(2I5)
      NV1=NV+1
      DO 1 I2=1,NV
      READ(7,9980) IV(I2),(C(I1,I2),I1=1,NC)
    1 CONTINUE
 9980 FORMAT(I4,9X,4F13.5)
      READ(7,9970) (C(I1,NV1),I1=1,NC)
 9970 FORMAT(13X,4F13.5)
      READ(8,9960) MC1,MC2,MC3,NVT,NCA,(LR(I),I=1,4),(LC(I),I=1,4)
```

```
 9960 FORMAT(A2,2A4/2I5/4A4/4A4)
      NVT=NVT+5
      DO 30 I3=1,NCA
      IF(MC1.EQ.MCA) READ(1,9950,END=1000) (IX(I1),I1=1,4),TIME
      IF(MC1.NE.MCA) READ(1,9951,END=1000) (IX(I1),I1=1,4),TIME
 9950 FORMAT(I3,2I5,I3,F10.3)
 9951 FORMAT(I3,2I5,I3,F13.3)
      IF(IX(1).EQ.12.AND.IX(2).EQ.1619) IX(3)=0
      IF(IX(3).EQ.2) IX(3)=0
      IF(IX(3).EQ.100) IX(3)=2
      IF(IX(3).GE.100) WRITE(3,8890) IX(1),IX(2),IX(3)
 8890 FORMAT('ERROR IN LABELING',3I5)
      IX(3)=IX(3)+1
      IF(MC1.EQ.MCA) READ(1,9940) (X(I1),I1=6,NVT)
      IF(MC1.EQ.MCTA.AND.NC.EQ.2) READ(1,9941) (X(I1),I1=6,NVT)
      IF(MC1.EQ.MCTA.AND.NC.EQ.3) READ(1,9942) (X(I1),I1=6,NVT)
      IF(MC1.EQ.MCTS.AND.NC.EQ.2) READ(1,9943) (X(I1),I1=6,NVT)
      IF(MC1.EQ.MCTS.AND.NC.EQ.3) READ(1,9944) (X(I1),I1=6,NVT)
      IF(MC1.EQ.MCTC.AND.NC.EQ.2) READ(1,9945) (X(I1),I1=6,NVT)
      IF(MC1.EQ.MCTC.AND.NC.EQ.3) READ(1,9946) (X(I1),I1=6,NVT)
 9940 FORMAT(4F10.3)
 9941 FORMAT(F13.3)
 9942 FORMAT(2F13.3)
 9943 FORMAT(13X,F13.3)
 9944 FORMAT(26X,2F13.3)
 9945 FORMAT(26X,F13.3)
 9946 FORMAT(52X,2F13.3)
      DO 20 I1=1,NC
      S1=0.
      DO 10 I2=1,NV
   10 S1=S1+C(I1,I2)*X(IV(I2))
   20 S(I1)=S1+C(I1,NV1)
      CALL SRTPDR(S,1,IP,1,NC)
      CALL TABLE1(IX(3),IP(1),NC,IM,JCK)
      IF(JCK.EQ.0) GO TO 30
      I4=I4+1
      DO 25 J1=1,4
   25 IZ(J1,I4)=IX(J1)
      IZ(5,I4)=IP(1)
      TIMEX(I4)=TIME
   30 CONTINUE
 1000 CONTINUE
      CALL TABLE2(NC,MC1,MCA,I4,IZ)
C
      WRITE(3,9930) MC1,MC2,MC3,IX(1),(LR(I),I=1,4)
 9930 FORMAT(1H1,'TABLE OF CLASSIFICATION  BY ',A2,2A4,' : ORIGINAL'/
     &1H ,' IN FILE',I3/1H ,10X,4(6X,A4))
      DO 40 I1=1,4
      WRITE(3,9920) LC(I1),(IM(I1,I2),I2=1,NC)
   40 CONTINUE
 9920 FORMAT(1H ,6X,A4,4I10)
      WRITE(3,9910)
 9910 FORMAT(//)
C
```

```
      IF(I4.EQ.0) GO TO 55
      DO 50 I1=1,I4
      IF(IZ(6,I1).EQ.0) GO TO 50
      IZ1=IZ(3,I1)
      IZ2=IZ(5,I1)
      IM(IZ1,IZ2)=IM(IZ1,IZ2)-1
      IM(IZ1,IZ1)=IM(IZ1,IZ1)+1
   50 CONTINUE
C
   55 WRITE(3,9900) MC1,MC2,MC3,IX(1),(LR(I),I=1,4)
 9900 FORMAT(1H0,'TABLE OF CLASSIFICATION  BY ',A2,2A4,' : CORRECTED'/
     &1H ,' IN FILE',I3/1H ,10X,4(6X,A4))
      DO 60 I1=1,4
      WRITE(3,9920) LC(I1),(IM(I1,I2),I2=1,NC)
   60 CONTINUE
      WRITE(3,9910)
C
      WRITE(3,9890) MC1,MC2,MC3
 9890 FORMAT(1H0,'LIST OF EVENTS EXCEPT FOR CORRECTLY CLASSIFIED BACKGRO
     &UND BY ',A2,2A4/1H ,6X,'FILE',5X,'EVENT',6X,'TYPE',4X,'PREDIC',2X,
     &'CORRECTN',6X,'TIME')
      IF(I4.EQ.0) GO TO 80
      DO 70 I1=1,I4
   70 WRITE(3,9880) IZ(1,I1),IZ(2,I1),LC(IZ(3,I1)),LR(IZ(5,I1)),
     &IZ(6,I1),TIMEX(I1)
 9880 FORMAT(1H ,2I10,2(6X,A4),I10,F10.3)
   80 WRITE(3,9910)
      STOP
      END
C*****************************************************************************
      SUBROUTINE TABLE1(IX3,IP1,NC,IM,JCK)
      DIMENSION IM(4,4)
      JCK=0
      DO 10 I2=1,NC
      DO 10 I1=1,4
      IF(IX3.NE.I1.OR.IP1.NE.I2) GO TO 10
      IM(I1,I2)=IM(I1,I2)+1
      IF(I1.NE.1.OR.I2.NE.1) JCK=1
   10 CONTINUE
      RETURN
      END
C*****************************************************************************
      SUBROUTINE TABLE2(NC,MC1,MCA,I0,IZ)
      DIMENSION IZ(7,101)
      DO 10 I=1,I0
      IZ(6,I)=0
      IZ(7,I)=IZ(5,I)
      IF(MC1.NE.MCA.AND.NC.EQ.3.AND.IZ(5,I).EQ.3) IZ(7,I)=2
      IF(NC.NE.4) GO TO 10
      IF(IZ(5,I).EQ.3) IZ(7,I)=2
      IF(IZ(5,I).EQ.4) IZ(7,I)=3
   10 CONTINUE
C
      DO 20 K=1,2
```

```
      I2=0
      DO 20 I=1,I0
      IK1=I+K
      IK2=I-K
      IF(IK1.LE.I0) CALL CORRCT(I,IK1,IZ)
      IF(IK2.GE.1) CALL CORRCT(I,IK2,IZ)
   20 CONTINUE
      RETURN
      END
C*******************************************************************************************
      SUBROUTINE CORRCT(I,IK,IZ)
      DIMENSION IZ(7,101)
      ID=IABS(IZ(2,IK)-IZ(2,I))
      IF(ID.GT.4) RETURN
      IF(IZ(3,I).EQ.1.AND.IZ(7,I).EQ.2.AND.IZ(3,IK).EQ.2) IZ(6,I)=1
      IF(IZ(3,I).EQ.1.AND.IZ(7,I).EQ.3.AND.IZ(3,IK).EQ.3) IZ(6,I)=1
      IF(IZ(3,I) .NE. 2 .OR. IZ(7,I) .NE. 1) GO TO 10
      IF(IZ(3,IK).EQ. 1 .AND.IZ(7,IK).EQ. 2) IZ(6,I)=1
   10 IF(IZ(3,I) .NE. 2 .OR. IZ(7,I) .NE. 3) GO TO 20
      IF(IZ(3,IK).EQ. 1 .AND.IZ(7,IK).EQ. 2) IZ(6,I)=1
   20 IF(IZ(3,I) .NE. 3 .OR. IZ(7,I) .NE. 1) GO TO 30
      IF(IZ(3,IK).EQ. 1 .AND.IZ(7,IK).EQ. 3) IZ(6,I)=1
   30 IF(IZ(3,I) .NE. 3 .OR. IZ(7,I) .NE. 2) GO TO 40
      IF(IZ(3,IK).EQ. 1 .AND.IZ(7,IK).EQ. 3) IZ(6,I)=1
   40 CONTINUE
      RETURN
      END
```

DATA SET NAME = PAR.M3.A13R

```
 A13R.S05
   72 1000
BCK SSW ART
BCK SSW ART DBS
```

DATA SET NAME = PAR.M3.TA13R

```
TA13R.S05
   38 1000
BCK SSWASSWB
BCK SSW ART DBS
```

DATA SET NAME = CLF.A13RS05

```
    3    5
  40 S29           0.40681      0.45161     -4.69353
  42 AM10          0.08027     -0.91834     -0.75741
  44 S210          0.12176     -1.95277    -10.61063
  45 DU10        120.49611   -178.94417   -138.35342
  47 S111         -0.80868      3.13877     11.99979
  00              -3.01535    -61.77582   -282.77930
```

DATA SET NAME = SUB

```
C*******************************************************************************
C
C SUBROUTINES
C
C*******************************************************************************
C
C*******************************************************************************
      SUBROUTINE BACK(Y,N)
      DIMENSION Y(N)
      N1=N/2
      DO 10 I1=1,N1
      I2=N-I1+1
      T1=Y(I1)
      Y(I1)=Y(I2)
      Y(I2)=T1
   10 CONTINUE
      RETURN
      END
C*******************************************************************************
      SUBROUTINE GETD(Y,N,YD1,D1,D2)
      DIMENSION Y(N)
      NF=(N-1)/2
      N1=NF+1
      N2=N1-1
      F1=FLOAT(NF)
      YD1=Y(N2)-Y(N1)
      D1=(Y(N1)-Y(N))/F1
      D2=(Y(1)-Y(N1))/F1
      RETURN
      END
C*******************************************************************************
      SUBROUTINE GETL(Y,H,N,YL1)
      DIMENSION Y(N),H(N)
      YL1=0.0
      DO 10 I1=1,N
      I2=N-I1+1
      YL1=YL1+H(I1)*Y(I2)
   10 CONTINUE
      RETURN
      END
C*******************************************************************************
      SUBROUTINE GETP(YD1,D1,D2,KS,ICK1)
      ICK1=0
      GO TO (10,20), KS
   10 IF(YD1.LE.0.0) GO TO 30
      IF(D1.GT.0.0.OR.D2.LE.0.0) GO TO 30
      ICK1=-1
      KS=2
      GO TO 30
   20 IF(YD1.GE.0.0) GO TO 30
      IF(D1.LT.0.0.OR.D2.GE.0.0) GO TO 30
      ICK1=1
```

```
      KS=1
   30 CONTINUE
      RETURN
      END
C*******************************************************************************
      SUBROUTINE SHFTIM(Y,YI,M,N)
      INTEGER Y(M,N),YI(M),T1,T2
      DO 20 I1=1,M
      T1=Y(I1,N)
      DO 10 I2=2,N
      I3=N-I2+1
      T2=Y(I1,I3)
      Y(I1,I3)=T1
      T1=T2
   10 CONTINUE
      Y(I1,N)=YI(I1)
   20 CONTINUE
      RETURN
      END
C*******************************************************************************
      SUBROUTINE SHFTRM(Y,YI,M,N)
      REAL Y(M,N),YI(M)
      DO 20 I1=1,M
      T1=Y(I1,N)
      DO 10 I2=2,N
      I3=N-I2+1
      T2=Y(I1,I3)
      Y(I1,I3)=T1
      T1=T2
   10 CONTINUE
      Y(I1,N)=YI(I1)
   20 CONTINUE
      RETURN
      END
C*******************************************************************************
      SUBROUTINE SHIFT(Y,Y1,N)
      DIMENSION Y(N)
      T1=Y(1)
      DO 10 I=2,N
      T2=Y(I)
      Y(I)=T1
      T1=T2
   10 CONTINUE
      Y(1)=Y1
      RETURN
      END
C*******************************************************************************
      SUBROUTINE TMABS(Y,T,NL,V1)
      DIMENSION Y(NL),T(NL)
      V1=0.
      DO 10 I1=1,NL
   10 V1=V1+ABS(Y(I1)-T(I1))
      V1=V1/FLOAT(NL)
      RETURN
```

```
      END
C********************************************************************************
      SUBROUTINE TMCOR(Y,T,NL,R4)
      DIMENSION Y(NL),T(NL)
      C1=1./FLOAT(NL)
      SY=0.
      ST=0.
      R1=0.
      R2=0.
      R3=0.
      DO 10 I1=1,NL
      SY=SY+Y(I1)
      ST=ST+T(I1)
      R1=R1+Y(I1)*T(I1)
      R2=R2+Y(I1)**2
      R3=R3+T(I1)**2
   10 CONTINUE
      RT=(R2-C1*SY**2)*(R3-C1*ST**2)
      IF(RT.GT.0.1E-7) R4=(R1-SY*ST*C1)/SQRT(RT)
      IF(RT.LE.0.1E-7) R4=-2.
      IF(RT.LT.0.) R4=-3.
      RETURN
      END
C********************************************************************************
      SUBROUTINE TMSQE(Y,T,NL,V1)
      DIMENSION Y(NL),T(NL)
      V1=0.
      DO 10 I1=1,NL
   10 V1=V1+(Y(I1)-T(I1))**2
      V1=V1/FLOAT(NL)
      RETURN
      END
```

DATA SET NAME = B7M.A13R

```
//HOMMAB7M JOB (0905-6-000-AA-00,:16,6),'BOX #4 HOMMA',REGION=1024K
//  EXEC BMDP,PROG=BMDP7M,REGION=128K
//* ***************************************************************************
//*
//* PROGRAM BAMP7M for A13R
//*
//* ***************************************************************************
//* THIS IS AN EXAMPLE OF THE BMAP7M PROGRAM. THE INPUT IS THE DATA SET
//* LST.A01RM, WHICH IS DERIVED FROM THE ORIGINAL DATA SET DATA01,
//* PARAMETERIZED, AND LABELED.
//* ***************************************************************************
//G.SYSIN DD *
/PROB
   TITLE='EEG EVENT CLASSIFICATION : A13R'.
/INP
   VAR=77.
   FORM='(A3,1X,A4,F5.0,F3.0,F10.3,18(/4F10.3))'.
   UNIT=7.
```

```
/VAR
   NAME=FILE,EVENT,TYPE,IC,TTOP,
        AM1,S11,S21,DU1,AM2,S12,S22,DU2,AM3,S13,S23,DU3,
        AM4,S14,S24,DU4,AM5,S15,S25,DU5,AM6,S16,S26,DU6,
        AM7,S17,S27,DU7,AM8,S18,S28,DU8,AM9,S19,S29,DU9,
        AM10,S110,S210,DU10,AM11,S111,S211,DU11,AM12,S112,S212,DU12,
        AM13,S113,S213,DU13,AM14,S114,S214,DU14,AM15,S115,S215,DU15,
        AM16,S116,S216,DU16,AM17,S117,S217,DU17,AM18,S118,S218,DU18.
   USE= AM1,S11,S21,DU1,AM2,S12,S22,DU2,AM3,S13,S23,DU3,
        AM4,S14,S24,DU4,AM5,S15,S25,DU5,AM6,S16,S26,DU6,
        AM7,S17,S27,DU7,AM8,S18,S28,DU8,AM9,S19,S29,DU9,
        AM10,S110,S210,DU10,AM11,S111,S211,DU11,AM12,S112,S212,DU12,
        AM13,S113,S213,DU13,AM14,S114,S214,DU14,AM15,S115,S215,DU15,
        AM16,S116,S216,DU16,AM17,S117,S217,DU17,AM18,S118,S218,DU18.
   LABEL=FILE,EVENT.
   BLANK=ZERO.
   GROUPING=TYPE.
/CATEGORY
   CUTPOINT(3)=0.1,1.5.
   NAME(3)=BCK,SSW,ART.
   PRIOR=0.98,0.01,0.01.
/TRAN
   IF(TYPE EQ 2.) THEN USE=0.
   IF(TYPE EQ 3.) THEN USE=0.
   IF(TYPE EQ 4.) THEN USE=0.
/DISC
   METHOD=1.
   STEP=144.
   TOL=0.005.
/PRINT
   CLASS=1 TO 144.
   NO POINT.
   NO POST.
/PLOT
   CONTR.
/COMMENT='DATA: LST.A01RM.'.
/END
/*
//G.FT07F001 DD DSN=HOMMA.LST.A01RM,
//      DCB=(LRECL=80,RECFM=FB,BLKSIZE=4080),
//      DISP=(OLD,KEEP,KEEP),SPACE=(CYL,(1,2),RLSE),
//      UNIT=DISK
//
```

Appendix E

Instructions for Running Programs

The following illustrates the instructions when running the programs for the experiments A13R and TA13R, and the classifiers A13R.S05 and TA13R.S05, using the first data set DATA01. The comments appear with a regular type, and the commands for the computer terminal TSO in clemson university appear with a bold type. The character ↓ is for the carriage return (or enter) key.

Instructions:

(1) Create a temporary load library.

ALLOCLIB NAME(CAL) INC(CYL) PRM(2) SEC(4) DIR(2) ↓

(2) Load the programs.

X $LOAD MG ↓
X $LOAD M1A ↓
X $LOAD M1T ↓
X $LOAD M2 ↓
X $LOAD M3 ↓

(3) Execute the program MG using the IBM3277 terminal and the TEKTRONIX618 graphic display.

ALLOCATE FI(FT01F001) DA(*) ↓
ALLOCATE FI(FT03F001) DA(*) ↓
ALLOCATE FI(FT07F001) DA('HOMMA.DATA01') ↓
CALL 'HOMMA.CAL(MG)' ↓

SSWs and other waves of interest are marked by a supervisor, using the graphic display, and the corresponding waves are labeled as follows. The label 0 for background events, 1 for SSW, 2 for successive SSW, 3 for doubious SSW, and 4 for adjacent events to SSW. When SSW is divided into SSWA and SSWB, the event identifiers IFILE and IEVENT were used to specify SSWB events in the BMDP7M program. The event that has IFILE=12 and IEVENT=1619 was first considered as an artifact event, but later considered as a background event. The label of this event is changed so in the program M3.

(4) Execute the program M1A to get wave parameters in Method A.

