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REAL-TIME COMPUTER AIDED ANALYSIS OF THE ELECTROENCEPHALOGRAM: A TWO-DIMENSIONAL APPROACH

by

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A Thesis Submitted for the Degree of
Doctor of Philosophy

THE CITY UNIVERSITY
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LIST OF ABBREVIATIONS

Amplitude modulation - double sideband	AM-DSB
Computed tomography	CT
Spike enhancer	DIFMOD
Electroencephalogram / Electroencephalography	EEG
Electroencephalographer	EEGer
Fast Fourier transform	FFT
Finite impulse response	FIR
Frequency modulation	FM
International League Against Epilepsy	ILAE
Magnetic resonance imaging	MRI
Spike-and-(slow)-wave complex	SAWC
Slow wave	SW
Short-time Fourier transform	STFT
Triangle function	tri
World Health Organization	WHO

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DECLARATION

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ABSTRACT

This thesis is concerned with the application of computer aided measurement techniques to the analysis of electroencephalographic (EEG) signals. In particular, it deals with the detection of spike-and-slow-wave complexes (SAWCs) which are characteristic of the onset of an epileptic absence.

Numerous algorithms have been developed to provide the above detection and a review of some of the more important of these is presented. From this review, an alternative model and algorithm are developed based on an FIR (finite impulse response) filter, that represents a differentiator in series with a Hilbert transformer, followed by a cubic filter, which effectively reduces the background noise.

This algorithm, like its predecessors, suffers from the difficulty of where the detection levels should be set in order to achieve no missed features with no false alarms. An alternative approach is then investigated based on the Wigner Distribution, which provides a simultaneous time and frequency domain analysis. The results of this work are presented and appear to offer significant advantages over the more usual one-domain analyses.

Finally, some discussion of the results obtained and suggestions for further work are made, mainly in the area of improving the computational speed of the Wigner Distribution and associated SAWC detection algorithms.

CHAPTER 1

INTRODUCTION

Despite major advances in medical science, the origins and treatment of many conditions remain as elusive as they were in previous epochs. Disorders of the brain, many of which bring with them certain variations in behavioural patterns from the accepted norm, are perhaps still some of the least well understood and treatable conditions. In some cases there is an obvious physical reason for the disorder (e.g. brain damage, tumour, etc) but in many others there is no obvious cause. Perhaps one of the most well known of these disorders is epilepsy, to which reference has been made since the earliest of times.

In comparatively recent times, the medical profession has been provided with very effective drugs and electronic diagnostic aids to tackle this condition. It is the latter of these which forms the subject matter of this thesis. Clearly, the objective for any piece of equipment is to be as reliable and accurate as possible. This is especially true in the case of epilepsy as a wrong diagnosis can involve very serious implications for the patient. An incorrect positive indication can in many ways be more serious than an erroneous false result. Although not life threatening, anybody diagnosed as suffering from epilepsy will suffer a considerable disruption to their life; e.g. disqualification from certain types of employment, ineligi-

bility to hold a driving licence, inability to drink alcohol (which has an adverse reaction with anticonvulsant drugs), etc.

In addition to the above practical limitations, a person with epilepsy may be subjected to an increased level of stress. A full tonic-clonic epileptic fit can be a very disturbing and even frightening event to witness. Part of this fear is undoubtedly attributable to a lack of understanding of what is happening which has been compounded down the ages by such beliefs as a fit equates to some form of "demonic possession" (Engel Jr., 1989). Fortunately, the ideas of possession and mental illness are slowly being dispelled but many people still exhibit irrational fear towards those unfortunate enough to suffer this affliction. The resulting stress and possible isolation are very serious issues which, from the author's own experience, should not be underestimated.

It is clear from the above that any diagnostic aid to be used for the detection of epilepsy must be highly accurate. This however poses considerable problems, not least because human identification appears to be based more on an acquired intuitive basis rather than any rigorously defined set of rules. This makes it very difficult to define a set of criteria and hence develop a suitable model on which a decision could be based. Add to this the problems associated with the signal itself, which is of very low amplitude, non-stationary and, frequently, heavily corrupted by noise, and some idea of the magnitude of the problem becomes apparent.

One factor which has been generally accepted in recent years is the need for long-term monitoring for reliable diagno-

sis. This can create additional problems in terms of the volume of data to be analysed, and the manner in which it is collected; it is clearly unreasonable to expect the patient to spend long periods in an EEG laboratory physically attached to an EEG machine. Various techniques have been developed to permit long-term monitoring to be conducted in as near a normal environment as possible. These have been in the main, based on radio telemetry systems where the patient is reasonably free to move around a special flat which has been fitted with radio receivers which are in turn connected to a central computer.

The approach adopted and reported in this thesis involves a portable microprocessor based instrument. This is used to analyse the EEG record in real-time and, ultimately to record (on a cassette or other suitable medium) only those portions of the record where an abnormality is suspected. The work has concentrated on the development of a suitable model and signal processing techniques with which to perform the real-time analysis.

A review of some of the previous work in this area has been conducted and some of the algorithms and models which appeared to offer some prospect for real-time implementation were identified. A few of these were coded and run on a Motorola 68000 based system with varying degrees of success. From this work, a detection model was derived to identify the characteristic spike-and-wave complex, based on a Hilbert-transformed differentiator, a cubic filter and a level detector for the spike and a separate filter and level discriminator for the wave. The results of this work are recorded in Chapters 4 and 5 of this thesis.

The real-time detection method developed was tested with pre-recorded data and produced good results. However, it suffered from the common problem of having to trade with missed features against false alarms. For zero missed features, a number of false alarms arose and for zero false alarms, a number of features were missed. From comments made earlier in this chapter, neither case is acceptable.

This led to work on an alternative approach. From discussions with EEG technicians, it became apparent that human observations were in some subtle way based on a simultaneous time and frequency domain analysis. The terms "sharp" and "high frequency", "slow" and "low frequency" were constantly intermixed. This produced an interest in algorithms which offered such a capability and a technique known as the Wigner Distribution was identified as a possible candidate. This was implemented in a suitable format with quite startling results. A very characteristic output was obtained for the spike-and-wave complex from which it was comparatively easy to separate out other types of input (e.g. artifact bursts which are the most common cause of false alarms). The results of this work are recorded in Chapter 6.

Some work is still required before a fully engineered instrument based on the Wigner Distribution would be available for field trials. Some suggestions are made for further work at the end of the thesis. It is the author's opinion that , based on the initial results, the technique could prove to be of considerable importance in the future.

CHAPTER 2

EPILEPSY

2.1 - Introduction

During the last decades, many goals have been reached in the scientific world. For example, human beings have already put their feet on the Moon and interplanetary spacecraft have made what was known about distant planets more clear. Channels are dug under seas, organs are transplanted from person to person and surgery is carried out on babies still inside their mothers' wombs. However, despite all this progress and despite surgical interventions and modern drugs that have been synthesized in order to try to eliminate epileptic seizures, which have been known for the last 6000 years, these are still causing trouble to millions of people all over the globe every day.

Known over the centuries as "the sacred disease" or "the falling sickness", epilepsy was and unfortunately still is equated with spirit possession, both as a form of punishment for sin and as a type of mental illness. In fact it is just a condition characterized by recurrent events of cerebral origin, during which a disturbance of movement, sensation, consciousness and behaviour occurs (Sutherland and Tait, 1969).

New means of communication, including modern medical textbooks, have given the public more detailed information about

many modern diseases, but leave a very high percentage of the population uninformed about what epilepsy is and about what to do when a colleague at work or a person in the streets has an epileptic attack. For example, Lennox (1960) states that, in the fifth century B.C., 2.6% of the "Hippocratic writings" were about epilepsy whilst Engel Jr. (1989) states that the 1988 edition of the Cecil Textbook of Medicine has a chapter about epilepsy that constitutes 0.5% of the whole book.

To provide a full introduction to the subject of epilepsy, a general idea about the different types, their causes and consequences, the modern forms of diagnosis and treatment and the story of the author's own life as a person who has epilepsy will be included in this chapter.

2.2 - Epilepsies and Seizures

2.2.1 - Medical history

According to O. Temkin, in his book "The Falling Sickness" (1945), the first reference to epilepsy was made about 6000 years ago in the Babylonian Code of Hamurabi. It was related to the laws pertinent to the marriage and employment of people who had epilepsy. The Indian writings "Ayurvedic", from the same era, also contained a detailed description of epilepsy.

About the year 400 B.C., Hippocrates attributed seizures to a disorder of the brain and he and his disciples decided to abandon the term "sacred disease" (this term had been in use because of the general belief that those who had epileptic sei-

zures were possessed by evil spirits or gods and should be treated by the invocation of occult and religious powers). They knew that there was a relationship between skull fractures and seizures involving limbs on the opposite side of the body. The term epilepsy became more usual.

In the first century A.D., the Bible has some passages that describe typical epileptic seizures, where the patient is considered to be possessed by evil (see item 2.2.2). Five centuries later, Galen made another notable contribution by suggesting that there were also extracranial causes. He introduced the terms idiopathic or protopathic for epilepsies originating in the brain and sympathetic for those originating outside the brain. He also introduced the term aura for a certain kind of warning that the patient has before the attack.

Although some natural therapies included appropriate diet and hygiene, superstition still dominated leading to the prescription of human blood, powdered skull, onion and garlic. Cauterization of both the occiput and the bregma was advocated. Until the nineteenth century, castration was also prescribed, not only to prevent genetic transmission of epilepsy but also because there was a belief among practitioners of natural medicine that some convulsions originated in the testes and that masturbation made it worse.

In medieval times, the remarkable insight of Hippocrates and Galen disappeared in Europe and the old ideas that those who suffered from epilepsy (still known then as "the falling sickness") were possessed by evil spirits and should be avoided came back. By the sixteenth and seventeenth centuries,

more humane treatment of epileptic people was advocated by Paracelsus and Thomas Willis; the belief that epilepsy was infectious was discarded and other diseases such as smallpox, ergotism and syphilis were considered as causes of epileptic attacks in some patients.

In 1754, Pedro de Horta, a Spanish physician who worked at the Capuchin convent of Los Angeles, a village in New Spain, wrote a book totally concerned with epilepsy, called Informe Medico-Moral de la Penosissima, y Rigorosa Enfermedad de la Epilepsia (A Medico-Moral Account of the Most Painful and Rigorous Illness of Epilepsy). The book was published in Madrid in 1763. It was a treatise on epilepsy as possession by demons (Engel Jr., 1989).

In 1770, Simon A. Tissot recognized that chronic cerebral dysfunction acted as a predisposing factor for epilepsy and that this should be distinguished from the provoking cause. He also defined idiopathic epilepsy, with known brain injury, as different from essential epilepsy, presumably due to an epileptic disposition. In 1815, Esquirol defined both grand mal and petit mal seizures. In 1824, Calmeil introduced a classification of epileptic seizures based on their severity and described absences and generalized convulsive status epilepticus, while , in 1825, Bouchet and Cazauvieilh, through the analysis of brains at autopsy from patients with epilepsy, described that atrophy of the temporal lobes was common. In 1854, Delasiauve, redefined idiopathic and symptomatic as these terms are used nowadays. In 1859, the National Hospital for the Paralysed and Epileptic at Queens Square, was founded in London (because members of the

British royal family had epilepsy). In 1880, after microscopic analysis became possible, W. Sommer disclosed that the loss of neurons had occurred in brains of epileptic persons. In 1886, the neurosurgeon Victor Horsley, helped by Ferrier, resected a cortical scar on a patient who had a depressed skull fracture and suffered from focal motor seizures, rendering the patient seizure-free.

In 1873, John Hughlings Jackson defined epilepsy as follows (Trimble and Reynolds, 1988):

> "Epilepsy is the name for occasional, sudden, excessive rapid and local discharges of the grey matter."

Major advances in pharmacotherapy came with the introduction of phenobarbital by Hauptmann in 1912 and with the demonstration in 1937, by Merritt and Putnam, with phenytoin, that antiepileptic drugs could be dissected from their sedative and hypnotic properties. (Engel Jr., 1989).

Underlined by the invention of the electroencephalograph (EEG) by Hans Berger in 1929 and supported later by more specialized methods such as the depth electrode implantation, lobectomy (removal of the temporal lobe) was introduced as a form of treatment for epilepsy in medically intractable cases.

Gibbs, Davis and Lennox defined, in 1935, "petit mal absences" as brief interruptions of consciousness associated with a rhythmic 3 cycles per second discharge of regular spike and wave complexes on the EEG.

In 1969, a classification of epileptic seizures, de-

veloped by Henri Gastaut, was adopted by the International League Against Epilepsy (ILAE). In 1981, an International Classification of Epilepsies and Epileptic Syndromes was developed by a commission charged by ILAE and it has been reviewed since then because there has been no general agreement (Dam and others, 1987).

During the last two decades, new harmless means of detecting brain abnormalities, such as computerized axial tomography (the CT scan), magnetic resonance imaging, the magnetoencephalogram and the telemetric EEG, have appeared in the market.

2.2.2 - Religious remarks

The persecution of epileptics and the use of religious practices as forms of treatment have been used since the most remote times . Temkin (1945), Lennox (1960) and Beran (1987) give several examples of religious and historical episodes, where one or more of the people involved had epilepsy. Many of these examples are in the bible and, probably, the most famous is the story of Jesus expelling the evil from an epileptic child (Matthew, 17:14-18; Mark, 9:17-27 and Luke, 9:38-42). The text below corresponds to Luke, 9:38-42 (Holy Bible, New International Version, 1984).

> 38 A man in the crowd called out, "Teacher,I beg you to look at my son, for he is my only child.
>
> 39 A spirit seizes him and he suddenly screams; it throws him into convulsions so that he foams at the mouth. It scarcely ever leaves him.
>
> 40 I begged your disciples to drive it out, but

they could not."

41 "O unbelieving and perverse generation", Jesus replied, "how long shall I stay with you and put up with you? Bring your son here."

42 Even while the boy was coming, the demon threw him to the ground in a convulsion. But Jesus rebuked the evil spirit, healed the boy and gave him back to his father.

Other cited passages that are possible references to epileptic symptoms are: Numbers, 24:4; 1 Samuel, 19:24; Ezekiel 1:28, 43:3; Daniel 8:17; Acts, 9:4-18 (Saul, who was also called Paul, suffers in the road to Damascus) and Revelations, 1:17. The symptoms described may also be provoked by migraine (a severe recurring form of headache, often with nausea and disturbance of vision), syncope (simple faint) and anorexia (lack of appetite for food).

Buddha has been considered epileptic by some authors but there is no evidence that his mystical experiences had anything to do with epilepsy. On the other side, according to Lennox, Mohammed had seizures from the age of three years old and admitted once:

"This is a common affliction of the prophets, of whom you know I wish to be counted as one."

Temkin wrote that the Byzantine Christians, in order to discredit Mohammed, might have called him epileptic. Temkin and Beran have also interpreted mystical experiences by St. Ignatius, St. Teresa of Avila, the Mormon prophet Joseph Smith and the Hebrew prophets Hosea, Jeremiah, Isaiah and Ezekiel as epileptic.

There is no proof that a special relationship exists between epilepsy and exceptional talents, but Lennox and others accept the names of many famous rulers, warriors (probably due to traumas caused during fights), philosophers, scientists and artists as epileptic, among them Alexander the Great, Caligula, Julius Caesar, Peter the Great, Pythagoras, Socrates, Charles Dickens, Molière, Pascal, Newton, Nobel, Paganini, Dostoyevski, van Gogh, Handel, Tchaikovsky, Beethoven and Truman Capote.

2.2.3 - Epilepsy in literature

Feodor M. Dostoyevsky included epileptic characters in the novels The Insulted and Injured, The Idiot, The Brothers Karamazov and The Possessed. Silas Marner is George Elliot's epileptic character. Michael Crichton gave a wrong idea about an epileptic person in the novel The Terminal Man, apologising formally in the paperback edition (Engel Jr., 1989). Shakespeare, in his plays Othello and Julius Caesar made the main characters have fits. In Julius Caesar, Act 1, Scene 2, the following happens:

CASSIUS: But soft, I pray you. What, did Caesar swound ?

CASCA: He fell down in the market-place, and foam'd at the mouth, and was speechless.

BRUTUS: 'T is very like: he hath the falling sickness.

2.2.4 - Terminology and definitions

To help the reader to understand the technical vocabulary that will be used in this work, the definitions of some specific medical terms will be given below. Except where noted, such definitions are based on Engel Jr.'s work (1989). The reader, however, shall keep in mind that the main idea, in both Chapters 2 and 3, is just to give a very basic introduction to the subject. For this reason, the reader is encouraged to refer to specialized literature for more detailed information.

1) Epileptic seizures

> "Epileptic seizures are the clinical manifestations (symptoms and signs) of excessive and/or hypersynchronous, usually self-limited, abnormal activity of neurons in the cerebral cortex. Many types of epileptic seizures occur. The behavioral features of an epileptic seizure reflect the functions of the cerebral cortical areas where the neuronal activity originates and spreads. An epileptic seizure may consist of impaired higher mental function or altered consciousness, involuntary movements or cessation of movement, sensory or psychic experiences, or autonomic disturbances; it often occurs as a combination of dysfunctions and a progression of symptoms. Epileptic seizures have electrophysiological correlates that usually, but not always, can be recorded by a scalp enlectroencephalogram (EEG)...Epileptic seizures are so commonly referred to as seizures..."

In this work, the words epileptic seizure / epileptic attack may be replaced by seizure and fit.

2) Epileptic disorders

> "An epileptic disorder is a chronic neurological condition characterized by recurrent epi-

leptic seizures. The diagnosis of an epileptic disorder implies that a neurological abnormality responsible for generating epileptic seizures persists between these events."

3) Epilepsy

"The word epilepsy, in general sense, is variously used to refer to the existence of a class of symptoms, epileptic seizures. In the specific sense, the word epilepsy is used to refer only to those conditions of chronic recurrent epileptic seizures that can be considered epileptic disorders. Because there are many types of epileptic disorders, it is more correct to refer to them as epilepsies."

"... there is no disease named epilepsy. What is called epilepsy is the chronic recurrence of sudden abnormal reactions of the brain such as epileptic seizures...The term 'epilepsy' should be used with caution in order to avoid the notion of a disease entity. Terms such as 'the epilepsies' or 'epileptic seizure disorders' are preferable". (Niedermeyer and L. da Silva, 1987)

In Brazil, the word epilepsy is popularly denominated cerebral dysrhythmia. Bannister (1987) also uses such a denomination.

4) Ictal, postictal and interictal

"Ictus and ictal event refer to the epileptic seizure itself, as identified clinically or electrophysiologically. Postictal phenomena are transient clinical and/or electrophysiological abnormalities in brain function that result from the ictus and appear when the ictal event has ended. The period of time during which postictal symptoms persist (usually seconds to a few days) is referred to as postictal period. The interictal period is the time between the resolution of postictal abnormalities and the beginning of the next ictal event."

5) Epileptic focus

"An epileptic focus is defined electrophysiologically as the cortical area that appears to be the major source of interictal epileptiform

EEG discharge. EEG epileptiform discharges are usually focal, indicating a single epileptic focus; bilateral and independent, indicating epileptic foci in the two hemispheres; multifocal, indicating three or more epileptic foci; or diffuse (either widespread or generalized), in which case there is no apparent epileptic focus.

6) Aura

"An aura is typically regarded as a warning that precedes an epileptic seizure, although most auras are now known to actually be the beginning of the ictal event."

7) Pseudoseizure

"The term pseudoseizure is used in the general sense to denote any nonepileptic event that resembles an epileptic seizure."

2.2.4.1 - Definitions of epilepsy

As seen before, the classification of different kinds of epilepsy and epileptic seizures have always brought disagreement, controversy and confusion even among the most famous specialists in the area. As M. Parsonage wrote:

"At the moment it would appear that the whole matter remains sub-judice and there seems to be little likelihood of any final pronouncements in the immediate future" (Laidlaw and others, 1988).

For this reason, several definitions of the terms epilepsy and seizure, given by different authors, will be listed ahead.

1) "...epilepsy is thus a disease of grey matter, and has not any uniform seat. It is a

disease of tissue, not of structure" (Gowers, 1881) [ref: Niedermeyer and L. da Silva, 1987].

2) "Epilepsy is an occasional sudden, excessive, rapid and local discharge of the grey matter of some part of the brain." (H. Jackson, 1873) [ref: Laidlaw and others, 1988].

3) "Epilepsy is an established tendency to recurrent seizures." (Jeavons and Aspinall, 1985)

4) "Epilepsy is a condition characterized by recurrent discrete episodes, primarily of cerebral origin, in which there is a disturbance of movement, sensation, behaviour or consciousness" (Sutherland and Tait, 1969).

5) "Epilepsy is a paroxysmal and transitory disturbance of the functions of the brain which develops suddenly, ceases spontaneously, and exhibits a conspicuous tendency to recurrence" (Walton, 1977).

6) "A person is said to suffer from epilepsy if he has a continuing tendency to epileptic seizures" (Hopkins, 1985).

7) "There is no disease named "epilepsy". Rather, epileptic seizures are abnormal reactions of the brain caused by a large number of diseases" (Niedermeyer and L. da Silva, 1987).

8) "Epilepsy is a symptom of a discharging lesion, which may be situated in many different areas of the brain and be due to many different causes" (Bannister, 1987).

2.2.4.2 - Definitions of seizure

1) "Epileptic seizure is a paroxysmal discharge of cerebral neurones apparent to the subject and/or an observer" (Hopkins, 1985).

2) "An epileptic attack is the manifestation of a paroxysmal discharge of abnormal electrical rhythms in some part of the brain...Loss or impairment of consciousness frequently occurs in association with an attack, but a paroxysmal electrical discharge may involve certain parts of the brain without interfering with consciousness" (Bannister, 1987).

2.2.5 - Classifications

As prognosis and treatment may be determined on the diagnosis of a specific epileptic syndrome, which is based on the seizure type and other clinical information, it is useful to classify both the epileptic seizures and the epilepsies independently.

2.2.5.1 - Classification of epileptic seizures

There are basically three types of seizures. Their denominations and definitions follow below.

1) Generalized seizures are those in which the first clinical changes indicate initial involvement of both hemispheres.

2) Partial seizures are those in which the first clinical changes indicate initial activation of a system of neurons limited to part of one cerebral hemisphere.

3) Unclassifiable seizures are those that cannot be classified because of inadequate or incomplete information and some that defy, until now, classification in other categories.

As a more detailed classification is out of the scope of this thesis, a simple and practical classification that highlights some fundamental concepts, based on the clinical features of fits and differences in their pathophysiology, follows below. (It is similar to the Classification of Epileptic

TABLE 2.1 - CLASSIFICATION OF SEIZURES

1. GENERALIZED (involvement of both hemispheres)
   a. Tonic-clonic (grand mal)
   b. Tonic
   c. Atonic
   d. Absence (petit mal)
   e. Myoclonic

2. PARTIAL (focal - involvement of one hemisphere)
   i. Without loss of consciousness (simple)
   ii. With loss of consciousness (complex)
      a. With motor signs (e.g. movement of head, eyes, tongue, limbs)
      b. With somato- or special sensory symptoms (e.g. auditory, gustatory, olfactory, visual)
      c. With autonomic features (e.g. epigastric sensations, nausea, vomiting)
      d. With psychic symptoms (e.g. fear, déjà vu, jamais vu)
      e. With automatisms

3. PARTIAL SEIZURES SECONDARILY GENERALIZED
   i.e. clinical or electrical evidence of focal discharge before, during or after the generalized seizure

4. UNCLASSIFIABLE

Examples in neonatal seizures: rhythmic eye movements, chewing movements and swimming movements.

Seizures that was published by the Commission on Classification and Terminology of the International League Against Epilepsy - ILAE on 1981.)

2.2.5.2 - Classification of epilepsies

Centuries ago, the epileptic disorders were classified according to the type of seizure. For this reason, they have been divided into petit mal and grand mal. Later, distinctions were made between partial and generalized epilepsies. The specific disorder of psychomotor or temporal lobe epilepsy was also recognized. In terms of the respective causes, the epilepsies have been classified as primary (idiopathic) or secondary (symptomatic). These definitions follow below.

1) Primary or idiopathic epilepsies are those in which there is no identifiable cause (the patient seems to have an inherited liability to seizures which are provoked by genetic factors).

2) Secondary or symptomatic epilepsies are those that can be attributed to identifiable intracranial and/or extracranial lesions.

Primary epilepsy was more common years ago. In fact, it

Table 2.2 - CLASSIFICATION OF EPILEPSIES

1. BY ETIOLOGY (causes)
   a. Primary
   b. Trauma
   c. Perinatal brain damage
   d. Tumour
   e. Cerebrovascular accident
   f. Parasitic disease
   g. Infectious disease
   h. Metabolic or toxic
   i. Other (sleep-related, etc.)
   j. Unspecified brain damage

2. GENERALIZED NONCONVULSIVE EPILEPSY
   a. Typical absence epilepsy (petit mal)
   b. Atypical absence epilepsy
   c. Others

3. GENERALIZED CONVULSIVE EPILEPSY
   i. Major epilepsy (grand mal)
      a. Tonic-clonic epilepsy
      b. Tonic epilepsy
      c. Clonic epilepsy
      d. Others

4. PETIT MAL STATUS (EPILEPTIC ABSENCE STATUS)

5. GRAND MAL STATUS EPILEPTICUS
   a. Tonic-clonic status epilepticus
   b. Others

6. PARTIAL EPILEPSY, WITH AND WITHOUT IMPAIRMENT OF CONSCIOUSNESS
   a. Motor signs
   b. Sensory symptoms
   c. Autonomic symptoms (visceral)
   d. Psychic symptoms
   e. Others

7. INFANTILE SPASMS

8. OTHERS

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was provoked by a lack of knowledge. In the last years, thanks to modern methods of investigation, more causes of secondary epilepsies have been discovered, which has led to the expansion of this group. Sometimes it has been said that all epilepsies are secondary because they are caused by some kind of cerebral disorder.

Three different international classifications have been published during the last two decades, which are: 1) The 1970 International Classification of the Epilepsies (ILAE), 2) The 1985 International Classification of the Epilepsies and Epileptic

Syndromes (ILAE), which is a more sophisticated version of the previous one (the word partial has been substituted by localization-related) and 3) The 1987 World Health Organization Classification on Diseases to Neurology, that allows disorders to be classified by etiology (cause) or seizure type and whose main feature is to recognize different kinds of status epilepticus.

Table 2.2 shows a condensation of the WHO classification (Engel Jr., 1989).

2.2.6 - Causes of epilepsy

There are several diseases that cause epilepsy. The most common causes, shown on table 2.3, can be summarized according to the age of the patient (Laidlaw and others, 1988).

2.3 - Clinical Manifestations

According to Gloor and Fariello (1988),

> "The investigation of the mechanisms that cause seizures to suddenly arise in a generalized fashion all over the brain has received less attention in epilepsy research than studies on the cellular mechanisms causing partial (focal) epilepsy, where a small group of neurons is thought to give rise to localized epileptic discharge."

From the homeopathic point of view, both internal and external phenomena may provoke the occurrence of seizures. For example, Borland (1988) states that in case of women "They (the seizures) occur either during or near the period" and in general

Table 2.3 - CAUSES OF EPILEPSY AS A FUNCTION OF AGE

1. NEONATAL (1st. month)
   a. Birth injury (cardiac arrest, respiratory arrest, perinatal brain injury, haemorrhage, etc.)
   b. Congenital abnormalities (arteriovenous malformation, etc.)
   c. Metabolic disorders (hypoglycemia, hypocalcemia, etc.)
   d. Meningitis and other infection

2. INFANCY (1 - 6 months)
   a. As above
   b. Infantile spasms

3. EARLY CHILDHOOD (6 months to 3 years)
   a. Febrile fits (chronic maternal ill health, parental subfertility, delivery by Caesarian section, etc.)
   b. Birth injury (cerebral malformation, etc.)
   c. Infection (meningitis, neurosyphilis, etc.)
   d. Trauma (intracranial hemorrhage, etc.)
   e. Poisons
   f. Metabolic defects (hepatic failure, etc.)
   g. Cerebral degenerations

4. CHILDHOOD AND ADOLESCENCE
   a. Primary epilepsy (hereditary predisposition)

b. Birth injury

c. Trauma

d. Infection

e. Cerebral degenerations

f. Poisons

5. EARLY ADULT LIFE

a. Trauma (penetrating wounds and closed wounds - people most at risk include combatants in wars, motorists and their passengers, workers on building sites, rugby players, boxers, etc.)

b. Tumour

c. Primary epilepsy (hereditary predisposition)

d. Birth injury

e. Infection

f. Cerebral degenerations

g. Poisons (alcohol, cocaine, insulin, lead, ether, insecticides, barbiturates, etc.; withdrawal of alcohol, antiepileptic drugs, narcotic analgesics, barbiturates and other drugs)

6. LATE ADULT LIFE

a. Vascular disease

b. Trauma

c. Tumour (glioma, meningioma, etc. - growth of strange cells, not neurons, in the brain - popularly denominated cancer of the brain)

d. Cerebral degenerations

"there tends to be an aggravation at the new moon". To give the reader an idea about the most famous types of generalized seizures (those that involve both hemispheres), that are the absence seizure and the tonic-clonic seizure, a resume will be presented.

There are contradictions, even among specialists, concerning items such as the duration of the events and the occurrence or not of auras at the beginning of a tonic-clonic seizure.

2.3.1 - Absence seizure (petit mal)

Petit mal epilepsy is invariably a disorder of childhood. It is often associated with contractions of the muscles. These contractions are very brief having no meaning in asking the patient if he has or not lost consciousness (Hopkins, 1985). The patient has no warning of these attacks during which his higher mental functions are disturbed to a variable degree.

A typical attack starts and ends abruptly, rarely lasting more than 10 seconds. The main ictal events are a cessation by the child of the ongoing activities and a motionless stare. The child's face may look a little pale, the eyes may be rotated upwards, the eyelids may flutter and the head may be slightly dropped forwards. Posture of the limbs and trunk is usually kept in the pre-ictal position avoiding fall of the child. After the seizure, the child is usually unaware that an absence has occurred and resumes what was being done before. There is no convulsion, unless the petit mal seizure is associated with major seizures (Sutherland and Tait, 1969). Sometimes,

during very slight attacks, the patient may not be totally unconscious, but is aware of an abnormal feeling , a state often described as "sensation".

Petit mal seizures may be very frequent; patients that have from 10 to 50 seizures a day are occasionally encountered. In some particular cases, the abnormal electrical discharges occur almost continually (benign or petit mal status epilepticus) and the patient remains in a state of relative confusion. Absence seizures that are associated only with loss of consciousness constitute approximately 10% of all absence seizures. Most fits are characterized by myoclonic jerks, which have bilateral manifestation (both eyelids blink, for example). These fits are particularly frequent soon after waking.

Petit mal seizures may disappear or be replaced by grand mal seizures in adolescence.

2.3.2 - Tonic-clonic seizure (grand mal)

Comparing an absence seizure to a drizzle, a tonic-clonic seizure may be compared to a storm or even a hurricane.

The patient may feel some involuntary muscular contractions and be irritated, depressed and giddy for several hours or days before the seizure.

In about three-fifths of all cases (Bannister, 1987), the seizure begins with a warning of the attack, known as an aura. Depending on the area of the brain that is affected by the discharge, the patient may experience abnormal feelings in one of the senses, such as visions (flashing lights, balls of fire,

etc.), tastes, sounds and smells; other sensations include feelings of unreality (jamais vu), feelings of familiarity (déjà vu), fear, strong impulse to speak with inability to do so, etc. It occurs before consciousness is lost and in some cases, the patient manages to take some form of precaution against damage such as lying down. In the rest of the cases, the patient has no warning and loses consciousness at the onset of the attack.

Immediately after the aura or at the very beginning of the attack, the convulsion itself starts with a widespread contraction of muscles that make the body rigid and incapable of keeping a normal posture and causing the fall of the person to the ground which may cause injuries. Due to the contraction of the respiratory muscles, the air that is expelled from the lungs may provoke the emission of a cry or a grunt. There are several consequences of the lack of coordination in the movements of the muscles. For example:

1) The jaws are contracted and both the tongue and the cheek may be bitten.

2) Breathing is stopped, and the lack of oxygen in the blood changes the colour of the patient, mainly the face, to dusky blue (cyanosis).

3) Movements of swallowing are stopped and salivation occurs.

4) Incontinence of urine and sometimes feces occurs (Hopkins, 1985).

Due to all these contractions, the patient will later feel his muscles to be painful. Although the discharge involves both hemispheres, sometimes the person may rotate his head and

eyes and draw his mouth to one side.

After this first phase known as the tonic phase (from the Greek word tonos, "tension"), which lasts from a few seconds to not more than thirty seconds (Bannister, 1987), the clonic stage (from the Greek word klonos, "violent motion") begins. During the clonic stage, a series of shock-like short and interrupted jerks of the face, arms, body and legs take place. A few minutes later, the interval between these movements becomes longer and the jerks cease, leaving the patient usually unconscious for a period of up to half an hour. When consciousness comes back, a state of confusion and unreality still dominates, and it may be better for the patient to sleep for several hours. Headache is common after the seizure.

The EEG signal that characterizes the grand mal convulsion consists of multiple high-amplitude spikes that are normally widespread and synchronous in both hemispheres (see Chapter 3).

2.4 - Incidence and Prevalence

Both incidence and prevalence rates are determined by epidemiologists. These rates are difficult to establish. Factors like methodology (definition of epilepsy, definition of seizure, etc.) and population taken into account (general population or population of patients in general practice, house-to-house survey or medical files, country where the study was carried out, etc.) lead to different results. The sex and age-specific rates also vary from author to author.

In different studies, the incidence rate has varied

from 0.2% to 0.6%; in those studies where single seizures that occurred at some time were taken into account, the incidence rate is about 3% (Richens, 1988). The prevalence rate, which is more difficult to establish, owing to factors like the varying presentation of seizures, the long-term remissions and the case-finding methods, has varied from 0.1% to 5% (Laidlaw and others, 1988).

2.5 - Means of Investigation

The most common tests are the EEG (electroencephalogram), the CT (CAT) scan [computerized (axial) tomography] and the skull X-ray. Other modern methods of investigation include the MRI (magnetic resonance imaging) and the MG (magnetoencephalogram). For a more detailed description of these methods, the reader should refer to Chapter 3.

2.6 - The Modern Treatment of Epilepsy

2.6.1 - The diagnosis of epilepsy

In 1988, A. Richens wrote:

> "Few neurologists have a major interest in epilepsy. Once a diagnosis has been made, effective drug therapy, sympathetic social support and willingness to sit and listen are the most important aspects of good management. These requirements have never been prominent in neurological training, with the result that adult epilepsy is often ill-managed, commonly by changing junior staff. The essential continuity in care is totally lacking....The misdiagnosis of epilepsy is common."

A valuable confirmatory evidence of epilepsy may be provided in some patients by the evidence from an EEG, particularly in the cases where specialized techniques, such as ambulatory or telemetric EEG, are used to register the occurrence of epileptic events.

Unfortunately, too much importance is given sometimes to insignificant abnormalities reported from standard EEG recordings, which leads to wrong diagnosis. For example, in 1983, Betts found that 20% of the patients who had been admitted to a psychiatric hospital with a diagnosis of epilepsy did not have the disorder. In cases where it is very difficult to obtain a clear diagnosis, the best thing to do is to let time clear the matter, avoiding "therapeutic trials" of antiepileptic drugs. It seems better to delay treatment until seizures have occurred because there is no clear evidence that antiepileptic treatment is effective in preventing late epilepsy (Chadwick, 1988; Dam and others, 1987).

2.6.2 - The antiepileptic drugs

There are more than 20 antiepileptic drugs. Those that are recommended as a first choice are listed in Table 2.4 according to the type of epilepsy (Aicardi, 1988).

The efficacy of these drugs depends a lot on their own properties and on metabolism, that varies according to the patient's age. Consequently, age becomes an important factor in the determination of the dose itself and the number of doses.

The adverse effects of medication for a long period can

TABLE 2.4

RECOMMENDED DRUGS FOR TREATMENT OF EPILEPSY

EPILEPSY TYPE	DRUGS
Partial seizure, primarily or secondarily generalized tonic-clonic seizures	Carbamazepine, phenytoin, phenobarbitone, primidone.
Absence, juvenile myoclonic epilepsy, myoclonic or atonic seizures	Ethosuximide, sodium valproate/valproate acid.

be divided into 3 categories, that are:

1) those that are caused by the drugs' unwanted side-effects;

2) those that are caused by excessive dosage of the drugs and

3) the idiosyncratic reactions between the drugs and the patients' body chemistry.

All drugs provoke side-effects. Less than 50% of epileptic patients who are receiving treatment can expect to become seizure-free without unacceptable side effects. Some typical toxic side-effects caused by antiepileptic drugs, that are normally dose-dependent, are:

1) gastrointestinal disturbances (nausea, gastric

distress, vomiting, diarrhoea, etc);

2) neuropsychiatric disturbances (slurred speech, tremor, disturbance of balance causing difficulty in controlling one's body movements - ataxia, diplopia, dizziness, blurred vision, etc);

3) weight gain, skin reactions (acne, urticaria, etc), hair loss (reversible), overgrowth of the gums, etc (Engel Jr., 1989; Hopkins, 1985; Laidlaw and others, 1988).

According to Iivanainen and Lehtinen (1979), chronic intoxication with phenytoin and/or phenobarbitone has already been a common additional cause of death in patients who died of pneumonia or seizures.

The barbiturates are the most prescribed anticonvulsant drugs worldwide. A consequence of overuse (including dependence and addiction) of this sort of drugs is chronic intoxication, with clinical characteristics such as sluggishness, lethargy, difficulty in thinking, poor memory and learning disabilities, which are also typical of chronic epileptic patients. For this reason, the use of barbiturates as antiepileptic drugs must be seriously considered, mainly in the treatment of epileptic children (Niedermeyer and L. da Silva, 1987). Another problem is the fact that a barbiturate addict may be mistakenly diagnosed as an epileptic person because the clinical characteristics of both are similar. As seen in item 2.2.6, although barbiturates are used as antiepileptic drugs, both use and withdrawal of barbiturates may cause epilepsy.

Patients with chronic epilepsy, mainly those who live in institutions for the mentally retarded, have traditionally

been exposed to increasing doses of multiple drugs with frequent changes of drugs and dosages. Adverse reactions due to drug interactions, most of which affect the central nervous system and increase the risk of disturbing cognitive functions ("patients often complain of poor memory function, of slowing of their thinking or of difficulties in maintaining concentration", Dam and others, 1987), are common and improvement in seizure control is not ensured. Such a policy has been questioned in the last few years. In patients receiving, and complying with, optimal doses of a single antiepileptic drug, the addition of further agents is likely to result in a significant (> 75%) improvement in seizure control in only 10% of patients (Beghi and others, 1987; Chadwick, 1988).

Neil Gordon, in 1988, wrote:

> "It is relatively recently that doctors have realized that fits sometimes can be reduced in number, and even stopped, by reducing drugs. Even status epilepticus can be halted occasionally by curarising the patient and withdrawing all anticonvulsants. This is obviously a complex situation which may involve many factors, such as direct toxic effects of the drug, side-effects such as drowsiness, and even wrong diagnosis. However, it may well be true that the anti-epileptic drugs are interfering with the 'normal' mechanisms that are supposed to be preventing the fits, and so are doing much more harm than good."

Based on these facts, the neurologists have now a general agreement that monotherapy shall be used wherever possible (Richens, 1988). Even a poem has been written in order to emphasize monotherapy.

"An epileptic young girl of St Kitts,
had too many drugs for her fits,
but she will grow prettier
more clever and wittier,
the more of these drugs that she quits."

Still far from ideal conditions, approximately 20% of patients are resistant to antiepileptic drugs. As there is also the problem of chronic toxicity, more effective and less toxic drugs are still to be developed. Only one new antiepileptic drug [vigabatrin (Sabril)] has been launched in the UK during the last 16 years. It is the first drug to be obtained as a result of research into inhibitory neurotransmission (Richens, 1990).

2.6.2.1 - Antiepileptic drugs and pregnancy

During pregnancy, an epileptic mother may suffer several grand mal seizures. The baby may be harmed due to direct injury to the mother's abdomen when the mother falls, or due to the lack of oxygen in mother's blood during the convulsion. Although these circumstances may be unusual, the use of anticonvulsants during pregnancy is advized by neurologists.

The effects of antiepileptic drugs on the fetus must be considered. The results of two studies will be shown here as examples.

1) Based on the Rochester (Minnesota-USA) population, Annegers and others determined in 1978 that 2.4% of children born to mothers with epilepsy not taking antiepileptic drugs during

pregnancy, 10.7% of children born to mothers who took drugs during pregnancy and 3.8% of children of men with epilepsy, had malformations.

2) In Montreal, Dansky and others determined in 1982 that 15.9% of children born to mothers who were taking antiepileptic medication had congenital malformations, as compared with 6.5% for mothers who were not (Laidlaw and others, 1988).

2.7 - Social and Emotional Aspects

Although references about convulsions and laws pertinent to the employment and marriage of people with epilepsy were already included in the Babylonian code of Hammurabi thousands of years ago, misconceptions about epilepsy are still common in our modern times. Most of them have religious roots.

People all over the globe are still ill-informed and have strange ideas about epilepsy. It happens mainly because a tonic-clonic seizure is frightening to see and comes without warning. This can make people who are around the victim think that it has something to do with the devil or an evil spirit, and can lead to the partial or total rejection of that person by society. Sometimes, the doctor prescribes the correct medication but gives no information about what is going on, cooperating this way to the propagation of catastrophic wrong ideas.

