ESTIMATION OF THE LEVEL OF ANESTHESIA DURING SURGERY BY AUTOMATIC EEG PATTERN RECOGNITION

by

JAMES ALLEN McEWEN
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Department of Electrical Engineering

The University of British Columbia
2075 Wesbrook Place
Vancouver, Canada
V6T 1W5

Date July 28 1975

ABSTRACT

The feasibility of developing an automatic electroencephalographic (EEG) pattern recognition system for reliably estimating the level of consciousness of surgical patients during general anesthesia is investigated.

An effort was made to establish a valid methodology, by identifying and controlling as many extraneous variables as possible and by ensuring that the work would be relevant to current anesthetic practice. The data base that was established for use in all experimental investigations consists of 938 EEG pattern samples from 72 subjects and three types of anesthesia. Each EEG pattern sample corresponds to one of five possible clinical levels of anesthesia.

The use of automatic pattern recognition techniques, in conjunction with heuristic techniques of clinical EEG analysis, to develop spectral and time domain EEG pattern recognition systems is described. All of the initially developed systems extract a small number of heuristically derived features from unknown EEG pattern samples. The classifiers in these systems employ Bayes decision rule under the assumption that the extracted features are statistically independent. A rationale concerning the choice of this particular feature extraction scheme and pattern classification algorithm is presented and discussed.

Consideration is given to the general problem of how to use a relatively small set of available EEG pattern samples to effectively evaluate the performance of EEG pattern recognition systems. Two nonparametric techniques which provide particularly informative and efficient estimates of the performance of such systems are formulated. Results obtained by employing these techniques to estimate the performance of the initially developed spectral and time domain EEG pattern recognition systems are presented. The results clearly demonstrate the feasibility

of estimating the level of anesthesia by means of automatic EEG pattern recognition. However, the results also indicate that the initially developed systems are not sufficiently reliable for immediate and general clinical application.

Theoretical techniques are developed to model some relevant statistical properties of spontaneous EEG activity, with a view to improving the performance of the initially developed EEG pattern recognition systems. Results which were obtained by applying the modelling techniques to some specific ensembles of EEG pattern samples are presented. The comparative advantages of employing alternate methods of EEG analysis are then discussed in relation to the estimated statistical characteristics of the particular EEG ensembles under consideration.

Several factors which could adversely affect the reliable performance of EEG pattern recognition systems in general, and the initially developed systems in particular, are identified and discussed. Various schemes for improving the performance of the initially developed systems are suggested and an evaluation of the practicability of each is presented.

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CHAPTER I

INTRODUCTION

1.1 Problem Area

The need for a reliable method of assessing the level of consciousness of surgical patients during general anesthesia has existed since the introduction of the first general anesthetic agents more than a century ago. The clinical signs and stages of anesthetic depth that traditionally have been employed have never been entirely satisfactory. However, as a result of recent advances in anesthesiology, many of these traditional signs and stages have clearly become unreliable and inadequate in terms of modern anesthetic practice. It is significant that the electroencephalogram, an intuitively appealing indicator of the gross electrical activity of the brain, is not among the indicators which are routinely evaluated in attempting to assess the level of anesthesia. In fact, electroencephalographic activity is rarely even monitored during general anesthesia at present. The possibility of developing a computer-based system for reliably estimating the level of anesthesia by means of electroencephalographic pattern recognition is the subject of this thesis.

General anesthesia can be defined as a state of unconsciousness, produced by anesthetic agents, with an absence of pain sensation over the entire body and a greater or lesser degree of muscular relaxation. An electroencephalogram (EEG) is an electrical signal which is generated by the brain and recorded from electrodes attached to the scalp. Spontaneous electroencephalographic activity (or EEG activity) is characterized by voltages which are usually less than 100 μV, by frequencies which are essentially bandlimited to 30 Hz and by a wide range of patterns or waveforms, some of which are associated with different states of consciousness.

Because a number of general references are available in the areas of anesthesiology (e.g. [1-4]) and electroencephalography (e.g. [5-8]), further information of a fundamental nature in these particular areas will not be included in the thesis.

Intuitively, because general anesthesia is defined primarily in terms of brain function, it is reasonable to suspect that different levels of anesthesia, i.e. different levels of consciousness, could be manifested by different spontaneous EEG patterns. Considerable motivation exists for the development of an automatic system which could reliably estimate the level of anesthesia by means of spontaneous EEG pattern recognition. Some of the potential applications are immediately apparent.

1) Such a system could be employed to monitor the level of anesthesia throughout surgery, i.e. to provide a continually updated estimate of the anesthesia level. This would permit an anesthesiologist to more accurately control the administration of anesthetic agents, thereby reducing the probability of subjecting the patient to unnecessarily deep, life-threatening levels of anesthesia or, alternatively, to very light levels of anesthesia which might result in periods of consciousness or awareness during surgery.
2) The system could provide a rapid and sensitive indication of the occurrence of anesthetic accidents.
3) It would be particularly valuable in certain kinds of operations where most clinical, non-EEG signs of anesthetic depth are unavailable, e.g. during the critical cardiopulmonary bypass phase of open-heart surgery.
4) It could be employed in the clinical evaluation of new anesthetic agents.
5) It could be of value in the instruction of anesthesiologists.

1.2 Evaluation of Previous Research

The prospect of using the EEG to estimate the level of anesthesia was first suggested in 1937 as a practical application of observed correlations between different EEG patterns and various levels of anesthesia induced by ether [9]. During the next two decades similar correlations between observed EEG patterns and anesthetic depth were described for other anesthetic agents including cyclopropane, nitrous oxide - ether and nitrous oxide - thiopental [10-12]. More quantitative correlations were also investigated by relating observed EEG patterns to the arterial blood concentrations of different anesthetic agents [13,14]. Over the years, subjective descriptions of recognizable time domain EEG patterns at various anesthetic levels have been reported for most of the commonly used anesthetic agents. An extensive review of the correlations between various general anesthetics and observed EEG patterns was recently published [15].

In a 1959 review paper, Martin et al. proposed that most of the general anesthetics that were then in common use had a similar, dose-dependent relationship to a recognizable sequence of EEG patterns [16]. This relationship seemed to suggest that a reliable method for estimating the level of anesthesia could eventually be developed by identifying and classifying the various EEG patterns produced by different patients and different anesthetics. This expectation was not realized, however, largely because of a variety of methodological problems relating to the validity and reliability of previous work. EEG validity in this instance may be defined as the extent to which the EEG contains information concerning the actual level of anesthesia, while reliability refers to the dependability of a particular method for extracting such information from the EEG in order to correctly estimate the level of anesthesia.

Four major unresolved problems relating to the validity and reliability of previous work can be identified. Martin et al. recognized the basic problem of level definition: a precise definition of the different possible levels of anesthesia is necessary before one can properly consider the question of whether or not the EEG constitutes a valid indicator of those levels. A second problem involving the reliability of EEG pattern definition has also been acknowledged: different investigators may vary considerably in their subjective definitions of what constitutes recognizably different EEG patterns [17]. In addition, the use of a variety of anesthetic agents results in pattern variability, thereby increasing the complexity of the pattern recognition task. Finally, the inter-rater reliability of visual EEG assessment among experienced clinical raters, even with an established set of objective criteria for pattern identification, may be surprisingly low. No study of inter-rater reliability has been conducted using EEG data from different levels of anesthesia. However, in a recent study based on clinical EEG data, the highest average intraclass correlation reported among seven experienced clinical EEG raters was 0.56 [18].

Largely because of such methodological problems, the results of many attempts to estimate anesthesia levels on the basis of visual EEG assessment have been confusing and contradictory. For example, one group which studied EEG activity at different levels of halothane anesthesia reported that seven distinct EEG patterns were observed [19], but a second group which studied the same type of anesthesia reported that only two distinct EEG patterns could be identified [20]. Furthermore, the second group stated that the classical sequence of EEG changes associated with progressively deeper levels of ether anesthesia could not be observed during halothane anesthesia.

It should be noted that the issue of whether or not the EEG constitutes a valid indicator of the level of anesthesia was not resolved

simply because the results of investigations based on visual EEG assessment were not reliable. Intuitively, the EEG still appears to be the single, most valid parameter to evaluate in attempting to estimate the level of anesthesia. From a practical viewpoint EEG monitoring is safe, non-invasive, and can usually be performed with relative ease in the operating room.

Recent advances in the fields of automatic EEG analysis [21-23] and pattern recognition [24-26] have provided a valuable new perspective for reconsidering the anesthetic level estimation problem. A few automatic techniques have already been used to analyse EEG activity during anesthesia, e.g. [27-32], but this work has been confined to the implementation of various methods of EEG data compression and parameter identification. Hence the pattern recognition task, i.e. the identification and interpretation of any changes in EEG characteristics during anesthesia, would still be performed subjectively, presumably by an experienced anesthesiologist. The work to be described in this thesis represents a significant departure from previous research: it constitutes the first comprehensive investigation into the possibility of developing a computer-based EEG pattern recognition system for reliably estimating the level of anesthesia during surgery.

1.3 Scope of Thesis

The overall objective of the research described in this thesis was to investigate the feasibility of reliably estimating the level of anesthesia during surgery by means of an EEG pattern recognition system. The specific objectives were:

1) to define a set of clinically valid levels of anesthesia in terms of objective, non-EEG criteria;
2) to establish a sample EEG data base, consisting of a set of EEG pattern samples corresponding to known clinical anesthesia levels,

for one or more commonly used types of anesthesia;

3) to develop systems for estimating anesthesia levels by the recognition of different spectral and time domain EEG patterns;

4) to establish a method for effectively evaluating the performance of EEG pattern recognition systems on the basis of a finite set of available EEG pattern samples;

5) to evaluate the performance of the initially developed spectral and time domain EEG pattern recognition systems;

6) to develop theoretical techniques which enable the degree of wide-sense stationarity and Gaussianity of spontaneous EEG activity to be modelled;

7) to model the degree of wide-sense stationarity and Gaussianity of some specific ensembles of EEG pattern samples, with a view to improving the performance of the initially developed pattern recognition systems;

8) to identify the major factors which affect the performance of EEG pattern recognition systems; and

9) to investigate any schemes which appear likely to improve the performance of the initially developed systems.

Chapter II describes the establishment of a sample EEG data base, consisting of a number of digitized, multichannel EEG segments which correspond to different levels of anesthesia. In the course of establishing the data base, a considerable effort was made to control a wide range of extraneous variables because it was recognized that the control of such variables was crucial to the success of subsequent work involving the data base. Accordingly, in addition to describing the preparation and organization of the sample EEG data base, Chapter II outlines the effort that

was made to identify and control as many extraneous variables as possible. For example, explicit definitions of the different possible levels of anesthesia were established to control the incidence of errors in clinical, non-EEG assessments of anesthetic depth. Chapter II also describes how a number of other potential sources of variability were controlled, e.g. by restricting the number of different types of anesthesia under consideration, by establishing a standardized anesthetic technique and by taking a variety of precautions during the preparation of digital EEG pattern samples.

Chapter III describes the initial development and performance evaluation of spectral and time domain EEG pattern recognition systems. All of the initially developed systems extract a small number of heuristically derived features from unknown EEG pattern samples. The classifiers in these systems employ Bayes decision rule under the assumption that the extracted features are statistically independent. A rationale concerning the choice of this particular feature extraction scheme and classification rule is presented and discussed in Chapter III. Then the general problem of how to use a relatively small set of available EEG pattern samples to effectively evaluate the performance of an EEG pattern recognition system is discussed. Two nonparametric techniques which provide particularly informative and efficient estimates of the performance of such systems are suggested. Results which were obtained by employing these techniques to estimate the performance of the initially developed spectral and time domain EEG pattern recognition systems are then presented. These results clearly demonstrate the feasibility of estimating the level of anesthesia by means of automatic EEG pattern recognition.

Chapter IV describes the development of a statistical model of spontaneous EEG activity. It was thought that such a model could be of value in improving the performance of the initially developed EEG pattern

recognition systems. Almost all methods of quantitative EEG analysis are based on certain implicit assumptions regarding the statistical characteristics of the underlying random process, particularly with respect to the extent of stationarity and Gaussianity of the process. The efficacy of alternate methods of analysis therefore depends upon the degree to which such assumptions are justified by the characteristics of the particular ensembles of EEG segments being analysed. In Chapter IV, theoretical techniques are developed which enable the degree of wide-sense stationarity and Gaussianity of spontaneous EEG activity to be modelled. Results which were obtained by applying these techniques to some specific ensembles of EEG pattern samples are presented. The comparative advantages of employing alternate methods of EEG analysis are then discussed in relation to the estimated degree of stationarity and Gaussianity of the particular EEG ensembles under consideration.

Chapter IV contains a discussion of possible methods for improving the performance of the initially developed pattern recognition systems by taking into account the actual statistical characteristics of the EEG data being analysed. Chapter V describes the investigation of other possible strategies for improving the performance of the initially developed systems. Most of these strategies involve changes in the initial feature extraction scheme and pattern classification algorithm. In the same chapter, it is argued that intersubject EEG variation is one of the major factors which adversely affect the performance of EEG pattern recognition systems. Accordingly, most of the work described in Chapter V was directed toward estimating and reducing the effect of intersubject EEG variation.

A few concluding remarks are presented in Chapter VI. In addition, the major original contributions of the research described in the thesis are briefly summarized and some suggestions are made regarding

possible areas for further research. The Appendices contain detailed information about the sample EEG data base that was established. This information should be sufficient to allow the data base to be readily used and expanded in future investigations. The Appendices also contain listings of the major programs that were written in the course of this investigation. The program listings serve a dual purpose: they provide detailed documentation concerning specific computational procedures and they facilitate the use of such procedures by others.

For reference purposes, it should be noted that some of the original results presented in subsequent chapters have already been published elsewhere [33-39,140].

CHAPTER II

EXPERIMENTAL CONTROLS AND DATA ACQUISITION

2.1 Objectives

This chapter describes the establishment of a data base, consisting of a relatively large number of sample EEG segments which correspond to different clinical anesthesia levels. During the establishment of this data base a substantial effort was made to identify and control as many extraneous variables as practicable, because it was recognized that the subsequent value of the acquired data would obviously be dependent on the extent to which such variables could be identified and controlled. To control the incidence of errors in clinical, non-EEG assessments of the level of anesthesia, it was necessary to establish explicit definitions of the different possible anesthesia levels in terms of reliable clinical criteria. Section 2.2.2 discusses the inadequacy of the traditional stages and signs of anesthesia for this purpose; section 2.2.3 describes how five clinically significant levels of anesthesia were defined, in terms of relatively objective non-EEG criteria, for this research. To eliminate some potential sources of variability, the number of different types of anesthesia under consideration was restricted and a standardized anesthetic technique was established, as described in section 2.3.1 and section 2.3.2. The data acquisition procedure which was followed is outlined in section 2.3.3 and the control of extraneous variables during data acquisition is discussed in section 2.3.4. Finally, sections 2.4.1 and 2.4.2 describe the preparation of a digital EEG data base from the experimental data collected.

2.2 Establishment of Anesthesia Levels

2.2.1 Introduction

General anesthesia may be defined as a state of unconsciousness produced by anesthetic agents, with absence of pain sensation over the entire body and a greater or lesser degree of muscular relaxation [40]. At present, different dosages of a wide variety of anesthetic agents and drugs, administered either by inhalation or intravenously, can be used to produce different levels of general anesthesia. For the purposes of this research a set of five possible levels of general anesthesia was explicitly defined in terms of clinical, non-EEG signs of anesthetic depth.

2.2.2 Historical Perspective

The first description of different stages of anesthesia was contained in a monograph published in 1847 [41]. The monograph described five recognizable stages of anesthesia with ether, based primarily on changes in the character of respiration and the degree of suppression of reflex activity. In subsequent years, various possible clinical signs of different anesthesia stages were investigated, including heart rate, blood pressure, respiration, pupil diameter and reactivity to light, tearing and eye movement. Several of these signs were eventually incorporated into a detailed description of four different stages of anesthesia which was published in a fairly complete form in 1937 [42]. For many years this description of clinical signs and stages served as the standard reference for inhalational anesthesia. It should be noted, however, that only a small number of inhalational anesthetic agents were then in common use and the primary goal of the anesthesiologist in this period was simply to administer one of the available agents in sufficient concentration to produce a stage of anesthesia associated with unconsciousness and an adequate degree of muscular relaxation, without seriously endangering the

patient's life. Unfortunately, this rather admirable goal was not always satisfactorily achieved.

Recent developments in anesthesiology have decreased the mortality rate associated with the administration of general anesthesia, but have eliminated or obscured many of the traditional clinical signs and stages of anesthesia [43]. For example, the clinical use of drugs which specifically produce good muscle relaxation and the emergence of controlled respiration to assure adequate patient ventilation have largely eliminated two formerly valuable clinical signs: the degree of muscle relaxation and the character of respiration [44]. Furthermore, factors such as the introduction of preanesthetic medication, the use of a combination of drugs during anesthesia and the increasing variety of anesthetic agents have contributed to the complexity of correctly interpreting changes in many of the remaining clinical signs [43-46]. In addition, modern anesthetic practise has reduced the significance of some of the traditional stages of anesthesia and has provided increased motivation for the definition of some new stages: for example, the current practise of rapid induction of anesthesia has essentially eliminated one of the traditional stages, while recent reports of consciousness occurring at apparent surgical levels of anesthesia [47-52] indicate the need for a new definition of anesthesia levels.

Thus, at least two important problems associated with the definition of anesthesia levels are apparent. First, many of the traditional clinical signs and stages of anesthesia are not relevant to modern anesthetic practise. Second, any available clinical signs may often be equivocal and require considerable subjective interpretation.

2.2.3 Definition of Anesthesia Levels

For this research, the set of possible levels of anesthesia was defined in a unique manner to clearly establish its validity in terms of

modern anesthetic practise. After considerable discussion, experienced anesthesiologists[1] defined five clinically significant levels of anesthesia in terms of non-EEG criteria that they considered to be meaningful and appropriate. Subsequently, minor revisions of the criteria were made to resolve possible ambiguities in the wording, to allow for a more objective differentiation of levels, and to facilitate the use of the same set of criteria with three common types of general anesthesia (to be described in section 2.3.1). The resultant set of clinical criteria is given in Table 2-1. The criteria are based primarily upon a patient's responsiveness to various stimuli and upon changes in his blood pressure and pulse rate. A concerted effort was made to keep all criteria as objective and quantitative as practicable.

Table 2-1 Clinical Criteria for Estimating Levels of Anesthesia

Level	Clinical Criteria
0	(Consciousness) Patient is alert with spontaneous speech.
1	(Light Anesthesia) Movement in response to the preparation and surgery if not paralyzed. Movement in response to vocal command during emergence. Tachycardia and hypertension during surgery.
2	(Light Surgical Anesthesia) Movement in response to surgical stimulation but not in response to the preparation or similar light stimulation. Tachycardia and hypertension during surgery.
3	(Surgical Anesthesia) No movement in response to the preparation or surgical stimulation. No tachycardia or bradycardia. Patient is either normotensive or mildly hypotensive, i.e. within 20 percent of normal.
4	(Deep Surgical Anesthesia) No movement in response to the preparation or surgical stimulation. Bradycardia and hypotension, i.e. greater than a 20 percent deviation from normal.

[1] Dr. L.C. Jenkins, Professor and Head of the Department, and Dr. B.A. Saunders, Clinical Assistant Professor, Department of Anaesthesiology, Faculty of Medicine, University of B.C.

2.3 Acquisition of Experimental Data

2.3.1 Types of Anesthesia Considered

The different types of general anesthesia are commonly differentiated by referring to the combination of agents employed to maintain an adequate level of anesthesia. Hence the three types of anesthesia to be considered in this thesis are generally known to anesthesiologists as halothane-nitrous oxide-relaxant anesthesia, narcotic-nitrous oxide-relaxant anesthesia and enflurane-nitrous oxide-relaxant anesthesia. The first two types of anesthesia account for most of the general anesthetics administered in North America today. For example, of 28,988 inhalational anesthetics which were administered at the Vancouver General Hospital in 1974, approximately 33 percent employed some variation of the halothane-nitrous oxide-relaxant technique and 63 percent employed some variation of the narcotic-nitrous oxide-relaxant technique [53]. The third type of anesthesia, i.e. enflurane-nitrous oxide-relaxant anesthesia, is relatively new but is rapidly gaining in popularity and may be in common usage within a few years. For convenience, these three types of anesthesia will subsequently be referred to in the thesis as halothane anesthesia, narcotic anesthesia and enflurane anesthesia, respectively.

2.3.2 Standardized Anesthetic Technique

The following standardized technique was established for the administration of all three types of anesthesia. Approximately one hour before surgery, a premedication consisting of morphine (10-15 mg) or meperidine (50-100 mg) and atropine (0.6 mg) or scopolamine (0.4 mg) was administered. Induction of anesthesia was accomplished with sodium thiopentone (5 mg/kg body weight) and tracheal intubation was facilitated by the administration of succinylcholine (1 mg/kg). Halothane anesthesia

was maintained with halothane vapour (0.75 percent initially) as the primary anesthetic agent supplemented by a mixture of 60 percent nitrous oxide and 40 percent oxygen. Similarly, enflurane anesthesia was maintained with enflurane vapour (1.0 percent initially) as the primary anesthetic agent supplemented by a mixture of 60 percent nitrous oxide and 40 percent oxygen. The administered concentration of both primary anesthetic agents was changed occasionally during surgery to change the level of anesthesia of patients. The third type of anesthesia, narcotic anesthesia, was maintained with a mixture of 60 percent nitrous oxide and 40 percent oxygen in conjunction with small increments (5-15 mg) of alphaprodine, a narcotic analgesic, which were given intravenously as necessary during surgery. In all cases, adequate muscle relaxation was obtained with d-tubocurarine (0.3 mg/kg initially, with more as required during longer operations). A Bird Mark 8 Respirator was used to provide controlled respiration, with respiratory rates and tidal volumes initially determined by a Radford nomogram [54]. To ensure adequate ventilation during anesthesia, a Beckman LB-1 Medical Gas Analyzer was used to monitor each patient's end-tidal carbon dioxide concentration and the respirator was adjusted so that the end-tidal carbon dioxide concentration and the respirator was adjusted so that the end-tidal carbon dioxide concentration was always between 35 and 45 mm Hg. At the end of each operation the action of the muscle relaxant was reversed with atropine (1.2 mg) and neostigmine (2.5 mg).

Detailed information regarding the different anesthetic techniques and procedures and the properties of various anesthetic agents and drugs can be found in many general references, e.g. [7, 8], and will not be given here. Thorough reviews of possible EEG effects of a wide variety of general anesthetics are also available, e.g. [15-17], as are many

papers dealing specifically with relevant EEG and cardiovascular effects of the anesthetic agents and drugs used in the thesis research, e.g. nitrous oxide [55,56], sodium thiopentone [12], d-tubocurarine [57], halothane [19,20,58-60], narcotics [50,61] and enflurane [62-66]. At present, the most serious clinical problems associated with the three types of anesthesia considered in the thesis are: possible hepatitis resulting from halothane anesthesia [67-69], reported incidents of awareness during narcotic anesthesia [47-52] and occasional central nervous system irritability during enflurane anesthesia [62,64]. It should be noted in passing that the latter two problems are currently being investigated by means of EEG analysis.

2.3.3 Data Acquisition

Fig. 2-1a shows most of the equipment employed to acquire experimental data, as well as some of the usual anesthetic equipment in the operating room. Fig. 2-1b shows the actual configuration of the equipment for data acquisition during an operation. The anesthetic equipment cart seen in Fig. 2-1a contains a Bird Respirator, an anesthetic gas vaporizer and supplies of various anesthetic agents and drugs. The EEG electrodes seen in Fig. 2-1b are standard cup electrodes, filled with conductive paste, which have been attached to the patient at positions defined by the International 10-20 System [70] to establish four differential EEG channels: F3-C3, C3-O1, F4-C4 and C4-O2. The relative locations of these two bilaterally symmetric pairs of channels are indicated in Fig. 2-3. The EEG electrodes were connected to a termination box (Fig. 2-1a) which can be used in one mode to measure the electrode contact resistance and in another mode as a preamplifier for the EEG machine. A Beckman 8-channel EEG machine, with its lowpass filters set at 50 Hz and its highpass

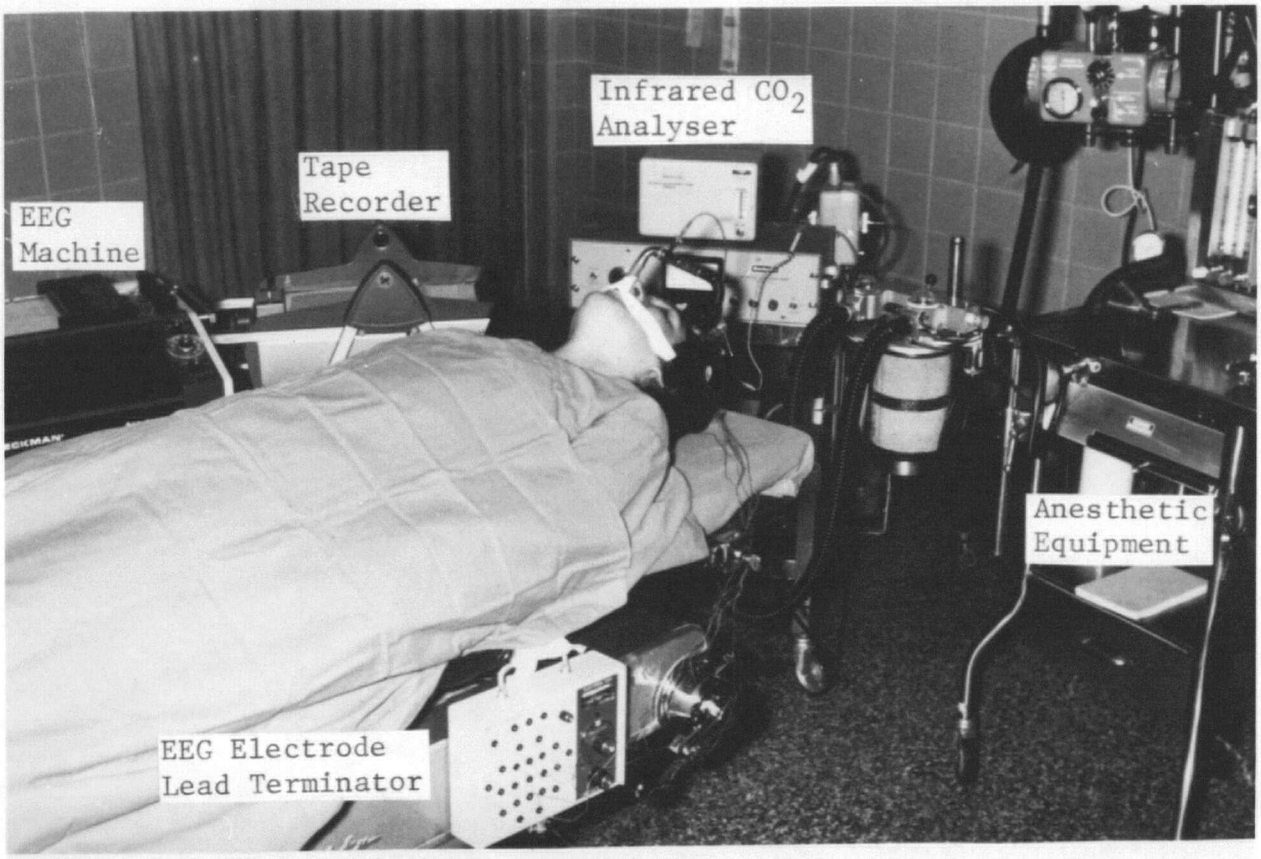

Fig. 2-1a Data Acquisition Equipment

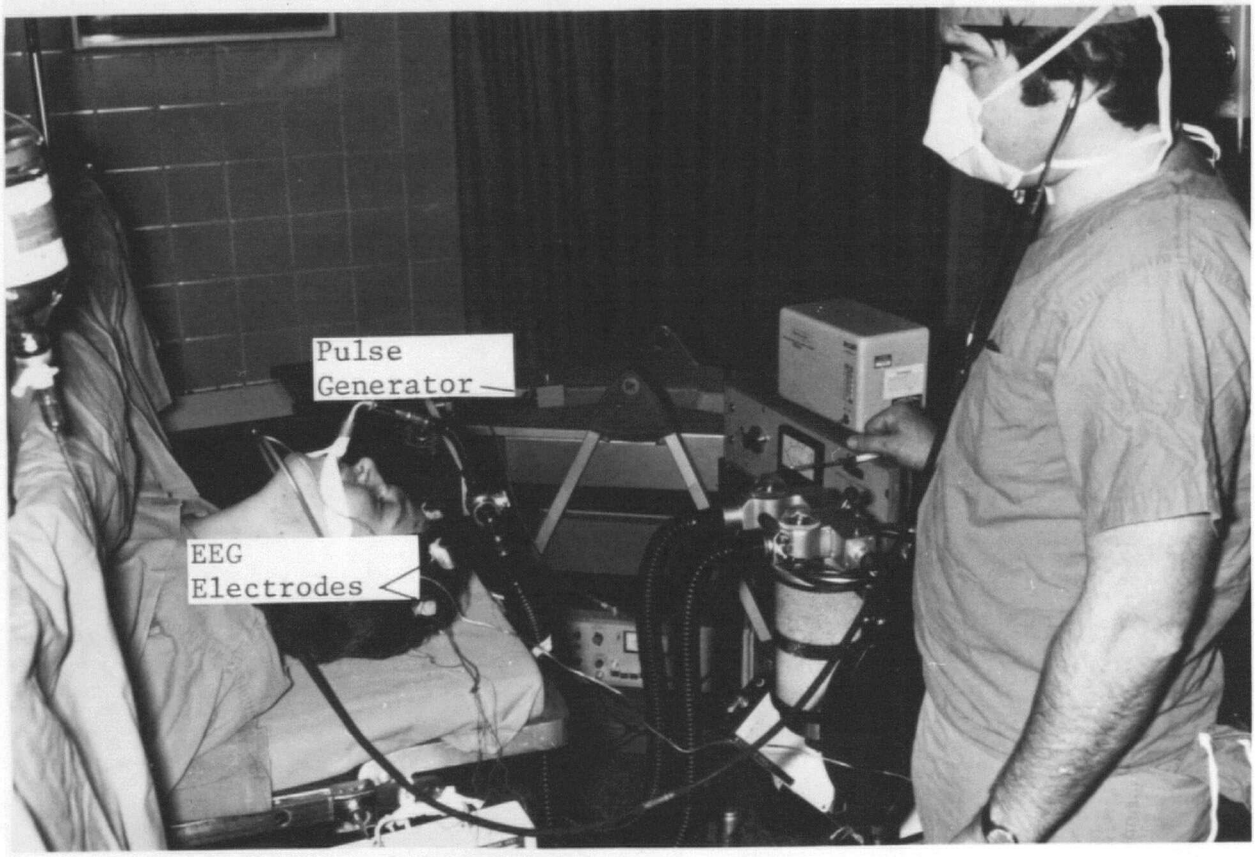

Fig. 2-1b Acquisition of Data in the Operating Room

filters set at 0.54 Hz to reduce artifact,was used to amplify the EEG and to plot the amplified EEG on chart paper for immediate visual inspection. A Hewlett-Packard Model 3960A instrumentation tape recorder was connected to the EEG machine; at a tape speed of 15/16 ips the recorder could store four channels of EEG activity for more than four hours on one reel of 3M Type 871 instrumentation tape. The pulse generator seen in Fig. 2-1b was connected to the recorder so that short pulses could be inserted into one channel of the recording to identify EEG segments of interest. As mentioned in section 2.3.2, an infrared CO_2 analyser was used to monitor the end-tidal carbon dioxide concentration throughout each operation. Not evident in either Fig. 2-1a or Fig. 2-1b is a Tektronix 410 Monitor which was used to monitor electrocardiographic activity.

The acquisition of experimental data proceeded in the following manner. After a suitable surgical patient had been identified by one of the anesthesiologists participating in this research, the patient was visited pre-operatively and informed consent was obtained. EEG electrodes were then attached and, before the standard premedication was administered, the patient's baseline EEG activity was recorded for several minutes while he or she was resting with eyes closed; the pulse generator was used to mark at least two 64s segments of baseline EEG activity for subsequent analysis. EEG recording was later resumed when the patient entered the operating room and was continued until the patient was moved to a post-operative recovery area. Estimations of the level of anesthesia, based on the clinical criteria given in Table 2-1, were made by an anesthesiologist at intervals of approximately five minutes during the operation. The pulse generator was used to mark 64s EEG segments which corresponded to the clinically estimated anesthesia levels. If the anesthesiologist was uncertain of the level of anesthesia as defined by the clinical

criteria, e.g. during a period of transition between levels, no further attempt was made to estimate the level at that time. Similarly, no attempt was made to estimate the level of anesthesia when the EEG contained obvious and excessive artifact, e.g. while the electrosurgical unit was in use. The Level of Anesthesia Evaluation Form shown in Appendix A was employed to record each estimated level of anesthesia and the number of the pulse which identified the corresponding EEG segment, as well as all other relevant information about the operation.

2.3.4 Control of Variables During Data Acquisition

An attempt was made to control several extraneous variables during the acquisition of experimental data. Many of these variables tended to increase the range of EEG pattern variability and the incidence of errors in clinically estimated anesthesia levels. Obviously the subsequent value of the acquired data is highly dependent on the extent to which such extraneous variables could be controlled.

To reduce the range of EEG variability resulting from the use of different anesthetic agents and drugs, only the three most common types of general anesthesia were considered and a standardized anesthetic technique was established. Furthermore, data was acquired only from healthy adult patients who underwent similar kinds of surgery, thus reducing the extent of EEG variability due to differences in age, general health status, intensity of surgical stimulation and duration of anesthesia. EEG variability associated with abnormal carbon dioxide levels in the blood [71] was controlled by monitoring the patient's carbon dioxide level and adjusting the respirator to keep it within normal limits, as described in section 2.3.2.

Additional precautions were taken to reduce the amount of

artifact present in recorded EEG activity. The EEG electrodes were firmly attached with gauze pads soaked in collodion, a special glue and sealant which prevented the electrode paste from drying out during the operation and thus reduced the possibility of artifact due to poor electrode contacts. Any artifact above 50 Hz, e.g. 60 Hz electrical interference, and below 0.54 Hz, e.g. some movement artifact, was eliminated by setting the lowpass and highpass filters on the EEG machine to 50 Hz and 0.54 Hz respectively. EEG activity was not recorded while the electrosurgical unit was being used because artifact from the unit saturated the EEG amplifiers.

Attempts were also made to reduce the incidence of incorrect estimations of anesthesia levels caused by errors in clinical judgement and by possible non-stationarities in the actual level of anesthesia over the 64s duration of the corresponding EEG segment. Errors in clinical judgement were reduced by developing an explicit set of objective clinical criteria (Table 2-1) and by minimizing the number of anesthesiologists who made clinical estimations of levels; these anesthesiologists became familiar with the standardized anesthetic technique and became quite proficient at estimating anesthesia levels on the basis of the clinical criteria. When they could not confidently estimate levels on the basis of the criteria, they were asked to refrain from guessing. The incidence of non-stationary anesthesia levels within the 64s intervals corresponding to identified EEG segments was reduced in two ways. First, whenever possible, a clinical level estimation was made at the beginning and end of a 64s interval and the corresponding EEG segment was only retained for analysis if both estimations were the same. Second, at least three minutes was allowed to elapse between a change in the administered concentration of the primary anesthetic agent and the time that the next clinical level estimation was made, so that the concentration of anesthetic agents in the blood could approach equilibrium;

it would have been preferable to determine a state of equilibrium by directly monitoring the arterial blood concentrations of the various anesthetic agents, but it was not possible to do so because the appropriate equipment was not available.

2.4 Establishment of EEG Data Base

2.4.1 Description of Analog EEG Data Collected

As stated previously, the operations from which data was collected consisted primarily of general surgical cases involving patients who were in the best surgical risk categories, i.e. who were in either Class I or Class II as defined by the American Society of Anesthesiologists ([8], pp. 401-402). Data which was collected from an operation was not retained for analysis when there was a significant deviation from the standardized anesthetic procedure outlined in section 2.3.2, or when it was apparent that the control of variables described in section 2.3.4 was inadequate. In total, EEG recordings and clinical data from 72 operations were retained for analysis. Of this total, halothane anesthesia was used in 21 cases, narcotic anesthesia was used in 26 cases and enflurane anesthesia accounted for the remaining 25 cases. Fig. 2-2 shows sample multichannel segments of baseline EEG activity (Level 0) and EEG activity at a surgical level of anesthesia (Level 3) for the three different types of anesthesia.

The halothane anesthesia data was obtained from 8 male and 13 female patients ranging in age from 17 to 65 years, with an average age of 46 years. The average duration of anesthesia was 70 min, although the duration of individual cases varied from 30 min to 135 min. The number of anesthesiologists who made clinical estimations of the level of anesthesia during halothane anesthesia was limited to three.

Of the 26 narcotic anesthesia cases, 9 involved male patients

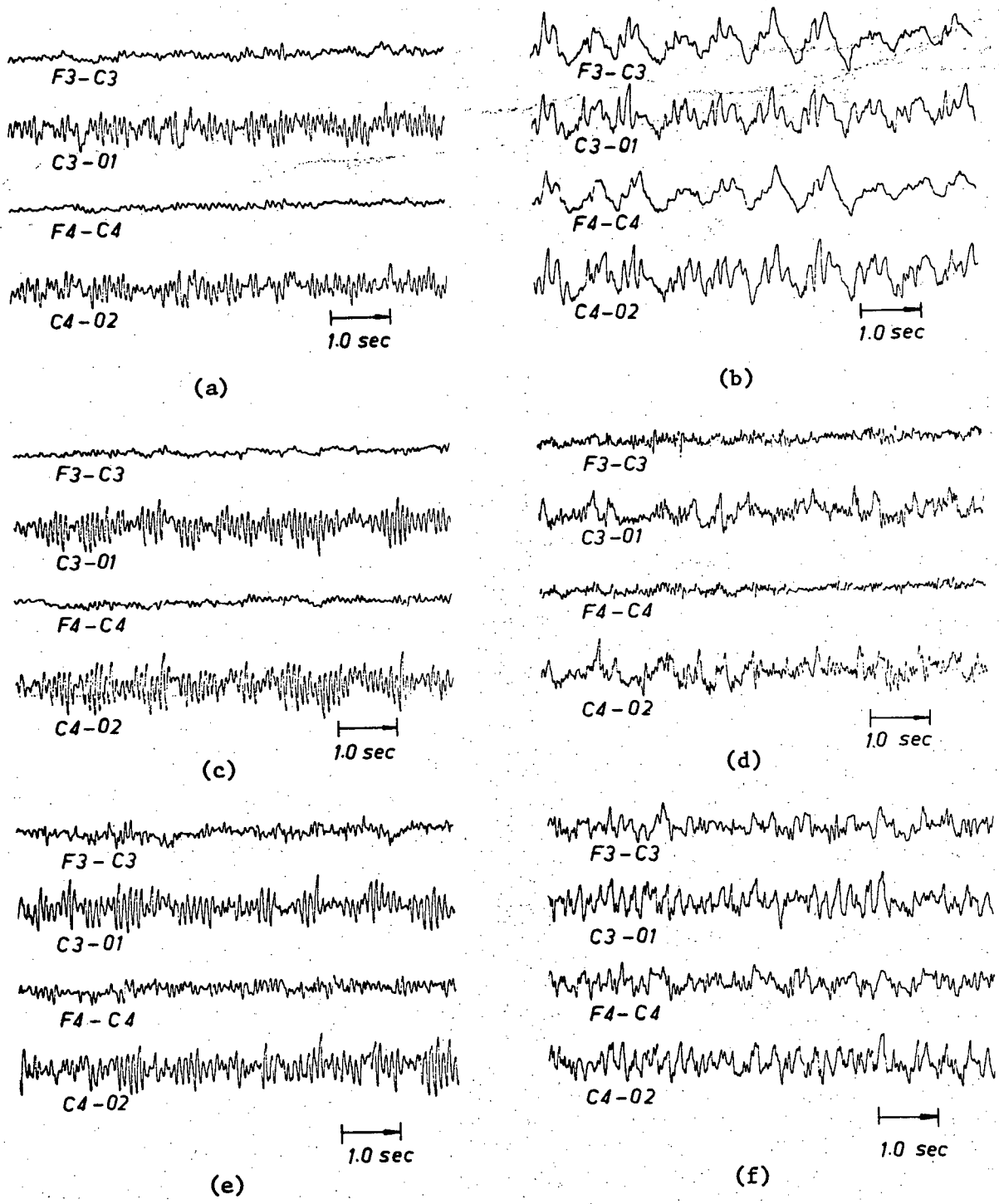

Fig. 2-2 Sample Segments of Multichannel EEG Activity. Samples of EEG activity at Anesthesia Level 0 and Anesthesia Level 3 for three subjects having similar baseline EEG characteristics are shown in (a)-(b), (c)-(d), and (e)-(f). Segments (b), (d) and (f) were recorded during halothane anesthesia, narcotic anesthesia and enflurane anesthesia, respectively.

and 17 involved female patients. Their ages ranged from 20 to 64 years, with an average age of 44 years. The anesthetic was administered for between 30 min and 150 min; the average duration was 90 min. Thirteen anesthesiologists made clinical estimations of the level of anesthesia during narcotic anesthesia.

The enflurane anesthesia data was obtained from 9 male and 16 female patients. All were between 23 and 70 years of age, with an average age of 47 years. The anesthesia varied from 60 min to 150 min in duration, with an average duration of approximately 90 min. Three anesthesiologists were involved in making clinical estimations of anesthesia levels.

For reasons which will be given elsewhere in the thesis, it was considered desirable to collect some data from patients who were undergoing two successive operations within a short period of time. This was possible in a few instances, i.e. where female patients underwent tissue biopsies followed by mastectomies or hysterectomies. Consequently, the halothane anesthesia data included data from one pair of operations performed on the same patient and the narcotic anesthesia data included data from three such pairs of operations.