```
X $M1A 01 ↓
```

(5) Execute the program M1T to get wave parameters in Method T.

```
X $M1T 01 T1W TE1W ↓
```

(6) Execute the program M2 to get event parameters, after merging a line for NEVENT, M, M1, ISEL on the top of LST.A01 and LST.T1W01.

```
CEDIT LST.A01 SIZE(*) ↓
1  2000   19   10    0 ↓
REPLACE ↓
END ↓
```

Merge for LST.T1W01 likewise.

```
CEDIT LST.T1W01 SIZE(*) ↓
1  2000   19   10    2 ↓
REPLACE ↓
END ↓
```

Then,

```
X $M2A LST.A01 LST.A01M ↓
X $M2T LST.T1W01 LST.T1W01M ↓.
```

(7) Execute the program M3 to get the original and corrected classification tables (the latter table is explained in Chapter 5).

```
X $M3 LST.A01M OUT.A13RS05.DAT01 CLF.A13RS05 PAR.M3.A13R ↓
X $M3 LST.T1W01M OUT.TA13RS05.DAT01 CLF.TA13RS05
PAR.M3.TA13R ↓
```

Appendix F

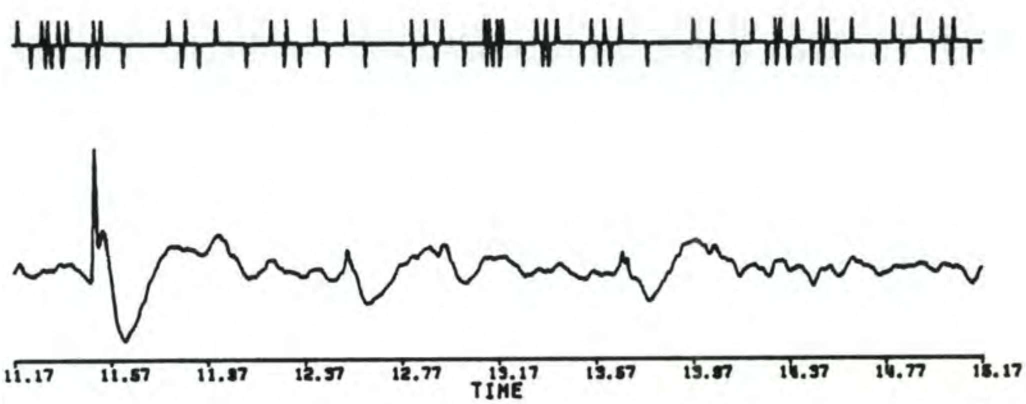
Output Examples of Programs

Output examples of the programs listed in Appendix D are shown in the following.

(1) A partial list of the original data with parameters for the program M1A or M1T on the top line.

```
   1     40   1200 14336      5      5      5      50 0.005
  17   15   25   17   25   29   33   38   34   35   36   33   32   31   30   27
  25   19   15   17   13    9    6   10    9    6    8    6    5    9   11   15
  20   21   17   19   17   17   10   14   15   18   20   17   11   14   17   17
  17   15   17   19   19   18   20   16   19   23   20   22   22   25   28   24
  22   21   22   13   16   24   18   27   24   24   14   12   15   19   19   25
                                        :
                                        :
```

(2) An output example of the program MG.



(3) A partial list of the data of wave parameters LST.A01 with parameters for the program M2 on the top line.

```
2000   19   10    0
   1    1   -1          -0.025     0.0        0.0        0.0
   1    2    1           0.035   -35.750     -3.375      0.375
   1    3   -1           0.135    -6.250      0.500     -1.125
   1    4    1           0.165   -19.750     -2.250      0.875
   1    5   -1           0.190   -12.750      2.375     -1.375
                           :
                           :
```

(4) A partial list of the data of event parameters LST.A01M.

```
 1   11      0      0.335
  29.500    -3.375      0.375      0.100
 -13.500     0.500     -1.125      0.030
   7.000    -2.250      0.875      0.025
  -6.000     2.375     -1.375      0.020
   5.500    -1.625      2.750      0.010
  -5.500     2.750     -1.500      0.040
   1.000    -0.875      0.125      0.015
  -8.500     0.500     -1.750      0.035
  10.250    -1.750      2.000      0.025
  -8.750     2.750     -2.250      0.025
  11.500    -1.500      4.375      0.015
 -13.000     4.125     -2.375      0.040
  22.000    -2.375      0.625      0.055
 -12.500     3.125     -3.125      0.035
  11.500    -0.500      1.750      0.020
 -11.750     4.000     -0.500      0.050
  12.000    -1.750      1.750      0.030
  -2.750     2.375     -1.375      0.010
 1   13      0      0.375
   7.000    -2.250      0.875      0.025
  -6.000     2.375     -1.375      0.020
   5.500    -1.625      2.750      0.010
                  :
                  :
```

(5) An example of the outputs from the program M3.

```
 TABLE OF CLASSIFICATION  BY  A13R.S05  : ORIGINAL
  IN FILE  1
                  BCK        SPK        ART
       BCK        857          2          0
       SPK          1          8          0
       ART          0          0          1
       DBS          0          0          0