In 1893, the Charity Organization Society estimated that 2 to 3 in 1000 children were epileptic in the United Kingdom and found that very few were in school. The Society consid-

ered this to be the beginning of a sad downhill path. They wrote:

> "The life of many epileptics may soon be told. As a child, he is not educated. As a young man, he fails to obtain employment, or obtaining it with difficulty, he keeps it only on sufferance. As years advance, and strength decreases, he retires to the workhouse or to the asylum." (Morgan and Kurtz, 1987).

This grim picture is unfortunately not just a thing of the past, it is all too common today and not only in third-world countries (see the examples below).

In the foreword of Hazeldine's publication "EPILEPSY, What it is, ..." (1986), A. Aspinall wrote:

> "Although epilepsy is primarily a medical phenomenon, those who live with it frequently suffer more from public attitudes than from the epilepsy. It is not an exaggeration to say that the stigma of epilepsy still exists in this modern age."

For example, an experiment was taken by Sands and Zalkind in the United States in 1972 (Dinnage, 1986). A campaign was mounted to educate employers about epilepsy, in order to help epileptic people become employed. It had no effect. The attitudes of the employers were not modified. Only one third of them would recommend employing a person who had epilepsy. This number was the same in other cities that were not involved by the campaign.

Three other examples are given by Laidlaw and others (1988).

First, in 1971 in a survey in the UK, only 57% of the

population agreed that epileptic people should be employed and 32% said that they would not permit their child to play with a child with epilepsy.

Second, The British Medical Association Working Party on Immigration recommended as recently as 1965 that "for social and economic reasons" epileptic people should not be permitted to enter this country.

Third, even people with well-controlled epilepsy have difficulties in entering the medical, nursing or teaching professions in the UK.

All these examples confirm Aspinall's point of view and prove that people with epilepsy are still rejected.

There is no doubt that to feel rejected is to feel stressed. So, from the emotional point of view, to have epilepsy is to be stressed. As the level of stress increases, the number of fits increases becoming, sometimes, a self-reinforcing phenomenon.

Public attitudes must change. Unfortunately, it is a slow progress (Jeavons and Aspinall, 1985).

2.7.1 - The author's life as an epileptic person

Many textbooks concerned with epilepsy contain stories about the lives of some people who have epilepsy, but these stories are normally told by the doctors, which may cause some distortion. Based on this fact, the author has decided to include his own story, which follows below.

My family lived in Araucaria, a small city located

20 km from Curitiba, the capital of Parana State, in Brazil.

According to information given by my parents, I was born in normal conditions and was also a very healthy baby till the age of 1 year and 3 months, when I was inoculated against infantile paralysis. A few weeks later, I lost appetite, had severe intestinal problems and became very frightened. As time passed, I started to have seizures. The doctor, who had given assistance in my birth, insisted it had nothing to do with the vaccine, but was probably caused by some kind of infection in the throat (maybe the doctor was hiding the truth - later, he prescribed anticonvulsants).

Brain injuries may also have been the primary cause. I also had two falls, once beating my head against a box made of wood and another against a pile of bricks.

As far as I remember, I have had both petit mal and grand mal seizures from the age of 6 years old. Days before the seizures occurred, I became very nervous. That was enough to give my parents the idea that the seizures were approaching themselves. By the age of 8, following the doctor's advice, my parents took me to Curitiba where my throat was examined by a specialist who said it was in perfect conditions. This specialist recommended an electroencephalogram. This EEG was sufficient to reveal that I had epilepsy and medication was started immediately.

One year later, my family moved to Curitiba and I was treated by a neurologist. I received medication for ten years. During these years, I had a normal life, with good scores in my studies. A few seizures occurred during the first years of

medication. The only recommendation given by the neurologist was that I should not swim. As a result of this, at the age of 33, I am still unable to swim.

When I was 18 years old, medication was stopped. I went on studying, got a job as a teacher, took the BSc degree in Electrical Engineering and had a normal life until the age of 27. By then, while I was writing my MSc dissertation, I was nominated the principal of the department in which I worked. With so many preoccupations on my mind, under stressful conditions for approximately 8 months, I had another grand mal seizure and medication had to be restarted.

I gave up to the position I had been nominated to and got the MSc degree as soon as possible. During the next 2 years, taking 400 mg of carbamazepine daily, I went on teaching. I had no seizures in the meantime. At the end of this period, I came to London to study for a PhD, a goal I have always had in mind.

During the first 12 months in London, I was very happy and nothing went wrong.

In the second year, far from home and from friends, I had another grand mal seizure while working in the laboratory. The daily dose of carbamazepine was increased to 800 mg and one year later, after another tonic clonic seizure, it was increased to 1200 mg. In the last months, while writing the thesis, 1400 mg have been prescribed in order to raise the seizure threshold. Having already reached 78% of the maximum dose recommended for adults, I still feel "a little distant" (like dreams) sometimes. Some of these "sensations" are followed by handtremors, without loss of consciousness.

Maybe these attacks are just a consequence of a stressful life. If they are, I hope the number of fits decreases when I go back to Brazil so that the dose of the drug may be reduced because I feel that my memory has not been as good as it was a few years ago. I don't achieve to memorize new phone numbers, addresses, names, etc. I was informed by a doctor that it may be due to drug toxicity, even when it is kept in the therapeutic range. Fortunately, an awareness of the toxic effect of anticonvulsant drugs on the cognitive function has been increasing in the last years (Trimble and Reynolds, 1988).

From the psychological point of view, it is not easy to bear in mind the idea that you may fall in the streets; or scream and have convulsions during a concert; or say a lot of strange words while giving a conference or "get lost" and look to the ceiling of the classroom while teaching. Will those who are around understand what is going on? Shall I have some hope in future drugs? Why can't I go to the pub with my friends and drink some beers? Why can't I, as a responsible person, take a car and go somewhere on a bank holiday?

There is one way to react more positively. The best thing to do is to think that all I have is epilepsy and, if there is not a major handicap in parallel, my life is practically normal. All I need are some milligrams of an anticonvulsant drug, courage to do what I want and, mainly, comprehension from society if something goes wrong. There are other people who suffer much more.

2.8 - Summary

The same way a runny nose is a symptom that characterizes diseases such as influenza, for example, the epilepsies are also symptoms that characterize several different brain diseases. The epilepsies are not diseases in their own right.

Subdivided in two basic groups, the epilepsies are classified as "symptomatic" (those that may be attributed to cerebral lesions) and "idiopathic" (those that cannot be attributed to obvious cerebral damage).

Epileptic seizures, that in most cases prove that a person has some kind of epilepsy, are recurrent discharges of cerebral neurones in some part of the brain, leading normally to some degree of impairment of consciousness and movements of the limbs. The seizures may be apparent to the subject and/or to an observer and are basically classified as generalized or partial.

In generalized seizures, the electrical discharges disrupt both brain hemispheres, causing loss of consciousness and bilateral movements of the limbs whilst in partial seizures the discharges disrupt just one hemisphere. In this case, the patient retains some degree of consciousness and the limbs that are localized on the side opposite to the disrupted hemisphere are moved.

The two most famous types of seizures are both generalized and they are denominated "absence (petit mal) seizure" and "tonic-clonic (grand mal) seizures". During an absence fit, the patient stops his activities, stares, looks pale and remains unresponsive to his surroundings for some seconds, after which he

restarts what he was doing . The patient does not fall and there is no convulsion. It is characteristic of childhood.

A tonic-clonic seizure is much more dramatic and is the manifestation of a high degree of disorder in the brain. In approximately 3/5 of all cases, it starts with an aura (a sensation similar to a dream). After this, the tonic (full of contractions) phase starts, with the patient loosing consciousness, becoming rigid in extension, falling to the ground and maybe urinating. After 30 seconds, approximately, the tonic phase is followed by the clonic (convulsive) one, which is characterized by a rhythmic generalized jerking of face, body and limbs and foaming by the mouth. A few minutes later, the convulsion ends and consciousness starts to return slowly. For several minutes, the patient stays in a state of confusion and drowsiness, with headache and muscular stiffness.

Probably due to the fact that a grand mal seizure is quite frightening, the person who has epilepsy has been considered along the centuries as a messenger from the devil who is capable of dealing with evil spirits. Such ideas and a lot of other myths, many with religious background, are still common. As a serious consequence of this, people who have epilepsy are still rejected by modern society, having difficulties in schools, employment and life in general, even when modern drugs and surgery have permitted approximately 80% of epileptic people to have a seizure-free life.

Those who have epilepsy and those who don't still have a lot to learn about it.

CHAPTER 3

THE ELECTROENCEPHALOGRAM

3.1 - Introduction

In 1985, it occurred in Mexico City. In 1988, it was in Armenia. On 17 October 1989, 83 years after a similar tragedy, San Francisco (USA) was the city that suffered most of the consequences.

Earthquakes! Enormous tectonic plates, moving in opposite directions at the rate of a few centimetres a year, become locked. Strain builds up until the moment a sudden release produces an earthquake.

The hypocenter, the point of first slip, is usually located about 10 kilometres down from the surface. In San Francisco, it was 18 kilometres.

The main quake is preceded and followed by low intensity quakes, that are called foreshocks and aftershocks respectively. Other faint seismic chatters, known as microquakes, emanate from many faults. All these tremors have intrigued the scientists over the years. In order to detect them, the seismologists, have set out arrays of seismometers.

By studying these different sorts of signals, the geologists have tried to forecast the occurrence of major quakes. David Oppenheimer, from the U.S. Geological Survey, said:

> "Microquakes occur along a fault as a result of stress buildup. Over time, we see that their activity leaves one area quiet. Foreshocks behave the same way - their hypocenters appear anywhere but in that quiet area. That quiet area is where the sides are locked; that is where the earthquake will occur. The time aspect is the wild card..." (Canby, 1990).

Although the forecasts have been gross and imprecise so far, they have been, no doubt, helpful.

As the signals detected by seismometers represent the activity of the planet's crust, a record of signals, detected with several electrodes applied to the scalp, represents the electrical activity of the brain. This is the electroencephalogram (EEG).

The same way a quiet area surrounded by quakes represents the region where an earthquake will take place, a quiet area of the brain may represent the region where a brain tumour is located, but, in the case of a seizure, it is the most active area, showing high-amplitude signals, that represents the region of the brain where abnormal electrical discharges of neurons are taking place.

The geologists would like to forecast the earthquakes with high precision in order to avoid tragedies. Similarly, those who study the human brain also have the hope that it will one day be possible to forecast the occurrence of seizures in epileptic people, so that precautions may be taken. It is not possible to avoid an earthquake but it is possible to avoid a seizure.

Surrounded by modern techniques such as the computerized tomography, magnetic resonance imaging and magnetoencephalography, electroencephalography remains the best way to monitor

the brain for long periods.

3.2 - Origins of the EEG

Connecting non-polarizable electrodes from a galvanometer with optical magnification to the cortex of animals, the British physiologist Richard Caton studied the electrical activity of the brains of cats, monkeys and rabbits. In 1875, he reported:

> "Feeble currents of varying direction pass through the multiplier when electrodes are placed on two points of the external surface (of the brain), or one electrode in the grey matter, and one in the surface of the skull".

In 1910, the Russian Kaufman commented that it was very difficult to maintain the electrode contact during seizures. In Poland in 1914, Cybulski recorded an epileptic seizure caused by stimulation to the cortex of a dog. Neminski demonstrated in 1925 that signals could be recorded through the intact skull. Until 1930, when valve amplifiers with a.c. coupling appeared, several workers had already studied successfully the changes in steady potentials of the cortex with the use of string galvanometers, that came into general use about 1906.

Using scalp electrodes, the Austrian psychiatrist Hans Berger recorded signals from the human brain on 6 July 1924 in Jena and published in 1929 the first report on the electroencephalogram of man. In his experiments, he used many different types of electrode driving string or double coil galvanometers. He had

received help from neurosurgeons who provided him with patients in whom pieces of the skull had been removed. The papers published by Berger were ignored until 1934, when Adrian and Matthews published the results they had obtained with scalp investigations (Brazier, 1968).

During the 1930s, oscilloscopes replaced the galvanometers. In the beginning, the results were recorded in photographs. In the 1940s, pen writers became available and made it possible to have an immediate lasting record. Another great technical advance came with the differential amplifier, which eliminated much of the external interference. The transistor, in the 1950s, made it possible to return to d.c. recording.

In the last decades, much effort has been made to construct reliable multichannel recorders. The electrodes are nowadays the major obstacle, mainly for d.c. recording (Cooper and others, 1980).

3.3 - The Basic EEG Machine

An EEG apparatus is usually manufactured as a complete unit that may have up to 20 channels, although 8 or 16 channels are more common. All these channels have the same basic characteristics.

As shown in figure 3.1, an EEG machine is basically made up of four distinct sections:

1) the electrodes,

2) the montage selector,

3) the filters and amplifiers and

4) the recording system.

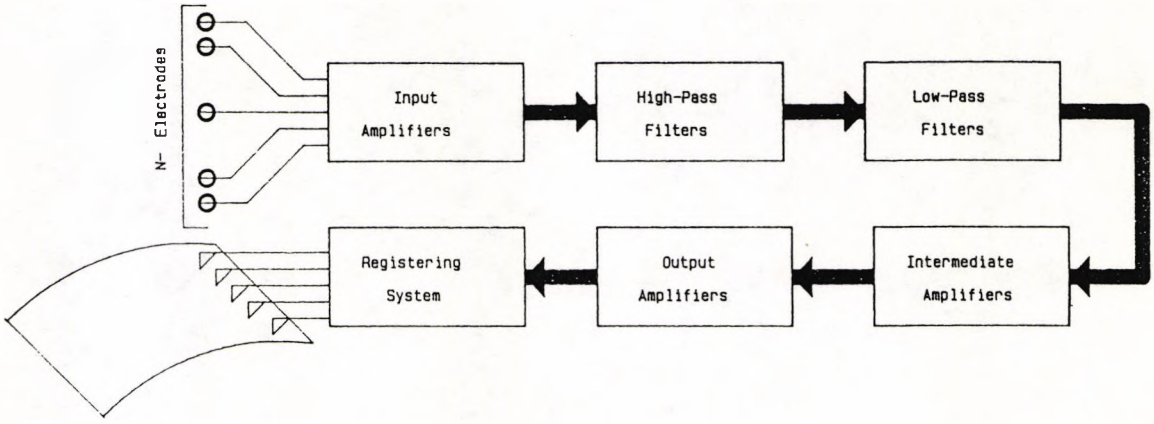


Figure 3.1 - Block diagram of an EEG machine.

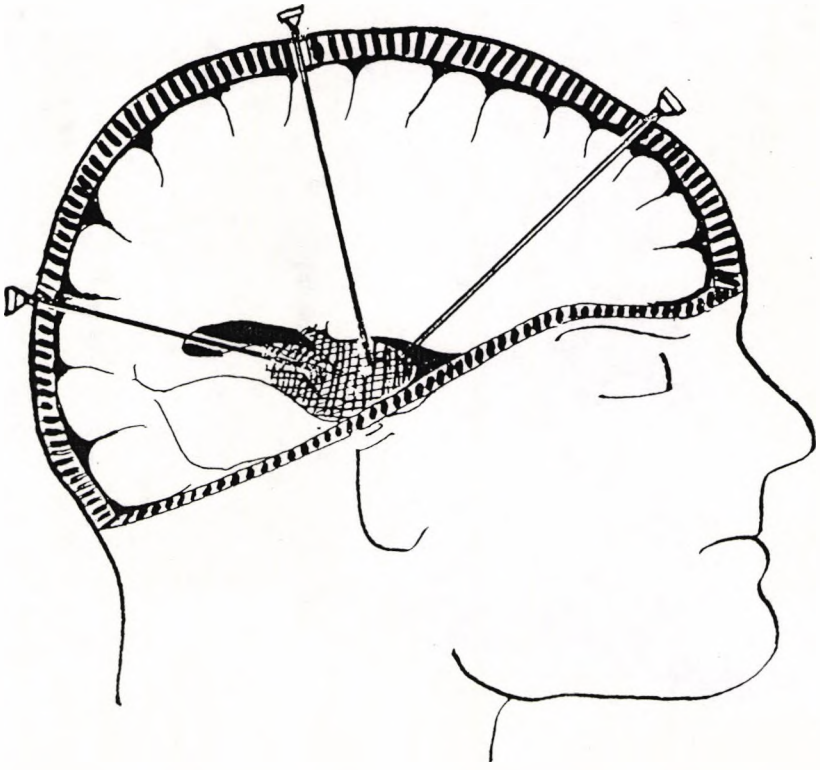


Figure 3.2 - Intracranial electrodes.

3.3.1 - The electrodes

The electrodes connect the conducting fluid of the tissue, from which the electrical activities are to be recorded, to the input amplifier.

There are several types of electrodes, made in various formats and from various materials. A very common type of electrode is the scalp electrode, which normally has a disc form with an approximate area of 1 square centimetre. Movement of the electrode in relation to the tissue leads to the generation of artifacts. To avoid this and to increase conductivity, this type of electrode is attached to the scalp with an adhesive paste (jelly). Two main problems appear with this kind of electrode. First, when the electrode is pressed against the scalp, there is the possibility of spreading the paste over a large area if it is used in excess, increasing the size of the area from which the signal is recorded (the areas should be small and as equal as possible) and maybe shorting out neighbour electrodes. Second, as time passes, the paste dries, decreasing the adherence and consequently changes the impedance. Such pastes are not appropriate for use in recordings that last more than 45 minutes. Collodion is another substance that is used to solve this kind of problem, being used in over-hour recordings. In this case, the electrode has a hole in the surface, through which the substance may be added, making it possible to reach periods of five days without causing problems to the skin.

Another type is the needle electrode, which lies under the dermis and stays in place without the necessity of using

special ingredients to hold it (it may fall out if the head is abruptly moved). The development of self-adhering electrodes has also been tried.

For these kinds of electrodes, the amplitude of the EEG signal is very low (see item 3.4). The impedance of the electrode attachment must be as low as possible. More than 5000 ohms cannot be accepted. When the skin is prepared appropriately, the impedance may fall to 3000 or even 1000 ohms. Several ingredients like acetone, alcohol and soapy water have been used during the years to cleanse the skull surface. Nowadays, substances that are conducting electrolytes have been used. Sometimes the skin is scratched (the author may say that it is quite unpleasant) to lower the impedance.

When electrode attachment was checked years ago, resistance instead of impedance was measured. This brought discomfort and hazards to patients. For example, if a standard resistance meter was used, the patient would probably feel some pain provoked by the current. Many modern machines may check the impedance in one or all channels without causing any discomfort to the patient.

As the scalp EEG shows only a fraction of the activity inside the brain, it is sometimes necessary to record signals directly from the cortex. In this case, very special intracranial electrodes are used (see figure 3.2 and item 3.4.2.2).

Hans Berger used to place the electrodes on the front and back of the head. As time passed, new techniques and forms of interpretation proliferated. As each region of the brain may have its own signal pattern, such as the alpha rhythm on the occipital

region (see item 3.4.1), researchers started to place the electrodes on different areas of the scalp. In order to standardize the manner of electrode placement in all laboratories, the International Federation of Societies for Electroencephalography and Clinical Neurophysiology recommended the system now known as "The International 10-20 System".

By using specific anatomical landmarks such as the nasion and the inion, from which the measurements are made, the electrodes are placed at 10% or 20% of predetermined distances. In this way, the relative placements remain the same as the individual grows. With letters designating the anatomical area, the general-purpose 10-20 system is illustrated in figure 3.3. The odd-numbered electrodes are placed on the left side and the even-numbered ones are placed on the right side. Both are separated by the midline or zero electrodes. A total of twenty one electrodes is normally used, but other electrodes may be inserted if necessary.

Due to muscle movements, the electrodes are also sources of artifacts (noise). As Cooper and others (1980) wrote,

> "Unfortunately, at the present time, electrodes are far less stable than the amplifiers that are available..."

3.3.2 - The montage selector

Normally, the electrode leads are connected to an array of sockets known as the head box, which is located near the patient. The head box is connected to the amplifier inputs

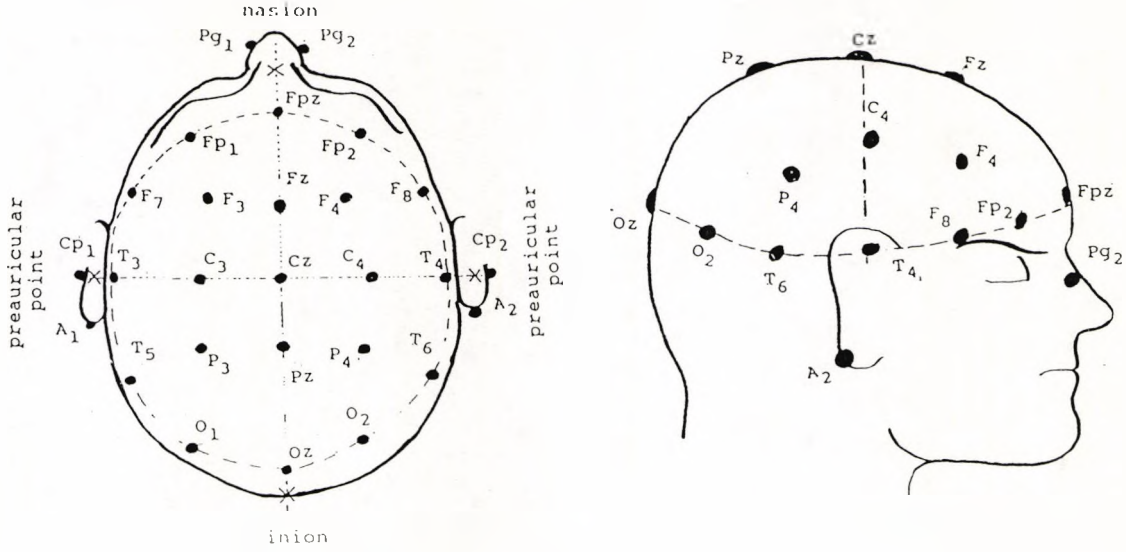


Figure 3.3 - 10-20 system.

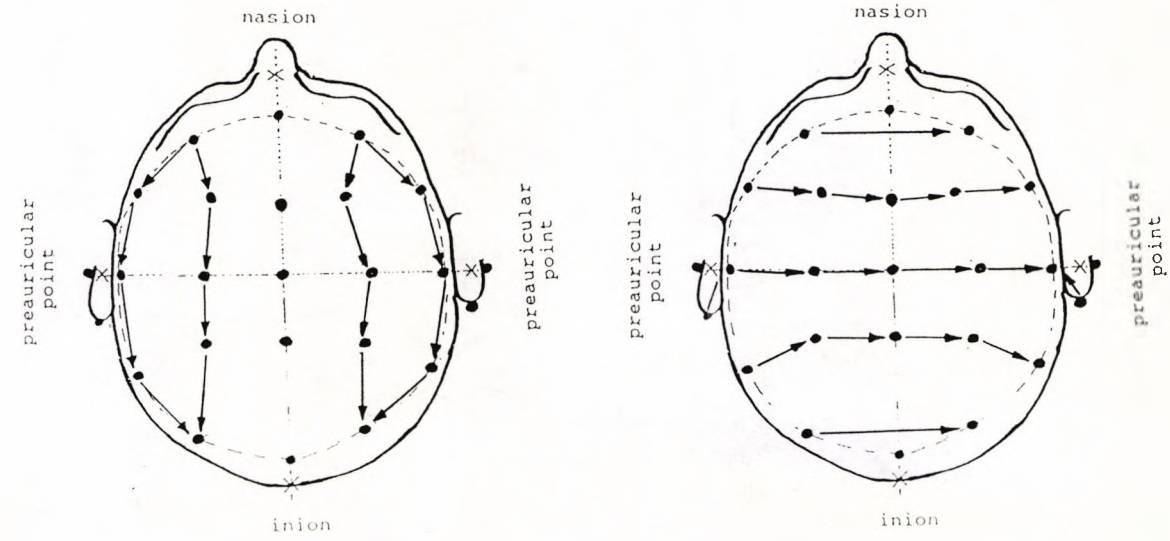


Figure 3.4 - Different forms of montage.

through a multiwire cable and a set of switches.

This set of switches permits the electroencephalographer (EEGer) to select the appropriate "montage", that is a particular combination of electrodes at a particular point in time (Niedermeyer and L. da Silva, 1987). By using different montages, it may be easier for the reader to notice some special form of activity that would not be revealed by one single form of montage. Figure 3.4 shows two forms of montage.

Of great importance is the method by which the electrodes are connected to the amplifiers. There are two basic methods, these are known as bipolar and unipolar (reference). In fact, both are bipolar.

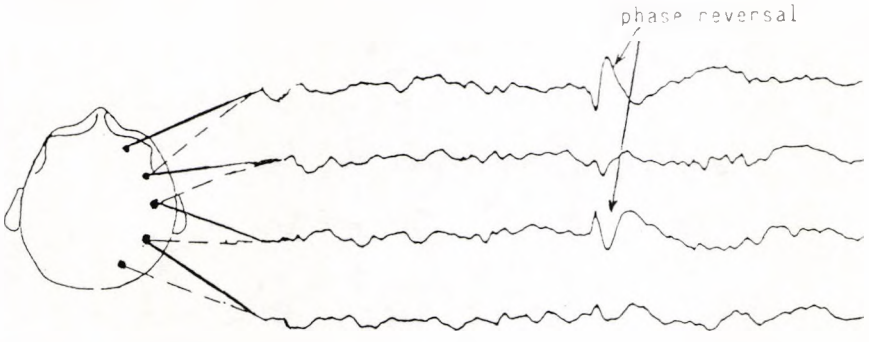
In the bipolar method, the one most used in Europe, each amplifier measures the potential difference between two electrodes both of which are affected by appreciable EEG potentials. In scalp-to-scalp linkages, this method is very useful to show changes in polarity. It is caused by the phase-reversal phenomenon as shown in figure 3.5. In 1958, Jasper recommended that "bipolar recording should always include montages with linked serial pairs in straight anteroposterior and transverse lines".

The reference method is an attempt to make the signal registered at a particular point be a real representation of the electrical activity at that point only. In this method, one electrode (the reference) is common to all or to a group of electrodes and the electrode that lies nearest to the focus of activity shows the greatest difference in potential. It is a good method of registering striking patterns such as spike-and-

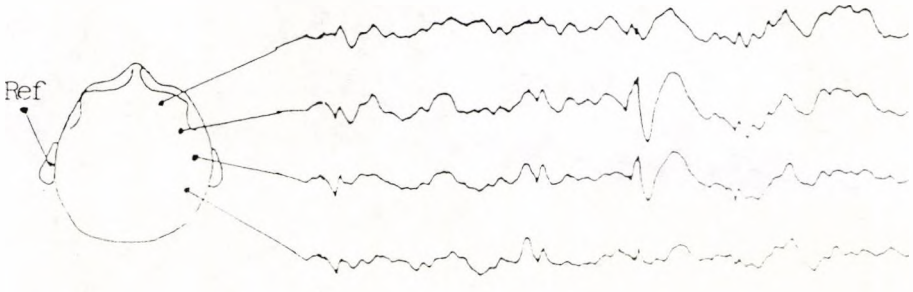
slow-wave complexes.

Three possibilities of choosing a reference arise. In the first one, any electrode may be used as reference. In the second one, the ear lobe and in the third one, a point inside the EEG machine, where the average value of all signals is obtained, are used as references. No matter where this "neutral" electrode is placed, the brain potentials that affect it cannot be ignored, especially when different points on the scalp have common components.

Each method has its advantages and disadvantages. This has been a subject of debate in the EEG community for a long time.



(a)



(b)

Figure 3.5 - (a) Bipolar and (b) unipolar derivations.

3.3.3 - The filters and the amplifiers

EEG signals are normally described as functions of several different waveforms and their respective amplitudes. In order to permit the EEGer to select the appropriate waveform and amplitude, eliminating most noises, each channel contains basically two filters and three amplifiers.

A lowpass and a highpass filter are provided, both with variable cutoff frequencies, usually covering the band 0 - 100 Hz. The degree of attenuation for the cutoff frequencies may depend on the manufacturer.

The amplifying sections are an input balanced amplifier, an intermediate amplifier, that has variable gain, and an output amplifier. The total gain may have to reach, for example, the order of 20000 so that a 50 μV signal may cause a deflection of 1 cm in the pen.

3.3.4 - The recording system

The recording system usually comprises a writing system (polygraph). The output signal of each channel drives a moving coil or moving iron electromagnetic system to which a pen or a very thin tube (ink-jet system) is attached. As this electromagnetic system stays in a fixed position, the time scale for the record is provided by a recording paper that travels perpendicularly to the direction of the pen deflection. The paper driving system has to be very stable and accurate.

The driver amplifiers have to be matched to the elec-

tromechanical characteristics of the writing system and this has to be well calibrated in terms of its oscillatory properties, so that each trace represents the real corresponding signal.

Both the inertia and the friction of the writing system are factors that determine the high frequency response of an EEG apparatus. Whilst the pen writers reach a usual upper cutoff frequency of 100 Hz, the ink-jet writers, that have low inertia and low friction, may reach up to 1 kHz.

3.3.5 - Electrical safety

All electrical equipment used in medical practice must meet special safety requirements. In the case of the electroencephalograph, a very low value of earth leakage current must be assured. If the patient has to be in contact with other electrical equipment, as during a surgery, for example, the electroencephalograph must be completely insulated from the others.

Special attention must be given to safety conditions if connections are made with data acquisition, data storage and data processing equipment. This is not only the case of sophisticated electroencephalographs, but also of portable monitors that are carried by the patient.

3.4 - The EEG Signal

It is not easy for astronomers, for example, to understand what is really going on inside the Sun when all they can see is its surface. Similarly, it is not easy for neurologists to

study the brain based on a few signals collected from the skull surface or even from the cortex, which are just a gross representation of the its activities. For this reason, the EEG has been a source of disagreement among those who have worked in the area. While some researchers have reported good results, others have said that no meaningful information may be obtained from such a complex and distorted signal (Stowell, 1970).

A typical EEG machine has 8-20 electrodes of approximately 1 cm^2 whilst the number of neurons in the brain reaches the millions. It means that the signal recorded by each channel represents the raw average value of all neuronal activity of the underlying cerebral cortex over an area of about 6 cm^2. Consequently, only the synchronized signals emitted by a lot of cells will be picked up by each electrode.

If the brain of an individual is in perfect condition, the synchronous neuronal activity will be considered normal, but, if the individual's brain has some imperfection, then the neurons will generate abnormal synchronous discharges. This is what happens, for example, in individuals who have epilepsy.

It is very difficult to describe an EEG signal quantitatively. It is neither deterministic nor random. The waveform has, in general, a nonstationary form that cannot be represented by a single model. Different models that describe just a few EEG phenomena such as the alpha rhythm and the petit mal seizure spikes have been elaborated during the last decade (Niedermeyer and L. da Silva, 1987). In terms of amplitude, the peak-to-peak value of the scalp EEG lies between 10 and 100 μV (in adults, more commonly between 10 and 50 μV), with spikes reaching 200 μV.

For corticographic (cortex) discharges, it may vary from 500 to 1500 μV, reaching several millivolts in prominent spiking. In terms of frequency, the range may vary from DC to several kilohertz, although for the majority of cases the frequency response goes from 0.16 Hz to 100 Hz.

There are many waveforms that characterize normal or abnormal brain activities. Some of the best known waveforms found in EEGs of adults will be considered next.

3.4.1 - The EEG of a normal person

In order to determine the boundaries of normality and abnormality, the EEGs of normal people have been recorded since the previous works led by Hans Berger.

The frequency range 0.1 - 70 Hz is the most important from the clinical point of view. In order to make it easier to describe EEG records quantitatively, EEG frequencies were classified into the following bands:

delta	below 3.5 Hz (usually 0.1-3.5 Hz)
theta	4-7.5 Hz
alpha	8-13 Hz
beta	above 13 Hz (usually 14-40 Hz)

In a normal adult person, the medium (8 - 13 Hz) and the fast (14 -30 Hz) ranges predominate whilst both the slow (0.3 - 7 Hz) and the very fast (> 30 Hz) ranges are not common.

Both the "alpha" and the "beta" rhythms were introduced by Berger in his second report, published in 1930. Although the

first one refers to the range 8 - 13 Hz, it was defined by Chatrian and others (1974) as having the extra properties of being

> "most prominent in the posterior areas, present most markedly when the eyes are closed, and attenuated during attention, especially visual."

This phenomenon is illustrated in figure 3.6.

The beta rhythm, with an usual amplitude lower than 30 μV and a maximum frequency of 35 Hz, predominates in the frontal and the central regions. It is blocked by motor activity or tactile stimulation.

It has been observed empirically that the maximum amplitude of each rhythm is an inverse function of its frequency range.

There is no logic in the sequence of Greek letters. The reason is purely historical (Niedermeyer and L. da Silva, 1987; Cooper and others, 1980). Other rhythms such as the "mu" rhythm and the "kappa" rhythm are out of the scope of this work.

It is quite obvious that only scalp EEGs have been used with normal people.

3.4.2 - The EEG of an epileptic person

3.4.2.1 - Epileptic patterns

Epilepsy is generally characterized by the appearance of spiky waveforms (single spikes, multiple spikes, sharp waves and spike-and-wave complexes) in both ictal (during attack) and

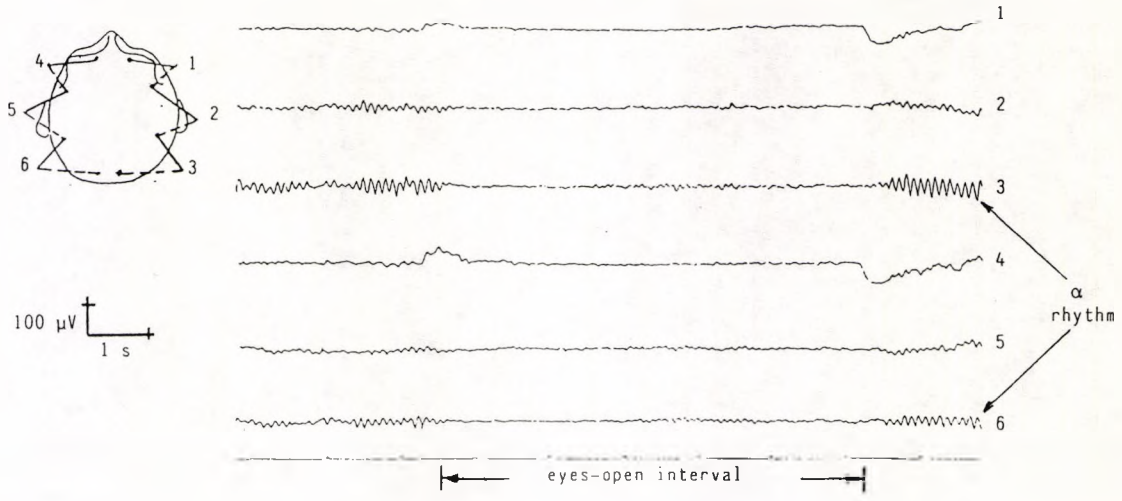


Figure 3.6 - The alpha rhythm, prominent in the occipital region (channels 3 and 6), is blocked by eye opening.

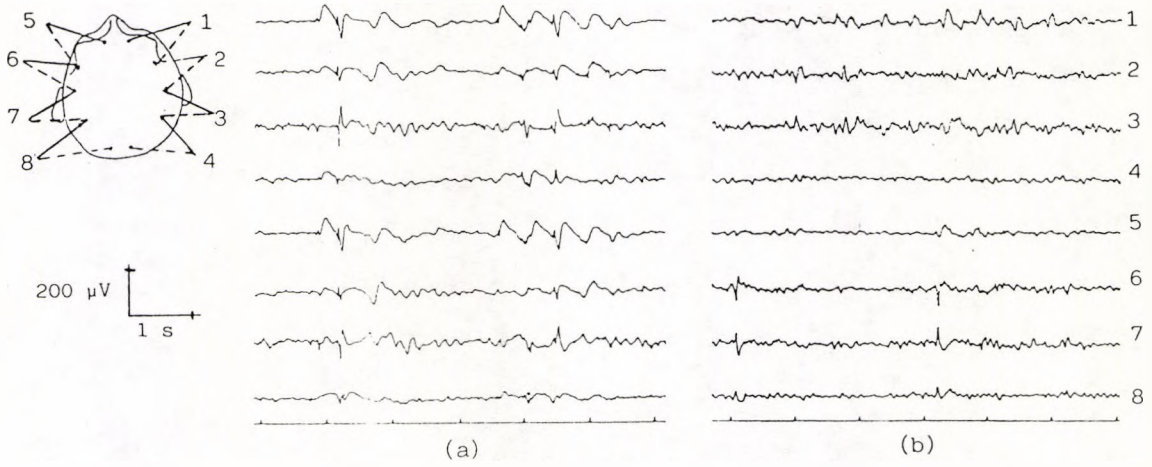


Figure 3.7 - Typical epileptiform waveforms.

interictal (between attacks) EEGs, as shown in figure 3.7.

It must be stressed here that such waveforms, when interpreted in a wide sense, are also seen in the clinical EEGs of healthy individuals who do not have epilepsy. The appearance

of epileptiform discharges in an EEG without the occurrence of seizure does not constitute epilepsy (Laidlaw and others, 1988). The misuse of terms like "petit mal discharges" and "3/sec spike-wave complexes" that may be registered in conditions other than absence seizures and the lack of communication between epileptologists and EEGers, has provoked serious mistakes like the prescription of the wrong drug (Niedermeyer and L. da Silva, 1987).

3.4.2.2 - Intracranial (depth) recording

Partial epilepsies are characterized by localized epileptiform events, i.e., events that are generated in a special region of the brain (by tumours, for example).

In such cases, the scalp EEG, which is in fact a simplification of the depth EEG, may not register these sharply localized ictal events. In the case of neurosurgical treatment, the possibility of the insertion of intracranial electrodes arises. These electrodes have an approximate surface area of 1 mm^2 and are generally more numerous than in the scalp EEG.

Assuming that the electrodes are appropriately placed in the damaged cortical region (see figure 3.2), the recording of spiky waveforms is practically constant.

3.4.2.3 - Scalp recording

Unlike the depth recording, the scalp EEG does not necessarily show spiky epileptiform events, especially in the

case of partial seizures. A simple change in the amplitude of the ongoing activity or the appearance of a different kind of activity, within the alpha, beta or theta range, in the channels that cover the damaged cortical region, may be sufficient to indicate that the person has partial epilepsy. Sometimes, ictal changes in the scalp EEG may not be registered at all in partial epilepsies.

In the case of generalized epilepsies, the scalp EEG is much more efficient. For example, a tonic-clonic seizure is characterized by a fast buildup of spikes that are followed by spike-wave activity in all channels (there are no localizing features). Both activities become less frequent and irregular as the convulsion ends. During the clonic phase, due to muscle jerks, the traces are constantly contaminated by artifacts. The EEG recording of an absence seizure is in general characterized by the appearance in all channels of a relatively symmetrical and regular sequence of spike-and-wave complexes (SAWCs) with a repetition rate of about 3 Hz and duration of approximately 10 seconds. This characteristic signal starts abruptly 1 or 2 seconds before any clinical manifestation may be noticed and may continue shortly after consciousness starts to return.

Figure 3.8 shows part of an EEG that registered an absence seizure followed by a tonic-clonic one.

3.5 - The EEG in Epilepsy

3.5.1 - The routine EEG

A routine EEG may have a duration varying from 15 to

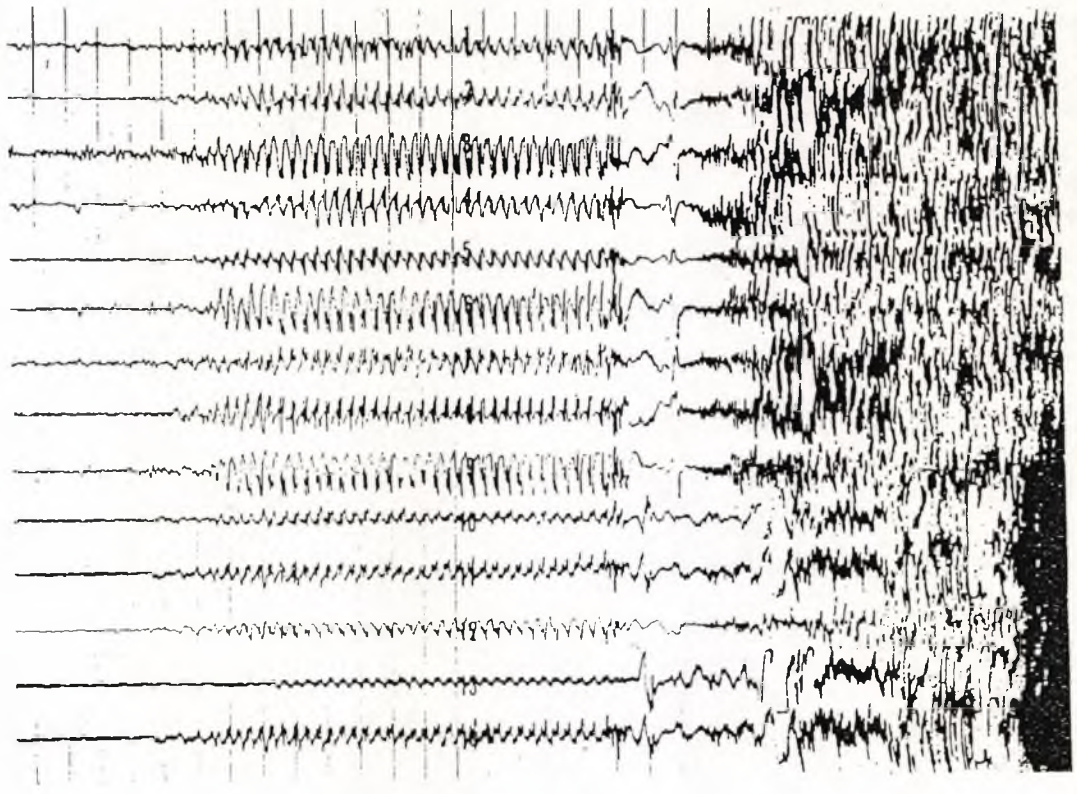


Figure 3.8 - Tonic-clonic seizure preceded by an absence seizure.