2.4.2 Digitization and Preparation of Digital EEG Data Base

Fig. 2-3 shows the general configuration of the system that was developed to prepare and screen digitized EEG pattern samples. As described in section 2.3.3, throughout each operation an instrumentation tape recorder was used to record four channels (F3-C3, C3-O1, F4-C4 and C4-O2) of spontaneous EEG activity. Short pulses which were inserted in one channel of the recording identified all EEG segments corresponding to known clinical anesthesia levels. The system shown in Fig. 2-3 was used to digitize these EEG recordings, to separate digitized EEG pattern samples

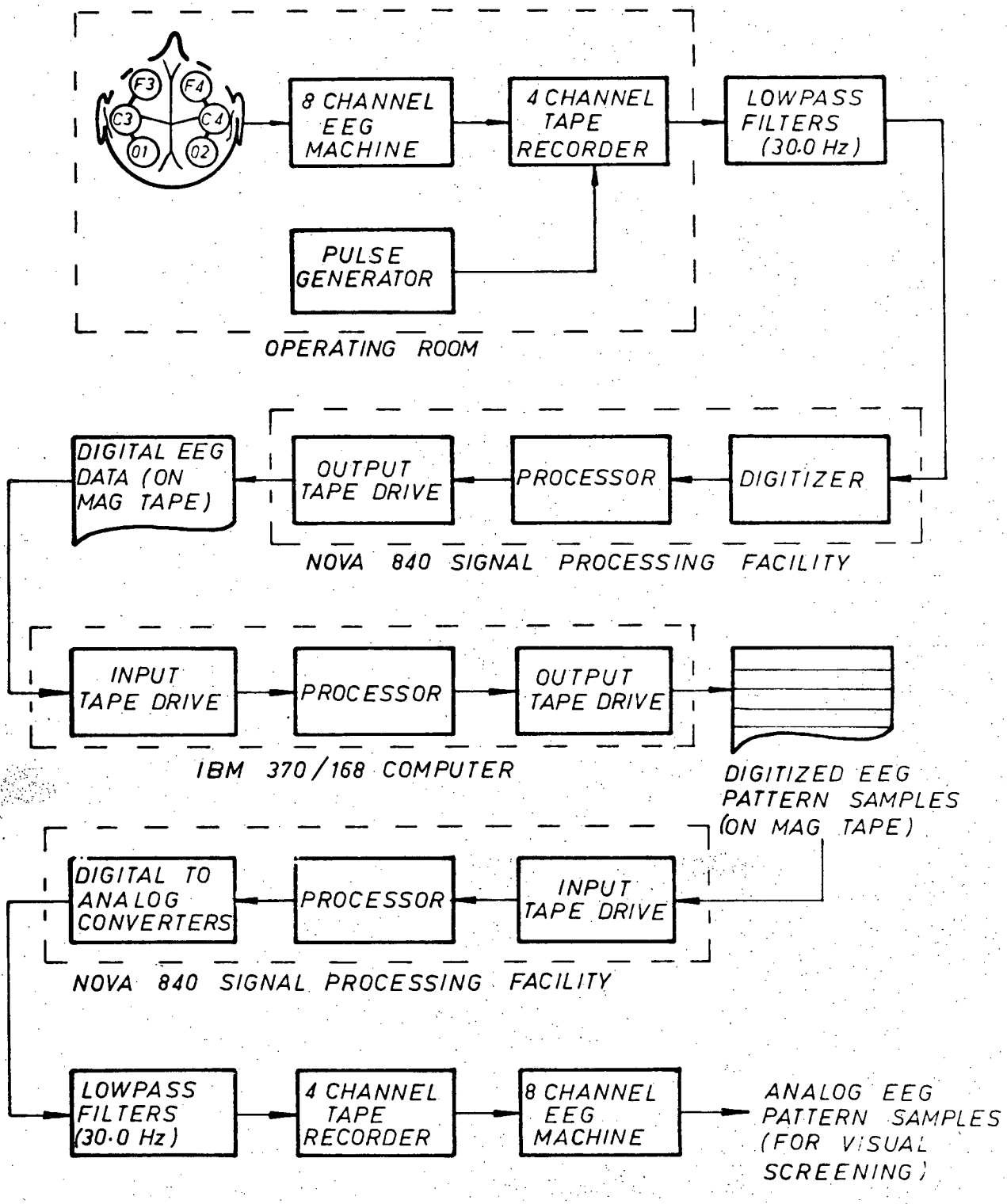

Fig. 2-3 Configuration of System Used for Preparing and Screening EEG Pattern Samples

corresponding to known anesthesia levels, and to plot these pattern samples for visual screening.

The Nova 840 Signal Processing Facility at the U.B.C. Electrical Engineering Department was used to convert all analog EEG records to digital records stored on digital data tapes. To accomplish this, as illustrated in Fig. 2-3, the recorded EEG activity was first reproduced on the instrumentation recorder, lowpass filtered at 30.0 Hz with Krohn-Hite 3342R filters and then the filtered data was digitized and stored on 9-track, IBM-compatible tapes using the Nova 840 Signal Processing Facility. The digitizer consisted of a multiplexer which sampled each EEG channel at 128 samples/s and a 10-bit analog/digital converter which converted each sample to binary form. For programming ease, each digital sample value was stored in two successive bytes on tape although the maximum resolution was limited to 10 bits.

The digital data tapes were transferred to the IBM 370/168 computer at the U.B.C. Computing Centre. A FORTRAN program was used to find the pulse locations on each tape. After the pulse locations were verified by checking the pulse information which had been recorded on the Level of Anesthesia Evaluation Forms (Appendix A), a second program was used to extract a 64s EEG segment from each location and then to copy each extracted segment into a separate file on a new digital tape. Thus, each file on the new tape contained a digitized 64s EEG pattern sample corresponding to a known level of anesthesia.

After all EEG pattern samples had been extracted, they were visually screened in order to reject samples containing obvious and excessive artifact. The visual screening procedure was facilitated by reproducing all EEG pattern samples in analog form on standard EEG chart paper. To do this, as indicated in Fig. 2-3, the digitized EEG pattern

samples were first converted to analog form using the Nova 840 Signal Processing Facility: each digitized EEG pattern sample was read from a tape, demultiplexed and transferred to digital/analog converters. The resultant analog EEG samples were lowpass filtered at 30.0 Hz and were then recorded on the instrumentation tape recorder. By later connecting the recorder to an 8-channel EEG machine at the Vancouver General Hospital, the EEG pattern samples could be reproduced on standard EEG chart paper in a format suitable for visual screening.

An EEG pattern sample was usually rejected if it contained more than 10s of visually apparent artifact in more than one channel. Major sources of visually recognizable artifact included interference from electrosurgical units in the operating rooms, poor electrode contacts, eyeblinks, electrocardiographic activity, movement and muscle activity. EEG pattern samples containing primarily low frequency artifact, e.g. movement artifact below 0.5 Hz, were not rejected because it was known that all data would again be highpass filtered (digitally) at 0.54 Hz before being analysed. EEG pattern samples containing small amounts of visually apparent artifact were not rejected in order to retain as large a data base as possible. Approximately 20 percent of the EEG pattern samples which were visually screened were rejected because of artifact.

Table 2-2 indicates the number of EEG pattern samples which were retained after visual screening. A total of 938 samples from 72 subjects and three types of anesthesia were retained for subsequent analysis. The screened EEG pattern samples associated with each type of anesthesia were transferred to the digital tapes listed in Table 2-2. In addition, the three disk files identified in Table 2-2 were used to store the following information about each EEG pattern sample: its location on the appropriate tape, its corresponding level of anesthesia and the identity of the patient

from which it was obtained. The structure of data on the digital tapes and in the disk files is documented in Appendix B. In addition, Appendix B contains the listing for an input subroutine which can be used to transfer a specified EEG pattern sample from tape to a FORTRAN array.

Table 2-2 Description of Resulting EEG Data Base

EEG Data Base Information	Type of Anesthesia		
	Halothane	Narcotic	Enflurane
Number of EEG pattern samples:			
Level 0	56	51	92
Level 1	37	47	58
Level 2	12	86	15
Level 3	125	152	81
Level 4	50	5	71
Total number of EEG pattern samples	280	341	317
Number of cases from which the samples were obtained	21	26	25
Rack number of the digital tape which contains the EEG pattern samples	RA0562	RA0558	RA0561
Name of disk file which contains labels for the EEG pattern samples	HS.I	AS.I	ES.I

CHAPTER III

DEVELOPMENT OF EEG PATTERN RECOGNITION SYSTEMS

3.1 EEG Pattern Recognition Systems

3.1.1 Basic Description

This chapter describes the initial development and performance evaluation of various systems for estimating the level of anesthesia by means of EEG pattern recognition. Fig. 3-1 contains a simple block diagram of an EEG pattern recognition system. The preprocessor transforms an EEG pattern sample into a form which allows meaningful features to be more easily extracted. The amplification, filtering and digitization of EEG pattern samples could all be considered to be examples of preprocessing. As indicated in Fig. 3-1, a feature extractor analyses each preprocessed sample and quantitatively evaluates it in terms of a specified set of features. For example, feature extraction might consist of the calculation of a power density spectrum for each preprocessed EEG pattern sample, followed by the evaluation of features such as the peak frequency and the relative energy in different frequency bands. Each set of extracted feature values is transferred to a classifier which employs some algorithm, in conjunction with stored data, to classify the corresponding EEG pattern sample into one of five possible classes, i.e. five possible levels of anesthesia.

There is no optimum procedure for selecting the best features to be used in discriminating among EEG pattern samples corresponding to different levels of anesthesia. However, in selecting features for specific pattern recognition problems, experience has shown that a few well chosen, heuristically derived features are usually better than a

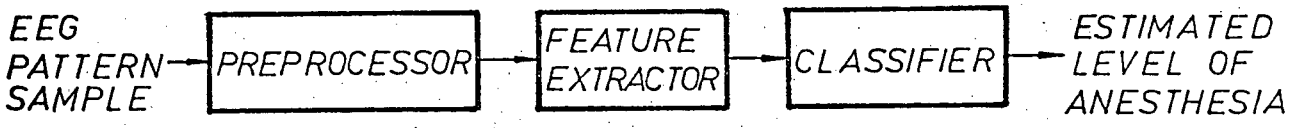

Fig. 3-1 EEG Pattern Recognition System

larger number chosen more randomly. This is primarily because processing many features requires more computing time, more storage and more data for training a classifier [72,73]. Consequently, the EEG features considered in this research were restricted to a relatively small number of features which had an established clinical significance or which had previously been described as meaningful in the literature on automatic EEG analysis.

3.1.2 Development and Performance Evaluation

With the exception of highpass filtering, all preprocessing had been performed during the preparation of the sets of EEG pattern samples which are listed in Table 2-2. The calculation of EEG power spectra from the preprocessed pattern samples and the subsequent extraction of spectral features is described in section 3.2. A description of relevant time domain EEG measurements and the extraction of time domain features is given in section 3.3. Section 3.4 outlines the classification algorithm which was employed in all spectral and time domain EEG pattern recognition systems. The problem of estimating the performance of such systems is described in section 3.5.1; the development of two nonparametric techniques which provide particularly useful and efficient estimates of the performance of EEG pattern recognition systems is then described in sections 3.5.2 - 3.5.4. Results obtained

by using these techniques to estimate the performance of various spectral and time domain EEG pattern recognition systems are presented in section 3.6. Finally, in section 3.7, the significance of the results is discussed.

3.2 Spectral Feature Extraction

3.2.1 EEG Spectral Analysis

Spectral analysis of EEG activity only became a popular analytic technique after 1965, when the introduction of the Fast Fourier Transform algorithm made digital spectral analysis fast and economically feasible [21,74-76]. During the last decade EEG spectral analysis has been employed with mixed success in a wide variety of diagnostic investigations (e.g. [77-79]), monitoring studies (e.g. [31,80] and sleep research projects (e.g. [81-83]).

EEG spectral analysis treats the amplitude of spontaneous EEG activity as a random variable. If the EEG activity from one channel is denoted by x(t) then, if it is assumed that the underlying random process is ergodic ([84], pp. 343-344), the EEG power density spectrum (or more simply, the EEG spectrum) can be defined:

$$\begin{aligned} S(f) &= E\{|X(f)|^2\} \\ &= E\{X(f)X^*(f)\} \\ &= \lim_{T\to\infty} \{\frac{1}{T}[X(f)X^*(f)]\} \end{aligned} \tag{3.1}$$

where X(f) denotes the Fourier transform of x(t) in the interval

$$-\frac{T}{2} \leq t \leq +\frac{T}{2},$$

i.e.

$$\begin{aligned} X(f) &= \mathcal{F}[x(t)] \\ &= \int_{-T/2}^{T/2} x(t)e^{-j2\pi ft}\, dt, \end{aligned} \tag{3.2}$$

and where X*(f) denotes the complex conjugate of X(f) [76]. The

relevance to EEG spectral analysis of certain assumptions concerning the stationarity and Gaussianity of the underlying random process will be considered in Chapter IV.

At present, EEG spectra can be computed by three different methods: digital bandpass filtering [86], Fourier transformation of autocorrelation functions [87], or the Direct Method, i.e. direct Fourier transformation with subsequent smoothing [21,88]. The Direct Method was employed in the computation of all EEG spectra in this research because it was found to be the fastest and most convenient of the three methods.

3.2.2 Computation of EEG Spectra

As described in section 2.4.2, all of the EEG pattern samples listed in Table 2-2 had been lowpass filtered at 30.0 Hz and digitized at 128 samples/s. By considering every second sample value it was therefore possible to analyse data with an effective sampling rate of 64 samples/s. Assume that $\{x_1,\ldots,x_N\}$ represents the set of samples obtained by sampling one EEG channel at 64 samples/s for 64s, i.e. N = 4096. The discrete Fourier transform of $\{x_1,\ldots,x_N\}$ was computed as follows:

$$T(f_k) = \sum_{\ell=1}^{N} x_\ell \exp\{\frac{-2\Pi k(\ell-1)}{N}\} \qquad (3.3)$$

for $k = 0,1,\ldots,(N/2)$, where $T(f_k)$ is the kth complex coefficient of the transform at the fundamental frequency

$$f_k = \frac{k}{N\Delta t}$$

$$= \frac{k}{64} \text{ Hz} \qquad (3.4)$$

since $\Delta t = (1/64)$s, the sampling interval [89,90]. To remove any artifact below 0.54 Hz, as mentioned in section 2.4.2, the data was highpass filtered in the frequency domain:

$$C(f_k) = H(f_k)T(f_k) \qquad k = 0,1,\ldots,(N/2) \qquad (3.5)$$

where

$$H(f_k) = \begin{cases} 0 & 0.0 \leq f_k < 0.50 \\ (f_k - 0.50)/0.8 & 0.50 \leq f_k < 0.58 \\ 1 & 0.58 \leq f_k \leq 32.0 \end{cases} \tag{3.6}$$

From the filtered Fourier coefficients $C(f_k)$ a periodogram was calculated:

$$I(f_k) = \frac{\Delta t}{N} |C(f_k)|^2 \qquad k = 0,1,\ldots,(N/2). \tag{3.7}$$

To improve the statistical properties of the raw spectral estimates provided by (3.7), averaging was performed over adjacent frequencies by means of a spectral window G_i to yield the smoothed periodogram

$$\tilde{I}(f_k) = \sum_{i=-W}^{W} G_i I(f_{k-i}) \tag{3.8}$$

where

$$\sum_{i=-W}^{W} G_i = 1. \tag{3.9}$$

G_i was chosen to be a rectangular window of width 15/64 Hz, i.e.

$$G_i = \begin{cases} \frac{1}{2W+1} & i = -W,\ldots,W \\ 0 & \text{otherwise} \end{cases} \tag{3.10}$$

where W = 7. Finally, from (3.8) a smoothed EEG spectrum with spectral estimates at 0.125 Hz intervals from 0 - 32 Hz was computed:

$$\hat{S}(f_m) = \frac{1}{8} \sum_{\ell=1}^{8} \tilde{I}(f_{8m+\ell}) \tag{3.11}$$

for

$$\frac{(m-1)}{8} \leq f_m < \frac{m}{8}, \qquad m = 1,\ldots,256. \tag{3.12}$$

More detailed information concerning the computation of EEG spectra in this manner may be found elsewhere ([85], pp. 43-52). Appendix C contains a listing of the program which was used to compute EEG spectra by the method described above.

3.2.3 Spectral Feature Vectors

Table 3-1 contains a description of the set of features $\{\sigma_i\}$, $1 \leq i \leq 13$, chosen for extraction from the spectra corresponding to each EEG pattern sample. It should be noted that, for the reasons given in section 3.1.1, only a relatively small number of features from two EEG channels were initially considered. These particular features were heuristically chosen after reviewing the literature on computer-based EEG spectral analysis (e.g. [77-83, 91]) and after considerable consultation with an academically well qualified and clinically experienced electroencephalographer[1]. From (3.11) - (3.12) and from the description of features given in Table 3-1, it is evident that

$$\sigma_1 = \sum_{f_m=f_{a_1}}^{f_{b_1}} \hat{S}(f_m)\Delta f$$

$$= \Delta f \sum_{m=a_1}^{b_1} \hat{S}(f_m)$$

$$= 0.125 \sum_{m=1}^{256} \hat{S}(f_m), \qquad (3.13)$$

because $\Delta f = 0.125$, a_1 is the smallest integer greater than $8f_{a_1}$ and $b_1 = 8f_{b_1}$. Knowing σ_1, the subset of features $\{\sigma_i\}$, $2 \leq i \leq 7$, can be evaluated:

$$\sigma_i = \frac{100}{\sigma_1} \sum_{f_m=f_{a_i}}^{f_{b_i}} \hat{S}(f_m)\Delta f$$

$$= \frac{12.5}{\sigma_1} \sum_{m=a_i}^{b_i} \hat{S}(f_m) \qquad 2 \leq i \leq 7. \qquad (3.14)$$

---

[1] Dr. M.D. Low, Associate Professor of Neurology at the University of British Columbia and Director of the EEG Department at the Vancouver General Hospital.

Table 3-1 Description of Spectral Feature Set

Spectral Feature σ_i			Frequency Range (Hz)	
i=	Description	Channel	f_{a_i}	f_{b_i}
1	Total spectral energy	C4-02	0.00	32.00
2	Relative energy: Δ band	C4-02	0.00	4.00
3	Relative energy: θ band	C4-02	4.01	8.00
4	Relative energy: α band	C4-02	8.01	13.00
5	Relative energy: σ band	C4-02	13.01	15.00
6	Relative energy: β_1 band	C4-02	15.01	32.00
7	Relative energy: β_2 band	C4-02	18.01	24.00
8	Mean spectral frequency	C4-02	0.00	32.00
9	Second moment	C4-02	0.00	32.00
10	Peak intensity: α band	C4-02	8.01	13.00
11	Peak frequency: α band	C4-02	8.01	13.00
12	Peak intensity: α band	F4-C4	8.01	13.00
13	Peak frequency: α band	F4-C4	8.01	13.00

The features corresponding to the first and second moments of the spectrum, i.e.

$$\sigma_8 = \frac{1}{\sigma_1} \sum_{m=a_1}^{b_1} \hat{S}(f_m) f_m \Delta f \tag{3.15}$$

and

$$\sigma_9 = \frac{1}{\sigma_1} \sum_{m=a_1}^{b_1} \hat{S}(f_m) f_m^2 \Delta f, \tag{3.16}$$

can easily be computed. The value of σ_8 indicates the mean spectral frequency. The value of σ_9 is of interest because, assuming that the underlying random process is stationary and Gaussian with zero mean ([84], pp. 485-495), σ_9 is related to a popular time domain EEG feature: the mean EEG zero-crossing rate [92-94]. The remaining subset of features $\{\sigma_i\}$, $10 \leq i \leq 13$, can be quickly evaluated: for i = 10 (with spectral data from C4-02) and i = 12 (with spectral data from F4-C4), if

$$\hat{S}(f_m) > \hat{S}(f_n) \quad \text{for} \quad \begin{cases} f_{a_i} \leq f_n \leq f_{b_i} \\ f_{a_i} \leq f_m \leq f_{b_i} \\ f_m \neq f_n \end{cases} \tag{3.17}$$

then $$\sigma_i = \hat{S}(f_m) \tag{3.18}$$

and $$\sigma_{i+1} = f_m. \tag{3.19}$$

The extraction of spectral features proceeded in the following manner. First, EEG spectra were computed for all of the 938 pattern samples listed in Table 2-2. Then, for each pattern sample, the set of 13 features summarized in Table 3-1 was evaluated. Appendix D contains the listing of a program that was written to evaluate spectral features. The resultant 13-element feature vectors were stored for subsequent use in the development and evaluation of various pattern classifiers.

3.3 Time Domain EEG Feature Extraction

3.3.1 Time Domain EEG Analysis

It is known that EEG spectra will contain complete statistical information about the underlying random processes if the processes are stationary and Gaussian ([84], pp. 474-475). However it was initially suspected, and subsequently confirmed by the results in Chapter IV, that the assumptions of stationarity and Gaussianity are not generally valid. It was also known that visual EEG assessment is based primarily on the evaluation of time domain EEG features, not spectral features [22,95]. Therefore it was decided to develop EEG pattern recognition systems based on clinically relevant time domain features, so that their performance could be evaluated and compared to the performance of spectral pattern recognition systems.

After reviewing much of the literature on automatic time domain EEG analysis (e.g. [21,81, 92-94, 96]), and after discussions with Dr.

M.D. Low, it was decided that the clinically relevant features described in Table 3-2 would be extracted from EEG pattern samples. It should be noted that, as with spectral analysis, only two channels of EEG data (F4-C4 and C4-O2) were considered initially. Of the 10 features in the set $\{\tau_i\}$, $1 \leq i \leq 10$, four are derived from a period analysis of EEG activity and six are derived from an amplitude analysis. If x(t) denotes the EEG activity from one channel then the mean zero-crossing rate is the average number of times per second that $x(t) = 0$. The mean zero-crossing rate of the time derivative corresponds to the average number of times per second that x(t) reaches an extremum, i.e. that

$$\frac{d\ x(t)}{dt} = 0. \tag{3.20}$$

All of the EEG amplitude features can be derived from p(x), the amplitude probability distribution of x(t): if

$$m_1 = \int_{-\infty}^{\infty} xp(x)\ dx \tag{3.21}$$

and

$$m_n = \int_{-\infty}^{\infty} (x - m_1)^n p(x)dx, \quad n = 2,3,4, \tag{3.22}$$

then the standard deviation of the amplitude

$$\beta_0 = (m_2)^{\frac{1}{2}}, \tag{3.23}$$

the skewness

$$\beta_1 = \frac{m_3}{(m_2)^{3/2}} \tag{3.24}$$

and the excess of kurtosis

$$\beta_2 = \frac{m_4}{(m_2)^2} - 3 \tag{3.25}$$

are easily obtained [97]. The skewness feature indicates the relative asymmetry of p(x), i.e. in the case of a symmetrical distribution $\beta_1 = 0$; the excess of kurtosis indicates the relative flatness of p(x) in comparison to a Gaussian distribution, for which $\beta_2 = 0$ ([85], pp. 39-40).

Table 3-2 Description of Time Domain EEG Feature Set

i=	Time Domain Feature τ_i	Channel
1	Mean zero-crossing rate	F4-C4
2	Mean zero-crossing rate of first derivative	F4-C4
3	Standard deviation of amplitude	F4-C4
4	Skewness	F4-C4
5	Excess of kurtosis	F4-C4
6	Mean zero-crossing rate	C4-O2
7	Mean zero-crossing rate of first derivative	C4-O2
8	Standard deviation of amplitude	C4-O2
9	Skewness	C4-O2
10	Excess of kurtosis	C4-O2

3.3.2 Time Domain Feature Vectors

This section outlines the procedure for evaluating individual pattern samples in terms of the feature set $\{\tau_i\}$, $1 \leq i \leq 10$, summarized in Table 3-2 and described in the previous section. Before any features were evaluated, EEG pattern samples were digitally filtered with

$$B(f) = \begin{cases} 0 & 0 \leq f < 0.50 \\ (f-0.50)/0.8 & 0.50 \leq f < 0.58 \\ 1 & 0.58 \leq f \leq f_{LP} \\ 0 & f > f_{LP} \end{cases} \qquad (3.26)$$

to remove any artifact below 0.54 Hz and to remove high frequency EEG activity above f_{LP} Hz which, in visual EEG assessment at least, often tended to obscure significant changes in time domain feature values. The different choices for f_{LP} will be described in section 3.6.2. To illustrate the feature evaluation procedure let $\{x_1,\ldots,x_N\}$ denote the set of values obtained by digitizing the EEG activity from channel F4-C4 at 64 samples/s for T = 64s, i.e. N = 4096, and then bandpass filtering the digitized EEG

with B(f) in (3.26). The mean zero-crossing rates of the EEG and its first derivative can be evaluated from the following equations:

$$\tau_1 = \frac{1}{2T} \sum_{k=1}^{N} [1 - \text{sgn}(x_{k+1})\text{sgn}(x_k)] \tag{3.27}$$

and

$$\tau_2 = \frac{1}{2T} \sum_{k=1}^{N} [1 - \text{sgn}(\Delta_{k+1})\text{sgn}(\Delta_k)] \tag{3.28}$$

where

$$\Delta_k = [x_{k+1} - x_k]. \tag{3.29}$$

To evaluate the amplitude features defined in (3.23)-(3.25), the sample mean

$$\hat{m}_1 = \frac{1}{N} \sum_{k=1}^{N} x_k \tag{3.30}$$

and higher order central moments

$$\hat{m}_n = \frac{1}{(N-1)} \sum_{k=1}^{N} (x_k - \hat{m}_1)^n \quad , \quad n = 2,3,4 \quad , \tag{3.31}$$

are employed:

$$\tau_3 = (\hat{m}_2)^{\frac{1}{2}} \tag{3.32}$$

$$\tau_4 = \frac{\hat{m}_3}{(\hat{m}_2)^{3/2}} \tag{3.33}$$

$$\tau_5 = \frac{\hat{m}_4}{(\hat{m}_2)^2} - 3. \tag{3.34}$$

Similarly, features $\tau_6 - \tau_{10}$ can be evaluated using the sample EEG data from channel C4-O2.

Appendix E contains the listing of a program that was written to evaluate EEG pattern samples in terms of the time domain features in Table 3-2. This program was used to prepare time domain feature vectors for all available pattern samples. The resultant feature vectors were stored for later use.

Fig. 3.2 summarizes the procedure for preparing spectral and time domain EEG feature vectors for subsequent use in classifier development and performance evaluation.

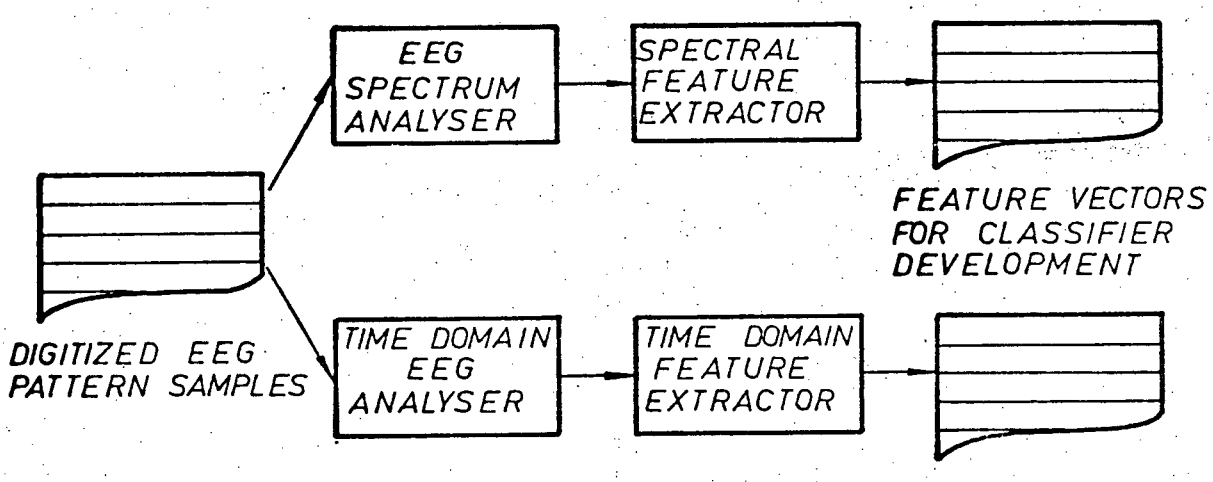

Fig. 3-2 Preparation of Spectral and Time Domain Feature Vectors

3.4 Classification Algorithm

A wide variety of algorithms have been developed to classify unknown pattern samples on the basis of a specified set of extracted feature values [24]. In EEG pattern recognition, many of the classifiers described in the literature have been heuristically derived and are based on ad hoc decision rules (e.g. [32,79,98]). Consequently the conditions under which such classifiers may be optimal are unknown, and meaningful comparisons of performance are often difficult or impossible.

Of the few EEG pattern classification algorithms which have a firm theoretical basis, the most popular is an algorithm based on linear discriminant analysis [99]. Under the assumptions that all sample feature values are from a multivariate normal population and that the feature

covariance matrices for the different classes are identical, this algorithm creates linear discriminant functions (in a stepwise manner) which can be used to classify unknown feature vectors [77,100]. However in many EEG applications the assumptions of normality and identical covariance matrices are obviously invalid (e.g.[101]), thus affecting the optimality of the classifier and the accuracy of parametric performance estimates. Despite these and other problems, stepwise discriminant analysis is at present perhaps the most widely used EEG pattern classification algorithm (e.g. [77,78, 83,91,101]).

The classification algorithm chosen for this investigation makes only one assumption about the feature data: it is based on Bayes decision rule ([102],p. 13) under the assumption that all features are statistically independent. Although the algorithm has certain characteristics which indicate that it might be particularly appropriate for EEG pattern classification problems, apparently it has not been extensively studied in this context previous to this investigation. To explain the algorithm, let $(\underline{d}_u, \theta_u)$ represent an observed EEG pattern sample from an unknown class: $\underline{d}_u$ is a row vector containing N feature values or measurements from the pattern sample and θ_u is the label identifying the class to which the pattern sample belongs. The purpose of the classification algorithm is to decide on a value for θ_u. It is known that the observed feature vector $\underline{d}_u$ must belong to one of M possible classes $C_0,\ldots,C_{M-1}$; in this problem M = 5 and the five possible classes correspond to the five different levels of anesthesia.

The classification algorithm is based on the maximum likelihood principle, i.e. one asks which class (or level of anesthesia) was most likely to produce the observed sample vector $\underline{d}_u$ and decides $\hat{\theta}_u = C_j$, $0 \leq j \leq (M-1)$, if

$$P(C_j|\underline{d}_u) > P(C_m|\underline{d}_u) \quad \text{for } \begin{cases} m=0,\ldots,M-1 \\ m\neq j. \end{cases} \tag{3.35}$$

By using Bayes Rule ([102],p.11) the a posteriori probabilities in (3.35) can be expressed in terms of conditional and a priori probabilites, e.g.

$$P(C_m|\underline{d}_u) = \frac{P(\underline{d}_u|C_m)P(C_m)}{P(\underline{d}_u)} . \tag{3.36}$$

Therefore, using (3.36), the decision rule in (3.35) becomes: decide $\hat{\theta}_u = C_j$ if

$$\frac{P(\underline{d}_u|C_j)P(C_j)}{P(\underline{d}_u)} > \frac{P(\underline{d}_u|C_m)P(C_m)}{P(\underline{d}_u)} \tag{3.37}$$

or

$$P(\underline{d}_u|C_j)P(C_j) > P(\underline{d}_u|C_m)P(C_m) \tag{3.38}$$

$$\text{for } \begin{cases} m=0,\ldots,M-1 \\ m\neq j. \end{cases}$$

The amounts of storage, computation time and training data required to implement (3.38) are greatly reduced [24,72,73] if it is assumed that the vector components d_{un}, $1 \leq n \leq N$, are statistically independent of one another, i.e. if it is assumed that

$$P(\underline{d}_u|C_m) = \prod_{n=1}^{N} P(d_{un}|C_m). \tag{3.39}$$

Under this assumption, and after taking logarithms of both sides, the decision rule in (3.38) becomes: decide $\hat{\theta}_u = C_j$ if

$$R_j > R_m \qquad \begin{cases} m = 0,\ldots,M-1 \\ m \neq j \end{cases} \tag{3.40}$$

where

$$R_m = \sum_{n=1}^{N} \ell n[P(d_{un}|C_m)] + \ell n[P(C_m)]. \tag{3.41}$$

This classification rule minimizes the probability of an error when the features are statistically independent and when $P(d_{un}|C_m)$ and $P(C_m)$ in (3.41) are either known exactly or estimated using Bayes estimation procedure [103]. Assume that a total of S pattern samples are available for estimating the

probability distributions and that the kth pattern sample is represented by $(\underline{d}_k, \theta_k)$, $1 \leq k \leq S$, where $\underline{d}_k$ is the extracted feature vector and θ_k is the label which identifies the corresponding level of anesthesia. If each of the N feature measurements is scaled and quantized to some value ℓ, $1 \leq \ell \leq L$, then Bayes estimates of $P(d_{un} = \ell | C_m)$ and $P(C_m)$, denoted by $\hat{P}(d_{un} = \ell | C_m)$ and $\hat{P}(C_m)$ respectively, are given by

$$\hat{P}(d_{un} = \ell | C_m) = \frac{q^{\ell}_{n/m} + 1}{s_m + L} \tag{3.42}$$

and

$$\hat{P}(C_m) = \frac{s_m + 1}{S + M} . \tag{3.43}$$

In (3.42) $q^{\ell}_{n/m}$ denotes the number of available pattern samples belonging to class C_m in which $d_{kn} = \ell$, while s_m in (3.43) denotes the total number of available pattern samples belonging to C_m, i.e.

$$q^{\ell}_{n/m} = \sum_{k=1}^{S} g(d_{kn}, \theta_k, \ell, C_m) \tag{3.44}$$

and

$$s_m = \sum_{k=1}^{S} f(\theta_k, C_m) \tag{3.45}$$

where

$$g(d_{kn}, \theta_k, \ell, C_m) = \begin{cases} 1 \text{ if } \theta_k = C_m \text{ and } d_{kn} = \ell \\ 0 \text{ otherwise.} \end{cases} \tag{3.46}$$

and

$$f(\theta_k, C_m) = \begin{cases} 1 \text{ if } \theta_k = C_m \\ 0 \text{ otherwise.} \end{cases} \tag{3.47}$$

In general, the assumption that the features are statistically independent may not be valid. However the performance of a classifier based on Bayes decision rule, under the assumption of statistically independent features, does provide a bound on the performance that would be possible if any existing feature interdependence could be exploited.

This follows from the argument that an invalid assumption regarding the feature probability distributions cannot increase the probability that unknown pattern samples will be correctly classified.

3.5 Evaluation of System Performance

3.5.1 The Performance Estimation Problem

The criterion usually adopted for assessing the overall performance of a pattern recognition system is its probability of misclassification error, denoted here by P_e. If the system preprocessor and feature extractor have been specified, then evaluating the performance of the system is equivalent to evaluating the performance of the pattern classifier. However, P_e for the classifier is not readily evaluated. Assume that the set of available pattern samples $\{\underline{d},\theta\}$ contains a total of S pattern samples from J subjects, where each pattern sample consists of an extracted feature vector and a label which identifies the corresponding anesthesia level. If the complete set $\{\underline{d},\theta\}$ is used to train the pattern classifier, i.e. to estimate $P(d_{un}|C_m)$ and $P(C_m)$ in (3.41) using (3.42)-(3.47), then P_e is defined as the probability that future pattern samples will be incorrectly classified. Obviously P_e cannot be evaluated because, by definition, all available pattern samples would be used for training the classifier and none would be left for testing its performance. Hence, as depicted in Fig. 3-3, some technique must be employed to estimate P_e on the basis of the set of available pattern samples.

3.5.2 Performance Estimation Techniques

Several parametric and nonparametric methods have been developed to estimate P_e for different types of classifiers on the basis of a finite set of pattern samples [25]. However, only a few of these methods are appropriate for estimating the performance of EEG pattern classifiers.

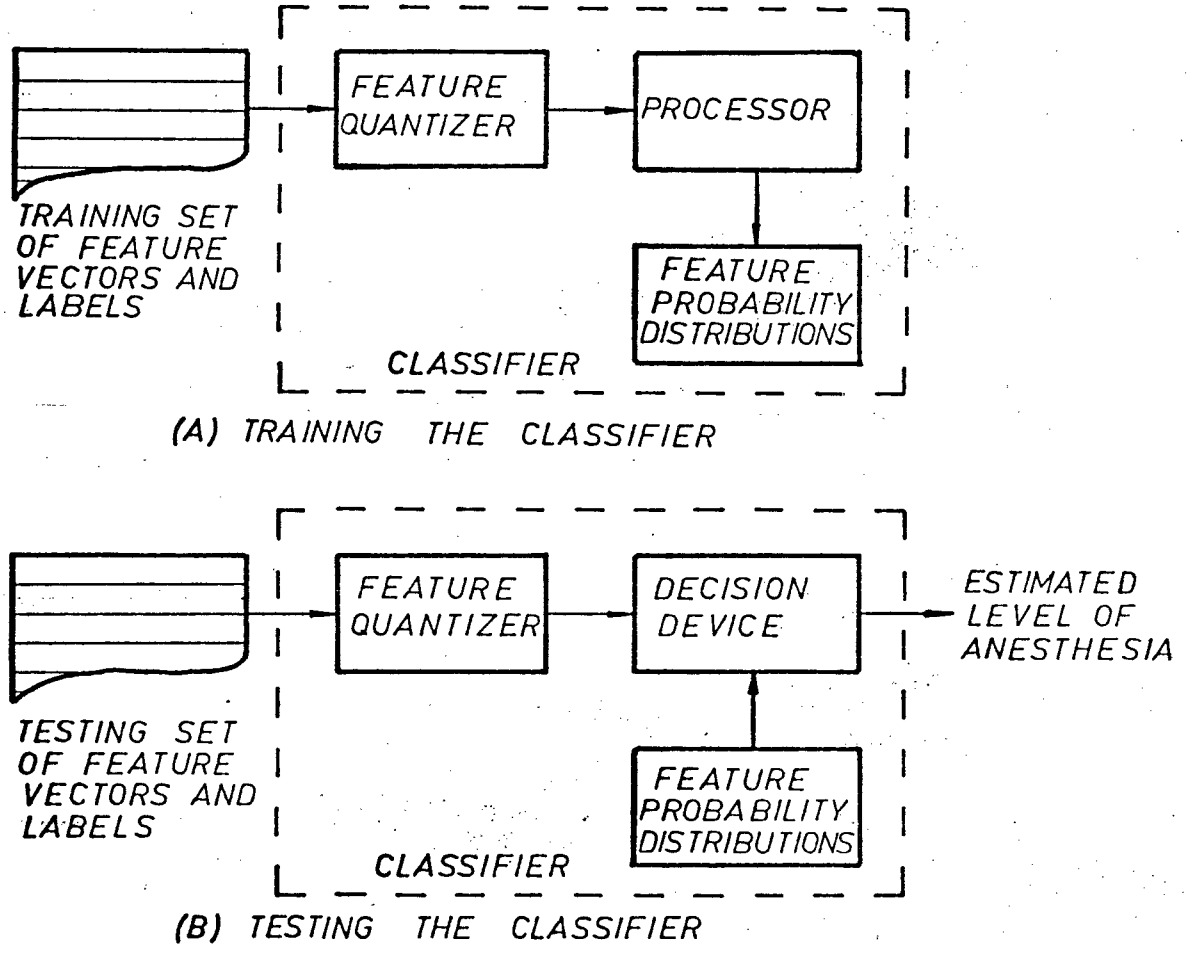

Fig. 3-3 Estimating Classifier Performance. The available set of pattern samples, i.e. feature vectors and labels, must somehow be used for training the classifier and for testing its performance.

A method of performance estimation that is appropriate for EEG classifiers should possess some or all of the following characteristics. First, it should be a nonparametric method because, in general, little is known about the underlying nature of the feature distributions. Second, the method should make efficient use of the available pattern samples because in most EEG pattern recognition investigations the set of available pattern samples is relatively small. Third, the method should yield an estimate of P_e that is as unbiased as possible, i.e. an estimate that is neither overly optimistic nor overly pessimistic [104]. Finally, it should provide

an indication of the variability of the estimate: it is important to have some indication of the extent to which the performance of the classifier will be affected by the normal range of variability among pattern samples. It appears that the major source of variability in small sets of EEG pattern samples is due to differences in EEG characteristics among different subjects, i.e. intersubject EEG variation. Some early investigations of EEG pattern recognition systems indicated that intersubject EEG variation apparently had a significant effect on the performance of such systems [77,105]. These findings were supported by some initial results which were obtained in the course of this research [37]. Therefore, it was concluded that a satisfactory method of performance estimation should also be capable of providing an indication of the expected effect of intersubject EEG variation on classifier performance.

No single, existing method of performance estimation was found to satisfy all of the above requirements. However, two nonparametric techniques were formulated which, together, satisfied many of the above requirements and provided particularly useful estimates of the performance of EEG pattern classifiers. Because these techniques were based on two popular nonparametric methods of performance estimation, known in the literature as the Π method [106,107] and the U method [108,109], they will subsequently be referred to in this thesis as the Π^* technique and the U* technique, respectively. The Π^* technique, to be described in section 3.5.3, produces an estimate of P_e which indicates the expected performance of the classifier on future EEG data from a population of subjects. The U* technique, to be described in section 3.5.4, produces an estimate of P_e which indicates the expected performance of the classifier on future EEG data from only one subject, or the performance that would be possible across a

subject population if the effect of intersubject EEG variation could somehow be eliminated.

To permit concise descriptions of the Π* and U* techniques in the following sections, let the set of S available pattern samples from J subjects be partitioned into J mutually exclusive sets, denoted by

$$\{\underline{d},\theta\}^1, \{\underline{d},\theta\}^2,\ldots,\{\underline{d},\theta\}^J,$$

where each set corresponds to the pattern samples obtained from one subject. Then

$$\{\underline{d},\theta\}^j \triangleq \{\underline{d}_1^j, \theta_1^j;\cdots; \underline{d}_{p(j)}^j, \theta_{p(j)}^j\} \tag{3.48}$$

for j = 1,...,J where $\underline{d}_k^j$ and θ_k^j denote, respectively, the feature vector and the label of the kth pattern sample from the jth subject, and

$$\sum_{j=1}^{J} p(j) = S, \tag{3.49}$$

i.e. p(j) denotes the number of available pattern samples from the jth subject.