 TABLE OF CLASSIFICATION  BY  A13R.S05  : CORRECTED
  IN FILE  1
                  BCK        SPK        ART
       BCK        859          0          0
       SPK          1          8          0
       ART          0          0          1
       DBS          0          0          0
```

LIST OF EVENTS EXCEPT FOR CORRECTLY CLASSIFIED BACKGROUND BY A13R.S05

FILE	EVENT	TYPE	PREDIC	CORRECTN	TIME
1	309	SPK	SPK	0	11.510
1	311	BCK	SPK	1	11.540
1	325	SPK	SPK	0	12.550
1	351	SPK	SPK	0	13.685
1	581	SPK	SPK	0	22.970
1	1163	SPK	SPK	0	47.110
1	1181	SPK	SPK	0	48.130
1	1185	BCK	SPK	1	48.325
1	1191	SPK	SPK	0	48.795
1	1569	SPK	SPK	0	63.595
1	1613	ART	ART	0	65.415
1	1659	SPK	BCK	0	67.255

Appendix G

Classifications at Training Stage

Table G-1 Classifications at Training Stage.

Classifier	PRE			BCK ->		SSW ->	
	P1	P2	P3	BCK	SSW	BCK	SSW
A12 .S 1	0.775	0.579	0.663	855	5	2	7
A12 .S 2	0.775	0.775	0.775	858	2	2	7
A12 .S 3	0.776	0.874	0.822	859	1	2	7
A12 .S 4	0.776	0.874	0.822	859	1	2	7
A12 .S 5	0.776	0.874	0.822	859	1	2	7
A12 .S 6	0.776	0.874	0.822	859	1	2	7
A12 .S 7	0.776	0.874	0.822	859	1	2	7
A12 .S 8	1.000	0.899	0.947	859	1	0	9
A12 .S 9	1.000	0.899	0.947	859	1	0	9
A12 .S10	0.888	0.888	0.888	859	1	1	8
A12 .S11	1.000	0.899	0.947	859	1	0	9
A12 .S12	0.888	0.888	0.888	859	1	1	8
A12 .S13	0.888	0.888	0.888	859	1	1	8
A12 .S14	0.888	0.888	0.888	859	1	1	8
A12 .S15	0.888	0.888	0.888	859	1	1	8
A12 .S16	0.888	0.888	0.888	859	1	1	8
A12 .S17	0.888	0.888	0.888	859	1	1	8
A12 .S18	0.888	0.888	0.888	859	1	1	8
A12 .S19	0.888	0.888	0.888	859	1	1	8
A12R .S 1	0.888	0.888	0.888	744	1	1	8
A12R .S 2	0.775	0.873	0.822	744	1	2	7
A12R .S 3	0.888	0.888	0.888	744	1	1	8
A12R .S 4	0.888	0.888	0.888	744	1	1	8
A12R .S 5	1.000	0.899	0.947	744	1	0	9
A12R .S 6	1.000	0.899	0.947	744	1	0	9
A12R .S 7	1.000	0.899	0.947	744	1	0	9
A12R .S 8	1.000	0.899	0.947	744	1	0	9
A12R .S 9	1.000	0.899	0.947	744	1	0	9
A12R .S10	1.000	0.899	0.947	744	1	0	9
A12R .S11	0.888	0.888	0.888	744	1	1	8
A12R .S12	0.888	0.888	0.888	744	1	1	8
A12R .S13	0.888	0.888	0.888	744	1	1	8

Table G-1 (Cont'd.)

Classifier	PRE			BCK ->		SSW ->	
	P1	P2	P3	BCK	SSW	BCK	SSW
A22R .S 1	0.497	0.798	0.612	1515	2	8	8
A22R .S 2	0.811	0.811	0.811	1514	3	3	13
A22R .S 3	0.874	0.822	0.847	1514	3	2	14
A22R .S 4	0.874	0.775	0.822	1513	4	2	14
A22R .S 5	0.811	0.811	0.811	1514	3	3	13
A22R .S 6	0.874	0.775	0.822	1513	4	2	14
A22R .S 7	0.874	0.822	0.847	1514	3	2	14
A22R .S 8	0.874	0.874	0.874	1515	2	2	14
A22R .S 9	0.811	0.865	0.837	1515	2	3	13
A22R .S10	0.874	0.874	0.874	1515	2	2	14
A22R .S11	0.937	0.881	0.908	1515	2	1	15
A22R .S12	0.937	0.881	0.908	1515	2	1	15
A22R .S13	0.937	0.832	0.881	1514	3	1	15
A22R .S14	0.937	0.832	0.881	1514	3	1	15
A22R .S15	0.937	0.881	0.908	1515	2	1	15
A22R .S16	0.937	0.881	0.908	1515	2	1	15
A22R .S17	0.937	0.881	0.908	1515	2	1	15
A22R .S18	0.937	0.881	0.908	1515	2	1	15
A22R .S19	0.937	0.881	0.908	1515	2	1	15
A32R .S 1	0.874	0.838	0.856	2287	4	3	21
A32R .S 2	0.832	0.832	0.832	2287	4	4	20
A32R .S 3	0.832	0.832	0.832	2287	4	4	20
A32R .S 4	0.874	0.838	0.856	2287	4	3	21
A32R .S 5	0.916	0.813	0.861	2286	5	2	22
A32R .S 6	0.874	0.838	0.856	2287	4	3	21
A32R .S 7	0.832	0.832	0.832	2287	4	4	20
A32R .S 8	0.916	0.879	0.897	2288	3	2	22
A32R .S 9	0.916	0.845	0.879	2287	4	2	22
A32R .S10	0.916	0.845	0.879	2287	4	2	22
A32R .S11	0.916	0.845	0.879	2287	4	2	22
A32R .S12	0.916	0.879	0.897	2288	3	2	22
A32R .S13	0.916	0.916	0.916	2289	2	2	22
A32R .S14	0.916	0.879	0.897	2288	3	2	22
A32R .S15	0.916	0.879	0.897	2288	3	2	22
A32R .S16	0.916	0.879	0.897	2288	3	2	22
A32R .S17	0.916	0.879	0.897	2288	3	2	22
A32R .S18	0.916	0.879	0.897	2288	3	2	22
A32R .S19	0.916	0.879	0.897	2288	3	2	22
A32R .S20	0.916	0.879	0.897	2288	3	2	22
A32R .S21	0.916	0.879	0.897	2288	3	2	22
A32R .S22	0.916	0.916	0.916	2289	2	2	22
A32R .S23	0.916	0.916	0.916	2289	2	2	22
A32R .S24	0.916	0.879	0.897	2288	3	2	22
A32R .S25	0.916	0.916	0.916	2289	2	2	22
A32R .S26	0.916	0.916	0.916	2289	2	2	22

Table G-1 (Cont'd.)

CLASSIFIER	PRE			BCK ->			SSW ->			ART ->		
	P1	P2	P3	BCK	SSW	ART	BCK	SSW	ART	BCK	SSW	ART
A13 .S 1	0.220	1.000	0.361	859	0	0	6	2	1	0	0	1
A13 .S 2	0.442	1.000	0.613	859	0	0	4	4	1	0	0	1
A13 .S 3	0.664	0.856	0.748	858	1	0	2	6	1	0	0	1
A13 .S 4	0.776	0.874	0.822	858	1	0	2	7	0	0	0	1
A13 .S 5	0.888	0.888	0.888	858	1	0	1	8	0	0	0	1
A13 .S 6	0.888	1.000	0.941	859	0	0	1	8	0	0	0	1
A13 .S 7	0.888	1.000	0.941	859	0	0	1	8	0	0	0	1
A13 .S 8	0.888	1.000	0.941	859	0	0	1	8	0	0	0	1
A13 .S 9	0.888	1.000	0.941	859	0	0	1	8	0	0	0	1
A13 .S10	0.888	1.000	0.941	859	0	0	1	8	0	0	0	1
A13 .S11	1.000	1.000	1.000	859	0	0	0	9	0	0	0	1
A13 .S12	1.000	1.000	1.000	859	0	0	0	9	0	0	0	1
A13R .S 1	0.441	1.000	0.613	742	0	2	0	4	5	0	0	1
A13R .S 2	0.664	1.000	0.798	744	0	0	2	6	1	0	0	1
A13R .S 3	0.776	1.000	0.874	744	0	0	1	7	1	0	0	1
A13R .S 4	0.776	1.000	0.874	744	0	0	1	7	1	0	0	1
A13R .S 5	0.888	1.000	0.941	744	0	0	1	8	0	0	0	1
A13R .S 6	0.888	1.000	0.941	744	0	0	1	8	0	0	0	1
A13R .S 7	0.888	1.000	0.941	744	0	0	1	8	0	0	0	1
A13R .S 8	0.888	1.000	0.941	744	0	0	1	8	0	0	0	1
A13R .S 9	0.888	1.000	0.941	744	0	0	1	8	0	0	0	1
A13R .S10	1.000	1.000	1.000	744	0	0	0	9	0	0	0	1
A13R .S11	1.000	1.000	1.000	744	0	0	0	9	0	0	0	1
A13R .S12	1.000	1.000	1.000	744	0	0	0	9	0	0	0	1
A13R .S13	1.000	1.000	1.000	744	0	0	0	9	0	0	0	1
A13R .S14	1.000	1.000	1.000	744	0	0	0	9	0	0	0	1
A13R .S15	1.000	1.000	1.000	744	0	0	0	9	0	0	0	1
A23R .S 1	0.372	0.856	0.519	1515	1	0	8	6	2	0	0	1
A23R .S 2	0.685	0.845	0.756	1514	2	0	3	11	2	0	0	1
A23R .S 3	0.748	0.856	0.798	1514	2	0	3	12	1	0	0	1
A23R .S 4	0.685	0.783	0.731	1513	3	0	4	11	1	0	0	1
A23R .S 5	0.811	0.865	0.837	1514	2	0	2	13	1	0	0	1
A23R .S 6	0.811	0.865	0.837	1514	2	0	2	13	1	0	0	1
A23R .S 7	0.874	0.874	0.874	1514	2	0	1	14	1	0	0	1
A23R .S 8	0.874	0.933	0.902	1515	1	0	1	14	1	0	0	1
A23R .S 9	0.874	0.933	0.902	1515	1	0	1	14	1	0	0	1
A23R .S10	0.874	0.933	0.902	1515	1	0	1	14	1	0	0	1
A23R .S11	0.874	0.933	0.902	1515	1	0	1	14	1	0	0	1
A23R .S12	0.811	0.928	0.865	1515	1	0	2	13	1	0	0	1
A23R .S13	0.811	0.865	0.837	1514	2	0	2	13	1	0	0	1
A23R .S14	0.811	0.865	0.837	1514	2	0	2	13	1	0	0	1
A23R .S15	0.874	0.874	0.874	1514	2	0	1	14	1	0	0	1
A23R .S16	0.874	0.874	0.874	1514	2	0	1	14	1	0	0	1

Table G-1 (Cont'd.)

CLASSIFIER	PRE			BCK ->			SSW ->			ART ->		
	P1	P2	P3	BCK	SSW	ART	BCK	SSW	ART	BCK	SSW	ART
A23R .S17	0.874	0.874	0.874	1514	2	0	1	14	1	0	0	1
A23R .S18	0.874	0.874	0.874	1514	2	0	1	14	1	0	0	1
A23R .S19	0.874	0.874	0.874	1514	2	0	1	14	1	0	0	1
A23R .S20	0.874	0.874	0.874	1514	2	0	1	14	1	0	0	1
A33R .S 1	0.330	0.798	0.467	2288	2	0	13	8	3	0	0	1
A33R .S 2	0.706	0.848	0.771	2287	3	0	4	17	3	0	0	1
A33R .S 3	0.706	0.808	0.753	2286	4	0	5	17	2	0	0	1
A33R .S 4	0.706	0.770	0.737	2285	5	0	5	17	2	0	0	1
A33R .S 5	0.790	0.824	0.807	2286	4	0	3	19	2	0	0	1
A33R .S 6	0.832	0.832	0.832	2286	4	0	3	20	1	0	0	1
A33R .S 7	0.874	0.806	0.838	2285	5	0	2	21	1	0	0	1
A33R .S 8	0.874	0.874	0.874	2287	3	0	2	21	1	0	0	1
A33R .S 9	0.874	0.874	0.874	2287	3	0	2	21	1	0	0	1
A33R .S10	0.832	0.868	0.850	2287	3	0	3	20	1	0	0	1
A33R .S11	0.790	0.824	0.807	2286	4	0	4	19	1	0	0	1
A33R .S12	0.832	0.868	0.850	2287	3	0	3	20	1	0	0	1
A33R .S13	0.790	0.862	0.824	2287	3	0	4	19	1	0	0	1
A33R .S14	0.832	0.868	0.850	2287	3	0	3	20	1	0	0	1
A33R .S15	0.832	0.868	0.850	2287	3	0	3	20	1	0	0	1
A33R .S16	0.874	0.874	0.874	2287	3	0	2	21	1	0	0	1
A33R .S17	0.874	0.838	0.856	2286	4	0	2	21	1	0	0	1
A33R .S18	0.874	0.838	0.856	2286	4	0	2	21	1	0	0	1
A33R .S19	0.874	0.838	0.856	2286	4	0	2	21	1	0	0	1
A33R .S20	0.874	0.912	0.893	2288	2	0	2	21	1	0	0	1

CLASSIFIER	PRE			BCK ->				SSWA ->				SSWB ->				ART ->			
	P1	P2	P3	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART
A14 .S 1	1.000	0.816	0.899	857	2	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14 .S 2	1.000	0.689	0.816	855	4	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14 .S 3	1.000	0.689	0.816	855	4	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14 .S 4	1.000	0.639	0.780	854	5	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14 .S 5	1.000	0.639	0.780	854	5	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14 .S 6	1.000	0.639	0.780	854	5	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14 .S 7	0.888	0.798	0.840	857	2	0	0	1	7	0	0	0	0	1	0	0	0	0	1
A14 .S 8	1.000	0.816	0.899	857	2	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14 .S 9	1.000	0.747	0.855	856	3	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14 .S10	1.000	0.747	0.855	856	3	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14 .S11	1.000	0.747	0.855	856	3	0	0	0	8	0	0	0	0	1	0	0	0	0	1

Table G-1 (Cont'd.)

CLASSIFIER	PRE			BCK ->				SSWA ->				SSWB ->				ART ->			
	P1	P2	P3	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART
A14 .S12	1.000	0.747	0.855	856	3	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14 .S13	1.000	0.747	0.855	856	3	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S 1	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S 2	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S 3	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S 4	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S 5	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S 6	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S 7	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S 8	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S 9	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S10	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S11	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S12	1.000	0.899	0.947	743	1	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S13	1.000	1.000	1.000	744	0	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S14	1.000	1.000	1.000	744	0	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S15	1.000	1.000	1.000	744	0	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A14R .S16	1.000	1.000	1.000	744	0	0	0	0	8	0	0	0	0	1	0	0	0	0	1
A24R .S 1	0.684	0.684	0.684	1511	5	0	0	4	10	0	0	0	0	1	1	0	0	0	1
A24R .S 2	0.747	0.663	0.703	1510	6	0	0	4	10	0	0	0	0	2	0	0	0	0	1
A24R .S 3	0.937	0.787	0.856	1512	4	0	0	1	13	0	0	0	0	2	0	0	0	0	1
A24R .S 4	1.000	0.724	0.840	1510	6	0	0	0	14	0	0	0	0	2	0	0	0	0	1
A24R .S 5	1.000	0.692	0.818	1509	7	0	0	0	14	0	0	0	0	2	0	0	0	0	1
A24R .S 6	0.937	0.678	0.787	1509	7	0	0	1	13	0	0	0	0	2	0	0	0	0	1
A24R .S 7	0.937	0.711	0.809	1510	6	0	0	1	13	0	0	0	0	2	0	0	0	0	1
A24R .S 8	0.937	0.747	0.831	1511	5	0	0	1	13	0	0	0	0	2	0	0	0	0	1
A24R .S 9	1.000	0.759	0.863	1511	5	0	0	0	14	0	0	0	0	2	0	0	0	0	1
A24R .S10	1.000	0.798	0.888	1512	4	0	0	0	14	0	0	0	0	2	0	0	0	0	1
A24R .S11	1.000	0.759	0.863	1511	5	0	0	0	14	0	0	0	0	2	0	0	0	0	1
A24R .S12	1.000	0.759	0.863	1511	5	0	0	0	14	0	0	0	0	2	0	0	0	0	1
A24R .S13	1.000	0.759	0.863	1511	5	0	0	0	14	0	0	0	0	2	0	0	0	0	1
A34R .S 1	0.831	0.711	0.767	2282	8	0	0	3	18	0	0	0	0	2	1	0	0	0	1
A34R .S 2	0.873	0.674	0.761	2280	10	0	0	2	19	0	0	0	0	2	1	0	0	0	1
A34R .S 3	0.915	0.684	0.783	2280	10	0	0	1	20	0	0	0	0	2	1	0	0	0	1
A34R .S 4	0.958	0.694	0.805	2280	10	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S 5	0.958	0.694	0.805	2280	10	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S 6	0.958	0.694	0.805	2280	10	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S 7	0.958	0.716	0.819	2281	9	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S 8	0.958	0.716	0.819	2281	9	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S 9	0.958	0.791	0.866	2284	6	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S10	0.958	0.791	0.866	2284	6	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S11	0.958	0.791	0.866	2284	6	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S12	0.958	0.764	0.850	2283	7	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S13	0.958	0.820	0.883	2285	5	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S14	0.958	0.820	0.883	2285	5	0	0	1	20	0	0	0	0	3	0	0	0	0	1

Table G-1 (Cont'd.)

CLASSIFIER	PRE			BCK ->				SSWA ->				SSWB ->				ART ->			
	P1	P2	P3	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART	BCK	SSWA	SSWB	ART
A34R .S15	0.958	0.791	0.866	2284	6	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S16	0.958	0.764	0.850	2283	7	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S17	0.958	0.764	0.850	2283	7	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S18	0.958	0.791	0.866	2284	6	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S19	0.958	0.791	0.866	2284	6	0	0	1	20	0	0	0	0	3	0	0	0	0	1
A34R .S20	0.958	0.764	0.850	2283	7	0	0	1	20	0	0	0	0	3	0	0	0	0	1

Classifier	PRE			BCK ->		SSW ->	
	P1	P2	P3	BCK	SSW	BCK	SSW
TA12 .S 1	0.324	0.242	0.277	851	9	6	3
TA12 .S 2	0.662	0.495	0.566	854	6	3	6
TA12 .S 3	0.773	0.406	0.532	850	10	2	7
TA12 .S 4	0.887	0.663	0.759	856	4	1	8
TA12 .S 5	0.775	0.697	0.734	857	3	2	7
TA12 .S 6	0.887	0.724	0.798	857	3	1	8
TA12 .S 7	0.888	0.798	0.840	858	2	1	8
TA12 .S 8	0.888	0.798	0.840	858	2	1	8
TA12 .S 9	1.000	0.816	0.899	858	2	0	9
TA12 .S10	1.000	0.816	0.899	858	2	0	9
TS12 .S 1	0.212	0.173	0.191	851	9	7	2
TS12 .S 2	0.551	0.621	0.584	857	3	4	5
TS12 .S 3	0.775	0.579	0.663	855	5	2	7
TS12 .S 4	1.000	0.816	0.899	858	2	0	9
TS12 .S 5	0.888	0.798	0.840	858	2	1	8
TS12 .S 6	0.888	0.798	0.840	858	2	1	8
TS12 .S 7	0.888	0.798	0.840	858	2	1	8
TS12 .S 8	0.888	0.798	0.840	858	2	1	8
TS12 .S 9	0.888	0.798	0.840	858	2	1	8
TC12 .S 1	0.0	1.000	0.0	860	0	9	0
TC12 .S 2	0.549	0.411	0.470	853	7	4	5
TC12 .S 3	0.550	0.449	0.494	854	6	4	5
TC12 .S 4	0.661	0.423	0.516	852	8	3	6
TC12 .S 5	0.661	0.423	0.516	852	8	3	6
TA12R.S 1	0.553	1.000	0.712	745	0	4	5