40 minutes approximately. By the end, many meters of paper, folded into pages, will have been obtained. Based on the recorded traces and on a report written by the EEGer, the neurologist will do the interpretation in order to avoid mistakes.

The fact that a patient is epileptic does not mean that a single routine EEG will show epileptic waveforms. This is due to the fact that epilepsy is not a static condition. The probability of recording a seizure during a routine EEG is quite low and the probability of recording epileptiform events is not high. For example, Ajmone Marsan and Zivin reported in 1970 that, from a series of routine EEGs performed in a large number of epileptic patients, approximately 35% showed interictal epileptiform sig-

nals, 15% never did , even with 10 or more repeated EEGs, and 50% showed epileptiform discharges in some tracings only.

3.5.2 - The long-term EEG

As a normal EEG does not exclude epilepsy and an abnormal EEG may be recorded from a normal person, a single routine EEG may not be sufficient under certain circumstances. To avoid mistakes that may cause prejudice towards the patient, the best thing to do is to increase the time of observation, increasing in this way the chance of recording a seizure. For this reason, since the 1960s, the investigators have sometimes employed the long-term EEG (hours or even days). To make it possible to differentiate epileptic attacks from non-epileptic attacks, the recording of the patient's movements on cine film in the 60s and nowadays on video, has also been employed. It is now known that not all epileptic seizures are accompanied by EEG changes (Binnie, 1988), which makes video monitoring very useful.

In order to allow the patient to stay in a normal environment instead of a closed EEG room, ambulatory monitoring has also been used, which has been made possible thanks to cassette recorders and telemetric systems by cable and radio .

To show the importance of the long-term EEG, part of a report by J. Sivenius and others (in Dam and others, 1987) is transcribed below (VTM EEG = video telemetric EEG):

> "The indications for the study in the first 100 patients were differential diagnosis of seizures (46 patients), determination of the type of seizures (47 patients), and other

> paroxysmal symptoms (6 patients). Seizures with simultaneous irritative EEG finding were found for 27 patients, while seizures without irritative finding were recorded in 29 patients. Four patients had seizures both with and without bursts in EEG. Forty patients had no seizures during the registration.
>
> In 40 patients the VTM EEG examination led to a change in therapy. For 10 patients the anticonvulsant therapy was stopped and for 22 patients considerable changes were made in medical therapy. Ten patients were referred to the hospital psychiatrist...
>
> For the majority of epileptic patients medical control of seizures causes no serious problems. When the seizures are atypical or EEG findings are missing and the seizures occur frequently, there is a need for long-term EEG monitoring. Inadequate control of seizures despite adequate antiepileptic drug concentrations may be due to false diagnosis or to medication that is not suitable for the type of seizures. With VTM EEG non-epileptic and epileptic seizures can be differentiated reliably."

The long-term EEGs, mainly those that are just recorded on magnetic tape, are not so "easy" to interpret. Costing two or three times more than a 16-channel routine EEG, they are also time consuming. Their examination is very laborious and requires specialized staff (Blumhardt, 1986). For this reason, computers have been employed during the last few decades in the analysis of EEG signals, mainly in the detection of epileptiform events.

The theory of some spike-detectors developed by several authors will be discussed in Chapter 4.

3.6 - New Techniques

Thanks to modern computers, new techniques, that give the neurologist a deeper view of the human brain, have emerged in

the last few decades.

A few characteristics of some of these techniques will be presented in the next section. Each technique has it's advantages and disadvantages. For a more detailed description, the reader should refer to appropriate bibliographical references.

3.6.1 - The x-ray

In the same way a simple chest radiograph may reveal unsuspected lung diseases or cardiac lesions, causes of epilepsy such as intracranial calcifications and bony changes may be revealed by a skull x-ray (Laidlaw and others, 1988).

3.6.2 - Magnetic resonance imaging (MRI)

A sequence of radio-frequency pulses induces resonance in a series of sensitive nucleons. The Fourier transformation of these spatially coded signals generates a series of two-dimensional images that represent 5 mm-thick cross-sectional slices of the brain, which are used to construct a three-dimensional image. As resolution is the main shortcoming, a long time (up to one hour) use to be necessary in order to make enough measurements to obtain a high-resolution image (Siemens, -).

The latest commercially available MRI models have made it possible to obtain an image in 5-10 minutes, using 1mm-thick slices.

Less invasive than X-ray, this technique may be repeat-

ed as many times as necessary.

3.6.3 - Computed tomography (CT)

Materials of different densities such as bone or calcification, soft tissue or water, fat and air may be distinguished in a radiograph. A more quantitative reading of tissue density that makes it possible to distinguish between the different intracranial tissues is given by CT .

A collimated x-ray beam, with a thickness of 1-13 mm, is transmitted through the skull from many directions and angles. Its intensity is measured before and after transmission. Depending on the average absorption level provoked by each tissue in each location, the respective result is obtained by a computer and printed out in a corresponding location. The method requires that the patient stays still from some seconds to a minute.

When CT is performed carefully, a very high percentage (> 95%) of intracerebral abnormalities such as tumours, infarcts and haemorrhages may be detected and accurately localized (symptomatic epilepsy). In relation to an EEG, which detects up to 90% of the irregularities caused by brain tumours and is accurate in only 60% of their localizations, CT is still considered complementary to the EEG (General Electric, 1976; Scott, 1987).

3.6.4 - Magnetoencephalogram

Not only electrical fields but also magnetic fields are originated by ionic currents at the cellular level in the central

nervous system. This magnetic field has a strength in the order of magnitude of 10^{-8} Gauss whilst the earth's magnetic field has a strength of 0.5 Gauss.

Thanks to a special magnetometer that was introduced some years ago, which is based on the superconducting effect at the temperature of liquid helium and is sensitive enough to measure fields in the order of 10^{-10}, it is now possible to measure the magnetic field produced by the human brain. External magnetic fields, that are almost constant over long distances, are eliminated by subtracting the potentials that are induced in two coils that are placed closely to each other.

Like the CT, the MEG is also valuable in the management of symptomatic epilepsy.

3.7 - Summary

Reported by Hans Berger more than 60 years ago, the EEG is still a subject of controversy.

Representing the electrical activity of the brain and obtained through a series of electrodes attached to the scalp (extracranial electrodes) or inserted into the brain (intracranial electrodes), it is considered by some clinicians as a series of distorted scratchy ink-on-paper traces from which no significant information may be obtained (Stowell, 1970). Other researchers have reported special and significant results.

Even with the advent of computer-assisted diagnostic systems such as computed tomography, EEG is still paramount in the management of epilepsy (Richens, 1988) and is quite valuable

when measuring the effect of medical treatment (Ebersole, 1989).

The long-term EEG, used in the last few years in order to minimize mistakes, has transformed electroencephalography into a computer-assisted process.

CHAPTER 4

COMPUTER ANALYSIS IN ELECTROENCEPHALOGRAPHY

PATTERN RECOGNITION TECHNIQUES

4.1 - Introduction

In 1989, the American interplanetary spacecraft Voyager 2, that had been launched 12 years before, passed by the planet Neptune.

As it approached the planet, it started to show some of the planet's characteristics that were still unknown, including three great spots on its surface, two of which were dark with slow rotation (relative), with the third one in between. This last was the smallest; it was white and had fast rotation. The greatest dark spot, with a diameter equivalent to that of Earth, showed a white cloud in its surroundings, which left the scientists very curious. Due to the planet's rotation the spot(s) appeared and disappeared. This factor made the scientists have some suspicion that the white cloud could not be the same but a new distinct one at each time.

Curiosity is always a good factor in research. The research team that was responsible for data collection and analysis was not satisfied with the results obtained so far. The scientists wanted to obtain more detailed information about the great spot and all they could do was to process the images that were sent by the spacecraft.

A technique the research team employed was to select two series of pictures, one of them always showing the big spot as the reference in the centre and the other having the polar cap as the main reference, as if the pictures had been taken at each Neptunian day, and to replay them at higher speed. That was enough to show that the great dark spot rotated counter-clockwise and that the white cloud in question seemed to be the same while other white clouds appeared and disappeared. This way, it was possible to have a basic idea about the weather in the distant planet.

All this was made possible thanks to computers (including the 3 computers that controlled the spacecraft and all its activities and the computers on Earth) and to the fact that Voyager 2 filmed the planet for several hours. If the spacecraft had taken only a few pictures, maybe none of the spots would have been revealed. If they had not been revealed, no special details about them or the whole planet would be known.

In electroencephalography, a few EEGs may not show any special detail. If some epileptiform patterns appear in the EEG, it does not mean that the person has epilepsy. If the EEG is normal, it does not prove that the patient is not epileptic. If the person has epilepsy, what kind of epilepsy is it? Is the treatment effective? All these questions may have more precise answers nowadays, but, as discussed in Chapter 3, long-term monitoring is a necessary tool and its analysis must be made automatically by computers whenever possible.

Even pronounced disagreements may exist among EEGers and among neurologists. In 1964, W. B. Matthews, who worked at

the Derbyshire Royal Infirmary, wrote:

> "It is common knowledge that in this country it (the EEG) is mainly used by those with no training in neurophysiology and often with insufficient experience of clinical neurology."

This has been the author's own experience during the last three years in London. Having the same EEG and the same report in their hands, two neurologists said it was "normal". The third one said it "contained abnormalities".

Scarcity of qualified specialists is another reason to make use of computer evaluation of EEGs, even routine EEGs. This way, mistakes made by non-specialized technicians may be avoided and the good EEGer will be free to give more attention to very special recordings instead of spending time with the analysis of easily classifiable EEGs (Barlow, 1979).

In this chapter, a general idea will be given about different methods that have been developed during the last two decades to analyze EEG signals, with emphasis on the detection of spikes and SAWCs. A few of them were implemented in analogue form, others were implemented either in hybrid or digital form.

4.2 - Analysis of EEG Signals

In 1938, EEG pioneers Albert Grass and Frederick Gibbs tried, maybe for the first time, to automate the analysis of EEG signals. Recording the EEG on film and playing it back repetitively through an electronic filter (like the soundtrack of a

movie), they obtained, by Fourier transformation, the frequency spectrum of the recorded data and concluded:

> "After having made transforms of 300 electroencephalograms, we are convinced that the system not only expresses data in a manner more useful and concise than is possible by present methods, but that in many cases it indicates important changes in the electroencephalogram which would otherwise remain hidden."

The application of computers to the analysis of brain electromagnetic signals has received reasonable attention during the last twenty years. Glover and his co-workers (1986) gave four basic advantages that automated scoring of EEGs can offer over visual scoring:

1) They can ease the work of the EEGer by providing off-line, faster than real-time analysis of lengthy records.

2) They can provide reliability and repeatability in the analysis of data.

3) They can offer a tool for detailed quantification of sharp transient (ST) activity, which could be used to study the effect of drug treatment.

4) They could eventually lead to a comprehensive definition of an ST, and thus contribute to the standardization of ST detection.

As discussed in Chapter 3, there are two main kinds of EEG activity in general terms. One is what is denominated "the normal EEG" and the other is "abnormal", many of which will be the EEG of the epileptic person. In the first case, the basic

idea is to monitor the background (stationary) activity. In the second case, it is necessary to detect transients (nonstationarities), mainly spikes and spike-and-wave complexes (SAWCs).

Methods of analysis in both the time and the frequency domains have been used.

In the time domain, amplitude and time interval are the main factors to be analyzed. To analyze amplitude, the use of statistical features such as mean value, standard deviation, skewness and curtosis is made. When analysis of the time interval is carried out, features like level (zero) crossing of the original signal and both its first and second derivatives are commonly employed. Combination of amplitude and time interval analysis gives different sets of features that can be used to classify the EEG signal (Niedermeyer and L. da Silva, 1987).

In the frequency domain, spectral amplitude and power intensities are the features commonly selected to study the signal in the empirically defined bands (subdivisions of the classical frequency bands have been adopted by several authors).

4.2.1 - Analysis of background activity

Long-term monitoring of background activity is mostly unnecessary in normal clinical practice , but it is useful, for example:

1) in the scoring of EEGs obtained during "sleep stages" [study of brain signals in sleep analysis] (Haustein and others, 1986),

2) when the effect of medical treatment is being

measured and

3) in intra-operative neurological monitoring (Gotman, 1989).

In the last case, for example, a patient who is undergoing cardiac or carotid surgery (both disturb the blood flow to the brain) or neurosurgery, may benefit from such kind of monitoring. In fact, it is always important whenever there is a possibility of brain damage, be it direct (neurosurgery) or indirect (anesthesia, bleeding during the introduction of a catheter, etc).

Spectral analysis is the main method of characterization of background EEGs. The basic method of determination of spectra by complex demodulation or heterodyning (Walter and Brazier, 1968) has not been widely applied in EEG analysis .

To avoid ringing in the presence of transients, low-Q analogue filters , succeeded by 12-bit digital filters (in the 70s 8-bit wordlength machines were shown to be inadequate) and threshold detectors were originally employed to extract information about period and amplitude, variables constantly used in pattern recognition algorithms (Principe and others, 1979). More recently, the Fast Fourier Transform has commonly been used to obtain the important banded intensities that characterize the EEG in each case, such as the alpha rhythm. Normally, the final result comes in the form of a histogram showing the frequency variation of a sequence of EEG segments. To decrease the processing time of the FFT, the use of both Haar and Walsh functions, that have values equal to "+1" and "-1" only, have been tried as

orthogonal functions, in place of sine and cosine functions, but satisfactory results have not been obtained (Barlow, 1979; Weide and others, 1978).

As on-line real time analysis is necessary in these situations, a drastic reduction of bandwidth (2-15 Hz) was normal 20 years ago. Lately, this bandwidth has been increased to 0-40 Hz (Niedermeyer and L. da Silva, 1987).

Spectral estimators that operate based on autoregressive (AR) models have also been used (Jansen and others, 1981; Smith and Lager, 1986; Blinowska and others, 1988).

4.2.2 - Detection of transient activities

The detection of epileptiform signals generated by the brain during seizures (ictal) or in between seizures (interictal) may help, for example, in the localization of an epileptogenic focus in cases of partial epilepsies, such as temporal lobe epilepsy. Once it has been proved that the person is epileptic, it may also be useful for detecting seizures (Viglione and others, 1970 and 1973). Due to the great interest that exists in studying correlations between behaviour and the occurrences of petit mal absences, much effort has been expended in order to detect them, this being the main area of application of seizure detection (Niedermeyer and L. da Silva, 1987).

The detection of transient nonstationarities is by itself a goal. Another goal is the reduction of the size of the data set, which facilitates the classification of the data.

Two important types of epileptiform features are the

spike and the spike-and-wave complex. Sharp waves, that have a duration in the range 70-200 ms, are out of the scope of this work. It must be emphasised here that not all transient events are necessarily epileptiform.

If an electroencephalographer is asked why a particular section of an EEG was considered to contain an abnormal paroxysmal pattern (transient), the EEGer will consistently answer that the section in question differed from background activity (Carrie, 1972). For this reason, in this kind of analysis, the epileptiform event is considered to be the "signal" whereas the background activity is considered to be the "noise", making the detection of these features a typical example of the application of a pattern recognition approach in EEG analysis. This has led to several pattern recognition methods, including:

1) matched filtering,

2) various combinations of amplitude, slope and sharpness, normally of the leading and trailing edges of the spike,

3) band filtering,

4) decomposition of the EEG into segments and

5) autoregressive estimation.

4.2.2.1 - Matched filter

The matched filter is mainly used to detect the presence of signals embedded in white noise. Keeping this idea in mind, it has been used mainly in the detection of SAWCs (signal), where a SAWC pattern, that constitutes the template, is convolved

with the input EEG (noise). When the signal matches the template, a high value is obtained at the output. One problem is the fact that the background EEG cannot be represented by white noise (Comley and Brignell, 1981). The basic block diagram and waveforms are shown in figure 4.1.

In a similar way, the computation of the crosscorrelation coefficient between the EEG signal and the template, which is not reversed in time, has also been employed.

Looking at the template in figure 4.1, it becomes easy to understand that, although the input signal is characterized by both the spike and the slow wave, the slow wave contributes to most of the output signal. In this way, a high correlation coefficient may be obtained for an input signal that has a large slow wave and a very-low-amplitude spike or no spike at all, which will lead to detection errors.

To overcome this problem, Weinberg and Cooper (1972) used two distinct templates, one for the spike and another for the slow wave. The 'recognition index' was obtained by multiplying both coefficients when they were positive.

Some practical results will be discussed on Chapter 5.

4.2.2.2 - Use of derivatives

The application of differentiators in the detection of sharp transients is very basic.

The two criteria most often mentioned for the visual recognition of epileptiform spikes are duration and sharpness. Duration may be obtained by measuring level crossings of the

slopes which depend on the first derivative, while sharpness is a function of second derivative. Shown in figure 4.2, are a typical spike and both its first and second derivatives (a spike is defined as having a duration from 20 to under 70 ms - in the

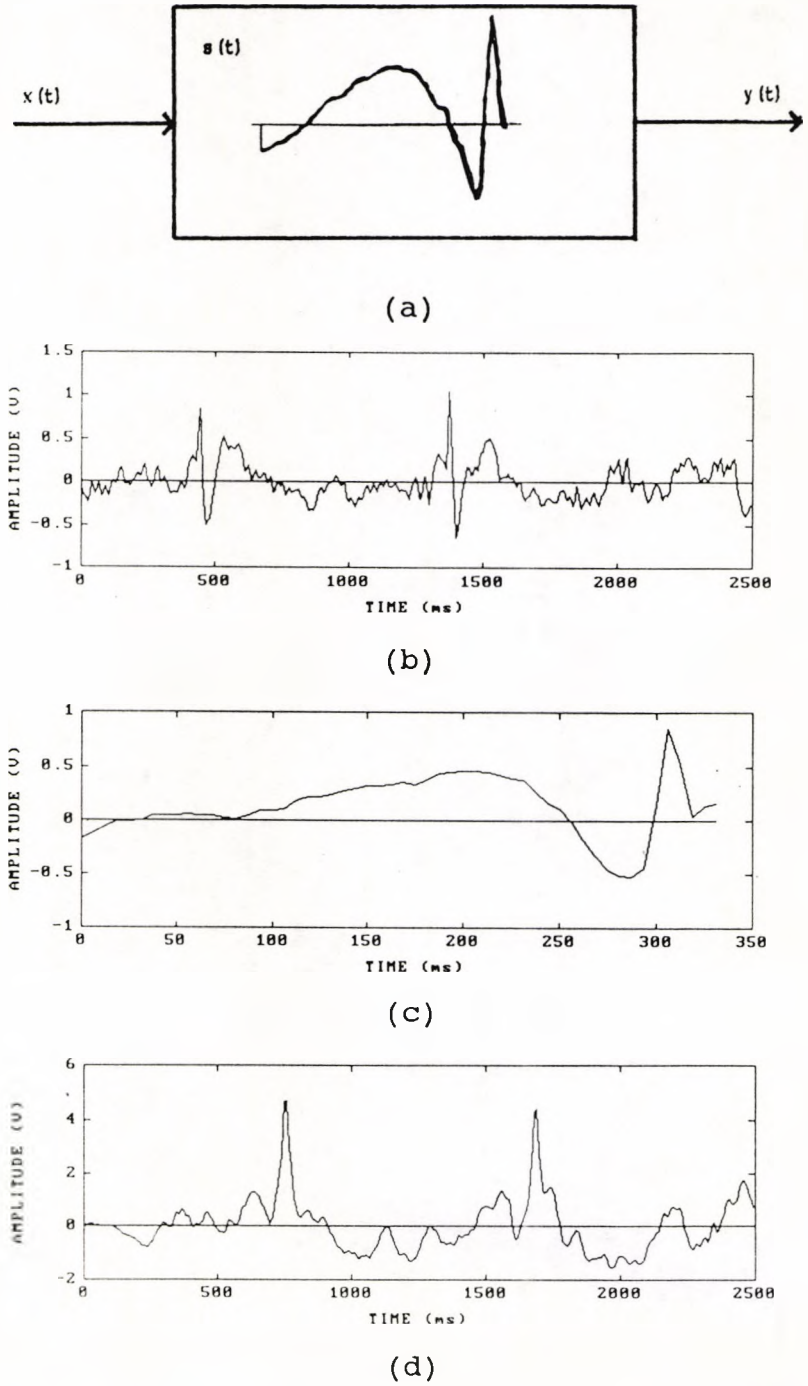
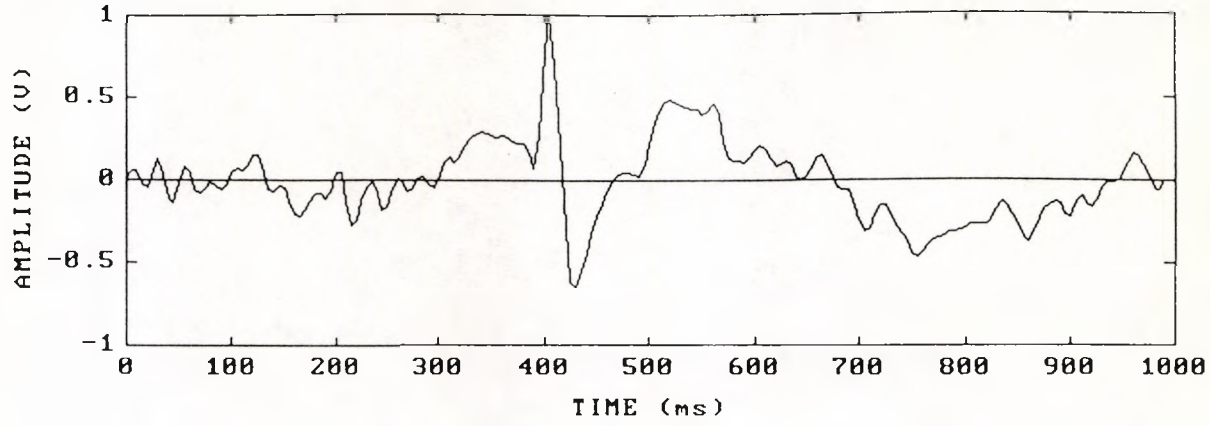
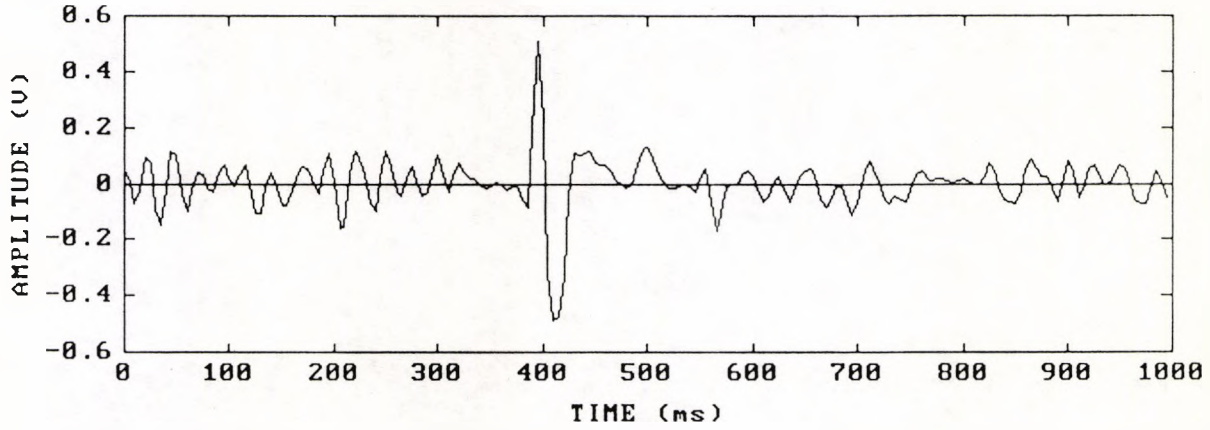


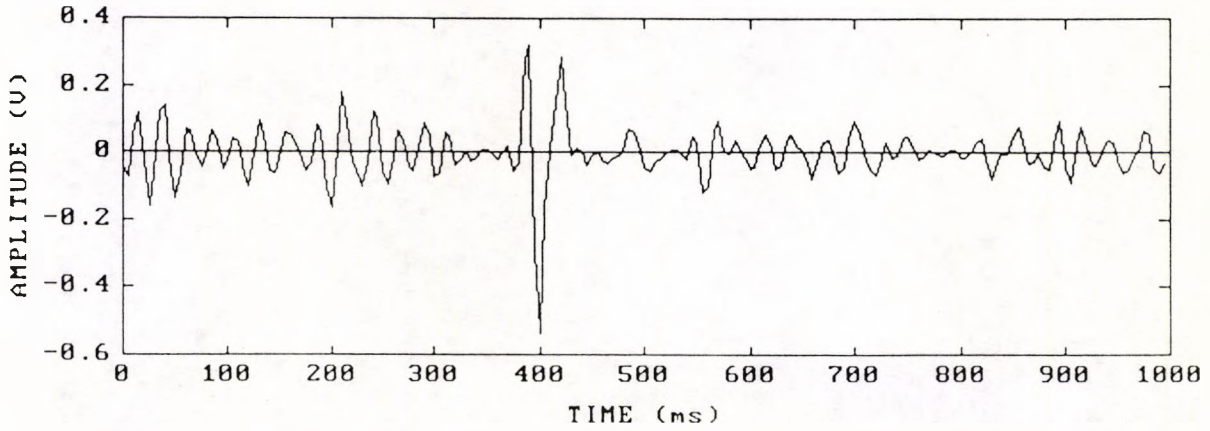
Figure 4.1 - Matched filter. (a) Block diagram, (b) input signal, (c) template and (d) output signal.



(a)



(b)



(c)

Figure 4.2 - (a) Spike, (b) first and (c) second derivatives. (The amplitudes are not absolute).

past, it was considered to have a duration below 1/12 s or 83.3 ms).

Some basic characteristics and some of the main differences in the methods that are based on derivatives will now be discussed.

1) An heuristically derived method was developed by Carrie in 1972. He used a hybrid computer to process signals from one channel only. The detection of a spike was considered to be when the peak voltage level that was reached in the (filtered) second derivative was three or more times greater than the moving average value for this measurement for a preceding epoch. According to Carrie, other authors had already used similar methods, but with fixed threshold values.

The author mentions that the use of the second derivative is more efficient in the discrimination of sharp transients than the first derivative, mainly in segments that contain low-amplitude spikes and high-amplitude slow waves, where the highest value for the first derivative may occur during the slow wave and not during the spike.

Later, in 1977, Carrie and Frost used the same technique to monitor a single channel in the detection of SAWCs.

2) In 1973, Walter and his colleagues presented a very simple analogue circuit that was intended to help in the quantification of sharpness of EEG transients. The circuit consisted of four operational amplifiers, two used to obtain the first and the second derivative signals and the two others to full-wave rectify both signals. A "deadband" is included in the rectifiers

to avoid the detection of low-amplitude signals. The second derivative has been considered of main interest.

Following this report, a comment is made on it by E. Glaser, recommending great caution in the use of the second derivative as a factor of characterization of the shape (sharpness) of a waveform because the amplitude of the second derivative is proportional not only to the sharpness of the signal but also to its original amplitude. As an example, Glaser mentions that if a component in an EEG signal is seen simultaneously by two electrodes A and B located apart and if the amplitude of this component is K times higher in A than in B, so will be the second derivative. Using such criterion, the wave may be considered sharp only at electrode A, which is not true.

3) J. Smith, in 1974, avoided measuring the sharpness through the second derivative as this method enhances the high-frequency noise present in the data, making it susceptible to errors. He decided to measure, instead, the time interval (T2) it took for the slope to change from the magnitude of one polarity to a large magnitude of the opposite polarity. This time interval should be sufficiently short.

The sequence of measurements chosen by Smith was:

(1) to measure the slope of the first half of the spike (first leg) through the first derivative and check if it exceeded some threshold for some preset time,

(2) to check the sharpness and

(3) to check if the slope of the second half remained above threshold for a specific time interval.

Digital circuitry was used to measure the time intervals.

The author passed the EEG signal through a lowpass filter with a cutoff frequency of 60 Hz, admitting that 30 Hz could be selected if necessary, in which case the threshold levels would have had to be changed. An analogue pseudo-differentiator with a transfer function given by "G(s)=s/(s+b)" was simulated. A PDP-8/I minicomputer was used by Smith.

This technique of measuring a time interval instead of the second derivative was used later, in 1981, by Comley and Brignell. Implementing the algorithm in a prototype based on the CP1600 microprocessor, they found an interval of 8 ms to be suitable to specify the rate of change of apex.

4) Ktonas and Smith proposed in 1974 a set of 6 parameters (S1, S2,..., S6) to characterize a spike. Illustrated in Figure 4.3-a, these parameters respectively represent:

(1) maximum spike slope before reaching the peak;

(2) maximum spike slope after reaching the peak;

(3) time it takes for the spike to reach its peak after attaining maximum slope;

(4) time it takes for the spike to reach maximum slope after reaching its peak;

(5) sum of S3 and S4, that is a measure inversely proportional to the spike sharpness;

(6) time interval between two zero crossings of the same polarity of the first derivative.

Based on this work, another set of 10 parameters was

redefined in 1981 by Ktonas and his coworkers. Seven parameters are shown in figure 4.3-b. The other three are:

(1) slope 1 and slope 2, defined as the maximum magnitude of the first derivative during the leading and the trailing edges of the spike, respectively, and

(2) sharpness, defined as the second time derivative of the spike at its peak.

Spike detection algorithms based on these parameters have been developed by other researchers (Oliveira and others, 1983; Glover and others, 1986).

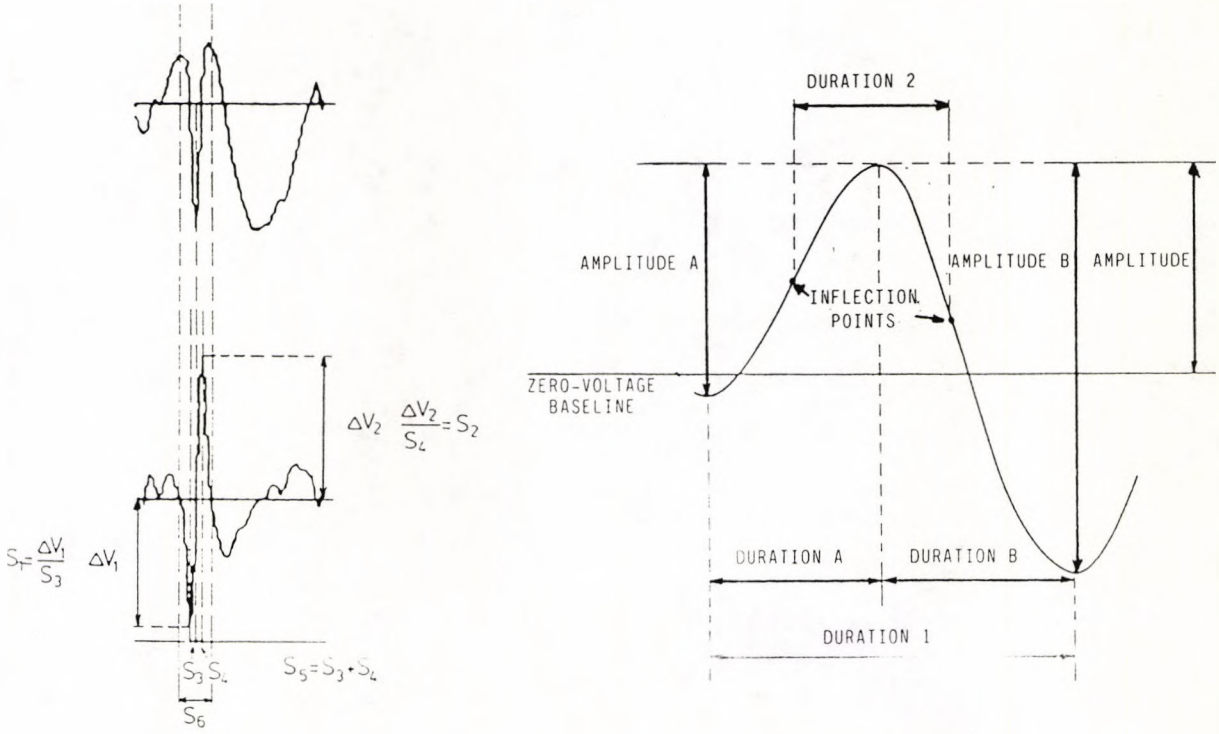


Figure 4.3 - Sets of parameters defined to characterize a spike.

5) In 1983, in order to obtain some of the parameters described before and some that were derived, Oliveira, Queiroz and Silva also used derivatives. In an hybrid microcomputer system, the first-order and the second-order differentiators were analogue. The main difference was the fact that both differentiators were independently configured in parallel, being, this way, more stable. An advantage the authors gave is the fact that the analogue circuitry permits a very high time definition without the need to sample the signals at high rates.

6) Qian, Barlow and Beddoes (1988) presented the results of a sharp transients detector, consisting of two main stages. The first stage was another kind of differentiator. Its output consisted of the difference between the current input sample and another one that occurred a number of samples earlier [x(n) - x(n-m), where m > 1]. The second stage was a product operator, the inputs for which were the present sample and a slightly delayed sample of the differentiator output signal.

For more details, see Chapter 5.

4.2.2.3 - Bandpass filters

In order to detect a spike followed by a slow-wave (SAWC), a signal that characterizes petit mal epilepsy, some authors have employed two independent bandpass filters. A basic description of three distinct methods follows below. The first one was reported by Quy, Fitch and Allison in 1980, the second by De Vries, Wisman and Binnie in 1981 and the third by Principe and

Smith, in 1982.

1) The system was developed to help in the detection of petit-mal-seizure signals (not individual SAWCs) previously recorded on cassette tapes. As the signals were analyzed at a speed 60 times greater than real-time speed, the detection of slow waves was obtained with a 120-240 Hz bandpass filter (equivalent to 2-4 Hz in real time) while the detection of spikes was obtained with a 720-1080 Hz filter (equivalent to 12-18 Hz). Both signals were rectified and converted to DC levels; the signal that corresponded to the spikes was passed through a 120-240 Hz filter (equivalent to 2-4 Hz) in order to isolate the rhythmic spikes. Both signals were then compared to threshold levels and passed through an AND gate in order to activate the output when a seizure was detected.

2) To monitor one channel of EEG, two analogue and active 4th-order bandpass filters were configured in parallel. One of the filters, with a bandwidth of 15-30 Hz (β band), was used to detect the spikes. The other filter, with a bandwidth of 1-4 Hz (δ band) , was used to detect the slow waves. Both filters were followed by Schmitt triggers. A monostable circuit was triggered by the spike, remaining "HIGH" for 300 ms. During this interval, if a slow wave was detected, a SAWC was considered to have been recognized.

3) A fourth-order digital bandpass filter covering the range 10-25 Hz, sampled at 240 Hz, and another covering the range 0.8-6 Hz, re-sampled at 80 Hz , were used to detect the

spike and the slow wave, respectively. Period discrimination and threshold logic circuitry was used to analyze the filtered data.

4.2.2.4 - Breakdown of the EEG into segments

Developed by Gotman and Gloor (1976), the method involved the breakdown of the EEG into smaller units, as shown in figure 4.4. First, the signal was broken down into segments, where a segment was defined as the section between two consecutive extrema of amplitude. The segments were then grouped into sequences. The end of a sequence was determined when a segment that could not belong to that sequence was found. Two segments, two sequences or a segment and a sequence, that were adjacent and of opposite direction, were then used to form a wave, in which both a segment and a sequence were referred to as half-waves. By using segments and sequences to compose the waves, the activity of both sharp waves and slow waves could be examined. In the case of rhythmic activity, both signals, composed of segments or sequences, would be equal (each sequence would contain only one segment).

Later, the waves were submitted to appropriate decision criterion, that included amplitude relative to background activity, sharpness and duration.

4.2.2.5 - Inverse autoregressive filtering

Assuming that an EEG signal could be represented by a filtered noise signal with normal distribution, Lopes da Silva

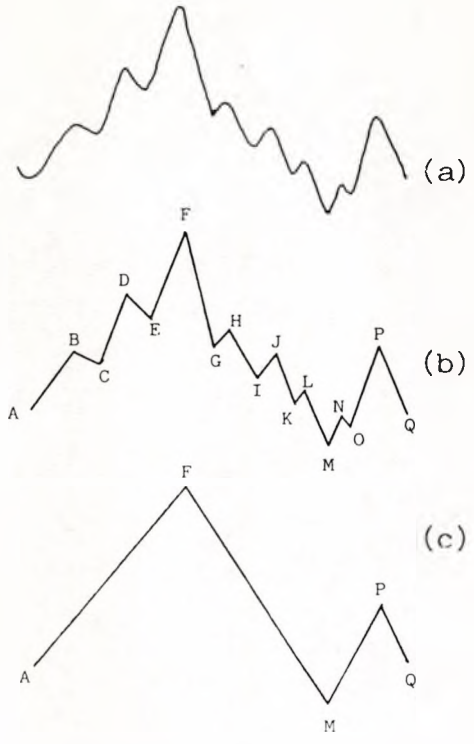


Figure 4.4 - Decomposition of an (a) EEG into (b) segments, (c) sequences and waves. Examples of waves: ABC is composed of 2 segments; AFM is composed of 2 sequences and AFG is composed of a sequence and a segment.

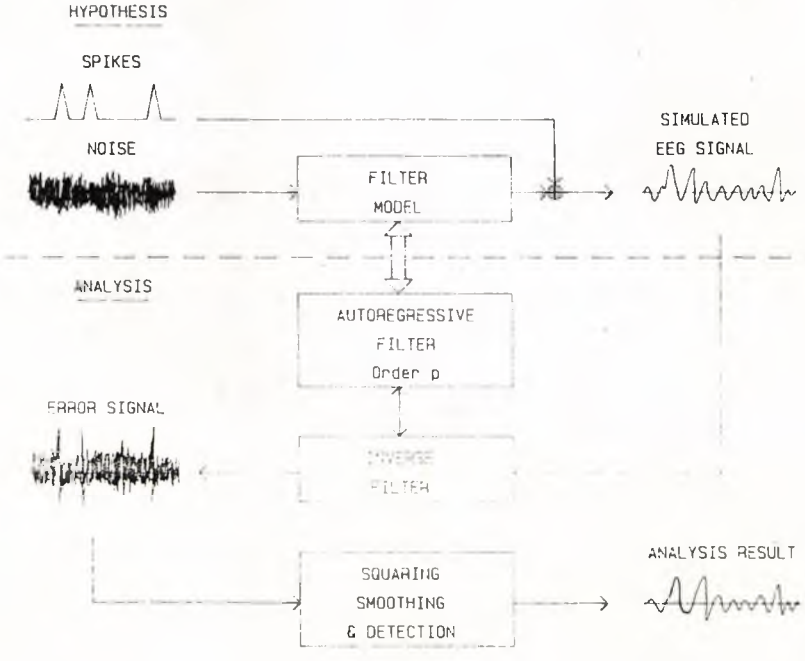


Figure 4.5 - Inverse autoregressive filtering.

and his colleagues (1975, 1977) tried to detect the presence of non-stationarities by passing the EEG signal through an inverse autoregressive filter (the autoregressive filter model should provide the best fit for the on-going EEG activity) and checking the generated error signal with chi-square statistics, as shown in figure 4.5.

Considering that the interictal EEG of an epileptic patient resulted from filtered noise to which spikes were added, the output of the inverse filter would, in normal conditions, be a noise signal with normal distribution. If the error signal deviated at a certain probability level from a normally distributed noise, a nonstationary signal such as a spike, for example, was considered to be present.

The selected EEG epochs had a typical duration of about 10 seconds and were analysed off-line by a PDP-11/20 computer.

4.3 - Summary

Some methods of automatic detection of non-stationarities in EEGs, which have been developed during the last twenty years, have been reviewed.

The need for automated detection was discussed and some of the major problems considered, e.g. problems of model definition, non-stationarity of the EEG signal, etc.

CHAPTER 5

DETECTOR OF SPIKE-AND-SLOW-WAVE COMPLEXES

5.1 - Introduction

Several years ago, a six-year-old boy was taking a test of his mother language during his first year at primary school. It was one of his first tests. Although he did his best, he didn't achieve the maximum mark because he wrote a very strange four-word sentence, that was not part of the story being dictated by the teacher. Days later, showing the results and the tests to his parents, the boy said that all he could remember was the moment he was writing the last of those four words, a non-existent word, when he tried to remember the grammar rules that specified if it should be written with an **s** or a **z**. That strange sentence was certainly a consequence of a petit mal attack (absence), that lasted just a few seconds, but nobody could be sure of this. Nowadays, it would be possible to be sure. The patient may carry a long-term EEG monitor that will register the signals on such occasions, so that a higher degree of confidence can be put on the diagnostic results.