3.5.3 The Π* Technique

Let the estimate of P_e produced by the Π* technique be denoted by $\hat{P}_e[\Pi^*]$. Then the Π* technique for estimating classifier performance can be conveniently described by the following algorithm.

1) Set aside $\{\underline{d},\theta\}^j$, the set of pattern samples from the jth subject, for testing the classifier.

2) Train the classifier on all pattern samples from the J-1 remaining sets, i.e. from

$$\{\underline{d},\theta\}^m \qquad \begin{cases} m = 1,\ldots,J \\ m \neq j. \end{cases}$$

3) Test the classifier on $\{\underline{d},\theta\}^j$ to obtain a proportion of

errors denoted by

$$\hat{P}_e[\Pi^*]_j = \frac{1}{p(j)} \sum_{k=1}^{p(j)} e_k^j \tag{3.50}$$

where

$$e_k^j = \begin{cases} 0 \text{ if } \underline{d}_k^j \text{ is correctly classified} \\ 1 \text{ otherwise,} \end{cases} \tag{3.51}$$

i.e. e_k^j acts as an error indicator.

4) Repeat steps 1)-3) for j = 1,...,J to obtain the proportions of errors $\hat{P}_e[\Pi^*]_j$ for j = 1,...,J.

5) The Π^* estimate of P_e can then be computed:

$$\hat{P}_e[\Pi^*] = \sum_{j=1}^{J} \frac{p(j)}{S} \hat{P}_e[\Pi^*]_j. \tag{3.52}$$

Appendix F contains the listing of a program that was written to compute $\hat{P}_e[\Pi^*]$ for the classifier described in section 3.4. The program can accommodate up to 500 pattern samples, i.e. up to 500 spectral or time domain feature vectors and their labels. The program allows the classifier's feature quantization scheme to be varied, and also permits the a priori class probabilities $P(C_m)$ in equation (3.41) to be assumed equal or to be estimated by (3.43).

3.5.4 The U* Technique

Let the estimate of P_e produced by the U* technique be denoted by $\hat{P}_e[U^*]$. Then $\hat{P}_e[U^*]$ for a given classifier can be computed by means of the following algorithm:

1) Consider only the set of pattern samples from the jth subject, i.e. $\{\underline{d},\theta\}^j$ for $1 \le j \le J$.

2) Take out the kth pattern sample $(\underline{d}_k^j, \theta_k^j)$ and then define

$$\{\underline{d},\theta\}_k^j \triangleq \{\underline{d}_1^j,\theta_1^j;\cdots;\underline{d}_{k-1}^j,\theta_{k-1}^j;\underline{d}_{k+1}^j,\theta_{k+1}^j;\cdots;\underline{d}_{p(j)}^j,\theta_{p(j)}^j\}. \tag{3.53}$$

3) Train the classifier on $\{\underline{d},\theta\}_k^j$.

4) Test the classifier on $(\underline{d}_k^j,\theta_k^j)$ and use e_k^j for an error indicator, as in equation (3.51).

5) Repeat steps 2)-4) for k = 1,...,p(j) to obtain e_k^j values for some fixed j and for k = 1,...,p(j).

6) Repeat steps 1)-5) for j = 1,...,J. Thus e_k^j values are obtained for all j = 1,...,J and k = 1,...,p(j).

7) The U* estimate of P_e is then computed in the following manner:

$$\hat{P}_e[U^*] = \frac{1}{S} \sum_{j=1}^{J} \sum_{k=1}^{p(j)} e_k^j. \qquad (3.54)$$

The program listed in Appendix G was written to compute $\hat{P}_e[U^*]$ for the classifier described in section 3.4. The only exception to the above algorithm was in the case of very small sets $\{\underline{d},\theta\}^j$: the classifier was not tested on $(\underline{d}_k^j, \theta_k^j)$ if the training set $\{\underline{d},\theta\}_k^j$ did not include at least one pattern sample from the level corresponding to θ_k^j. As with the Π^* performance estimation program, the U* performance estimation program listed in Appendix G permits changes in the classifier's feature quantization scheme and a priori class probability assignments, and can accommodate up to 500 pattern samples.

3.6 Results

3.6.1 EEG Spectral Pattern Recognition Systems

The Π^* and U* techniques described in the previous sections were used to estimate the performance of various EEG spectral pattern recognition systems. To simplify the description of these different systems, it should be recalled that all EEG pattern recognition systems can be regarded as consisting of the three basic elements depicted in

Fig. 3-1: a preprocessor, a feature extractor and a classifier. In all of the spectral pattern recognition systems which were considered, the preprocessor and feature extractor remained unchanged. Therefore, the different systems varied only in the structure of their classifiers.

As stated in section 3.1.1, the basic function of a system preprocessor is to transform an EEG sample into a form which allows features to be more easily extracted. The preprocessor chosen for all spectral pattern recognition systems consisted of an amplifier to increase EEG amplitudes to convenient levels, a bandpass filter (0.54-30.0 Hz) to reduce artifact, and a digitizer to convert each amplified and filtered EEG sample to digital form. The spectral feature extractor had two functions: the computation of spectra corresponding to each preprocessed 64s EEG sample and the subsequent evaluation of the 13 spectral features listed in Table 3-1. In the feature extractor, the spectra were to be computed in the manner outlined in section 3.2.2 and the spectral features were to be evaluated as described in section 3.2.3.

Fig. 3-3 shows the basic configuration of the classifier employed in all spectral pattern recognition systems. It consists of a feature quantizer, a decision device and a memory for storing estimates of the class-conditional feature probabilities and the a priori class probabilities. The feature quantizer was linear in all systems, but the quantization range and the number of possible quantization levels were changed to study their possible effect on performance. The different quantization ranges were defined in terms of a specified maximum number of standard deviations from the mean feature values, where the means and standard deviations were calculated from the available training data. The decision rule that was described in section 3.4 constituted the "decision device" shown in Fig. 3-3. In some

classifiers the a priori class probabilities $P(C_m)$ were estimated by the Bayes probability estimates defined in equation (3.43). For comparative purposes, similar classifiers were also considered in which the a priori class probabilities were assumed to be equal.

The performance of each different spectral pattern recognition system was estimated by the Π^* and U^* techniques. These techniques made use of the three sets of available spectral feature vectors, corresponding to the three types of anesthesia, which had been prepared as described in section 3.2.3. Estimating the overall performance of a system on the basis of a set of available pattern samples was therefore equivalent to estimating the performance of the system's classifier on the basis of the corresponding set of spectral feature vectors, because all preprocessing and feature extraction operations had already been performed on the EEG samples during the preparation of the feature vectors. The results obtained for many of the spectral pattern recognition systems which were developed for halothane anesthesia, narcotic anesthesia and enflurane anesthesia are summarized in Tables 3-3, 3-4 and 3-5, respectively. As stated in section 3.5.2, the estimate of misclassification error probability provided by the Π^* technique, i.e. the value of $\hat{P}_e[\Pi^*]$, indicates the expected performance of the system on future EEG data from a population of subjects. Alternatively, the U^* performance estimate ($P_e[U^*]$) for the same system indicates its expected performance on future EEG data from only one subject, or the performance that would be possible across a subject population if the effect of intersubject EEG variation could somehow be eliminated.

The best spectral pattern recognition system among those compared in Table 3-3, Table 3-4 or Table 3-5 was considered to be the one which minimized the mean of the two estimates of error probability, i.e.

the one which minimized

$$\hat{P}_e[\text{Mean}] \triangleq \tfrac{1}{2}\{\hat{P}_e[\Pi^*] + \hat{P}_e[U^*]\} \ . \qquad (3.55)$$

Table 3-3 Performance of Spectral Pattern Recognition Systems on EEG Data from Halothane Anesthesia

Feature Quantizer		Type of $P(C_m)$ Estimates Employed	Estimated Error Probability		
Range	Number of Levels		$P_e[\Pi^*]$	$\hat{P}_e[U^*]$	Mean
± 5.0 sd	16	Equal	0.454	0.142	0.298
± 5.0 sd	32	Equal	0.393	0.149	0.271
± 5.0 sd	64	Equal	0.389*	0.108*	0.248*
± 5.0 sd	128	Equal	0.471	0.175	0.323
± 5.0 sd	64	Bayes	0.404	0.138	0.271
± 1.0 sd	64	Equal	0.475	0.224	0.349
±50.0 sd	64	Equal	0.396	0.108	0.252

Table 3-4 Performance of Spectral Pattern Recognition Systems on EEG Data from Narcotic Anesthesia

Feature Quantizer		Type of $P(C_m)$ Estimates Employed	Estimated Error Probability		
Range	Number of Levels		$\hat{P}_e[\Pi^*]$	$\hat{P}_e[U^*]$	Mean
± 5.0 sd	16	Equal	0.463	0.256	0.359
± 5.0 sd	32	Equal	0.460	0.240	0.350
± 5.0 sd	64	Equal	0.449*	0.211*	0.330*
± 5.0 sd	128	Equal	0.519	0.250	0.384
± 5.0 sd	64	Bayes	0.478	0.244	0.361
± 1.0 sd	64	Equal	0.490	0.279	0.384
±50.0 sd	64	Equal	0.481	0.211	0.346

Table 3-5 Performance of Spectral Pattern Recognition Systems on EEG Data from Enflurane Anesthesia

Feature Quantizer		Type of $P(C_m)$ Estimates Employed	Estimated Error Probability		
Range	Number of Levels		$\hat{P}_e[\Pi^*]$	$\hat{P}_e[U^*]$	Mean
± 5.0 sd	16	Equal	0.426	0.122	0.274
± 5.0 sd	32	Equal	0.420	0.135	0.277
± 5.0 sd	64	Equal	0.420	0.132	0.276
± 5.0 sd	128	Equal	0.413	0.168	0.290
± 5.0 sd	64	Bayes	0.432	0.178	0.305
± 1.0 sd	64	Equal	0.420	0.148	0.284
±50.0 sd	64	Equal	0.416	0.132	0.274
± 5.0 sd	16	Bayes	0.404	0.148	0.276
± 1.0 sd	16	Equal	0.432	0.145	0.288
±50.0 sd	16	Equal	0.413*	0.122*	0.267*

In Table 3-3, Table 3-4 and Table 3-5 the best system is identified with asterisks. Accordingly, from the results in Table 3-3, the best spectral pattern recognition system developed for halothane anesthesia can be expected to classify between 61.1 percent and 89.2 percent of future EEG samples correctly. This system has a linear feature quantizer with 64 possible quantization levels over a range of ±5.0 sd (standard deviations) and employs equal a priori class probability estimates. From the results in Table 3-4 it is evident that the best spectral pattern recognition system for narcotic anesthesia has the same feature quantization scheme and uses the same probability estimates. However, its performance is slightly inferior: it can only be expected to correctly classify between 55.1

percent and 78.9 percent of future EEG samples. Finally, the results in Table 3-5 indicate that between 58.7 percent and 87.8 percent of future EEG samples from enflurane anesthesia will be correctly classified by the best spectral pattern recognition system. This system employs equal class probability estimates, as do the best systems for halothane and narcotic anesthesia, but has a feature quantizer with only 16 possible quantization levels over a range of ±50.0 sd.

3.6.2 Time Domain EEG Pattern Recognition Systems

In addition to spectral pattern recognition systems, various systems based on the recognition of time domain EEG patterns were developed. As stated in section 3.3.1, these systems were investigated because it was suspected that the conditions under which some form of spectral pattern recognition system would be optimal were not satisfied, and because it was known that visual EEG assessment is based primarily on the evaluation of time domain EEG features, not spectral features. Time domain EEG pattern recognition systems were therefore developed so that their performance could be estimated and compared to the estimated performance of spectral pattern recognition systems.

The structure of all time domain EEG pattern recognition systems which were considered was similar to the structure of the spectral pattern recognition systems described in section 3.6.1. Both consisted of the three basic elements shown in Fig. 3-1: a preprocessor, a feature extractor and a classifier. The preprocessors in all time domain systems were identical to the preprocessors in spectral pattern recognition systems, with the following exception: instead of a bandpass filter from 0.54-30.0 Hz, the filter defined in (3.26) was employed and the lowpass filter frequency f_{LP} was set at 8.0, 16.0, 24.0 and 30.0

Hz in different systems to study the effect of prefiltering on system performance. As mentioned in section 3.3.2, this additional prefiltering was performed to eliminate high frequency EEG activity above f_{LP} Hz which, at least in visual EEG assessment, seemed to obscure significant changes in time domain feature values.

The function of the feature extractor employed in all time domain EEG pattern recognition systems was to evaluate each preprocessed 64s EEG sample in terms of the set of 10 time domain features listed in Table 3-2, so that the EEG sample could subsequently be classified on the basis of the set of extracted feature values. The classifiers in all time domain systems had the same basic structure as the classifiers in spectral systems, consisting of a feature quantizer, a decision device and a memory for storing estimates of the relevant probability distributions, as indicated in Fig. 3-3. The quantization range and the number of possible quantization levels were changed in different systems, in the manner described in section 3.6.1, in an attempt to establish the best linear feature quantization scheme. An implementation of the decision rule described in section 3.4 constituted the "decision device" in all time domain system classifiers. For comparative purposes the *a priori* class probabilities were assumed to be equal in some systems, while the Bayes probability estimates defined in (3.43) were employed in other systems.

Using the sets of available pattern samples from halothane anesthesia, narcotic anesthesia and enflurane anesthesia, estimates of the misclassification error probability for various time domain EEG pattern recognition systems were obtained by the Π^* and U^* techniques described in section 3.5.3 and section 3.5.4, respectively. The resulting values of $\hat{P}_e[\Pi^*]$ and $\hat{P}_e[U^*]$ are presented in Table 3-6, Table 3-7 and

Table 3-6 Performance of Time Domain Pattern Recognition Systems on EEG Data from Halothane Anesthesia

Lowpass Prefilter Frequency f_{LP} (Hz)	Feature Quantizer		Estimated Error Probability		
	Range	Number of Levels	$\hat{P}_e[\Pi^*]$	$\hat{P}_e[U^*]$	Mean
8.0	± 5.0 sd	8	0.500	0.213	0.356
8.0	± 5.0 sd	16	0.471	0.187	0.329
8.0	± 5.0 sd	32	0.514	0.291	0.402
16.0	± 5.0 sd	8	0.500	0.127	0.313
16.0	± 5.0 sd	16	0.450	0.179	0.314
16.0	± 5.0 sd	32	0.518	0.231	0.374
24.0	± 5.0 sd	8	0.532	0.179	0.355
24.0	± 5.0 sd	16	0.514	0.198	0.356
24.0	± 5.0 sd	32	0.525	0.213	0.369
16.0	± 1.0 sd	8	0.496	0.243	0.369
16.0	±50.0 sd	8	0.486*	0.127*	0.306*

Table 3-8. Because their performance was consistently better, only systems which employ equal, rather than Bayes, a priori class probability estimates are described in these three tables. The best system among those presented in each table was considered to be the one which minimized the mean of the two error estimates, i.e. the one which minimized (3.55). The best system in each of the three tables is identified with asterisks. From the results presented in Table 3-6, the best time domain EEG pattern recognition system developed for halothane anesthesia can be expected to classify between 51.4 percent and 87.3 percent of future EEG samples correctly. In this system the lowpass filter frequency f_{LP} is 16.0 Hz and the feature quantizer has 8 possible quantization levels extending over a range of 50.0 sd. The results in Table 3-7 indicate that between

Table 3-7 Performance of Time Domain Pattern Recognition Systems on EEG Data from Narcotic Anesthesia

Lowpass Prefilter Frequency f_{LP} (Hz)	Feature Quantizer		Estimated Error Probability		
	Range	Number of Levels	$\hat{P}_e[\Pi^*]$	$\hat{P}_e[U^*]$	Mean
8.0	± 5.0 sd	8	0.504*	0.320*	0.412*
8.0	± 5.0 sd	16	0.522	0.349	0.435
8.0	± 5.0 sd	32	0.519	0.391	0.455
16.0	± 5.0 sd	8	0.548	0.288	0.418
16.0	± 5.0 sd	16	0.578	0.317	0.447
16.0	± 5.0 sd	32	0.592	0.378	0.485
24.0	± 5.0 sd	8	0.578	0.276	0.427
24.0	± 5.0 sd	16	0.572	0.305	0.438
24.0	± 5.0 sd	32	0.566	0.359	0.462
8.0	± 1.0 sd	8	0.551	0.378	0.464
8.0	±50.0 sd	8	0.507	0.320	0.413

49.6 percent and 68.0 percent of future EEG samples from narcotic anesthesia could be correctly classified by the best time domain EEG pattern recognition system. The lowpass filter frequency f_{LP} is 8.0 Hz in the preprocessor of this system and the feature quantizer has 8 possible quantization levels over a range of ±5.0 sd. Finally, from the results in Table 3-8, the best time domain EEG pattern recognition system developed for enflurane anesthesia can be expected to correctly classify between 62.8 percent and 89.8 percent of future EEG samples. In this system the feature quantizer has 8 possible quantization levels extending over a range of ±5.0 sd and, in contrast to the best systems in Table 3-6 and Table 3-7, the lowpass filter frequency f_{LP} is 30.0 Hz, i.e. the

Table 3-8 Performance of Time Domain Pattern Recognition Systems on EEG Data from Enflurane Anesthesia

Lowpass Prefilter Frequency f_{LP} (Hz)	Feature Quantizer		Estimated Error Probability		
	Range	Number of Levels	$\hat{P}_e[\Pi^*]$	$\hat{P}_e[U^*]$	Mean
8.0	± 5.0 sd	8	0.435	0.204	0.319
8.0	± 5.0 sd	16	0.410	0.224	0.317
8.0	± 5.0 sd	32	0.410	0.250	0.330
16.0	± 5.0 sd	8	0.394	0.141	0.267
16.0	± 5.0 sd	16	0.404	0.135	0.269
16.0	± 5.0 sd	32	0.416	0.197	0.306
24.0	± 5.0 sd	8	0.397	0.095	0.246
24.0	± 5.0 sd	16	0.347	0.132	0.239
24.0	± 5.0 sd	32	0.369	0.161	0.265
30.0	± 5.0 sd	8	0.372*	0.102*	0.237*
30.0	± 5.0 sd	16	0.369	0.145	0.257
30.0	± 5.0 sd	32	0.404	0.184	0.294
30.0	± 1.0 sd	8	0.401	0.138	0.269
30.0	±50.0 sd	8	0.385	0.102	0.243

elimination of high frequency EEG activity did not result in an improvement in system performance.

3.7 Discussion

3.7.1 Spectral and Time Domain EEG Pattern Recognition Systems

The primary objective of the work described in this chapter was to study the feasibility of estimating anesthesia levels by means of EEG

pattern recognition. It was assumed that the clinical, non-EEG criteria listed in Table 2-1 defined five clinically valid levels of anesthesia for patients during halothane, narcotic or enflurane anesthesia. The various spectral and time domain EEG pattern recognition systems described in sections 3.6.1 - 3.6.2 were developed in an attempt to reliably estimate the different levels of anesthesia, i.e. to agree with assessments made by anesthesiologists on the basis of the non-EEG criteria. Specifically, the function of each EEG pattern recognition system was to estimate the level of anesthesia by classifying an unknown EEG sample on the basis of a set of extracted feature values, corresponding to the spectral features listed in Table 3-1 or the time domain features listed in Table 3-2.

The performance of each EEG pattern recognition system on future data was evaluated, in terms of the estimated probability of misclassification error, by means of the Π^* technique and the U^* technique as described in sections 3.5.2 - 3.5.4. The resulting values of $\hat{P}_e[\Pi^*]$ and $\hat{P}_e[U^*]$ for various spectral and time domain EEG pattern recognition systems are summarized in Tables 3-3 to 3-8. In section 3.5.2 it was pointed out that the Π^* and U^* techniques provide particularly informative and efficient estimates of the performance of EEG pattern recognition systems. It is suspected that the values of $\hat{P}_e[\Pi^*]$ and $\hat{P}_e[U^*]$ obtained for a specific system could be decreased, i.e. performance could be improved, by increasing the number of EEG pattern samples available for training the system. This follows from the argument that the error between the actual feature probability distributions needed to evaluate the decision rule in (3.41) and the Bayes estimates of those distributions, defined in (3.42) , can be expected to decrease with an increase in sample size.

The best systems among those compared in Tables 3-3 to 3-8 were considered to be the ones which minimized the mean error estimate defined in (3.55). It should be noted that all of the best systems in terms of this criterion employed equal, rather than Bayes, estimates of the a priori class probabilities. Assuming that future EEG samples will be from M=5 equiprobable classes, the performance of these systems can reasonably be compared to the expected performance of a completely random pattern classification system, for which

$$\begin{aligned} \hat{P}_e[\Pi^*] &= \hat{P}_e[U^*] \\ &= 1 - M^{-1} \\ &= 0.8, \end{aligned} \tag{3.56}$$

i.e. only 20 percent of future EEG samples would be correctly classified. In contrast, the results obtained for the best spectral pattern recognition systems (in Tables 3-3 to 3-5) indicate that between 61.1 - 89.2 percent, 55.1 - 78.9 percent and 58.7 - 87.8 percent of future EEG samples from, respectively, halothane anesthesia, narcotic anesthesia and enflurane anesthesia will be correctly classified. The best time domain EEG pattern recognition systems (in Tables 3-6 to 3-8) have slightly inferior performance compared to the best spectral systems for halothane and narcotic anesthesia, but slightly superior performance for enflurane anesthesia: it is expected that between 51.4 - 87.3 percent, 49.6 - 68.0 percent and 62.8 - 89.8 percent of future EEG samples from halothane, narcotic and enflurane anesthesia, respectively, could be correctly classified by these systems.

It would obviously be desirable to compare the results obtained for the best spectral and time domain EEG pattern recognition systems to the expected reliability of visual EEG assessment. Although an exact

comparison is not possible, the results of a recent investigation concerning the reliability of visual EEG assessment, discussed previously in Chapter I , are relevant. The results of this investigation indicate that, even with an established set of objective criteria for pattern identification, the reliability of visual EEG assessment may be surprisingly low: the highest average intraclass correlation coefficient among seven experienced clinical EEG raters was reported to be 0.56 [18].

One additional point concerning the results is worthy of consideration. An IBM 370/168 computer was used to develop all EEG pattern recognition systems and to estimate their performance. Consequently, the differing amounts of memory and processing time required by the various systems were not apparent. However, these factors are of practical significance since one would obviously prefer to use the smallest, least expensive computer when actually implementing such a system for use on a routine basis in a hospital environment. It was calculated that the implementation of the best spectral pattern recognition systems would require a computer with at least 8000 bytes of memory and an efficient version of the Fast Fourier Transform (FFT) algorithm. In contrast, the best time domain EEG pattern recognition systems would require approximately 50 percent less memory and would be computationally faster and simpler, primarily because the FFT would not be required.

3.7.2 Evaluation of EEG Pattern Recognition Approach

The results presented in this chapter have clearly demonstrated the feasibility of obtaining reliable estimations of the level of anesthesia during surgical operations by means of computer-based EEG pattern recognition. Perhaps the value of this approach, in relation to earlier attempts to visually evaluate EEG activity during anesthesia, can best be

assessed in terms of the four methodological problems associated with earlier work which were discussed previously (section 1.2.4): the definition of anesthesia levels, the definition of EEG patterns, EEG pattern variability and the extent of inter-rater reliability.

In this research, the different levels of anesthesia were defined by a set of clinically valid, non-EEG criteria. Estimations of the level of anesthesia which were made on the basis of these criteria were assumed to be correct and EEG pattern recognition systems were then designed to agree with the estimations. Of course, any error introduced by the inability of anesthesiologists to consistently identify levels of anesthesia on the basis of the clinical criteria would obviously be incorporated into such systems. Attempts to control this possible source of error were described in sections 2.3.3 - 2.3.4.

The earlier difficulty associated with the reliability of EEG pattern definition was resolved in this research by explicitly defining sets of heuristically derived features so that EEG samples could be quantitatively evaluated in terms of these features. Although it was assumed that all features were statistically independent for computational simplicity, this assumption is not necessarily justified. As stated in section 3.4, it is therefore theoretically possible to develop a more reliable EEG pattern recognition system by exploiting any statistical dependence that may exist among features. However, taking statistical dependencies into account can easily prove to be a formidable task because of an exponential increase in the measurement complexity, where the measurement complexity refers to the total number of discrete probability values to be estimated [73]. For example, the measurement complexity C of a set of N statistically independent features, each of which can assume L possible quantization values, is given by

$$C = L \cdot N \; ; \qquad (3.57)$$

however, if the features are interdependent the measurement complexity is given by

$$C = L^N , \tag{3.58}$$

an enormous increase for reasonable values of L and N. This is significant because as a rule of thumb the amount of data required to adequately train a classifier, as well as the memory and computation time required in its subsequent utilization, is proportional to the measurement complexity of the feature data. In the event that many of the features are thought to be strongly interdependent the use of a different pattern recognition technique such as stepwise discriminant analysis, which does not assume statistically independent features, might prove to be more tractable. However, in the theoretical development of stepwise discriminant analysis other simplifying assumptions concerning the statistical properties of the feature set are made which are also not necessarily valid.

The previously encountered methodological problems associated with the variability of EEG patterns among different anesthetic agents and different patients for the same level of anesthesia were reduced in three ways. First, only three specified combinations of anesthetic agents were considered in this initial investigation. In addition, only healthy adult patients in the best surgical risk categories were selected as subjects. Finally, because the EEG pattern recognition systems were developed by processing all available training data and storing the extracted feature values, no simplifying assumptions concerning the underlying feature distributions were necessary. However the fact that the available data base is relatively small, corresponding to a limited number of patients, means that EEG pattern variability must still be regarded as a major potential source of variability in the performance of EEG pattern recognition systems which were trained on the available set of pattern samples.

Obviously, the inter-rater reliability problems which were evident in earlier studies based on visual EEG assessment are effectively eliminated by the computer-based EEG pattern recognition approach. Once one reliable EEG pattern recognition system has been developed, other replicas can easily be produced to provide consistent and continuous estimations of the level of anesthesia during surgery.

3.7.3 Further Work

Aside from the factors already mentioned, the performance of the EEG pattern recognition systems described in this chapter could have been affected by invalid assumptions concerning the underlying statistical characteristics of the EEG data, by the limited number and type of features extracted, by the presence of undetected artifact in EEG samples and by a marked degree of EEG pattern variability and intersubject EEG variation. Each of these factors should be investigated further with a view to improving system performance.

In Chapter IV, for example, some relevant statistical characteristics of spontaneous EEG activity will be investigated. Specifically, it would be useful to know over what time interval (if any) the EEG can be considered to be a sample function from a stationary, or at least a wide-sense stationary, random process. In addition, it would be potentially useful to have an indication of the extent to which a sample EEG amplitude distribution deviates from a Gaussian distribution. With such information an appropriate EEG source model could be generated and subsequently employed in developing improved computer-based systems for monitoring the level of anesthesia.

All systems considered in this chapter were based on the extraction of relatively small sets of spectral or time domain features. These

features were chosen either because they had an established clinical significance or because they had previously been described as meaningful in the literature on automatic EEG analysis. The extraction of additional, heuristically derived features to improve the performance of specific EEG pattern recognition systems will be considered in Chapter V. Alternatively, although beyond the scope of this thesis, the use of statistical feature selection techniques (e.g. [110]) to choose a small set of good features from a large number of more randomly chosen ones might also be explored.

As stated in section 3.4, it is theoretically possible to develop more reliable EEG pattern recognition systems by exploiting any statistical interdependencies that may exist among spectral or time domain EEG features. In Chapter V the magnitude of any interdependencies, or at least the magnitude of any intercorrelations, that may exist among spectral features will be investigated. Also in Chapter V, methods for reducing the effect of intersubject EEG variation on the performance of EEG pattern recognition systems will be explored.

Finally, instead of considering only spontaneous EEG pattern recognition systems, the possibility of developing systems which are based on the recognition of different sensory evoked responses during anesthesia (e.g., see [15]) might also be considered.

CHAPTER IV

MODELLING THE STATIONARITY AND GAUSSIANITY OF EEG ACTIVITY

4.1 Introduction

4.1.1 Motivation

Considerable motivation exists for the development of an adequate statistical model for spontaneous EEG activity. For example, it was mentioned in section 3.7.3 that such a model might be of value in the development of EEG pattern recognition systems for monitoring anesthesia levels. More generally, almost all methods of quantitative EEG analysis are based on certain implicit assumptions regarding the statistical characteristics of the underlying random process, particularly with respect to the extent of stationarity and Gaussianity of the process. The efficacy of alternate analytic techniques depends upon the degree to which such assumptions are justified by the characteristics of the particular ensemble of EEG segments being analysed. In addition, a better understanding of some of the statistical properties of different EEG ensembles might eventually result in a better understanding of the neurophysiological mechanism of spontaneous EEG generation, a mechanism which is still not well understood. Despite such motivation, relatively few investigations of the statistical properties of specific EEG ensembles have been described in the literature.

4.1.2 Evaluation of Previous Investigations

The first studies of the EEG amplitude probability distribution suggested a striking similarity to the normal or Gaussian distribution [111,112]. A later analysis of one 8.33s EEG segment from each of four subjects also showed that in two cases the amplitude distributions closely

fitted a Gaussian distribution [113]. However, subsequent reports by others contained rather contradictory results. For example, tests of thirty 52.8s EEG segments for Gaussianity resulted in 29 rejections; the investigators concluded that the spontaneous EEG could not be modelled as a normal random process because not even its amplitude distribution was Gaussian [114]. Elul suggested that this study illustrated an extreme case where non-stationarity of the EEG was erroneously construed as indiative of a non-Gaussian distribution [115]. He tested successive 2s EEG segments from one subject and reported that the EEG was Gaussian 66 percent of the time in the resting state, shifting to 32 percent during a mental arithmetic task. Although the results of some later studies appear to agree with those of Elul (e.g. [116]), others do not. For example, Dumermuth et al. commented that most of the 40s EEG segments which they had analysed deviated from Gaussianity [21]. Following the suggestion of Elul they also analysed 4s EEG segments in an attempt to reduce effects due to non-stationarity but reported even stronger deviations from a Gaussian model [117,118].

Several factors can be identified which have contributed to the previously described inconsistencies in the literature. Many early investigations involved relatively small ensembles of EEG segments from very few subjects. Frequently, EEG data from only one non-standardized channel was considered. The reliability and comparability of the results obtained in such studies were therefore affected by topological differences, by statistical variability due to small sample sizes and by inter-subject EEG variation. Another factor contributing to discrepancies among published findings concerns the different EEG digitization rates which were used: it will be shown in this chapter that different sampling

rates change the efficacy of statistical hypothesis tests. Finally, the problem of estimating the degree of stationarity of a particular ensemble of EEG segments has seldom been considered directly in such investigations. Attempts were instead made to circumvent the problem of stationarity when investigating Gaussianity by subdividing the EEG into very short segments in the expectation that any non-stationary effects would be reduced.

4.1.3 Outline of Chapter

In this chapter, a technique is proposed for estimating the degree of wide-sense stationarity and the degree of Gaussianity of an ensemble of EEG records. Results which have been obtained by applying this technique to three relatively large ensembles of multichannel EEG data are also described. In addition, the comparative advantages of employing alternate methods of EEG analysis are discussed in relation to the estimated degree of stationarity and Gaussianity of the particular EEG ensembles under consideration. Finally, the specific relevance of the results presented in this chapter to the development of EEG pattern recognition systems for monitoring anesthesia levels is discussed.

4.2 Random Process Characterization

The ensemble of all possible time functions which can be generated by a particular source together with their respective probabilities of occurrence defines a random process. Spontaneous EEG activity may therefore be modelled as a random process. Any such process, denoted by $X(t)$, is said to be completely characterized or modelled if its nth order

distribution function

$$F[x_1,\ldots,x_n;\ t_1,\ldots,t_n] = P\ [X(t_1) \leq x_1,\ldots,X(t_n) \leq x_n] \quad (4.1)$$

is known for any n and any set of sampling times $t_1,\ldots,t_n$ ([84], pp. 296-297). For most random processes it is difficult to obtain empirical estimates of (4.1). However, if a particular random process is both Gaussian and stationary then the problem of modelling it by estimating (4.1) is greatly simplified.

Briefly, a random process X(t) is said to be Gaussian or normal if its nth order probability density function

$$f[x_1,\ldots,x_n;\ t_1,\ldots,t_n],$$

obtained by differentiating (4.1) with respect to all variables x_i, takes the form of a jointly Gaussian distribution, i.e.

$$f(x_1,\ldots,x_n;\ t_1,\ldots,t_n) = \frac{\exp\{-\frac{1}{2}(\underline{x} - \underline{u})[K]^{-1}(\underline{x} - \underline{u})^T\}}{(2\pi)^{n/2}(|K|)^{\frac{1}{2}}}, \quad (4.2)$$

where

$$\underline{x} = [x_1,\ldots,x_n], \quad (4.3)$$

$$\underline{u} = [E\{X(t_1)\},\ldots,E\{X(t_n)\}]$$

$$= [u_1,\ldots,u_n], \quad (4.4)$$

$$[K] = \begin{bmatrix} k_{11} & \cdots & k_{1n} \\ \vdots & & \vdots \\ k_{n1} & \cdots & k_{nn} \end{bmatrix}, \quad (4.5)$$

$$k_{ij} = E\{(x_i - u_i)(x_j - u_j)\}, \quad (4.6)$$

and $|K|$ is the determinant of [K], the covariance matrix ([119], pp. 111-112).

A random process X(t) is said to be strictly stationary if none of its statistics are affected by a shift in time origin, i.e. if the two

processes X(t) and X(t+ξ) have the same statistics for any ξ. A much weaker condition is that of wide-sense stationarity in a finite time interval: if

$$E[X(t)] = \mu = \text{constant} \tag{4.7}$$

and if the autocorrelation function is given by

$$R(t_i,t_j) = R(\tau), \tag{4.8}$$

where

$$\tau = |t_j - t_i| , \tag{4.9}$$

for all t, t_i and t_j $\varepsilon[0,T]$ then X(t) is said to be wide-sense stationary in the interval [0,T] ([84], pp. 300-304). Under this condition, (4.6) becomes

$$\begin{aligned} k_{ij} &= E\{(x_i - u_i)(x_j - u_j)\} \\ &= E\{x_i x_j\} - u_i u_j \\ &= R(t_i,t_j) - \mu^2 \\ &= R(\tau) - \mu^2 \end{aligned} \tag{4.10}$$

for all t_i, t_j $\varepsilon[0,T]$. From (4.2) and (4.10) it is therefore evident that, under the condition of wide-sense stationarity in the interval [0,T], a Gaussian random process X(t) is completely specified by its mean and autocorrelation function in the interval.

If a random process X(t) is ergodic [120] then such statistics as the mean and autocorrelation function can be calculated from a single sample function, denoted by x(t), i.e.

$$E[X(t)] = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} x(t)\, dt = \mu \tag{4.11}$$

and

$$\begin{aligned} R(\tau) &= E[X(t)X(t+\tau)] \\ &= \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} x(t)x(t+\tau)dt \\ &= \mathcal{R}(\tau) , \end{aligned} \tag{4.12}$$

where $\mathcal{R}(\tau)$ represents the time autocorrelation function. However, an empirical test for ergodicity would require extensive ensemble calculations and would certainly not be feasible when only a limited number of sample functions of relatively short duration are available. Under these conditions ergodicity is usually assumed and any desired ensemble statistics are estimated from the individual characteristics of all available sample functions. For example, if all sample functions can be modelled as the output of a wide-sense stationary Gaussian process in an interval [0,T] then the mean and autocorrelation function are sufficient statistical descriptors of the process in the interval. These ensemble descriptors can be estimated in practise by averaging the means and the time autocorrelation functions (or equivalently the power spectra) of the available sample functions.

A necessary requirement before any such modelling of observed EEG activity can be attempted is that some empirical procedures be established for testing individual EEG segments, at a specified significance level, for wide-sense stationarity and Gaussianity.

4.3 Establishment of Empirical Testing Procedures

4.3.1 Testing for Wide-Sense Stationarity

Assume that $[x_1,\ldots,x_{2n}]$ has been obtained by sampling a band-limited EEG signal x(t) at or above the Nyquist rate during the time interval [0,2T]. Although an exact determination of the degree of wide-sense stationarity and Gaussianity of x(t) in the given interval is not possible, useful estimates of these statistical properties can be obtained by the application of certain hypothesis testing procedures.

A procedure for determining whether or not $[x_1,\ldots,x_{2n}]$ can be considered to be a set of samples from a wide-sense stationary function

can be based on the requirement that the amplitude distributions and the power spectra calculated for the sample subsets $[x_1,\ldots,x_n]$ and $[x_{n+1},\ldots,x_{2n}]$ must not be significantly different. Specifically, a test for the wide-sense stationarity of a given sample set can be constructed by first dividing the set into two equal subsets and calculating an amplitude histogram and power spectrum for each. Then the two-sample Kolmogorov-Smirnov (K-S) test [121,122] can be employed to compare the sample amplitude and spectral distribution functions of each. The two-sample K-S test is based on the statistic D_2 which is defined as

$$D_2 = \sup_{\text{all } s} |F_n(s) - G_n(s)| \quad , \tag{4.13}$$

where $F_n(s)$ and $G_n(s)$ are distribution functions calculated from a set of samples of size n from populations F and G respectively. A large value of D_2 resulting from application of the two-sample K-S test would indicate rejection, at some significance level, of the null hypothesis that F and G are identical. When $[x_1,\ldots,x_n]$ and $[x_{n+1},\ldots,x_{2n}]$ are tested in this manner, rejection of either the hypothesis of identical amplitude distributions or the hypothesis of identical spectral distributions indicates that the original EEG signal cannot be modelled with confidence as a sample function of a random process that is wide-sense stationary over the interval [0,2T]. Thus, rejection of either hypothesis for a given set of samples constitutes an empirical upper bound on the interval of wide-sense stationarity, i.e. in this instance the interval of wide-sense stationarity for the random process of which x(t) is a sample function is assumed to be less than 2T.

4.3.2 Testing for Gaussianity

Testing the amplitude distribution of a set of EEG samples

$[x_1,\ldots,x_{2n}]$ for Gaussianity or normality is accomplished by means of a goodness of fit test. The K-S goodness of fit test is employed because it has been shown that, with the population mean and variance estimated by the sample mean and variance, it yields a test for normality which is more powerful than the more popular chi-square test [121-123]. The K-S statistic D_1 represents the least upper bound of the differences between the empirical and assumed distribution functions:

$$D_1 = \sup_{\text{all } s} |F_{2n}(s) - F(s)| , \tag{4.14}$$

where $F_{2n}(s)$ is the distribution function calculated from the set of 2n samples and F(s) is the assumed distribution function. If D_1 is too large, the null hypothesis that F(s) represents the population distribution function is rejected.

4.4 Experiment

4.4.1 Selection of Sample EEG Data

In order to apply the previously described tests for Gaussianity and wide-sense stationarity to some actual EEG ensembles, three sets of sample EEG segments were selected from the available EEG data base (described in Table 2-2). Because of the extensive computation involved in testing for Gaussianity and wide-sense stationarity, it was necessary from a practical standpoint to limit the amount of sample EEG data under consideration. Consequently, only sample EEG segments from the two most common types of general anesthesia, previously referred to in this thesis as halothane and narcotic anesthesia, were considered. It was also necessary to restrict the number of sample EEG segments from each type of anesthesia because of computational time and cost considerations. Accordingly, it was decided that four multichannel EEG segments without

visually apparent artifact from each of 30 subjects would be considered: 15 of the subjects who were chosen had received halothane anesthesia and the other 15 subjects had received narcotic anesthesia.

Detailed descriptions of the EEG data acquisition procedure and the preparation of sample EEG segments corresponding to clinical anesthesia levels were given in Chapter II. Briefly, EEG activity was recorded from two pairs of bilaterally symmetric, differential channels: F3-C3, C3-01, F4-C4 and C4-02, according to the International 10-20 System of electrode placement [70]. The recorded data was later lowpass filtered at 30.0 Hz and then the 4-channel, 64s sample EEG segments were prepared. As stated above, four filtered multichannel EEG segments were selected from each of 30 different subjects for the modelling investigation. Two of the 64s segments from each subject were baseline EEG segments corresponding to Anesthesia Level 0, i.e. they were recorded while the subject was awake and resting with eyes closed, approximately one hour before surgery. The two additional EEG segments from the same subject corresponded to Anesthesia Level 3, i.e. they were recorded at a surgical level of anesthesia.

Three different sets of multichannel EEG segments were thus selected for consideration: one set of 60 baseline segments from 30 awake and resting subjects, a second set of 30 segments from 15 of these subjects during halothane anesthesia, and a third set of 30 segments from the other 15 subjects during narcotic anesthesia. Some samples of multichannel EEG activity from each of these three sets of data can be seen in Fig. 2-2(a)-(d).

4.4.2 Determination of Optimum Sampling Rate

After the three sets of sample EEG data had been selected for the modelling investigation, it was desired to determine the best rate at

which to sample and digitize the data. Because the EEG segments had already been lowpass filtered at 30.0 Hz, the theoretical minimum sampling rate, as given by the Sampling Theorem ([119], pp.400-405), was 60.0 Hz, i.e. the Nyquist rate. The filter roll-off characteristics and the computational desirability of setting the sampling rate to a power of two indicated that the most practical minimum sampling rate, denoted by F_s, would be 64 Hz. Most of the previous investigations of Gaussianity or stationarity have considered EEG data sampled at rates of from $2F_s$ to $4F_s$ and even higher. However, statistical hypothesis tests such as the K-S and chi-square tests assume that the set of samples to be tested corresponds to a set of statistically independent random variables or observations. Therefore, when this assumption of statistical independence is violated because of an unnecessarily high sampling rate, one can expect the efficacy of such tests to decrease accordingly.

To examine and illustrate the effect of different sampling rates on statistical hypothesis tests, 30 of the recorded 64s baseline EEG segments from channel C4-O2 were reproduced, bandpass filtered from 0.54 Hz to 30.0 Hz, and digitized at a rate of 512 Hz or $8F_s$. By considering every second, fourth or eighth sample it was also possible to study EEG data with an effective sampling rate of $4F_s$, $2F_s$, or F_s, respectively. At each of these sampling rates a K-S goodness of fit test for Gaussianity, at the 0.05 significance level, was performed on each of the M available EEG segments of T sec duration, where

$$T = 2^i \ , \ i = 0,1,\ldots,6 \ , \tag{4.15}$$

and

$$M = \frac{30 \cdot 64}{T} \tag{4.16}$$

The results of these tests are summarized in Fig. 4-1 and clearly indicate the desirability of using a sampling rate as little above the Nyquist rate as practicable.