TA12R.S 2	0.775	0.873	0.822	744	1	2	7
TA12R.S 3	1.000	0.816	0.899	743	2	0	9

Table G-1 (Cont'd.)

Classifier	PRE			BCK ->		SSW ->	
	P1	P2	P3	BCK	SSW	BCK	SSW
TA12R.S 4	0.888	1.000	0.941	745	0	1	8
TA12R.S 5	0.888	1.000	0.941	745	0	1	8
TA12R.S 6	0.776	1.000	0.874	745	0	2	7
TA12R.S 7	0.776	1.000	0.874	745	0	2	7
TA12R.S 8	0.776	1.000	0.874	745	0	2	7
TA12R.S 9	0.776	1.000	0.874	745	0	2	7
TA12R.S10	0.776	1.000	0.874	745	0	2	7
TA12R.S11	0.776	1.000	0.874	745	0	2	7
TS12R.S 1	0.331	1.000	0.497	745	0	6	3
TS12R.S 2	0.776	1.000	0.874	745	0	2	7
TS12R.S 3	1.000	0.816	0.899	743	2	0	9
TS12R.S 4	0.888	1.000	0.941	745	0	1	8
TS12R.S 5	0.888	1.000	0.941	745	0	1	8
TS12R.S 6	0.888	1.000	0.941	745	0	1	8
TS12R.S 7	0.888	1.000	0.941	745	0	1	8
TS12R.S 8	0.888	1.000	0.941	745	0	1	8
TS12R.S 9	0.888	1.000	0.941	745	0	1	8
TS12R.S10	0.888	1.000	0.941	745	0	1	8
TS12R.S11	0.888	1.000	0.941	745	0	1	8
TC12R.S 1	0.0	1.000	0.0	745	0	9	0
TC12R.S 2	0.548	0.410	0.469	738	7	4	5
TC12R.S 3	0.549	0.448	0.493	739	6	4	5
TC12R.S 4	0.660	0.422	0.515	737	8	3	6
TA22R.S 1	0.494	0.465	0.479	1509	9	8	8
TA22R.S 2	0.495	0.495	0.495	1510	8	8	8
TA22R.S 3	0.495	0.528	0.511	1511	7	8	8
TA22R.S 4	0.747	0.628	0.682	1511	7	4	12
TA22R.S 5	0.747	0.628	0.682	1511	7	4	12
TA22R.S 6	0.810	0.615	0.699	1510	8	3	13
TA22R.S 7	0.810	0.719	0.762	1513	5	3	13
TA22R.S 8	0.810	0.762	0.786	1514	4	3	13
TA22R.S 9	0.810	0.762	0.786	1514	4	3	13
TA22R.S10	0.810	0.762	0.786	1514	4	3	13
TA22R.S11	0.810	0.762	0.786	1514	4	3	13
TS22R.S 1	0.558	0.558	0.558	1511	7	7	9
TS22R.S 2	0.558	0.558	0.558	1511	7	7	9
TS22R.S 3	0.810	0.681	0.740	1512	6	3	13
TS22R.S 4	0.747	0.703	0.724	1513	5	4	12
TS22R.S 5	0.747	0.703	0.724	1513	5	4	12
TS22R.S 6	0.747	0.703	0.724	1513	5	4	12
TS22R.S 7	0.747	0.703	0.724	1513	5	4	12
TS22R.S 8	0.748	0.798	0.772	1515	3	4	12
TS22R.S 9	0.748	0.798	0.772	1515	3	4	12

Table G-1 (Cont'd.)

Classifier	PRE			BCK ->		SSW ->	
	P1	P2	P3	BCK	SSW	BCK	SSW
TS22R.S10	0.748	0.798	0.772	1515	3	4	12
TS22R.S11	0.748	0.798	0.772	1515	3	4	12
TC22R.S 1	0.0	1.000	0.0	1518	0	16	0
TC22R.S 2	0.495	0.495	0.495	1510	8	8	8
TC22R.S 3	0.429	0.311	0.361	1503	15	9	7
TC22R.S 4	0.430	0.343	0.382	1505	13	9	7
TA32R.S 1	0.536	0.476	0.504	2278	14	11	13
TA32R.S 2	0.789	0.701	0.742	2284	8	5	19
TA32R.S 3	0.831	0.738	0.782	2285	7	4	20
TA32R.S 4	0.747	0.717	0.732	2285	7	6	18
TA32R.S 5	0.916	0.707	0.798	2283	9	2	22
TA32R.S 6	0.916	0.707	0.798	2283	9	2	22
TA32R.S 7	0.873	0.721	0.790	2284	8	3	21
TA32R.S 8	0.874	0.775	0.822	2286	6	3	21
TA32R.S 9	0.874	0.806	0.838	2287	5	3	21
TA32R.S10	0.874	0.806	0.838	2287	5	3	21
TA32R.S11	0.874	0.806	0.838	2287	5	3	21
TS32R.S 1	0.537	0.615	0.574	2284	8	11	13
TS32R.S 2	0.622	0.747	0.679	2287	5	9	15
TS32R.S 3	0.790	0.862	0.824	2289	3	5	19
TS32R.S 4	0.790	0.824	0.807	2288	4	5	19
TS32R.S 5	0.748	0.816	0.780	2288	4	6	18
TS32R.S 6	0.789	0.789	0.789	2287	5	5	19
TS32R.S 7	0.790	0.824	0.807	2288	4	5	19
TS32R.S 8	0.832	0.832	0.832	2288	4	4	20
TS32R.S 9	0.832	0.832	0.832	2288	4	4	20
TS32R.S10	0.832	0.832	0.832	2288	4	4	20
TS32R.S11	0.832	0.832	0.832	2288	4	4	20
TC32R.S 1	0.373	1.000	0.543	2292	0	15	9
TC32R.S 2	0.577	0.394	0.468	2271	21	10	14
TC32R.S 3	0.575	0.311	0.404	2262	30	10	14
TC32R.S 4	0.491	0.278	0.355	2262	30	12	12
TC32R.S 5	0.533	0.288	0.374	2261	31	11	13
TC32R.S 6	0.491	0.272	0.350	2261	31	12	12

Table G-1 (Cont'd.)

CLASSIFIER	PRE			BCK ->			SSWA ->			SSWB ->		
	P1	P2	P3	BCK	SSWA	SSWB	BCK	SSWA	SSWB	BCK	SSWA	SSWB
TA13 .S 1	0.551	0.551	0.551	856	4	0	4	4	0	0	0	1
TA13 .S 2	0.661	0.394	0.493	851	9	0	3	5	0	0	0	1
TA13 .S 3	0.887	0.528	0.662	853	7	0	1	7	0	0	0	1
TA13 .S 4	0.775	0.579	0.663	855	5	0	2	6	0	0	0	1
TA13 .S 5	0.774	0.534	0.632	854	6	0	2	6	0	0	0	1
TA13 .S 6	0.775	0.633	0.697	856	4	0	2	6	0	0	0	1
TA13 .S 7	0.775	0.579	0.663	855	5	0	2	6	0	0	0	1
TA13 .S 8	0.888	0.798	0.840	858	2	0	1	7	0	0	0	1
TA13 .S 9	0.776	0.874	0.822	859	1	0	2	6	0	0	0	1
TA13 .S10	0.888	0.798	0.840	858	2	0	1	7	0	0	0	1
TA13 .S11	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TA13 .S12	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TA13 .S13	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TA13 .S14	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TA13 .S15	0.888	0.798	0.840	858	2	0	1	7	0	0	0	1
TA13 .S16	0.888	0.798	0.840	858	2	0	1	7	0	0	0	1
TA13 .S17	0.888	0.798	0.840	858	2	0	1	7	0	0	0	1
TA13 .S18	1.000	0.816	0.899	858	2	0	0	8	0	0	0	1
TA13 .S19	0.888	0.798	0.840	858	2	0	1	7	0	0	0	1
TS13 .S 1	0.212	0.173	0.191	851	6	3	7	1	0	0	0	1
TS13 .S 2	0.662	0.541	0.595	855	5	0	3	5	0	0	0	1
TS13 .S 3	0.661	0.423	0.516	852	8	0	3	5	0	0	0	1
TS13 .S 4	1.000	0.596	0.747	854	6	0	0	8	0	0	0	1
TS13 .S 5	1.000	0.596	0.747	854	6	0	0	8	0	0	0	1
TS13 .S 6	1.000	0.596	0.747	854	6	0	0	8	0	0	0	1
TS13 .S 7	1.000	0.639	0.780	855	5	0	0	8	0	0	0	1
TS13 .S 8	1.000	0.639	0.780	855	5	0	0	8	0	0	0	1
TS13 .S 9	0.887	0.611	0.724	855	5	0	1	7	0	0	0	1
TS13 .S10	0.887	0.611	0.724	855	5	0	1	7	0	0	0	1
TS13 .S11	0.887	0.611	0.724	855	5	0	1	7	0	0	0	1
TS13 .S12	0.887	0.611	0.724	855	5	0	1	7	0	0	0	1
TS13 .S13	0.887	0.611	0.724	855	5	0	1	7	0	0	0	1
TS13 .S14	0.887	0.663	0.759	856	4	0	1	7	0	0	0	1
TS13 .S15	0.887	0.663	0.759	856	4	0	1	7	0	0	0	1
TS13 .S16	0.887	0.663	0.759	856	4	0	1	7	0	0	0	1
TS13 .S17	0.887	0.663	0.759	856	4	0	1	7	0	0	0	1
TS13 .S18	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TS13 .S19	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TS13 .S20	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TS13 .S21	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TS13 .S22	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TS13 .S23	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TS13 .S24	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TS13 .S25	0.887	0.724	0.798	857	3	0	1	7	0	0	0	1
TS13 .S26	0.887	0.663	0.759	856	4	0	1	7	0	0	0	1

Table G-1 (Cont'd.)

CLASSIFIER	PRE			BCK ->			SSWA ->			SSWB ->		
	P1	P2	P3	BCK	SSWA	SSWB	BCK	SSWA	SSWB	BCK	SSWA	SSWB
TS13R.S15	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S16	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S17	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S18	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S19	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S20	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S21	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S22	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S23	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S24	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S25	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S26	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S27	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S28	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S29	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TC13R.S 1	0.0	1.000	0.0	745	0	0	8	0	0	1	0	0
TC13R.S 2	0.321	0.205	0.250	734	9	2	5	3	0	1	0	0
TC13R.S 3	0.772	0.361	0.492	733	10	2	2	6	0	0	0	1
TC13R.S 4	0.660	0.393	0.492	736	7	2	3	5	0	0	0	1
TC13R.S 5	0.661	0.494	0.566	739	5	1	3	5	0	0	0	1
TC13R.S 6	0.774	0.494	0.603	738	5	2	2	5	1	0	0	1
TC13R.S 7	0.773	0.431	0.553	736	8	1	2	5	1	0	0	1
TC13R.S 8	0.774	0.494	0.603	738	6	1	2	5	1	0	0	1
TA23R.S 1	0.684	0.607	0.643	1512	6	1	5	9	0	0	0	2
TA23R.S 2	0.746	0.541	0.627	1509	9	1	4	10	0	0	0	2
TA23R.S 3	0.746	0.541	0.627	1509	10	0	4	10	0	0	0	2
TA23R.S 4	0.810	0.561	0.663	1509	10	0	3	11	0	0	0	2
TA23R.S 5	0.810	0.646	0.719	1512	7	0	3	11	0	0	0	2
TA23R.S 6	0.810	0.646	0.719	1512	7	0	3	11	0	0	0	2
TA23R.S 7	0.810	0.646	0.719	1512	7	0	3	11	0	0	0	2
TA23R.S 8	0.810	0.646	0.719	1512	7	0	3	11	0	0	0	2
TA23R.S 9	0.810	0.646	0.719	1512	7	0	3	11	0	0	0	2
TA23R.S10	0.810	0.646	0.719	1512	7	0	3	11	0	0	0	2
TA23R.S11	0.747	0.628	0.682	1512	7	0	4	10	0	0	0	2
TA23R.S12	0.810	0.646	0.719	1512	7	0	3	11	0	0	0	2
TA23R.S13	0.810	0.681	0.740	1513	6	0	3	11	0	0	0	2
TA23R.S14	0.810	0.681	0.740	1513	6	0	3	11	0	0	0	2
TA23R.S15	0.810	0.681	0.740	1513	6	0	3	11	0	0	0	2
TA23R.S16	0.810	0.681	0.740	1513	6	0	3	11	0	0	0	2
TA23R.S17	0.810	0.762	0.786	1515	4	0	3	11	0	0	0	2
TA23R.S18	0.810	0.762	0.786	1515	4	0	3	11	0	0	0	2
TA23R.S19	0.810	0.719	0.762	1514	5	0	3	11	0	0	0	2
TA23R.S20	0.810	0.719	0.762	1514	5	0	3	11	0	0	0	2
TA23R.S21	0.810	0.681	0.740	1513	6	0	3	11	0	0	0	2
TA23R.S22	0.810	0.681	0.740	1513	6	0	3	11	0	0	0	2
TA23R.S23	0.810	0.719	0.762	1514	5	0	3	11	0	0	0	2

Table G-1 (Cont'd.)

CLASSIFIER	PRE			BCK ->			SSWA ->			SSWB ->		
	P1	P2	P3	BCK	SSWA	SSWB	BCK	SSWA	SSWB	BCK	SSWA	SSWB
TC13 .S 1	0.0	1.000	0.0	860	0	0	8	0	0	1	0	0
TC13 .S 2	0.322	0.206	0.251	849	9	2	5	3	0	1	0	0
TC13 .S 3	0.773	0.343	0.475	847	12	1	2	6	0	0	0	1
TC13 .S 4	0.660	0.368	0.473	850	8	2	3	5	0	0	0	1
TC13 .S 5	0.662	0.456	0.540	853	6	1	3	5	0	0	0	1
TC13 .S 6	0.660	0.368	0.473	850	9	1	3	5	0	0	0	1
TC13 .S 7	0.773	0.406	0.532	850	10	0	2	5	1	0	0	1
TC13 .S 8	0.774	0.432	0.554	851	9	0	2	5	1	0	0	1
TC13 .S 9	0.774	0.495	0.604	853	6	1	2	5	1	0	0	1
TC13 .S10	0.773	0.362	0.493	848	9	3	2	5	1	0	0	1
TC13 .S11	0.773	0.343	0.475	847	9	4	2	5	1	0	0	1
TA13R.S 1	0.550	0.494	0.520	740	5	0	4	4	0	0	0	1
TA13R.S 2	0.774	0.632	0.696	741	4	0	2	6	0	0	0	1
TA13R.S 3	0.887	0.663	0.759	741	4	0	1	7	0	0	0	1
TA13R.S 4	0.887	0.663	0.759	741	4	0	1	7	0	0	0	1
TA13R.S 5	0.887	0.663	0.759	741	4	0	1	7	0	0	0	1
TA13R.S 6	0.887	0.663	0.759	741	4	0	1	7	0	0	0	1
TA13R.S 7	0.887	0.798	0.840	743	2	0	1	7	0	0	0	1
TA13R.S 8	0.775	0.873	0.822	744	1	0	2	6	0	0	0	1
TA13R.S 9	0.775	0.873	0.822	744	1	0	2	6	0	0	0	1
TA13R.S10	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TA13R.S11	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TA13R.S12	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TA13R.S13	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TA13R.S14	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TA13R.S15	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TA13R.S16	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TA13R.S17	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TA13R.S18	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TA13R.S19	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TA13R.S20	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TA13R.S21	0.888	0.888	0.888	744	1	0	1	7	0	0	0	1
TS13R.S 1	0.663	0.747	0.703	743	2	0	3	5	0	0	0	1
TS13R.S 2	0.776	1.000	0.874	745	0	0	2	6	0	0	0	1
TS13R.S 3	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S 4	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S 5	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S 6	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S 7	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S 8	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S 9	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S10	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S11	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S12	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S13	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1
TS13R.S14	0.888	1.000	0.941	745	0	0	1	7	0	0	0	1

Table G-1 (Cont'd.)

CLASSIFIER	PRE			BCK ->			SSWA ->			SSWB ->		
	P1	P2	P3	BCK	SSWA	SSWB	BCK	SSWA	SSWB	BCK	SSWA	SSWB
TA23R.S24	0.810	0.719	0.762	1514	5	0	3	11	0	0	0	2
TA23R.S25	0.810	0.719	0.762	1514	5	0	3	11	0	0	0	2
TA23R.S26	0.810	0.719	0.762	1514	5	0	3	11	0	0	0	2
TA23R.S27	0.810	0.719	0.762	1514	5	0	3	11	0	0	0	2
TA23R.S28	0.810	0.719	0.762	1514	5	0	3	11	0	0	0	2
TS23R.S 1	0.432	0.432	0.432	1510	9	0	9	4	1	0	1	1
TS23R.S 2	0.620	0.471	0.535	1508	11	0	6	8	0	0	1	1
TS23R.S 3	0.810	0.681	0.740	1513	6	0	3	11	0	0	1	1
TS23R.S 4	0.747	0.663	0.703	1513	6	0	4	10	0	0	0	2
TS23R.S 5	0.747	0.747	0.747	1515	4	0	4	10	0	0	0	2
TS23R.S 6	0.747	0.703	0.724	1514	5	0	4	10	0	0	0	2
TS23R.S 7	0.747	0.703	0.724	1514	5	0	4	10	0	0	0	2
TS23R.S 8	0.747	0.703	0.724	1514	5	0	4	10	0	0	0	2
TS23R.S 9	0.747	0.703	0.724	1514	5	0	4	10	0	0	0	2
TS23R.S10	0.810	0.719	0.762	1514	5	0	3	11	0	0	0	2
TS23R.S11	0.873	0.734	0.798	1514	5	0	2	12	0	0	0	2
TS23R.S12	0.873	0.734	0.798	1514	5	0	2	12	0	0	0	2
TS23R.S13	0.810	0.719	0.762	1514	5	0	3	11	0	0	0	2
TS23R.S14	0.747	0.747	0.747	1515	4	0	4	10	0	0	0	2
TS23R.S15	0.747	0.747	0.747	1515	4	0	4	10	0	0	0	2
TS23R.S16	0.747	0.747	0.747	1515	4	0	4	10	0	0	0	2
TS23R.S17	0.747	0.747	0.747	1515	4	0	4	10	0	0	0	2
TS23R.S18	0.874	0.775	0.822	1515	4	0	2	12	0	0	0	2
TS23R.S19	0.874	0.775	0.822	1515	4	0	2	12	0	0	0	2
TS23R.S20	0.810	0.762	0.786	1515	4	0	3	11	0	0	0	2
TS23R.S21	0.873	0.697	0.775	1513	6	0	2	12	0	0	0	2
TS23R.S22	0.873	0.697	0.775	1513	6	0	2	12	0	0	0	2
TS23R.S23	0.873	0.734	0.798	1514	5	0	2	12	0	0	0	2
TS23R.S24	0.873	0.734	0.798	1514	5	0	2	12	0	0	0	2
TS23R.S25	0.873	0.734	0.798	1514	5	0	2	12	0	0	0	2
TS23R.S26	0.873	0.734	0.798	1514	5	0	2	12	0	0	0	2
TS23R.S27	0.873	0.697	0.775	1513	6	0	2	12	0	0	0	2
TS23R.S28	0.873	0.697	0.775	1513	6	0	2	12	0	0	0	2
TS23R.S29	0.873	0.734	0.798	1514	5	0	2	12	0	0	0	2
TS23R.S30	0.873	0.697	0.775	1513	6	0	2	12	0	0	0	2
TC23R.S 1	0.0	1.000	0.0	1519	0	0	14	0	0	2	0	0
TC23R.S 2	0.367	0.293	0.326	1505	12	2	9	5	0	1	0	1
TC23R.S 3	0.619	0.411	0.494	1505	13	1	6	7	1	0	0	2
TC23R.S 4	0.681	0.360	0.471	1500	18	1	5	8	1	0	0	2
TC23R.S 5	0.682	0.417	0.518	1504	14	1	5	8	1	0	0	2
TC23R.S 6	0.620	0.449	0.521	1507	12	0	6	7	1	0	0	2
TC23R.S 7	0.683	0.519	0.590	1509	10	0	5	7	2	0	0	2
TC23R.S 8	0.682	0.401	0.505	1503	13	3	5	7	2	0	0	2
TC23R.S 9	0.745	0.394	0.515	1501	14	4	4	7	3	0	0	2
TC23R.S10	0.809	0.442	0.572	1503	13	3	3	8	3	0	0	2
TC23R.S11	0.809	0.442	0.572	1503	13	3	3	8	3	0	0	2

Table G-1 (Cont'd.)

CLASSIFIER	PRE			BCK ->			SSWA ->			SSWB ->		