As seen in Chapter 2, petit mal epilepsy, a form of generalized epilepsy, is a typical disorder of childhood (adults may also have it). An absence attack, with an usual duration from 5 to 20 seconds, consists of impaired consciousness and is com-

monly associated with some kind of automatism (a clinical absence is usually present when the discharge lasts more than 5 seconds). Sometimes the patient does not lose consciousness and it is described as a "sensation". The patient has no warning of these attacks (Gloor and Fariello, 1988). The characteristic EEG waveform is a generalized 3 Hz spike and wave discharge, that may start at a 4 Hz rate and slow down quickly to 3 Hz and even 2.5 Hz during the final phase, as shown in figure 5.1. According to Niedermeyer and L. da Silva (1987),

> "... the spike wave discharge apparently represents a succession of excitation and inhibition. The clinical ictal activities are thus constantly curbed by intervening inhibitory impulses that prevent the attack from progressing into massive downward discharges with motor effects..."

(such as a grand mal attack).

During an EEG, special activating techniques are used to precipitate discharges. In the case of absences, a powerful technique is hyperventilation, which was known prior to the advent of EEG. Sometimes the most powerful activating techniques are used but abnormalities may not emerge (Chadwick, 1988), which is a good reason to make use of long-term EEG monitoring equipment.

In 1979, Barlow wrote:

> "...mixed fast and slow transients, such as spike and slow-wave complexes ... have received rather less attention, and hence, this is an area especially requiring further work since these kinds of events are also very much a part of clinical EEG".

Having in mind these words and the future development of a portable SAWC (spike-and-wave complex) monitor that may be carried by the patient, a SAWC detector has been developed and the study of its features is the subject of this chapter.

The fact that 3 Hz spike-wave complexes are not only characteristic of petit mal epilepsy must be remembered here.

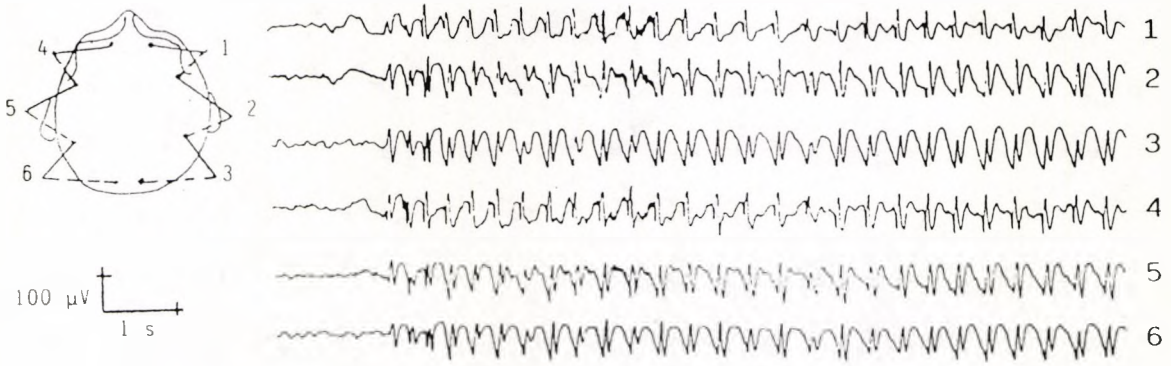


Figure 5.1 - EEG of a typical absence attack.

5.2 - The Spike-and-Slow-Wave Complex (SAWC)

Officially termed spike-and-slow-wave complex (hyphenation facilitates use in plural form), it is defined as a pattern consisting of a spike followed by a slow wave (IFSECN, 1974). The use of older terms like spike-and-dome complex, dart-and-dome complex and wave-and-dart complex has been discouraged.

5.2.1 - The SAWC waveform and its spectrum

Classical 3/s SAWCs are not standard in their format. By isolating some of these complexes from a pre-recorded EEG, the

respective spectra were obtained by employing the Fourier series method, using equation 5.1, in order to obtain both the even and the odd components, since the waveform is neither even nor odd. In this method, the waveform is considered to be repetitive as it is during a petit mal discharge.

$$x(t) = \frac{A_0}{2} + \sum_{n=1}^{\infty} [A_n \cos(2\pi n f_o t) + B_n \sin(2\pi n f_o t)] \qquad (5.1)$$

where: $A_n = \frac{2}{T_o} \int_0^{T_o} x(t) \cos(2\pi n f_o t)\, dt$

$$B_n = \frac{2}{T_o} \int_0^{T_o} x(t) \sin(2\pi n f_o t)\, dt$$

The results obtained are shown in figure 5.2. Due to the distortion caused by the different windows (rectangular, Hamming, hanning, etc), especially when the total number of samples is relatively low as in this case, the use of FFT has been avoided in this section.

5.2.2 - SAWC models defined in the time domain and their respective spectra.

As discussed earlier, the formats of the SAWCs differ substantially. This presents problems when an attempt is made to define a general-purpose mathematical model. Simple mathematical models can be derived for models used by other researchers. Equation 5.2 describes a model where the spike is represented by

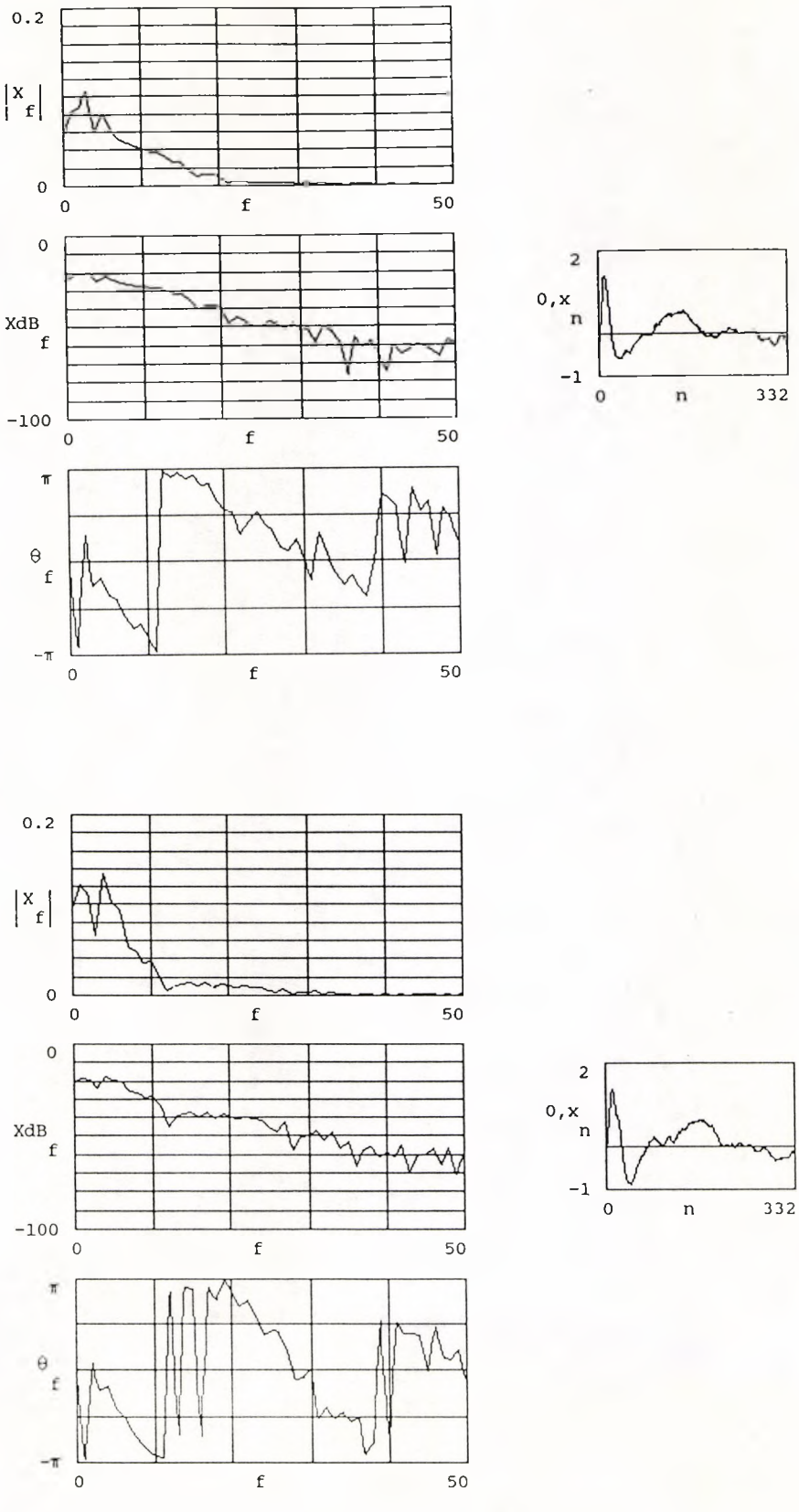


Figure 5.2-a - Examples of SAWCs and their respective spectra.

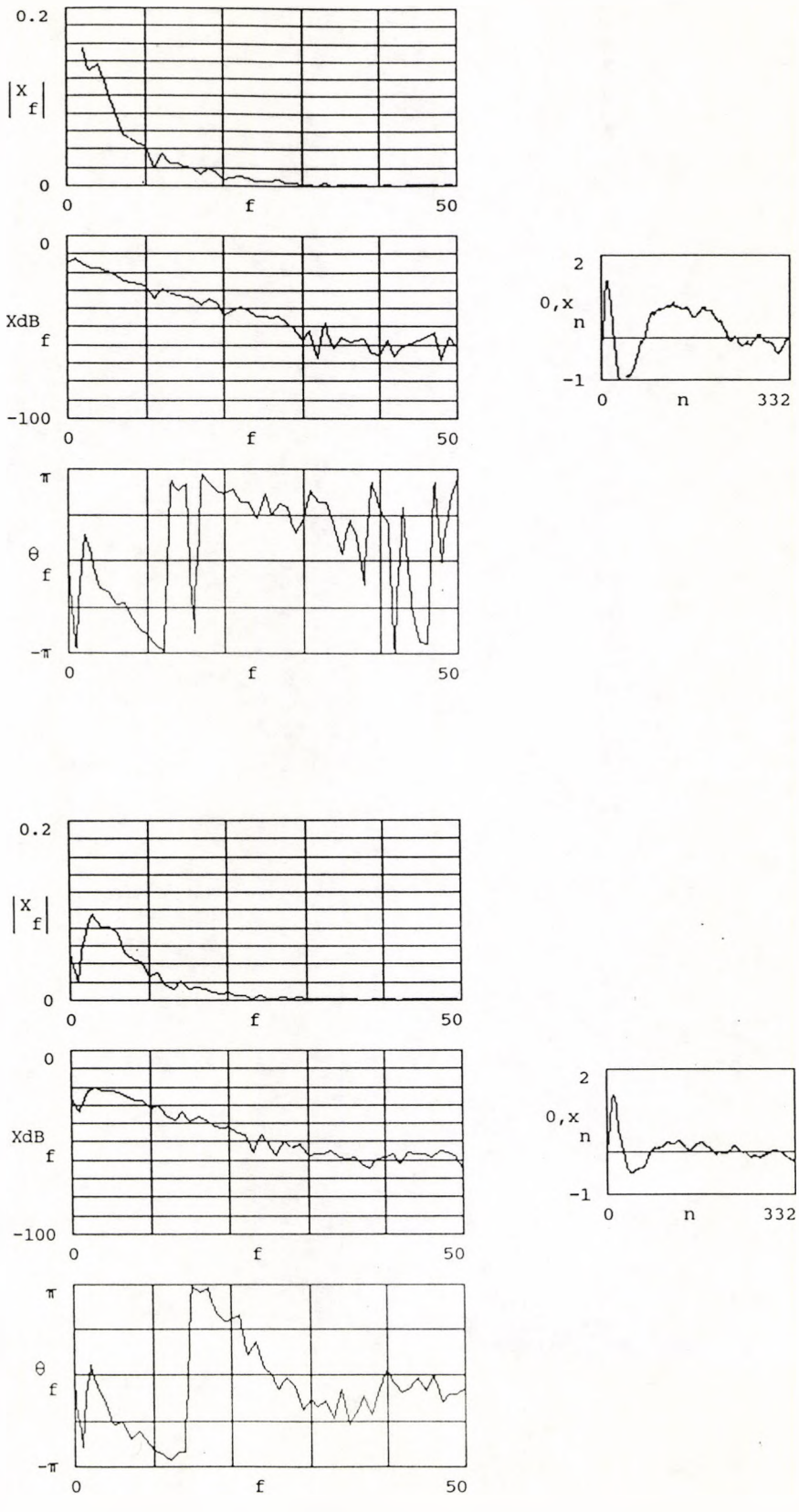


Figure 5.2-b - Examples of SAWCs and their respective spectra (cont).

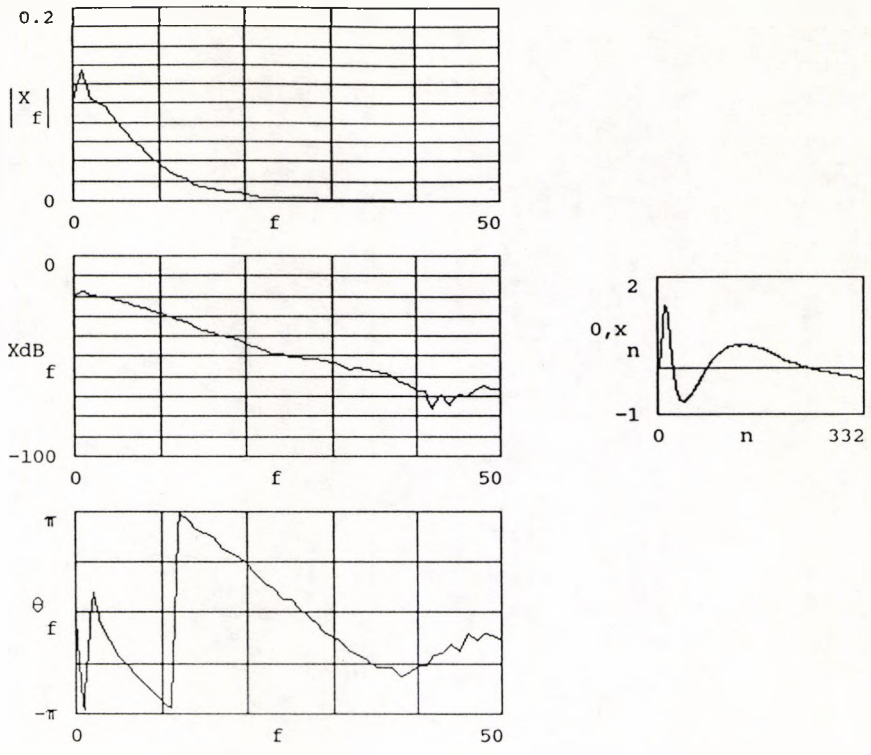


Figure 5.3 - Real-time SAWC model and its spectrum.

a triangle and the slow wave by the positive half of a sine-wave cycle (Niedermeyer and L. da Silva, 1987). Other authors (Comley and Brignell, 1981) substituted the triangle by two straight lines of different lengths, as shown by equation 5.3 (this model shall be used to represent isolated SAWCs only).

In order to obtain a more sophisticated mathematical model, primarily for the slow wave, it was decided, in first place, to derive a real-time SAWC model and then base the mathematical model on this. With this idea in mind, a total of 52 SAWCs that were available from a 70-Hz-bandwidth EEG record were sampled at a rate of 600 Hz and digitized using the ILS software package running on an IBM PC-AT. (A sampling rate of 600 Hz was chosen to give a good resolution to the waveform). The SAWCs were

then aligned according to the maximum value of their spikes and the total mean value was calculated. The resulting average SAWC is shown in figure 5.3 with its respective spectrum.

Based on this real-time model, two other mathematical models represented by equations 5.4 and 5.5 and illustrated in figure 5.4, were then defined.

$$x(n) = 1.550\ (1 - \frac{\|n - 21\|}{21}) - 0.550 \qquad 0 \leq n \leq 42 \qquad (5.2\text{-a})$$

$$x(n) = \sin(\pi \frac{n - 42}{291}) - 0.550 \qquad 42 \leq n \leq 332 \qquad (5.2\text{-b})$$

$$x(n) = \frac{n}{12} \qquad 0 \leq n < 12 \qquad (5.3\text{-a})$$

$$x(n) = - 0.0548\ n + 1.6570 \qquad 12 \leq n < 40 \qquad (5.3\text{-b})$$

$$x(n) = \sin(\pi \frac{n - 40}{293}) - 0.535 \qquad 41 \leq n \leq 332 \qquad (5.3\text{-c})$$

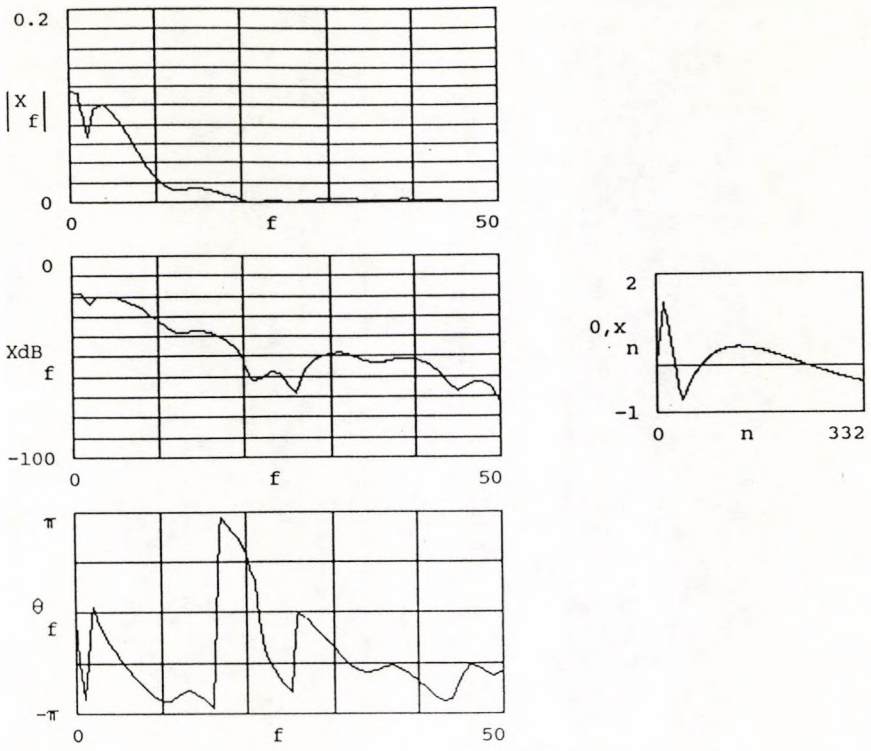
$$x(n) = \frac{n}{12} \qquad 0 \leq n < 12 \qquad (5.4\text{-a})$$

$$x(n) = - 0.0548\ n + 1.6570 \qquad 12 \leq n < 41 \qquad (5.4\text{-b})$$

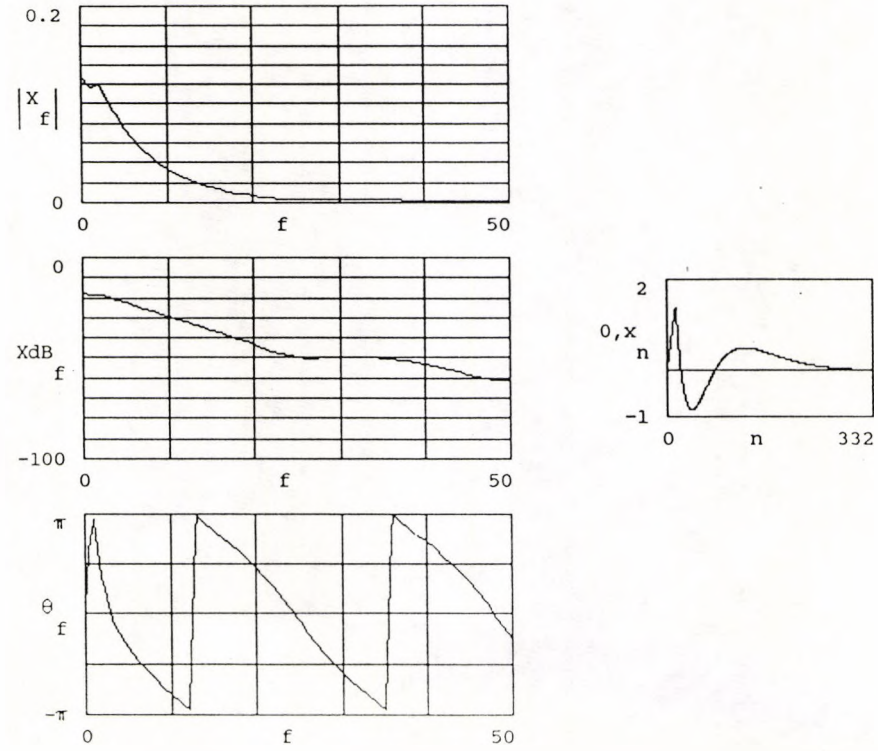
$$x(n) = - 0.0253\ (n - 41)\ e^{-(\frac{n - 41}{90})} - 0.5333 \qquad 41 \leq n \leq 332 \qquad (5.4\text{-c})$$

$$x(n) = \frac{n}{14} \qquad 0 \leq n \leq 14 \qquad (5.5\text{-a})$$

$$x(n) = [1 - 2\frac{n - 14}{14} + \frac{1}{2.5}(\frac{n - 14}{14})^2]\ e^{-\frac{n - 14}{33}} \qquad 14 < n \leq 332 \qquad (5.5\text{-b})$$



(a)



(b)

Figure 5.4 - Spectra of the mathematical SAWC models. (a) With reference to equation 5.4 and (b) with reference to equation 5.5.

5.3 - The First Experiments

In order to make it possible to process signals in real time with a Motorola 68000-system MVME-133, a data acquisition board has been developed. Its main components are a 10-bit analog-digital converter that has an input scale ranging from 0 to 5 volts, an 8-bit digital-analog converter with two outputs ranging from 0 to 2.5 volts and an 8-channel multiplexer. A full circuit diagram is illustrated in Appendix E.

Making use of the ILS digital-signal-processing package and/or basic algorithms appropriately developed for the Motorola system, three experiments concerned with the detection of SAWCs, that had been previously carried out by other authors, were repeated in order to gain experience in the area. No major attention was given to false alarms caused by artifacts.

The experiments were concerned with the following techniques:

1) matched filter,
2) differentiation and
3) arithmetic detector.

5.3.1 - A basic matched filter

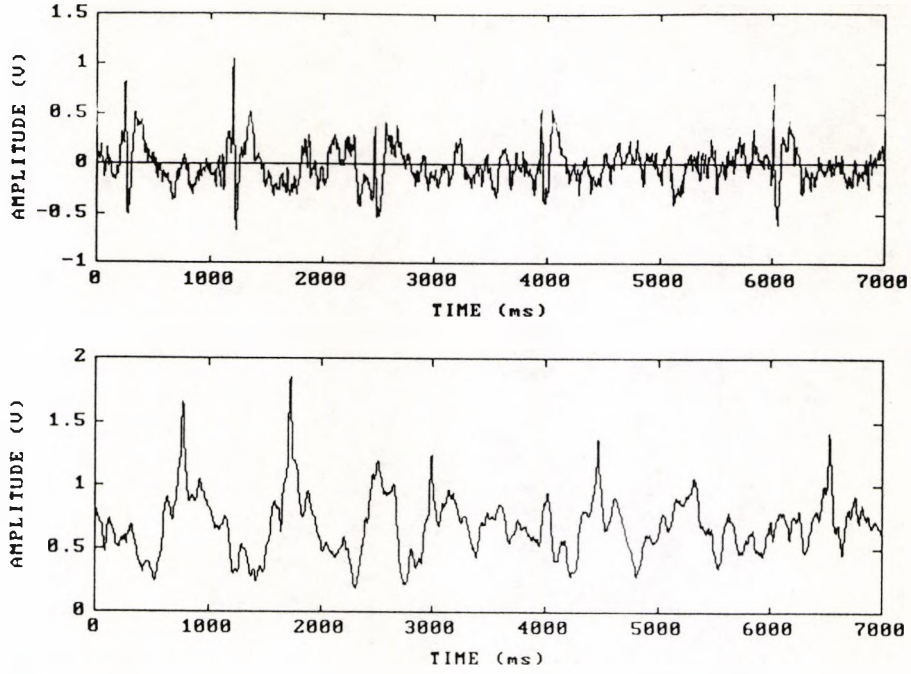
Previously described in Chapter 4, the matched filter can be used to detect the presence of a known form of signal embedded in white noise. Its characteristic equation is defined by equation 5.6, where s(t) represents the template and x(t) and y(t) represent the input and the output signals, respectively

(Niedermeyer and L. da Silva, 1987; Turin, 1960).

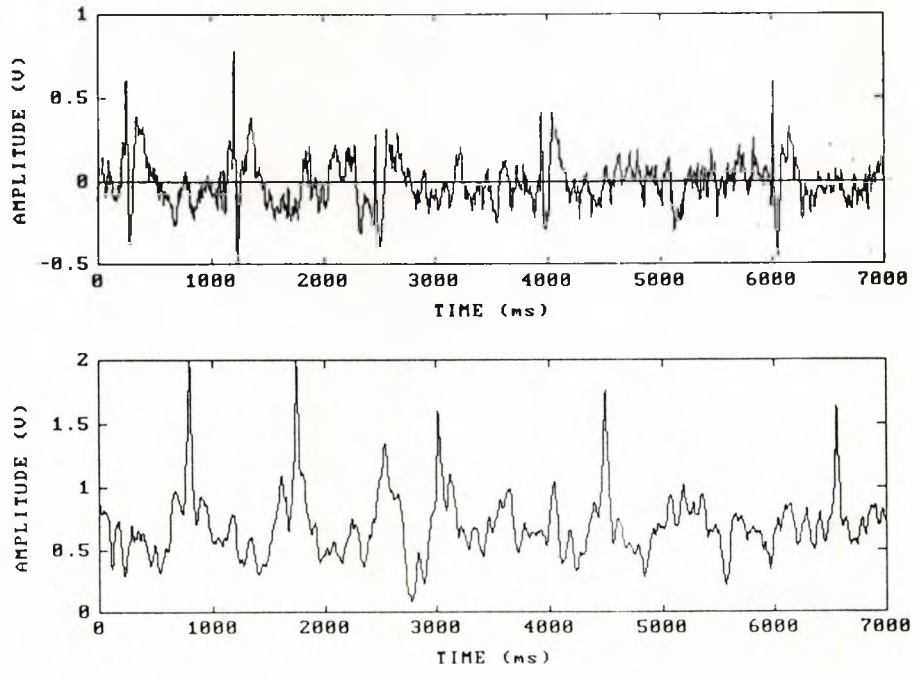
$$y(t) = \int_0^T x(\lambda)\, s(\lambda - t)\, d\lambda \qquad (5.6)$$

Making use of ILS and using the segment of EEG shown in figure 5.5, the first trial was carried out by selecting as the template the first SAWC (on the left) and the second trial was carried out by selecting as the template the meanvalue of the first four SAWCs. As can be observed, the obtained results demonstrate that the first selected template was not so good as the second, which could be expected since the SAWC waveforms differ significantly, mainly in terms of spike amplitude. Such problems were mentioned in Chapter 4. Once the template has been selected, the selection of the detection level is also an obstacle, since false alarms (see figure 5.5 for t=2530 ms) must be avoided. Another problem is the fact that the input EEG signal cannot be represented by white noise. To check if any improvement could be obtained by making it "more white", the original EEG signal was contaminated with white noise at different levels and the results checked again. As shown in figure 5.6, there was no improvement.

A very simple correlation algorithm was written in assembler for the Motorola 68000-system in order to implement the matched filter in real time. The spike-and-wave template, that had a total of 200 samples (sampling frequency of 600 Hz), was stored in memory in reversed order.

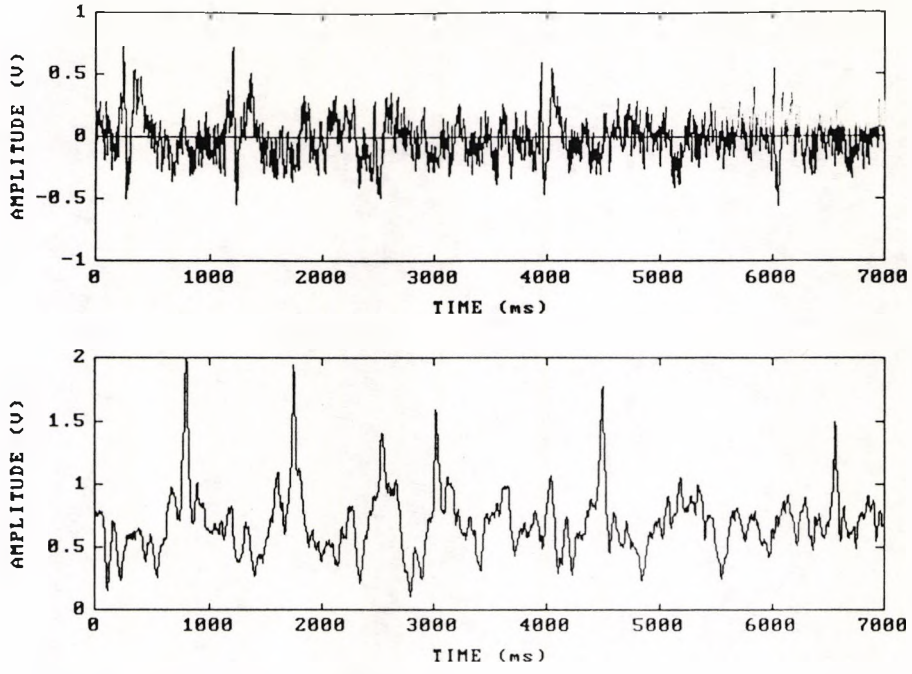


(a)

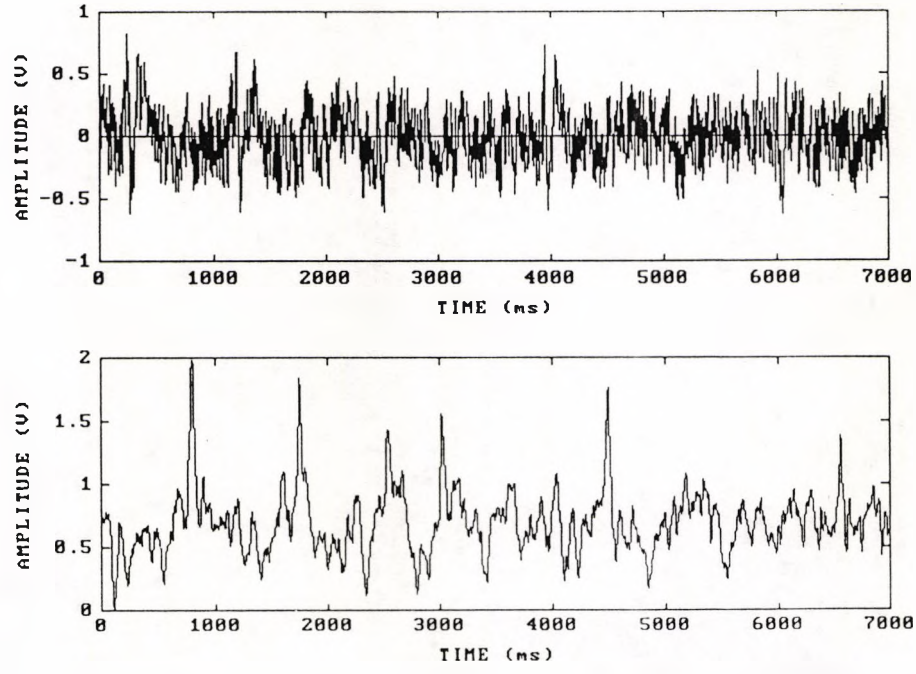


(b)

Figure 5.5 - Matched filter. (a) First SAWC used as template, (b) mean value of the first 4 SAWCs used as template.



(a)



(b)

Figure 5.6 - Matched filter. Input signal contaminated with white noise at different levels. (a) SNR = 0 dB and (b) SNR = -5dB. (Mean value of the first 4 SAWCs used as template.)

The most serious problem was the excessively long processing time, which was a consequence of the high number of multiplications and shifts, since the template was defined to have a high resolution. For the selected sampling frequency, it took 1.38 ms to process each sample, which corresponds to 87 % of the sampling period. To decrease the processing time, the sampling frequency should be reduced in order to decrease the template resolution and a better algorithm developed.

5.3.2 - Differentiation

After employing ILS to check the waveforms that were obtained with a differentiator, as shown in figure 5.7, the experiment carried out by Comley and Brignell (1981) was repeated in real time. In this case, instead of using the second derivative to check the sharpness of the spikes (the second derivative is noisy), the time interval taken by the input signal to change from a positive to a negative slope was used. This is equivalent to the time taken by the first derivative to change from a positive to a negative value (considering only the positive detection level, as shown in figure 5.8-a). The first derivative was approximated by the function x(n) - x(n-1) and later filtered through a second-order Butterworth lowpass filter with a cutoff frequency of 50 Hz in order to decrease the false alarm rate caused by the noise introduced by the differentiation process.

The matched filter detects the presence of both the spike and the slow-wave. A fourth-order Butterworth lowpass filter with a cutoff frequency of 7 Hz (for more details, see

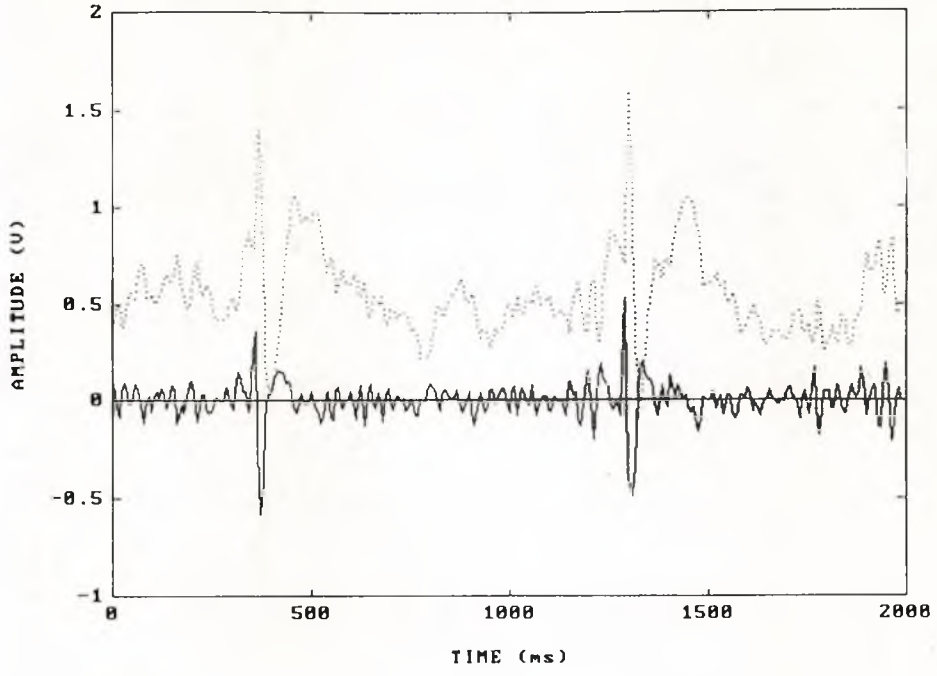


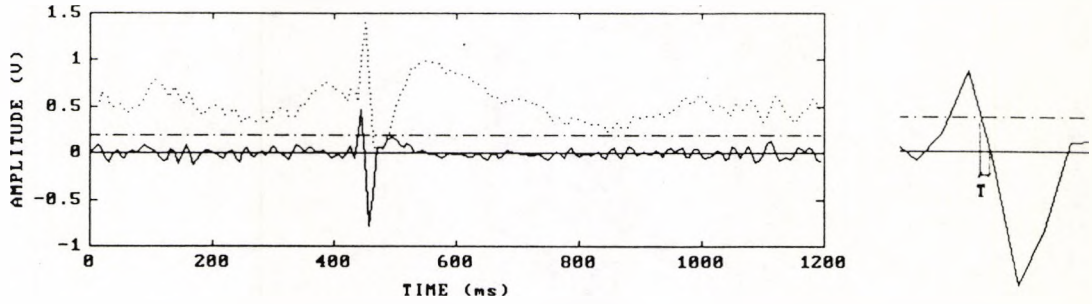
Figure 5.7 - Differentiation of a segment of EEG signal containing SAWC features.

item 5.4.4), was added to the spike detector to make the methods equivalent. In this way the detection of isolated spikes would not be taken into account. Both this filter and the 50 Hz lowpass filter mentioned above were designed by employing the widely used method known as bilinear transformation (Open University, 1984; Rabiner and Gold, 1985). The detector output was activated only when the presence of both the spike and the slow wave were confirmed.

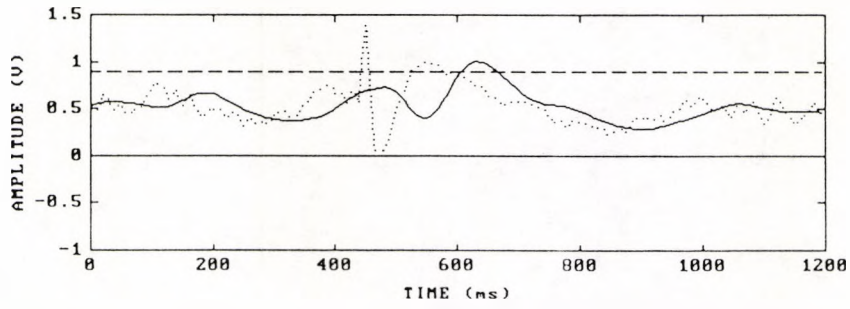
The value of 7 Hz for the cutoff frequency was selected based on the fact that the slow waves differ quite a lot in format (see figure 5.2) and some of them have very low amplitude, which causes difficulty in their detection. As they normally have a sharp rise at the beginning, the capture of this part (of the wave) is the best way to detect them. Cutoff frequencies of 4 Hz

and 10 Hz were also tried, but some problems arose. In the first case, it was too difficult to detect those slow waves with low amplitude and the time delay caused by the filter was excessive. In the second case, the output signal was too noisy. Based on the results and on the fact that Principe and Smith (1982) used an upper frequency of 6 Hz for the slow-wave bandpass filter (see Chapter 4), 7 Hz was selected.

Once more, the greatest difficulty was to select the appropriate detection levels for the first derivative and for the slow wave.



(a)

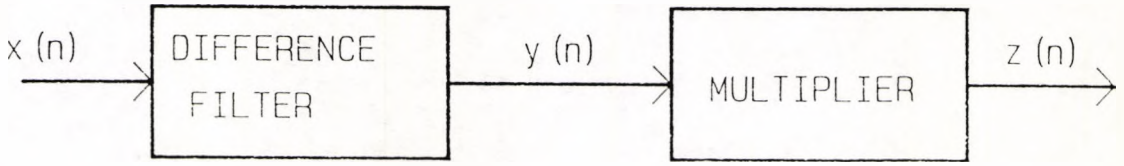


(b)

Figure 5.8 - Association of (a) a differentiator and (b) a lowpass filter for the detection of a SAWC. (The time interval T was used to check the spike sharpness).

5.3.3 - An arithmetic detector

A so called arithmetic detector, with a block diagram illustrated in figure 5.9, that had been recently published (Qian and others, 1988) with the purpose of detecting sharp transients, was first checked with the software package MATHCAD and later implemented in real time.



y(n)=x(n)-x(n-N)

z(n)=y(n).y(n-M)

Figure 5.9 - Arithmetic detector.

The difference filter is in fact a comb filter (Proakis and Manolakis, 1988; Terrel, 1980) and the corresponding difference equation is given by equation 5.7. Its transfer function is represented by equation 5.8, which has N zeros spaced around the unit circle in the z-plane at the locations given by equation 5.9.

$$y(n) = x(n) - x(n-N) \tag{5.7}$$

$$H(z) = 1 - z^{-N} \tag{5.8}$$

$$z_n = e^{j2\pi\frac{n}{N}} \qquad \text{where} \qquad n = 0, 1, 2, \ldots, N-1 \tag{5.9}$$

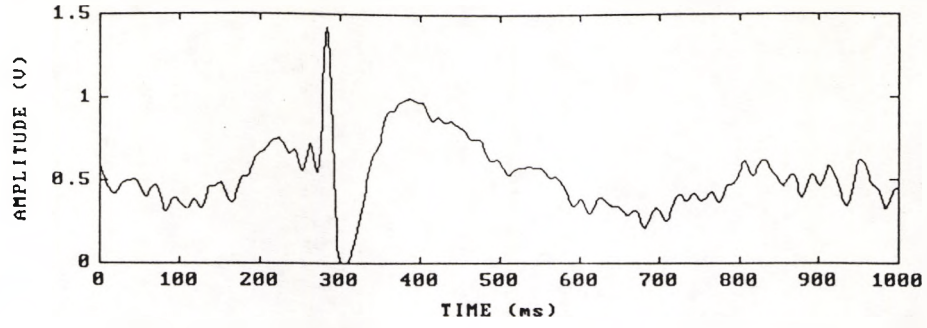
$$\|H(f)\| = 2\,\|\sin(n\pi f T_s)\| \tag{5.10}$$

In the frequency domain, the transfer function is given by equation 5.10. Depending on the selected value of N, a chosen frequency range may be emphasized. In this experiment, using 600 Hz as the sampling frequency (Ts=1.67 ms), N was made equal to 18. This value was chosen in order to obtain a frequency range limited by zeros located at 0 Hz and 33.33 Hz, with a central frequency of 16.66 Hz, following suggestions given by the authors.