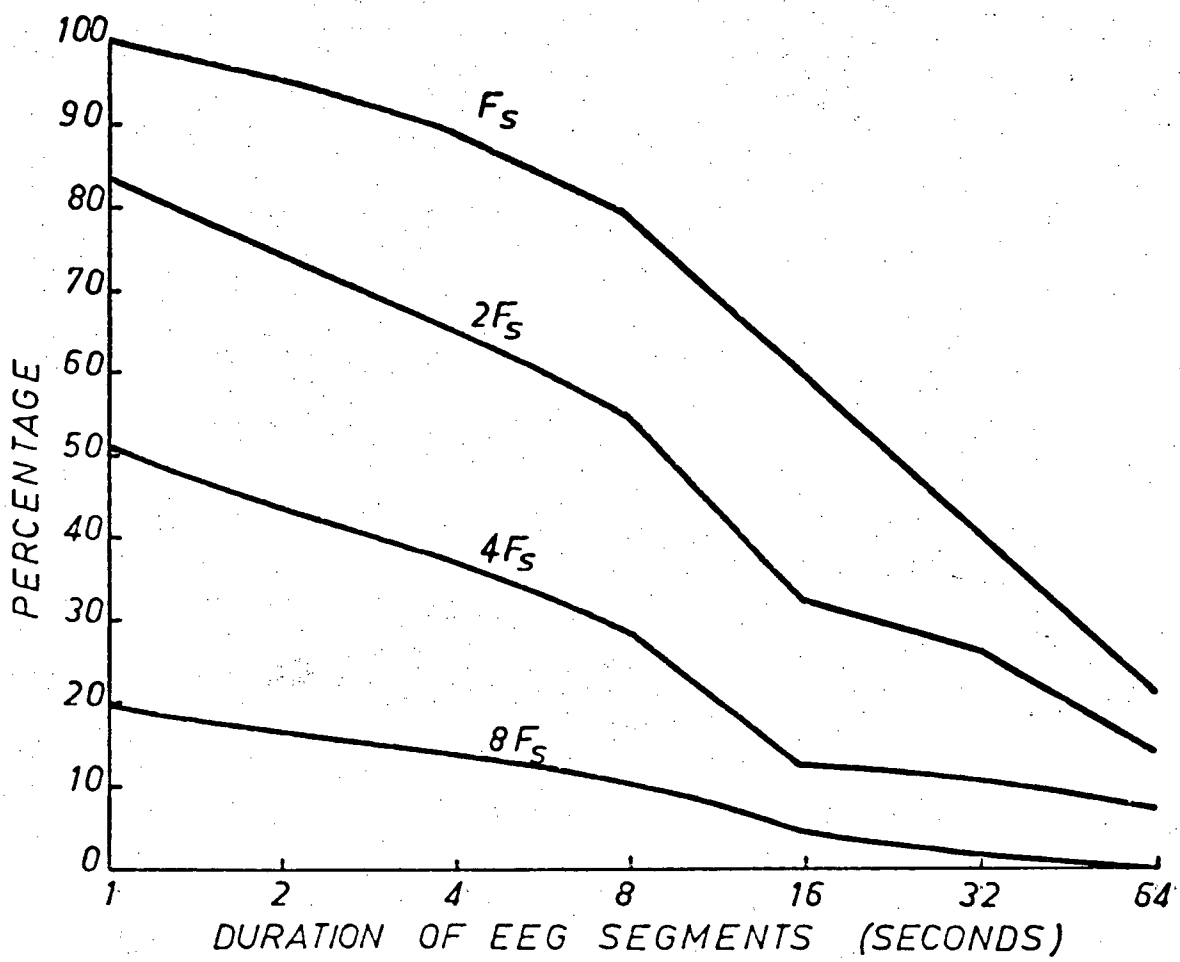

Fig. 4-1 Effect of Increased Sampling Rates on K-S Goodness of Fit Tests for Gaussianity. F_s is equal to 64 Hz, slightly above the Nyquist rate. The percentage of EEG segments of a specified duration which could be modelled as Gaussian is plotted for 4 different sampling rates.

4.4.3 Application of Tests for Wide-Sense Stationarity and Gaussianity

To reduce error in the computation of power spectra, a sampling rate of 128 Hz was used to digitize all 120 EEG segments from the three ensembles under consideration. However, in view of the results in Fig. 4-1, EEG data with an effective sampling rate of 64 Hz was prepared by considering every second sample value and was used to compute all sample amplitude distribution functions needed for the previously described tests

for wide-sense stationarity and Gaussianity.

Recall from section 4.3.1 that, for an EEG segment x(t) to be modelled as a sample function of a process that is wide-sense stationary in the interval [0,2T], a necessary condition is that the amplitude distribution functions and the power spectral distribution functions of x(t) in the intervals [0,T] and [T,2T] must not be significantly different. The distribution functions can be compared by means of the two-sample K-S test. It should also be recalled from section 4.3.2 that x(t) in the interval [0,2T] can be tested for Gaussianity by means of the K-S goodness of fit test, with the mean and variance of the Gaussian population estimated by the sample mean and variance. Values for the two-sample K-S test ([121], p.487) and for the K-S goodness of fit test with unknown mean and variance [124], at the 0.05 level of significance, were used. After testing all 120 EEG segments of 64s duration for wide-sense stationarity and Gaussianity, each segment was subdivided into two segments of 32s duration which were also tested in the same manner. This procedure of successively subdividing and testing was repeated until all available EEG segments of 1s duration were tested. In total, 4M EEG segments of T seconds duration were tested, 2M segments from the baseline ensemble and M segments from each of the anesthesia ensembles, where T and M are given by (4.15) and (4.16) respectively. For each of the three ensembles, the percentage of EEG segments of a specified duration which could be modelled as being wide-sense stationary, Gaussian, or both wide-sense stationary and Gaussian was calculated. All results were then corrected for type I errors arising from false rejection of the hypotheses being tested.

The computation of power spectra required as part of the previously described test for wide-sense stationarity was performed by the

Direct Method, i.e. direct Fourier transformation of the data with consecutive averaging over frequency, as described in section 3.2.1. Before Fourier transformation, each digitized EEG segment of T seconds duration, consisting of a set of 128T sample values, was first tapered with a time window W(t) of the form

$$W(t) = \begin{cases} \frac{1}{2}[1 - \cos(\frac{\pi t}{0.1T})] & 0 \leq t < 0.1T \\ 1 & 0.1T \leq t < 0.9T \\ \frac{1}{2}[1 - \cos(\pi \frac{T-t}{0.1T}] & 0.9T \leq t \leq T. \end{cases} \qquad (4.17)$$

Each tapered EEG segment was then transformed via the Fast Fourier Transform algorithm. A periodogram was calculated from the complex Fourier coefficients for each fundamental frequency k/T Hz, where k=0,1,...,64T. Smoothing of the periodogram was performed using a rectangular window with 7 non-zero coefficients. In this manner a set of (64T + 1) smoothed spectral estimates from 0-64 Hz was calculated for each EEG segment of T seconds duration. The distribution function of the subset of spectral estimates between 1 Hz and 30 Hz was then used in the previously described test for wide-sense stationarity.

Appendix H contains a listing of the program that was used to compute EEG amplitude distribution functions and to evaluate the appropriate one-sample and two-sample K-S statistics. A companion program that was used to compute EEG power spectra and to evaluate the two-sample K-S statistics for the appropriate spectral distribution functions is listed in Appendix I. Finally a third program, listed in Appendix J., performed K-S tests on the sample statistics evaluated by the first two programs, and calculated the corrected percentages of EEG segments of different durations which could be modelled as Gaussian,or wide-sense stationary, or both.

4.5 Results

4.5.1 Interpretation of Results

The results of the modelling investigation are summarized graphically in Fig. 4-1 to Fig. 4-5. In Fig. 4-2 to Fig. 4-5, the results for each EEG channel are presented topologically, i.e. the results are located on a stylized representation of the head in a position corresponding to the location of the electrodes from which the EEG activity was recorded. Although all results have already been corrected for type I errors due to false rejections of the hypothesis being tested, type II errors due to false acceptances of the hypothesis may still exist. Also, these results are based on empirical tests for necessary, but not sufficient, properties that sample EEG segments must possess in order to be modelled as the output of a particular type of random process. For these reasons, the estimated percentages given in Fig. 4-1 to Fig. 4-5 therefore represent useful empirical upper bounds on the corresponding "true" percentages.

4.5.2 Effect of Sampling Rate of Empirical Tests

The effect of different sampling rates upon the outcome of statistical hypothesis tests is illustrated in Fig. 4-1. This marked and previously unexplored relationship may account for some discrepancies apparent in the literature. The problem arises from the assumption, made in the formulation of both the chi-square and the K-S tests, that the set of samples to be tested represents a set of independent random observations. In practise, as the rate of sampling a bandlimited EEG segment increases above the Nyquist rate, successive samples become more interdependent and the efficacy of statistical hypotheses tests is consequently affected [125,126]. It is therefore not surprising that one study of 2s EEG segments which were sampled at 200 Hz concluded that resting EEG activity is

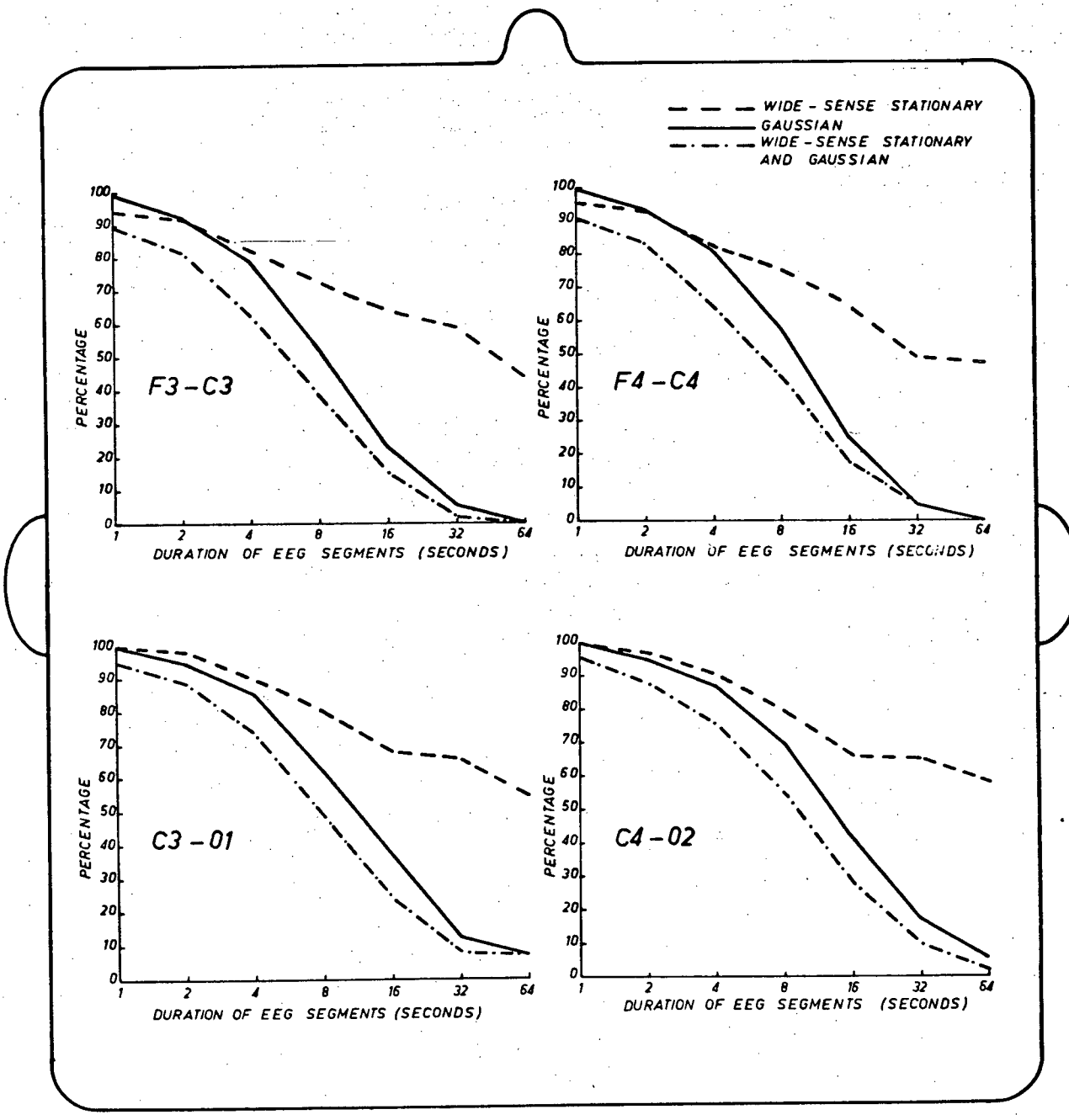

Fig. 4-2 Mean Ensemble Characteristics of the Baseline EEG Activity of 30 Subjects Who Were Resting With Eyes Closed. Results are based on a total of 3840s of EEG activity from each of 4 channels, collected in the form of two multichannel EEG samples of 64s duration per subject.

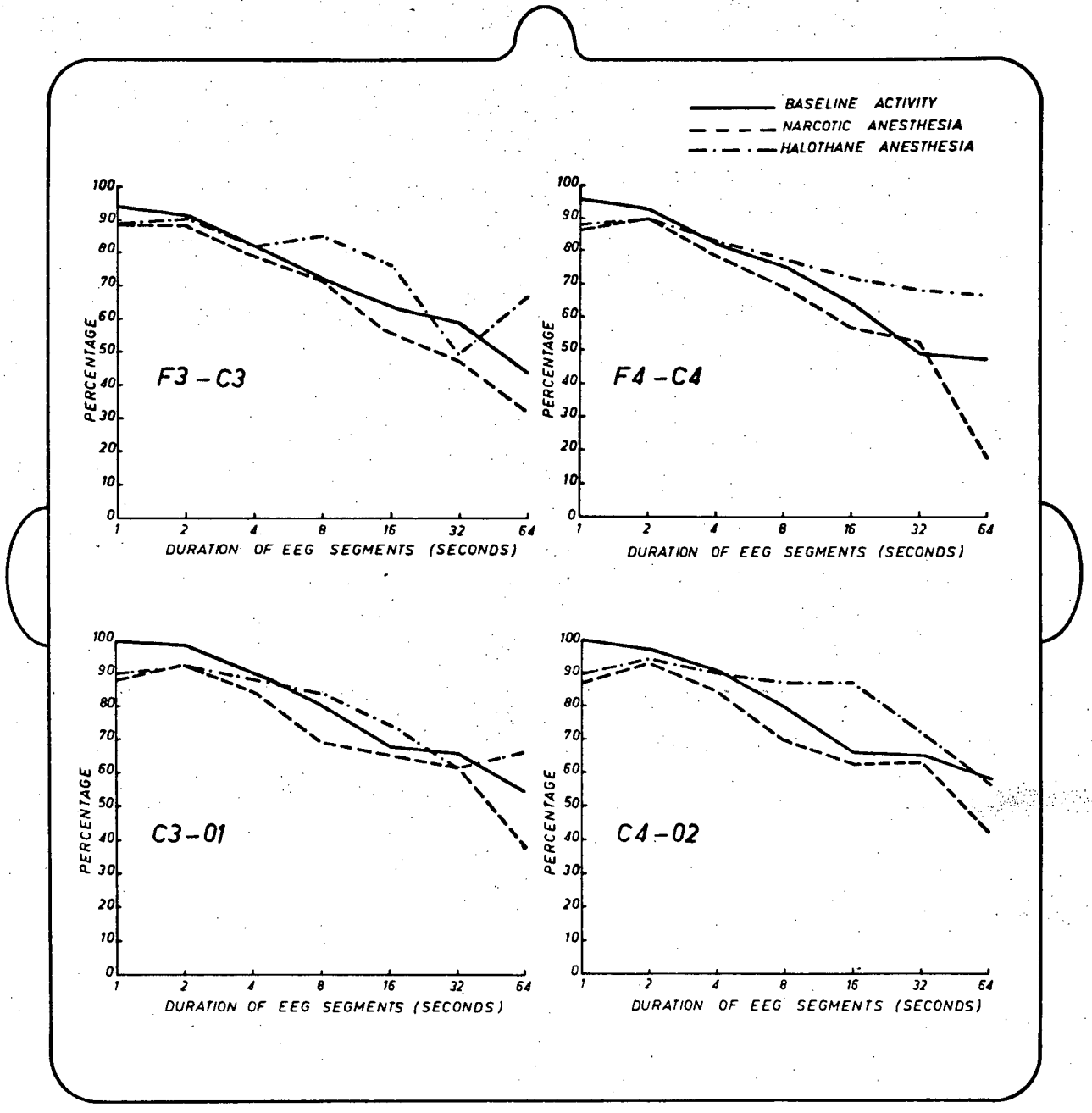

Fig. 4-3 Estimated Percentage of EEG Segments of Various Durations From Three Different Ensembles Which Can Be Modelled as Wide-Sense Stationary.

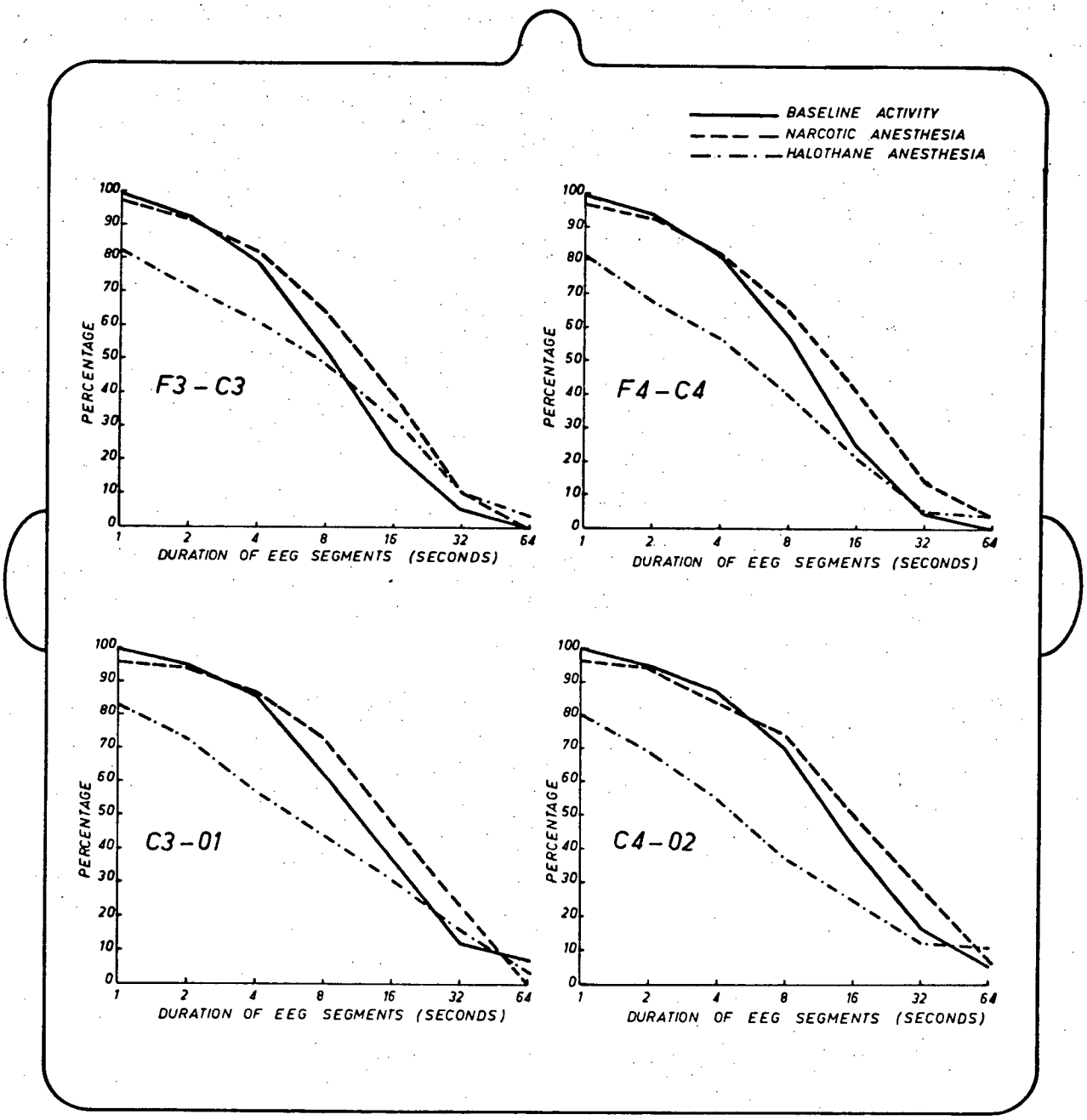

Fig. 4-4 Estimated Percentage of EEG Segments of Various Durations from Three Different Ensembles Which Can Be Modelled as Gaussian.

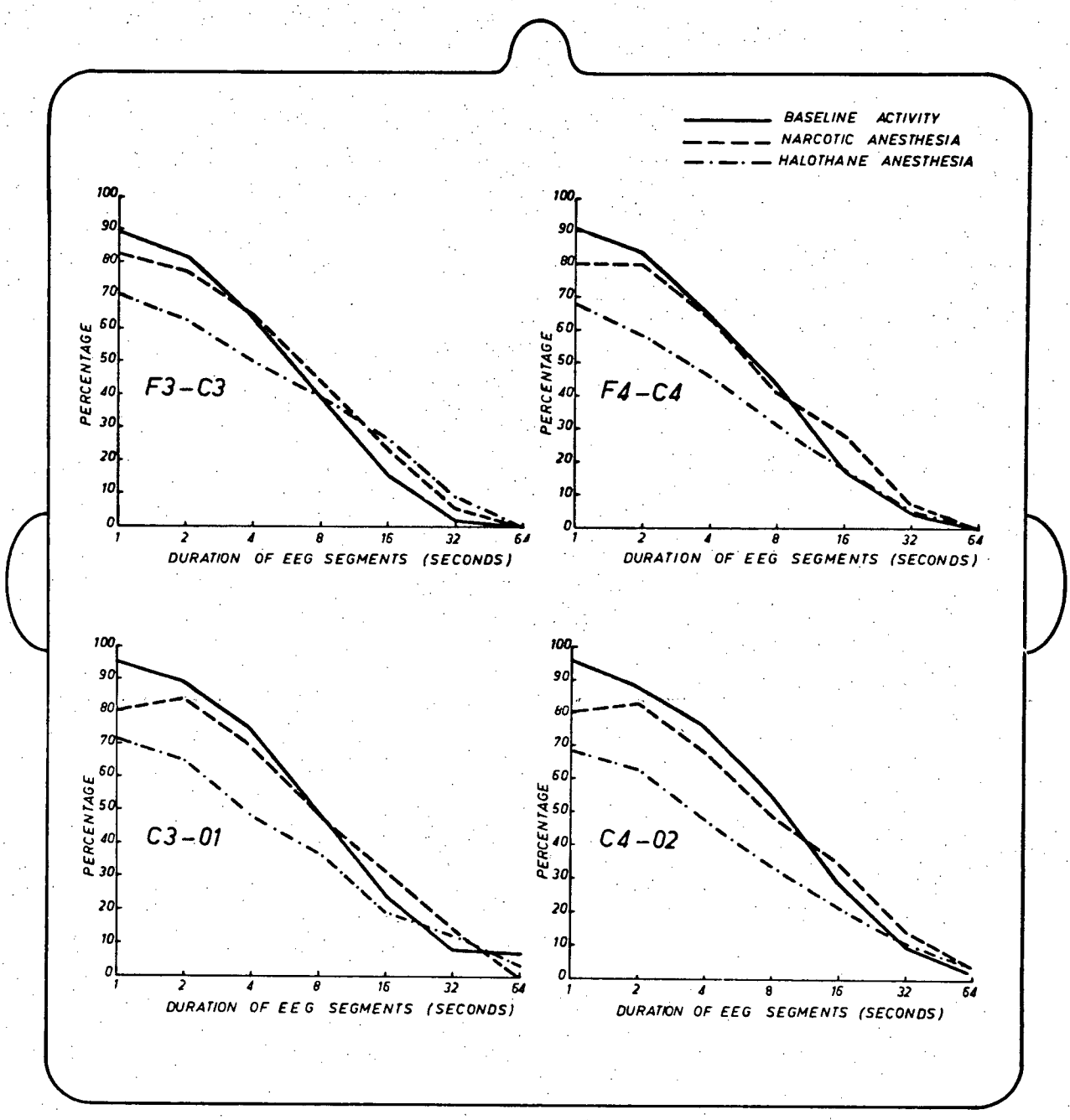

Fig. 4-5 Estimated Percentage of EEG Segments of Various Durations from Three Different Ensembles Which Can Be Modelled as Both Wide-Sense Stationary and Gaussian.

Gaussian 66 percent of the time [115], while other studies of EEG segments of similar duration which were sampled at 5000 Hz concluded that resting EEG activity is strongly non-Gaussian [21,117,118]. Fig. 4-1 indicates that, if it is desired to investigate the characteristics of EEG segments by means of statistical hypothesis tests, the best tradeoff between the requirement to adequately sample a bandlimited signal and the desirability of satisfying the assumption of a statistically independent sample set is reached if the sampling rate is set as little above the Nyquist rate as is practicable.

4.5.3 Estimated Baseline EEG Characteristics

The estimated statistical characteristics of the ensemble of baseline EEG activity are presented in Fig. 4-2. The percentage of EEG segments which can be modelled as being Gaussian, wide-sense stationary, or both is given for each of the 4 differential channels under consideration. In Fig. 4-2 the strong dependence of the results on the duration of the EEG segments being tested is apparent. This dependence accounts for many of the discrepancies in the literature, e.g. the results presented here are consistent with one previous finding [113] that two of four baseline EEG segments (of 8.33s duration) tested were Gaussian and they are also consistent with another report that only 3.3 percent of 30 baseline EEG segments (of 52.8s duration) were found to be Gaussian [114]. The results in Fig. 4-2 also clearly differentiate between the properties of Gaussianity and stationarity: for example, in channel C4-O2 over 57 percent of EEG segments of 64s duration were modelled as wide-sense stationary but only 5.3 percent were found to be Gaussian and less than 2.0 percent could be considered both Gaussian and wide-sense stationary. Fig. 4-2 also reveals striking similarities among corresponding results for

all 4 channels, and even stronger similarities between results for pairs of bilaterally symmetric channels. Thus, while no obvious inter-hemispheric EEG differences were found, occipital EEG activity appears to be consistently more Gaussian and more stationary than frontal EEG activity.

4.5.4 Wide-Sense Stationarity

In Fig. 4-3 to Fig. 4-5 the estimated statistical characteristics of baseline EEG activity are compared to the corresponding characteristics during narcotic anesthesia and during halothane anesthesia. The data base for each type of anesthesia consisted of 1920s of EEG activity from 15 subjects, i.e. two 64s segments per subject, and the baseline data consisted of a total of 3840s of EEG activity from all 30 subjects.

Fig. 4-3 shows the estimated percentage of sample EEG segments of various durations from each of the three different ensembles which can be modelled as wide-sense stationary. If the stationarity of EEG segments of the same duration is considered, it appears that EEG activity during halothane anesthesia is marginally more stationary than baseline activity while EEG activity during narcotic anesthesia is slightly less stationary than baseline activity. The results in Fig. 4-3 indicate that, for sample EEG segments less than 32s in duration from any channel and from any of the three ensembles, the assumption of wide-sense stationarity may be valid more than 50 percent of the time.

4.5.5 Gaussianity

Fig. 4-4 gives the estimated percentage of sample EEG segments from each ensemble which can be modelled as Gaussian. EEG segments from halothane anesthesia are generally less Gaussian than the baseline activity,

particularly in channels C3-O1 and C4-O2, while EEG segments from narcotic anesthesia are marginally more Gaussian than the baseline activity. In all channels, EEG activity during halothane anesthesia is consistently less Gaussian than EEG activity during narcotic anesthesia.

4.5.6 Wide-Sense Stationarity and Gaussianity

In Fig. 4-5, the percentage of sample EEG segments from each of the three ensembles which can be modelled as both Gaussian and wide-sense stationary is presented. A bilateral symmetry is immediately apparent in these results. In all channels, the percentage of EEG segments from halothane anesthesia which are wide-sense stationary and Gaussian is markedly smaller than the corresponding percentage from narcotic anesthesia. Also, from Fig. 4-5 it is evident that less than 10 percent of the 64s EEG segments from any ensemble can be modelled as wide-sense stationary and Gaussian.

4.6 Significance of Results

4.6.1 Development of EEG Monitoring Systems

The estimated degree to which ensembles of EEG activity may be modelled as stationary and Gaussian, e.g. the results presented in Fig. 4-3 and Fig. 4-5, should be an important consideration in the choice of an appropriate technique for analysing sample EEG segments from those ensembles. For example, the primary motivation for investigating the statistical characteristics of the three specific ensembles of EEG activity described in this chapter was the expectation that the results would assist in the development of a computer-based system for monitoring the level of anesthesia during surgery by means of an automatic analysis of spontaneous EEG activity. In the development of such a system, decisions must be made with respect to the duration of the EEG segments to

be analysed, the rate at which the estimated level should be updated, the choice of an analytic technique, and the significance which may be attached to the results of the analysis.It should be noted that the feasibility of employing EEG monitoring systems to continuously assess a patient's status during sleep, serious illness, coma, and possible cerebral death is also currently being investigated by others, e.g. [83,127,128]. The statistical characteristics of the particular ensembles of EEG activity being analysed in each instance should be an important consideration in the development of the appropriate monitoring system.

To illustrate how knowledge concerning the degree of stationarity of the three ensembles described in this chapter might influence the development of a system for monitoring and analysing EEG activity during anesthesia, the problem of selecting the most appropriate duration for sample EEG segments on the basis of the results in Fig. 4-3 will be briefly considered. It would obviously be desirable to analyse EEG segments of long duration because the significance of any transient noise and artifact is thereby reduced, because a high resolution in the estimation of power spectra is possible, and because a potentially large data reduction can be realized if such segments can be adequately characterized. However, in the theoretical development of most analytic techniques the assumption is made that the signal under consideration represents a sample function from a random process that is at least stationary to some extent over the interval of interest. Fig. 4-3 indicates that the assumption of wide-sense stationarity for the three ensembles under consideration is only partially justified, even for EEG segments of relatively short duration. The a priori selection of the most suitable analytic technique therefore cannot be made on a firm theoretical basis. Under

such conditions, the results in Fig. 4-3 indicate that the choice of 32s duration for sample EEG segments might, in this instance, represent a reasonable compromise. For all three ensembles at least one half of the EEG segments of this duration could be modelled as wide-sense stationary. An analytic technique which assumes wide-sense stationarity could then reasonably be applied to the 32s segments and any inherent non-stationarity could be taken into account by some ancillary technique. For example, the previously described K-S D_2 statistics could be included in the analysis as parameters indicating the degree of non-stationarity of the segment being analysed and hence could be used in interpreting the significance of the results. Alternatively, individual EEG segments could be tested for wide-sense stationarity as described previously and only those segments found to be stationary would be analysed. If non-stationarities are to be considered for some particular EEG ensembles, and they cannot adequately be taken into account by such ancillary techniques, then a non-stationary analysis of the EEG could be attempted [129-131].

4.6.2 Evaluation of Alternate Analytic Techniques

This section will consider some implications of the results in Fig. 4-5 with respect to the choice of the most appropriate technique for analysing EEG segments of a specified duration from any of the three ensembles. For the reasons stated previously in section 4.2, power spectrum analysis of the EEG segments would be preferable if the segments could be modelled as both wide-sense stationary and Gaussian. However, Fig. 4-5 shows that only a certain proportion of sample EEG segments may be so modelled, e.g. for all ensembles less than 50 percent of the 8s segments from any channel could be considered wide-sense stationary and Gaussian. It cannot therefore be assumed that spectral analysis will provide a

sufficient characterization of such sample EEG segments. When it is known that a certain proportion of the EEG segments to be analysed cannot be modelled as the output of a stationary Gaussian random process, alternate analytic strategies might be considered. Of course, any analytic technique could arbitrarily be applied to the data in the hope that the results might somehow provide an ad hoc justification for its usage. However, if it can be assumed that most of the segments under consideration are wide-sense stationary, or that any inherent non-stationarity has been taken into account by one of the techniques described previously, then certain analytic strategies might be more profitably investigated. For example, if the EEG segments are stationary and only slightly non-Gaussian, ancillary parameters which indicate the degree of non-Gaussianity (e.g. skewness and kurtosis [97] or the previously described K-S D_1 statistic) might be employed in addition to spectral analysis. Alternatively, if the EEG segments to be analysed are stationary but very non-Gaussian, then the information provided by EEG spectral analysis could be supplemented by the use of other analytic techniques, e.g., bispectral analysis [117].

4.6.3 Further Work

The modelling investigation described in this chapter also indicates some areas for further work that are beyond the scope of this thesis. It has been suggested that, on the basis of the Central Limit Theorem, increased Gaussianity in observed EEG activity may reflect an increased degree of independence among individual cortical neural generators [115].If one accepts this premise, then Fig. 4-4 and Fig. 4-5 indicate that the cortical generators are considerably more interdependent during halothane anesthesia than during narcotic anesthesia. The possible neurophysiological significance of this result could be investigated,

perhaps by studies of EEG coherence in individual subjects and by considering more sample data from more channels. In addition, the technique described in this chapter for estimating the degree of wide-sense stationarity and Gaussianity of an ensemble of EEG segments could obviously be applied to many other ensembles of EEG activity corresponding to other states of consciousness.

CHAPTER V PERFORMANCE IMPROVEMENT SCHEMES

5.1 Introduction

The initial results presented in Chapter III demonstrated the feasibility of using EEG pattern recognition systems to estimate the level of anesthesia. To a large extent, the modelling results presented in Chapter IV vindicated the initial EEG pattern recognition approach. In addition, Chapter IV contained a discussion of possible methods for improving the performance of the initially developed systems by giving greater consideration to the actual statistical characteristics of the EEG data. In this chapter, other possible methods for improving performance will be investigated; for illustrative purposes each of these methods will be investigated with a view to improving the performance of three specific EEG spectral pattern recognition systems. It should be recalled that all such systems classified an unknown EEG pattern sample on the basis of a set of thirteen extracted spectral feature values. The Bayes classifier that was employed in all systems was optimal only if all features were statistically independent and if the required class-conditional feature probabilities either were known exactly or were given by the corresponding Bayes estimates. Most of the performance improvement schemes considered in this chapter involve changes in the initial feature extraction procedure and pattern classification algorithm.

The three initially developed EEG spectral pattern recognition systems which were employed in the work described in this chapter had the same structure, i.e. all contained a linear feature quantizer with 64 possible levels and a classifier which assumed equal a priori class probabilities. However, each was trained on the set of available EEG pattern samples from a different type of anesthesia. Fig. 5-1 depicts the "confusion" matrices which were calculated for these three systems. The i-jth element in each confusion matrix contains the number of pattern samples from class

$$\begin{bmatrix} 49 & 5 & 1 & 1 & 0 \\ 8 & 23 & 2 & 4 & 0 \\ 0 & 4 & 7 & 1 & 0 \\ 9 & 27 & 10 & 50 & 29 \\ 0 & 1 & 0 & 7 & 42 \end{bmatrix} \qquad \begin{bmatrix} 52 & 1 & 0 & 0 & 0 \\ 6 & 21 & 5 & 0 & 0 \\ 0 & 1 & 5 & 1 & 1 \\ 0 & 5 & 0 & 114 & 6 \\ 0 & 0 & 1 & 2 & 47 \end{bmatrix}$$

Halothane Anesthesia

$$\begin{bmatrix} 38 & 5 & 5 & 3 & 0 \\ 6 & 15 & 19 & 7 & 0 \\ 5 & 10 & 51 & 19 & 1 \\ 0 & 11 & 58 & 82 & 1 \\ 0 & 1 & 1 & 1 & 2 \end{bmatrix} \qquad \begin{bmatrix} 42 & 2 & 0 & 0 & 0 \\ 4 & 24 & 5 & 2 & 0 \\ 1 & 9 & 62 & 8 & 1 \\ 5 & 10 & 15 & 117 & 1 \\ 0 & 0 & 2 & 1 & 1 \end{bmatrix}$$

Narcotic Anesthesia

$$\begin{bmatrix} 58 & 9 & 4 & 16 & 5 \\ 10 & 34 & 0 & 13 & 1 \\ 1 & 7 & 2 & 5 & 0 \\ 5 & 29 & 2 & 27 & 18 \\ 1 & 0 & 0 & 7 & 63 \end{bmatrix} \qquad \begin{bmatrix} 91 & 0 & 0 & 0 & 0 \\ 8 & 34 & 3 & 6 & 1 \\ 1 & 0 & 10 & 0 & 0 \\ 3 & 7 & 5 & 60 & 5 \\ 0 & 0 & 0 & 1 & 69 \end{bmatrix}$$

Enflurane Anesthesia

Fig. 5-1 Confusion Matrices for Systems Which Extracted 13 Spectral Features. The matrices on the left resulted from performance estimation by the Π^* technique and those on the right resulted from performance estimation by the U^* technique.

i, $0 \leq i \leq 4$, which the system identified as belonging to class j, $0 \leq j \leq 4$. The actual numbers are given, rather than the corresponding probabilities, to indicate the unequal number of available pattern samples per class for the different types of anesthesia. The matrices on the left in Fig. 5-1 resulted from performance estimation by the Π^* technique and those on the right resulted from performance estimation by the U* technique. Thus the performance estimates for the three systems, which were given previously in Tables 3-3 to 3-5, can be derived from the appropriate confusion matrices in Fig. 5-1: $\hat{P}_e[\Pi^*]$ and $\hat{P}_e[U^*]$ were 0.389 and 0.108 for the halothane anesthesia system, 0.449 and 0.211 for the narcotic anesthesia system, and 0.420 and 0.132 for the enflurane anesthesia system.

From the definitions of the Π^* and U* techniques (section 3.5), it is evident that the difference between $\hat{P}_e[\Pi^*]$ and $\hat{P}_e[U^*]$ for a specific system provides an indication of the effect of intersubject EEG variation on system performance [39]. The relatively large magnitude of this effect is apparent when the difference between $\hat{P}_e[\Pi^*]$ and $\hat{P}_e[U^*]$ is evaluated for each of the systems considered in Chapter III. Similar results have been reported in the literature for other types of EEG pattern recognition systems (e.g. [77,132]). Accordingly, intersubject EEG variation must be regarded as a major obstacle preventing the development of more reliable systems. Much of the work described in this chapter was directed toward reducing the effect of intersubject EEG variation.

In section 5.2 the possibility of improving performance by increasing the number of extracted features is considered. The feasibility of exploiting statistical interdependencies among features is discussed in section 5.3. In section 5.4 a "nearest subject" scheme for reducing the effect of intersubject EEG variation on classifier performance is explored.

5.2 Extraction of Additional Features

5.2.1 Rationale

The EEG spectral pattern recognition systems that were initially developed were based on the extraction of a total of 13 spectral features from two EEG channels. All of these features were heuristically derived, i.e. they either had an established clinical relevance or they had previously been described as meaningful in the literature on EEG pattern recognition. Each EEG pattern sample was evaluated in terms of these features and was subsequently classified on the basis of the extracted set of feature values. Because of computational time and cost considerations in the initial phase of the research it was necessary to limit the number of extracted features, i.e. to limit the extent to which EEG pattern samples could be characterized. In spite of this limitation, the results of the initial phase of the research (as described in Chapter III) clearly established the feasibility of estimating the level of anesthesia by means of EEG pattern recognition systems. Consequently, after the feasibility had been established it seemed worthwhile to investigate the possibility that the performance of the initially developed EEG spectral pattern recognition systems could be improved by the inclusion of additional features in the extracted feature set.

To investigate this possibility, it was decided that the selection of an appropriate set of additional features would proceed in the following manner. First, a large set of additional, heuristically derived features would be defined. It was recognized that adding each of these features to the extracted feature set would not necessarily result in an improvement in performance. It was also recognized that there was a practical constraint on the large number of additional features that should be selected from the large set, because of the limited computational time

that would be available for extracting features from successive EEG pattern samples in an on-line monitoring system. For the purposes of this investigation, therefore, the maximum number of additional features to be selected was arbitrarily set at 13, i.e. it was decided that the total number of extracted features would be increased by a factor of two. However, in general there is no optimal procedure for selecting the best subset of features from a large set, except by the exhaustive evaluation of all possible subsets [110]. Since that would be computationally impractical here, it was decided that various suboptimal feature selection criteria would be used to choose alternate sets of 13 additional features. EEG spectral pattern recognition systems which included these additional features in their extracted feature sets would then be developed and their performance would be estimated.

5.2.2 Definition of Additional Features

To define the relatively large number of additional, heuristically derived features from which various sets of 13 features would later be selected, the notation that was introduced in section 3.2.1 will be extended: let x(t) and y(t) denote the sample EEG activity from two specified channels, let X(f) and Y(f) represent their Fourier transforms, as defined in (3.2), and let X*(f) and Y*(f) denote the complex conjugates of X(f) and Y(f), respectively. From (3.1) it follows that the EEG spectra, or more specifically the EEG autospectra, corresponding to x(t) and y(t) are given by

$$S_{xx}(f) = E\{X(f)\ X^*(f)\} \qquad (5.1)$$

and

$$S_{yy}(f) = E\{Y(f)\ Y^*(f)\}\ . \qquad (5.2)$$

The 13 features which were initially chosen for extraction from the EEG autospectra corresponding to two of the four available channels were described previously in section 3.2.3.