	P1	P2	P3	BCK	SSWA	SSWB	BCK	SSWA	SSWB	BCK	SSWA	SSWB
TC23R.S12	0.809	0.442	0.572	1503	13	3	3	8	3	0	0	2
TC23R.S13	0.745	0.381	0.504	1500	16	3	4	8	2	0	0	2
TC23R.S14	0.681	0.373	0.482	1501	15	3	5	8	1	0	0	2
TC23R.S15	0.681	0.360	0.471	1500	16	3	5	8	1	0	0	2
TC23R.S16	0.681	0.373	0.482	1501	15	3	5	8	1	0	0	2
TC23R.S17	0.746	0.439	0.552	1504	13	2	4	8	2	0	0	2
TA33R.S 1	0.747	0.717	0.732	2283	7	0	6	13	2	0	0	3
TA33R.S 2	0.831	0.711	0.767	2282	7	1	4	15	2	0	0	3
TA33R.S 3	0.831	0.686	0.752	2281	9	0	4	17	0	0	0	3
TA33R.S 4	0.873	0.721	0.790	2282	8	0	3	18	0	0	0	3
TA33R.S 5	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TA33R.S 6	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TA33R.S 7	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TA33R.S 8	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TA33R.S 9	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TA33R.S10	0.916	0.783	0.844	2284	6	0	2	19	0	0	0	3
TA33R.S11	0.916	0.783	0.844	2284	6	0	2	19	0	0	0	3
TA33R.S12	0.916	0.756	0.828	2283	7	0	2	19	0	0	0	3
TA33R.S13	0.916	0.783	0.844	2284	6	0	2	19	0	0	0	3
TA33R.S14	0.916	0.756	0.828	2283	7	0	2	19	0	0	0	3
TA33R.S15	0.916	0.756	0.828	2283	6	1	2	19	0	0	0	3
TA33R.S16	0.916	0.756	0.828	2283	6	1	2	19	0	0	0	3
TA33R.S17	0.916	0.756	0.828	2283	6	1	2	19	0	0	0	3
TA33R.S18	0.916	0.756	0.828	2283	6	1	2	19	0	0	0	3
TA33R.S19	0.916	0.756	0.828	2283	6	1	2	19	0	0	0	3
TA33R.S20	0.916	0.756	0.828	2283	7	0	2	19	0	0	0	3
TS33R.S 1	0.705	0.626	0.663	2280	10	0	7	13	1	0	1	2
TS33R.S 2	0.705	0.650	0.677	2281	9	0	7	13	1	0	1	2
TS33R.S 3	0.705	0.650	0.677	2281	9	0	7	13	1	0	0	3
TS33R.S 4	0.831	0.686	0.752	2281	9	0	4	16	1	0	0	3
TS33R.S 5	0.832	0.798	0.814	2285	5	0	4	16	1	0	0	3
TS33R.S 6	0.874	0.806	0.838	2285	5	0	3	17	1	0	0	3
TS33R.S 7	0.874	0.806	0.838	2285	5	0	3	18	0	0	0	3
TS33R.S 8	0.874	0.806	0.838	2285	5	0	3	18	0	0	0	3
TS33R.S 9	0.874	0.806	0.838	2285	5	0	3	18	0	0	0	3
TS33R.S10	0.874	0.806	0.838	2285	5	0	3	18	0	0	0	3
TS33R.S11	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S12	0.873	0.747	0.806	2283	7	0	3	18	0	0	0	3
TS33R.S13	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S14	0.916	0.783	0.844	2284	6	0	2	19	0	0	0	3
TS33R.S15	0.916	0.783	0.844	2284	6	0	2	19	0	0	0	3
TS33R.S16	0.916	0.783	0.844	2284	6	0	2	19	0	0	0	3
TS33R.S17	0.916	0.783	0.844	2284	6	0	2	19	0	0	0	3
TS33R.S18	0.916	0.783	0.844	2284	6	0	2	19	0	0	0	3
TS33R.S19	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S20	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3

Table G-1 (Cont'd.)

CLASSIFIER	PRE			BCK ->			SSWA ->			SSWB ->		
	P1	P2	P3	BCK	SSWA	SSWB	BCK	SSWA	SSWB	BCK	SSWA	SSWB
TS33R.S21	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S22	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S23	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S24	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S25	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S26	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S27	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S28	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S29	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S30	0.873	0.747	0.806	2283	7	0	3	18	0	0	0	3
TS33R.S31	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S32	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S33	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S34	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S35	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S36	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S37	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S38	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S39	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S40	0.874	0.775	0.822	2284	6	0	3	18	0	0	0	3
TS33R.S41	0.874	0.838	0.856	2286	4	0	3	18	0	0	0	3
TS33R.S42	0.874	0.838	0.856	2286	4	0	3	18	0	0	0	3
TS33R.S43	0.874	0.838	0.856	2286	4	0	3	18	0	0	0	3
TS33R.S44	0.874	0.838	0.856	2286	4	0	3	18	0	0	0	3
TC33R.S 1	0.372	0.899	0.527	2289	0	1	14	0	7	1	0	2
TC33R.S 2	0.745	0.413	0.531	2265	22	3	6	14	1	0	0	3
TC33R.S 3	0.745	0.377	0.500	2261	28	1	6	13	2	0	0	3
TC33R.S 4	0.787	0.398	0.529	2262	26	2	5	14	2	0	0	3
TC33R.S 5	0.788	0.426	0.553	2265	23	2	5	14	2	0	0	3
TC33R.S 6	0.787	0.359	0.493	2257	26	7	5	13	3	0	0	3
TC33R.S 7	0.788	0.416	0.545	2264	22	4	5	13	3	0	0	3
TC33R.S 8	0.830	0.429	0.566	2264	21	5	4	14	3	0	0	3
TC33R.S 9	0.830	0.411	0.549	2262	23	5	4	14	3	0	0	3
TC33R.S10	0.872	0.423	0.569	2262	24	4	3	14	4	0	0	3
TC33R.S11	0.830	0.394	0.534	2260	26	4	4	13	4	0	0	3
TC33R.S12	0.745	0.361	0.486	2259	26	5	6	13	2	0	0	3
TC33R.S13	0.788	0.426	0.553	2265	20	5	5	14	2	0	0	3
TC33R.S14	0.746	0.444	0.557	2268	18	4	6	13	2	0	0	3
TC33R.S15	0.830	0.449	0.583	2266	18	6	4	13	4	0	0	3
TC33R.S16	0.703	0.442	0.543	2269	18	3	7	13	1	0	0	3
TC33R.S17	0.788	0.436	0.561	2266	21	3	5	13	3	0	0	3
TC33R.S18	0.746	0.444	0.557	2268	19	3	6	13	2	0	0	3

Appendix H

Example List of Events with Classificaiton
and Posterior Probabilities

Table H-1 List of Classified Events Except Correctly Classified Backgrounds by A14R.S14, with Event Identifiers (FILE, EVENT, TIME), Classification (TYPE: Original label, PERDICTD: Classified label, CORRECTN: Correction indicator), and Posterior probabilities P(.).

FILE	EVENT	TYPE	PREDICTD	CORRECTN	TIME	P(BCK)	P(SSWA)	P(SSWB)	P(ART)
1	307	BCK	SSWA	1	11.410	0.0	1.000	0.0	0.0
1	309	SSW	SSWB	0	11.510	0.0	0.0	1.000	0.0
1	311	BCK	SSWA	1	11.540	0.0	1.000	0.0	0.0
1	325	SSW	SSWA	0	12.550	0.0	1.000	0.0	0.0
1	351	SSW	SSWA	0	13.685	0.0	1.000	0.0	0.0
1	581	SSW	SSWA	0	22.970	0.0	1.000	0.0	0.0
1	1163	SSW	SSWA	0	47.110	0.0	1.000	0.0	0.0
1	1181	SSW	SSWA	0	48.130	0.0	1.000	0.0	0.0
1	1183	BCK	SSWA	1	48.295	0.0	1.000	0.0	0.0
1	1185	BCK	SSWA	1	48.325	0.444	0.556	0.0	0.0
1	1191	SSW	SSWA	0	48.795	0.0	1.000	0.0	0.0
1	1193	BCK	SSWA	1	48.865	0.056	0.944	0.0	0.0
1	1565	BCK	SSWA	1	63.440	0.002	0.998	0.0	0.0
1	1569	SSW	SSWA	0	63.595	0.0	1.000	0.0	0.0
1	1613	ART	ART	0	65.415	0.0	0.0	0.0	1.000
1	1659	SSW	SSWA	0	67.255	0.0	1.000	0.0	0.0
2	53	BCK	SSWA	0	2.210	0.006	0.994	0.0	0.0
2	89	SSW	SSWA	0	3.855	0.0	1.000	0.0	0.0
2	101	SSW	SSWA	0	4.595	0.0	1.000	0.0	0.0
2	255	SSW	SSWA	0	10.695	0.0	1.000	0.0	0.0
2	271	SSW	SSWA	0	11.700	0.0	1.000	0.0	0.0
2	727	SSW	BCK	1	30.465	1.000	0.0	0.0	0.0
2	729	BCK	SSWA	1	30.495	0.0	1.000	0.0	0.0
2	731	BCK	SSWA	1	30.705	0.0	0.952	0.0	0.048
2	913	BCK	SSWA	0	38.060	0.0	1.000	0.0	0.0
2	1241	BCK	SSWA	0	51.005	0.0	1.000	0.0	0.0
2	1269	BCK	SSWA	0	52.570	0.0	1.000	0.0	0.0
2	1365	BCK	SSWA	0	56.620	0.0	1.000	0.0	0.0
2	1401	BCK	SSWA	1	58.035	0.0	1.000	0.0	0.0
2	1403	SSW	ART	1	58.150	0.0	0.0	0.0	1.000
2	1405	BCK	SSWA	1	58.185	0.0	1.000	0.0	0.0
2	1419	SSW	SSWA	0	58.850	0.0	1.000	0.0	0.0
3	95	BCK	SSWA	1	3.415	0.0	1.000	0.0	0.0
3	97	SSW	SSWB	0	3.480	0.0	0.0	1.000	0.0
3	99	BCK	SSWA	1	3.510	0.0	1.000	0.0	0.0

Table H-1 (Cont'd.)

FILE	EVENT	TYPE	PREDICTD	CORRECTN	TIME	P(BCK)	P(SSWA)	P(SSWB)	P(ART)
3	105	BCK	SSWA	0	3.915	0.033	0.967	0.0	0.0
3	225	SSW	SSWA	0	9.005	0.0	1.000	0.0	0.0
3	471	SSW	BCK	0	18.805	1.000	0.0	0.0	0.0
3	745	SSW	SSWA	0	29.185	0.0	1.000	0.0	0.0
3	757	SSW	SSWA	0	29.770	0.0	1.000	0.0	0.0
3	769	BCK	SSWA	0	30.450	0.209	0.791	0.0	0.0
3	875	SSW	SSWA	0	34.525	0.0	1.000	0.0	0.0
3	1069	BCK	SSWA	0	42.440	0.0	1.000	0.0	0.0
3	1429	BCK	SSWA	0	56.600	0.0	1.000	0.0	0.0
3	1515	BCK	SSWA	0	60.370	0.0	1.000	0.0	0.0
3	1569	SSW	SSWA	0	62.640	0.0	1.000	0.0	0.0
3	1571	BCK	SSWA	1	62.880	0.0	1.000	0.0	0.0
3	1597	BCK	SSWA	1	63.955	0.038	0.962	0.0	0.0
3	1599	SSW	SSWA	0	63.995	0.0	1.000	0.0	0.0
3	1601	BCK	SSWA	1	64.055	0.0	1.000	0.0	0.0
4	345	BCK	SSWA	0	13.155	0.0	1.000	0.0	0.0
4	613	BCK	SSWA	1	23.515	0.0	1.000	0.0	0.0
4	615	SSW	ART	1	23.655	0.0	0.0	0.0	1.000
4	673	SSW	SSWA	0	26.330	0.0	1.000	0.0	0.0
4	733	SSW	SSWB	0	29.135	0.0	0.0	1.000	0.0
4	735	BCK	SSWA	1	29.165	0.0	1.000	0.0	0.0
4	1621	SSW	SSWA	0	64.415	0.0	1.000	0.0	0.0
5	347	BCK	SSWA	0	13.010	0.343	0.657	0.0	0.0
5	955	SSW	BCK	1	36.845	1.000	0.0	0.0	0.0
5	957	BCK	SSWA	1	36.880	0.0	1.000	0.0	0.0
5	1423	SSW	ART	1	56.545	0.0	0.0	0.0	1.000
5	1425	BCK	SSWA	1	56.570	0.0	1.000	0.0	0.0
5	1461	SSW	SSWA	0	58.210	0.0	1.000	0.0	0.0
5	1595	BCK	SSWA	0	63.655	0.0	1.000	0.0	0.0
6	257	BCK	SSWA	0	9.540	0.0	1.000	0.0	0.0
6	349	BCK	SSWA	0	13.365	0.0	1.000	0.0	0.0
6	577	SSW	SSWA	0	22.955	0.0	1.000	0.0	0.0
6	595	BCK	SSWA	0	23.960	0.0	1.000	0.0	0.0
6	871	SSW	SSWA	0	34.780	0.0	1.000	0.0	0.0
6	873	BCK	SSWA	1	35.085	0.0	1.000	0.0	0.0
6	1429	BCK	SSWA	0	56.745	0.001	0.999	0.0	0.0
6	1447	SSW	SSWA	0	57.585	0.0	1.000	0.0	0.0
6	1569	BCK	SSWA	0	62.240	0.0	1.000	0.0	0.0
7	49	SSW	SSWA	0	1.460	0.0	1.000	0.0	0.0
7	527	SSW	ART	1	21.140	0.0	0.0	0.0	1.000

Table H-1 (Cont'd.)

FILE	EVENT	TYPE	PREDICTD	CORRECTN	TIME	P(BCK)	P(SSWA)	P(SSWB)	P(ART)
7	529	BCK	SSWA	1	21.170	0.0	1.000	0.0	0.0
7	613	SSW	ART	1	24.355	0.0	0.0	0.0	1.000
7	615	BCK	SSWA	1	24.380	0.0	1.000	0.0	0.0
7	741	SSW	SSWA	0	29.665	0.0	1.000	0.0	0.0
7	743	BCK	SSWA	1	29.930	0.0	1.000	0.0	0.0
7	785	DBS	BCK	0	31.995	0.789	0.211	0.0	0.0
7	801	BCK	SSWA	0	32.700	0.0	1.000	0.0	0.0
7	1101	SSW	SSWA	0	44.205	0.0	1.000	0.0	0.0
7	1531	BCK	SSWA	1	60.925	0.0	1.000	0.0	0.0
7	1533	SSW	SSWB	0	61.030	0.0	0.0	1.000	0.0
7	1535	BCK	SSWA	1	61.070	0.0	1.000	0.0	0.0
7	1651	BCK	SSWA	1	65.450	0.0	1.000	0.0	0.0
7	1653	SSW	ART	1	65.535	0.0	0.0	0.0	1.000
7	1655	BCK	SSWA	1	65.570	0.0	1.000	0.0	0.0
7	1739	BCK	SSWA	0	68.880	0.007	0.993	0.0	0.0
8	113	DBS	SSWA	0	4.095	0.0	1.000	0.0	0.0
8	115	DBS	SSWA	0	4.195	0.0	1.000	0.0	0.0
8	185	BCK	SSWA	0	7.330	0.0	1.000	0.0	0.0
8	939	DBS	SSWA	0	36.490	0.0	1.000	0.0	0.0
8	1099	SSW	SSWA	0	43.105	0.0	1.000	0.0	0.0
8	1147	SSW	SSWA	0	45.610	0.0	1.000	0.0	0.0
8	1599	BCK	SSWA	0	63.090	0.0	1.000	0.0	0.0
8	1607	SSW	BCK	1	63.610	1.000	0.0	0.0	0.0
8	1609	BCK	SSWA	1	63.640	0.0	1.000	0.0	0.0
9	13	BCK	SSWA	0	0.615	0.439	0.561	0.0	0.0
9	319	BCK	SSWA	0	13.660	0.0	1.000	0.0	0.0
9	421	SSW	BCK	1	17.760	1.000	0.0	0.0	0.0
9	423	BCK	SSWA	1	17.835	0.028	0.972	0.0	0.0
9	935	BCK	SSWA	0	39.430	0.0	1.000	0.0	0.0
9	955	BCK	SSWA	0	40.550	0.0	1.000	0.0	0.0
9	1091	DBS	SSWA	0	45.920	0.0	1.000	0.0	0.0
10	449	SSW	BCK	0	17.865	0.989	0.011	0.0	0.0
10	549	SSW	SSWA	0	21.395	0.0	1.000	0.0	0.0
10	551	BCK	SSWA	1	21.425	0.0	1.000	0.0	0.0
10	553	BCK	SSWB	1	21.600	0.0	0.0	1.000	0.0
10	555	BCK	SSWA	0	21:635	0.0	1.000	0.0	0.0
10	557	BCK	ART	0	21.895	0.0	0.0	0.0	1.000
10	707	DBS	SSWA	0	28.505	0.0	1.000	0.0	0.0
10	963	ART	SSWA	0	37.870	0.0	1.000	0.0	0.0
10	1033	BCK	SSWA	0	40.150	0.001	0.999	0.0	0.0

Table H-1 (Cont'd.)

FILE	EVENT	TYPE	PREDICTD	CORRECTN	TIME	P(BCK)	P(SSWA)	P(SSWB)	P(ART)
10	1307	DBS	SSWA	0	50.430	0.108	0.892	0.0	0.0
10	1755	BCK	SSWA	0	68.460	0.0	1.000	0.0	0.0
10	1763	SSW	SSWA	0	68.950	0.0	1.000	0.0	0.0
11	131	DBS	SSWA	0	4.920	0.0	1.000	0.0	0.0
11	205	SSW	SSWA	0	7.955	0.0	1.000	0.0	0.0
11	207	BCK	SSWA	1	7.985	0.496	0.504	0.0	0.0
11	249	SSW	SSWA	0	9.970	0.0	1.000	0.0	0.0
11	251	BCK	SSWA	1	10.200	0.073	0.927	0.0	0.0
11	253	BCK	ART	0	10.245	0.0	0.0	0.0	1.000
11	393	SSW	SSWA	0	16.205	0.0	1.000	0.0	0.0
11	971	BCK	SSWA	1	41.525	0.002	0.998	0.0	0.0
11	973	SSW	SSWA	0	41.645	0.0	1.000	0.0	0.0
11	1051	SSW	SSWA	0	44.935	0.0	1.000	0.0	0.0
11	1437	SSW	SSWA	0	61.980	0.0	1.000	0.0	0.0
11	1517	SSW	SSWA	0	65.420	0.0	1.000	0.0	0.0
12	55	BCK	SSWA	1	2.545	0.0	1.000	0.0	0.0
12	57	SSW	SSWB	0	2.600	0.0	0.0	1.000	0.0
12	59	BCK	SSWA	1	2.625	0.0	1.000	0.0	0.0
12	373	BCK	SSWA	0	15.190	0.0	1.000	0.0	0.0
12	393	BCK	SSWA	0	16.075	0.049	0.951	0.0	0.0
12	531	BCK	SSWA	1	21.880	0.0	1.000	0.0	0.0
12	533	SSW	SSWB	0	21.990	0.0	0.0	1.000	0.0
12	535	BCK	SSWA	1	22.020	0.0	1.000	0.0	0.0
12	679	BCK	SSWA	0	28.095	0.0	1.000	0.0	0.0
12	1071	SSW	ART	0	44.530	0.0	0.0	0.0	1.000
12	1109	BCK	SSWA	0	46.345	0.0	1.000	0.0	0.0
12	1277	SSW	SSWA	0	53.265	0.0	1.000	0.0	0.0
12	1281	BCK	SSWA	1	53.585	0.0	1.000	0.0	0.0
12	1317	BCK	SSWA	1	55.050	0.004	0.996	0.0	0.0
12	1319	SSW	ART	1	55.175	0.0	0.0	0.0	1.000
12	1321	BCK	SSWA	1	55.200	0.0	1.000	0.0	0.0
12	1327	BCK	SSWA	0	55.670	0.0	1.000	0.0	0.0
12	1335	SSW	SSWA	0	56.145	0.0	1.000	0.0	0.0
12	1385	SSW	SSWA	0	58.315	0.0	1.000	0.0	0.0
12	1425	BCK	SSWA	0	60.055	0.0	1.000	0.0	0.0
12	1507	DBS	SSWA	0	63.590	0.0	1.000	0.0	0.0
13	205	SSW	SSWA	0	8.550	0.0	1.000	0.0	0.0
13	207	BCK	SSWA	1	8.805	0.0	1.000	0.0	0.0
13	241	SSW	SSWA	0	10.075	0.0	1.000	0.0	0.0
13	243	BCK	SSWA	1	10.175	0.0	1.000	0.0	0.0

Table H-1 (Cont'd.)

FILE	EVENT	TYPE	PREDICID	CORRECTN	TIME	P(BCK)	P(SSWA)	P(SSWB)	P(ART)
13	437	BCK	SSWA	0	17.900	0.001	0.999	0.0	0.0
13	447	SSW	SSWA	0	18.280	0.0	1.000	0.0	0.0
13	635	BCK	SSWA	0	26.155	0.0	1.000	0.0	0.0
13	995	SSW	SSWA	0	41.385	0.0	1.000	0.0	0.0
13	1111	ART	ART	0	46.300	0.0	0.0	0.0	1.000
13	1199	SSW	SSWA	0	50.020	0.0	1.000	0.0	0.0
13	1277	BCK	SSWA	1	53.370	0.0	1.000	0.0	0.0
13	1279	SSW	SSWB	0	53.475	0.0	0.0	1.000	0.0
13	1281	BCK	SSWA	1	53.505	0.0	1.000	0.0	0.0
13	1325	SSW	SSWA	0	55.470	0.0	1.000	0.0	0.0
13	1327	BCK	SSWA	1	55.640	0.0	1.000	0.0	0.0
13	1329	BCK	SSWA	1	55.700	0.0	1.000	0.0	0.0
14	373	BCK	SSWA	0	14.815	0.0	1.000	0.0	0.0
14	475	SSW	SSWA	0	19.210	0.0	1.000	0.0	0.0
14	477	BCK	SSWA	1	19.265	0.0	1.000	0.0	0.0
14	479	BCK	SSWA	1	19.505	0.0	1.000	0.0	0.0
14	555	BCK	SSWA	0	22.875	0.0	1.000	0.0	0.0
14	927	BCK	SSWA	1	38.725	0.0	1.000	0.0	0.0
14	929	SSW	ART	1	38.820	0.0	0.0	0.0	1.000
14	931	BCK	SSWA	1	38.850	0.0	1.000	0.0	0.0
14	1145	SSW	SSWA	0	47.625	0.0	1.000	0.0	0.0
14	1163	BCK	SSWA	0	48.665	0.0	1.000	0.0	0.0
14	1199	SSW	SSWA	0	50.585	0.0	1.000	0.0	0.0
14	1351	DBS	BCK	0	56.475	1.000	0.0	0.0	0.0
14	1403	SSW	SSWA	0	58.795	0.0	1.000	0.0	0.0
14	1425	BCK	SSWA	0	60.035	0.0	1.000	0.0	0.0