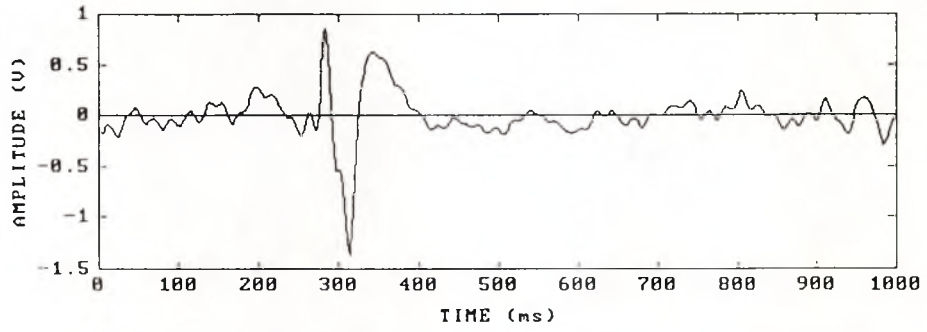
The product operator was tested for different values of M and the respective waveforms are shown in figure 5.10. In this case, as there is a single detection level, the difficulties mentioned earlier decreased.

5.4 - The Spike-and-Wave Detector

Based on the differentiation theorem, demonstrated by equation 5.11 (Carlson, 1981), it is very common to employ some degree of differentiation in the detection of sharp transients



(a)



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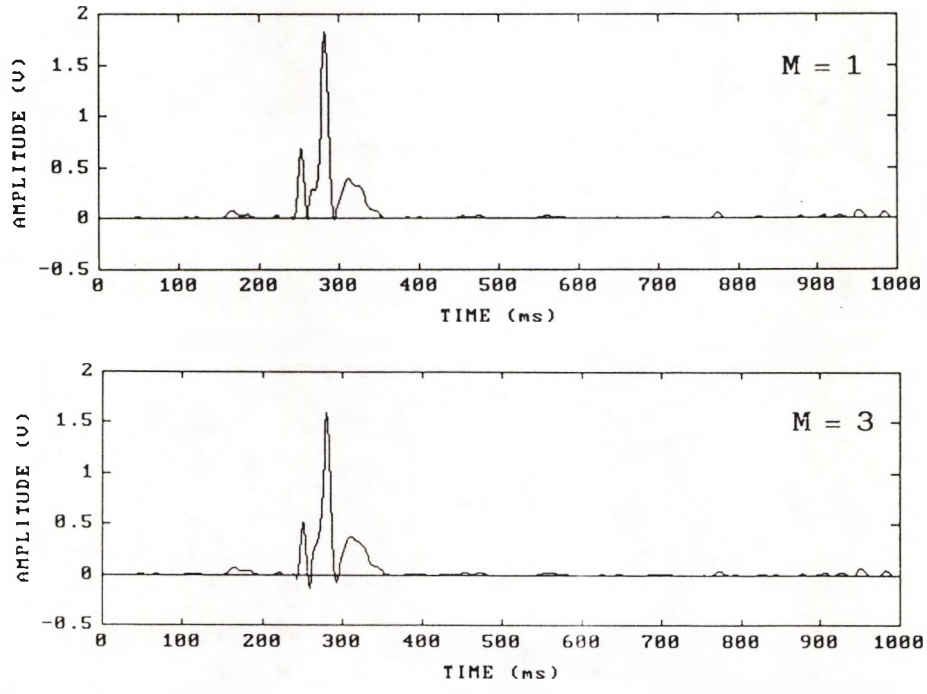


(c)

Figure 5.10 - Arithmetic detector waveforms. (a) Input signal, (b) difference-filter output signal for N=18 and (c) multiplier output signal for M=1 and M=3.

(see Chapter 4). Both the frequency and the impulse responses of a differentiator are odd functions.

$$x(t) \quad \text{------>} \quad X(f) \tag{5.11-a}$$

$$\frac{d[x(t)]}{dt} \quad \text{------>} \quad j2\pi f \,.\, X(f) \tag{5.11-b}$$

or

$$H_{dif}(f) = j2\pi f \tag{5.11-c}$$

In digital filtering, a differentiator may be realized in the form of an FIR (finite impulse response) filter or approximated by a comb filter (N=1 in equation 5.7). In the first case, due to the sawtooth waveform of the frequency response (see figures 5.11-a and 5.11-b), the discrete impulse response must be composed of a high number of samples and the use of a window other than the rectangular window is advisable, in order to avoid the Gibbs phenomenon (Strum and Kirk, 1988). In the second case, the frequency response is approximated by a sinusoidal function instead of a straight line, as shown in figure 5.11-c.

It can be shown that a differentiator produces a bipolar output that will, in the case of spike detection, be asymmetrical, presenting serious problems for reliable detection (see figure 5.7). Having in mind the idea that only one detection level should be used (the output signal should be unipolar) and that a spike is unipolar (it may be represented by a triangle), an even frequency response function was adopted for the

spike detector. The triangular shape was chosen in order to give the high-frequency components the same degree of enhancement as given by a differentiator and to keep the number of samples of the discrete impulse response low.

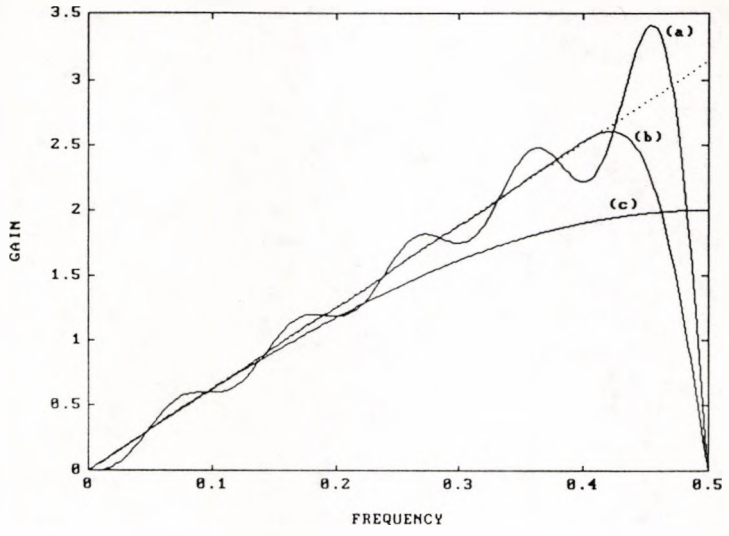


Figure 5.11 - Frequency response of a differentiator. (a) FIR - rectangular window, (b) FIR - Hamming window and (c) comb filter.

5.4.1 - The spike detector - DIFMOD

Shown in figure 5.12-a and 5.12-c are the respective frequency response curves of a digital differentiator and that of the chosen transient enhancer. As can be seen, the phase components are nil in the second case. In other words, the chosen transient enhancer is equivalent to a differentiator connected in series with a Hilbert transformer, which has a frequency response curve like that illustrated in figure 5.12-b. All the Hilbert transformer does is to change the phase of positive frequency components by -90 degrees and negative frequency components by 90

degrees (for this reason it is also known as a quadrature phase shifter). For example, a signal that is obtained through the summation of a series of cosines becomes the summation of a series of sines.

The transient enhancer will be denominated DIFMOD.

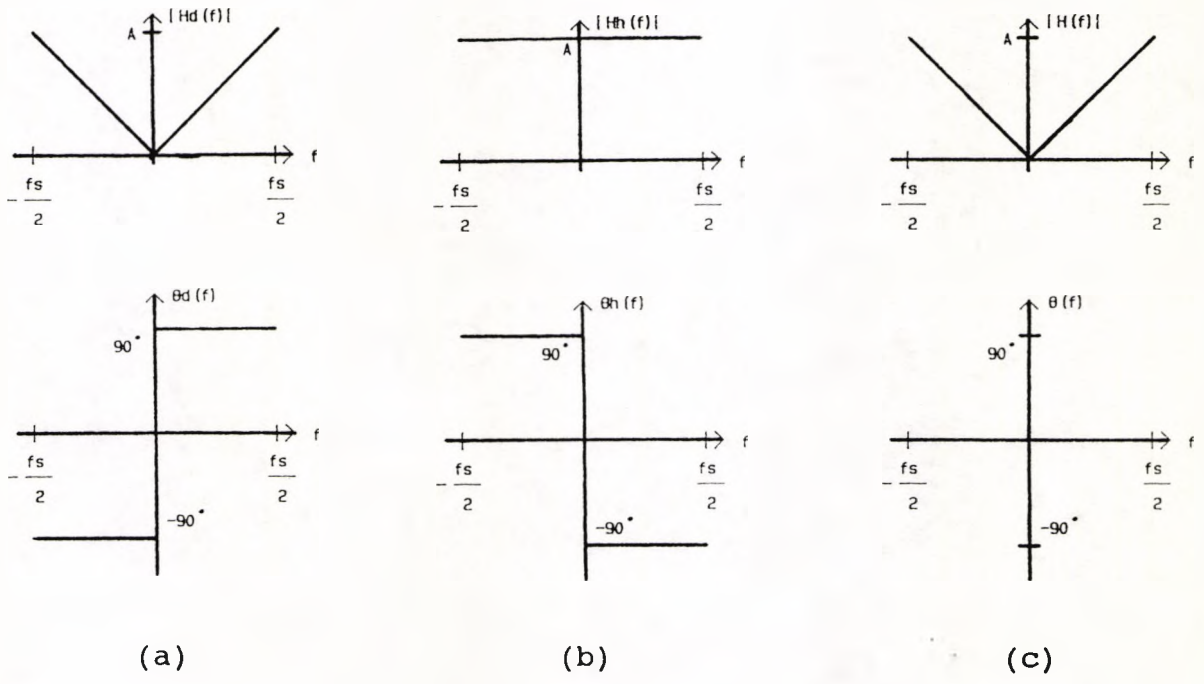
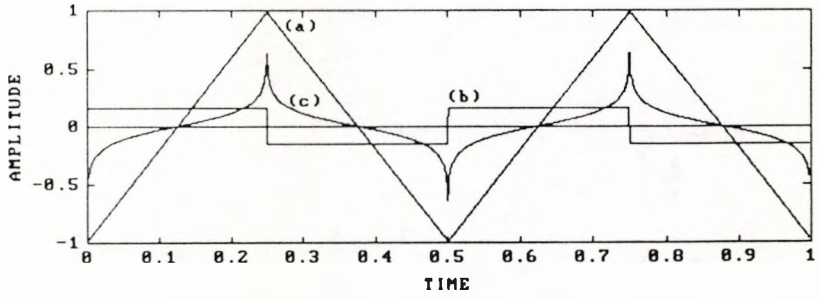


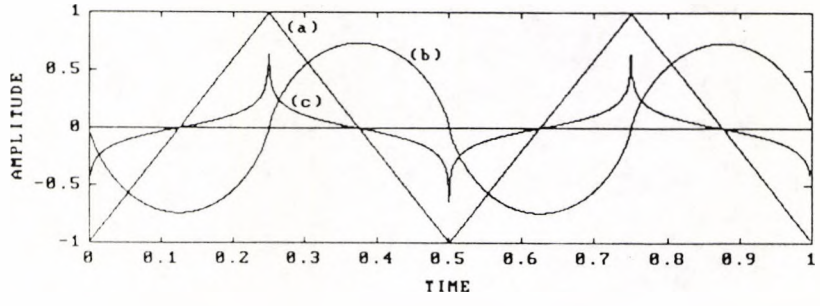
Figure 5.12 - Frequency response of the spike enhancer - (a) differentiator, (b) Hilbert transformer and (c) DIFMOD.

To give the reader a basic idea of how DIFMOD works, two sequences of waveforms will be used. The first sequence, illustrated in figure 5.13-a, represents the DIFMOD beingcomposed of a differentiator followed by a Hilbert transformer and the second, illustrated in figure 5.13-b, represents these blocks in reversed order.

Making the input signal an even triangular waveform, that is obtained with a summation of cosine functions, in the first case, the differentiated signal becomes a summation of negative sines that is transformed into a new summation of cosines by the Hilbert transformer. In the second case, the Hilbert transformer changes a summation of cosines into a summation of sines and this, after being differentiated, becomes a new summation of cosines. As can be observed, the maximum and the minimum values of the output signal correspond to the positive and negative peaks of the triangular waveform, since these points have the highest degree of sharpness.



(1)



(2)

Figure 5.13 - Changes caused in a triangular waveform by the DIFMOD. (1) Differentiator followed by a Hilbert transformer and (2) Hilbert transformer followed by a differentiator. (a) Input signal, (b) output from the first stage and (c) output from the second stage (the amplitudes are not absolute).

For the implementation of the DIFMOD, the first idea that may be considered is just to implement the Hilbert transformer and to associate it with a differentiator approximated by equation 5.7 (N=1). The main problem is the fact that the Hilbert transformer frequency response curve has the shape of a signum function (also known as sign function) and its discrete impulse response has an infinite number of terms that do not decrease rapidly (see equation 5.12), which makes it necessary to use a high number of terms to approximate it. In practice, an optimum Hilbert transformer is not easy to be approximated, no matter what the chosen number of terms is, mainly due to Gibbs phenomenon near the origin, which makes it even more complicated than the FIR differentiator.

$$h_{Hilb}(n) = \frac{2}{\pi} \frac{\sin^2(\frac{n\pi}{2})}{n} \qquad n \neq 0 \tag{5.12-a}$$

$$h_{Hilb}(n) = 0 \qquad n = 0 \tag{5.12-b}$$

A simple way that may be employed to derive the discrete impulse response for the DIFMOD is by convolving a triangle function (Carlson, 1981) with two impulse functions, as shown in figure 5.14. These functions and their respective impulse responses are represented by equations 5.13, 5.14 and 5.15.

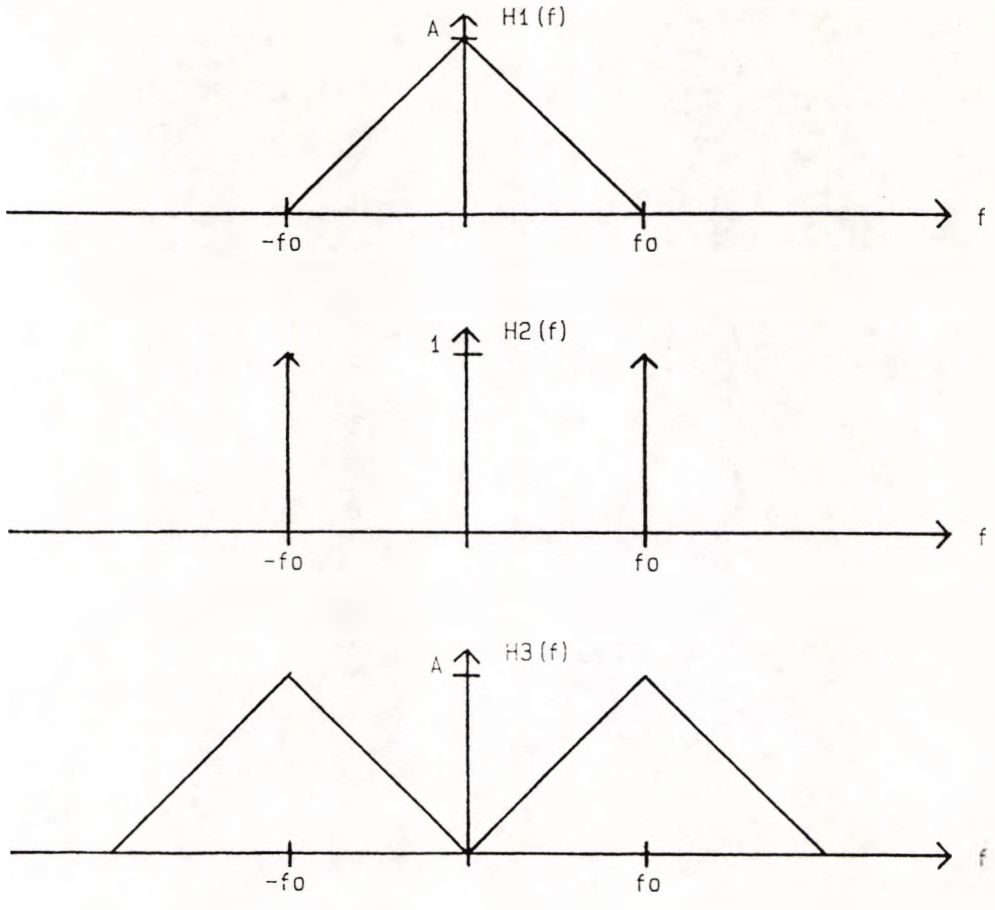


Figure 5.14 - Frequency response of the spike detector [H3(f) = H1(f) * H2(f)] .

$$H1(f) = A \ \ tri(\frac{f}{f_o}) \tag{5.13-a}$$

$$h1(t) = Af_o \ \ sinc^2(f_o t) \tag{5.13-b}$$

$$H2(f) = \delta(f - f_o) + \delta(f + f_o) \tag{5.14-a}$$

$$h2(t) = 2 \ \ \cos(2\pi f_o t) \tag{5.14-b}$$

$$H3(f) = H1(f) * H2(f) \tag{5.15-a}$$

$$H3(f) = A \left\{ tri\frac{(f + f_o)}{f_o} + tri\frac{(f - f_o)}{f_o} \right\} \tag{5.15-b}$$

$$h3(t) = h1(t)\, h2(t) \tag{5.15-c}$$

$$h3(t) = 2Af_o \ sinc^2(f_o t) \ \cos(2\pi f_o t) \tag{5.15-d}$$

Now, comparing figure 5.14-c with figure 5.12-c, it can be seen that the slopes located between -fs/2 and fs/2 correspond to the slopes located between -fo and fo, respectively. This way, by making t=n.Ts=n/fs, where fs is the sampling frequency and by making fo=fs/2, the general formula for h(n.Ts), which depends on fs, is obtained. By making fs=1, the normalized discrete impulse response h(n), represented by equation 5.16, is obtained.

$$h(n) = A \ sinc^2(\frac{n}{2}) \ \cos(n\pi) \tag{5.16}$$

Both its graphical representation and table of values are illustrated in figure 5.15.

n	h(n)
-20	0
-19	-0.001
-18	0
-17	-0.001
-16	0
-15	-0.002
-14	0
-13	-0.002
-12	0
-11	-0.003
-10	0
-9	-0.005
-8	0
-7	-0.008
-6	0
-5	-0.016
-4	0
-3	-0.045
-2	0
-1	-0.405
0	1
1	-0.405
2	0
3	-0.045
4	0
5	-0.016
6	0
7	-0.008
8	0
9	-0.005
10	0
11	-0.003
12	0
13	-0.002
14	0
15	-0.002
16	0
17	-0.001
18	0
19	-0.001
20	0

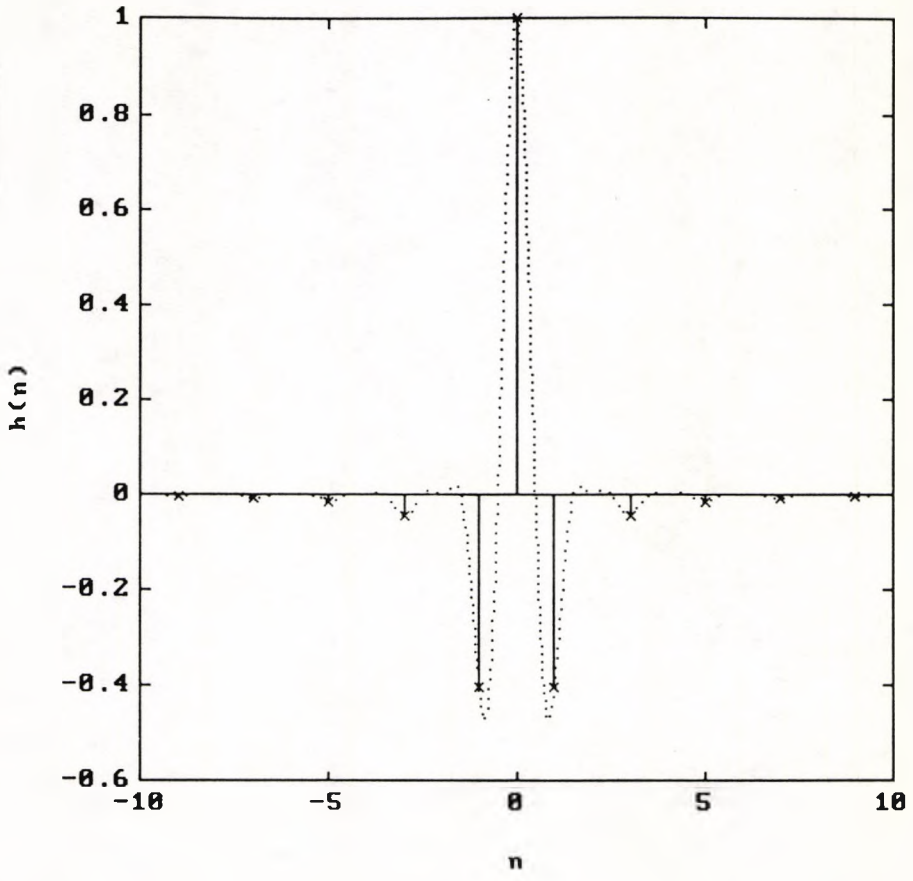


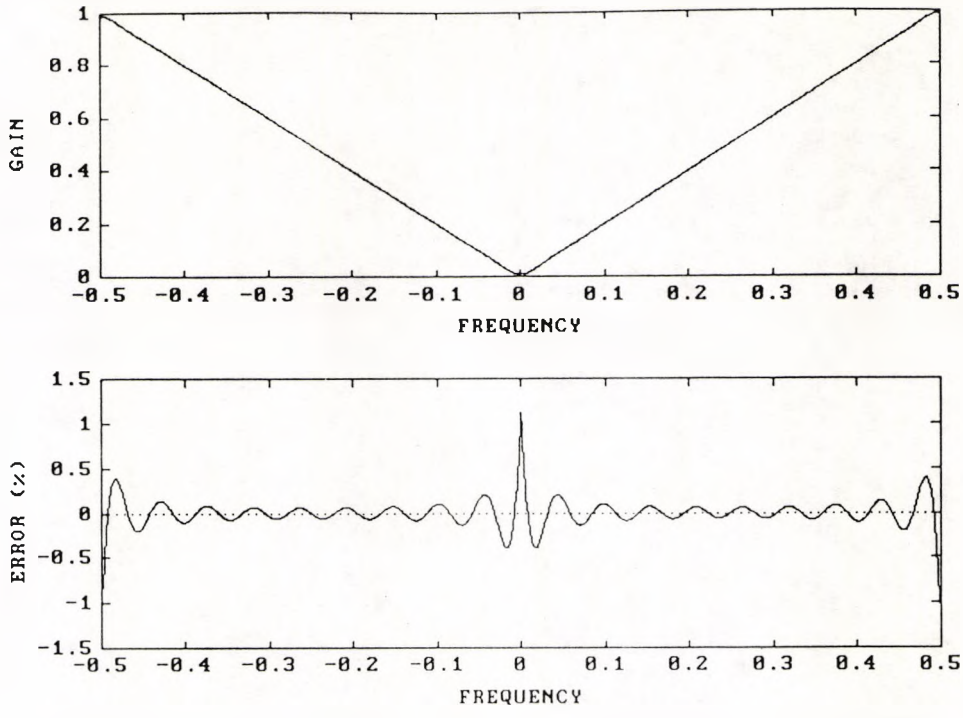
Figure 5.15 - Impulse response for the DIFMOD. (a) Table of values for $|n| < 21$ and (b) graphical representation for $|n| < 11$.

The values of h(n) are A at the origin, zero for even values of n and proportional to $\text{sinc}^2(n/2)$ for odd values of n; for this reason they decrease rapidly for increasing values of n. All these factors contribute significantly to a reduced processing time, if compared, for example, to the FIR differentiator or Hilbert transformer. Here, it must be emphasized that if it is decided to make fo=fs/10 or fo=fs/4, for example, in equation

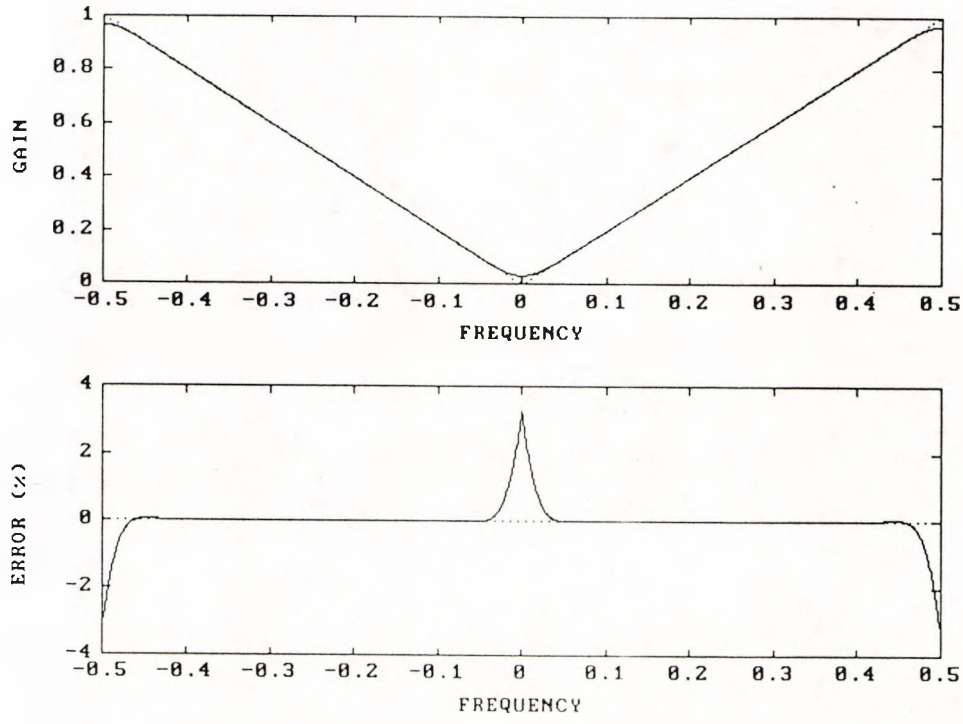
5.14-d, instead of making fo=fs/2, the only disadvantage will be the increase of the significant number of terms for h(n) (i.e. the fundamental frequency of the frequency response curve increases).

As can be seen from the table of values in figure 5.15, the value of h(17) is already equal to a thousandth of the maximum value. In order to obtain a good compromise between accuracy and speed of computation, a maximum value of n=17 was chosen for the preliminary studies. Both a rectangular and a Hamming window were used. The respective frequency response curves and relative-error curves, shown in figure 5.16, were obtained. As expected, the Hamming window reduces the error in the central region of the curve, but it decreases the linearity near the origin making the gain for DC levels and low frequency components much higher than expected. For this reason, the rectangular window was considered more appropriate.

Unlike a differentiator, the DIFMOD cannot be approximated by a very simple function and for this reason it has to be implemented as an FIR filter by convoluting the input signal with the sample impulse response. If the number of terms of h(n) is reduced to a total of 3, in order to reduce the processing time, an approximation that may be used is that obtained with equation 5.17, which is derived from the function that approximates a differentiator through the autoconvolution of its unit sample response. The main difference, is the fact that the gain at the origin will not tend to zero in the first case. Distortion in H(f) will exist in both cases, and for this reason no approximation has been used in the implemented algorithm.



(a)



(b)

Figure 5.16 - Frequency response curves and the respective error curves for the DIFMOD (N=17), using (a) rectangular window and (b) Hamming window.

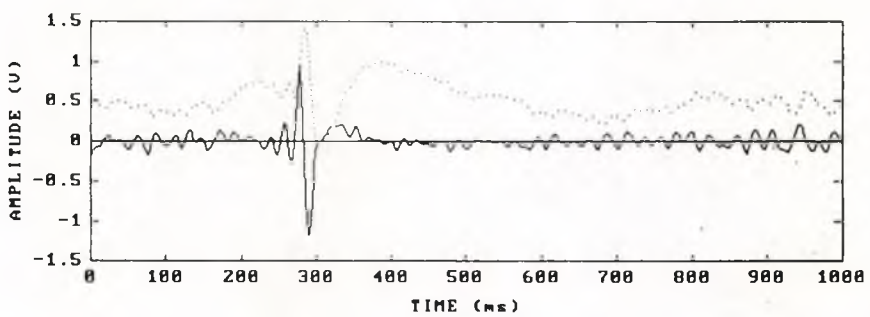
$$h(n) = \frac{h_{dif}(n)}{2} * \frac{h_{dif}(n)}{2} = \begin{cases} -0.5 & n = -1 \\ 1.0 & n = 0 \\ -0.5 & n = 1 \end{cases} \qquad (5.17\text{-a})$$

or

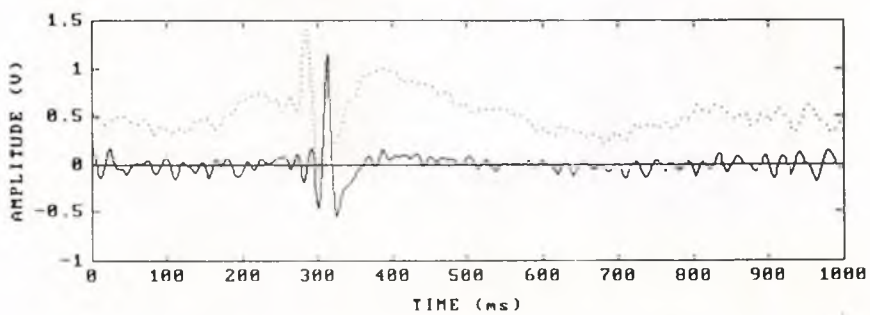
$$H(f) = \sin^2(\pi \frac{f}{f_s}) \qquad (5.17\text{-b})$$

The DIFMOD frequency response curve may be approximated by other functions such as the absolute value of a sine wave or a pair of parabolas limited in time, but the number of terms of the respective sample impulse responses will be high, offering no major advantages.

In figure 5.17, the outputs from a differentiator and from the DIFMOD, having a SAWC at the input, are compared to show the change of waveform introduced by the Hilbert transformer. The chosen sampling frequency was 600 Hz.



(a)



(b)

Figure 5.17 - Outputs from (a) a differentiator and from (b) the DIFMOD in response to a typical SAWC. (The amplitudes are not absolute).

5.4.2 - The cubic filter

A spike enhancer process is normally followed by some kind of filter or comparator that further processes the output of the first section. Some authors use a simple amplitude comparator to detect the spikes, having a high rate of false alarms . Other authors include a lowpass filter before the detector in order to decrease the level of noise and, in consequence, the false detection rate, but the main disadvantage of this process is the fact that not only the "background noise" from the enhancement process is decreased but also the amplitude of the spike feature, making the level-detection process less reliable and more sensitive to the threshold setting (Stelle and Comley, 1989).

As can be appreciated from figure 5.17-c, the normal spike feature has a peak amplitude that is 3 or 4 times higher than the noise amplitude. Based on the technique applied by Qian and her colleagues (see item 5.3.3), where the present output sample was multiplied by a preceding sample [y(n).y(n-k)], the output samples could simply be squared (k=0) enhancing, this way, the important part of the signal [y(n) relatively greater than or equal to 1] and shrinking the noisy samples [y(n) relatively smaller than 1]. The disadvantage of this technique is the fact that a possible negative noise spike would become positive and be considered as a real spike. For this reason, a cubic filter, that elevates the input signal to the power of 3, was considered more appropriate. This way the spikes would be enhanced even more than in the case of squaring, the background noise would become very low and the negative values would remain negative and could be

ignored (made equal to zero). To avoid overflow during the cubing process, the input signal was firstly squared and divided by a constant. This result was then multiplied by the original input sample and divided once more by another constant. The values of these constants depend on the maximum value of the input signal. Appropriately scaled, the output of the cubic filter is shown in figure 5.18.

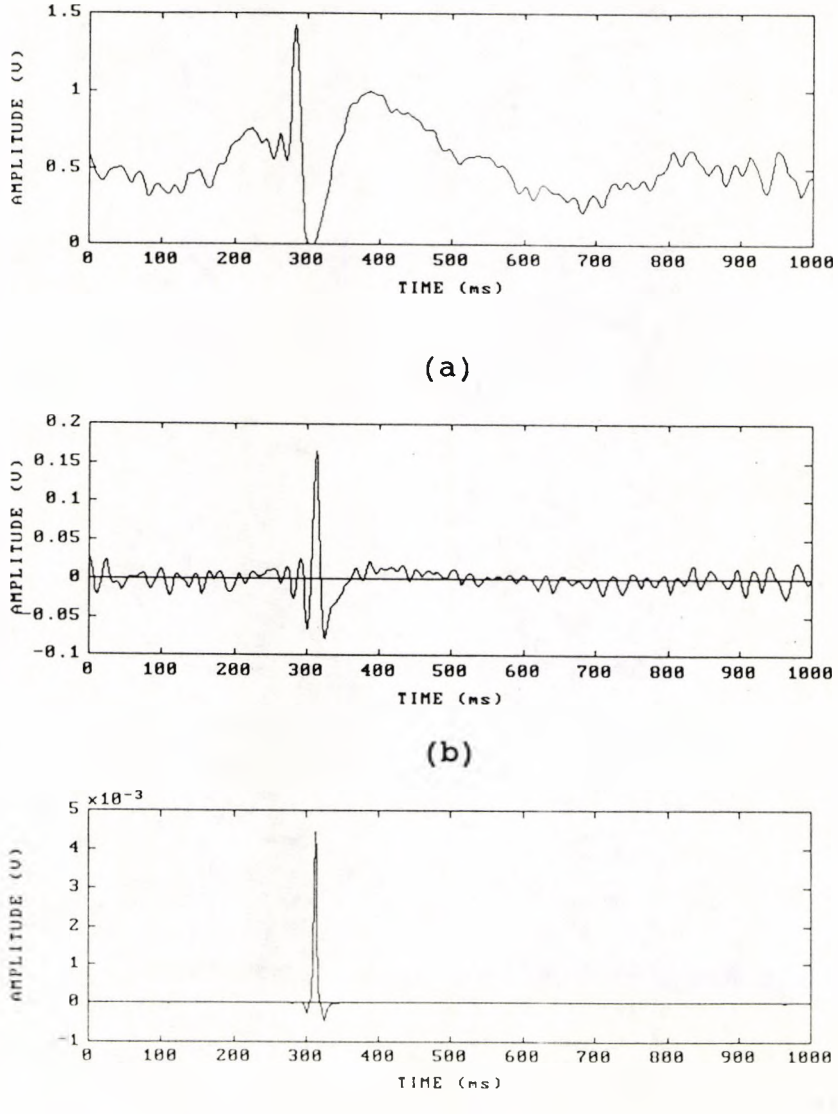


Figure 5.18 - Waveforms of the complete spike detector in response to a SAWC. (a) SAWC, (b) DIFMOD output and (c) cubic filter output.

The cubic filter is highly non-linear and the DIFMOD does not have a gain exactly equal to zero for DC values. In order to avoid problems during the cubing process, it is better to eliminate the DC level of the cubic-filter input signal.

5.4.3 - The moving average

At the beginning of the experiments, fixed values were selected for both the spike and the slow-wave detection levels (see next item). In the future, it would result in a series of difficulties because such levels would have to be individually adjusted for each subject (Gotman and Gloor, 1976). A basic idea is to make the detection levels dependent on the DC level of the input signal. For this reason and for the reason exposed on item 5.4.2 (the cubic filter input signal must have a zero mean value), the running average of the background activity had to be calculated.

The technique used is known as moving average. Once the DC level was estimated, its value was subtracted from the original EEG signal before this entered the DIFMOD (the original sample, with DC level, was stored in memory) and the detection levels were derived.

In practical terms, the most basic idea to represent the moving average process is that shown in the example below and represented by equation 5.18, where a total of 3 samples is used (average of the current and past L samples, where L=2). Although equation 5.18 may induce the reader to think that the present result depends on the last output value, in fact it depends only

on the input values as shows the demonstration below. The implemented algorithm was based on this equation.

Considering x(n) as the input signal and y(n) as the output signal and supposing that the process has been running for some time, it can be said that:

$$y(0) = \frac{1}{3}\,[x(-2) + x(-1) + x(0)]$$

$$y(1) = \frac{1}{3}\,[x(-1) + x(0) + x(1)]$$

$$y(2) = \frac{1}{3}\,[x(0) + x(1) + x(2)]$$

or

$$y(2) = \frac{1}{3}\,[x(-1) + x(0) + x(1)] + \frac{1}{3}\,[x(2) - x(-1)]$$

This way, the general equation becomes:

$$y(n) = y(n-1) + \frac{1}{3}\,[x(n) - x(n-3)]$$

or, in a more general form,

$$y(n) = y(n-1) + \frac{1}{L+1}\,\{x(n) - x[n-(L+1)]\} \qquad (5.18)$$

where L+1 represents the total number of samples and x(n-(L+1)) represents the oldest sample.

In theory, the moving average is known as a parametric method of spectral estimation (Candy, 1988) and is an all-zero model that may be described by equation 5.19-a, where it is seen that the total number of samples is L+1 and that there are no

delayed outputs, which would provoke the appearance of poles (Kuc, 1988; Proakis and Manolakis, 1988; Strum and Kirk, 1988). The system function and respective frequency response are represented by equations 5.19-b and 5.19-c/5.19-d. The first zero, that is of major interest, occurs for f=fs/(L+1), where fs is the sampling frequency.

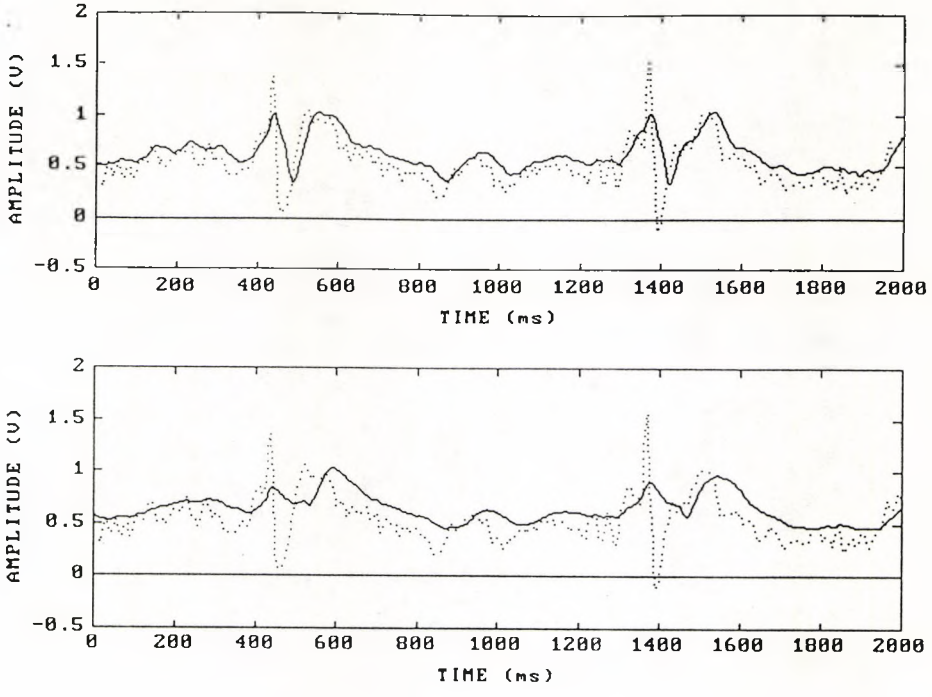
$$y(n) = \frac{1}{L+1} \sum_{k=0}^{L} x(n-k) \tag{5.19-a}$$

$$H(z) = \frac{1}{L+1} \sum_{k=0}^{L} z^{-k} \tag{5.19-b}$$

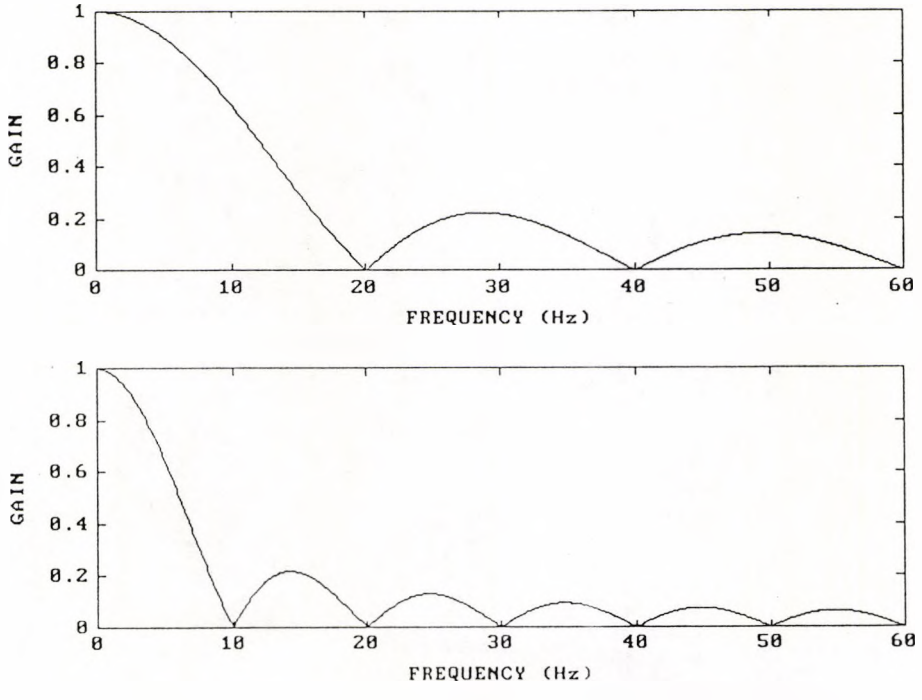
$$H(e^{j2\pi fT_s}) = H(e^{j\theta}) = \frac{1}{L+1} \sum_{k=0}^{L} e^{-j\theta k} = \frac{e^{-j\theta\frac{L}{2}}}{L+1} \frac{\sin[\theta(\frac{L+1}{2})]}{\sin(\frac{\theta}{2})} \tag{5.19-c}$$

$$\|H(f)\| = \frac{1}{L+1} \frac{\sin[\pi fT_s(L+1)]}{\sin(\pi fT_s)} \tag{5.19-d}$$

As an example, figure 5.19 shows the effects it causes on a segment of EEG in the time domain for both L=9 and L=19 and the respective frequency response curves. The sampling frequency that was used in this case was 200 Hz instead of 600 Hz, in order to reduce the total number of stored samples. As can be noticed, a disadvantage of this process in practical terms is the fact that a high number of samples is made necessary when the first zero is located near the origin, but, in compensation, it has the advantage that only one summation, one subtraction and one division are, in fact, necessary for its computation, which may help to keep the processing time relatively low (see the next item).