Many of the additional features which were chosen for extraction are derived from the EEG autospectra corresponding to all four available channels. Other features were defined in terms of the EEG coherence spectrum: if

$$S_{xy}(f) = E\{X(f)\ Y^*(f)\} \quad , \tag{5.3}$$

i.e. $S_{xy}(f)$ denotes the cross-spectrum, then the coherence spectrum $C_{xy}(f)$ is defined as

$$C_{xy}(f) \triangleq \frac{|S_{xy}(f)|}{[S_{xx}(f)\ S_{yy}(f)]^{\frac{1}{2}}} \quad , \tag{5.4}$$

where $S_{xx}(f)$ and $S_{yy}(f)$ are given by (5.1) and (5.2), respectively [21,133]. It should be pointed out that the quantity in (5.4) is the square root of the quantity defined as coherence in some references (e.g. [91,134]). From the definition in (5.4) it is evident that the coherence spectrum $C_{xy}(f)$ is a real-valued function of frequency for which

$$C_{xy}(f) = C_{yx}(f) \tag{5.5}$$

and for which

$$0 \leq C_{xy}(f) \leq 1. \tag{5.6}$$

It should also be noted from (5.4) that, if x(t) and y(t) are linearly related, i.e. if

$$Y(f) = H(f)\ X(f) \tag{5.7}$$

for some H(f), then $C_{xy}(f) = 1$. Accordingly, the coherence spectrum can be regarded as a measure of the degree of linear relationship between the EEG activity from two specified channels as a function of frequency [134, 135]. This has motivated the investigation of various "coherence features", i.e. features derived from the coherence spectrum, as potentially significant descriptors of multichannel EEG activity (e.g. [78,81,91]).

In this research, additional features were derived from "bilateral" coherence spectra and from "unilateral" coherence spectra. For

convenience in defining these features, let channels F3-C3, C3-O1, F4-C4 and C4-O2 (in Fig. 2-3) be denoted as channels 1, 2, 3 and 4, respectively. Then bilateral coherence features refer to features derived from a coherence spectrum corresponding to a symmetrically located pair of channels, i.e. channels 1 and 3 or channels 2 and 4. Unilateral coherence features refer to those features derived from the coherence spectrum corresponding to an anterior-posterior channel pair, i.e. channels 1 and 2 or channels 3 and 4.

Coherence spectra were computed, smoothed and averaged in a manner analogous to the procedure outlined previously in section 3.2.2 for autospectra. Appendix C contains a listing of the program that was used to compute the autospectra and the coherence spectrum for sample EEG data from any two specified channels. The results of all spectral and coherence calculations that were performed on each EEG pattern sample consisted of four smoothed autospectra

$$\hat{S}_{jj}(f_m) , \qquad \text{for } j = 1,2,3,4$$

and four smoothed coherence spectra

$$\hat{C}_{jk}(f_m) \qquad \text{for} \begin{cases} j = 1, k = 2 \\ j = 1, k = 3 \\ j = 2, k = 4 \\ j = 3, k = 4 , \end{cases}$$

where j and k correspond to the appropriate channel numbers and where

$$f_m = \frac{m-1}{8} \text{ Hz}, \qquad \text{for } m=1,\ldots,256. \qquad (5.8)$$

Table 5-1 describes all of the spectral and coherence features chosen for extraction from each EEG channel. In Table 5-1, channel j refers to the channel under consideration and channels k and ℓ refer, respectively, to the corresponding unilateral and bilateral channels. Three autospectral features and two coherence features were chosen for extraction

Table 5-1 Spectral and Coherence Features Chosen for Extraction From Each EEG Channel

Frequency Range	Spectral and Coherence Features	
	Description	Symbol
0.00 - 4.00 Hz (Δ band)	Relative spectral energy	$e_{\Delta j}$
	Peak spectral frequency	$f_{\Delta j}$
	Peak spectral intensity	$i_{\Delta j}$
	Mean coherence (unilateral)	$u_{\Delta jk}$
	Mean coherence (bilateral)	$b_{\Delta j\ell}$
4.01 - 8.00 Hz (θ band)	Relative spectral energy	$e_{\theta j}$
	Peak spectral frequency	$f_{\theta j}$
	Peak spectral intensity	$i_{\theta j}$
	Mean coherence (unilateral)	$u_{\theta jk}$
	Mean coherence (bilateral)	$b_{\theta j\ell}$
8.01 - 13.00 Hz (α band)	Relative spectral energy	$e_{\alpha j}$
	Peak spectral frequency	$f_{\alpha j}$
	Peak spectral intensity	$i_{\alpha j}$
	Mean coherence (unilateral)	$u_{\alpha jk}$
	Mean coherence (bilateral)	$b_{\alpha j\ell}$
13.01 - 15.00 Hz (σ band)	Relative spectral energy	$e_{\sigma j}$
	Peak spectral frequency	$f_{\sigma j}$
	Peak spectral intensity	$i_{\sigma j}$
	Mean coherence (unilateral)	$u_{\sigma jk}$
	Mean coherence (bilateral)	$b_{\sigma j\ell}$
15.01 - 32.00 Hz (β_1 band)	Relative spectral energy	$e_{\beta j}$
	Peak spectral frequency	$f_{\beta j}$
	Peak spectral intensity	$i_{\beta j}$
	Mean coherence (unilateral)	$u_{\beta jk}$
	Mean coherence (bilateral)	$b_{\beta j\ell}$
18.00 - 24.00 Hz (β_2 band)	Relative spectral energy	$e_{\beta_2 j}$
0.00 - 32.00 Hz (Total)	Total spectral energy	E_j
	Mean spectral frequency	$\bar{f}_j$
	Second moment	$\bar{f}_j^2$

from each of the five traditional EEG frequency bands. The last three features listed in Table 5-1, i.e. the total spectral energy, the mean spectral frequency and the mean second moment, were defined previously in equations (3.13), (3.15) and (3.16), respectively. All other autospectral features describing the relative energy, the peak frequency and the peak intensity in the traditional frequency bands were evaluated as indicated in (3.14) and (3.17) - (3.19) for the corresponding α-band features. The coherence features described in Table 5-1 were evaluated in a similar manner.

In total, Table 5-1 describes 76 spectral features and 20 coherence features corresponding to four EEG channels. However, because 13 of these features constituted the initially chosen spectral feature set, only 83 additional spectral and coherence features are described by Table 5-1. To facilitate the subsequent selection of various sets of 13 additional features, all available EEG pattern samples were evaluated in terms of the additional features in Table 5-1 and the resultant 83-element feature vectors were stored for later use.

5.2.3 Feature Selection

The purpose of selecting additional features was to explore the possibility of improving the performance of the initially developed EEG spectral pattern recognition systems by expanding their extracted feature sets. As stated in section 5.2.1, it was decided to increase the size of the extracted feature set by a factor of two, i.e. to select 13 additional features. Alternate sets of 13 additional features were therefore chosen from the 83 spectral and coherence features described in section 5.2.2 by means of various feature selection criteria. EEG spectral pattern recognition systems which extracted the additional features thus selected

were then developed and their performance was estimated. The systems employed 64 feature quantization levels over a range of ±5.0 sd and assumed that the a priori class probabilities were equal. A summary of their estimated performance, based on the extraction of 13 spectral features, was given in section 5.1.

Several alternate feature selection criteria were considered. In each instance, a set of the 13 "best" features was selected after all 83 available features had been ranked on the basis of some criterion such as the magnitude of their interclass/intraclass F ratios [136,137], their relative lack of correlation with other features, and their estimated error probabilities when used separately [110]. The performance of each EEG spectral pattern recognition system which employed a set of additional features selected in this manner was estimated by the Π^* and U^* techniques. Results indicated that only marginal improvements in system performance could be achieved with most of the feature selection criteria that were initially considered.

However, the use of one particular criterion in conjunction with a stepwise feature selection algorithm did result in significant improvements in system performance. To describe the criterion and the algorithm, let $\{\sigma_i\}$, $1 \leq i \leq n$, denote the complete set of features chosen for extraction from each EEG pattern sample ($n = 13$ initially) and let $\{a_j\}$, $1 \leq j \leq N$, denote the set of additional features described in section 5.2.2 which have not yet been included in the extracted feature set ($N = 83$ initially). Furthermore, let

$$(\hat{P}_e[\Pi^*])_{\sigma_{n+1}} = a_j$$

indicate the misclassification error probability, as estimated by the Π^* technique, for an EEG spectral pattern recognition system in which a_j was selected to be the additional extracted feature σ_{n+1}. The feature selection

criterion can then be described as follows: at each step choose $\sigma_{n+1} = a_j$ if

$$(\hat{P}_e[\Pi^*])_{\sigma_{n+1} = a_j} < (\hat{P}_e[\Pi^*])_{\sigma_{n+1} = a_k} \qquad (5.9)$$

for $k = 1,\ldots,N$ and $k \neq j$. An algorithm was implemented to select 13 additional features, in terms of the above criterion, in a stepwise manner. Table 5-2 lists the additional features which were selected in this way for each of the three different types of anesthesia under consideration. The symbols used in Table 5-2 correspond to those defined previously in Table 5-1.

Table 5-2 Summary of Selected Spectral and Coherence Features

Selected Feature Number	Type of Anesthesia		
	Halothane	Narcotic	Enflurane
14	$e_{\sigma 3}$	$\bar{f}_2^2$	$f_{\theta 2}$
15	$i_{\alpha 2}$	$i_{\alpha 2}$	E_1
16	$f_{\theta 3}$	$f_{\Delta 3}$	$f_{\theta 1}$
17	$f_{\Delta 4}$	$e_{\beta 1}$	$f_{\Delta 1}$
18	$b_{\Delta 13}$	$b_{\theta 13}$	$f_{\beta 1}$
19	$f_{\Delta 1}$	$b_{\Delta 24}$	$f_{\Delta 2}$
20	$i_{\sigma 3}$	$i_{\beta 1}$	$f_{\sigma 2}$
21	$f_{\theta 1}$	$b_{\alpha 24}$	$i_{\theta 1}$
22	$b_{\beta 13}$	$f_{\sigma 2}$	$b_{\alpha 13}$
23	$f_{\sigma 2}$	$\bar{f}_2$	$b_{\sigma 24}$
24	$b_{\alpha 13}$	$f_{\sigma 4}$	$\bar{f}_2$
25	$f_{\beta 3}$	$f_{\theta 1}$	$e_{\theta 1}$
26	$f_{\theta 2}$	$i_{\Delta 3}$	$b_{\sigma 13}$

EEG spectral pattern recognition systems which extracted the additional features listed in Table 5-2, as well as the 13 initially chosen features, were developed and their performance was estimated. The results

are summarized in Figs. 5-2 to 5-4. In each figure the estimated probability of correct classification for a given system is plotted as a function of the number of features included in the extracted feature set. It should be noted that, to facilitate the subjective interpretation of results, estimated probabilities of correct classification are given in Figs. 5-2 to 5-4, i.e.

$$\hat{P}_c[U^*] = 1 - \hat{P}_e[U^*], \tag{5.10}$$

$$\hat{P}_c[\Pi^*] = 1 - \hat{P}_e[\Pi^*] \tag{5.11}$$

and

$$\hat{P}_c[\text{Mean}] = (\hat{P}_c[U^*] - \hat{P}_c[\Pi^*])/2$$

$$= 1 - \hat{P}_e[\text{Mean}], \tag{5.12}$$

where $\hat{P}_e[\Pi^*]$ and $\hat{P}_e[U^*]$ were described in sections 3.5.3 - 3.5.4 and $\hat{P}_e[\text{Mean}]$ was defined in (3.55).

5.2.4 Resulting Improvement in Performance

The results presented in Figs. 5-2 to 5-4 indicate that significant improvements in performance have been achieved by the selection of additional, heuristically derived features for inclusion in the extracted feature set. The improvement in performance is reflected by increased values of $\hat{P}_c[U^*]$, $\hat{P}_c[\Pi^*]$, and hence $\hat{P}_c[\text{Mean}]$ for the systems under consideration. Improved performance is also indicated by a decrease in the value of

$$\Delta \triangleq |\hat{P}_c[U^*] - \hat{P}_c[\Pi^*]| \tag{5.13}$$

for systems which extracted the additional features, as shown in Figs. 5-2 to 5-4. From the definitions of the Π^* and U^* techniques (section 3.5), it is evident that the value of Δ, i.e. the magnitude of the difference between the two estimates of performance, can be regarded as an estimate of the effect of intersubject EEG variation on system performance [39].

In considering the results presented in Fig. 5-2 for halothane anesthesia, it is evident that the values of $\hat{P}_c[\Pi^*]$ and $\hat{P}_c[U^*]$ changed

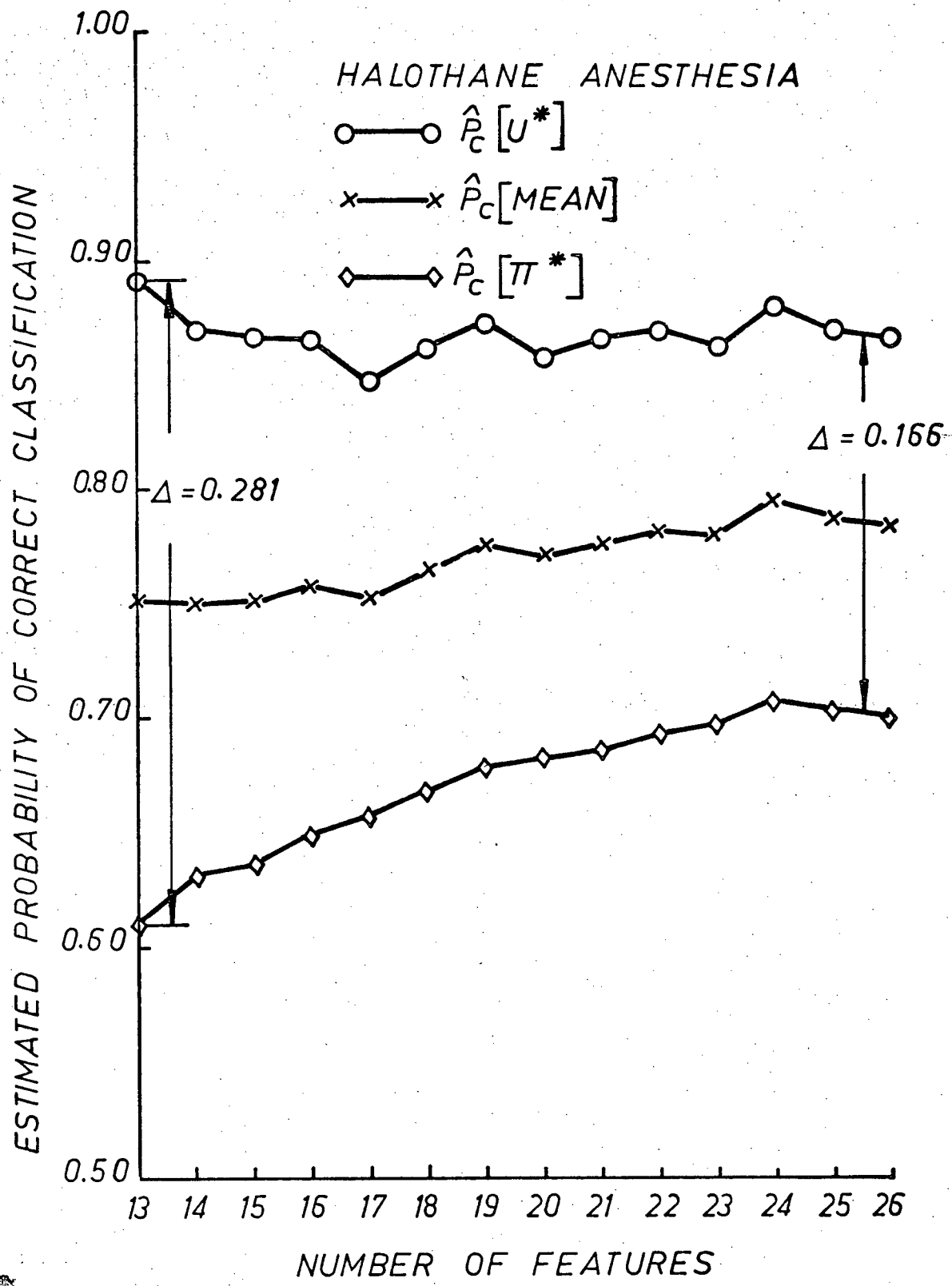

Fig. 5-2 Improvement in the Performance of an EEG Spectral Pattern Recognition System Developed for Halothane Anesthesia

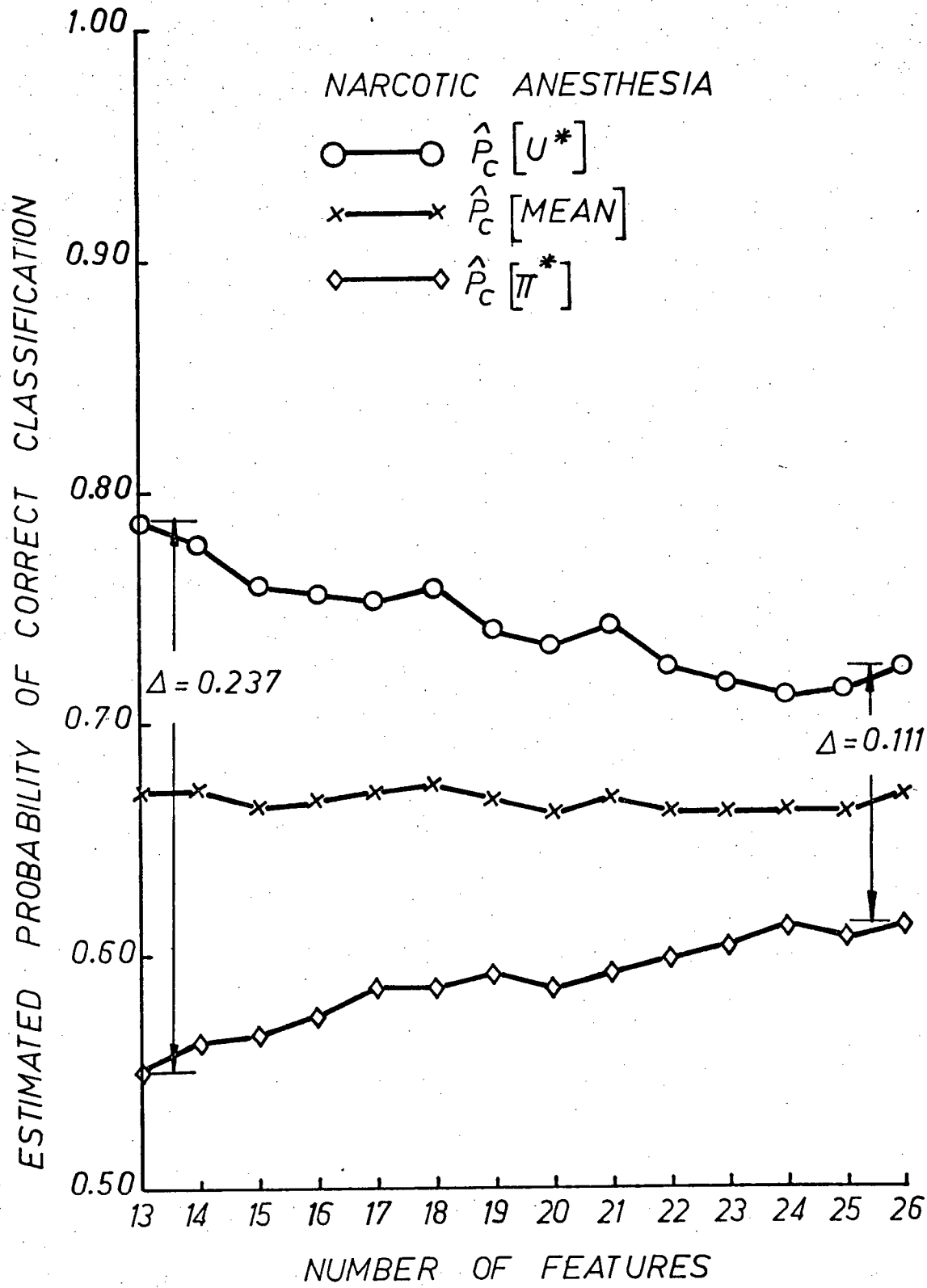

Fig. 5-3 Improvement in the Performance of an EEG Spectral Pattern Recognition System Developed for Narcotic Anesthesia

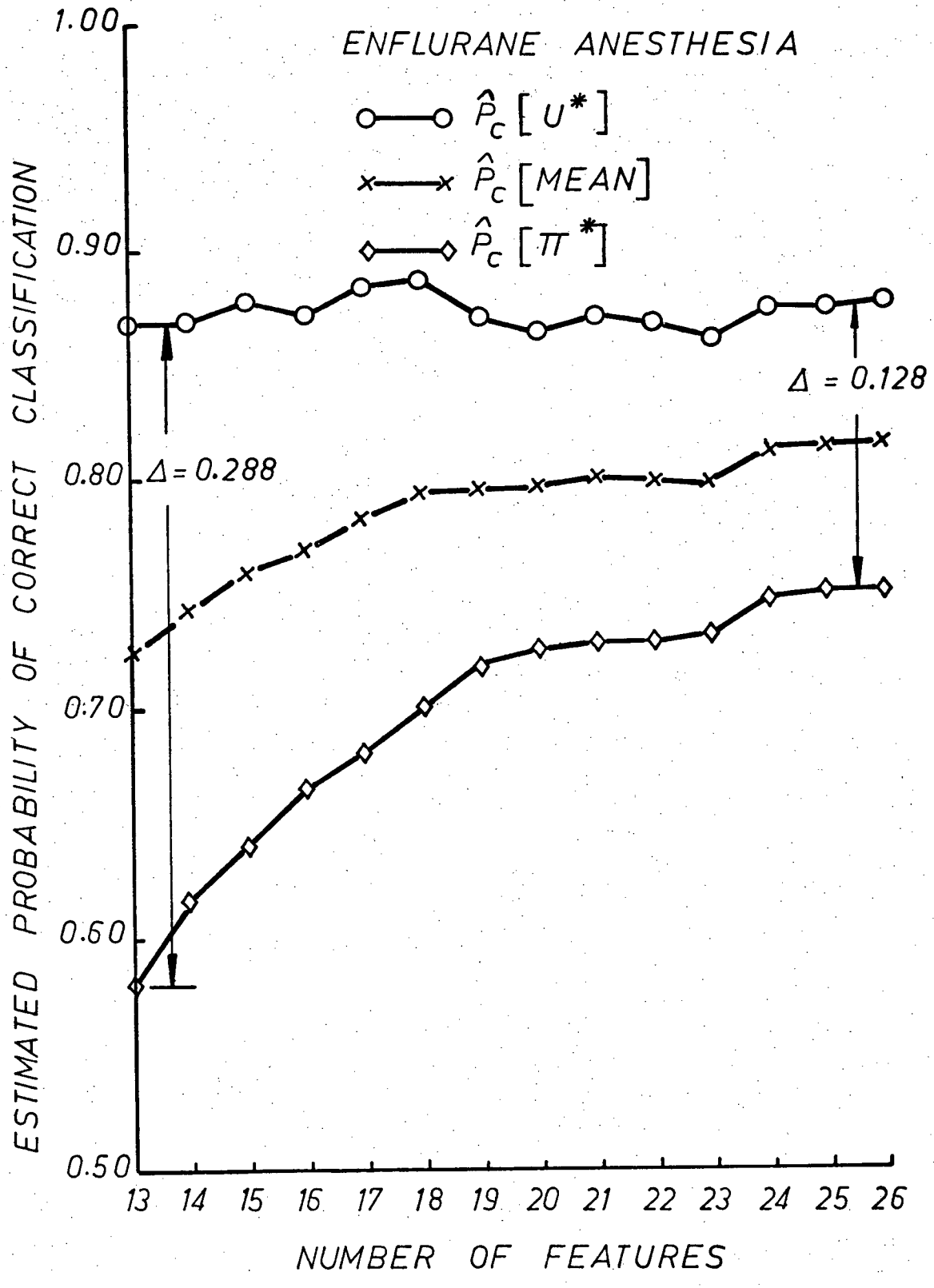

Fig. 5-4 Improvement in the Performance of an EEG Spectral Pattern Recognition System Developed for Enflurane Anesthesia

from 0.611 and 0.892, respectively, for 13 extracted features to 0.700 and 0.866 for 26 extracted features. There was a corresponding increase in the value of $\hat{P}_c$[Mean] from 0.751 to 0.783. It can also be seen in Fig. 5-2 that Δ decreased from 0.281 initially to 0.166 finally, a relative decrease of more than 40 percent in the value of Δ.

For narcotic anesthesia, the results in Fig. 5-3 show that the extraction of the 13 additional features listed in Table 5-2 resulted in a change of $\hat{P}_c[\Pi^*]$ and $\hat{P}_c[U^*]$ from 0.551 and 0.788 initially to 0.613 and 0.724. This did not represent an improvement in the value of $\hat{P}_c$[Mean], which changed from 0.670 to 0.669. However, Fig. 5-3 shows that for narcotic anesthesia the value of Δ decreased from 0.237 for 13 extracted features to 0.111 for 26 features, a decrease of more than 53 percent.

The results presented in Fig. 5-4 for enflurane anesthesia indicate the greatest improvement in performance. In Fig. 5-4 it can be seen that the values of $\hat{P}_c[\Pi^*]$ and $\hat{P}_c[U^*]$ were 0.580 and 0.868 initially, but increased to 0.751 and 0.878 with the inclusion of the 13 additional features in the extracted feature set. The value of $\hat{P}_c$[Mean] showed a significant increase, from 0.724 for 13 extracted features to 0.815 for 26 extracted features. There was also a marked decrease of more than 55 percent in the value of Δ, from 0.288 to 0.128.

The confusion matrices for the systems which extracted 26 features are presented in Fig. 5-5. The improvement in the performance of these systems is evident when the matrices in Fig. 5-5 are compared with those in Fig. 5-1. To summarize, the results indicate that the initially developed EEG spectral pattern recognition systems were significantly improved by expanding the extracted feature set to include to appropriate set of additional features listed in Table 5-2. The manner in which these additional features were selected suggests some promising areas for further work. For example, a larger number and a wider variety of possible

$$\begin{bmatrix} 53 & 0 & 0 & 3 & 0 \\ 6 & 27 & 0 & 4 & 0 \\ 0 & 6 & 2 & 4 & 0 \\ 5 & 18 & 3 & 72 & 27 \\ 0 & 0 & 0 & 8 & 42 \end{bmatrix} \qquad \begin{bmatrix} 49 & 1 & 0 & 1 & 2 \\ 6 & 23 & 0 & 2 & 1 \\ 2 & 2 & 2 & 2 & 0 \\ 2 & 2 & 1 & 111 & 9 \\ 0 & 0 & 0 & 3 & 47 \end{bmatrix}$$

Halothane Anesthesia

$$\begin{bmatrix} 42 & 2 & 5 & 2 & 0 \\ 6 & 15 & 20 & 6 & 0 \\ 2 & 4 & 62 & 17 & 1 \\ 1 & 5 & 56 & 90 & 0 \\ 0 & 2 & 3 & 0 & 0 \end{bmatrix} \qquad \begin{bmatrix} 39 & 2 & 1 & 2 & 0 \\ 3 & 19 & 8 & 4 & 1 \\ 2 & 15 & 47 & 16 & 1 \\ 5 & 6 & 15 & 121 & 1 \\ 0 & 1 & 2 & 1 & 0 \end{bmatrix}$$

Narcotic Anesthesia

$$\begin{bmatrix} 83 & 6 & 1 & 2 & 0 \\ 15 & 40 & 0 & 3 & 0 \\ 3 & 6 & 2 & 4 & 0 \\ 2 & 15 & 0 & 47 & 17 \\ 0 & 0 & 0 & 5 & 66 \end{bmatrix} \qquad \begin{bmatrix} 90 & 1 & 0 & 0 & 0 \\ 11 & 34 & 3 & 3 & 1 \\ 1 & 0 & 9 & 1 & 0 \\ 2 & 4 & 2 & 65 & 7 \\ 0 & 0 & 1 & 0 & 69 \end{bmatrix}$$

Enflurane Anesthesia

Fig. 5-5 Confusion Matrices for Systems Which Extracted 26 Spectral and Coherence Features. The matrices on the left resulted from performance estimation by the Π^* technique and those on the right resulted from performance estimation by the U^* technique.

additional features could be defined. Other feature selection criteria, such as those suggested in [110], might also be explored. In fact, the efficacy of choosing the complete extracted feature set on the basis of some feature selection criterion could be investigated. Alternatively, the effect of including more than 13 additional features in the extracted feature set might be considered. It should be recalled, however, that the maximum number of features that could actually be extracted from successive EEG pattern samples in an on-line monitoring environment must ultimately be determined by the nature of the pattern recognition system implementation.

5.3 Exploitation of Statistical Interdependencies Among Features

5.3.1 Method of Investigation

In the initial development of EEG pattern classifiers it was assumed that all of the features chosen for extraction were statistically independent. This assumption allowed the decision rule in (3.38) to be simplified and thereby reduced the amount of storage, computation time and training data required to implement various classifiers based on that decision rule. Such classifiers are optimal only if the assumption of statistically independent features is valid. Otherwise the decision rule in (3.38) will not be evaluated correctly because the estimates of $P(\underline{d}_u|C_j)$, i.e. the estimates of the class-conditional feature probabilities formed by these classifiers, will not be accurate. Therefore, if the features are not in fact statistically independent, the initially developed classifiers are suboptimal and classifiers with improved performance could theoretically be developed by exploiting statistical interdependencies among features.

To obtain some indication of the feasibility of improving

performance in this manner, it was decided to investigate the validity of the assumption of statistically independent features. Because no practical method of directly determining the degree of statistical interdependence among the features was available, the following property was employed to obtain an indirect indication: if two features (or two random variables) are statistically independent then they are uncorrelated, i.e. the lack of correlation is a necessary condition for statistical independence ([84], pp. 211-212). It should be noted that this is a necessary but not sufficient condition: two random variables can be uncorrelated but not statistically independent (for an example, see [138], p. 135). However, a non-zero correlation coefficient does indicate that the features in question are not statistically independent.

To be more specific, let $\{\sigma_i\}$, $1 \leq i \leq N$, represent the set of spectral features chosen for extraction; descriptions of the N=13 initially chosen spectral features can be found in Table 3-1. The correlation coefficient for any two features σ_i and σ_j is given by

$$\rho_{ij} = \frac{E\{(\sigma_i-\bar{\sigma}_i)(\sigma_j-\bar{\sigma}_j)\}}{\sqrt{E\{(\sigma_i-\bar{\sigma}_i)^2\}\cdot E\{(\sigma_j-\bar{\sigma}_j)^2\}}} \tag{5.14}$$

for $1 \leq i \leq N$ and $1 \leq j \leq N$. If the features are statistically independent then, by the definition of statistical independence, (5.14) becomes

$$\rho_{ij} = \frac{E\{(\sigma_i-\bar{\sigma}_i)\}\cdot E\{(\sigma_j-\bar{\sigma}_j)\}}{\sqrt{E\{(\sigma_i-\bar{\sigma}_i)^2\}\cdot E\{(\sigma_j-\bar{\sigma}_j)^2\}}} \tag{5.15}$$

$$= 0,$$

i.e. the features are also uncorrelated.

To estimate the magnitudes of any intercorrelations among the 13 initially chosen spectral features, a sample correlation matrix

$$R = (r_{ij}) \qquad \text{for} \begin{cases} i = 1,\ldots,N \\ j = 1,\ldots,N \end{cases} \tag{5.16}$$

was calculated for each of the three available sets of spectral feature vectors (described in section 3.2.3), which correspond to the three types of anesthesia under consideration. Let each spectral feature σ_i be regarded as a random variable which assumes the value d_{ki} in the kth feature vector, where $1 \leq k \leq S$. To calculate (5.16), the sample means

$$\bar{d}_i = \frac{1}{S} \sum_{k=1}^{S} d_{ki}, \qquad \text{for } i = 1,\ldots,N, \tag{5.17}$$

were first obtained. The sample covariance matrix

$$T = (t_{ij}) \tag{5.18}$$

was then formed by evaluating

$$t_{ij} = \frac{1}{S-1} \sum_{k=1}^{S} (d_{ki}-\bar{d}_i)(d_{kj}-\bar{d}_j) \tag{5.19}$$

$$\text{for} \begin{cases} i = 1,\ldots,N \\ j = 1,\ldots,N . \end{cases}$$

After (5.18) had been formed, the sample correlation matrix in (5.16) was computed:

$$r_{ij} = \frac{t_{ij}}{\sqrt{t_{ii}\, t_{jj}}} \qquad \text{for} \begin{cases} i = 1,\ldots,N \\ j = 1,\ldots,N . \end{cases} \tag{5.20}$$

Only half of the elements in each sample correlation matrix were computed because $r_{ij}=r_{ji}$, i.e. R is symmetric. Finally, the average correlation coefficient magnitude for each feature was evaluated:

$$a_i = \frac{1}{N-1} \sum_{j\neq 1}^{N} |r_{ij}| , \qquad \text{for } i = 1,\ldots,N. \tag{5.21}$$

The quantity defined in (5.21) indicates the average correlation of a specific feature with all other features in the set. Table 5-3 lists the values of a_i, for i=1,...,13, which were obtained for each of the three types of anesthesia under consideration.

Table 5-3 Average Correlation Coefficient Magnitudes

Spectral Feature Number	Type of Anesthesia		
	Halothane	Narcotic	Enflurane
1	.26	.10	.34
2	.59	.46	.52
3	.12	.20	.15
4	.41	.27	.32
5	.49	.28	.40
6	.51	.44	.48
7	.48	.43	.46
8	.60	.48	.57
9	.59	.45	.55
10	.29	.27	.30
11	.35	.23	.35
12	.31	.22	.24
13	.28	.23	.31

5.3.2 Results and Discussion

It is evident from the results in Table 5-3 that many spectral features are strongly correlated with other features in the set. Individual correlation coefficients for specific pairs of features can be seen in Fig. 5-6. The sample correlation matrices in Figs. 5-6(a) to 5-6(c) were obtained by evaluating (5.20) with the available sets of feature vectors from halothane anesthesia, narcotic anesthesia and enflurane anesthesia, respectively. Strong correlations between several pairs of features are evident in Fig. 5-6. For example, at least eight pairs of features in each sample correlation matrix have correlation coefficient magnitudes which are greater than 0.80. In view of such strong correlations, it

1.00	0.34	0.10	-0.27	-0.31	-0.32	-0.30	-0.38	-0.40	-0.18	-0.17	-0.23	-0.15
	1.00	-0.18	-0.78	-0.71	-0.70	-0.65	-0.91	-0.89	-0.60	-0.39	-0.59	-0.27
		1.00	-0.02	-0.11	-0.22	-0.22	-0.10	-0.08	0.00	-0.19	0.08	-0.15
			1.00	0.40	0.24	0.20	0.58	0.54	0.89	0.18	0.69	0.07
				1.00	0.70	0.64	0.76	0.76	0.14	0.60	0.27	0.52
					1.00	0.97	0.92	0.92	0.08	0.50	0.20	0.39
						1.00	0.86	0.86	0.07	0.48	0.16	0.38
							1.00	0.99	0.40	0.49	0.43	0.38
								1.00	0.34	0.50	0.40	0.39
									1.00	0.03	0.66	-0.08
										1.00	0.07	0.63
											1.00	0.00
												1.00

Fig. 5-6a Spectral Feature Correlation Matrix for Halothane Anesthesia Data

1.00	0.16	-0.07	-0.00	-0.06	-0.19	-0.17	-0.20	-0.20	0.04	0.04	0.07	-0.03
	1.00	0.09	-0.65	-0.46	-0.62	-0.61	-0.87	-0.79	-0.49	-0.18	-0.46	-0.17
		1.00	-0.26	-0.06	-0.24	-0.25	-0.25	-0.25	-0.24	-0.37	-0.02	-0.34
			1.00	0.02	-0.11	-0.08	0.28	0.15	0.89	0.07	0.70	0.02
				1.00	0.46	0.42	0.50	0.50	-0.16	0.37	-0.03	0.38
					1.00	0.97	0.91	0.94	-0.19	0.25	-0.13	0.29
						1.00	0.88	0.90	-0.16	0.26	-0.12	0.28
							1.00	0.98	0.14	0.28	0.15	0.29
								1.00	0.02	0.32	0.06	0.32
									1.00	-0.01	0.75	-0.07
										1.00	-0.05	0.51
											1.00	-0.06
												1.00

Fig. 5-6b Spectral Feature Correlation Matrix for Narcotic Anesthesia Data

1.00	0.48	0.08	-0.29	-0.32	-0.44	-0.43	-0.53	-0.57	-0.15	-0.34	-0.14	-0.33
	1.00	-0.11	-0.72	-0.52	-0.55	-0.55	-0.88	-0.82	-0.52	-0.34	-0.47	-0.28
		1.00	-0.24	0.04	-0.15	-0.17	-0.12	-0.11	-0.27	-0.28	-0.15	-0.15
			1.00	-0.00	-0.03	-0.01	0.46	0.34	0.89	0.16	0.66	0.04
				1.00	0.69	0.67	0.67	0.69	-0.23	0.49	-0.06	0.45
					1.00	0.99	0.86	0.90	-0.16	0.47	-0.02	0.45
						1.00	0.85	0.89	-0.14	0.45	-0.00	0.44
							1.00	0.98	0.26	0.49	0.30	0.42
								1.00	0.14	0.51	0.22	0.46
									1.00	0.01	0.69	-0.10
										1.00	0.08	0.53
											1.00	-0.04
												1.00

Fig. 5-6c Spectral Feature Correlation Matrix for Enflurane Anesthesia Data

is apparent that the assumption of statistically independent features is generally invalid. Therefore, the initially developed classifiers are suboptimal and the development of better classifiers is theoretically feasible.

However, as indicated previously in section 3.7.2, the exploitation of all possible statistical interdependencies would increase the amound of required memory, computation time and training data by a factor of

$$F = \frac{L^N}{L \cdot N}$$

$$= \frac{64^{13}}{64 \cdot 13} \qquad (5.22)$$

for a classifier with N=13 features and L=64 possible feature quantization levels. Even with a substantial reduction in both the number of statistical interdependencies taken into consideration and the number of possible feature quantization levels, the complexity of the classifiers

would be greatly increased. There would be a corresponding increase in the size of the EEG data base required to adequately train such classifiers. However, the relatively small EEG data base that was acquired in the course of this research was less than adequate for training classifiers which assumed statistically independent features. Clearly, a much larger EEG data base should be acquired before any attempts are made to exploit even the strongest of the observed feature intercorrelations.

5.4 "Nearest Subject" Scheme

5.4.1 Rationale

As stated in section 5.1, the magnitude of the difference between $\hat{P}_e[U^*]$ and $\hat{P}_e[\Pi^*]$ for a specific EEG pattern recognition system provides an indication of the effect of intersubject EEG variation on system performance. Based on this measure, it is evident from the results summarized in section 5.1 that the initially developed systems were significantly affected by intersubject EEG variation. Accordingly, considerable attention was directed toward the development of schemes for adapting the classifiers in these systems to the particular EEG characteristics of the subject to be monitored. However, the small size of the available EEG data base greatly limited the types of adaptive schemes which could be studied experimentally. One intuitively appealing adaptive scheme that was investigated was based on the following notion: a classifier trained only on data from a subject with EEG characteristics which are very similar to those of the test subject should perform more reliably than a classifier trained on all available data from the subject population. This scheme is analogous to schemes which have been considered previously in the context of multifont print recognition and multiauthor character recognition problems (e.g., see [139]). Among the

subjects represented in the set of available EEG training data, the one with EEG characteristics which are most similar to those of the test subject will be referred to as the "nearest subject". Assuming the availability of training data from a sufficiently large number of subjects, it was anticipated that the performance of a classifier trained only on data from the "nearest subject" could approach the U* estimate of classifier performance. This was anticipated because the U* technique (section 3.5.4) provides an estimate of the expected system performance when both training and testing data are from the same subject.

The feasibility of employing the "nearest subject" scheme for improving classifier performance was studied in two phases. The objective of the first phase was to determine the feasibility of training a classifier on data from a subject other than the one on which the classifier would be tested. Because this was established as feasible, the second phase of the study was undertaken. The objective was to determine whether the "nearest subject" could be identified on the basis of EEG pattern samples from class C_0 alone. To gain some insight into why the second phase of the study was undertaken, it should first be recalled from the description of the data acquisition procedure given in section 2.3.3 that EEG pattern samples from class C_0 could be obtained from a particular test subject before the induction of anesthesia. If the "nearest subject" could be identified on the basis of these pre-anesthesia EEG pattern samples, then the classifier could be trained with the appropriate subset of pattern samples at that time. Accordingly, the "nearest subject" scheme would have been shown to be a practicable means of improving classifier performance.

5.4.2 Feasibility

The following training/testing paradigm was used in the initial

phase of the feasibility study: an EEG classifier was first trained on the subset of available data from subject j, $1 \leq j \leq J$, and was then tested on the subset of available data from subject i, $1 \leq i \leq J$. Using this paradigm a J x J matrix was calculated for each of the three types of anesthesia; each element contained the percentage of EEG pattern samples from subject i which had been correctly classified by a classifier trained only on data from subject j. Some difficulties in the computation of these matrices arose because the subsets of available EEG pattern samples from individual subjects were frequently too small and because all of the classes which were represented in the test data were not necessarily represented in the training data. The latter problem was resolved as described in section 3.5.4.

The results of the first phase of the feasibility study were encouraging. For most test subjects, one or more appropriate training subjects were identified; when the classifier had been trained on the available data from any one of these subjects, its performance on data from the test subject was superior to the Π^* estimate (section 3.5.3) of the expected classifier performance on data from a subject population. Consequently, the second phase of the feasibility study was undertaken to ascertain whether certain techniques could be employed to identify the most appropriate training subject, i.e. to identify the "nearest subject" to the test subject, on the basis of the available C_o pattern samples. Consideration was given to the possibility of matching subjects by evaluating the relative dominance of alpha-band activity [82] or by using the mean C_o spectra as templates in a clustering algorithm (e.g. [132]). Euclidean distances, likelihoods and correlations (e.g. [24]) between C_o spectral feature vectors were also considered. However the initial results were inconclusive: the "nearest subjects" which were identified by these techniques did not consistently match the best

training subjects which had been identified in the first phase of the study.