14	1491	SSW	ART	0	62.585	0.0	0.0	0.0	1.000
14	1511	BCK	SSWA	0	63.545	0.0	1.000	0.0	0.0
14	1569	SSW	SSWA	0	66.040	0.0	1.000	0.0	0.0
15	33	BCK	SSWA	0	1.465	0.0	1.000	0.0	0.0
15	41	SSW	SSWA	0	1.965	0.0	1.000	0.0	0.0
15	43	BCK	SSWA	1	2.015	0.0	1.000	0.0	0.0
15	103	SSW	BCK	1	4.795	1.000	0.0	0.0	0.0
15	105	BCK	SSWA	1	4.875	0.009	0.991	0.0	0.0
15	571	BCK	SSWA	0	23.260	0.0	1.000	0.0	0.0
15	585	BCK	SSWA	0	24.005	0.0	1.000	0.0	0.0
15	833	SSW	SSWA	0	34.330	0.0	1.000	0.0	0.0
15	835	BCK	SSWA	1	34.450	0.335	0.665	0.0	0.0
15	891	SSW	SSWA	0	36.820	0.0	1.000	0.0	0.0

Appendix I

Comparison of Calculation Efficiency Between Three Types of Classifiers

In the following, the Bayes classifiers, the canonical classifiers with absolute measure, and the canonical classifiers with square measure are compared with each other in regard with calculation efficiency. The following discussion is based on the operation numbers presented in Table 6.2.

When the number of multiplications are compared, a canonical classifier with absolute measure always has the smallest. When the number s of multiplications between a Bayes classifier and a canonical classifier with square measure are compared, the number for the canonical classifiers is less if

$$J-K \geq \frac{K^2}{I-K} \tag{I.1}$$

stands where $K \leq \min(I-1,J)$.

When K=1, (6.1) stands except for (I,J)=(2,2).

When K=2, (6.1) stands except for (I,J)=(3,3),(4,3),(5,3),(6,3),(3,4),(4,4),(3,5),(3,6), and (L,2) where L=3,4,5,... .

When K=3, (6.1) stands except for (I,J)=(4,4),(5,4),(6,4),(7,4),(8,4),(9,4),(10,4),(11,4),(12,4),(4,5),(5,5),(6,5),(4,6),(5,6),(6,6),(4,7),(5,7),(4,8),(4,9),(4,10),(4,11),(4,12), and (L,3) where L=4,5,6,... .

If multiplications and additions are treated equally, and absolute operations, which can be done by changing a sign bit in a microcomputer, are ignored, the total number of operations for a Bayes classifier is $2*J*I$, and for a canonical classifier with absolute measure is $(2J-1)*K+I*(K-1)$. Let the total number of operations for a Bayes classifier, a canonical classifier with absolute measure, and a canonical classifier with square measure be named B, CA, and CS. Under a restriction of $K \le \min(I-1,J)$, the following stands.

When K=1, B≥CA and B≥CS stands always.

When K=2, B≥CA stands always, and B≥CS stands except for (I,J)= (3,2),(4,2),(5,2),(6,2), and (3,3).

When K=3, B≥CA stands except for (I,J)=(L,1) and (4,2) where L=4,5,6,...; Likewise, when K=3, B≥CS stands except for (I,J)=(L1,2),(L2,3), (4,4),(5,4),(6,4), (7,4),(4,5),(5,5),(4,6),(4,7), and (4,8) where L1=4,5,6,... and L2=4,5,6,...,15.

Appendix J

Averaged Parameter Values in Method A

Table J-1 Averaged Parameter Values in Method A in the First Three Data Sets, Obtained from the Output of BMDP7M in the Experiment A34R. The values are means with their standard deviations in parentheses. The units are [μV] for amplitudes, [μV/msec.] for slopes, and [sec.] for durations.

	BCK	SSWA	SSWB	ART
Sample Number	2290	21	3	1
AP1	6.67357 (5.23326)	8.75226 (11.64410)	6.32083 (5.68881)	1.11000 (0.0)
D11	-0.16890 (0.10168)	-0.16870 (0.12131)	-0.06783 (0.04171)	-0.18500 (0.0)
D21	0.16241 (0.11237)	0.16298 (0.12745)	0.09558 (0.03738)	0.10175 (0.0)
DU1	0.03890 (0.02728)	0.03881 (0.02345)	0.03667 (0.02021)	0.01500 (0.0)
AP2	-6.70790 (5.05884)	-11.07798 (10.68063)	-3.94667 (4.78533)	-3.14500 (0.0)
D12	0.16564 (0.12546)	0.19821 (0.16595)	0.18500 (0.13967)	0.06475 (0.0)
D22	-0.14919 (0.12578)	-0.20879 (0.21967)	-0.17267 (0.16812)	-0.02775 (0.0)
DU2	0.04101 (0.02350)	0.04952 (0.03482)	0.02500 (0.01323)	0.03500 (0.0)
AP3	6.67639 (5.21417)	8.57607 (6.41086)	4.68667 (5.07347)	12.21000 (0.0)
D13	-0.16909 (0.10166)	-0.22817 (0.18051)	-0.06167 (0.01068)	-0.14800 (0.0)
D23	0.16295 (0.11264)	0.20879 (0.10589)	0.17575 (0.0)	0.34225 (0.0)
DU3	0.03842 (0.02295)	0.03571 (0.01989)	0.02500 (0.02598)	0.05000 (0.0)
AP4	-6.70031 (5.02746)	-9.20595 (6.92030)	-3.17583 (2.06076)	-1.75750 (0.0)
D14	0.16541 (0.12519)	0.21715 (0.09656)	0.14183 (0.05875)	0.24975 (0.0)
D24	-0.14896 (0.12585)	-0.21715 (0.15170)	-0.12025 (0.06475)	-0.02775 (0.0)
DU4	0.04098 (0.02338)	0.04857 (0.02703)	0.03167 (0.03329)	0.04000 (0.0)
AP5	6.68100 (5.23195)	7.36476 (7.70000)	5.79667 (2.89915)	1.66500 (0.0)
D15	-0.16950 (0.10195)	-0.14404 (0.09598)	-0.15725 (0.06475)	-0.14800 (0.0)
D25	0.16289 (0.11266)	0.13655 (0.08116)	0.13258 (0.04656)	0.16650 (0.0)
DU5	0.03845 (0.02293)	0.04690 (0.03747)	0.04000 (0.03041)	0.01000 (0.0)
AP6	-6.68379 (5.03283)	-8.88881 (6.85503)	-6.59833 (3.88537)	-3.70000 (0.0)
D16	0.16528 (0.12523)	0.15196 (0.20104)	0.21275 (0.10005)	0.16650 (0.0)
D26	-0.14897 (0.12593)	-0.17179 (0.15260)	-0.14800 (0.12445)	-0.11100 (0.0)
DU6	0.04092 (0.02342)	0.04548 (0.02355)	0.02833 (0.00577)	0.03500 (0.0)
AP7	6.69789 (5.25628)	7.86690 (6.61148)	2.62083 (1.66585)	0.74000 (0.0)
D17	-0.16927 (0.10136)	-0.20835 (0.12661)	-0.19425 (0.14449)	-0.16650 (0.0)
D27	0.16276 (0.11239)	0.22905 (0.14469)	0.15725 (0.08222)	0.07400 (0.0)
DU7	0.03852 (0.02307)	0.03167 (0.01317)	0.02167 (0.00577)	0.01000 (0.0)
AP8	-6.67300 (5.01091)	-9.32928 (6.15964)	-10.94583 (6.59567)	-0.46250 (0.0)
D18	0.16479 (0.12471)	0.22861 (0.19383)	0.07400 (0.04895)	0.07400 (0.0)
D28	-0.14877 (0.12547)	-0.21760 (0.17413)	-0.15108 (0.07757)	-0.04625 (0.0)
DU8	0.04095 (0.02344)	0.04738 (0.02601)	0.06500 (0.01803)	0.01000 (0.0)
AP9	6.67830 (5.21525)	26.66202 (11.37940)	80.41333 (20.33745)	33.29999 (0.0)
D19	-0.16871 (0.10048)	-0.22024 (0.13015)	-0.14800 (0.01850)	-0.04625 (0.0)
D29	0.16229 (0.11165)	0.47219 (0.29606)	1.98875 (1.69209)	0.01850 (0.0)
DU9	0.03860 (0.02308)	0.04238 (0.01841)	0.02833 (0.01443)	0.04000 (0.0)

Table J-1 (Cont'd.)

	BCK	SSWA	SSWB	ART
AP10	-6.65386 (4.95848)	-40.49738 (10.86170)	-61.82083 (16.04077)	-35.24249 (0.0)
D110	0.16296 (0.10599)	0.85012 (0.38746)	5.49142 (1.63692)	3.27450 (0.0)
D210	-0.14717 (0.10453)	-0.97698 (0.30496)	-5.78741 (1.85151)	-3.45025 (0.0)
DU10	0.04097 (0.02342)	0.07857 (0.02684)	0.01500 (0.0)	0.03500 (0.0)
AP11	6.68327 (5.23642)	32.19440 (16.79884)	10.91500 (4.18198)	2.31250 (0.0)
D111	-0.16865 (0.10064)	-0.34269 (0.41535)	-3.17583 (0.63646)	-0.02775 (0.0)
D211	0.16176 (0.11128)	0.25063 (0.27449)	0.76467 (0.23985)	0.14800 (0.0)
DU11	0.03867 (0.02318)	0.12286 (0.06557)	0.01667 (0.00289)	0.02000 (0.0)
AP12	-6.65519 (5.00730)	-12.27166 (11.56861)	-66.59999 (16.00330)	-8.69500 (0.0)
D112	0.16410 (0.12438)	0.27794 (0.37881)	0.60433 (0.36725)	0.08325 (0.0)
D212	-0.14867 (0.12542)	-0.23081 (0.21544)	-0.47175 (0.15806)	-0.23125 (0.0)
DU12	0.04091 (0.02341)	0.04381 (0.02928)	0.08500 (0.01000)	0.05000 (0.0)
AP13	6.64452 (5.21896)	17.57500 (26.25447)	65.52083 (6.63318)	12.39500 (0.0)
D113	-0.16844 (0.10067)	-0.20086 (0.16258)	-0.12025 (0.03335)	-0.13875 (0.0)
D213	0.16179 (0.11148)	0.17487 (0.09595)	0.20658 (0.15039)	0.15725 (0.0)
DU13	0.03851 (0.02310)	0.06571 (0.05553)	0.18833 (0.02309)	0.05500 (0.0)
AP14	-6.64699 (5.00167)	-16.83499 (23.59531)	-3.73083 (0.78671)	-8.04750 (0.0)
D114	0.16372 (0.12432)	0.37969 (0.89572)	0.12950 (0.09110)	0.36075 (0.0)
D214	-0.14838 (0.12539)	-0.27706 (0.34179)	-0.15725 (0.05627)	-0.12950 (0.0)
DU14	0.04084 (0.02330)	0.06024 (0.03910)	0.02500 (0.01000)	0.05000 (0.0)
AP15	6.65915 (5.24154)	10.32916 (7.23395)	7.12250 (5.25625)	7.49250 (0.0)
D115	-0.16841 (0.10068)	-0.16254 (0.09787)	-0.20967 (0.03249)	-0.08325 (0.0)
D215	0.16168 (0.11135)	0.16210 (0.12436)	0.13258 (0.02328)	0.18500 (0.0)
DU15	0.03855 (0.02316)	0.05381 (0.03788)	0.04833 (0.02887)	0.04500 (0.0)
AP16	-6.66024 (5.00870)	-11.63298 (7.75113)	-7.15333 (1.76560)	-3.97750 (0.0)
D116	0.16367 (0.12444)	0.21011 (0.12213)	0.16650 (0.08011)	0.06475 (0.0)
D216	-0.14863 (0.12541)	-0.21627 (0.13935)	-0.23125 (0.16048)	-0.11100 (0.0)
DU16	0.04088 (0.02341)	0.05357 (0.02613)	0.03833 (0.02363)	0.04500 (0.0)
AP17	6.66545 (5.25235)	6.90226 (7.01552)	10.45250 (5.50899)	2.31250 (0.0)
D117	-0.16829 (0.10105)	-0.15769 (0.08650)	-0.25283 (0.22927)	-0.12950 (0.0)
D217	0.16174 (0.11161)	0.15813 (0.08828)	0.16342 (0.07702)	0.06475 (0.0)
DU17	0.03856 (0.02313)	0.03619 (0.02559)	0.03667 (0.02021)	0.02000 (0.0)
AP18	-6.65079 (5.03671)	-7.72154 (6.50660)	-30.18582 (4.26036)	-1.38750 (0.0)
D118	0.16346 (0.12449)	0.18676 (0.14094)	0.31758 (0.13854)	0.16650 (0.0)
D218	-0.14813 (0.12540)	-0.16210 (0.08030)	-0.28367 (0.15404)	-0.13875 (0.0)
DU18	94.76944 (4533.13672)	0.04786 (0.03888)	0.08833 (0.03819)	0.01000 (0.0)

LITERATURE CITED

Abenstein, J. P. and Tompkins, W. J. (1982). "A new data-reduction algorithm for real-time ECG analysis." *IEEE Transactions on Biomedical Engineering*, vol. BME-29, no. 1, pp. 43-48.

Adey, W. R. (1973),. "The influences of impressed electrical fields of EEG frequencies on brain and bahavior." *Behavior and Brain Electrical Activity*. Burch, N. and Altshuler, H. L., eds., New York: Plenum Press, pp. 363-390.

Angeleri, F., Scarpino, O., Manro, A. M. and Giuliani, G. (1981). "Automatic computerized investigation on EEG interictal spikes of human focal epilepsies." *Epilepsy: A clinical and experimental research, Monogr. neural Sci. (Karger, Basel)*, vol. 5, pp. 63-73

Aunon, J. I. (1983). "Digital Signal Processing of Evoked Potentials." *IEEE Transactions on Biomedical Engineering*, vol. BME-30, no. 8, p.549.

Ayala, G., Dichter, M., Gumnit, R. J., Matsumoto, H. and Spencer, W. A. (1973). "Genesis of epileptic interictal spikes. New knowledge of cortical feedback systems suggests a neurophysiological explanation of brief paroxysms." *Brain Research*, vol. 52, pp. 1-17.

Bar-On, E. and Andreassen, S. (1981). "Microprocessor based system for high speed detection and classification of events and background activity in 24h. EEG recordings." *10th International Congress of Electroencephalograph and clinical Neurophysiology*, Sept. 13-18, Kyoto, JAPAN.

Barbanera, S., Carelli, P., Fenici, R., Modena, I. and Romani, G. L. (1981). "Use of a superconducting instrumentation for biomagnetic measurements performed in a hospital." *IEEE Transactions on Magnetics*, vol. MAG-17, pp. 849-852.

Barlow, J. S. (1979). "Computerized clinical electroencephalography in perspective." *IEEE Trans. on Biomedical Engineering*, vol. BME-26, no. 7, pp.377-391.

Barlow, J. S. and Sokolov, E. N. (1975). "Selective on-line EEG filtering by means of a minicomputer." *Electroencephalography and clinical Neurophysiology*, vol. 39, p. 208.

Barlow, J. S. and Dubinsky, J. (1976). "Some computer approaches to continuous automatic clinical EEG monitoring." *Quantitative Analytic Studies in Epilepsy*, Kellaway, P. and Petersen, I., eds., New York: Raven Press, pp. 309-327.

Barth, D. S., Sutherling, W., Engel, J.,Jr. and Beatty, J. (1982). "Neuromagnetic localization of epileptiform spike activity in the human brain." *Science*, vol. 218, pp. 891-894.

Berger, H. (1929). "Uber das Elekrenkephalogram des Menschen." *Arch. Psychiat. Nervenkrankheiten*,. vol. 87, pp. 527-570.

Berglund, K and Hjorth, B. (1973). *Normierte Steilheits - Beschreibungsparameter und deren physikalischer Sinn hinsichlich der EEG-Detung*. G. K. Telefunken, Konstanz, pp. 249-257.

Bickford, R. G. (1959). "An automatic recognition system for spike-and-wave with simultaneous testing for motor response." *Electroencephalography and clinical Neurophysiology*, vol. 11, pp. 397-398.

Bickford, R. G., Gose, E., Brimm, J. and Roberts, W. (1974). "Compressed spectral array (CSA) with spike recognition." *Electroencephalography and clinical Neurophysiology*, vol. 37, pp. 206.

Birkemeier, W. P., Fontaine, A. B., Celesia, G. G. and Ma, K. M. (1978). "Pattern recognition techniques for the detection of epileptic transients in EEG." *IEEE Transactions on Biomedical Engineering*, vol. BME-25, no. 3, pp. 213-217.

Bishop, A. O., Jr., Snelsire, R. W., Wilcox, L. C. and Wilson, W. P. (1970). "The moving window approach to on-line real-time waveform recognition." *Proc. San Diego Biomedical Symp.*, San Diego, California, pp. 77-83.

Bodenstein, G. and Praetorious, H. M. (1977). "Pattern recognition of EEG by adaptive segmentation." *Biomedical Computing*, Perkins, W. J., ed., London: Pitman Medical Publishing Co Ltd, pp. 20-31.

Boineau, J. P., Schuessler, R. B., Hackel, D. B., Miller, C. B., Brockus, C. W. and Wylds, A. (1980). "Widespread distribution and rate differentiation of the arterial pacemaker complex." *American Journal of Physiology*, vol. 239, pp. H406-H415.

Bonzino, J. D., Forbes, W. and Morgane, P. J. (1980). "Quantitative indices of the EEG amplitude histograph." *IEEE Frontiers of Engineering in Health Care, IEEE/Engineering in Medicine and Biology Society Second Annual Conference*, pp. 186-189.

Bowling, P. S. and Bourne, J. R. (1978). "Discriminant analysis of electroencephalograms recorded from renal patients." *IEEE Transactions on Biomedical Engineering*, vol. BME-25, no. 1, pp. 12-17.

Burch, N. R. (1959). "Automatic analysis of the electroencephalogram: A review and classification of systems." *Electroencephalography and clinical Neurophysiology*, vol. 11, pp. 827-834.

Burger, D. (1980). "Analysis of electrophysiological signals: A comparative study of two algorithms." *Computers and Biomedical Research*, vol. 13, pp. 73-86.

Cadzow, J. A. (1982). "ARMA modeling of time series." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-4, no. 2, pp. 124-128.