(a)



(b)

Figure 5.19 - Moving average filter. (a) Effects caused on a segment of EEG for L=9 and L=19 and (b) the respective frequency response curves.

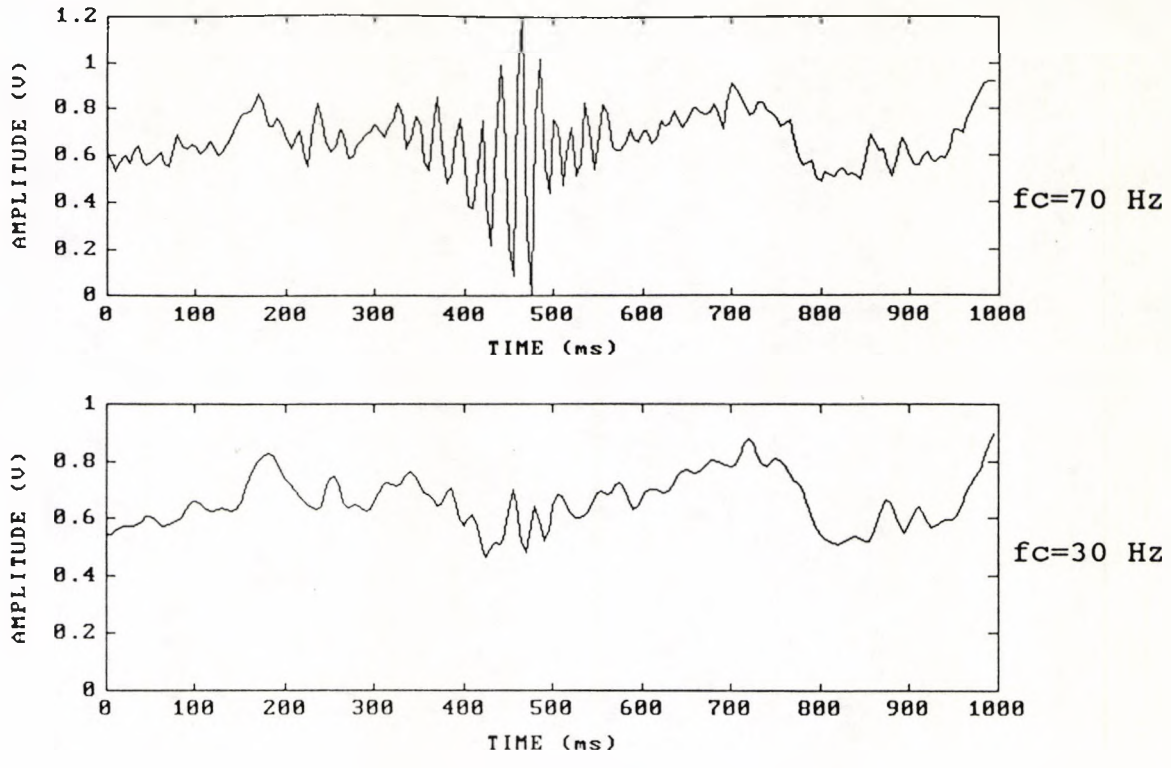
5.4.4 - The lowpass filter

If only noise-free EEG signals were to be analysed, which is possible in the case of analysis in non-real time where artifacts similar to the one illustrated in figure 5.20-a may be previously eliminated from the recordings, the spike detector would be enough to signal the presence of spike-and-wave features, but this is not the case in real-time analysis. A very basic technique that is constantly used to reduce the number of false detections is to pre-filter the EEG signal leaving it with a maximum frequency range of 30 Hz or even less (Barlow, 1984), but this technique causes an abrupt distortion to the SAWC, as shown in figure 5.20-b, bringing serious difficulties for the normal spike detection. According to Niedermeyer and Lopes da Silva (1987),

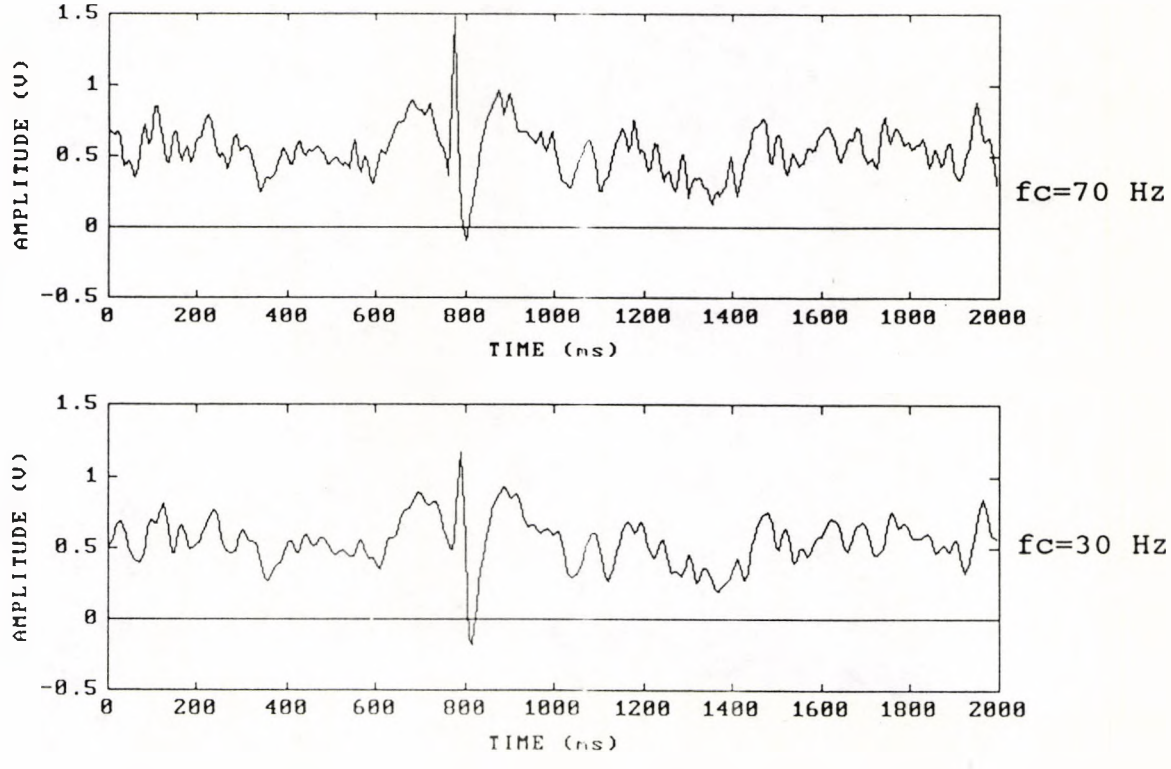
> "spikes are easier to differentiate from muscle artifact with an open high frequency filter than in a highly filtered and so uninterpretable recording".

Keeping this idea in mind and noting previous results obtained with the differentiator associated with a lowpass filter (see item 5.3.2), a slow-wave detector was added in order to guarantee that only a spike followed by a slow wave would be considered as a SAWC candidate; this technique had already been employed by other researchers (Bickford, 1959; De Vries and others, 1981; Principe and Smith, 1982).

It was first implemented in the form of a fourth-order Butterworth lowpass filter with a 7 Hz cutoff frequency followed



(a)



(b)

Figure 5.20 - Effect of pre-filtering on the EEG signal. (a) Artifact and (b) SAWC.

by a level detector (method already mentioned in item 5.3.2). Represented by equation 5.20 and with a frequency response curve illustrated in figure 5.21-a, the filter was first calculated for a sampling frequency of 600 Hz, which had previously been adopted for the DIFMOD. Later, in order to increase the coefficients accuracy, the sampling frequency for the lowpass filter was changed to 200 Hz [the bilinear transformation depends on the sampling frequency (Rabiner and Gold, 1985)], which was being used by the running-mean process to calculate the DC level. The processing time was 60 μs and the time delay was 75 ms.

A fourth-order 6.4 Hz 0.5-dB Chebyshev filter (- 3 dB at 7 Hz), whose frequency response curve is shown in figure 5.21-b, was also implemented, but its main disadvantages were a higher value time delay (110 ms) and the ringing factor (see figure 5.22).

$$H(s) = \frac{1}{(s^2 + 0.76536686\,s + 1)} \; \frac{1}{(s^2 + 1.84775907\,s + 1)} \qquad (5.20\text{-a})$$

$$H(z) = \frac{13 + 26\,z^{-1} + 13\,z^{-2}}{10000 - 19405\,z^{-1} + 9457\,z^{-2}} \; \frac{12.5 + 25\,z^{-1} + 12.5\,z^{-2}}{10000 - 18686\,z^{-1} + 8736\,z^{-2}} \qquad (5.20\text{-b})$$

Due to the number of multiplications and divisions that are necessary to process each sample through a 4th-order lowpass filter, the processing time is relatively high. In order to try to decrease it, another option of lowpass filter with a total

7 Hz cutoff frequency, which consisted of a moving average section (L=8) followed by a first-order Butterworth filter (fc=11 Hz), was first tried. As can be seen from figure 5.21-a, the degree of attenuation to high frequencies was not very good. Experimentally, the averager section (The Open University, 1984) was modified and a good result was finally obtained for L=12, with a total cutoff frequency of 5.5 Hz, which compensates the low attenuation factor that it has for the higher frequencies. While the processing time was reduced to 38 μs, 20 μs of which were spent on the moving-average section, the time delay was reduced to 50 ms. Both values were the lowest obtained during the experiments. For this reason, this kind of filter was adopted. To keep the number of memory cells used by the averager relatively low, 200 Hz was kept as the sampling frequency.

The typical SAWC response waveforms obtained with the three different types of lowpass filters described above are illustrated in figure 5.22.

Figure 5.23 illustrates the final sequence of a SAWC, the detected spike, the filtered slow wave obtained with the averager-Butterworth filter and the detection levels. The ground level was selected as reference for the three waveforms.

As can be observed from figure 5.23, there is a delay caused by the lowpass filter. Consequently, a problem that arises is the time interval that exists between the spike-detector output and the real-slow-wave signal obtained from the lowpass filter. The real slow-wave may be anticipated by a false slow-wave, which is caused by factors such as the low-amplitude slow-wave that precedes the spike in some cases and/or the

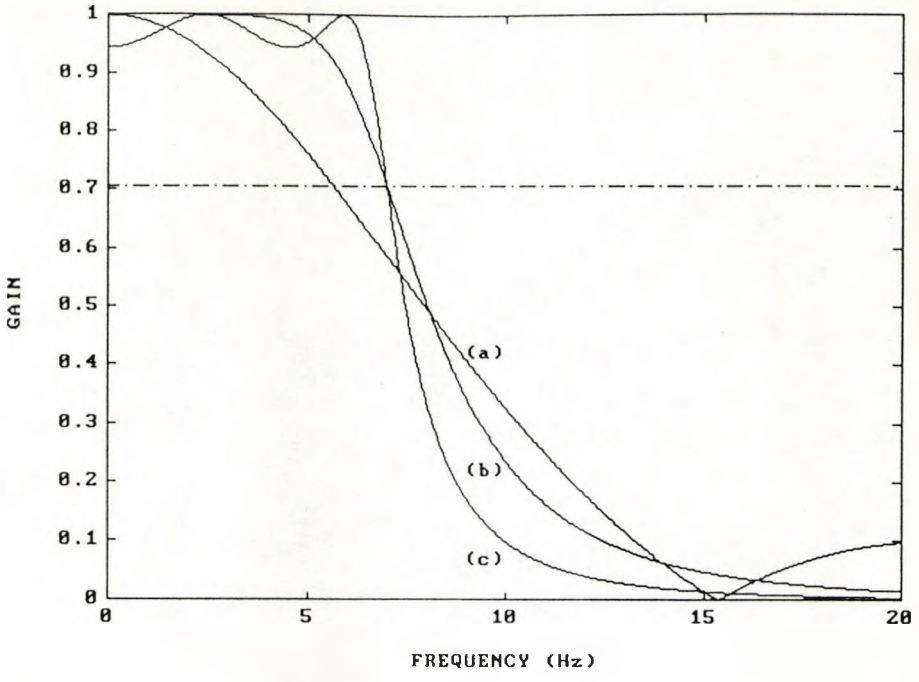


Figure 5.21 - Three versions of lowpass filters tested for the detection of slow waves. (a) Moving average (L=12) in series with a first-order Butterworth, (b) fourth-order Butterworth and (c) fourth-order 0.5-dB Chebyshev.

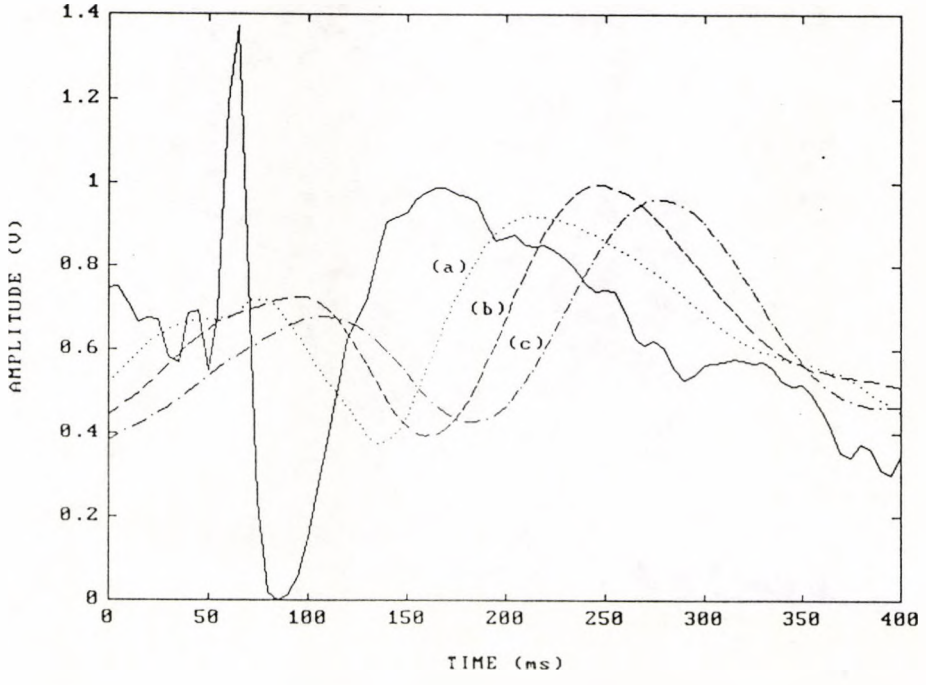


Figure 5.22 - Time response of three different lowpass filters to a typical SAWC. (a) Averager-Butterworth, (b) fourth-order Butterworth and (c) fourth-order Chebyshev.

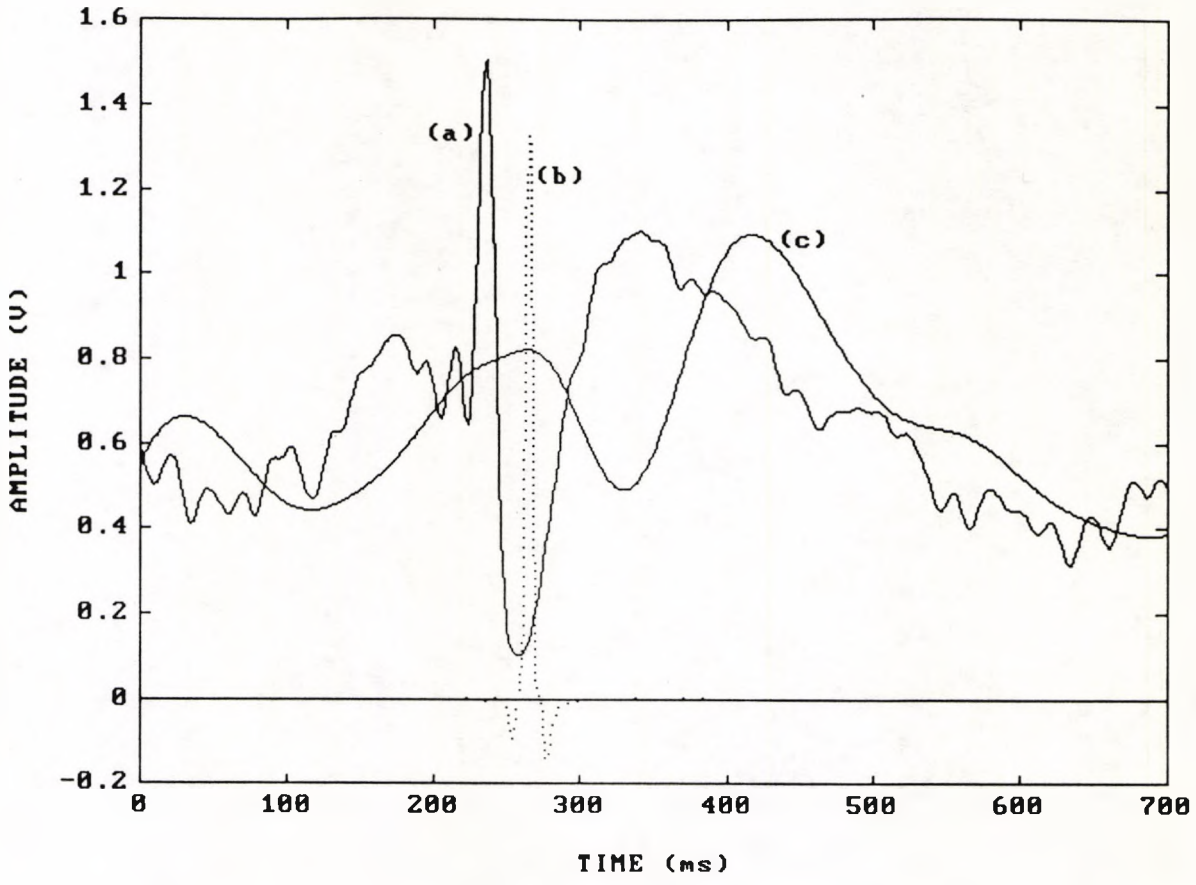
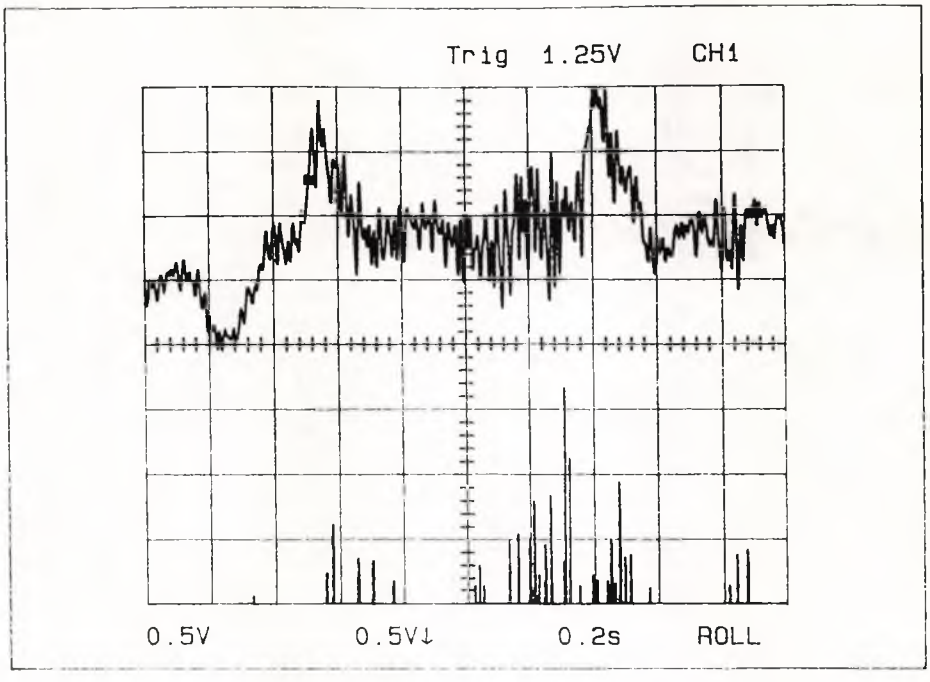


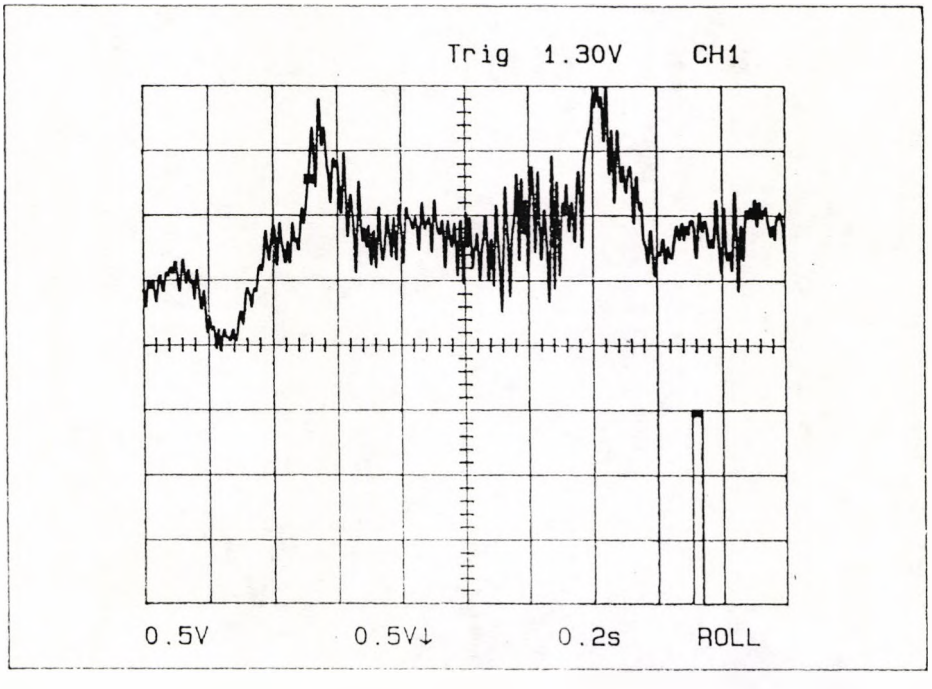
Figure 5.23 - Final sequence of the most important waveforms. (a) SAWC, (b) cubic filter output and (c) lowpass filter output.

response of the lowpass filter to the spike. To avoid the detection of this false slow-wave, a preset time interval has to be counted before the slow-wave detector is activated.

In general, the addition of the slow-wave detector produced a significant decrease in the number of false detections. Figure 5.24 shows as example an artifact, where the initial number of 31 detected spikes (false alarms) was reduced to 1 by the inclusion of the lowpass filter.



(a)



(b)

Figure 5.24 - Reduction in the number of false alarms as a consequence of the inclusion of the lowpass filter in the algorithm. (a) Without and (b) with lowpass filter.

In terms of SAWC detections, major difficulties arose only when the slow waves had very low amplitude or when spiky transients appeared (see items 5.3.2 and 5.6.2).

5.4.5 - The artifact rejection subroutines

The first basic algorithm was constituted of three elements:

1) the spike detector,
2) the slow-wave detector and
3) the spike/slow-wave time interval counter.

The idea of activating the slow-wave detector after the detection of a spike was not good because of the transient response that would be caused by the lowpass filter each time it was activated. For this reason, both detectors were always kept active. At the beginning, the detection levels were fixed. Later, they were made dependent on the DC level of the input signal.

If there were no artifacts at all or if the artifacts contained only spikes, the basic process mentioned above would be enough to provide a high SAWC detection and a low false alarm rate. Unfortunately, this is not always the case.

An examination of figure 5.25 shows that the artifacts may contain both spiky and slow-wave components. During tests with pre-recorded data, several algorithm changes were made in order to decrease the number of false alarms. The subroutines that were developed with such purpose were based on two main factors, which are:

1) the maximum number of spikes (1, 2 or 3) that may precede a slow wave and that can be accepted in a predetermined time interval and

2) the maximum value of the lowpass-filter output signal cannot be greater than a preset level (three times the DC level, for example).

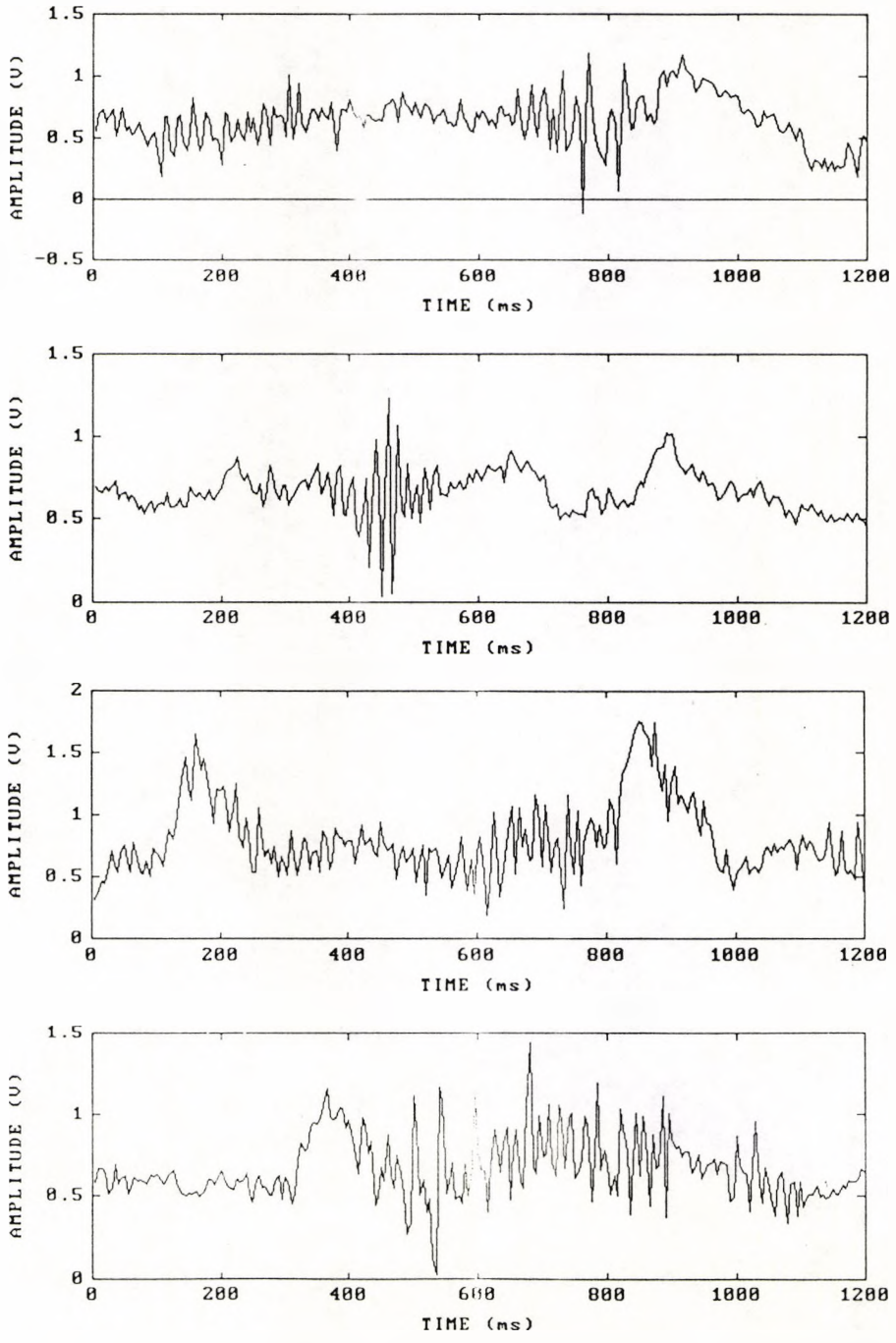


Figure 5.25 - Artifacts

If the detection of a polyspike-and-wave event is desired, the preselected number of spikes may be made equal to two or three, otherwise it is made equal to one. In fact, the poly-spike-and-wave will be registered as a single event; consequently, the detection of the last spike and of the slow wave will be enough to register the occurrence and so the number of spikes can be made equal to one, which decreases the false alarm rate significantly.

Having a 3Hz SAWC sequence as a reference, the time period of 333 ms was used as an analysis time-window. In this interval, there cannot be more than one spike. A more detailed description of the main algorithm follows in the next item. The possibility of a false alarm still exists when the last spike of the artifact is followed by a slow wave.

5.5 - The Algorithm

The main algorithm was developed in order to guarantee the detection of a single SAWC or of sequence of SAWCs and to reject artifacts that have several spikes or very high amplitude slow waves. Once the first results were obtained with the first algorithm, that simply detected the spike and, some milliseconds later, the slow-wave, two time differences of special interest were measured. As figure 5.26 shows, they are T1 and T2. The respective values for the fourth-order Butterworth and for the averager filters, described in item 5.4.4, are 75 ms / 50 ms for T1 and 250 ms / 275 ms for T2. The main part of the algorithm, that is related to the detection of individual or multiple spikes

and slow-waves, was made totally dependent on what happens during these intervals.

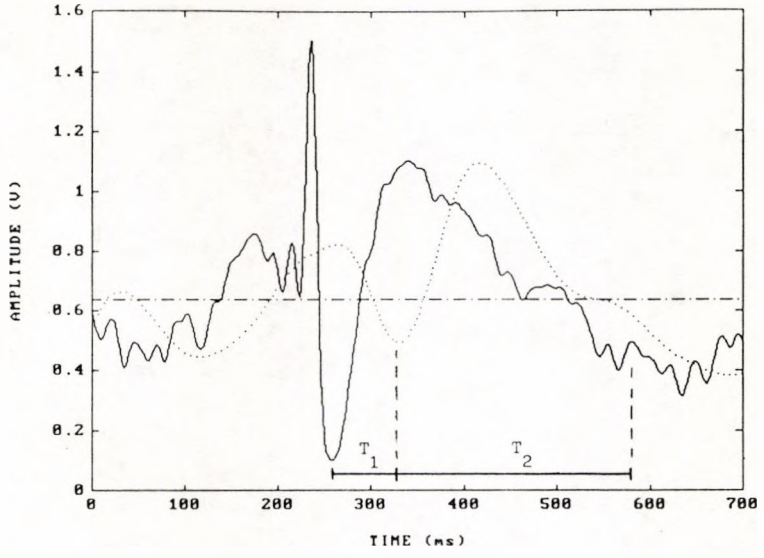


Figure 5.26 - Important time intervals in the detection of a spike and a slow wave.

A brief description of the algorithm will be made in the form of a sequence for a set of different possible waveforms, that are:

1) a single spike,

2) two or more single spikes following one another (possibly an artifact),

3) a single SAWC,

4) two spikes and a single slow-wave (SW) and

5) a spike followed by a half slow-wave (a probable SAWC) and another spike.

In the description below, SPCOUNTER is the spike counter and OUTPUT is normally nil, becoming equal to 1 when a SAWC is detected. RESET resets both SPCOUNTER and the time counter.

The reader is reminded that both detectors are always active.

I - A single spike

1) Look first for a spike.

2) Once a spike has been detected, make SPCOUNTER=1 and wait till the end of T1 to look for a SW.

3) Start to look for a slow-wave (SW).

4) If no SW has been detected till the end of T2, RESET.

II - Two or more spikes

Depending on the preselected number of spikes (SP) that are allowed to precede a SW, there are two possibilities.

(a) First, for SP greater than one (SP= 2 or 3, for example), which is better for the detection of polyspikes, the algorithm is:

1) Look first for a spike.

2) Once a spike has been detected, make SPCOUNTER=1 and wait till the end of T1 to look for a SW.

3) If in the meantime (till the end of T2) another spike is detected, add 1 to SPCOUNTER, clear the time counter and go on looking for a SW as before.

4) If the SPCOUNTER exceeds SP or the end of T2 is reached, RESET.

(b) Second, for SP=1, which is better for the rejection of multiple-spike artifacts, the algorithm is:

1) Look first for a spike.

2) Once a spike has been detected, make SPCOUNTER=1 and wait till the end of T1 to look for a SW.

3) If in the meantime (till the end of T2) another spike is detected, RESET and go to step 2 (ignore the first spike).

III - A single SAWC

1) Look first for a spike.

2) Once a spike has been detected, make SPCOUNTER=1 and wait till the end of T1 to look for a SW.

3) Start to look for a slow-wave (SW).

4) If a SW is detected during T2, wait till the end of T2 to make OUTPUT=1.

5) Some milliseconds after making OUTPUT=1, RESET.

IV - Two or more spikes and a single SW

By combining II and III, there are two possibilities.

(a) First, for SP greater than one, the algorithm is:

1) Look first for a spike.

2) Once a spike has been detected, make SPCOUNTER=1 and wait till the end of T1 to look for a SW.

3) If in the meantime, before the detection of a SW, another spike is detected, add 1 to SPCOUNTER, clear the time counter and go on looking for a SW as before.

4) If the SPCOUNTER exceeds SP or the end of T2 is reached, RESET.

5) If a SW is detected during T2, wait till the end of T2 to make OUTPUT=1.

6) Some milliseconds after making OUTPUT=1, RESET.

(b) Second, for SP=1, the algorithm is:

1) Look first for a spike.

2) Once a spike has been detected, make SPCOUNTER=1 and wait till the end of T1 to look for a SW.

3) If in the meantime, before the detection of a SW, another spike is detected, RESET and go to step 2 (ignore the first spike).

4) If a SW is detected during T2, wait till the end of T2 to make OUTPUT=1.

5) Some milliseconds after making OUTPUT=1, RESET.

V - A spike, half a slow-wave (a probable SAWC) and another spike.

1) Look first for a spike.

2) Once a spike has been detected, make SPCOUNTER=1 and wait till the end of T1 to look for a SW.

3) Start to look for a slow-wave (SW).

4) If a SW is detected during T2, wait till the end of T2 to make OUTPUT=1.

5) If another spike is detected before the end of T2, RESET and go to step 2 (ignore the probable SAWC).

6) If a SW is detected during T2, wait till the end of T2 to make OUTPUT=1.

7) Some milliseconds after making OUTPUT=1, RESET.

An observation must be made here. Several modifications are possible in the sequences discussed above. For example, if it is desirable to detect the presence of a probable SAWC (a spike followed by half a slow wave), T2 may be subdivided into T2a and T2b or simply decreased. In the first case, as soon as T2a is exceeded, OUTPUT goes to 1. The end of T2b may still be used to control the maximum time during which a SW may be detected. In the real-time algorithms developed for the Motorola system MVME-133, T1, T2a and T2b are controlled by m_min, m_med and m_max, respectively (see Appendix B).

5.6 - Detection Levels and Results

Both the spike detection level and the slow-wave detec-

tion level were made dependent on the DC level of the input signal. In order to select the appropriate values for these levels and to check the general performance of the developed algorithm, a non-contaminated EEG record with a duration of 150 seconds and a maximum amplitude of 1.8 volts, containing a total of 57 SAWCs, was used. Four of the SAWCs were not taken into account because their spikes were not very sharp and had very low amplitude in comparison to the others in the record.

5.6.1 - Spike detection level

Varying the spike detection level from DC/30 to 2.DC in eleven steps, the total number of true and false detections was recorded. The respective results are listed in Table 5.1 and illustrated in figure 5.27.

Table 5.1 - Variation of the number of true and false detections as a function of the detection level.

DETECTION LEVEL	TRUE DETECTIONS	FALSE DETECTIONS
DC/30	53	70
DC/20	53	25
DC/10	53	7
DC/8	53	4
DC/5	53	1
DC/4	53	0
DC/3	49	0
DC/2	47	0
DC	38	0
1.5 DC	31	0
2.0 DC	25	0

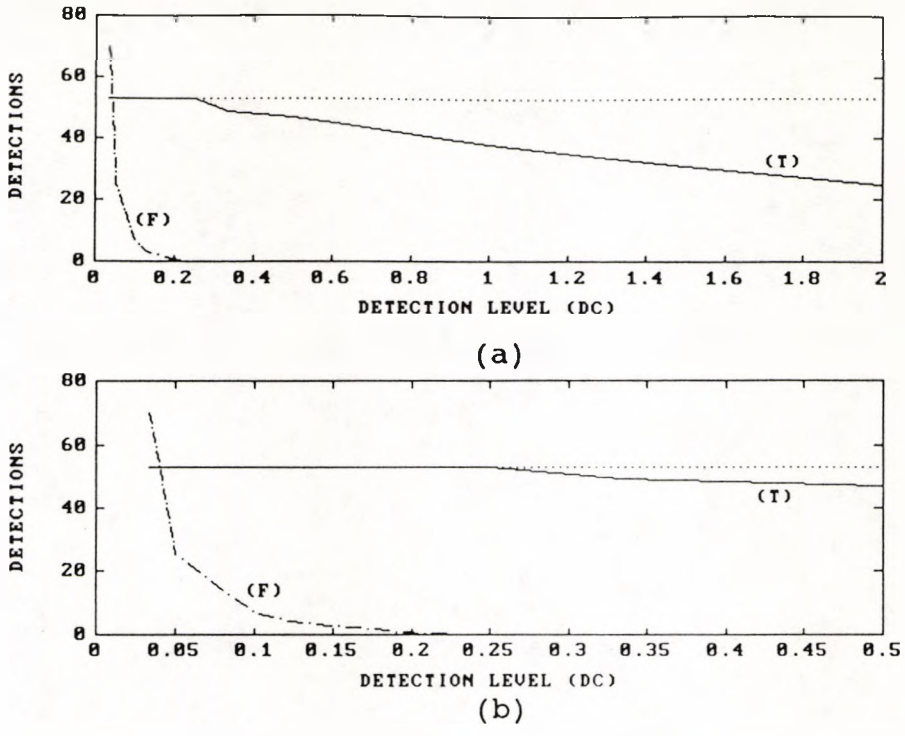


Figure 5.27 - Variation of the number of true (T) and false (F) spike detections as a function of the detection level. (a) From DC/30 to 2.DC and (b) from DC/30 to DC/2.

As can be observed, there is a compromise between the number of true and false detections. Considering that the four SAWCs with very low amplitude did not belong to a group of normal SAWCs, any level between DC/4 and DC/3 may be chosen as the spike detection level, since all the other features may be detected without false alarms. As it is easy to divide a number by 4 in binary logic, DC/4 was adopted.

5.6.2 - Slow-wave detection level

A visual inspection of the output from the 7 Hz lowpass filter (taken via the DAC and output on a storage oscilloscope) suggested that the DC level would prove to be an adequate choice

for the detection threshold and that no further enhancement of the signal would be required. To avoid false detections caused by isolated spiky transients, which cause variations in the output levels of both the spike and the slow-wave detectors, a level of DC+DC/8, that is 11.25 % above the DC level, was found to be more appropriate. Higher values brought problems to the detection of very-low-amplitude slow waves. A typical example of the lowpass filter output signal is shown in figure 5.28. Using the chosen level gave a good detection vs. missed feature rate, 58/0 with the test record.

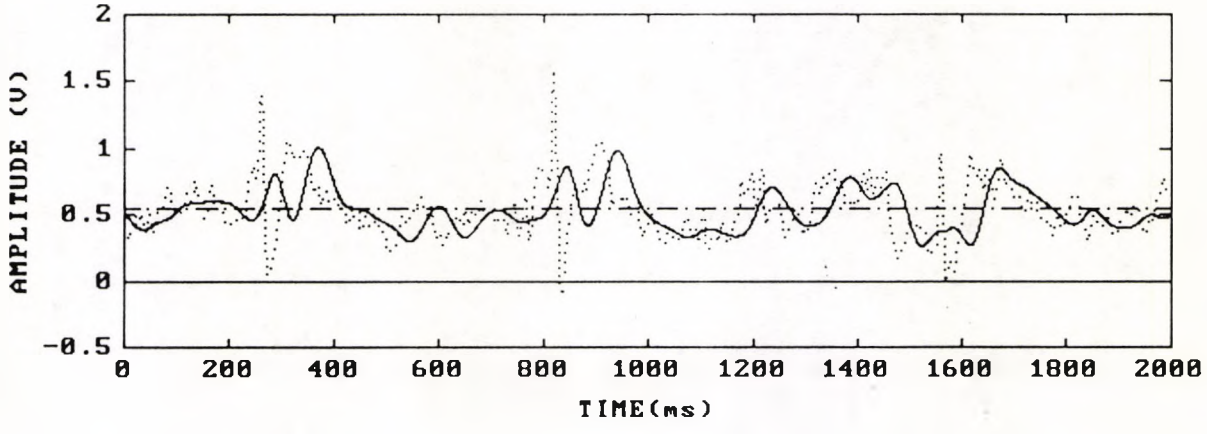


Figure 5.28 - Typical lowpass-filter output signal.