Thus the objective of the second phase might be infeasible, i.e. it might not be possible to identify the "nearest subject" on the basis of pre-anesthesia data from C_o only. Alternatively, the initial attempts to do so may have been hampered by the inadequacies of the available EEG data base. It has already been noted that many of the subsets of pattern samples corresponding to individual subjects were very small and/or did not contain samples from all possible classes. In addition, some subsets did not contain any artifact-free, pre-anesthesia EEG pattern samples. Finally, the relatively small number of subjects represented in the available data base may have prevented the accurate identification of the "nearest subject".

5.4.3 Discussion

The results of the initial phase of the feasibility study indicated that it was possible to train a classifier on data from one subject so that it would perform reliably on test data from another subject. However the results of the second phase of the study were equivocal: the practicability of using a small number of EEG pattern samples from class C_o to identify the most appropriate training subject, i.e. the "nearest subject", was not established. The resolution of this issue by the techniques mentioned in section 5.4.2 would be greatly facilitated if the available EEG data base could be expanded to include a larger number of subjects. The subset of data corresponding to each subject should also be expanded to include a larger number of artifact-free, pre-anesthesia EEG pattern samples, as well as an adequate number of pattern samples from all possible classes or levels of anesthesia.

It should perhaps be recalled that the "nearest subject" scheme

for improving performance was investigated because it was thought that such a scheme could be readily employed in some practical monitoring situations. Pre-anesthesia samples of baseline EEG activity could be obtained from a particular test subject and used to identify the "nearest subject" represented in the available data base. An EEG pattern recognition system could then be trained with the available subset of pattern samples corresponding to this subject. In some anesthesia monitoring situations the identification of the "nearest subject" might not be necessary, i.e. it might be possible to train the system with EEG pattern samples from the same subject. For example, sample EEG data which had been collected from a subject during one operation might be used to train an EEG pattern recognition system for monitoring the same subject during subsequent operations. Another example involves the development of a reliable system for estimating the level of anesthesia during open-heart surgery. In this situation, sample EEG data could be collected during the initial phase of the operation and could be used to train an EEG pattern recognition system; the trained system could then be employed during the critical cardiopulmonary bypass phase of the operation, when most clinical non-EEG signs of anesthetic depth are unavailable.

CHAPTER VI

CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

6.1 Conclusions

6.1.1 Summary

The work described in this thesis constitutes the first comprehensive investigation into the question of whether or not the level of anesthesia can be reliably estimated during surgery by means of an automatic EEG pattern recognition system. A valid methodology for conducting the research was first established and a digital EEG data base was prepared. Automatic pattern recognition techniques, in conjunction with heuristic techniques of clinical EEG analysis, were employed in the development of spectral and time domain EEG pattern recognition systems for three different types of general anesthesia. An evaluation of the performance of the initially developed systems clearly demonstrated the validity of the EEG pattern recognition approach, but also indicated that such systems are not sufficiently reliable for immediate and general clinical application. Accordingly, theoretical techniques were developed to model some relevant statistical properties of spontaneous EEG activity, with a view to improving the performance of the initially developed systems. Several factors which could adversely affect the reliable performance of EEG pattern recognition systems in general, and the initially developed systems in particular, were identified and discussed. Various schemes for improving the performance of the initially developed systems were suggested and an evaluation of the practicability of each was presented.

6.1.2 Major Original Contributions

The following items constitute the major original contributions of this work:

1) the establishment of a valid methodology for conducting research

into the question of whether or not the level of anesthesia can be estimated by EEG pattern recognition;

2) the first comprehensive application of automatic pattern recognition techniques to this problem area;[77]

3) the formulation of nonparametric techniques for effectively estimating the performance of EEG pattern recognition systems on future EEG data;

4) the demonstration that, with specified experimental controls, it is feasible to estimate the level of anesthesia by means of automatic EEG pattern recognition;

5) the development of theoretical techniques for modelling the degree of wide-sense stationarity and Gaussianity of spontaneous EEG activity;

6) the establishment of the first model of the degree of wide-sense stationarity and Gaussianity of spontaneous EEG activity; and

7) the suggestion and evaluation of a number of promising schemes for improving the performance of the initially developed EEG pattern recognition systems.

These points are discussed in more detail in the following sections.

6.1.3 Establishment of a Valid Research Methodology

It was largely because of methodological problems that the results of many previous attempts to estimate anesthesia levels by means of visual EEG assessment were confusing and contradictory. Therefore, a considerable effort was made throughout the present research to establish a valid methodology, by identifying and controlling as many extraneous variables as possible and by ensuring that the work would be relevant to current anesthetic practice. The methodology that was established was crucial to

the success of the research reported here and should also facilitate future research in the same area.

6.1.4 Introduction of Automatic Pattern Recognition Techniques

The present work does not constitute the first attempt to employ automatic techniques in the analysis of EEG activity during surgical anesthesia. However, previous work in this area has primarily been limited to considering various schemes for EEG data compression and parameter identification (e.g., see [27-32]). The work reported here is apparently the first attempt to develop an automatic EEG pattern recognition system capable of reliably estimating clinically relevant anesthesia levels. As such, it constitutes the first comprehensive application of automatic pattern recognition techniques, including preprocessing, feature extraction, feature selection, pattern classification and performance evaluation techniques, to this problem area.

6.1.5 Formulation of Performance Estimation Techniques

The two nonparametric performance estimation techniques formulated in this work are particularly suitable for estimating the performance of EEG pattern recognition systems. In most potential applications, such as the one under consideration, the set of available EEG pattern samples is relatively small. By making efficient use of the pattern samples which are available, the two techniques estimate the performance of a given system on future EEG data from only one subject, as well as its performance on future EEG data from a subject population. More generally, because the two performance estimation techniques are nonparametric, they can be applied to a wide variety of EEG pattern recognition systems to produce meaningful and comparable performance estimates. This is a potentially significant advance because, as noted elsewhere [22,39], meaningful

performance evaluations are conspicuously absent from much of the current literature on automatic EEG pattern recognition.

6.1.6 Demonstration of Feasibility

The demonstration that it is feasible to estimate the level of anesthesia by means of automatic EEG pattern recognition is the most important single contribution of this work. It should be emphasized that feasibility in this instance does not imply immediate practicability, i.e. the initially developed EEG pattern recognition systems are not sufficiently reliable for immediate and general clinical application. It should also be noted that the demonstration of feasibility was accomplished by the implementation of a wide range of experimental controls; the effect of modifying or relaxing these controls was not investigated.

6.1.7 Development of Theoretical Modelling Techniques

Theoretical techniques have been developed for modelling the degree of wide-sense stationarity and Gaussianity of spontaneous EEG activity. This is significant because almost all methods of quantitative EEG analysis are based on certain implicit assumptions regarding the statistical characteristics of the underlying random process, particularly with respect to the extent of stationarity and Gaussianity of the process. Therefore the efficacy of alternate methods of analysis depends upon the degree to which such assumptions are justified by the characteristics of the particular ensembles of EEG segments being analysed.

6.1.8 Establishment of a Statistical Model of EEG Activity

Relatively few investigations of the statistical properties of specific EEG ensembles have been reported in the literature. In this work, a model of the degree of wide-sense stationarity and Gaussianity of spontaneous EEG activity is established. The model resolves most of the major

inconsistencies in the literature with regard to the estimated degree of Gaussianity of spontaneous EEG activity. More significantly, the model provides the first comprehensive estimates of the extent to which ensembles of spontaneous EEG segments exhibit the properties of wide-sense stationarity and Gaussianity.

6.1.9 Evaluation of Performance Improvement Schemes

An evaluation of several promising schemes for improving the performance of the initially developed EEG pattern recognition systems is presented. For example, it is shown that the performance of the initially developed spectral pattern recognition systems can be significantly improved by doubling the number of extracted features. Some improvements in the initial pattern classification algorithm are also suggested, but only preliminary feasibility evaluations are possible because of the relatively small size of the available EEG data base. Finally, it appears that some schemes which were suggested for improving performance by reducing the effect of intersubject EEG variation could be of immediate practical significance.

6.2 Suggestions for Future Research

6.2.1 Performance Improvement Schemes

Many of the suggested schemes for improving the performance of the initially developed EEG pattern recognition systems should be explored further. A few of these schemes can be readily investigated but the exploration of others, particularly some of the most promising performance improvement schemes considered in Chapter V, cannot be undertaken at present because of the inadequacy of the available EEG data base.

The inadequacy of the available EEG data base also prevented the consideration of some appealing schemes for adapting the pattern classifiers to the particular EEG characteristics of individual test subjects.

Thus, a future expansion of the EEG data base is necessary if the efficacy of some promising performance improvement schemes is to be investigated. In any future expansion of the data base for this purpose, an effort should be made to collect as many EEG pattern samples as possible, corresponding to all levels of anesthesia, from each additional subject. Also, to facilitate future investigations into the feasibility of classifier adaptation and "nearest subject" identification (see Chapter V), the subset of data corresponding to each subject should contain a large number of artifact-free, pre-anesthesia EEG pattern samples.

Before the acquisition of more sample EEG data, an inter-rater reliability study might be conducted to estimate the rate of error in clinical assessments of the level of anesthesia on the basis of the criteria employed in this work. If warranted, anesthesiologists might then be asked to suggest refinements in the criteria and improvements in the clinical assessment procedure.

6.2.2 Experimental Controls

The effect of modifying or relaxing the experimental controls which were implemented in the work reported here should be explored. Hopefully, such research would identify the major clinical sources of variability which could adversely affect the reliable performance of the EEG pattern recognition systems developed in this work. This would provide a clear indication of the variables that must be adequately controlled if such systems are to be employed in a clinical environment. In addition, research in this area might eventually result in the development of adaptive systems which could take such variables into consideration, thereby improving their reliability and extending their range of applicability.

6.2.3 Time Domain EEG Pattern Recognition Systems

The feasibility of developing more reliable time domain EEG

pattern recognition systems should be studied. On the basis of the initial results reported in this work, the best time domain systems developed for halothane anesthesia and narcotic anesthesia were slightly less reliable than the corresponding spectral systems, but for enflurane anesthesia the best time domain system was more reliable than the best spectral system. From a practical viewpoint, implementation of the time domain systems considered here would be simpler and less expensive than implementation of the corresponding spectral systems. This is primarily because many of the time domain features could be more easily extracted, e.g. an implementation of the FFT algorithm would not be necessary. Thus, both experimental results and practical considerations provide motivation for attempting to increase the reliability of the initially developed time domain systems to a clinically acceptable level. In this regard, most of the performance improvement schemes which were suggested in this work and applied to spectral systems could also be applied to time domain systems.

6.2.4 The Reliability of Visual EEG Assessment

In attempting to view the performance of automatic EEG pattern recognition systems in perspective, it would be desirable to be able to compare their reliability to the expected reliability of experienced clinical EEG raters performing the same task. Unfortunately, almost no data is available concerning the expected reliability of visual EEG assessment. The few papers which have been published in this area indicate that the reliability of visual EEG assessment, even among experienced clinical EEG raters, may be surprisingly low (e.g. see [18]). Accordingly, a future interdisciplinary study, perhaps employing the EEG data base prepared in this work, seems to be warranted in order to obtain a quantitative estimate of the expected inter-rater reliability of visual EEG

assessment.

6.2.5 Modelling

The estimated statistical characteristics of spontaneous EEG activity should be exploited in a future attempt to develop more reliable EEG pattern recognition systems for monitoring the level of anesthesia. The model of spontaneous EEG activity established in this work should be of considerable value in a future reconsideration of the often arbitrary decisions which were made in the initial development of the EEG pattern recognition systems, e.g. decisions regarding the choice of analytic techniques, the duration of EEG segments to be analysed and the rate at which the estimated level of anesthesia should be updated.

The modelling techniques developed in this work could also be applied to many other ensembles of EEG activity corresponding to other states of consciousness. For example, it was noted previously that the feasibility of employing EEG pattern recognition systems to monitor the status of subjects during sleep, intensive care, coma and possible cerebral death is currently being investigated by others. In each instance, the statistical characteristics of the particular ensembles of EEG activity being analysed should be an important consideration in the development of the most appropriate monitoring system.

6.2.6 Identification of Artifact

Another area deserving further exploration, but beyond the scope of the present investigation, concerns the identification of EEG artifact. It should be recalled that artifact was defined as that component of the EEG which does not originate in the brain. Most of the visually recognizable artifact encountered in the work reported here may be attributed to interference from electrosurgical units in the operating rooms, poor

electrode contacts, eyeblinks, electrocardiographic activity, movement and muscle activity. In this work, digitized EEG segments were visually screened to eliminate those segments which contained excessive artifact. However, an EEG pattern recognition system suitable for monitoring the level of anesthesia should be capable of automatically identifying EEG pattern samples which contain excessive artifact. Therefore, the development of algorithms for the automatic identification of EEG artifact should be undertaken.

APPENDIX A

LEVEL OF ANESTHESIA EVALUATION FORM

Date: _____ Page____of_____

Patient: _____ Age:_____ Weight: _____ Sex: _____

Surgical Procedure: _____ Anesthetist: _____

Premedication: _____ Anesthetic Agents: _____

Analog Tape Number: _____ Footage: Start _____ End _____

EEG Machine Gain: _____ LP Filter Frequency: _____ Time Constant: ____

Coding Pulse	Level of Anesthesia	pCO_2 (mm Hg)	Time	Comments
1.				
2.				
3.				
4.				
5.				
6.				
7.				
8.				
9.				
10.				
11.				
12.				
13.				
14.				
15.				
16.				
17.				
18.				
19.				
20.				

APPENDIX B

DESCRIPTION OF EEG DATA BASE

Information concerning the sample EEG data base for each of the three types of anesthesia is given in Table B-1. All of the digital tapes listed in Table B-1 are 9-track, IBM-compatible tapes with a density of 1600 BPI and a block size of 4096 bytes. The tapes are unlabelled. Documentation which describes how to mount and use such tapes under the Michigan Terminal System (MTS) can be obtained from the U.B.C. Computing Centre.

Table B-1 EEG Data Base

Information	Type of Anesthesia		
	Halothane	Narcotic	Enflurane
Number of available EEG pattern samples	280	341	317
Rack number of digital tape containing EEG pattern samples	RA0562	RA0558	RA0561
Rack number of duplicate tape	RC0490	RA0559	RB0120
Name of disk file containing labels for EEG pattern samples	HS.I	AS.I	ES.I

Each EEG pattern sample, i.e. the digital representation of each four-channel EEG segment of 64s duration, is stored in a separate file on the appropriate tape. Each file on the tape therefore contains a total of 32768 sample values, the result of sampling four EEG channels (F3-C3, C3-O1, F4-C4 and C4-O2) at 128 Hz/channel for 64s. For programming ease, each sample value is stored in two bytes although the maximum resolution is limited to 10 bits. Each successive set of 8 bytes in a file therefore contains one sample value from each channel: F3-C3, C3-O1, F4-C4 and C4-O2, in that order. The 32768 samples in each file on the tape are grouped into 16 blocks, with 2048 samples (4096 bytes) per block.

The disk files listed in Table B-1 contain the following information about each EEG pattern sample: the sample identification number, the level of anesthesia and the subject identification number. This information is stored in integer form, with one disk file line per EEG sample, in the following FORTRAN format: (I5, 5X, 2I5). The "sample identification number" represents the number of the file on the appropriate tape which contains the sample EEG. The "level of anesthesia" represents the clinically estimated anesthesia level associated with the sample EEG. The "subject identification number" refers to the individual patient from which the sample EEG was obtained.

The following FORTRAN subroutine can be used to (i) read a sample identification number, (ii) locate the appropriate tape file, (iii) read the 16 blocks of sample data from the file, (iv) sort the

data by channels, and (v) store the sorted data in an array:

```
      SUBROUTINE INPUT(NFLAG)
C
C     NFLAG=0 INITIALLY;NFLAG=1 AT TAPE END
C     INDEXF CONTAINS CURRENT FILE NO
C     LUNIT INDICATES TAPE LOGICAL UNIT NO
C
      REAL DATIN(4,8192)
      COMMON /DATIN/ DATIN
      INTEGER*2 BLOCK(2048), LEN1
      INTEGER INDEXF /0/
      LUNIT=1
      NSKIP=0
C
C    READ THE FILE NO
      READ(5,20,END=10)NFILE
 20   FORMAT(I5)
      WRITE(6,12)NFILE
 12   FORMAT(' ****',I5)
C
C     PREPARE TO SKIP TO THE APPROPRIATE FILE
      ITEMP=NFILE-INDEXF-1
      CALL SKIP(ITEMP,NSKIP,LUNIT)
      INDEXF=NFILE-1
C
C     READ FILE DATA AND STORE IN ARRAY
      DO 14 IBLK=1,16
      INDX=(IBLK-1)*512
      CALL READ(BLOCK,LEN1,0,LINE1,LUNIT,&10)
      DO 14 ICH=1,4
      DO 14 ISAM=1,2048,4
      IR=INDX+1+(ISAM-1)/4
      IRR=(ICH-1)+ISAM
 14   DATIN(ICH,IR)=BLOCK(IRR)
C
      RETURN
 10   NFLAG=1
      RETURN
      END
```

APPENDIX C

COMPUTATION OF EEG SPECTRA

```
C-------------------------------------------------------------------------      1.000
C  APPENDIX C  COMPUTATION OF EEG SPECTRA                                      2.000
C                                                                             3.000
C  THIS PROGRAM COMPUTES THE POWER SPECTRA AND COHERENCE SPECTRUM FOR          4.000
C  TWO SELECTED CHANNELS OF EEG DATA.                                         5.000
C  INPUT:                                                                     6.000
C          *LUNIT 1: INPUT DATA TAPE (SEE APPENDIX B)                         7.000
C          *LUNIT 5: FILE CONTAINING DATA LABELS                              8.000
C  OUTPUT:                                                                    9.000
C          *LUNIT  8: POWER SPECTRUM FOR CHANNEL "A"                          10.000
C          *LUNIT  9: POWER SPECTRUM FOR CHANNEL "B"                          11.000
C          *LUNIT 10: COHERENCE SPECTRUM                                      12.000
C  LAST UPDATE:                                                               13.000
C          JANUARY 6 1975                                                     14.000
C-------------------------------------------------------------------------      15.000
C                                                                             16.000
0001          INTEGER NCHANA/1/,NCHANE/2/                                     17.000
0002          COMPLEX TRAN(2049),TR(2049)                                     18.000
0003          REAL DATA(4096),DATB(4096)                                      19.000
0004          COMMON / TRAN / TRAN,TR                                         20.000
0005          EQUIVALENCE (TRAN,DATA)                                         21.000
0006          EQUIVALENCE (TR,DATB)                                           22.000
0007          REAL DATIN(4,8192)                                              23.000
0008          COMMON / DATIN / DATIN,INDEXF,NFILE                             24.000
C                                                                             25.000
0009          NFLAG=0                                                         26.000
0010          INDEXF=0                                                        27.000
0011          NSAMP=8192                                                      28.000
0012          N=4096                                                          29.000
0013          SRATE=64.                                                       30.000
C                                                                             31.000
C     GET ALL FOUR EEG CHANS FROM A 64 SEC SA AND PUT IN DATIN                32.000
0014        3 CALL INPUT(NFLAG)                                               33.000
0015          IF(NFLAG.EQ.1)GO TO 4                                           34.000
C                                                                             35.000
C    COPY TWO CHANS AT 64 SA/SEC (NOT THE ORIG 128/SEC)                       36.000
0016          DO 1 J=1,NSAMP,2                                                37.000
0017          DATA((J-1)/2+1)=DATIN(NCHANA,J)                                 38.000
0018          DATB((J-1)/2+1)=DATIN(NCHANE,J)                                 39.000
0019        1 CONTINUE                                                        40.000
C                                                                             41.000
C    CALCULATE POWER SPECTRA AND COHERENCE (AND OUTPUT SAME)                  42.000
0020          CALL COHER(N,SRATE,NFILE)                                       43.000
0021          GO TO 3                                                         44.000
C                                                                             45.000
0022        4 STOP                                                            46.000
0023          END                                                             47.000
0001          SUBROUTINE INPUT(NFLAG)                                         48.000
C                                                                             49.000
0002          REAL DATIN(4,8192)                                              50.000
0003          COMMON /DATIN/ DATIN,INDEXF,NFILE                               51.000
0004          INTEGER*2 BLOCK(2048),LEN1                                      52.000
0005          LUNIT=1                                                         53.000
0006          NSKIP=0                                                         54.000
C                                                                             55.000
C     READ THE FILE NO                                                        56.000
0007          READ(5,20,END=10)NFILE                                          57.000
0008       20 FORMAT(I5)                                                      58.000
0009          WRITE(6,12)NFILE                                                59.000
0010       12 FORMAT(' ****',I5)                                              60.000
C                                                                             61.000
C     PREPARE TO SKIP TO THE APPROPRIATE FILE                                 62.000
0011          ITEMP=NFILE-INDEXF-1                                            63.000
0012          CALL SKIP(ITEMP,NSKIP,LUNIT)                                    64.000
0013          INDEXF=NFILE-1                                                  65.000
C                                                                             66.000
C                                                                             67.000
0014          DO 14 IBLK=1,16                                                 68.000
```

```
0015              INDX=(IBLK-1)*512                                                    69.000
0016              CALL READ(BLOCK,LEN1,0,LINE1,LUNIT,&10)                              70.000
0017              DO 14 ICH=1,4                                                        71.000
0018              DO 14 ISAM=1,2048,4                                                  72.000
0019              IR=INDX+1+(ISAM-1)/4                                                 73.000
0020              IRR=(ICH-1)*ISAM                                                     74.000
0021        14    DATIN(ICH,IR)=BLOCK(IRR)                                             75.000
                  C                                                                    76.000
0022              RETURN                                                               77.000
0023        10    NFLAG=1                                                              78.000
0024              RETURN                                                               79.000
0025              END                                                                  80.000
0001              SUBROUTINE COHER(N,SRATE,NFILE)                                      81.000
                  C     COMPUTES THE SPECTRA AND COHERENCE VIA METHOD OF DUNNMUTH ET AL, 82.000
                  C     IEEE TRANS AUDIO DEC '70.                                    83.000
                  C                                                                  84.000
0002              COMPLEX TRAN(2049),TR(2049)                                          85.000
0003              REAL DATA(4096),DATB(4096)                                           86.000
0004              COMMON /TRAN/ TRAN,TR                                                87.000
0005              EQUIVALENCE (TRAN,DATA)                                              88.000
0006              EQUIVALENCE (TR,DATB)                                                89.000
0007              REAL SP(256),SM4(2049),SM2(4096),SMOOTH(4096),SP2(256),SP3(256)      90.000
0008              COMPLEX XSPEC(2049),SM3(2049),SUM3                                   91.000
0009              INTEGER NN(1)                                                        92.000
                  C                                                                    93.000
                  C     GET FOURIER TRANSFORM VIA FFT ------------------------------   94.000
0010              NN(1)=N                                                              95.000
0011              ISIGN=-1                                                             96.000
0012              CALL FOUR2(DATA,NN,1,ISIGN,0)                                        97.000
0013              CALL FOUR2(DATB,NN,1,ISIGN,0)                                        98.000
                  C                                                                    99.000
                  C     HP FILTRING ------------------------------------------------ 100.000
0014              L1=32                                                                101.000
0015              L2=5                                                                 102.000
0016              DO 3 J=1,L1                                                          103.000
0017              TR(J)=(0.,0.)                                                        104.000
0018        3     TRAN(J)=(0.,0.)                                                      105.000
0019              DO 4 J=1,L2                                                          106.000
0020              TR(L1+J)=TR(L1+J)*(FLOAT(J)/FLOAT(L2))                               107.000
0021        4     TRAN(L1+J)=TRAN(L1+J)*(FLOAT(J)/FLOAT(L2))                           108.000
                  C                                                                    109.000
                  C     OBTAIN RAW SPECTRAL ESTIMATES (INCL CROSS-SPECTRA) ---------- 110.000
0022              FACTOR=1./(SRATE*FLOAT(N))                                           111.000
0023              MID=N/2+1                                                            112.000
0024              DO 99 I=1,MID                                                        113.000
0025              T=CABS(TRAN(I))                                                      114.000
0026              TT=CABS(TR(I))                                                       115.000
0027              XSPEC(I)=(CONJG(TR(I))*TRAN(I))                                      116.000
0028              DATA(I)=T*T*FACTOR                                                   117.000
0029              DATB(I)=TT*TT*FACTOR                                                 118.000
0030              XSPEC(I)=XSPEC(I)*FACTOR                                             119.000
0031        99    CONTINUE                                                             120.000
                  C                                                                    121.000
                  C     SMOOTHED SPECTRAL ESTIMATES OBTAINED VIA SQUARE WINDOW (2W+1)=15 122.000
                  C     THE FIRST AND LAST 8 POINTS ARE NOT SMOOTHED                 123.000
0032              DO 52 I=1,8                                                          124.000
0033              SM2(I)=DATB(I)                                                       125.000
0034              SM3(I)=XSPEC(I)                                                      126.000
0035        52    SMOOTH(I)=DATA(I)                                                    127.000
0036              DO 11 I=1,7                                                          128.000
0037              SM2(MID-7+I)=DATB(MID-7+I)                                           129.000
0038              SM3(MID-7+I)=XSPEC(MID-7+I)                                          130.000
0039        11    SMOOTH(MID-7+I)=DATA(MID-7+I)                                        131.000
                  C                                                                  132.000
0040              DO 50 I=9,2042                                                       133.000
0041              SUM=0.                                                               134.000
0042              SUM2=0.                                                              135.000
0043              SUM3=(0.,0.)                                                         136.000
0044              DO 51 J=1,15                                                         137.000
0045              SUM2=SUM2+DATB((I-1)+J-7)                                            138.000
0046              SUM3=SUM3+XSPEC((I-1)+J-7)                                           139.000
0047        51    SUM=SUM+DATA((I-1)+J-7)                                              140.000
0048              SMOOTH(I)=SUM/15.                                                    141.000
0049              SM2(I)=SUM2/15.                                                      142.000
0050              SM3(I)=SUM3/15.                                                      143.000
0051        50    CONTINUE                                                             144.000
                  C                                                                  145.000
                  C   COHERENCE CALCULATION ---------------------------------------- 146.000
0052              DO 1012 I=1,32                                                       147.000
0053        1012  SM4(I)=0.                                                            148.000
0054              DO 1011 I=33,MID                                                     149.000
```

```
0055                TTT=CABS(SM3(I))                                          150.000
0056                IF(SMCOTH(I).EQ.0.)SMCOTH(I)=.000001                      151.000
0057                IF(SM2(I).EQ.0.)SM2(I)=.000001                            152.000
0058          1011  SM4(I)=SQRT((TTT*TTT)/(SMCOTH(I)*SM2(I)))                153.000
                C                                                             154.000
                C     MEAN ENERGIES AND OTHER OF 8 POINT BANDS M1=M(12345678) --------  155.000
                C     TOTAL EN=POWER*(1/64)  MEAN POWER=EN/(1/8)              156.000
                C     THUS MEAN POWER = POWER*(1/64)*8 = POWER/8              157.000
0059                DENOM=8.                                                  158.000
0060                DO 100 I=1,256                                            159.000
0061                SUM2=0.                                                   160.000
0062                SUM4=0.                                                   161.000
0063                SUM=0.                                                    162.000
0064                DO 101 J=1,8                                              163.000
0065                SUM2=SUM2+SM2((I-1)*8+J)                                  164.000
0066                SUM4=SUM4+SM4((I-1)*8+J)                                  165.000
0067          101   SUM=SUM+SMOOTH((I-1)*8+J)                                 166.000
0068                SF(I)=SUM/DENOM                                           167.000
0069                SF2(I)=SUM2/DENOM                                         168.000
0070                SF3(I)=SUM4/DENOM                                         169.000
0071          100   CONTINUE                                                  170.000
                C                                                             171.000
                C     OUTPUT PHASE BEGINS ---------------------------------------  172.000
0072                WRITE(8,58)NFILE                                          173.000
0073                WRITE(10,58)NFILE                                         174.000
0074           58   FORMAT('     FREQ',' NFILE=',I5,' NCHAN=A')               175.000
0075                DO 60 I=1,255,8                                           176.000
0076                WRITE(8,63)(SF(I+J-1),J=1,8)                              177.000
0077           60   WRITE(10,65)(SF3(I+J-1),J=1,8)                            178.000
0078           65   FORMAT(8F9.6)                                             179.000
0079           63   FORMAT(' ',8F9.2)                                         180.000
0080                WRITE(9,59)NFILE                                          181.000
0081           59   FORMAT('     FREQ',' NFILE=',I5,' NCHAN=B')               182.000
0082                DO 61 I=1,255,8                                           183.000
0083           61   WRITE(9,63)(SF2(I+J-1),J=1,8)                             184.000
                C                                                             185.000
                C    OUTPUT PHASE ENDED -----------------------------------------  186.000
0084                RETURN                                                    187.000
0085                END                                                       188.000
```

APPENDIX D

SPECTRAL FEATURE EXTRACTION PROGRAM

```
C                                                                       1.000
C   APPENDIX D  SPECTRAL FEATURE EXTRACTION PROGRAM                     2.000
C                                                                       3.000
C   THIS PROGRAM CALCULATES ONE 44-ELEMENT AUTOSPECTRAL FEATURE VECTO   4.000
C   CORRESPONDING TO EACH 64 SEC EEG PATTERN SAMPLE.                    5.000
C   INPUT:                                                              6.000
C           *LUNIT 1: SPECTRAL DATA FROM CHAN 1 (F3:C3)                 7.000
C           *LUNIT 2: SPECTRAL DATA FROM CHAN 2 (C3:O1)                 8.000
C           *LUNIT 3: SPECTRAL DATA FROM CHAN 3 (F4:C4)                 9.000
C           *LUNIT 4: SPECTRAL DATA FROM CHAN 4 (C4:O2)                10.000
C           *LUNIT 5: INDEXING DATA FOR EACH EEG SEGMENT (F/LEV/PTNT)  11.000
C  OUTPUT:                                                             12.000
C           *LUNIT 11: FEATURE VECTORS                                 13.000
C           *LUNIT  6: ERROR MSGS                                      14.000
C  11 SPECTRAL FEATURE ELEMENTS CALCULATED FOR EACH EEG CHANNEL        15.000
C  LIMITATIONS:                                                        16.000
C           *NO MORE THAN 500 PATTERN SAMPLES                          17.000
C           *ONLY DATA FROM 64 SEC SPECTRAL CALCULATIONS               18.000
C  NOTES:                                                              19.000
C           1. DATA WAS PREPARED IN FMT SPECIFIED IN "APPENDIX C"      20.000
C           2. OUTPUT FILE (LUNIT 11) MUST BE SEQUENTIAL               21.000
C           3. SPECTRUM IS ASSUMED TO EXIST FROM 0-32 HZ, WITH         22.000
C              8 SAMPLES/HZ                                            23.000
C  LAST UPDATE:                                                        24.000
C           NOV 23 1974                                                25.000
C                                                                      26.000
C-----------------------------------------------------------------------27.000
      REAL DATA(256),FEATUR(80)                                        28.000
      COMMON /COM/ DATA,FEATUR                                         29.000
C                                                                      30.000
      DO 6 INDX=1,500                                                  31.000
      DO 99 IV=1,44                                                    32.000
 99   FEATUR(IV)=0.                                                    33.000
      DO 1 LUNIT=1,4                                                   34.000
C                                                                      35.000
C  THE SUBSET OF SPECTRAL FEATURE ELEMENTS ARE CALCULATED:             36.000
      READ(LUNIT,5,END=3)                                              37.000
 5    FORMAT()                                                         38.000
      DO 4 J=1,255,8                                                   39.000
 4    READ(LUNIT,2)(DATA((J+K-1)),K=1,8)                               40.000
 2    FORMAT(1X,8F9.2)                                                 41.000
      CALL SPECTF(LUNIT)                                               42.000
 1    CONTINUE                                                         43.000
C                                                                      44.000
C  OUTPUT THE COMPLETED FEATURE VECTOR AND INDEXING DATA:              45.000
      READ(5,11)FILE,LEV,IPTNT                                         46.000
      IFILE=FILE+0.1                                                   47.000
 11   FORMAT(5X,F5.0,2I5)                                              48.000
 6    WRITE(11,12)(FEATUR(JY),JY=1,44),IFILE,LEV,IPTNT,INDX            49.000
 12   FORMAT(44F14.6,4I4)                                              50.000
C                                                                      51.000
      WRITE(6,16)                                                      52.000
 16   FORMAT(///' **** ERROR: TOO MANY PATTERN SAMPLES**'///)          53.000
 3    INDX=INDX-1                                                      54.000
      WRITE(6,15)INDX                                                  55.000
 15   FORMAT(I5,' FEATURE VECTORS HAVE BEEN CALCULATED'//)             56.000
      STOP                                                             57.000
      END                                                              58.000
      SUBROUTINE SPECTF(LUNIT)                                         59.000
      REAL DATA(256),FEATUR(44)                                        60.000
      COMMON /COM/ DATA,FEATUR                                         61.000
      M=(LUNIT-1)*11                                                   62.000
C                                                                      63.000
C     ENERGIES: ------------------------------------------             64.000
      DO 1 I=2,256                                                     65.000
 1    FEATUR((M+1))=FEATUR((M+1))+DATA(I)                              66.000
C     DELTA: --------------------------                                67.000
C     0.125-4.00 HZ                                                    68.000
```

```
0007                DO 5 K=2,32                                                   69.000
0008          5     FEATUR((M+2))=FEATUR((M+2))+DATA(K)                           70.000
              C     THETA: ------------------------                               71.000
              C     4.00-8.00 HZ                                                  72.000
0009                DO  6 K=33,64                                                 73.000
0010          6     FEATUR((M+3))=FEATUR((M+3))+DATA(K)                           74.000
              C     ALPHA: ------------------------                               75.000
              C     8.00-13.00 HZ                                                 76.000
0011                DO 7 K=65,104                                                 77.000
0012          7     FEATUR((M+4))=FEATUR((M+4))+DATA(K)                           78.000
              C     SIGMA: ------------------------                               79.000
              C     13-15 HZ                                                      80.000
0013                DO 8 K=105,120                                                81.000
0014          8     FEATUR((M+5))=FEATUR((M+5))+DATA(K)                           82.000
              C     BETA: -------------------------                               83.000
              C     15.00-31.875 HZ                                               84.000
0015                DO 9 K=121,256                                                85.000
0016          9     FEATUR((M+6))=FEATUR((M+6))+DATA(K)                           86.000
              C     BETA2 -------------------------                               87.000
              C     18.00-24.00HZ                                                 88.000
0017                DO 50 K=145,192                                               89.000
0018          50    FEATUR((M+7))=FEATUR((M+7))+DATA(K)                           90.000
              C                                                                   91.000
              C     FREQ: FIRST AND SECCND MOMENTS ------------------             92.000
0019                DO 51 I=2,256                                                 93.000
0020                XX=(I-1)*0.125                                                94.000
0021                FEATUR((M+8))=FEATUR((M+8))+DATA(I)*XX                        95.000
0022          51    FEATUR((M+9))=FEATUR((M+9))+DATA(I)*XX*XX                     96.000
              C                                                                   97.000
              C     PEAK INTENSITY AND FREQUENCY IN ALPEA BAND --------           98.000
0023                DO 52 I=65,104                                                99.000
0024                IF(FEATUR((M+10)).GE.DATA(I)) GC TC 52                        100.000
0025                FEATUR((M+10))=DATA(I)                                        101.000
0026                FEATUR((M+11))=0.125*(I-1)                                    102.000
0027          52    CONTINUE                                                      103.000
              C                                                                   104.000
              C     RELATIVE ENERGIES: --------------------------------           105.000
0028                DO 10 K=2,10                                                  106.000
0029          10    FEATUR((M+K))=(FEATUR((M+K))/FEATUR((M+1)))*100.              107.000
0030                FEATUR((M+8))=FEATUR((M+8))/100.                              108.000
0031                FEATUR((M+9))=SQRT(FEATUR((M+9))/100.)                        109.000
0032                IF(FEATUR((M+1)).NE.100.)FEATUR((M+1))=FEATUR((M+1))*0.125    110.000
0033                RETURN                                                        111.000
0034                END                                                           112.000
```