Carrie, J. R. G. (1972a). "A technique for analyzing EEG transient abnormalities." *Electroencephalography and clinical Neurophysiology*, vol. 32, pp 199-201.

Carrie, J. R. G. (1972b). "A hybrid computer system for detecting and quantifying spike and wave EEG patterns." *Electroencephalography and clinical Neurophysiology*, vol. 33, pp. 339-341.

Chen, C. H. (1973). *Statistical Pattern Recognition*. Rochelle Park, New Jersey: Hayden Book Company.

Chen, C. H. (1982). "Adaptive and learning algorithms for seismic detection of personnel." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-4, no. 2, pp. 129-132.

Cohler, E. (1983). "Trends in array processors." *Trends & Perspectives in Signal Processing*, vol. 3, no. 2, pp. 11-15.

Cooley, J. W. and Tukey, J. (1965). "An algorithm for the machine calibration of complex fourier series." *Math. Comput.*, vol. 19, pp. 297-301.

Cooper,R., Osselton, J. W. and Shaw, J. C. (1971). *EEG Technology*, London: Butterworth & Co. Ltd.

Cox, J. R., Jr., Nolle, F. M., Fozzard, H. A. and Oliver, G. C., Jr. (1968). "AZTEC: A preprocessing program for real-time ECG rhythm analysis. *IEEE Transactions on Biomedical Engineering*, vol. BME-15, pp. 128-129.

Cox, J. R., Jr., Nolle, F. M. and Arthur, R. M. (1972). "Digital analysis of the electroencephalogram, the blood pressure wave, and the electrocardiogram." *Proceedings of the IEEE*, vol. 60, no. 10, pp. 1137-1164.

Cragg, B. G. (1967). "The density of synapses and neurons in the motor cortex and visual areas of the cerebral cortex." *Journal of Anatomy*, vol. 101, pp. 639-654.

Craib, A. R. and Perry, M. (1975). *EEG Handbook, 2nd ed.*, Beckman Instruments Inc.

De Figueiredo, R. J. P. and Hu, C. L. (1982). "Waveform feature extraction based on Tauberian approximation." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-4, no. 2, pp. 105-116.

De Vries, J., Wisman, T. and Binnie, C. D. (1981). "Evaluation of a simple spike-wave recognition system." *Electroencephalography and clinical Neurophysiology*, vol. 51, pp. 328-330.

Denoth, F. (1975). "Some general remarks on Hjorth's parameters used in EEG analysis." *CEAN - Computerized EEG Analysis*, Dolce, G. and Kunkel, H., eds., Stutgart, Germany: Fischer.

Depoortere, H., Matejcek, M. and Loew, D. M. (1973). "Visual and computer assisted analysis of the electroencephalogram of the rat during the sleep/wakefulness cycle: A sensitive procedure for assessing drug induced changes." *Die Quantifizierung des Elektroenzephalograms*, Schenk, G. K., ed., AEG-Telefunken, Konstanz, pp. 53-66.

Devos, J. E., Depoortere, H., Matejcek, M. and Loew, D. M. (1975). "Automatic discrimination of the sleep-wakefulness stages in the EEG of rats." *Sleep 1974*, Levin, P. and Koella, W. P., eds., Karger, Basel.

Dixon, W. J., ed. (1967). *BMD: Biomedical Computer Programs*. 2nd ed., Berkeley, University of California Press.

Dixon, W. J., ed. (1969). X-Series Supplement. *BMD: Biomedical Computer Programs*. 2nd ed., Berkeley, University of California Press.

Dixon, W. J., ed. (1973). *BMD: Biomedical Computer Programs*. 3rd ed., Berkeley: University of California Press.

Dixon, W. J., ed. (1975). *BMDP: Biomedical Computer Programs*. Berkeley: University of California Press.

Dumermuth, G. (1977). "Fundamentals of spectral analysis in electroencephalography." *EEG Informatics. A Didactic Review of Methods and Applications of EEG Data Processing*, Remond, A., ed., Amsterdam: Elsevier Scientific Publishing Company, pp. 83-105.

Dumermuth, G., Gasser, T., German, P., Hecker, A., Herdan, M. and Lange, B. (1977). "Studies on EEG - activities in the beta band." *Europ. Neurol.* vol. 16, pp. 197-202.

Dumermuth, G. (1977). "Fundamentals of spectral analysis in electroencephalograpy." *A Didactic Review of Methods and Applications of EEG Data* Processing, Remond, A., ed., Elsevier, North-Holland Biomedical Press, pp. 83-105.

Dumpala, S. R., Reddy, S. N. and Sarna, S. K. (1982). "An algorithm for the detection of peaks in biological signals." *Computer Programs in Biomedicine*, vol. 14, pp. 249-256.

Duquesnoy, A. (1975). "Analysis of non-stationary electro-encephalograms using a modified Kalman filter. An identification study." *94, MSc. Thesis,* University of Technology at Eindhoven.

Eisenstein, B. A. and Vaccaro, R. J. (1982). "Feature extraction by system identification." *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-12, no. 1, pp. 42-49.

Farver, T. B. and Dunn, O. J. (1979). "Stepwise variable selection in classification problems." *Biom. J.*, vol. 21, no. 2, pp. 145-153.

Feldman, C. L. (1983). "Computer detection of cardiac arrhythmias-Historic review." *IEEE Transactions on Biomedical Engineering*, vol. BME-30, no. 8, p.550.

Fenwick, P. B. C., Mitchie, P., Dollimore, J. and Fenton, G. W. (1969). "Application of the autoregressive models to EEG analysis." *Agressologie*, vol. 10, pp. 533-564.

Fridman, J., John, E. R., Bergelson, M., Kaiser, J. B. and Baird, H. W. (1982). "Application of digital filtering and automatic peak detection to brain stem auditory evoked potential." *Electroencephalography and clinical Neurophysiology*, vol. 53, pp. 405-416.

Frost, J. D., Jr. (1979). "Microprocessor-based EEG spike detection and quantification." *International Journal of Bio-Medical Computing*, vol. 10, pp. 357-373.

Fu, K. S., ed. (1977). *Syntactic Pattern Recognition, Applications*. Berlin: Springer-Verlag.

Fukunaga, K. (1972). *Introduction to Statistical Pattern Recognition*. New York: Academic Press.

Gastaut, H. and Broughton, R. (1972). *Epileptic Seizures. Clinical and Electrographic Features, Diagnosis and Treatment*. Springfield, Illinois: Charles C. Thomas Publisher.

Gastaut, H. (1973). *Dictionary of Epilepsy*. Genova: World Health Organization.

Gersch, W. and Goddard, G. V. (1970). "Epileptic focus location: spectral analysis method." *Science*, vol. 169, pp. 701-702.

Gersch, W. (1970). "Spectral analysis of EEG's by autoregressive decomposition of time series." *Mathematical Biosciences*, vol. 7, pp. 205-222.

Gevins, A. S. and Yeager, C. L. (1975). "An interactive developmental approach to real-time EEG analysis." *Behavior and Brain Electrical Activity*, Burch, N. and Altshuler, H. L., eds., New York: Plenum Press, pp. 221-263.

Gevins, A. S., Yeager, C. L., Diamond, S. L., Spire, J.-P., Zeitlin, G. M. and Gevins, A. H. (1975a). "Automated analysis of the electrical activity of the human brain (EEG): A progress report." *Proc. IEEE*, vol. 63, pp. 1382-1399.

Gevins, A. S., Yeager, C. L. and Diamond, S. L. (1975b). "Heuristic algorithms for the analysis of sharp transient EEG waveforms." *Electroencephalography and clinical Neurophysiology*, vol. 38, p. 549.

Gevins, A. S. (1980a). "Pattern recognition of human brain electrical potentials." *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. PAMI-2, no. 5, pp. 383-404.

Gevins, A. (1980b). "Analysis of brain electrical potential (BEP) in the 1980's." *IEEE 1980 Frontiers of Engineering in Health Care. IEEE/Engineering in Medicine and Biology Society Second Annual Conference*, pp. 227-230.

Gibbs, F. A., Gibbs, E. L. and Lennox, W. G. (1937). "Epilepsy a paroxysmal cerebral dysrhythmia." *Brain*, vol. 60, pp. 377-388.

Gibbs, F. A. and Gibbs, E. L. (1951). *Atlas of Electroencephalography. vol. one: Methodology and Controls*, 2nd ed. Reading, Mass.: Addison-Wesley Publishing Company.

Gibbs, F. A. and Gibbs, E. L. (1952). *Atlas of Electroencephalography. vol. two: Epilepsy*, 2nd ed. Reading, Mass.: Addison-Wesley Publishing Company.

Giese, D. A., Bourne, J. R. (1979). "Syntactic analysis of the electroencephalogram." *IEEE Transactions on Systems, Man and Cybernetics*, vol. SMC-9, no. 8, pp. 429-435.

Goldberg, P., Samson-dolfus, D., Bacherich, F. and Gremy, F. (1971). "Algorithmes pour une analyse automatique d'une derivation EEG." *Ann. Physiol. Biol. Med.* vol. 5, p. 33.

Gotman, J. and Gloor, P. (1976). "Automatic recognition and quantification of interictal epileptic activity in the human scalp EEG." *Electroencephalography and clinical Neurophysiology*, vol. 41, pp. 513-529.

Gotman, J., Gloor, P. and Schaul, N. (1978). "Comparison of traditional reading of the EEG and automatic recognition of interictal epileptic activity." *Electroencephalography and clinical Neurophysiology*, vol. 44, pp. 48-60.

Gotman, J. (1980). "Quantitative measurements of epileptic spike morphology in the human EEG." *Electroencephalography and clinical Neurophysiology*, vol. 48, pp. 551-557.

Guedes de Oliveira, P. H. H. and Lopes da Silva, F. H. (1980). "A topographical display of epileptiform transients based on a statistical approach." *Electroencephalography and clinical Neurophysiology*, vol. 48, pp. 710-714.

Habbema, J. D. F., Hermans, J. and Van Den Broek, K. (1974). "A stepwise discriminant analysis program using density estimation." *Compstat 1974, Proceedings in Computational Statistics*, Wien: Physica Verlag, pp. 101-110.

Habbema, J, D. F. and Hermans, J. (1977). "Selection of variables in discriminant analysis by F-statistic and error rate." *Technometrics*, vol. 19, no. 4.

Habbema, J. D. F. and Gelpke, G. J. (1981). "A computer program for selection of variables in diagnostic and prognostic problems." *Computer Programs in Biomedicine*, vol. 13, pp. 251-270.

Harner, R. N. and Ostergren, K. (1974). "Application of sequential analysis to clinical EEG." *Electroencephalography and clinical Neurophysiology*, vol. 37, p. 206.

Harner, R. N. and Ostergren, K. A. (1976). "Sequential analysis of quasi-stable and paroxysmal EEG activity." *Quantitative Analytic Studies in Epilepsy*, Kellaway, P. and Petersen, I., eds., New York: Raven Press, pp. 343-354.

Hawkins, D. M. (1976). "The subset problem in multivariate analysis of variance." *Journal of the Royal Statistical Society, Series B*, vol. 38, pp. 132-139.

Hilderbrand, D. K., Laing, J. D. and Rosenthal, H. (1977). *Prediction analysis of cross classifications*. New York: John Wiley & Sons.

Hill, A. G. and Townsend, H. R. A. (1973). "The automatic estimation of epileptic spike activity." *International Journal of Bio-Medical Computing*, vol. 4, pp. 149-156.

Hjorth, B. (1970). "EEG analysis based on time domain properties." *Electroencephalography and clinical Neurophysiology*, vol. 29, pp. 306-310.

Hjorth, B. (1973). "The physical significance of time domain descriptors in EEG analysis." *Electroencephalography and clinical Neurophysiology*, vol. 34, pp. 321-325.

Horowitz, J., Whitelaw, A. L. and Jacobs, C. (1981). "Real-time analysis of hippocampal neural activity in the intervals between interictal spikes." *Computer Programs in Biomedicine*, vol. 13, pp. 19-26.

Horowitz, S. L. (1977). "Peak recognition in waveforms." *Syntactic Pattern Recognition, Applications*, Fu, K. S., ed., Berlin, Spring-Verlag, pp. 31-49.

Isaksson, A. and Wennberg, A. (1976). "Spectral Properties of nonstationary EEG signals, evaluated by means of Kalman filtering: Applications examples from a vigilance test." *Quantitative Analytic Studies in Epilepsy*, Kellaway, P. and Petersen, I., eds., New York: Raven Press, pp. 389-402.

Isaksson, A., Wennberg, A. and Zetterberg, L. H. (1981). "Computer analysis of EEG signals with parametric models." *Proceedings of the IEEE*, vol. 69, pp.451-463.

Jansen, B. H., Hasman, A. and Lenten, R. (1981). "Piece-wise EEG analysis: an objective evaluation." *International Journal of Bio-Medical Computing*, vol. 12, pp. 17-27.

Jasper, H. H. (1936). "Cortical excitatory state and synchronism in the control of bioelectric autonomous rhythms." *Cold Spring Harbor Symp. Quant. Biol.*, vol. 4, pp. 320-338.

Jenden, D. J., Fairchild, M. D., Mickey, M. R., Silverman, R. W. and Yale, C. (1972). "A multivariate approach to the analysis of drug effects on the electroencephalogram." *Biometrics*, vol. 28, pp. 73-80.

John, E. R., Karmel, B. Z., Corning, W. C., Easton, P., Brown, D., Ahn, H., John, M., Harmony, T., Prichep, L., Toro, A., Gerson, I., Bartlett, F., Thatcher, R., Kaye, H., Valdes, P. and Schwartz, E. (1977). "Neurometrics." *Science*, vol. 196, no. 4297, pp. 1393-1410.

Johnson, T. L., Wright, S. C. and Segall, A. (1979). "Filtering of muscle artifact from the electroencephalogram." *IEEE Transactions on Biomedical Engineering*, vol. BME-26, no. 10, pp. 556-563.

Kaiser, E. (1976). "Telemetry and video recording on magnetic tape cassettes in long-term EEG ." *Quantitative Analytic Studies in Epilepsy*, Kellaway, P. and Petersen, I., eds., New York: Raven Press, pp. 279-288.

Kashyap, R. L. (1982). "Optimal choice of AR and MA parts in autoregressive moving average models." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-4, no. 2, pp. 99-104.

Kavanagh, R. N., Darcey, T. M. and Fender, D. H. (1976). "The dimensionality of the human visual evoked scalp potential." *EEG Journal*, vol. 40, pp. 633-644.

Kavanagh, R. N., Darcey, T. M., Lehmann, D. and Fender, D. H. (1978). "Evaluation of methods for three dimensional localization of electrical sources in the human brain." *IEEE Transactions on Biomedical Engineering*, vol. BME-25, no. 5, pp. 421-429.

Keane, B. (1978). "EEG phasic event detection by microcomputer." *IEEE Transactions on Biomedical Engineering*, vol. BME-25, no. 3, pp. 297-299.