5.6.3 - Results

In terms of SAWC detection and artifact rejection, the performance of the developed algorithm was very encouraging. As mentioned above, the missed features were characterized by low-amplitude and non-sharp spikes such as those shown in figure 5.29.

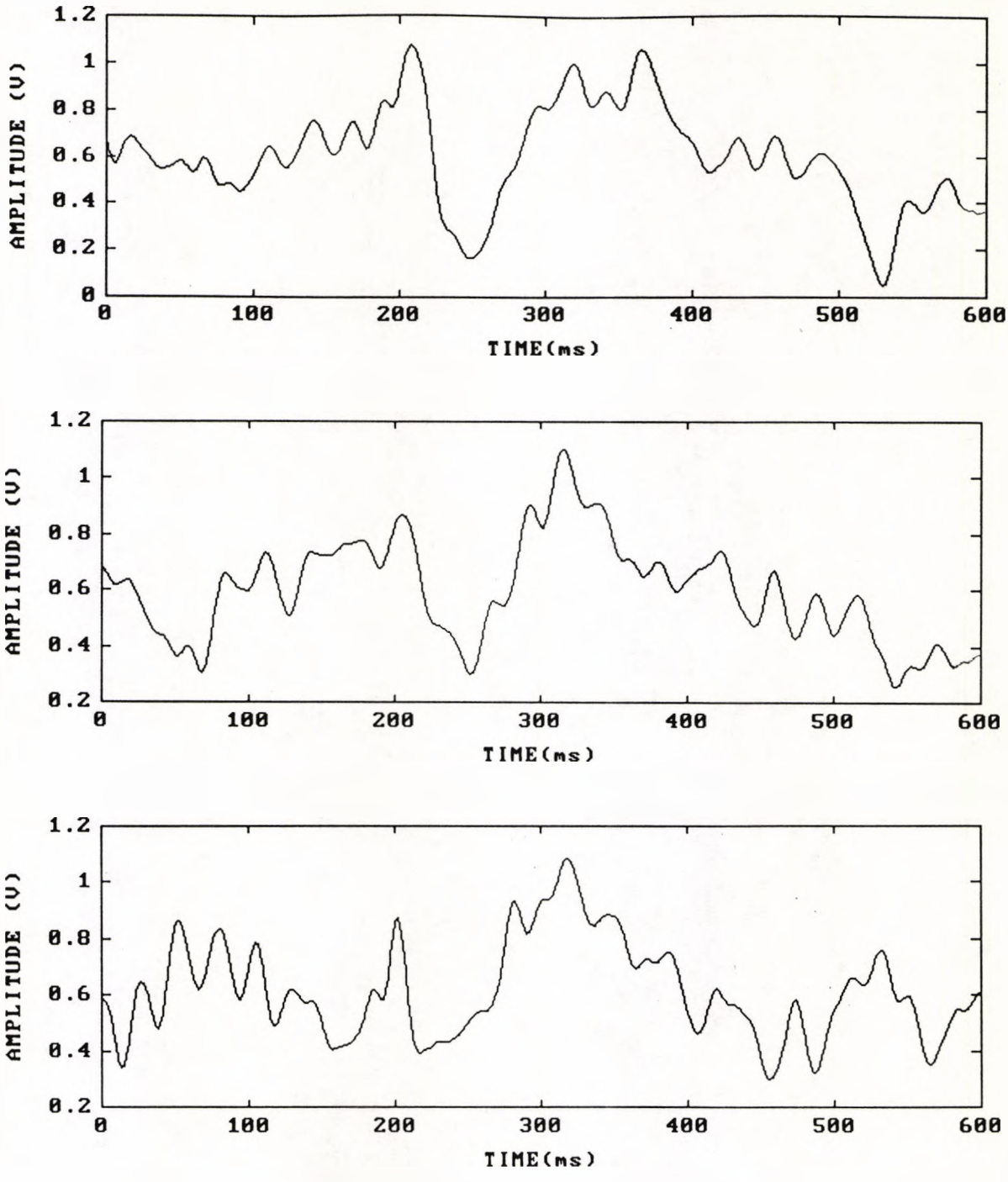


Figure 5.29 - Examples of missed features.

The false alarms occurred only where a high-frequency transient mixed with a low-frequency component was present (a rectangular pulse, for example) or during an artifact (normally at its end), when the last spike was followed by a slow wave. Two examples are illustrated in figure 5.30.

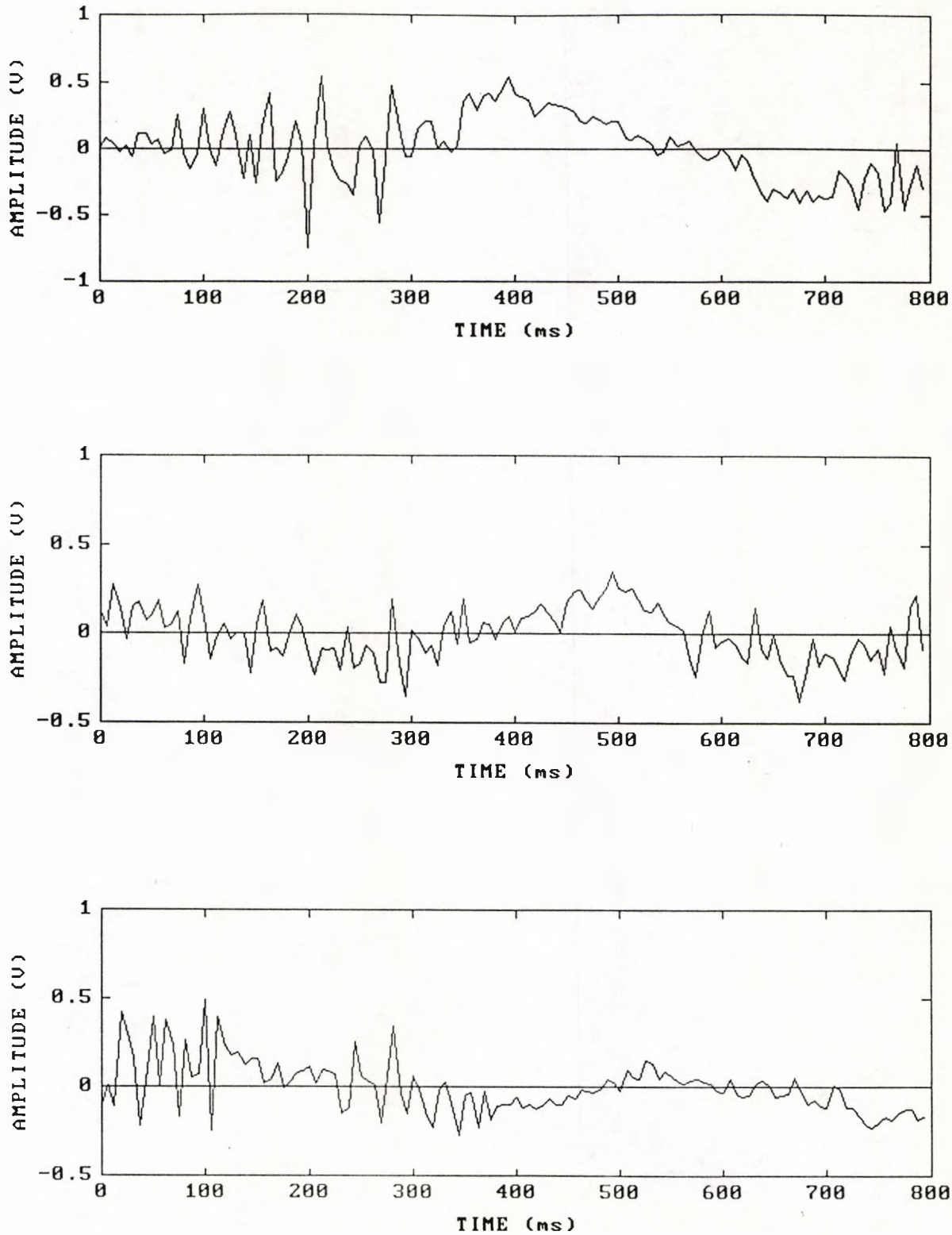


Figure 5.30 - Examples of false alarms.

5.7 - Discussion

A digital processing technique that permits the real-time detection of spike-and-wave complexes (SAWCs) has been described. The spike and the slow-wave features are detected separately, with both the spike detector and the slow-wave detector being always active. Basically, the detection of a spike followed by that of a slow-wave in a preset time interval are necessary to confirm the occurrence of a SAWC.

As the coupling of a lowpass filter with the spike detector is just a means of reducing the number of false alarms that would occur with a simple spike detector and taking into consideration the fact that it is not too difficult to detect a slow wave, unless it has very low amplitude, more emphasis has been given to the performance of the spike detector.

Constituted mainly of a spike enhancer, which represents a differentiator in series with a Hilbert transformer, and a cubic filter, the spike detector is what makes this technique differ from others. It is more normal practice to use some form of differentiation to isolate the spike and some sort of lowpass filtering to reduce the noise caused by the differentiator.

Considering the input signal to have a zero mean value and the spikes to be positive, the spike enhancer, when excited by a spike, reproduces a high-amplitude positive peak, that may be considered as an even function, followed by a negative peak of lower amplitude. The cubic filter, by taking the input values to the cube, further enhances the positive peak that corresponds to the detected spike and reduces the relative low-level samples to

almost zero (when the amplitude is normalized). A further feature is that the negative values remain negative. This way, while most of the noise is eliminated, the main peak is enhanced instead of having its amplitude reduced by a lowpass filter. One single detection level is enough since the negative values may be eliminated.

The cubic filter has a highly non-linear transfer function [Vout(t)=f(Vin(t))], which is highly dependent on the amplitude variations of the input-signal. This has posed some difficulties in the selection of the constants that help to attenuate the filter input and output signals [in order to avoid overflow (8 MSB)] and of the spike detection level. For the selected values, the original EEG signal varies between 0 and 1.8 volts. If the amplitude of the input signal is changed, then the detection level and the constants mentioned above may have to be modified. If only the constants are modified, the detection level may have to suffer modifications.

The spike detector performed well as a general purpose spike detector. From a total of 58 spikes, for the preset detection level (DC/4), 54 were detected without any false alarms. The spikes that were not detected and that were responsible for the non-detection of the respective SAWCs, belonged to a class of very-low-amplitude spikes. A decrease of the values of the attenuating constants of the cubing filter, which would increase the amplitude of the enhanced spikes, could be tried as a first step to detect them. Another possibility is a lowering of the spike-detection level, but the detection of these spikes could give rise to false alarms.

Both the fourth-order Butterworth lowpass filter and the averager/first-order-Butterworth lowpass filter are good options.

Compared to the first one, the second offers the advantage of a reduced time delay, which is essential for the detection of a sequence of SAWCS or of a spike followed by half a slow wave and another SAWC, for example. The main disadvantage is that it needs more memory to store the samples used by the averager. The same happens with the averaging filter from which the DC level of the input signal is obtained. Nowadays, the requirement for large quantities of memory does not seem to be a big problem.

The lowpass filter and the artifact rejection algorithm have been very helpful in the reduction of false alarms caused by isolated spikes or sequences of spikes with a low-frequency envelope (artifacts). As mentioned in item 5.4.5, the amplitude of the input signal was not used as a helping factor in the rejection of artifacts. It can, anyway, be checked and, if it is above a preset threshold, the real input signal can be ignored for some time (1000 ms, for example). During this interval, the input signal can be kept equal to an estimated value of the DC level (pre-calculated and stored in memory) in order to avoid abrupt changes in the detection levels and possible future false alarms. The real DC level shall not be used in such case because problems arise when it goes very low (when the input signal is nil for some time, for example). If the DC level is very low, the comparison level is very low and the input signal that follows such a period will be considered as an artifact and the program falls into a loop (low DC level => low comparison level => arti-

fact flag on => low input signal (DC) => low DC level ...).

During the experiments, information from only one channel was analyzed. In future, it is intended to expand the detection algorithm to deal with up to 5 or maybe 6 channels, which will permit the development of a more reliable interdependent SAWC detection and artifact rejection algorithm. For example, the ictal EEG of a typical absence seizure, that is a form of generalized seizure, is characterized by bilaterally synchronous, frontally predominant but generalized, 3/s SAWCs, which appear in all channels. Consequently, even if a SAWC is missed in some channels, its detection in another channel will be sufficient to confirm its presence.

To give a high resolution to the spike and to the corresponding signal at the output of the cubic filter, the spike detection algorithm was developed with a sampling frequency of 600 Hz. If necessary, a reduction to 200 Hz could be considered to allow the multiplexing of several channels but with the advent of modern microprocessors, even more sophisticated algorithms will be possible without the necessity of a reduction of the sampling frequency.

As the main idea is to build a monitor that can be carried by the patient, it must be as portable as possible and for this reason, neither the hardware nor the software can be too sophisticated at the moment (in a few-years time, they may be). So, the possibility of false detections exists. As mentioned in previous chapters, the EEG analysis must be as precise as possible so that correct decisions concerning diagnosis and treatment may be reached. For this reason, it is foreseen that

the SAWC detector under discussion will be used not as a definitive EEG-analysis tool but as an auxiliary tool that will select interesting segments of the EEG, which contain important features. These segments will be subjected to a more elaborate method of SAWC detection, including visual interpretation by the EEGer if necessary.

The discussed method and many others are based on both time-domain and frequency-domain analyses of the signal, but considered separately. It is possible that a more reliable method of EEG analysis may be obtained if the signal is analyzed simultaneously in both domains. A mathematical tool that facilitates this kind of analysis is the Wigner Distribution, which is the subject of the next chapter.

5.8 - Conclusion

The presented approach to a SAWC detector is relatively simple and seems to merit further sophistication and exploration as a method of detection of spike-and-slow-wave complexes in real time. As the algorithm was tested with just a few prerecorded signals that did not vary on a daily basis, which is what happens in real life, the validation of the system performance cannot be overemphasized by the moment.

CHAPTER 6

THE WIGNER DISTRIBUTION AND ITS APPLICATION TO THE MEASUREMENT OF EEG SIGNALS

6.1 - Introduction

Signal analysis and system modelling have typically been based on stationary signals and linear time-invariant systems. But, in practice, most signals, such as EEG, voice, image, radar and seismic signals ,to give only a few examples, are not stationary. For this reason, much attention has been given, during the last decades to non-stationary signal modelling and non-linear time-varying signal processing (Yu and Cheng, 1987).

In the study of a non-stationary signal, one of the most interesting aspects is the visualization of the variation of its spectrum as a function of time. The sound spectrogram (periodogram) was invented during the 1940s with this purpose in mind. In its modern form, it is calculated as the square of the Short-Time Fourier Transform (STFT), which consists of sliding a short-time window over the signal and computing the respective energy spectrum of each segment. This technique is very easy to compute and interpret, but it is useful only in the analysis of the local frequency characteristics of slowly time-varying signals, because good time-resolution requires a short-duration analysis window whereas good frequency-resolution requires a

long-duration window. This is a consequence of the uncertainty principle, which is supported by the scaling theorem (Papoulis, 1977). However, different windows (rectangular, triangular, Hamming, hanning, Kaiser) can be used for measuring different signal properties.

The Wigner Distribution (WD) is another type of time-frequency signal representation that overcomes the drawbacks presented by the STFT. Both the time-resolution and the frequency resolution are not dependent on a window function but rather on the intrinsic resolution of the signal itself. Furthermore, it has a great number of good properties and is of particular interest in the analysis of non-stationary signals, such as EEG signals. In 1932, the WD was proposed and applied in the area of quantum mechanics by E. Wigner. Later, in 1948, J. Ville proposed its use in signal analysis and since then it has also been known as The Wigner-Ville Distribution. It remained practically unnoticed and unused until 1980, when three definitive papers by T. A. C. M. Claasen and W. F. G. Mecklenbräuker were published.

6.2 - The Wigner Distribution

The Wigner Distribution is a two-dimensional transformation of a one-dimensional signal x(t), which shows its frequency characteristics as a function of its variation in the time domain. The WD can be written as:

$$W_x(t,\omega) = \int_{-\infty}^{\infty} x(t + \tfrac{\tau}{2})\, x^*(t - \tfrac{\tau}{2})\, e^{-j\omega\tau}\, d\tau \qquad (6.1)$$

where t is the time domain variable, ω is the frequency domain variable and $x^*(t)$ represents the complex conjugate of x(t).

As with the Fourier Transform, the definition given by equation 6.1 is not very useful in practical terms because the signal must be known for all times (infinite integral). However, it is valid for theoretical demonstrations. In order to apply the WD to discrete-time signal processing (Discrete Time Wigner Distribution) and to calculate it via FFT techniques, to take advantage of modern computer technology, equations 6.2 and 6.3 may be used (Claasen and Mecklenbräuker, 1980; Boudreaux-Bartels, 1985; Yu and Cheng, 1987). Equation 6.3 is a windowed version of equation 6.2, making it suitable for computer evaluation. The windowed version, also known as the Pseudo Wigner Distribution (PWD), causes some blurring in the frequency direction but no blur in the time direction. The results depend obviously on both the window size and type.

$$W_x(n,\omega) = 2 \sum_{m=-\infty}^{\infty} x(n+m)\, x^*(n-m)\, e^{-j2\omega m} \tag{6.2}$$

$$W_x(n,\omega) = 2 \sum_{m=-\infty}^{\infty} x(n+m)\, x^*(n-m)\, h(m)\, h^*(-m)\, e^{-j2\omega m} \tag{6.3}$$

The properties of the DTWD are similar to the continuous time case, with the exception of the periodicity in the frequency variable; this however is to be expected.

There are no restrictions imposed by the WD on the spectrum of the signal x(n) but as is known from discrete-signal theory (Oppenheim and Schafer, 1975), a sampled signal

has a spectrum that is periodic with period 2π (or fs). As can be seen from equations 6.2 and 6.3, the WD in fact has a period π. The consequence of this is that frequency components that are π apart in the spectrum will produce a similar effect in the WD. A simple solution to avoid such aliasing is to oversample the signal by a factor equal to or greater than twice the Nyquist rate ($fs \geq 4.fmax$).

Although oversampling may seem to be an easy solution, in practice, obstacles such as difficulties with interpolation methods and memory limitations imposed by computers (mainly personal computers) may appear.

Another factor is the aliasing caused by the rectangular window. This may be in part eliminated by the use of other well known windows but the "corruption" of good data by such non-rectangular windows is not easy to justify (Burg, 1975; Picone and others, 1988). In such case, the only solution is to make use of the analytic signal associated with the sampled signal x(n) (Martin and Flandrin, 1985; Boashash and Black, 1987). The analytic signal, also used in the communications field to facilitate the generation of single sideband signals, has a unilateral positive-frequency spectrum (information on negative frequencies of any real-valued signal is redundant). Consequently, not only the aliasing problem is solved but also the WD will vanish in the negative frequency plane, cutting both the memory storage and processing time required. Therefore, if the analytic signal is used, the sampling rate constraint becomes the Nyquist rate ($fs \geq 2.fmax$). More details about the analytic signal follow ahead.

The analytic signal (Bracewell, 1978; Mohanty 1987) corresponding to a real function x(t) is a complex function defined by:

$$x_a = x(t) + j\, x_{Hilb}(t) \tag{6.4}$$

where $x_{Hilb}(t)$ is the Hilbert Tranform of x(t).

It has already been shown in Chapter 5 that the Hilbert Transform is a signal transformation that alters only the phases of the frequency components by 90 degrees, keeping their amplitudes constant. It is defined by:

$$x_{Hilb}(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\lambda)}{\lambda - t}\, d\lambda \tag{6.5}$$

Using FFT algorithms, the Hilbert Transform of x(t) can be easily obtained in practice by convolving it with $1/(\pi t)$, as shown below:

$$x_{Hilb}(t) = \frac{1}{\pi t} * x(t) \tag{6.6}$$

where * denotes convolution.

Given a function x(t), its respective analytic function xa(t) may be written as:

$$x_a = e(t)\, e^{-j\Theta(t)} \tag{6.7}$$

where e(t) represents the function envelope and $\theta(t)$ represents

the phase. The instantaneous frequency is obtained by deriving the phase in relation to time as shown in equation 6.8 and the group delay, that represents the time delay experienced by each frequency component of x(t), is given by equation 6.9, where $\Phi(\omega)$ is the phase function of the Fourier Transform of x(t).

$$\Omega(t) = \frac{d\Theta(t)}{dt} \tag{6.8}$$

$$T(\omega) = -\frac{d\Phi(\omega)}{d\omega} \tag{6.9}$$

6.2.1 - Properties of the Wigner Distribution

The Wigner distribution of a continuous-time signal x(t) has several interesting properties which will be summarized below. Some of these properties are very useful in the analysis of EEG signals while others will be mentioned for the sake of completeness. For more detailed information, the references should be consulted. As mentioned earlier, keeping in mind that a periodicity occurs in the frequency domain, these properties are also valid for the DTWD. The properties are:

1) The WD of any real or complex signal is always real.

2) The WD of a real signal is an even function of the frequency.

3) The integration of the WD over the frequency variable at a certain time t1 yields the instantaneous signal power at that time, that is:

$$\|x(t)\|^2 = \frac{1}{2\pi}\int_{-\infty}^{\infty} W_x(t,\omega)\, d\omega \qquad (6.10)$$

4) The integration of the WD over the time variable at a certain frequency W1 yields the power spectral density at that frequency, that is:

$$\|X(\omega)\|^2 = \int_{-\infty}^{\infty} W_x(t,\omega)\, dt \qquad (6.11)$$

5) The WD has in the time domain the same support that the signal has. For example, the WD of a causal signal is nil for negative time.

6) The WD has in the frequency domain the same support that the spectrum of the signal has. For example, the WD of an analytic signal is nil for negative frequencies.

7) The WD preserves time shifts suffered by the signal.

8) The WD preserves frequency shifts suffered by the signal.

9) The convolution of two signals in the time domain results in a one-dimension convolution of their WD's in the time direction.

10) The WD of the sum of two signals is a bilinear function of the respective WD's and not only the sum of the WD's, as shown by equation 6.12.

$$WD(f + g) = WD(f) + WD(g) + 2\,Re[WD(f, g)] \qquad (6.12)$$

where WD[f] and WD[g] represent the autoterms and 2.Re[WD(f,g)] represents the crossterms.

11) The multiplication of two signals in the time domain results in a one-dimension convolution of their WD's in the frequency direction.

12) The first local moment of the WD over the frequency variable yields the instantaneous frequency of the signal. As defined in equation 6.8, the instantaneous frequency can be recovered from the WD by:

$$\Omega(t) = \frac{\int_{-\infty}^{\infty} \omega\, W_x(t,\omega)\, d\omega}{\int_{-\infty}^{\infty} W_x(t,\omega)\, d\omega} \qquad (6.13)$$

13) The first local moment of the WD over the time variable yields the group delay of the signal. As defined in equation 6.9, the group delay can be recovered from the WD by:

$$T(\omega) = \frac{\int_{-\infty}^{\infty} t\, W_x(t,\omega)\, dt}{\int_{-\infty}^{\infty} W_x(t,\omega)\, dt} \qquad (6.14)$$

6.2.2 - An example of the Wigner Distribution

The best way to appreciate the features that the Wigner Distribution offers in both the time and frequency domains is through an example, visualizing it through its perspective (three-dimensional) and its contour plots (two-dimensional). Using the causal formula, given by equation 6.3, with a rectangular window, the WD of a Gaussian function multiplied

by a sine function, is obtained by taking the following steps:

1) Given the original equation, represented by equation 6.15, the respective analytic signal is obtained.

2) For each value of m, the analytic signal is shifted in one direction and its complex conjugate in the opposite direction. Their product is then obtained and a matrix whose rows represent each product is constructed.

3) The Fourier Transform of each column of the matrix is taken.

4) The WD is then obtained by taking the real part of the matrix and multiplying the result by 2.

$$x(n) = e^{-a(\frac{n - n_0}{N})^2} \sin(2\pi f_0 \frac{n}{N}) \qquad (6.15)$$

The signal, its respective WD in three dimensions and in two dimensions are shown in figure 6.1. While the perspective view offers a qualitative interpretation of the signal, the contour plot in the time-frequency plane permits a quantification of the delay and the spreading of each frequency component in the time domain.

6.2.3 - Interference in the Wigner Distribution

The WD distribution suffers from some undesirable side effects. The one that has caused the most trouble in this work is the so called crossterms interference or artifacts.

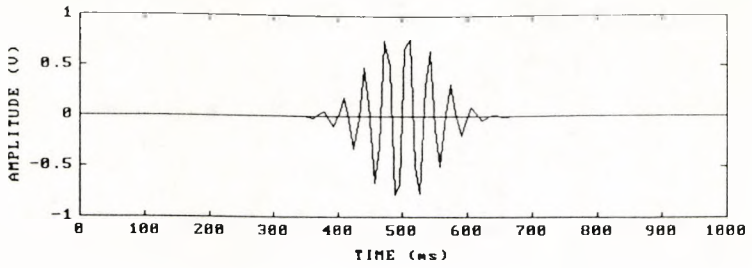
Based on properties 3 and 4, it would be a good idea to consider the WD as a totally positive function (Janssen,

1988; Johnston, 1989) but due to its bilinear structure, supported by property 10, there will always be an oscillation, that assumes positive and negative values, in between two functions (in time and/or in frequency). In other words, the WD may be not nil in an interval of time and/or frequency where the signal is nil (Bodreaux-Bartels, 1985). As an example, see Figure 6.3, which shows the WD of the signals described by (6.16).

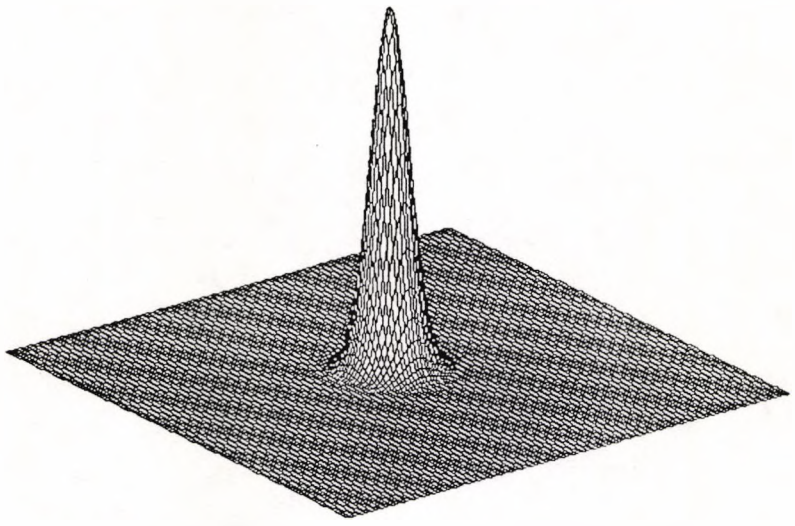
$$x(n) = e^{-a(\frac{n - n_1}{N})^2} \sin(2\pi f_1 \frac{n}{N}) + e^{-a(\frac{n - n_2}{N})^2} \sin(2\pi f_2 \frac{n}{N}) \qquad (6.16\text{-a})$$

$$x(n) = e^{-a(\frac{n - n_1}{N})^2} \sin(2\pi f_1 \frac{n}{N}) + e^{-b(\frac{n - n_2}{N})^2} \sin(2\pi f_2 \frac{n}{N}) \qquad (6.16\text{-b})$$

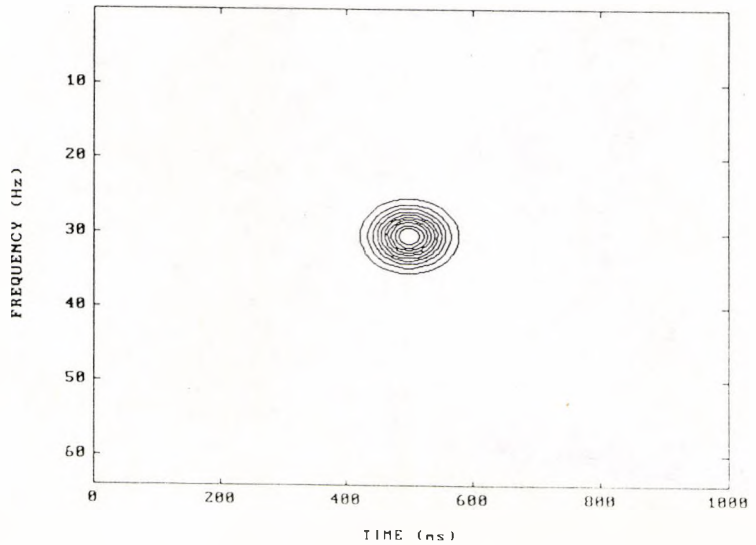
In the case of a sum of N sinusoidal signals, for example, there will always be (1/2.N(N-1)) spurious values (Cohen, 1989) and, consequently, in most practical cases, where the signals have an original wideband or a wideband provoked by discontinuities, caused by a rectangular window, for example, there will be interference obscuring the real WD. Unfortunately, the WD is totally positive only for one particular function, that is the Gaussian pulse (it may be shifted in time and it may be multiplied by a sine function, which causes a shift in frequency). This is the right time to enhance one more benefit brought by the use of the analytic signal, that is: no interference terms between positive and negative frequencies (DC level) shall appear (Martin and Flandrin, 1985; Yu and Cheng, 1987). When a signal that contains a



(a)



(b)



(c)

Figure 6.1 - WD of a Gaussian function multiplied by a sine function. (a) The signal, (b) perspective view and (c) contour plot of the WD.

DC level is windowed through a rectangular window, discontinuities normally appear. In order to avoid them, even when the analytic signal is in use, it is a good idea to eliminate the DC level.

The most basic way to eliminate part of this interference is to use non-rectangular windows in equation 6.3, the so called Pseudo-Wigner Distribution, that is a frequency-smoothed WD. A second choice is to make use of the Smoothed Pseudo-Wigner Distribution (Martin and Flandrin, 1985-a-b), given by equation 6.17, that is a double convolution.

$$PW_{2N-1}^{2M-1}(t,\omega) = 2 \sum_{r=-N+1}^{N-1} \left\| h_N(r) \right\|^2 \sum_{l=-M+1}^{M-1} g_M(l)\ x(t+l+\tau)\ x^*(t+l-\tau)\ e^{-j2\omega r} \qquad (6.17)$$

The third and most popular choice of smoothing, adopted in this work, is to convolute the original WD with a two-dimensional Gaussian function such as the one shown in figure 6.2 (Bertrand and others, 1983; Janssen and Claasen, 1985; Johnston, 1989; Cohen, 1989), as defined by equation 6.18. As an example of this method, making k=[-5:1:5], l=[-5:1:5], α=12 and β=12 (these values were selected experimentally and used throughout this work, except on the example concerned with equation 6.19, where k=l=[-3:1:3] and α=β=9 were used), the original WD's illustrated in figure 6.3 assume the forms shown in figure 6.4. As can be seen, a great percentage of the interference is eliminated and the WD tends to have only non-negative values, as desired. All this is due to the fact that the smoothing function has the effect of a lowpass filter in both dimensions, attenuating the signals that have sharp variations such as the

artifacts.

The final result is a function of the so called auto-terms.

$$L(k,l) = \frac{1}{\alpha\beta} e^{-\frac{k^2}{\alpha} - \frac{l^2}{\beta}} \qquad (6.18)$$

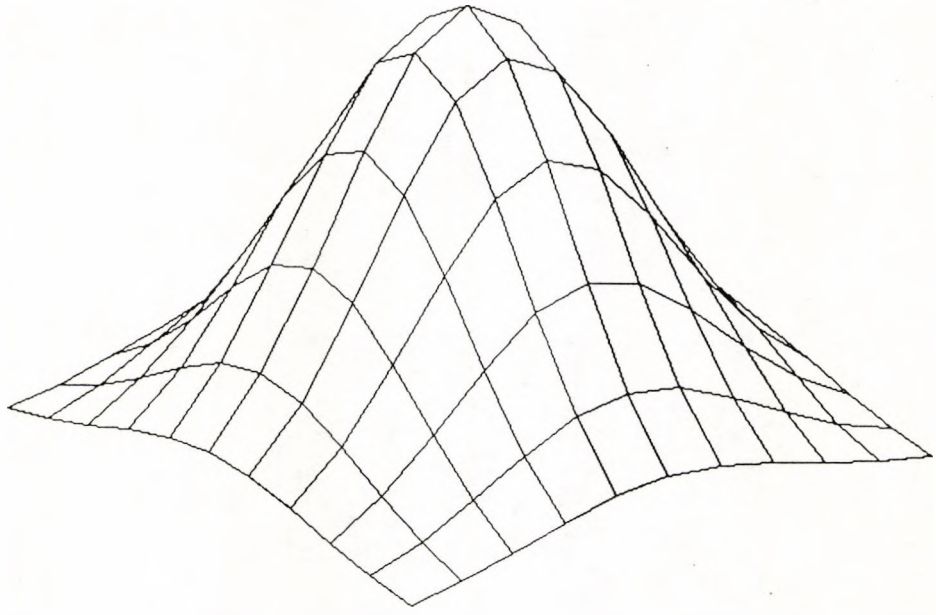
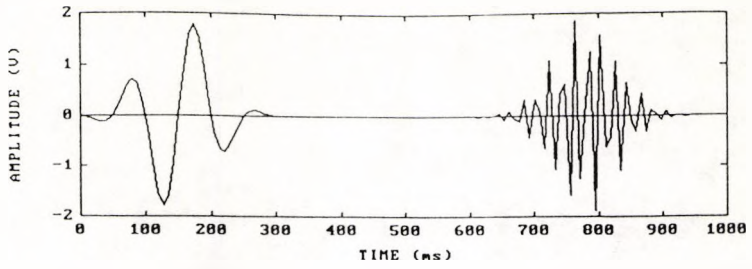
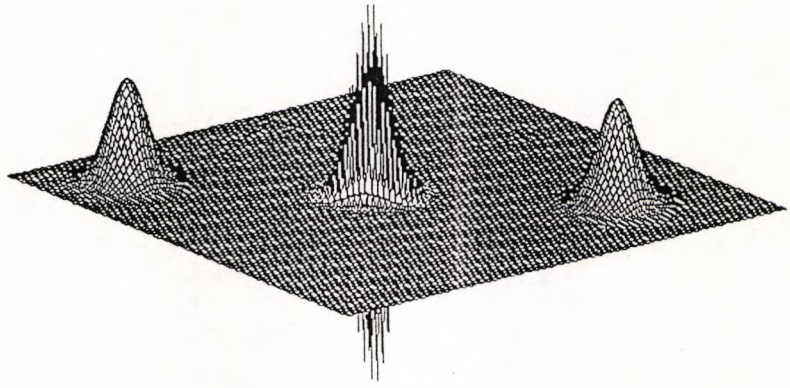


Figure 6.2 - Example of a two-dimensional Gaussian smoothing function.

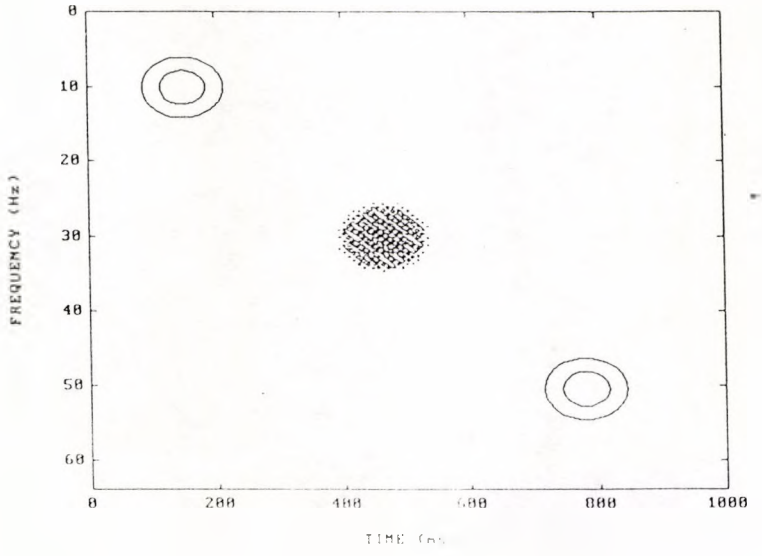
Unfortunately, as with the process of AM-DSB detection, for example, where the averaging filter may eliminate not only the carrier, but also the relatively high-frequency components of the modulating signal, one negative consequence of the smoothing process is the reduction in amplitude not only of the artifacts but also of components that have sharp variations (compare figures 6.3-b and 6.4-b). As the main idea was just to check the different forms of the WD as a function of the



(a)

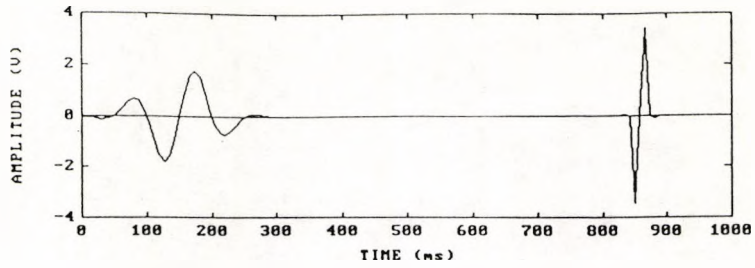


(b)

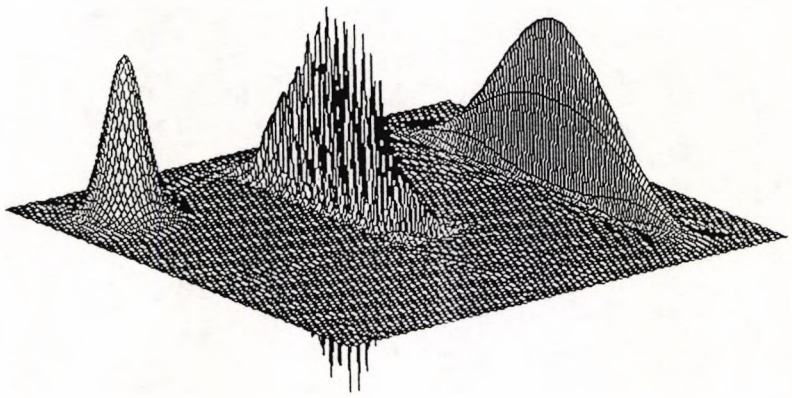


(c)

Figure 6.3-a - WD of the sum of two Gaussian functions shifted both in time and in frequency showing the artifact in between. (a) The signal, (b) perspective view and (c) contour plot of the WD. (With reference to equation 6.16-a.)



(a)



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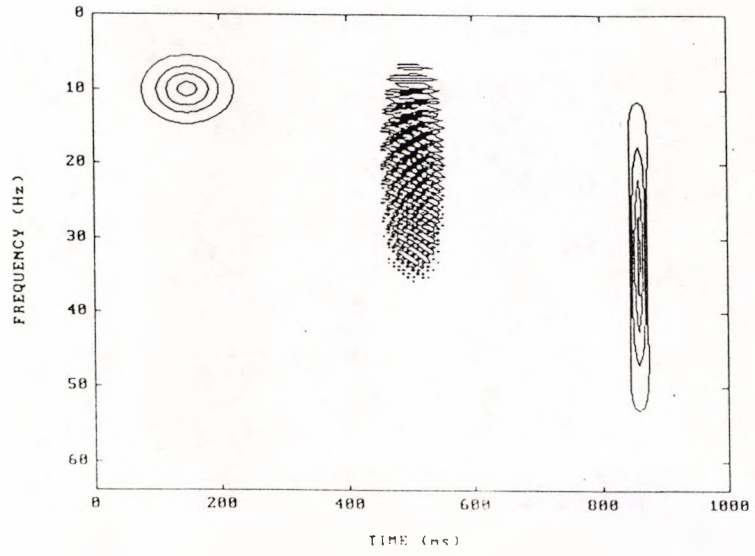
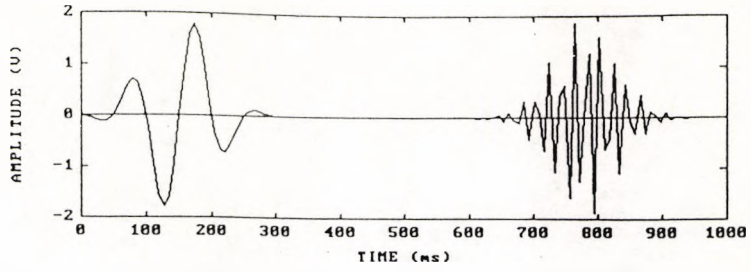
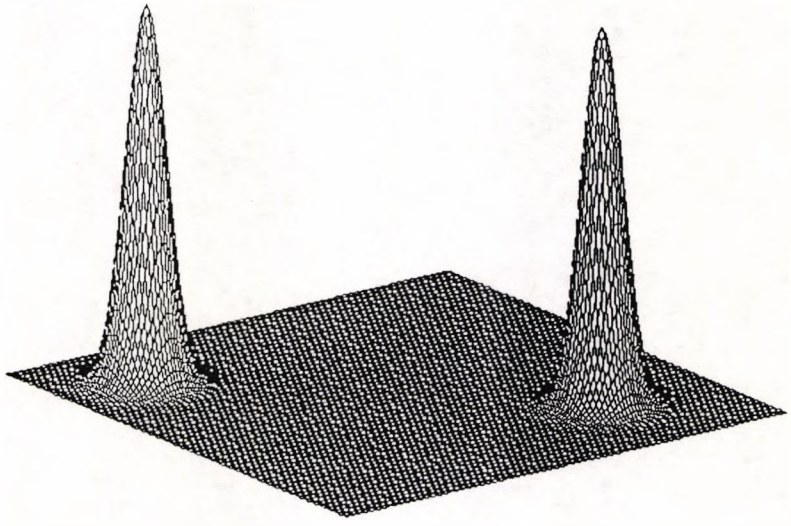


(c)

Figure 6.3-b - WD of the sum of two Gaussian functions shifted both in time and in frequency showing the artifact in between. (a) The signal, (b) perspective view and (c) contour plot of the WD. (With reference to equation 6.16-b.)