APPENDIX E

TIME DOMAIN ANALYSIS AND FEATURE EXTRACTION PROGRAM

```
C-------------------------------------------------------------------------      1.000
C  APPENDIX E  TIME DOMAIN ANALYSIS AND FEATURE EXTRACTION PROGRAM             2.000
C                                                                             3.000
C  THIS PROGRAM CALCULATES ONE 10-ELEMENT TIME DOMAIN FEATURE VECTOR          4.000
C  FOR EACH 64 SEC EEG PATTERN SAMPLE.                                        5.000
C  INPUT:                                                                     6.000
C           *LUNIT 1: INPUT DATA TAPE (SEE APPENDIX B)                        7.000
C           *LUNIT 4: FILE CONTAINING DATA LABELS                             8.000
C           *LUNIT 5: FILE CONTAINING DATA LABELS                             9.000
C  OUTPUT:                                                                    10.000
C           *LUNIT 7: OUTPUT FILE FOR 10-ELEMENT FEATURE VECTORS              11.000
C  LAST UPDATE:                                                               12.000
C           JANUARY 20 1975                                                   13.000
C-------------------------------------------------------------------------    14.000
C                                                                             15.000
0001        INTEGER NCHANA/3/,NCHANB/4/                                       16.000
0002        COMPLEX TRAN(2049)                                                17.000
0003        REAL DATA(4096),SRATE/64./                                        18.000
0004        COMMON  TRAN                                                      19.000
0005        EQUIVALENCE (TRAN,DATA)                                           20.000
0006        REAL DATIN(4,8192)                                                21.000
0007        COMMON / DATIN / DATIN,INDEXF,NFILE                               22.000
0008        INTEGER NFLAG/0/,NSEC/64/,NSAMP/8192/,N/4096/                     23.000
0009        INDEXF=0                                                          24.000
0010        PRN=N                                                             25.000
0011        FREQLP=16.                                                        26.000
C                                                                             27.000
C    GET ALL FOUR EEG CHANS FROM A 64 SEC SA AND PUT IN DATIN                 28.000
0012      3 CALL INPUT(NFLAG)                                                 29.000
0013        IF(NFLAG.EQ.1)GO TO 4                                             30.000
C                                                                             31.000
C   COPY ONE CHAN AT 64 SA/SEC (NOT THE ORIG 128/SEC)                         32.000
0014        DO 1 J=1,NSAMP,2                                                  33.000
0015      1 DATA((J-1)/2+1)=DATIN(NCHANA,J)                                   34.000
C                                                                             35.000
C   COMPUTE TIME DOMAIN FEATURE'S AFTER PREFILTERING OF SIGNAL                36.000
0016        CALL FILTLP(N,SRATE,FREQLP)                                       37.000
0017        CALL NORM(DATA,N,ZAVER,SM2,TM3,FM4)                               38.000
0018        CALL PSKEW(TM3,SM2,SKEW,VARSK,SDSK,PRN)                           39.000
0019        CALL RKURT(FM4,SM2,PRN,DKURT,VAKRT,SIKRT)                         40.000
0020        XXX=SQRT(SM2)                                                     41.000
0021        CALL ZCROSS(DATA,N,ZRATE,NSEC)                                    42.000
0022        CALL DCROSS(DATA,N,DRATE,NSEC)                                    43.000
0023        ZRATE=ZRATE/2.                                                    44.000
0024        DRATE=DRATE/2.                                                    45.000
C                                                                             46.000
C   COPY THE OTHER CHAN AND COMPUTE TIME DOMAIN FEATURE'S                     47.000
0025        DO 11 J=1,NSAMP,2                                                 48.000
0026     11 DATA((J-1)/2+1)=DATIN(NCHANB,J)                                   49.000
0027        CALL FILTLP(N,SRATE,FREQLP)                                       50.000
0028        CALL NORM(DATA,N,ZAVER,SM2,TM3,FM4)                               51.000
0029        CALL PSKEW(TM3,SM2,SKEW2,VARSK,SDSK,PRN)                          52.000
0030        CALL RKURT(FM4,SM2,PRN,DKURT2,VAKRT,SIKRT)                        53.000
0031        XXX2=SQRT(SM2)                                                    54.000
0032        CALL ZCROSS(DATA,N,ZRATE2,NSEC)                                   55.000
0033        CALL DCROSS(DATA,N,DRATE2,NSEC)                                   56.000
0034        ZRATE2=ZRATE2/2.                                                  57.000
0035        DRATE2=DRATE2/2.                                                  58.000
C                                                                             59.000
C   COMPLETE AND WRITE ONE FEATURE VECTOR                                     60.000
0036        READ(4,12)NF,LEV,NPTNT                                            61.000
0037     12 FORMAT(I5,5X,2I5)                                                 62.000
0038        WRITE(7,13)XXX,ZRATE,DRATE,SKEW,DKURT,XXX2,ZRATE2,DRATE2,SKEW2,   63.000
           1DKURT2,NF,LEV,NPTNT                                               64.000
0039     13 FORMAT(10F14.6,3I4)                                               65.000
0040        GO TO 3                                                           66.000
0041      4 STOP                                                              67.000
0042        END                                                               68.000
```

```
0001                SUBROUTINE INPUT(NFLAG)                                    69.000
                C   THIS SUBR WAS ADAPTED FROM SOBT.4.S JAN 10 1974            70.000
                C                                                              71.000
0002                REAL DATIN(4,8192)                                         72.000
0003                COMMON /DATIN/ DATIN,INDEXF,NFILE                          73.000
0004                INTEGER*2 BLOCK(2048),LEN1                                 74.000
0005                LUNIT=1                                                    75.000
0006                NSKIP=0                                                    76.000
                C                                                              77.000
                C   READ THE FILE NO                                          78.000
0007                READ(5,20,END=10)NFILE                                     79.000
0008             20 FORMAT(I5)                                                 80.000
0009                WRITE(6,12)NFILE                                           81.000
0010             12 FORMAT(' ****',I5)                                         82.000
                C                                                              83.000
                C   PREPARE TO SKIP TO THE APPROPRIATE FILE                   84.000
0011                ITEMP=NFILE-INDEXF-1                                       85.000
0012                CALL SKIP(ITEMP,NSKIP,LUNIT)                               86.000
0013                INDEXF=NFILE-1                                             87.000
                C                                                              88.000
0014                DO 14 IBLK=1,16                                            89.000
0015                INDX=(IBLK-1)*512                                          90.000
0016                CALL READ(BLOCK,LEN1,0,LINE1,LUNIT,&10)                    91.000
0017                DO 14 ICH=1,4                                              92.000
0018                DO 14 ISAM=1,2048,4                                        93.000
0019                IR=INDX+1+(ISAM-1)/4                                       94.000
0020                IRR=(ICH-1)*ISAM                                           95.000
0021             14 DATIN(ICH,IR)=BLOCK(IRR)                                   96.000
                C                                                              97.000
0022                RETURN                                                     98.000
0023             10 NFLAG=1                                                    99.000
0024                RETURN                                                    100.000
0025                END                                                       101.000
0001                SUBROUTINE FILTLP(NSAMP,SRATE,FREQLP)                     102.000
                C                                                             103.000
                C   LOWPASS FILTERS THE SIGNAL IN ARRAY 'DATA' VIA FFT AND    104.000
                C   CONVOLUTIONAL-TYPE FILTER.THEN PUTS RESULTS IN DATA.      105.000
                C                                                             106.000
0002                COMPLEX TRAN(2049)                                        107.000
0003                REAL DATA(4096)                                           108.000
0004                COMMON TRAN                                               109.000
0005                EQUIVALENCE (TRAN,DATA)                                   110.000
0006                INTEGER NN(1)                                             111.000
                C   FFT OF SIGNAL ----------------------------------------    112.000
                C                                                             113.000
0007                NN(1)=NSAMP                                               114.000
0008                ISIGN=-1                                                  115.000
0009                CALL FOUR2(DATA,NN,1,ISIGN,0)                             116.000
0010                MID=NSAMP/2+1                                             117.000
0011                ILIM=(FREQLP/(SRATE/2.))*(MID-1)+1.01                     118.000
                C                                                             119.000
                C   LP FILTERING -----------------------------------------    120.000
0012                DO 1 J=LLIM,MID                                           121.000
0013             1  TRAN(J)=(0.,0.)                                          122.000
                C                                                             123.000
                C   HP FILTERING -----------------------------------------    124.000
0014                L1=32                                                     125.000
0015                L2=5                                                      126.000
0016                DO 3 J=1,L1                                               127.000
0017             3  TRAN(J)=(0.,0.)                                          128.000
0018                DO 4 J=1,L2                                               129.000
0019             4  TRAN(L1+J)=TRAN(L1+J)*(FLOAT(J)/FLOAT(L2))               130.000
                C                                                             131.000
                C   INVERSE TRANSFORM ------------------------------------    132.000
0020                ISIGN=1                                                   133.000
0021                CALL FOUR2(DATA,NN,1,ISIGN,-1)                            134.000
0022                RN=NSAMP                                                  135.000
0023                DO 2 J=1,NSAMP                                            136.000
0024             2  DATA(J)=DATA(J)/RN                                        137.000
0025                RETURN                                                    138.000
0026                END                                                       139.000
0001                SUBROUTINE ZCROSS(X,N,AVEZC,NSEC)                         140.000
                C                                                             141.000
                C   THIS SUBR COUNTS THE NO. OF ZERO CROSSINGS IN AN ARRAY OF ARB.  142.000
                C   SIZE AND RETURNS THE AVERAGE CROSSING RATE                143.000
                C                                                             144.000
0002                REAL X(N)                                                 145.000
0003                ZC=0.                                                     146.000
0004                LIM=N-1                                                   147.000
                C                                                             148.000
0005                DO 1 I=1,LIM                                              149.000
0006                IF(X(I).GE.0.) GOTO 2                                     150.000
```

```
      C   IF NOT, X(I) MUST BE LT 0...                                    151.000
0007        IF(X(I+1).GE.0.)  ZC=ZC+1.                                    152.000
0008        GO TO 1                                                       153.000
0009     2  IF(X(I+1).LT.0.)ZC=ZC+1.                                      154.000
0010     1  CONTINUE                                                      155.000
      C                                                                   156.000
0011        AVEZC=ZC/NSEC                                                 157.000
0012        RETURN                                                        158.000
0013        END                                                           159.000
0001        SUBROUTINE DCROSS(DEL,N,AVEDC,NSEC)                           160.000
      C                                                                   161.000
      C   THIS SUBR COMPUTES THE AVER ZERO CROSSING RATE OF THE DERIV OF THE 162.000
      C     SIGNAL STORED IN ARRAY X.                                     163.000
      C   NOTE: CONTENTS OF ARG ARRAY ARE CHANGED.                        164.000
      C                                                                   165.000
0002        REAL DEL(N)                                                   166.000
0003        LIM=N-1                                                       167.000
0004        DC=0.                                                         168.000
0005        DO3 J=1,LIM                                                   169.000
0006     3  DEL(J)=DEL(J+1)-DEL(J)                                        170.000
0007        DEL(N)=DEL(N-1)+(DEL(N-1)-DEL(N-2))                           171.000
      C                                                                   172.000
0008        DO 1 I=1,LIM                                                  173.000
0009        IF(DEL(I).GE.0.) GO TO 2                                      174.000
      C    IF NOT,DEL(I) MUST BE LT 0....                                 175.000
0010        IF(DEL(I+1).GE.0.) DC=DC+1.                                   176.000
0011        GO TO 1                                                       177.000
0012     2  IF(DEL(I+1).LT.0.)DC=DC+1.                                    178.000
0013     1  CONTINUE                                                      179.000
      C                                                                   180.000
0014        AVEDC=DC/NSEC                                                 181.000
0015        RETURN                                                        182.000
0016        END                                                           183.000
0001        SUBROUTINE NORM(ARRAY,N,AVER,SVAR,TM3,FM4)                    184.000
      C                                                                   185.000
      C   THIS PROGRAM ACCEPTS AN ARRAY OF SIZE TO N=64*128=8192 AND      186.000
      C                  -COMPUTES THE MEAN,VARIANCE OF THE SAMPLE AND    187.000
      C                  COMPUTES THE  THIRD AND FOURTH MOMENTS,          188.000
      C                                                                   189.000
      C INITIALIZATION                                                    190.000
0002        DIMENSION ARRAY(N)                                            191.000
0003        SUM=0.                                                        192.000
0004        SVAR=0.                                                       193.000
0005        SS3=0.                                                        194.000
0006        SS4=0.                                                        195.000
0007        RN=N                                                          196.000
      C                                                                   197.000
      C  MEAN:                                                            198.000
0008        DO 1 J=1,N                                                    199.000
0009     1  SUM=SUM+ARRAY(J)                                              200.000
0010        AVER=SUM/RN                                                   201.000
      C                                                                   202.000
      C SAMPLE VARIANCE:                                                  203.000
0011        DO3 L=1,N                                                     204.000
0012        Z=ARRAY(L)-AVER                                               205.000
0013     3  SVAR=SVAR+Z*Z                                                 206.000
0014        SUMS=SVAR                                                     207.000
0015        SVAR=SVAR/(RN-1.)                                             208.000
0016        SDEV=SQRT(SVAR)                                               209.000
      C                                                                   210.000
      C    COMPUTE THIRD AND FOURTH MOMENTS...                            211.000
0017        DO 4 J=1,N                                                    212.000
0018        SS3=SS3+ARRAY(J)**3                                           213.000
0019        SS4=SS4+ARRAY(J)**4                                           214.000
0020     4  CONTINUE                                                      215.000
0021        SM=AVER                                                       216.000
      C                                                                   217.000
0022        TM3=SS3-3.*SM*SUMS+3.*SM*SM*SUM-RN*(SM**3)                    218.000
0023        TM3=TM3/RN                                                    219.000
0024        FM4=SS4-4.*SM*SS3+6.*SM*SM*SUMS-4.*(SM**3)*SUM+RN*(SM**4)     220.000
0025        FM4=FM4/RN                                                    221.000
      C                                                                   222.000
0026        RETURN                                                        223.000
0027        END                                                           224.000
0001        SUBROUTINE PSKEW(TM3,SM2,SKEW,VARSK,SDSK,RN)                  225.000
      C                                                                   226.000
      C THIS SUBROUTINE CALCULATES THE MOMENT OF SKEWNESS AND ITS         227.000
      C VARIANCE AND STANDARD DEVIATION                                   228.000
      C     TM3 IS THE 3RD MOMENT                                         229.000
      C     SM2 IS THE SECOND MOMENT (VARIANCE)                           230.000
      C     SKEW WILL CONTAIN THE MEASURE OF SKEWNESS                     231.000
```

```
C      VARSK WILL CONTAIN ITS VARIANCE                                  232.000
C      SDSK WILL CONTAIN ITS STANDARD DEVIATION                         233.000
C      RN IS THE NUMBER OF OBSERVATIONS                                 234.000
C      TK IS K3                                                         235.000
C      SK IS K2                                                         236.000
C                                                                       237.000
0002        TK=(RN*RN/((RN-1.)*(RN-2.)))*TM3                            238.000
0003        SK=(RN/(RN-1.))*SM2                                         239.000
0004        SKEW=TK/SQRT(SK**3)                                         240.000
C                                                                       241.000
C CALCULATE VARIANCE OF SKEWNESS                                        242.000
0005        VARSK=6. * RN * (RN-1.)                                     243.000
0006        VARSK=VARSK/((RN-2.)*(RN+1.)*(RN+3.))                       244.000
C                                                                       245.000
C GET S.D. OF SKEWNESS                                                  246.000
0007        SDSK=SQRT(VARSK)                                            247.000
0008        RETURN                                                      248.000
0009        END                                                         249.000
0001        SUBROUTINE RKURT(FM4,SM2,RN,DKURT,VAKRT,SDKRT)              250.000
C                                                                       251.000
C THIS SUBROUTINE CALCULATES A MEASURE OF KURTOSIS                      252.000
C      FM4 IS THE 4TH MOMENT ABOUT THE MEAN                             253.000
C      SM2 IS THE SECOND MOMENT ABOUT THE MEAN (VARIANCE)               254.000
C      RN IS THE NUMBER OF OBSERVATIONS                                 255.000
C      DKURT WILL CONTAIN THE MEASURE OF KURTOSIS                       256.000
C      VAKRT WILL CONTAIN ITS VARIANCE                                  257.000
C      SDKRT WILL CONTAIN ITS STANDARD DEVIATION                        258.000
C      FK IS K4                                                         259.000
C      TK IS K2                                                         260.000
C                                                                       261.000
0002        FK=RN*RN/((RN-1.)*(RN-2.)*(RN-3.))                          262.000
0003        FK=FK*((RN+1.)*FM4 - 3. *(RN-1.)*SM2*SM2)                   263.000
0004        TK=(RN/(RN-1.))*SM2                                         264.000
0005        DKURT=FK/(TK*TK)                                            265.000
C                                                                       266.000
C CALCULATE THE VARIANCE OF THE KURTOSIS                                267.000
0006        VAKRT=24. * RN * (RN-1.) * (RN-1.)                          268.000
0007        VAKRT=VAKRT/((RN-3.)*(RN-2.)*(RN+3.)*(RN+5.))               269.000
C                                                                       270.000
C GET STANDARD DEVIATION OF THE KURTOSIS                                271.000
0008        SDKRT=SQRT(VAKRT)                                           272.000
0009        RETURN                                                      273.000
0010        END                                                         274.000
```

APPENDIX F

PERFORMANCE ESTIMATION BY THE Π* TECHNIQUE

```
C-------------------------------------------------------------------------  1.000
C  APPENDIX F  PERFORMANCE ESTIMATION BY THE PI-* TECHNIQUE                 2.000
C                                                                          3.000
C  THIS PROGRAM CAN BE USED TO ESTIMATE THE PERFORMANCE OF SPECTRAL AND     4.000
C  TIME DOMAIN EEG PATTERN RECOGNITION SYSTEMS BY TH PI-* TECHNIQUE.       5.000
C  INPUT:                                                                  6.000
C           *LUNIT 4: FEATURE VECTORS AND LABELS                           7.000
C           *LUNIT 5: QUANTIZER PARAMETERS                                 8.000
C  OUTPUT:                                                                 9.000
C           *LUNIT 6: ALL OUTPUT                                          10.000
C  PARAMETERS:                                                            11.000
C           NEL = NUMBER OF ELEMENTS IN FEATURE VECTOR                    12.000
C           NQUANT = NUMBER OF POSSIBLE QUANTIZATION LEVELS               13.000
C           SD = NUMBER OF ST. DEV.'S ALLOWED FOR FEATURE VARIATION       14.000
C           IPROB = 0 IF EQUAL A PIORI CLASS PROB'S ARE TO BE USED        15.000
C           IPRINT = 0 TO PRINT TEST RESULTS AT EACH STEP                 16.000
C  LAST UPDATE:                                                           17.000
C           OCTOBER 19 1974                                               18.000
C-------------------------------------------------------------------------19.000
C                                                                         20.000
0001          REAL DATA(500,80)                                           21.000
0002          INTEGER IX(500,80),LEV(500),NUMP(500)                       22.000
0003          COMMON /CMAIN/ IX,LEV,NUMP                                  23.000
0004          COMMON /MPROG/ DATA                                         24.000
              C                                                           25.000
              C   READ IN ALL AVAILABLE FEATURE DATA:                    26.000
0005          NEL=80                                                      27.000
0006          DO 1 I=1,501                                                28.000
0007        1 READ(4,2,END=3)(DATA(I,J),J=1,NEL),LEV(I),NUMP(I)           29.000
0008         2  FORMAT(80F14.6,4X,2I4)                                    30.000
0009         3  NSAMP=I-1                                                 31.000
              C                                                           32.000
              C   INITIALIZATION OF PARAMETERS:                          33.000
0010          IPROB=1                                                     34.000
0011          IPRINT=1                                                    35.000
0012         56  READ(5,55,END=50)NQUANT,SD                              36.000
0013         55  FORMAT(I3,F5.0)                                         37.000
              C                                                           38.000
              C   'PI METHOD' OF PERFORMANCE ESTIMATION:                 39.000
0014          4  LOW=1                                                   40.000
0015          9  IHIGH=LOW                                               41.000
0016          8  IF(IHIGH.EQ.NSAMP)GO TO 7                               42.000
0017             IF(NUMP((IHIGH+1)).NE.NUMP(LOW))GO TO 7                  43.000
0018             IHIGH=IHIGH+1                                            44.000
0019             GO TO 8                                                  45.000
0020          7  CALL QUANT(LOW,IHIGH,NSAMP,NEL,NQUANT,SD)               46.000
0021             CALL TRAIN(LOW,IHIGH,NSAMP,NEL,NQUANT)                   47.000
0022             CALL TEST(LOW,IHIGH,NEL,IPRINT,IPROB)                    48.000
0023             IF(IHIGH.EQ.NSAMP)GO TO 6                                49.000
0024             LOW=IHIGH+1                                              50.000
0025             GO TO 9                                                  51.000
              C                                                           52.000
0026          6  CALL PRINT(NSAMP,NEL,NQUANT,IPROB)                      53.000
0027             GO TO 56                                                 54.000
0028         50  STOP                                                    55.000
0029             END                                                      56.000
0001          SUBROUTINE QUANT(IMID,IEND,NSAMP,NEL,NQUANT,SD)             57.000
              C     CONSIDERS ALL FEATURE VALUES FROM THE TRAINING DATA (IE,NOT  58.000
              C     SAMPLES FROM IMID,...,IEND) FOR EACH FEATURE. THE MIN, MAX, MEAN  59.000
              C     AND ST. DEV. ARE CALCULATED. ALL FEATURE VALUES ARE THEN QUANTIZED  60.000
              C                                                           61.000
0002          INTEGER IX(500,80)                                          62.000
0003          REAL DATA(500,80),DMIN(80),DMAX(80),DAVER(80),DSDEV(80),F(80)  63.000
0004          COMMON /MPROG/ DATA                                         64.000
0005          COMMON /CMAIN/ IX                                           65.000
              C                                                           66.000
              C   INITIALIZATION:                                        67.000
0006          RNSAMP=NSAMP-1-IEND+IMID                                    68.000
0007          DO 1 J=1,NEL                                                69.000
0008          DMIN(J)=999999.                                             70.000
0009          DMAX(J)=-999999.                                            71.000
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0010              DAVER(J)=0.                                                    72.000
0011           1  DSDEV(J)=0.                                                    73.000
0012              IF(IMID.EQ.1)GO TO 2                                           74.000
0013              LOW=1                                                          75.000
0014              IHIGH=IMID-1                                                   76.000
                C                                                              77.000
                C  FIND MIN, MAX, MEAN AND SD. DEV. FOR EACH FEATURE:          78.000
0015           5  DO 3 I=LOW,IHIGH                                               79.000
0016              DO 3 J=1,NEL                                                   80.000
0017              IF(DATA(I,J).LT.DMIN(J))DMIN(J)=DATA(I,J)                      81.000
0018              IF(DATA(I,J).GT.DMAX(J))DMAX(J)=DATA(I,J)                      82.000
0019              DAVER(J)=DAVER(J)+DATA(I,J)                                    83.000
0020           3  DSDEV(J)=DSDEV(J)+(DATA(I,J)*DATA(I,J))                       84.000
0021              IF((IHIGH.EQ.NSAMP).OR.(IEND.EQ.NSAMP))GO TO 4                 85.000
0022           2  LOW=IEND+1                                                     86.000
0023              IHIGH=NSAMP                                                    87.000
0024              GO TO  5                                                       88.000
                C                                                              89.000
                C  FIND CLASS WIDTH FOR LINEAR QUANTIZATION:                   90.000
0025           4  DO 6 J=1,NEL                                                   91.000
0026              DAVER(J)=DAVER(J)/RNSAMP                                       92.000
0027              DSDEV(J)=SQRT((DSDEV(J)-(RNSAMP*DAVER(J)*DAVER(J)))/(RNSAMP-1.))  93.000
0028              IF(DMIN(J).LT.(DAVER(J)-SD*DSDEV(J)))DMIN(J)=DAVER(J)-SD*DSDEV(J)  94.000
0029              IF(DMAX(J).GT.(DAVER(J)+SD*DSDEV(J)))DMAX(J)=DAVER(J)+SD*DSDEV(J)  95.000
0030           6  F(J)=(DMAX(J)-DMIN(J))/FLOAT(NQUANT)                          96.000
                C                                                              97.000
                C  QUANTIZE ALL SAMPLE DATA (TRAINING AND TESTING DATA):       98.000
0031              DO 10 I=1,NSAMP                                                99.000
0032              DO 10 J=1,NEL                                                  100.000
0033              IX(I,J)=(DATA(I,J)-DMIN(J))/F(J)                               101.000
0034              IX(I,J)=IX(I,J)+1                                              102.000
0035              IF(IX(I,J).LT.1)IX(I,J)=1                                      103.000
0036           10 IF(IX(I,J).GT.NQUANT)IX(I,J)=NQUANT                            104.000
0037              RETURN                                                         105.000
0038              END                                                            106.000
0001              SUBROUTINE TRAIN(LOW,IEND,NSAMP,NEL,NQUANT)                    107.000
                C                                                              108.000
0002              INTEGER IX(500,80),LEV(500)                                    109.000
0003              REAL PRCOND(5,80,128),PRCLAS(5)                                110.000
0004              COMMON /CMAIN/ IX,LEV                                          111.000
0005              COMMON /TST/ PRCOND,PRCLAS                                     112.000
                C                                                              113.000
                C  INITIALIZATION:                                             114.000
0006              DO 1 I=1,5                                                     115.000
0007              PRCLAS(I)=0.                                                   116.000
0008              DO 1 J=1,NEL                                                   117.000
0009              DO 1 K=1,NQUANT                                                118.000
0010           1  PRCOND(I,J,K)=0.                                              119.000
                C                                                              120.000
                C  USE TRAINING DATA TO ESTIMATE PROB DISTRIBUTIONS:           121.000
0011              IF(LOW.NE.1)GO TO 2                                            122.000
0012              IA=IEND+1                                                      123.000
0013              IB=NSAMP                                                       124.000
0014           5  DO 3 I=IA,IB                                                  125.000
0015              II=LEV(I)+1                                                    126.000
0016              DO 4 J=1,NEL                                                   127.000
0017           4  PRCOND(II,J,IX(I,J))=PRCOND(II,J,IX(I,J))+1.                  128.000
0018           3  PRCLAS(II)=PRCLAS(II)+1.                                      129.000
0019              IF(IB.EQ.NSAMP)GO TO 6                                         130.000
0020              IF(IEND.EQ.NSAMP)GO TO 6                                       131.000
0021              IA=IEND+1                                                      132.000
0022              IB=NSAMP                                                       133.000
0023              GO TO 5                                                        134.000
0024           2  IA=1                                                          135.000
0025              IB=LOW-1                                                       136.000
0026              GO TO 5                                                        137.000
                C                                                              138.000
                C  CHECK TRAINING DATA FOR UNREPRESENTED CLASSES:              139.000
0027           6  DO 9 K=1,5                                                    140.000
0028              KK=K-1                                                         141.000
0029           9  IF(PRCLAS(K).EQ.0.)WRITE(6,10)KK                              142.000
0030           10 FORMAT(/'  *** WARNING: NO SAMPLES FOR LEVEL',I3/)             143.000
                C                                                              144.000
                C  APPLY BAYES ESTIMATION PROCEDURE TO PROB MATRICES:          145.000
0031              S=PRCLAS(1)+PRCLAS(2)+PRCLAS(3)+PRCLAS(4)+PRCLAS(5)            146.000
0032              DO 7 I=1,5                                                     147.000
0033              DO 8 J=1,NEL                                                   148.000
0034              DO 8 K=1,NQUANT                                                149.000
0035           8  PRCOND(I,J,K)=(PRCOND(I,J,K)+1.)/(PRCLAS(I)+FLOAT(NQUANT))    150.000
0036           7  PRCLAS(I)=(PRCLAS(I)+1.)/(S+5.)                               151.000
0037              RETURN                                                         152.000
0038              END                                                            153.000
0001              SUBROUTINE TEST(LOW,IEND,NEL,IPRINT,IERROR)                    154.000
                C                                                              155.000
0002              INTEGER IX(500,80),LEV(500),NUMP(500)                          156.000
0003              REAL CLASSM(5,5),PRCOND(5,80,128),PRCLAS(5),PTEST(5)           157.000
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```
0004                COMMON /CMAIN/ IX,LEV,NUMF                                158.000
0005                COMMON /TST/ PRCOND,PRCLAS                                159.000
0006                COMMON /PRNT/ CLASSM                                      160.000
                C                                                             161.000
                C   INITIALIZATION ON FIRST SUBR CALL:                       162.000
0007                IF(LOW.NE.1)GO TO 1                                       163.000
0008                DO 2 I=1,5                                                164.000
0009                DO 2 J=1,5                                                165.000
0010             2  CLASSM(I,J)=0.                                           166.000
                C                                                             167.000
                C   GET CLASS CONDITIONAL ERROR ESTIMATES FOR TESTING SAMPLE(S):  168.000
0011             1  DO 10 I=LOW,IEND                                          169.000
0012                DO 3 K=1,5                                                170.000
0013             3  PTEST(K)=0.                                               171.000
0014                DO 4 ICLASS=1,5                                           172.000
0015                DO 4 IEL=1,NEL                                            173.000
0016             4  PTEST(ICLASS)=PTEST(ICLASS)+ALOG(PRCOND(ICLASS,IEL,IX(I,IEL)))  174.000
                C                                                             175.000
                C   INCLUDE A PRIORI CLASS ERROR'S AND ESTIMATE ANESTHESIA LEVEL:  176.000
0017                IF(IPROB.EQ.0)GO TO 5                                     177.000
0018                DO 6 ICLASS=1,5                                           178.000
0019             6  PTEST(ICLASS)=PTEST(ICLASS)+ALOG(PRCLAS(ICLASS))          179.000
0020             5  IR=1                                                      180.000
0021                DO 7 ICLASS=2,5                                           181.000
0022             7  IF(PTEST(ICLASS).GT.PTEST(IR))IR=ICLASS                   182.000
                C                                                             183.000
                C   UPDATE CLASSIFICATION MATRIX AND PRINT RESULTS IF DESIRED:  184.000
0023                II=LEV(I)+1                                               185.000
0024                CLASSM(II,IR)=CLASSM(II,IR)+1.                            186.000
0025                IF(IPRINT.NE.0)GO TO 10                                   187.000
0026                IRR=IR-1                                                  188.000
0027                IF(II.NE.IR)WRITE(6,8)I,LEV(I),IRR,NUMF(I)                189.000
0028                IF(II.EQ.IR)WRITE(6,9)I,NUMP(I),LEV(I)                    190.000
0029             8  FORMAT(5X,I3,'  WAS MISCLASSIFIED',I3,'-->',I1,5X,'#',I3)  191.000
0030             9  FORMAT(5X,I3,'  (#',I3,')  IS OK: LEVEL',I2)              192.000
0031             10 CONTINUE                                                  193.000
0032                RETURN                                                    194.000
0033                END                                                       195.000
0001                SUBROUTINE PRINT(NSAMP,NEL,NQUANT,IPROB)                  196.000
                C                                                             197.000
0002                REAL CLASSM(5,5),TOTAL(5)                                 198.000
0003                COMMON /PRNT/ CLASSM                                      199.000
0004                DO 78 IQ=1,5                                              200.000
0005             78 TOTAL(IQ)=0.                                              201.000
0006             10 WRITE(6,11)                                               202.000
0007             11 FORMAT('1',20X,' S U M M A R Y '////)                     203.000
0008                WRITE(6,12)NSAMP                                          204.000
0009             12 FORMAT(5X,'TOTAL NUMBER OF PATTERN SAMPLES=',I3/)         205.000
0010                WRITE(6,16)                                               206.000
0011             16 FORMAT(5X,'METHOD OF PERFORMANCE ESTIMATION: "PI-* METHOD"'/)  207.000
0012                IF(IPROB.NE.0)WRITE(6,13)                                 208.000
0013                IF(IPROB.EQ.0)WRITE(6,14)                                 209.000
0014             13 FORMAT(5X,'UNEQUAL A PRIORI CLASS PROBABILITIES WERE USED'/)  210.000
0015             14 FORMAT(5X,'EQUAL A PRIORI CLASS PROBABILITIES WERE USED'/)  211.000
0016                WRITE(6,17)NEL,NQUANT                                     212.000
0017             17 FORMAT(5X,I2,' ELEMENTS IN FEATURE VECTOR WITH',I4,' QUANTIZATION  213.000
                   1LEVELS PER FEATURE'/)                                     214.000
                C                                                             215.000
0018                WRITE(6,18)                                               216.000
0019             18 FORMAT(///10X,'CLASSIFICATION MATRIX:'//)                 217.000
0020                OK=0.                                                     218.000
0021                DO 19 I=1,5                                               219.000
0022                DO 20 J=1,5                                               220.000
0023             20 TOTAL(I)=TOTAL(I)+CLASSM(I,J)                             221.000
0024                OK=OK+CLASSM(I,I)                                         222.000
0025             19 WRITE(6,21)(CLASSM(I,J),J=1,5),TOTAL(I)                   223.000
0026             21 FORMAT(10X,5F10.2,10X,F6.0)                               224.000
0027                PERCNT=(OK/FLOAT(NSAMP))*100.                             225.000
0028                WRITE(6,22) PERCNT,OK                                     226.000
0029             22 FORMAT(///5X,'***',F8.3,' PERCENT OR',F5.0,' SAMPLES WERE CLASSIFI  227.000
                   1ED CORRECTLY.'/)                                          228.000
0030                BX=100.-PERCNT                                            229.000
0031                WRITE(6,27)BX                                             230.000
0032             27 FORMAT(5X,'***  MISCLASSIFICATION ERROR:',F8.3///)         231.000
                C                                                             232.000
0033                WRITE(6,23)                                               233.000
0034             23 FORMAT(10X,'CLASSIFICATION PROBABILITY MATRIX:'//)        234.000
0035                DO 24 I=1,5                                               235.000
0036                DO 25 J=1,5                                               236.000
0037             25 CLASSM(I,J)=(CLASSM(I,J)/TOTAL(I))*100.                   237.000
0038             24 WRITE(6,26)(CLASSM(I,J),J=1,5)                            238.000
0039             26 FORMAT(10X,5F10.2)                                        239.000
0040                RETURN                                                    240.000
0041                END                                                       241.000
```

APPENDIX G

PERFORMANCE ESTIMATION BY THE U* TECHNIQUE

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C-------------------------------------------------------------------------      1.CCO
C  APPENDIX G  PERFORMANCE ESTIMATION BY THE U* TECHNIQUE                       2.000
C                                                                             3.CCO
C  THIS PROGRAM CAN BE USED TO ESTIMATE THE PERFORMANCE OF SPECTRAL AND        4.CCO
C  TIME DOMAIN EEG PATTERN RECOGNITION SYSTEMS BY THE U* TECHNIQUE.           5.CCO
C  INPUT:                                                                     6.000
C           *LUNIT 4: NUMBER OF THE SUBJECTS TO BE CONSIDERED                 7.CCO
C           *LUNIT 5: FEATURE VECTORS AND LABELS                              8.CCO
C  OUTPUT:                                                                    9.000
C           *LUNIT 6: ALL OUTPUT                                             10.000
C  PARAMETERS:                                                               11.CCO
C           NEL = NUMBER OF ELEMENTS IN FEATURE VECTOR                       12.CCO
C           NQUANT = NUMBER OF POSSIBLE QUANTIZATION LEVELS                  13.CCO
C           SD = NUMBER OF ST. DEV.'S ALLOWED FOR FEATURE VARIATION          14.000
C           IPROB = 0 IF EQUAL A PIORI CLASS PROB'S ARE TO BE USED           15.CCO
C           IPRINT = 0 TO PRINT TEST RESULTS AT EACH STEP                    16.000
C  LAST UPDATE:                                                              17.CCO
C           JANUARY 20 1975                                                  18.CCO
C-------------------------------------------------------------------------   19.CCO
C                                                                            20.000
0001          REAL DATA(500,80)                                              21.CCO
0002          INTEGER IX(500,80),LEV(500),NUMP(500)                          22.CCO
0003          COMMON /CMAIN/ IX,LEV,NUMP                                     23.CCO
0004          COMMON /MERCG/ DATA                                            24.000
C                                                                            25.CCO
C   INITIALIZATION OF PARAMETERS:                                            26.000
0005          NEL=13                                                         27.CCO
0006          NQUANT=64                                                      28.000
0007          IPROB=0                                                        29.CCO
0008          SD=5.                                                          30.000
0009          IPRINT=0                                                       31.CCO
C                                                                            32.000
C   READ IN ALL AVAILABLE FEATURE DATA:                                      33.CCO
0010    11    READ(4,10,END=12) PTNT                                         34.000
0011    10    FORMAT(F5.0)                                                   35.CCO
0012          NPTNT=PTNT                                                     36.000
0013          I=1                                                            37.CCO
0014        1 READ(5,2,END=3) (DATA(I,J),J=1,NEL),LEV(I),NUMP(I)             38.000
0015    2     FORMAT(1X,13F9.2,4X,2I4)                                       39.CCO
0016          IF(NUMP(I).NE.NPTNT)GO TO 1                                    40.000
0017          I=I+1                                                          41.CCO
0018          GO TO 1                                                        42.000
0019    3     NSAMP=I-1                                                      43.000
C                                                                            44.CCO
C   'U METHOD' OF PERFORMANCE ESTIMATION:                                    45.CCO
0020          DO 5 I=1,NSAMP                                                 46.000
0021          CALL QUANT(I,I,NSAMP,NEL,NQUANT,SD)                            47.CCO
0022          CALL TRAIN(I,I,NSAMP,NEL,NQUANT)                               48.CCO
0023    5     CALL TEST(I,I,NEL,IPRINT,IPROB)                                49.CCO
0024          CALL PRINT(NSAMP,NEL,NQUANT,IPROB,NPTNT)                       50.000
0025          REWIND 5                                                       51.CCO
0026          GO TO 11                                                       52.000
C                                                                            53.CCO
0027    12    STOP                                                           54.000
0028          END                                                            55.CCO
0001          SUBROUTINE QUANT(IMID,IEND,NSAMP,NEL,NQUANT,SD)                56.000
C     CONSIDERS ALL FEATURE VALUES FROM THE TRAINING DATA (IE,NOT            57.CCO
C     SAMPLES FROM IMID,...,IEND) FOR EACH FEATURE. THE MIN, MAX, MEAN       58.000
C     AND ST. DEV. ARE CALCULATED. ALL FEATURE VALUES ARE THEN QUANTIZED     59.CCO
C                                                                            60.000
0002          INTEGER IX(500,80)                                             61.CCO
0003          REAL DATA(500,80),DMIN(80),DMAX(80),DAVER(80),DSDEV(80),F(80)  62.000
0004          COMMON /MERCG/ DATA                                            63.000
0005          COMMON /CMAIN/ IX                                              64.000
C                                                                            65.000
C   INITIALIZATION:                                                          66.000
0006          RNSAMP=NSAMP-1-IEND+IMID                                       67.000
0007          DO 1 J=1,NEL                                                   68.000
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```
0008                DMIN(J)=999999.                                          69.000
0009                DMAX(J)=-999999.                                         70.000
0010                DAVER(J)=0.                                              71.000
0011           1    DSDEV(J)=0.                                              72.000
0012                IF(IMID.EQ.1)GO TO 2                                     73.000
0013                LOW=1                                                    74.000
0014                IHIGH=IMID-1                                             75.000
               C                                                            76.000
               C    FIND MIN, MAX, MEAN AND SD. DEV. FOR EACH FEATURE:      77.000
0015           5    DO 3 I=LOW,IHIGH                                         78.000
0016                DO 3 J=1,NEL                                             79.000
0017                IF(DATA(I,J).LT.DMIN(J))DMIN(J)=DATA(I,J)                80.000
0018                IF(DATA(I,J).GT.DMAX(J))DMAX(J)=DATA(I,J)                81.000
0019                DAVER(J)=DAVER(J)+DATA(I,J)                              82.000
0020           3    DSDEV(J)=DSDEV(J)+(DATA(I,J)*DATA(I,J))                  83.000
0021                IF((IHIGH.EQ.NSAMP).OR.(IEND.EQ.NSAMP))GO TO 4           84.000
0022           2    LOW=IEND+1                                               85.000
0023                IHIGH=NSAMP                                              86.000
0024                GO TO  5                                                 87.000
               C                                                            88.000
               C    FIND CLASS WIDTH FOR LINEAR QUANTIZATION:               89.000
0025           4    DO 6 J=1,NEL                                             90.000
0026                DAVER(J)=DAVER(J)/RNSAMP                                 91.000
0027                DSDEV(J)=SQRT((DSDEV(J)-(RNSAMP*DAVER(J)*DAVER(J)))/(RNSAMP-1.))  92.000
0028                IF(DMIN(J).LT.(DAVER(J)-SD*DSDEV(J)))DMIN(J)=DAVER(J)-SD*DSDEV(J)  93.000
0029                IF(DMAX(J).GT.(DAVER(J)+DSDEV(J)*SD))DMAX(J)=DAVER(J)+SD*DSDEV(J)  94.000
0030           6    F(J)= (DMAX(J)-DMIN(J))/FLOAT(NQUANT)                    95.000
               C                                                            96.000
               C    QUANTIZE ALL SAMPLE DATA (TRAINING AND TESTING DATA):   97.000
0031                DO 10 I=1,NSAMP                                          98.000
0032                DO 10 J=1,NEL                                            99.000
0033                IX(I,J)=(DATA(I,J)-DMIN(J))/F(J)                        100.000
0034                IX(I,J)=IX(I,J)+1                                       101.000
0035                IF(IX(I,J).LT.1)IX(I,J)=1                               102.000
0036           10   IF(IX(I,J).GT.NQUANT)IX(I,J)=NQUANT                     103.000
0037                RETURN                                                  104.000
0038                END                                                     105.000
0001                SUBROUTINE TRAIN(LOW,IEND,NSAMP,NEL,NQUANT)             106.000
               C                                                            107.000
0002                INTEGER IFLAG(5),IX(500,80),LEV(500)                    108.000
0003                REAL PRCOND(5,80,128),PRCLAS(5)                         109.000
0004                COMMON /CMAIN/ IX,LEV                                   110.000
0005                COMMON /TST/ PRCOND,PRCLAS,IFLAG                        111.000
               C                                                            112.000
               C    INITIALIZATION:                                         113.000
0006                DO 1 I=1,5                                              114.000
0007                IFLAG(I)=0                                              115.000
0008                PRCLAS(I)=0.                                            116.000
0009                DO 1 J=1,NEL                                            117.000
0010                DO 1 K=1,NQUANT                                         118.000
0011           1    PRCOND(I,J,K)=0.                                        119.000
               C                                                            120.000
               C    USE TRAINING DATA TO ESTIMATE PROB DISTRIBUTIONS:       121.000
0012                IF(LOW.NE.1)GO TO 2                                     122.000
0013                IA=IEND+1                                               123.000
0014                IB=NSAMP                                                124.000
0015           5    DO 3 I=IA,IB                                            125.000
0016                II=LEV(I)+1                                             126.000
0017                DO 4 J=1,NEL                                            127.000
0018           4    PRCOND(II,J,IX(I,J))=PRCOND(II,J,IX(I,J))+1.            128.000
0019           3    PRCLAS(II)=PRCLAS(II)+1.                                129.000
0020                IF(IB.EQ.NSAMP)GO TO 6                                  130.000
0021                IF(IEND.EQ.NSAMP)GO TO 6                                131.000
0022                IA=IEND+1                                               132.000
0023                IB=NSAMP                                                133.000
0024                GO TO 5                                                 134.000
0025           2    IA=1                                                    135.000
0026                IB=LOW-1                                                136.000
0027                GO TO 5                                                 137.000
               C                                                            138.000
               C    CHECK TRAINING DATA FOR UNREPRESENTED CLASSES:          139.000
               C    AND FOR CLASSES WITH ONE SAMPLE ONLY:                   140.000
0028           6    DO 9 K=1,5                                              141.000
0029                KK=K-1                                                  142.000
0030                IF(PRCLAS(K).EQ.0.)IFLAG(K)=1                           143.000
0031           9    IF(PRCLAS(K).EQ.0.)WRITE(6,10)KK                        144.000
0032           10   FORMAT(' * WARNING: NO TRAINING SAMPLES FOR LEVEL',I3)  145.000
               C                                                            146.000
               C    APPLY BAYES ESTIMATION PROCEDURE TO PROB MATRICES:      147.000
0033                S=PRCLAS(1)+PRCLAS(2)+PRCLAS(3)+PRCLAS(4)+PRCLAS(5)     148.000
0034                DO 7 I=1,5                                              149.000
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```
0035            DO 8 J=1,NEI                                                    150.000
0036            DO 8 K=1,NQUANT                                                 151.000
0037          8 PRCOND(I,J,K)=(PRCOND(I,J,K)+1.)/(PRCLAS(I)+FLOAT(NQUANT))     152.000
0038          7 PRCLAS(I)=(PRCLAS(I)+1.)/(S+5.)                                 153.000
0039            RETURN                                                          154.000
0040            END                                                             155.000
0001            SUBROUTINE TEST(LOW,IEND,NEI,IPRINT,IPROB)                      156.000
              C                                                                 157.000
0002            INTEGER IFLAG(5),IX(500,80),LEV(500),NUMP(500)                  158.000
0003            REAL CLASSM(5,5),PRCOND(5,80,128),PRCLAS(5),PTEST(5)            159.000
0004            COMMON /CMAIN/ IX,LEV,NUMP                                      160.000
0005            COMMON /TST/ PRCOND,PRCLAS,IFLAG                                161.000
0006            COMMON /PRNT/ CLASSM                                            162.000
              C                                                                 163.000
              C   INITIALIZATION ON FIRST SUBR CALL:                           164.000
0007            IF(LOW.NE.1)GO TO 1                                             165.000
0008            DO 2 I=1,5                                                      166.000
0009            DO 2 J=1,5                                                      167.000
0010          2 CLASSM(I,J)=0.                                                  168.000
              C                                                                 169.000
              C   GET CLASS CONDITIONAL PROB ESTIMATES FOR TESTING SAMPLE(S):   170.000
0011          1 DO 10 I=LOW,IEND                                                171.000
0012            IF(IFLAG((LEV(I)+1)).EQ.1)GO TO 11                              172.000
0013            DO 3 K=1,5                                                      173.000
0014          3 PTEST(K)=0.                                                     174.000
0015            DO 4 ICLASS=1,5                                                 175.000
0016            DO 4 IEL=1,NEI                                                  176.000
0017          4 PTEST(ICLASS)=PTEST(ICLASS)+ALOG(PRCOND(ICLASS,IEL,IX(I,IEL)))  177.000
              C                                                                 178.000
              C   INCLUDE A PRIORI CLASS PROB'S AND ESTIMATE ANESTHESIA LEVEL:  179.000
0018            IF(IPROB.EQ.0)GO TO 5                                           180.000
0019            DO 6 ICLASS=1,5                                                 181.000
0020          6 PTEST(ICLASS)=PTEST(ICLASS)+ALOG(PRCLAS(ICLASS))                182.000
0021          5 IR=1                                                            183.000
0022            DO 7 ICLASS=2,5                                                 184.000
0023          7 IF(PTEST(ICLASS).GT.PTEST(IR))IR=ICLASS                         185.000
              C                                                                 186.000
              C   UPDATE CLASSIFICATION MATRIX AND PRINT RESULTS IF DESIRED:    187.000
0024            II=LEV(I)+1                                                     188.000
0025            CLASSM(II,IR)=CLASSM(II,IR)+1.                                  189.000
0026            IF(IPRINT.NE.0)GO TO 10                                         190.000
0027            IRR=IR-1                                                        191.000
0028            IF(II.NE.IR)WRITE(6,8)I,LEV(I),IRR,NUMP(I)                      192.000
0029            IF(II.EQ.IR)WRITE(6,9)I,NUMP(I),LEV(I)                          193.000
0030         11 IF(IFLAG((LEV(I)+1)).EQ.1)WRITE(6,12)LEV(I)                     194.000
0031         12 FORMAT(' LEVEL',I2,' NOT TESTED: ONLY ONE SAMPLE')              195.000
0032          8 FORMAT(5X,I3,'  WAS MISCLASSIFIED',I3,'-->',I1,5X,'#',I3)       196.000
0033          9 FORMAT(5X,I3,'  (#',I3,')  IS OK: LEVEL',I2)                   197.000
0034         10 CONTINUE                                                        198.000
0035            RETURN                                                          199.000
0036            END                                                             200.000
0001            SUBROUTINE PRINT(NSAMP,NEI,NQUANT,IPROB,NPINT)                  201.000
              C                                                                 202.000
0002            REAL CLASSM(5,5),TOTAL(5),TOK/0./,TOT/0./                       203.000
0003            COMMON /PRNT/ CLASSM                                            204.000
0004            WRITE(6,30)NPINT                                                205.000
0005         30 FORMAT(/5X,'SUBJECT NUMBER: ',I3)                               206.000
0006            WRITE(6,12)NSAMP                                                207.000
0007         12 FORMAT(5X,'TOTAL NUMBER OF PATTERN SAMPLES=',I3)                208.000
0008            WRITE(6,15)                                                     209.000
0009         15 FORMAT(5X,'METHOD OF PERFORMANCE ESTIMATION: "U" METHOD"')      210.000
0010         16 FORMAT(5X,'METHOD OF PERFORMANCE ESTIMATION: "PI METHOD"')      211.000
0011            IF(IPROB.NE.0)WRITE(6,13)                                       212.000
0012            IF(IPROB.EQ.0)WRITE(6,14)                                       213.000
0013         13 FORMAT(5X,'UNEQUAL A PRIORI CLASS PROBABILITIES WERE USED')     214.000
0014         14 FORMAT(5X,'EQUAL A PRIORI CLASS PROBABILITIES WERE USED')       215.000
0015            WRITE(6,17)NEI,NQUANT                                           216.000
0016         17 FORMAT(5X,I2,' ELEMENTS IN FEATURE VECTOR WITH',I4,' QUANTIZATION 217.000
                1LEVELS PER FEATURE')                                           218.000
              C                                                                 219.000
0017            DO 50 I=1,5                                                     220.000
0018         50 TOTAL(I)=0.                                                     221.000
0019            OK=0.                                                           222.000
0020            WRITE(6,18)                                                     223.000
0021         18 FORMAT(//10X,'CLASSIFICATION MATRIX:'//)                        224.000
0022            DO 19 I=1,5                                                     225.000
0023            DO 20 J=1,5                                                     226.000
0024         20 TOTAL(I)=TOTAL(I)+CLASSM(I,J)                                   227.000
0025            OK=OK+CLASSM(I,I)                                               228.000
0026         19 WRITE(6,21)(CLASSM(I,J),J=1,5),TOTAL(I)                         229.000
0027            T=TOTAL(1)+TOTAL(2)+TOTAL(3)+TOTAL(4)+TOTAL(5)                  230.000
```