Kohonen, T., Nemeth, G., Bry, K.-J., Jalanko, M. and Riitinen, H. (1979). "Spectral classification of phonemes by learning subspaces." *Proceedings of the 1979 IEEE International Joint Conference on Acoustics, Speech and Signal Processing, Washington, D. C., April 2-4*, pp. 97-100.

Kooi, K. A. (1971). *Fundamentals of electroencephalography*. New York: Medical Dept., Harper & Row Publishers.

Ktonas, P. Y., Luoh, W. M., Kejariwal, M. L., Reilly, E. L. and Seward, M. A. (1981). "Computer-aided quantification of EEG and sharp wave characteristics." *Electroencephalography and clinical Neurophysiology*, vol. 51, pp. 237-243.

Kulikowski, C. A. (1980). "Artificial intelligence methods and systems for medical consultation." *IEEE Transactions on Pattern Recognition and Machine Intelligence*, vol. PAMI-2, no. 5, pp. 464-476.

Kunkel, H., Luba, A. and Niethardt, P. (1976). "Topographic and psychosomatic aspects of spactral EEG analysis of drug effects." *Quantitative Analytic Studies in Epilepsy, Kellaway, P. and* Petersen, I., eds., New York: Raven Press, pp. 207-223.

Lachenbruch, P. A. (1975). *Discriminant Analysis*. New York: Hafner Press; A division of Macmillen Publishing Company.

Lake, R. B. (1982). "A high-speed data acquisition subsystem." *IEEE Transactions on Biomedical Engineering*, vol. BME-29, no. 10, pp. 678-686.

Larsen, H. and Lai, D. (1980). "Walsh spectral estimates with applications to the classification of EEG signals." *IEEE Transactions on Biomedical Engineering*, vol. BME-27, no. 9, pp. 485-492.

Larsen, L. E. and Walter, D. O. (1970). "On automatic method of sleep staging by EEG spectra." *Electroencephalography and clinical Neurophysiology*, vol. 28, pp. 459-467.

Leader, H. S., Cohn, R., Weihrer, A. L. and Caceres, C. A. (1967). "Pattern reading of the clinical electroencephalogram with a digital computer." *Electroencephalography and clinical Neurophysiology*, vol. 23, pp. 566-570.

Legewie, H. and Probst, W. (1969). "On-line analysis of EEG with a small computer (period-amplitude analysis." *Electroencephalography and clinical Neurophysiology*, vol. 27, pp. 533-535.

Lehmann, D. (1977). "The EEG as scalp field distribution." *EEG Informatics. A Didactic Review of Methods and Applications of EEG Data Processing*. Remond, A., ed., Amsterdam: Elsevier Scientific Publishing Company, pp. 365-384.

Lieb, J. P., Engel, J., Jr., Gevins, A. and Crandall, P. H. (1981). "Surface and deep EEG correlates of surgical outcome in temporal lobe epilepsy." *Epilepsia*, vol. 22, no. 5, pp. 515-538.

Lopes da Silva, F. H., ten Broeke, W., van Hulten, K. and Lommen, J. G. (1976). "EEG nonstationarities detected by inverse filtering in scalp and cortical recordings of epileptics: statistical analysis and spatial display." *Quantitative Analytic Studies in Epilepsy*, Kellaway, P. and Petersen, I., eds., New York: Raven Press, pp. 375-387.

Lopes da Silva, F. H., Van Hulten, K., Lommen, J. G., Storm van Leeuwen, W., Van Veelen, C. W. M. and Vliegenthart, W. (1977). "Automatic detection and localization of epileptic foci." *Electroencephalography and clinical Neurophysiology*, vol. 43, pp. 1-13.

Luders, H., Daube, J. R., Taylor, W. F. and Klass, D. W. (1976). "A computer system for statistical analysis of EEG transients." *Quantitative Analytic Studies in Epilepsy*, Kellaway, P. and Petersen, I., eds., New York: Raven Press, pp. 403-430.

Lynn, P. A. (1977). "Online digital filters for biological signals: some fast designs for a small computer," *Medical & Biological Engineering & Computing*, vol. 15, pp. 534-540.

MacGillivray, B. (1977). "The application for automated EEG analysis to the diagnosis of epilepsy," *EEG Informatics. A Didactic Review of Methods and Applications of EEG Data Processing*. Remond, A., ed., Amsterdam: Elsevier Scientific Publishing Company, pp. 243-261.

Malik, N. R. (1980). "Microcomputer realizations of Lynn's fast digital-filtering designs." *Medical & Biological Engineering & Computing*, vol. 18, pp. 638-642.

Mardia, K. V., Kent, J. T. and Bibby, J. M. (1979). *Multivariate Analysis*. London: Academic Press.

Martin, W. B., Johnson, L. C., Viglione, S. S., Naitoh, P., Joseph, R. D. and Moses, J. D. (1972). "Pattern Recognition of EEG-EOG as a technique for all-night sleep stage scoring." *Electroencephalography and clinical Neurophysiology*, vol. 32, pp. 417-427.

Matejcek, M. and Schenk, G. K. (1972). "Quantitative EEG - Auswertung in der Psychopharmakologie. Eine neue Variante der Intervall-analyse." *EEG-EMG*, vol. 3, p. 198.

Matejcek, M. and Devos, J. E. (1976). "Selected methods of quantitative EEG analysis and their applications in psychotropic drug research." *Quantitative Analytic Studies in Epilepsy*, Kellaway, P. and Petersen, I., eds., New York: Raven Press, pp. 183-205.

Matthis, P., Scheffner, D. and Benninger, C. (1981). "Spectral analysis of the EEG: Comparison of various spectral parameters." *Electroencephalography and clinical Neurophysiology*, vol. 52, pp. 218-221.

McCabe, G. P., Jr. (1975). "Computers for variable selection in discriminant analysis." *Technometrics*, vol. 17, pp. 103-109.

McKay, R. J. and Campbell, N. A. (1982a). "Variable selection techniques in discriminant analysis I. Description." *British J. Mathematical and Statistical Psychology*, vol. 35, pp. 1-29.

McKay, R. J. and Campbell, N. A. (1982b). "Variable selection techniques in discriminant analysis II. Allocation." *British J. Mathematical and Statistical Psychology*, vol. 35, pp. 30-41.

Moser, J. M., Aunon, J. I. and McGillem, C. D. (1980). "Modeling and decomposition of the electroencephalogram." *IEEE Frontiers of Engineering in Health Care, IEEE/Engineering in Medicine and Biology Society Second Annual Conference*, pp. 253-256.

Nie, N. H., Hull, C. H., Jenkins, J. G., Steinberger, K. and Bent, D. H. , eds. (1975). *Statistical Package for the Social Sciences* (*SPSS*), New York: McGraw-Hill.

Oja, E. and Kuusela, M. (1983). "The ALSM algorithm - an improved subspace method of classification." *Pattern Recognition*, vol. 16, no. 4, pp. 421-427.

O'Leary, J. L. and Goldberg, S. (1976). *Science and Epilepsy*, New York: Raven press.

Oliveira, P. G., Queiroz, C. and Lopes da Silva, F. (1983). "Spike detection based on a pattern recognition approach using a microcomputer." *Electroencephalography and clinical Neurophysiology*, vol. 56, pp. 97-103. New York: Raven press.

Oppenheim, A. V. and Schafer, R. W. (1975). *Digital Signal Processing*, Englewood Cliffs, New Jersey: Prentice-Hall.

Palem, K. and Barr, R. E. (1982). "Period-peak analysis of the EEG with microprocessor applications." *Computer Programs in Biomedicine* vol. 14, pp. 145-156.

Pfurtscheller, G. and Fischer, G. (1978). "A new approach to spike detection using a combination of inverse and matched filter techniques." *Quantitative Analytic Studies in Epilepsy*, Kellaway, P. and Petersen, I., eds., New York: Raven Press, pp. 243-247.

Pfurtscheller, G. and Cooper, R. (1975). "Frequency dependence of the transmission on the EEG from cortex to scalp." *Electroencephalography and clinical Neurophysiology*, vol. 38, pp. 93-96.

Remond, A. (1969). "The importance of topographic data phenomena, and an electrical model to reproduce them." in Advances in EEG Analysis, Walter, D. O. and Brazxier, M. A. B., eds., *Electroencephalography and clinical Neurophysiology, Supplement*, no 27, pp. 31-49.

Remond, A. and Renault, B. (1972). "La theorie des objects electrographiques." *Rev. EEG Neurophysiol.* vol. 3, pp. 241-256.

Rogowski, Z., Gath, I. and Bental, E. "On the prediction of epileptic seizures." *Biological Cybernetics*, vol. 42, pp. 9-15.

Romani, G. L, Williamson, S. J. and Kaufman, L. (1982). "Tonotopic organization of the human auditory cortex." *Science*, vol. 216, pp. 1339-1340.

Salb, J. (1980). "Microcomputer-based period and amplitude analysis of the electroencephalogram." *Med. and Biol. Eng. and Comput.* vol. 18, pp. 313-318.

Saltzberg, B., Heath, R. G. and Edwards, R. J. (1967). "EEG spike detection in schizophrenia research." *Dig. 7th Int. Conf. Med. Biol. Eng.*, Stockholm, Sweden, p. 266.

Saltzberg, B. and Burch, N. R. (1971). "Period analytic estimates of moments of the power spectrum: a simplified EEG time domain procedure." *Electroencephalography and clinical Neurophysiology*, vol. 30, pp. 568-570.

Saltzberg, B., Lustick, L. S. and Heath, R. G. (1971). "Detection of focal depth spiking in the scalp EEG of monkeys." *Electroencephalography and clinical Neurophysiology*, vol. 31, pp. 327-333.

Saltzberg, B. (1976). "The potential role of cepstral analysis in EEG research in epilepsy." *Quantitative Analytic Studies in Epilepsy*, Kellaway, P. and Petersen, I., eds., New York: Raven Press, pp. 559-563.

Saltzberg, B., Kellaway, P., Burton, W. D., Jr. and Frost, J. D., Jr. (1981). "Epilepsy: a heuristic model for relating nocturnal sleep EEG spike distributions to the risk of seizure." *International Journal of Bio-Medical Computing*, vol. 12, pp. 9-16.

Saridis, G. N. and Gootee, T. P. (1982). "EMG pattern analysis and classification for a prosthetic arm." *IEEE Transactions on Biomedical Engineering*, vol. BME-29, no. 6, pp. 403-412.

Schenk, G, K. (1976). "The pattern-oriented aspect of EEG quantification. Model and clinical basis of the iterative time-domain approach." *Quantitative Analytic Studies in Epilepsy*, Kellaway, P. and Petersen, I., eds., New York: Raven Press, pp. 431-461.

Shaw, J. C. and Roth, M. (1955). "Potential distribution analysis II: A theoretical consideration of its significance in terms of electrical field theory." *EEG Clin. Neur.*, vol. 7, pp. 285-292.

Sidman, R. D. and Smith, D. B. (1980). "A method for identifying noise-free evoked potential components - Application of DLM (Dipole Localization Method) to these components." *IEEE 1980 Frontiers of Engineering in Health Care, IEEE/Engineering in Medicine and Biology Society Second Annual Conference*, Washington Hilton Hotel, Washington D. C., pp. 137-140.

Sklansky, J., ed. (1973). *Pattern Recognition: Introduction and Foundations*. Stroudsburg: Dowden, Hutchinson & Ross.

Smith, D. B., Sidman, R. D., Henke, J. S., Flanigin, H., Labinar, D. and Evans, C. N. (1983). "Scalp and depth recordings of induced deep cerebral potentials." *Electroencephalography and clinical Neurophysiology*, vol. 55, pp. 145-150.

Smith, J. R. (1974). "Automatic analysis and detection of EEG spikes." *IEEE Transactions on Biomedical Engineering*, vol. BME-21, no. 1, pp. 1-7.

Smith, J. R., Funke, W. F., Yeo, W. C. and Ambuehl, R. A. (1975). "Detection of human sleep EEG waveforms." *Electroencephalography and clinical Neurophysiology*, vol. 38, pp. 435-437.

Steinberg, C. A., Abraham, S. and Caceres, C. A. (1962). "Pattern recognition in the clinical electrocardiogram." *IRE Transactions on Bio-Medical Electronics*, vol. 50, pp. 23-30.

Storm van Leeuwen, W., Bickford, R., Brazier,M., Cobb, W. A., Dondey ,M., Gastat, H., Gloor, P., Henry, C. E., Hess, R., Knott, J. R., Kugler, J., Lairy, G. C., Loeb, C., Magnus, O., Oller Daurella, L., Petsche, H., Schwab, R., Walter,W. G. and Widen, L. (1966). "Proposal for an EEG terminology by the Terminology Committee of the International Federation for Electroencephalography and clinical Neurophysiology." *Electroencephalography and clinical Neurophysiology*, vol 20, pp. 293-320.

Thatcher, R. W. and John, E. R. (1977). *Foundations of Cognitive Processes*, Hillsdale, New Jersey: Lawrence Erlbaum Associates, Publishers.

Walter, W. G, and Shipton, H. W. (1951). "A new toposcopic display systems." *Electroencephalography and clinical Neurophysiology*, pp. 281-292

Webster, J. G., ed. (1978). *Medical Instrumentation: Application and design*. Boston: Houghton Muffin Co.

Widrow, B. (1973). "The 'rubber-mask' technique - I. Pattern measurement and analysis." *Pattern Recognition*, vol. 5, pp. 175-197.

Widrow, B., Glover, J. R., Jr., McCool, J. M., Kaunitz, J., Williams, C. S., Hearn, R. H., Zeidler, J. R., Dong, E., Jr. and Goodlin, R. C. (1975). "Adaptive noise cancelling: Principles and applications." *Proceedings of the IEEE*, vol. 63, no. 12, pp. 1692-1716.

Williamson, S. J. and Kaufman, L. (1981). "Biomagnetism." *Journal of Magnetism and Magnetic Materials*, vol. 22, pp. 129-201.

Wyler, A. and Ward, A. A., Jr. (1981). "Neurons in human epileptic cortex. Response to direct cortical stimulation." *Journal of Neurosurg.*, vol. 55, pp. 904-908.

Wyper, A. Ballantyne, J. P., McGeorge, A. P. and Sompson, J. A. (1975). "Clinical assessment of a multiple channel EEG quantifier." *Electroencephalography and clinical Neurophysiology*, vol. 38, pp. 208-209.

Yeager, C. L. (1972). "An EEG reading plan." *NIH Grant Application*, NS-10471-01.

Zetterberg, L. H. (1969). "Estimation of parameters for a linear difference equation with application to EEG analysis." *Mathematical Biosciences*, vol. 5, pp. 227-275.

Zetterberg, L. H. (1973). "Spike detection by computer and by analog equipment." *Automation of Clinical Electroencephalography*, Kellaway, P. and Petersen, I., eds., New York: Raven Press, pp. 227-242.

Zetterberg, L. H. (1977). "Means and methods for processing of physiological signals with emphasis on EEG analysis." *Advances in Biological and Medical Physics*, vol. 16, pp. 41-91.