```
0028          21   FORMAT(10X,5F10.2,10X,F6.0)                                    231.000
0029               PERCNT=(CK/T)*100.                                             232.000
0030               WRITE(6,22) PERCNT,OK                                          233.000
0031          22   FORMAT(///5X,'***',F8.3,' PERCENT OF',F5.0,' SAMPLES WERE CLASSIFI  234.000
                  1ED CORRECTLY.'/)                                              235.000
0032               TOK=TOK+CK                                                     236.000
0033               TOT=TOT+T                                                      237.000
0034               TP=(TOK/TOT)*100.                                              238.000
0035               WRITE(6,51)TOK,TOT,TP                                          239.000
0036          51   FORMAT(5X,'***  TOTAL CORRECT: ',F4.0,' OF ',F4.0,' SAMPLES'  240.000
                  1,10X,'(',F6.2,')')                                            241.000
              C                                                                  242.000
0037               WRITE(6,11)                                                    243.000
0038          11   FORMAT('1')                                                    244.000
0039               RETURN                                                         245.000
0040               END                                                            246.000
```

APPENDIX H

EVALUATION OF K-S STATISTICS FOR EEG AMPLITUDE DISTRIBUTIONS

```
                C-------------------------------------------------------------------
                C  APPENDIX H  EVALUATION OF K-S STATISTICS FOR EEG AMPLITUDE DISTRIB'S
                C
                C  THIS PROGRAM CALCULATES D1 (FOR GAUSSIANITY) AND D2 (FOR FIRST-ORDER
                C  STATIONARITY) FOR EEG DATA SAMPLED AT A RATE OF 64 HZ. THE DATA HAS
                C  PREVIOUSLY BEEN (DIGITALLY) HP FILTERED AT 0.54 HZ AND LP FILTERED AT
                C  30.0 HZ.
                C  INPUT:
                C           *LUNIT 3: INPUT DATA TAPE
                C           *LUNIT 5: NUMBERS OF THE TAPE FILES TO BE ANALYSED
                C  OUTPUT:
                C           *LUNIT 1: K-S D1 VALUES
                C           *LUNIT 2: K-S D2 VALUES
                C  LAST UPDATE:
                C           JUNE 25 1974
                C-------------------------------------------------------------------
                C
0001                 INTEGER I1/1/,I2/2/,NREC/0/
0002                 REAL XA(4096),XB(4096),D(7,2,64,60)
0003                 INTEGER NSAMP/8192/,NFLAG/0/,NCHAN/4/
0004                 REAL DATA(8192)
0005                 COMMON /DATA/ DATA,INDEXF
0006                 INDEXF=0
0007                 SIGLEV=0.05
0008                 SRATE=64.
                C
                C  INPUT ONE CHANNEL OF DATA AND CHANGE SA RATE
0009                3    CALL INPUT(NFLAG,NCHAN)
0010                 IF(NFLAG.EQ.1)GO TO 44
0011                 NREC=NREC+1
0012                 DO 10 K=2,8192,2
0013                 KK=K/2
0014                10    DATA(KK)=DATA(K)
                C
                C   TEST SEGMENTS OF 2**N SEC DURATION,N=0,...,6
0015                 DO 1000 K=1,7
0016                 NSEC=2**(K-1)
0017                 N=(NSEC*SRATE)+0.1
0018                 NQ=N-1
0019                 MQ=(N/2)-1
0020                 CALL KS(NQ,SIGLEV,I1,DTHEO1)
0021                 CALL KS(MQ,SIGLEV,I2,DTHEO2)
0022                 WRITE(6,111)NSEC,NQ,MQ,DTHEO1,DTHEO2
0023                111  FORMAT('  NSEC=',I3,'  NQ=',I5,'  MQ=',I5,'  D1=',
                    1F9.6,'  D2=',F9.6)
                C
0024                 DO 4 JJ=NSEC,64,NSEC
0025                 LLIM=(JJ-NSEC)*SRATE+0.1
0026                 INDEX=JJ/NSEC
                C
0027                 DO 5 JJJ=1,N
0028                 XA(JJJ)=DATA(IIIM+JJJ)
0029                5    XB(JJJ)=DATA(LLIM+JJJ)
                C
                C   CALCULATE THE D VALUES AND STORE THEM
0030                 M=N/2
0031                 CALL CDFDEV(XB(1),XB(M+1),M,D2)
0032                 CALL DNCRMD(XA,XB,N,D1)
0033                 D(K,I2,INDEX,NREC)=D2
0034                4    D(K,I1,INDEX,NREC)=D1
0035                1000 CONTINUE
0036                 GO TO 3
                C
                C   OUTPUT  ALL D VALUES
0037                44   DO 45 K=1,7
0038                 LIM=64/(2**(K-1))
0039                 DO 45 IREC=1,NREC
0040                 WRITE(I1,46)(D(K,I1,LL,IREC),LL=1,LIM)
```

```
0041          45    WRITE(I2,46)(D(K,I2,LL,IREC),LL=1,LIM)                    69.000
0042          46    FORMAT(64F8.6)                                            70.000
0043                STOP                                                      71.000
0044                END                                                       72.000
0001                SUBROUTINE INPUT(NFLAG,ICH)                               73.000
              C   READS IN ONE CHANNEL OF DATA SAMPLED AT 128 HZ.             74.000
              C                                                               75.000
0002                REAL DATA(8192)                                           76.000
0003                COMMON /DATA/ DATA,INDEXF                                 77.000
0004                INTEGER*2 BLOCK(2048),LEN1                                78.000
0005                LUNIT=3                                                   79.000
0006                NSKIP=0                                                   80.000
              C                                                               81.000
              C     READ THE FILE NO                                          82.000
0007                READ(5,20,END=10)NFILE                                    83.000
0008          20    FORMAT(I5)                                                84.000
0009                WRITE(6,12)NFILE                                          85.000
0010          12    FORMAT(' *****',I5)                                       86.000
              C                                                               87.000
              C     PREPARE TO SKIP TO THE APPROPRIATE FILE                   88.000
0011                ITEMP=NFILE-INDEXF-1                                      89.000
0012                CALL SKIP(ITEMP,NSKIP,LUNIT)                              90.000
0013                INDEXF=NFILE-1                                            91.000
              C                                                               92.000
0014                DO 14 IBLK=1,16                                           93.000
0015                INDX=(IBLK-1)*512                                         94.000
0016                CALL READ(BLOCK,LEN1,0,LINE1,LUNIT,&10)                   95.000
0017                DO 14 ISAM=1,2048,4                                       96.000
0018                IR=INDX+1+(ISAM-1)/4                                      97.000
0019                IRR=(ICH-1)+ISAM                                          98.000
0020          14    DATA(IR)=BLOCK(IRR)                                       99.000
              C                                                              100.000
0021                RETURN                                                 101.000
0022          10    NFLAG=1                                                102.000
0023                RETURN                                                 103.000
0024                END                                                    104.000
0001                SUBROUTINE DNORMD(X1,X2,N,D)                           105.000
              C                                                              106.000
              C     THIS SUBR PERFORMS THE FOLLOWING FCNS:                   107.000
              C       1.COMPUTES THE CDF FOR DATA IN X1                      108.000
              C       2.GETS SAMPLE MEAN AND VAR VIA "STAT"                  109.000
              C       3. CALCULATES A CDF FOR THE CORRESPONDING              110.000
              C         NORMAL DISTN                                         111.000
              C       4.FINDS THE MAX DEV BETWEEN THE TWO CDF'S              112.000
              C                                                              113.000
0002                REAL X1(N),X2(N)                                       114.000
0003                ID=0                                                   115.000
0004                RN=N                                                   116.000
              C                                                              117.000
              C   FIRST,COMPUTE THE DIST FCN BY SORTING ARRAY VAL'S         118.000
0005                CALL SSORT(X1,N,3,&10,&10)                             119.000
0006                GO TO 2                                                120.000
0007          10    WRITE(6,1)                                             121.000
0008          1     FORMAT(' **** SORTING ERROR ****')                     122.000
0009                RETURN                                                 123.000
              C                                                              124.000
              C     CALC A CDF FOR A NORMAL DIST WITH SAMPLE MEAN            125.000
              C     AND VARIANCE.                                            126.000
0010             2  CALL STAT(X1,N,AVER,SDEV)                              127.000
0011                DO 100 JJ=1,N                                          128.000
0012                ZUL=(X1(JJ)-AVER)/SDEV                                 129.000
0013          100   X2(JJ)=0.5*ERF(ZUL/1.41421)+0.5                        130.000
              C                                                              131.000
              C   NEXT,FIND MAX DEV BETWEEN ARRAY INDICES FOR EACH SUCCESSIVE VAL  132.000
              C   OF X,USING X1 AS THE STANDARD.NOTE:ARRAY INDEX 1->N IS EQUIV TO  133.000
              C   0->N-1 OR 0->1                                             134.000
0014                D=0.                                                   135.000
0015                DO 3 J=1,N                                             136.000
0016                DEV=ABS((FLOAT(J)/FLOAT(N))-X2(J))                     137.000
0017          3     IF(DEV.GT.D)D=DEV                                      138.000
              C                                                              139.000
0018                RETURN                                                 140.000
0019                END                                                    141.000
0001                SUBROUTINE STAT(ARRAY,N,AVER,SDEV)                     142.000
              C     THIS SUBR COMPUTES THE MEAN AND STANDARD DEVIATION OF THE  143.000
              C     SAMPLES STORED IN ARRAY(N).......                        144.000
              C                                                              145.000
              C INITIALIZATION                                             146.000
0002                DIMENSION ARRAY(N)                                     147.000
0003                SUM=0.                                                 148.000
0004                SVAR=0.                                                149.000
0005                RN=N                                                   150.000
              C                                                              151.000
              C MEAN:                                                      152.000
0006                DO 1 J=1,N                                             153.000
0007          1     SUM=SUM+ARRAY(J)                                       154.000
```

```
0008              AVER=SUM/RN                                                  155.000
                C                                                              156.000
                C SAMPLE VARIANCE:                                             157.000
0009              DO 3 L=1,N                                                   158.000
0010              Z=ARRAY(L)-AVER                                              159.000
0011            3 SVAR=SVAR+Z*Z                                                160.000
0012              SVAR=SVAR/(RN-1.)                                            161.000
0013              SDEV=SQRT(SVAR)                                              162.000
0014              RETURN                                                       163.000
0015              END                                                          164.000
0001              SUBROUTINE KS(NSAMP,SIGLEV,NSIDES,DCRIT)                     165.000
                C                                                              166.000
                C   THIS SUBR FINDS THE CRIT VALUE OF D FOR THE ONE-SAMPLE     167.000
                C   OR 2-SAMPLE K-S TEST AT THESE LEVELS OF SIGNIFICANCE:      168.000
                C    /0.01,0.05,0.10,0.15,0.20 /                               169.000
                C   VALUES FOR THE ONE-SAMPLE TEST ARE FROM JASA,P399,1967.    170.000
                C   VALUES FOR 2-SAMPLE TEST FROM AN.M.STAT.,P279,1948.        171.000
                C   RESTRICTIONS:SAMPLES MUST BE GREATER THAN 100 AND IN       172.000
                C   THE 2-SAMPLE TEST,SIZES MUST BE EQUAL.                     173.000
                C                                                              174.000
0002              REAL DNKS(5)/1.031,0.886,0.805,0.768,0.736/                  175.000
0003              REAL TWOKS(5)/1.63,1.36,1.22,1.14,1.07/                      176.000
0004              I=0                                                          177.000
0005              RN=NSAMP                                                     178.000
0006              ROOT=SQRT(RN)                                                179.000
                C                                                              180.000
0007              IF(SIGLEV.EQ.0.01)I=1                                        181.000
0008              IF(SIGLEV.EQ.0.05)I=2                                        182.000
0009              IF(SIGLEV.EQ.0.10)I=3                                        183.000
0010              IF(SIGLEV.EQ.0.15)I=4                                        184.000
0011              IF(SIGLEV.EQ.0.20)I=5                                        185.000
0012              IF(I.EQ.0)WRITE(6,1)                                         186.000
0013            1 FORMAT('   *** ERROR IN KS ***  ')                          187.000
                C                                                              188.000
                C   GOODNESS OF FIT TEST (WITH MEAN AND VAR UNKNOWN)          189.000
0014              IF(NSIDES.EQ.2)GO TO 2                                       190.000
0015              IF(NSIDES.NE.1)WRITE(6,1)                                    191.000
0016              DCRIT=DNKS(I)/ROOT                                           192.000
0017              RETURN                                                       193.000
                C                                                              194.000
                C   TWO SAMPLE TEST (EQUAL SAMPLE SIZES)                       195.000
0018            2 FACTOR=SQRT(2./RN)                                           196.000
0019              DCRIT=FACTOR*TWOKS(I)                                        197.000
0020              RETURN                                                       198.000
0021              END                                                          199.000
0001              SUBROUTINE CDFDEV(X1,X2,N,D)                                 200.000
                C                                                              201.000
                C   THIS SUBR TAKES TWO ARRAYS OF EQUAL SIZE,COMPUTES THE DIST FCN FOR  202.000
                C   EACH,AND THEN CALCULATES THE MAXIMUM-DEVIATION BETWEEN THE TWO DIST 203.000
                C   FCNS....JAN 23,1970.                                       204.000
                C                                                              205.000
0002              REAL X1(N),X2(N)                                             206.000
0003              ID=0                                                         207.000
                C                                                              208.000
                C   FIRST,COMPUTE THE 2 DIST FCNS BY SORTING ARRAY VAL'S       209.000
0004              CALL SSORT(X1,N,3,&10,&10)                                   210.000
0005              CALL SSORT(X2,N,3,&10,&10)                                   211.000
0006              GO TO 2                                                      212.000
0007           10 WRITE(6,1)                                                   213.000
0008            1 FORMAT(' **** SORTING ERROR *****')                          214.000
0009              RETURN                                                       215.000
                C                                                              216.000
                C   NEXT,FIND MAX DEV BETWEEN ARRAY INDICES FOR EACH SUCCESSIVE VAL    217.000
                C   OF X,USING X1 AS THE STANDARD.NOTE:ARRAY INDEX 1->N IS EQUIV TO    218.000
                C   0->N-1 OR 0->1                                             219.000
0010            2 DO 3 J=1,N                                                   220.000
0011              XTEMP=X1(J)                                                  221.000
                C                                                              222.000
0012              DO 4 K=J,N                                                   223.000
0013              IF(X2(K).GE.XTEMP)GO TO 7                                    224.000
0014            4 CONTINUE                                                     225.000
0015            7 DO 6 IZZ=1,K                                                 226.000
0016              IZ=IZZ-1                                                     227.000
0017              IF(X2(K-IZ).LE.XTEMP)GO TO 5                                 228.000
0018            6 CONTINUE                                                     229.000
                C                                                              230.000
0019            5 IDTEMP=IABS(J-K+IZ)                                          231.000
0020              IF(IDTEMP.GT.ID)ID=IDTEMP                                    232.000
0021            3 CONTINUE                                                     233.000
                C                                                              234.000
                C   NOW,COMPUTE THE TRUE VAL OF DEVIATION D FOR USE IN 2 SAMPLE        235.000
                C   K-S TEST.                                                  236.000
0022              D=FLOAT(ID)/FLOAT((N-1))                                     237.000
0023              RETURN                                                       238.000
0024              END                                                          239.000
```

APPENDIX I

EVALUATION OF K-S STATISTICS FOR EEG SPECTRAL DISTRIBUTIONS

```
      C-------------------------------------------------------------------- 1.000
      C  APPENDIX I   EVALUATION OF K-S STATISTICS FOR EEG SPECTRAL DISTRIB'S 2.000
      C                                                                     3.000
      C  THIS PROGRAM CALCULATES D2 (FOR SPECTRAL DISTRIBUTION FUNCTIONS) FOR 4.000
      C  EEG DATA SAMPLED AT A RATE OF 128 HZ. THE DATA HAS PREVIOUSLY BEEN  5.000
      C  (DIGITALLY) HP FILTERED AT 0.54 HZ AND LP FILTERED AT 30.0 HZ.      6.000
      C  INPUT:                                                             7.000
      C           *LUNIT 3: INPUT DATA TAPE                                 8.000
      C           *LUNIT 5: NUMBERS OF THE TAPE FILES TO BE ANALYSED        9.000
      C  OUTPUT:                                                           10.000
      C           *LUNIT 2: K-S D2 (SPECTRAL) VALUES                       11.000
      C  LAST UPDATE:                                                      12.000
      C           JUNE 25 1974                                             13.000
      C-------------------------------------------------------------------- 14.000
      C                                                                     15.000
0001        INTEGER I1/1/,I2/2/,NREC/0/                                     16.000
0002        REAL SMOOTH(2049),S2(2049),D(7,64,60)                           17.000
0003        COMMON /SMOOTH/ SMOOTH                                          18.000
0004        INTEGER NSAMP/8192/,NFLAG/0/,NCHAN/4/                           19.000
0005        REAL DATA(8192),DATB(4098)                                      20.000
0006        COMMON /TRAN/ DATE                                              21.000
0007        COMMON /DATA/ DATA,INDEXF                                       22.000
0008        INDEXF=0                                                        23.000
0009        SIGLEV=0.05                                                     24.000
0010        SRATE=128.                                                      25.000
      C                                                                     26.000
      C  INPUT ONE CHANNEL OF DATA.                                         27.000
0011   3    CALL INPUT(NFLAG,NCHAN)                                         28.000
0012        IF(NFLAG.EQ.1)GO TO 44                                          29.000
0013        NREC=NREC+1                                                     30.000
      C                                                                     31.000
      C   TEST SEGMENTS OF 2**N SEC DURATION,N=0,...,6                     32.000
0014        DO 1000 K=1,7                                                   33.000
0015        NSEC=2**(K-1)                                                   34.000
0016        N=(NSEC*SRATE)+0.1                                              35.000
0017        ISPEC=(NSEC*64)/2+1                                             36.000
0018        NX=NSEC+1                                                       37.000
0019        IX=ISPEC-(2*NSEC)                                               38.000
0020        ISTHEO=IX-NX                                                    39.000
0021        CALL KS(ISTHEO,SIGLEV,I2,DTHECR)                                40.000
0022        WRITE(6,111)NSEC,ISTHEO,DTHEOR                                  41.000
0023   111  FORMAT('  NSEC=',I3,'    ISTHEC=',I5,'    DTHEOR=',F9.6)       42.000
      C                                                                     43.000
0024        DO 4 JJ=NSEC,64,NSEC                                            44.000
0025        LLIM=(JJ-NSEC)*SRATE+0.1                                        45.000
0026        INDEX=JJ/NSEC                                                   46.000
      C                                                                     47.000
      C   CALCULATE THE D VALUES AND STORE THEM                            48.000
      C   NOTE: ONLY THE SPECTRAL VALUES FROM 1-30 HZ ARE COMPARED.        49.000
0027        M=N/2                                                           50.000
0028        D3=1.                                                           51.000
0029        DO 33 J=1,M                                                     52.000
0030   33   DATB(J)=DATA(LLIM+J)                                            53.000
0031        CALL SPECT(M,SRATE)                                             54.000
0032        DO 331 J=1,ISPEC                                                55.000
0033   331  S2(J)=SMOOTH(J)                                                 56.000
0034        DO 332 J=1,M                                                    57.000
0035   332  DATB(J)=DATA(LLIM+M+J)                                          58.000
0036        CALL SPECT(M,SRATE)                                             59.000
0037        CALL CDFDEV(SMOOTH(NX),S2(NX),IX,D3)                            60.000
0038   4    D(K,INDEX,NREC)=D3                                              61.000
0039   1000 CONTINUE                                                       62.000
0040        GO TO 3                                                         63.000
      C                                                                     64.000
      C   OUTPUT  ALL D VALUES                                            65.000
0041   44   DO 45 K=1,7                                                     66.000
0042        LIM=64/(2**(K-1))                                               67.000
0043        DO 45 IREC=1,NREC                                               68.000
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```
0044          45    WRITE(I2,46)(D(K,IL,IREC),IL=1,LIM)                                  69.000
0045          46    FORMAT(6(F8.6)                                                       70.000
0046                STOP                                                                 71.000
0047                END                                                                  72.000
0001                SUBROUTINE SPECT(N,SRATE)                                            73.000
              C     COMPUTES THE POWER SPECTRUM VIA METHOD OF DUMERMUTH ET AL,           74.000
              C     IEEE TRANS AUDIO DEC '70.                                            75.000
0002                COMPLEX TRAN(2049)                                                   76.000
0003                REAL DATA(4096)                                                      77.000
0004                COMMON / TRAN / TRAN                                                 78.000
0005                EQUIVALENCE (TRAN,DATA)                                              79.000
0006                REAL SMOOTH(2049)                                                    80.000
0007                COMMON / SMOOTH / SMOOTH                                             81.000
0008                INTEGER NN(1)                                                        82.000
0009                REAL PI/3.141592/                                                    83.000
              C                                                                        84.000
              C     WINDOW DATA BEFORE FFT...SEE EEG HANDBOOK,V5-A,P50                  85.000
0010                LLIM=(N/10)+1                                                        86.000
0011                LIMUP=N-LLIM                                                         87.000
0012                XINT=FLOAT(LLIM)                                                     88.000
0013                DO 1 IQ=1,LLIM                                                       89.000
0014           1    DATA(IQ)=DATA(IQ)*0.5*(1.-COS(PI*FLOAT(IQ)/XINT))                    90.000
0015                DO 2 IQ=LIMUP,N                                                      91.000
0016           2    DATA(IQ)=DATA(IQ)*0.5*(1.-COS(PI*FLOAT(N-IQ)/XINT))                  92.000
              C                                                                        93.000
              C     GET RAW SPECTRAL ESTIMATES VIA FFT ----------------------------      94.000
0017                NN(1)=N                                                              95.000
0018                ISIGN=-1                                                             96.000
0019                CALL FOUR2(DATA,NN,1,ISIGN,0)                                        97.000
0020                DELT=1./SRATE                                                        98.000
              C     NOTE:EXTRA FACTOR NEEDED BECAUSE OF TAPER;(SPECTRA ARE 1-SIDED)      99.000
0021                FACTOR=(DELT/FLOAT(N))*1.14625                                      100.000
0022                MID=N/2+1                                                           101.000
0023                DO 99 I=1,MID                                                       102.000
0024                T=CABS(TRAN(I))                                                     103.000
0025                DATA(I)=T*T*FACTOR                                                  104.000
0026           99   CONTINUE                                                            105.000
              C                                                                       106.000
              C     SMOOTHED SPECTRAL ESTIMATES OBTAINED VIA SQUARE WINDOW (2W+1)=7     107.000
              C     THE FIRST AND LAST 3 POINTS ARE NOT SMOOTHED                        108.000
0027                DO 52 I=1,3                                                         109.000
0028           52   SMOOTH(I)=DATA(I)                                                   110.000
0029                DO 11 I=1,3                                                         111.000
0030           11   SMOOTH(MID-3+I)=DATA(MID-3+I)                                       112.000
              C                                                                       113.000
0031                LIM=MID-3                                                           114.000
0032                DO 50 I=4,LIM                                                       115.000
0033                SUM=0.                                                              116.000
0034                DO 51 J=1,7                                                         117.000
0035           51   SUM=SUM+DATA((I-1) J-3)                                             118.000
0036                SMOOTH(I)=SUM/7.                                                    119.000
0037           50   CONTINUE                                                            120.000
0038                RETURN                                                              121.000
0039                END                                                                 122.000
0001                SUBROUTINE INPUT(NFLAG,ICH)                                         123.000
              C   READS IN ONE CHANNEL OF DATA SAMPLED AT 128 HZ.                       124.000
              C                                                                       125.000
0002                REAL DATA(8192)                                                     126.000
0003                COMMON /DATA/ DATA,INDEXF                                           127.000
0004                INTEGER*2 BLOCK(2048),LEN1                                          128.000
0005                LUNIT=3                                                             129.000
0006                NSKIP=0                                                             130.000
              C                                                                       131.000
              C     READ THE FILE NO                                                  132.000
0007                READ(5,20,END=10)NFILE                                              133.000
0008           20   FORMAT(I5)                                                          134.000
0009                WRITE(6,12)NFILE                                                    135.000
0010           12   FORMAT(' *****',I5)                                                 136.000
              C                                                                       137.000
              C     PREPARE TO SKIP TO THE APPROPRIATE FILE                           138.000
0011                ITEMP=NFILE-INDEXF-1                                                139.000
0012                CALL SKIP(ITEMP,NSKIP,LUNIT)                                        140.000
0013                INDEXF=NFILE-1                                                      141.000
              C                                                                       142.000
0014                DO 14 IBLK=1,16                                                     143.000
0015                INDX=(IBLK-1)*512                                                   144.000
0016                CALL READ(BLOCK,LEN1,0,LINE1,LUNIT,&10)                             145.000
0017                DO 14 ISAM=1,2048,4                                                 146.000
0018                IR=INDX+1+(ISAM-1)/4                                                147.000
0019                IRR=(ICH-1)+ISAM                                                    148.000
0020           14   DATA(IR)=BLOCK(IRR)                                                 149.000
              C                                                                       150.000
```

```
0021            RETURN                                                  151.000
0022          10  NFLAG=1                                                152.000
0023            RETURN                                                  153.000
0024            END                                                     154.000
0001            SUBROUTINE STAT(ARRAY,N,AVER,SDEV)                      155.000
              C     THIS SUBR COMPUTES THE MEAN AND STANDARD DEVIATION OF THE 156.000
              C     SAMPLES STORED IN ARRAY(N).......                     157.000
              C                                                           158.000
              C INITIALIZATION                                          159.000
0002            DIMENSION ARRAY(N)                                      160.000
0003            SUM=0.                                                  161.000
0004            SVAR=0.                                                 162.000
0005            RN=N                                                    163.000
              C                                                         164.000
              C MEAN:                                                   165.000
0006            DO 1 J=1,N                                              166.000
0007          1 SUM=SUM+ARRAY(J)                                        167.000
0008            AVER=SUM/RN                                             168.000
              C                                                         169.000
              C SAMPLE VARIANCE:                                        170.000
0009            DO 3 L=1,N                                              171.000
0010            Z=ARRAY(L)-AVER                                         172.000
0011          3 SVAR=SVAR+Z*Z                                           173.000
0012            SVAR=SVAR/(RN-1.)                                       174.000
0013            SDEV=SQRT(SVAR)                                         175.000
0014            RETURN                                                  176.000
0015            END                                                     177.000
0001            SUBROUTINE KS(NSAMP,SIGLEV,NSIDES,DCRIT)                178.000
              C                                                         179.000
              C    THIS SUBR FINDS THE CRIT VALUE OF D FOR THE ONE-SAMPLE 180.000
              C    OR 2-SAMPLE K-S TEST AT THESE LEVELS OF SIGNIFICANCE: 181.000
              C     /0.01,0.05,0.10,0.15,0.20 /                         182.000
              C    VALUES FOR THE ONE-SAMPLE TEST ARE FROM JASA,P399,1967. 183.000
              C    VALUES FOR 2-SAMPLE TEST FROM AN.M.STAT.,P279,1948.  184.000
              C    RESTRICTIONS:SAMPLES MUST BE GREATER THAN 100 AND IN 185.000
              C    THE 2-SAMPLE TEST,SIZES MUST BE EQUAL.               186.000
              C                                                         187.000
0002            REAL DNKS(5)/1.031,0.886,0.805,0.768,0.736/             188.000
0003            REAL TWOKS(5)/1.63,1.36,1.22,1.14,1.07/                 189.000
0004            I=0                                                     190.000
0005            RN=NSAMP                                                191.000
0006            ROOT=SQRT(RN)                                           192.000
              C                                                         193.000
0007            IF(SIGLEV.EQ.0.01)I=1                                   194.000
0008            IF(SIGLEV.EQ.0.05)I=2                                   195.000
0009            IF(SIGLEV.EQ.0.10)I=3                                   196.000
0010            IF(SIGLEV.EQ.0.15)I=4                                   197.000
0011            IF(SIGLEV.EQ.0.20)I=5                                   198.000
0012            IF(I.EQ.0)WRITE(6,1)                                    199.000
0013          1 FORMAT('   *** ERROR IN KS ***  ')                     200.000
              C                                                         201.000
              C   GOODNESS OF FIT TEST (WITH MEAN AND VAR UNKNOWN)      202.000
0014            IF(NSIDES.EQ.2)GO TO 2                                  203.000
0015            IF(NSIDES.NE.1)WRITE(6,1)                               204.000
0016            DCRIT=DNKS(I)/ROOT                                      205.000
0017            RETURN                                                  206.000
              C                                                         207.000
              C   TWO SAMPLE TEST (EQUAL SAMPLE SIZES)                 208.000
0018          2 FACTOR=SQRT(2./RN)                                      209.000
0019            DCRIT=FACTOR*TWOKS(I)                                   210.000
0020            RETURN                                                  211.000
0021            END                                                     212.000
0001            SUBROUTINE CDFDEV(X1,X2,N,D)                            213.000
              C                                                         214.000
              C   THIS SUBR TAKES TWO ARRAYS OF EQUAL SIZE,COMPUTES THE DIST FCN FOR 215.000
              C   EACH,AND THEN CALCULATES THE MAXIMUM DEVIATION BETWEEN THE TWO DIST 216.000
              C   FCNS....JAN 23,1974.                                 217.000
              C                                                         218.000
0002            REAL X1(N),X2(N)                                        219.000
0003            ID=0                                                    220.000
              C                                                         221.000
              C   FIRST,COMPUTE THE 2 DIST FCNS BY SORTING ARRAY VAL'S  222.000
0004            CALL SSORT(X1,N,3,&10,&10)                              223.000
0005            CALL SSORT(X2,N,3,&10,&10)                              224.000
0006            GO TO 2                                                 225.000
0007          10 WRITE(6,1)                                             226.000
0008          1 FORMAT(' **** SORTING ERROR ****')                      227.000
0009            RETURN                                                  228.000
              C                                                         229.000
              C   NEXT,FIND MAX DEV BETWEEN ARRAY INDICES FOR EACH SUCCESSIVE VAL 230.000
              C   OF X,USING X1 AS THE STANDARD.NOTE:ARRAY INDEX 1->N IS EQUIV TO 231.000
```

```
      C   0->N-1 OR 0->1                                                    232.000
0010   2    DO 3 J=1,N                                                     233.000
0011        XTEMP=X1(J)                                                    234.000
      C                                                                    235.000
0012        DO 4 K=J,N                                                     236.000
0013        IF(X2(K).GE.XTEMP)GO TO 7                                      237.000
0014   4    CONTINUE                                                       238.000
0015   7    DO 6 IZZ=1,K                                                   239.000
0016        IZ=IZZ-1                                                       240.000
0017        IF(X2(K-IZ).LE.XTEMP)GO TO 5                                   241.000
0018   6    CONTINUE                                                       242.000
      C                                                                    243.000
0019   5    IDTEMP=IABS(J-K+IZ)                                            244.000
0020        IF(IDTEMP.GT.ID)ID=IDTEMP                                      245.000
0021   3    CONTINUE                                                       246.000
      C                                                                    247.000
      C   NOW, COMPUTE THE TRUE VAL OF DEVIATION D FOR USE IN 2 SAMPLE    248.000
      C   K-S TEST.                                                       249.000
0022        D=FLOAT(ID)/FLOAT((N-1))                                       250.000
0023        RETURN                                                         251.000
0024        END                                                            252.000
```

APPENDIX J

TESTS OF K-S STATISTICS

```
C-------------------------------------------------------------------------      1.000
C  APPENDIX J   TESTS OF K-S STATISTICS                                        2.000
C                                                                             3.000
C  THIS PROGRAM INTERPRETS THE SIGNIFICANCE OF THE K-S VALUES PRODUCED        4.000
C  BY MEANS OF THE PROGRAMS LISTED IN "APPENDIX H" AND "APPENDIX I".          5.000
C  INPUT:                                                                     6.000
C           *LUNIT  1: K-S D1 (AMPLITUDE) VALUES                              7.000
C           *LUNIT  2: K-S D2 (AMPLITUDE) VALUES                              8.000
C           *LUNIT  3: K-S D2 (SPECTRAL) VALUES                               9.000
C  OUTPUT:                                                                    10.000
C           *LUNIT  7: GAUSSIAN PERCENTAGES                                   11.000
C           *LUNIT  8: FIRST-ORDER STATIONARY PERCENTAGES                     12.000
C           *LUNIT  9: WIDE-SENSE STATIONARY PERCENTAGES                      13.000
C           *LUNIT 10: W-S STATIONARY AND GAUSSIAN PERCENTAGES                14.000
C  LAST UPDATE:                                                               15.000
C           JUNE 28 1974                                                      16.000
C-------------------------------------------------------------------------    17.000
C                                                                             18.000
0001        INTEGER I1/1/,I2/2/,L1/1/,L2/2/,L3/3/,L4/4/,ISKIP1/30/,ISKIP/0/   19.000
0002        REAL G(7)/7*0./,FS(7)/7*0./,WSS(7)/7*0./,WSSG(7)/7*0./            20.000
0003        INTEGER IG(7)/63,127,255,511,1023,2047,4095/                      21.000
0004        INTEGER IFS(7)/31,63,127,255,511,1023,2047/                       22.000
0005        INTEGER ISP(7)/29,58,116,232,464,928,1856/                        23.000
0006        REAL GKS(7),FSKS(7),SPKS(7),SIGLEV/0.05/,X(64),Y(64),Z(64)        24.000
C                                                                             25.000
C   CALCULATE VALUES FOR K-S TESTS AT SOME SIGNIFICANCE LEVEL:                26.000
0007          DO 1 I=1,7                                                      27.000
0008          CALL KS(IG(I),SIGLEV,I1,GKS(I))                                 28.000
0009          CALL KS(IFS(I),SIGLEV,I2,FSKS(I))                               29.000
0010          CALL KS(ISP(I),SIGLEV,I2,SPKS(I))                               30.000
0011          WRITE(6,102) IG(I),GKS(I),IFS(I),FSKS(I),ISP(I),SPKS(I)         31.000
0012       102  FORMAT('  IG=',I5,'  GKS=',F8.6,'  IFS=',I5,'  FSKS=',F8.6,'  ISP=  32.000
           1',I5,'  SPKS=',F8.6)                                               33.000
0013       1    CONTINUE                                                      34.000
C                                                                             35.000
C   INPUT D VALUES AND TEST THEM:                                             36.000
0014          CALL SKIP(0,ISKIP,1)                                            37.000
0015          CALL SKIP(0,ISKIP,2)                                            38.000
0016          CALL SKIP(0,ISKIP,3)                                            39.000
0017          DO 44 J=1,7                                                     40.000
0018          LIM=64/(2**(J-1));                                              41.000
0019          DO 4 N=1,30                                                     42.000
0020          READ(1,100) (X(L),L=1,LIM)                                      43.000
0021          READ(2,100) (Y(L),L=1,LIM)                                      44.000
0022          READ(3,100) (Z(L),L=1,LIM)                                      45.000
0023       100  FORMAT(64F8.6)                                                46.000
0024          DO 4  L=1,LIM                                                   47.000
0025          IF(X(L).LE.GKS(J))G(J)=G(J)+1.                                  48.000
0026          IF(Y(L).LE.FSKS(J))FS(J)=FS(J)+1.                               49.000
0027          IF((Z(L).LE.SPKS(J)).AND.(Y(L).LE.FSKS(J)))WSS(J)=WSS(J)+1.     50.000
0028          IF((Z(L).LE.SPKS(J)).AND.(Y(L).LE.FSKS(J)).AND.(X(L).LE.GKS(J)))  51.000
           1WSSG(J)=WSSG(J)+1.                                                52.000
0029       4    CONTINUE                                                      53.000
0030          CALL SKIP(0,ISKIP1,1)                                           54.000
0031          CALL SKIP(0,ISKIP1,2)                                           55.000
0032          CALL SKIP(0,ISKIP1,3)                                           56.000
0033       44   CONTINUE                                                      57.000
C                                                                             58.000
C   CALCULATE PERCENTAGES AND CORRECT FOR TYPE I ERRORS:                      59.000
0034          CORREC=1.-SIGLEV                                                60.000
0035          DO 5 J=1,7                                                      61.000
0036          DENOM=((64*30.)/(2**(J-1)))*CORREC                              62.000
0037          XX=J-1                                                          63.000
0038          G(J)=(G(J)/DENOM)*100.                                          64.000
0039          IF(G(J).GT.100.)G(J)=100.                                       65.000
0040          FS(J)=(FS(J)/DENOM)*100.                                        66.000
0041          IF(FS(J).GT.100.)FS(J)=100.                                     67.000
0042          WSS(J)=(WSS(J)/DENOM)*100.                                      68.000
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0043              IF(WSS(J).GT.100.)WSS(J)=100.                          69.000
0044              WSSG(J)=(WSSG(J)/DENOM)*100.                           70.000
                C                                                        71.000
                C   PREPARE A PLOTFILE:                                  72.000
0045              WRITE(7,13)XX,G(J),L4                                  73.000
0046              WRITE(8,13)XX,FS(J),L3                                 74.000
0047              WRITE(9,13)XX,WSS(J),L2                                75.000
0048             5  WRITE(10,13)XX,WSSG(J),L1                           76.000
0049            13  FORMAT(2F10.2,2X,I2)                                77.000
                C                                                        78.000
0050              DO 14 J=7,10                                           79.000
0051            14  WRITE(J,15)                                         80.000
0052            15  FORMAT('$ENDFILE')                                  81.000
0053              STOP                                                   82.000
0054              END                                                    83.000
0001              SUBROUTINE KS(NSAMP,SIGLEV,NSIDES,DCRIT)               84.000
                C                                                        85.000
                C   THIS SUBR FINDS THE CRIT VALUE OF D FOR THE ONE-SAMPLE  86.000
                C   OR 2-SAMPLE K-S TEST AT THESE LEVELS OF SIGNIFICANCE:  87.000
                C    /0.01,0.05,0.10,0.15,0.20 /                         88.000
                C   VALUES FOR THE ONE-SAMPLE TEST ARE FROM JASA,P399,1967.  89.000
                C   VALUES FOR 2-SAMPLE TEST FROM AN.M.STAT.,P279,1948.  90.000
                C   RESTRICTIONS:SAMPLES MUST BE GREATER THAN 100 AND IN  91.000
                C   THE 2-SAMPLE TEST,SIZES MUST BE EQUAL.               92.000
                C                                                        93.000
0002              REAL DNKS(5)/1.031,0.886,0.805,0.768,0.736/            94.000
0003              REAL TWOKS(5)/1.63,1.36,1.22,1.14,1.07/                95.000
0004              I=0                                                    96.000
0005              RN=NSAMP                                               97.000
0006              ROOT=SQRT(RN)                                          98.000
                C                                                        99.000
0007              IF(SIGLEV.EQ.0.01)I=1                                 100.000
0008              IF(SIGLEV.EQ.0.05)I=2                                 101.000
0009              IF(SIGLEV.EQ.0.10)I=3                                 102.000
0010              IF(SIGLEV.EQ.0.15)I=4                                 103.000
0011              IF(SIGLEV.EQ.0.20)I=5                                 104.000
0012              IF(I.EQ.0)WRITE(6,1)                                  105.000
0013            1 FORMAT('   *** ERROR IN KS ***  ')                   106.000
                C                                                       107.000
                C   GOODNESS OF FIT TEST (WITH MEAN AND VAR UNKNOWN)   108.000
0014              IF(NSIDES.EQ.2)GO TO 2                                109.000
0015              IF(NSIDES.NE.1)WRITE(6,1)                             110.000
0016              DCRIT=DNKS(I)/ROOT                                    111.000
0017              RETURN                                                112.000
                C                                                       113.000
                C   TWO SAMPLE TEST (EQUAL SAMPLE SIZES)               114.000
0018            2 FACTOR=SQRT(2./RN)                                    115.000
0019              DCRIT=FACTOR*TWOKS(I)                                 116.000
0020              RETURN                                                117.000
0021              END                                                   118.000
```

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