(a)



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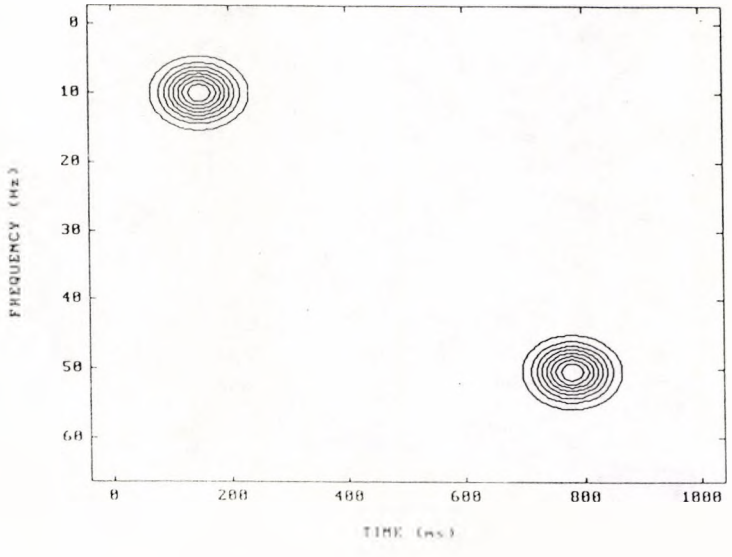
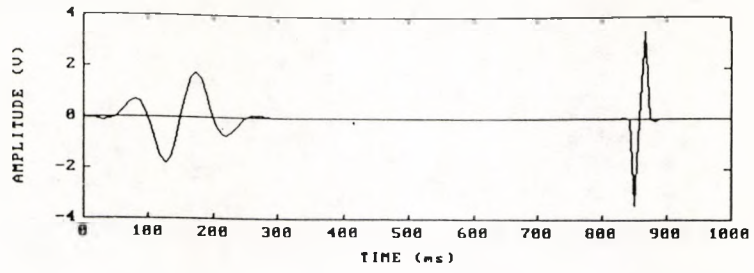


(c)

Figure 6.4-a - Smoothed WD of the sum of two Gaussian functions shifted both in time and in frequency. (a) The signal, (b) perspective view and (c) contour plot of the WD. (With reference to equation 6.16-a.)



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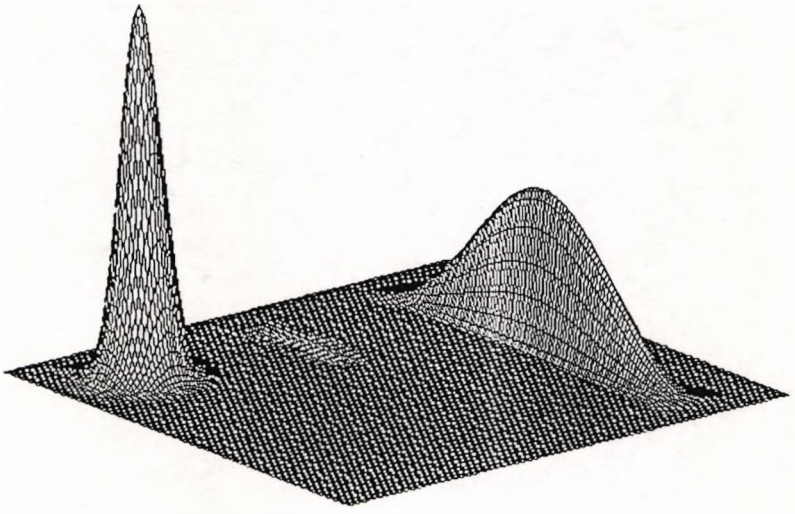

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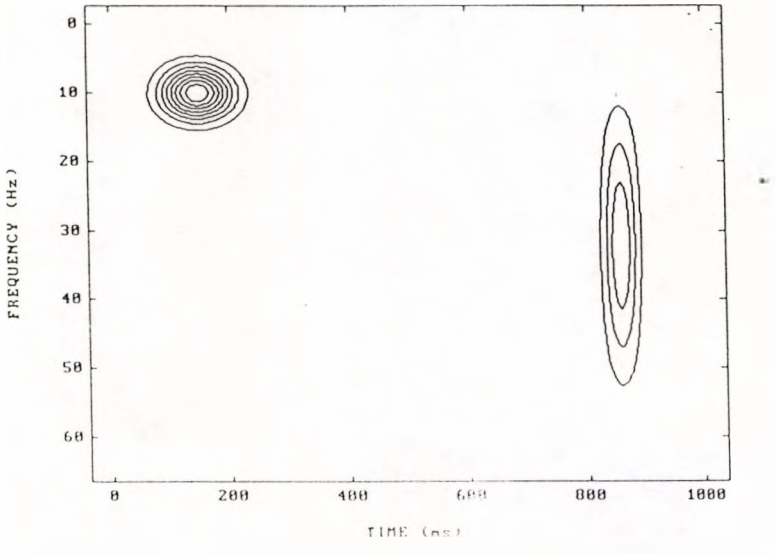


(c)

Figure 6.4-b - Smoothed WD of the sum of two Gaussian functions shifted both in time and in frequency. (a) The signal, (b) perspective view and (c) contour plot of the WD. (With reference to equation 6.16-b.)

signal waveforms, no major attention was given to the variations in amplitude that were caused by the smoothing process.

Another negative consequence is the smearing effect caused on the WD in both time and frequency domains. For such reasons, to achieve a good result, some time has to be spent in order to obtain an appropriate smoothing function for each particular case.

Although such drawbacks exist, the results justify by themselves the use of the Wigner Distribution in the analysis of both stationary and non-stationary signals.

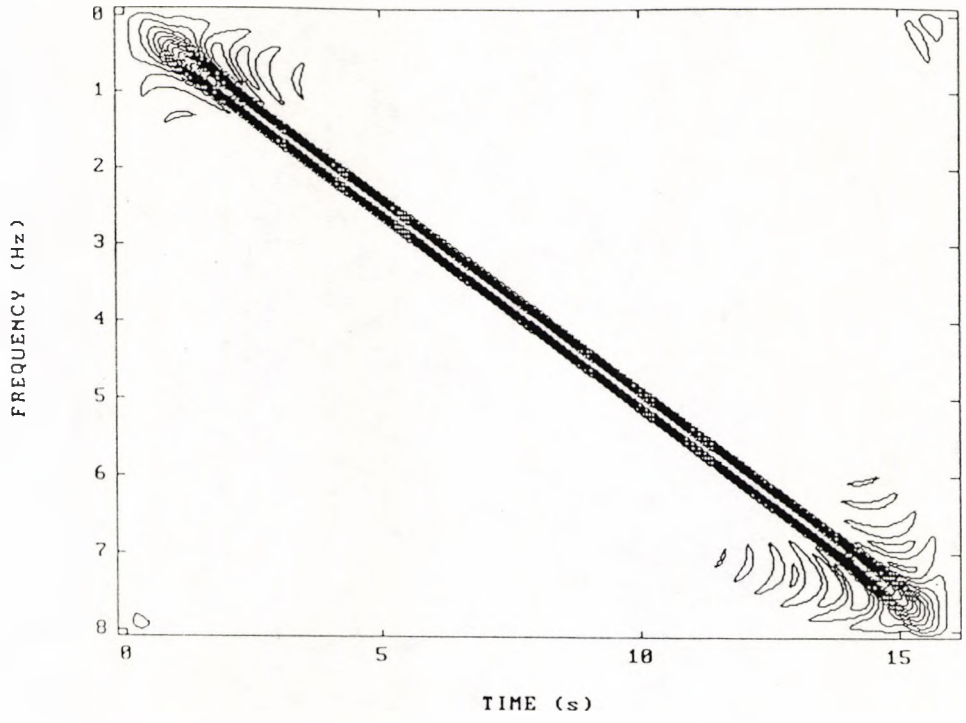
Two other examples, concerned with equation 6.19, are presented in figure 6.5. The first one represents a linear FM signal while the second represents a non-linear FM signal.

$$x(n) = A \sin\{2\pi[f_1 \frac{n}{N} + \frac{f_2 - f_1}{2} (\frac{n}{N})^2]\} \qquad (6.19\text{-a})$$

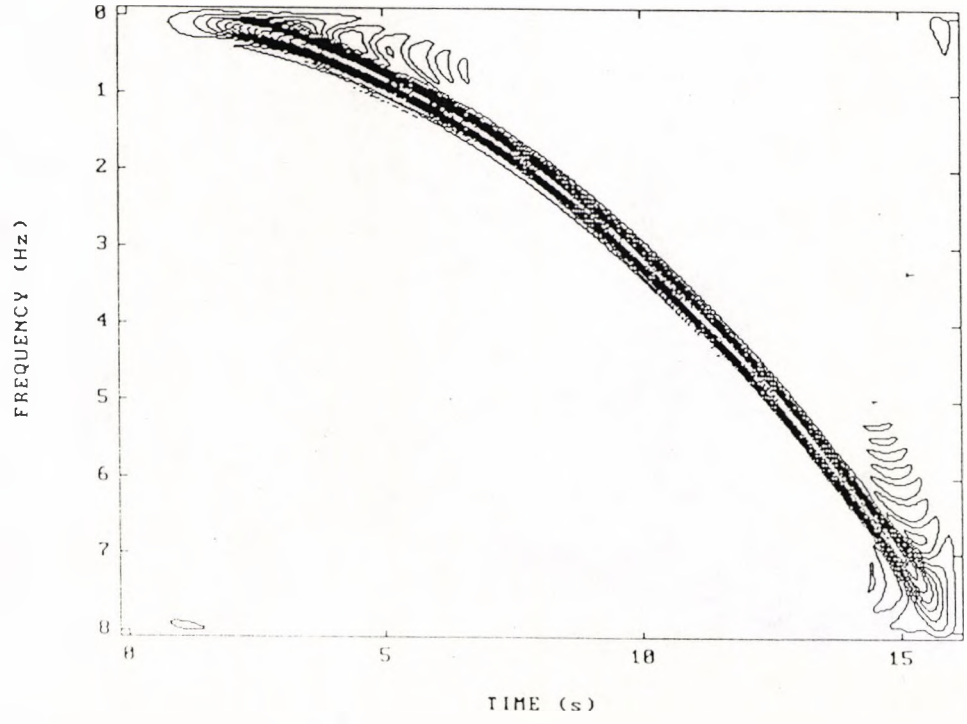
$$x(n) = A \sin\{2\pi[f_1 \frac{n}{N} + \frac{f_2 - f_1}{3} (\frac{n}{N})^3]\} \qquad (6.19\text{-b})$$

6.3 - Application of the WD to EEG Signals

Being one of Cohen's Class of Time-Frequency Energy Distribution Functions, the Wigner Distribution has been used, mainly since 1980, in the area of signal processing, for the investigation of time-frequency interdependent phenomena. To give some examples, it has been used in the processing of non-linear FM radar signals (Johnston, 1989), biological



(a)



(b)

Figure 6.5 - Contour plot of the smoothed WD of an FM signal. (a) Linear sweep and (b) non-linear sweep.

signals (Martin and Flandrin, 1985; Morgan and Gevins, 1986; Jacobson and Wechsler, 1988), seismic signals (Boashash, 1985) and ultrasound (Costa, 1989). Among these applications, there are two that are directly related to the human body. Morgan and Gevins have applied the WD in the analysis of event-related brain potentials while Jacobson and Wechsler have applied it in the analysis of visual information in the cortex.

In the present work, the WD has been employed to analyse several different forms of EEG signals, mainly spike-and-slow-wave complexes (SAWCs) and artifacts, since they are the major source of false detection of SAWCs.

6.3.1 - The experimental setup

Making use of the commercially available MATLAB-386 package, the algorithm (see Appendix C), that was originally written by E. T. Costa (Costa, 1989) to be run in a Vaxstation-3200, was implemented with some modifications (data input and output and smoothing process) and run on an IBM-compatible personal computer, which had a memory capacity of 7 Mbytes and a clock frequency of 36 MHz.

Based on the fact that the vector "x", that represents the input signal, can have a maximum of 256 elements (samples) for the specifications given above and that the processing time is proportional to the vector length, a few experiments were made using different sampling frequencies. A sampling frequency (fs) of 160 Hz was considered adequate, since the EEG signal could be kept band-limited to 70 Hz and a total of 128 elements

would represent a segment of 800 ms. This could represent a good part of a long duration artifact or a sequence of up to two SAWCs, while keeping the processing time to acceptable limits (see details below). As figure 6.6 shows, if 64 elements were used in order to decrease the processing time, only a single SAWC could be processed at such a sampling frequency. Although the result is equivalent to the one obtained with 128 elements in the limits of the SAWC (spreading in the time domain is different), it would not allow longer segments of EEGs to be processed, unless the sampling frequency were decreased, making it impossible to compare the results. A decrease in the sampling frequency would bring very low resolution to the spikes.

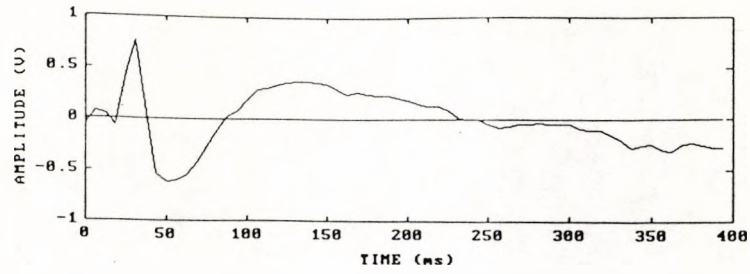
After digitization through the ILS package, the signal was stored in ASCII-format and transferred to MATLAB.

Once a WD matrix (or any other) is calculated, it can be displayed either in perspective (using the command MESH) or in the form of a contour plot (using the command CONTOUR). By using the command PLOT, the variation of amplitude of all rows or columns can also be displayed, allowing, for example, an inspection to be made to ascertain if the smoothed WD still contains negative values.

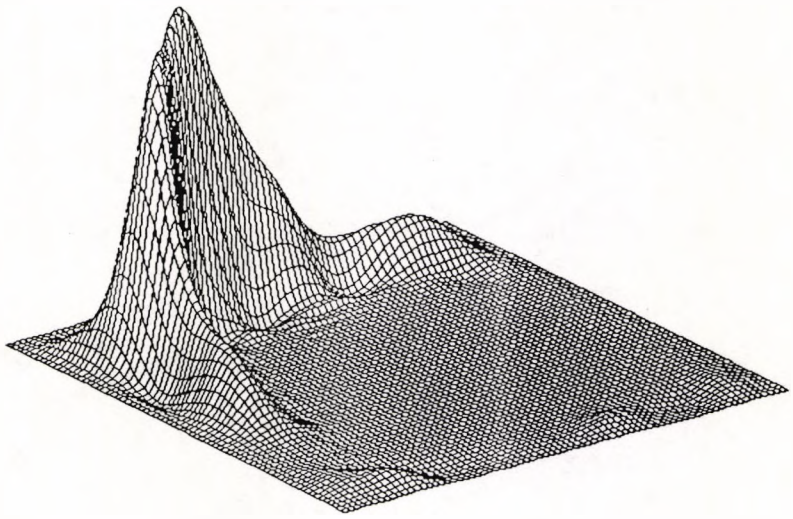
For x(n) containing a total of N elements, the WD original matrix (before smoothing) has a dimension N.N with a time scale going from 0 to (N-1)/fs and a frequency scale going from 0 to fs/2.

Two are the main factors that determine the total processing time:

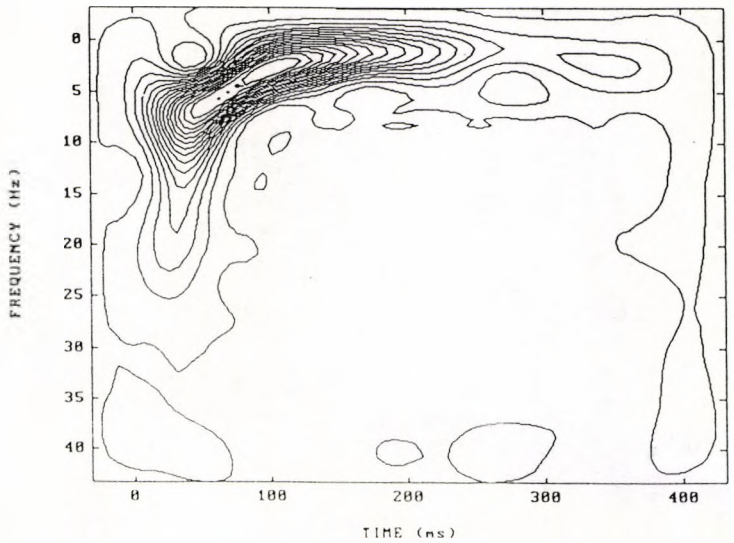
1) the value of N and



(a)



(b)



(c)

Figure 6.6 - SAWC represented by 64 samples and its smoothed WD. (a) The signal, (b) perspective view and (c) contour plot of the WD.

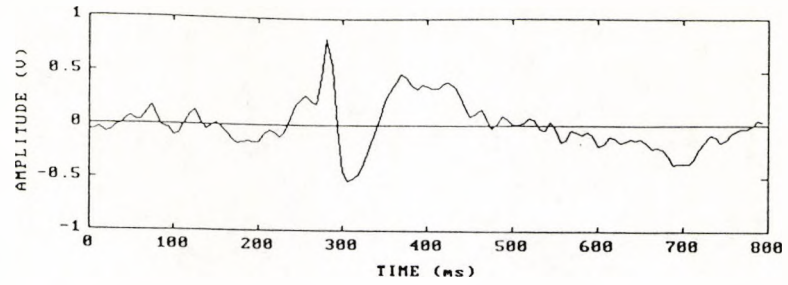
2) the total number of elements AB that compose the two-dimensional smoothing function L(k,l), where A=kmax-kmin+1 and B=lmax-lmin+1.

The smoothing process was simply performed by using the MATLAB command CONV2, which convolves two matrices in both dimensions. As the command does not make use of FFTs (it works like a filter, using differential equations), most time was spent on this process. For example, using the same smoothing function, with A=B=11, and making N=128 and N=256, it took 5 minutes in the first case and 40 minutes in the second to obtain the final smoothed WD matrix!

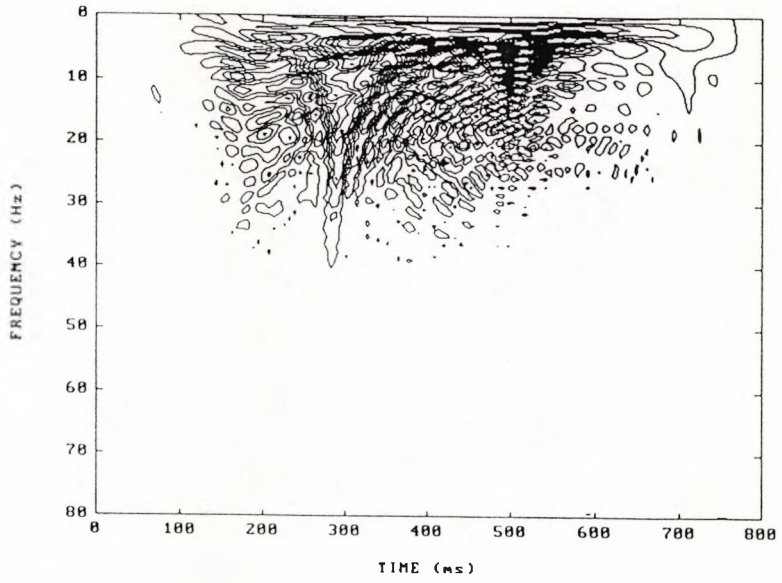
6.3.2 - Examples

The first three examples illustrated on figures 6.7, 6.8 and 6.9 demonstrate the application of the Wigner Distribution to a typical SAWC, a segment of normal EEG and an artifact. The graphs represent the complete matrices of both the unsmoothed WD (0 to 800 ms and 0 to 80 Hz) and the smoothed WD (-32 ms to 832 ms and -3.2 Hz to 83.2 Hz, approximately).

These results demonstrated that it would be enough to smooth only the lower frequency half of the original WD matrix, since most of the energy of the EEG signal was located below 40 Hz. This was considered to be the best way to decrease the processing time without the necessity of either altering the resolution of the signal in the time domain or writing a special program to obtain the double convolution. Using this



(a)



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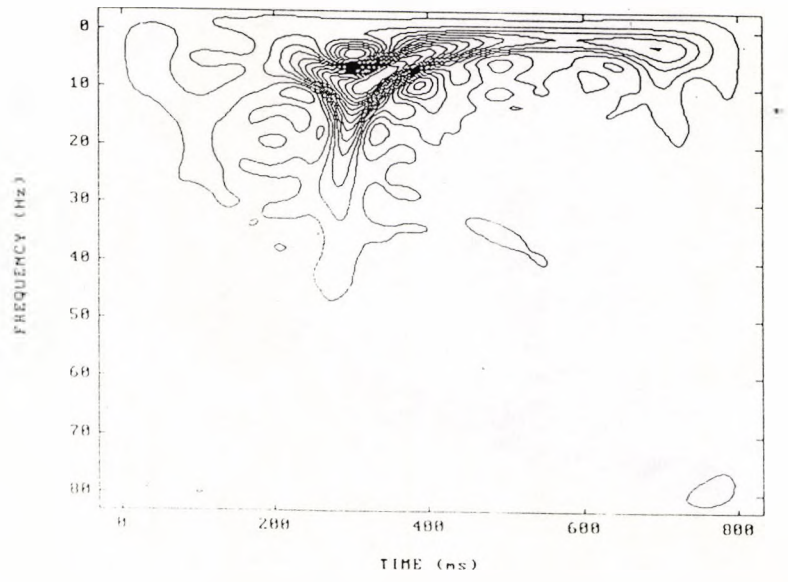
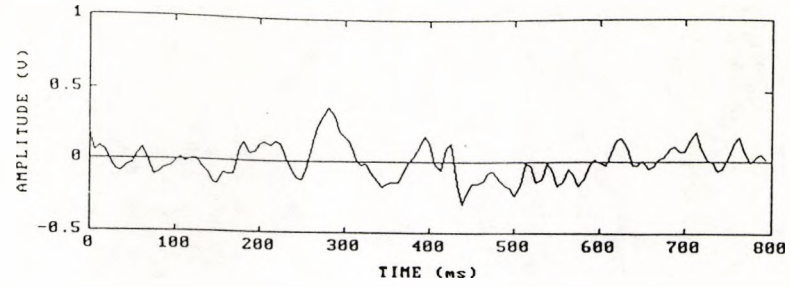
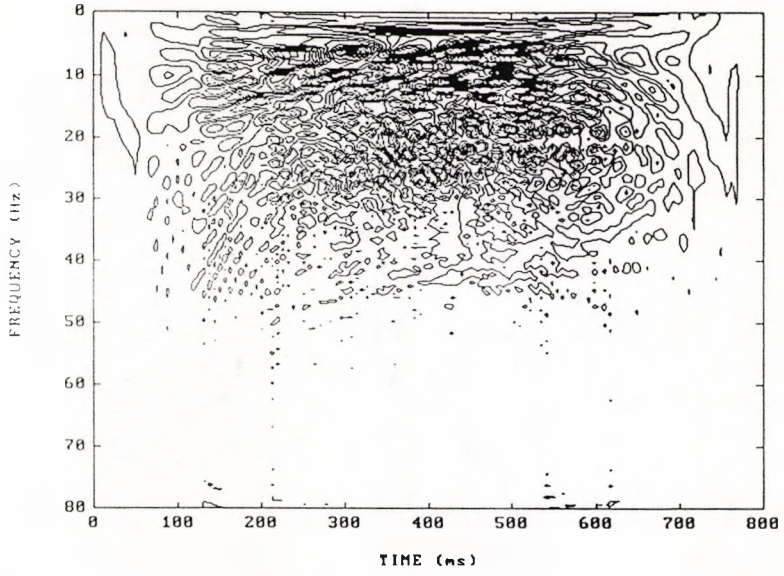


(c)

Figure 6.7 - WD of a typical SAWC. (a) SAWC, (b) unsmoothed WD and (c) smoothed WD.



(a)



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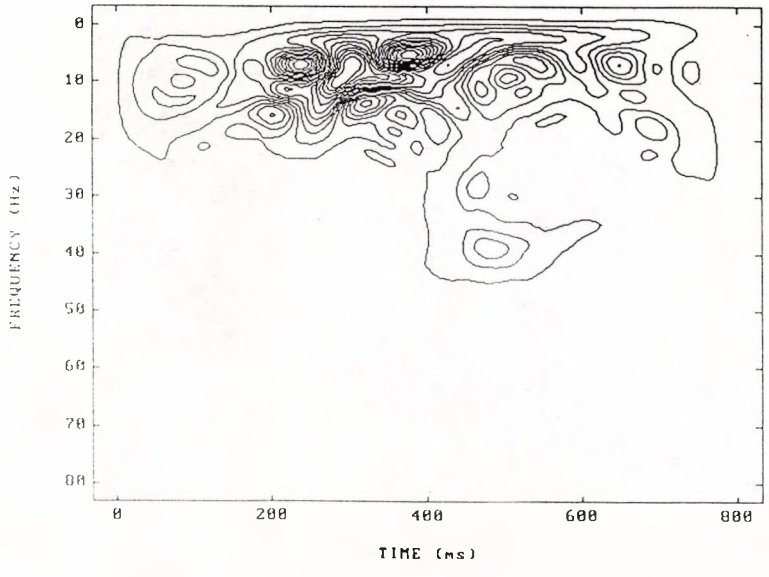
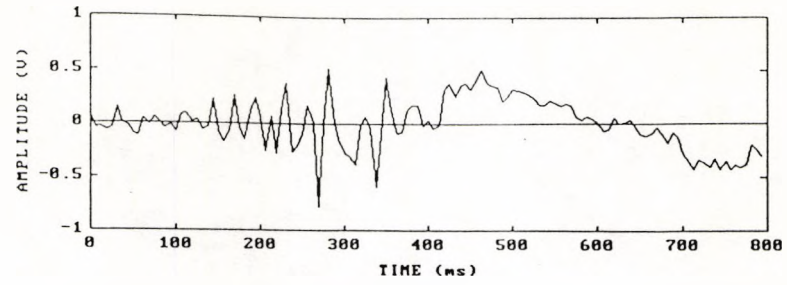
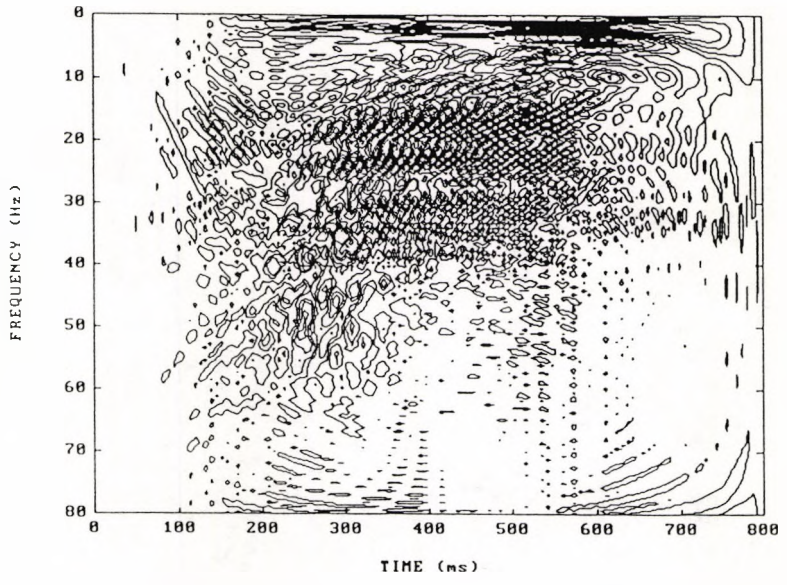


(c)

Figure 6.8 - WD of a segment of normal EEG. (a) EEG, (b) unsmoothed WD and (c) smoothed WD.



(a)



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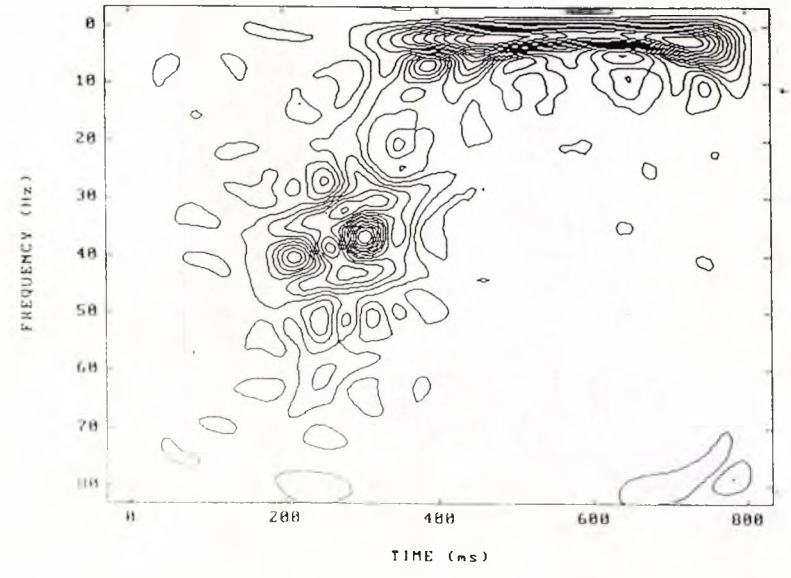


(c)

Figure 6.9 - WD of an artifact. (a) Artifact, (b) unsmoothed WD and (c) smoothed WD.

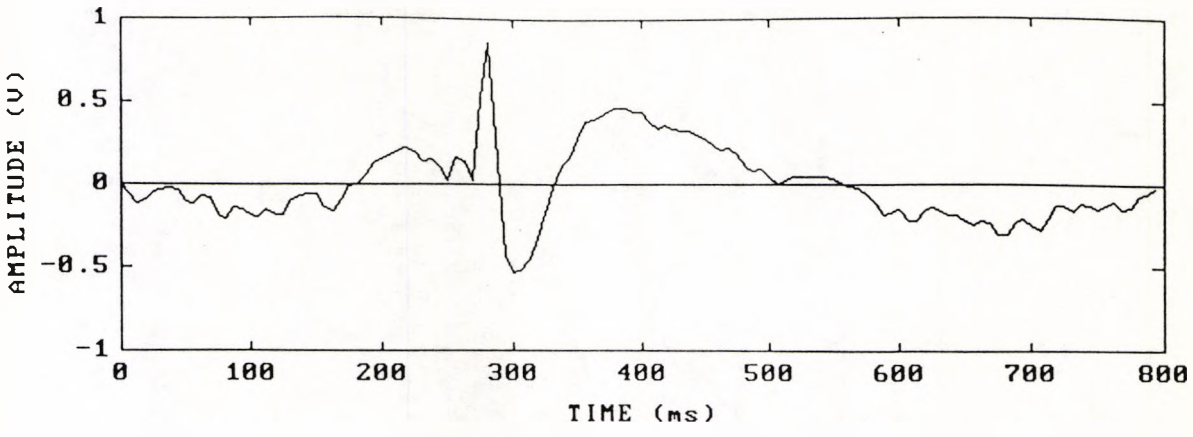
modified algorithm, the processing time was reduced from 5 to 2 minutes. In the next examples, the smoothed WDs have a frequency scale that goes from -3.2 Hz to 43.3 Hz, approximately. The time scale is not altered.

The next twelve figures correspond to the WDs of four different SAWCs (more examples are given in Appendix D), four artifacts and four other segments of EEG that caused false alarms in the SAWC detector when the spike detection level was lowered. Since major importance was given to the shapes of the WDs and not to their amplitudes, the contour plots are normalized (all with 17 contour lines).

Figure 6.10 shows that the spike-and-wave complexes, no matter how different they may be in terms of amplitude, have similar WDs (in terms of shape), whose contour plots are characterized by a "T" shape, while figures 6.8, 6.11 and 6.12 show that the WDs of a normal EEG, artifacts, and false-alarm SAWCs, respectively, have shapes that exhibit significant differences among themselves and in relation to the WDs of SAWCs. These results give considerable weight to the idea that the Wigner Distribution provides the basis for a more elaborate and reliable method of analysis of EEG signals.

It is quite easy to distinguish one WD from another by visual inspection, but, no matter if the WDs are computed either by a post-processor or by a real-time processor, an algorithm is required that allows such distinction to be made automatically.

A time-consuming method could be developed based on a two-dimensional matched filter, where the template is the WD of



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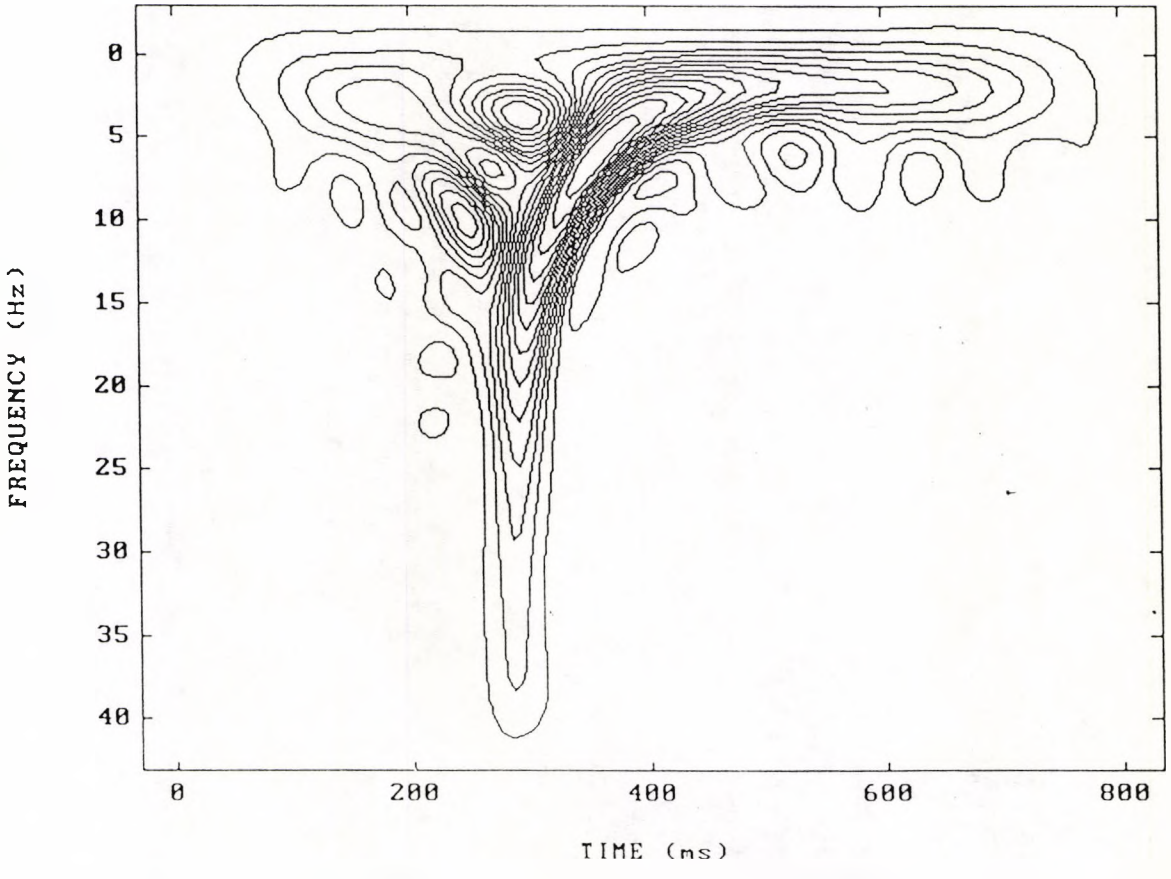
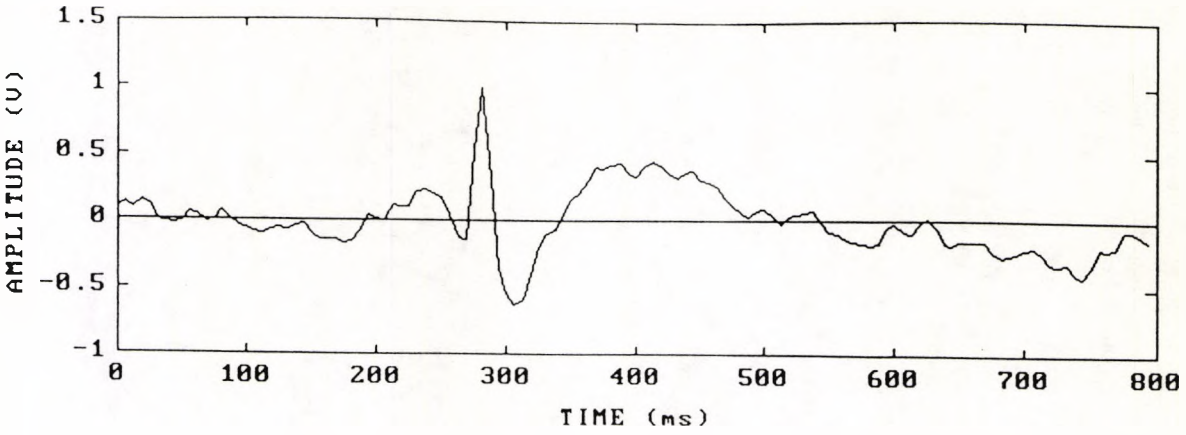
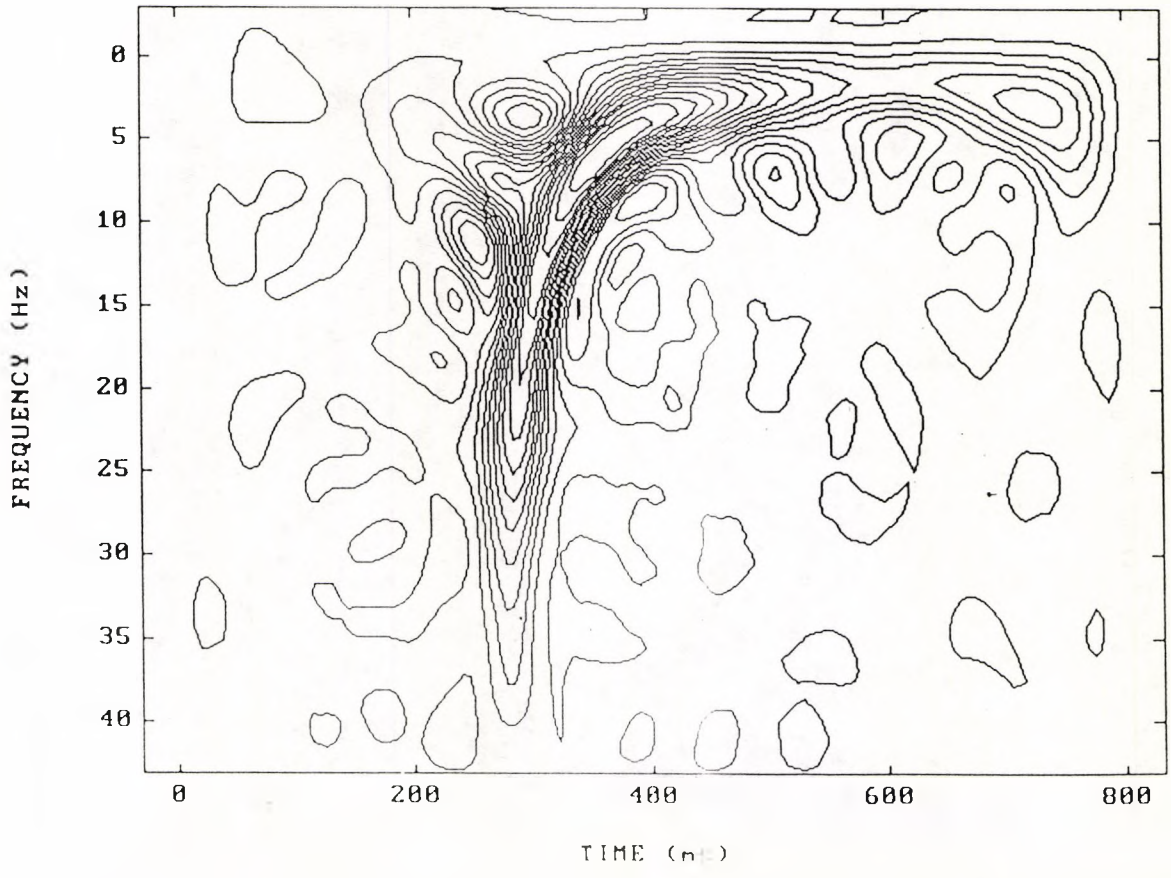


(b)

Figure 6.10-a - Smoothed WD of a SAWC. (a) The signal and (b) contour plot of its WD.

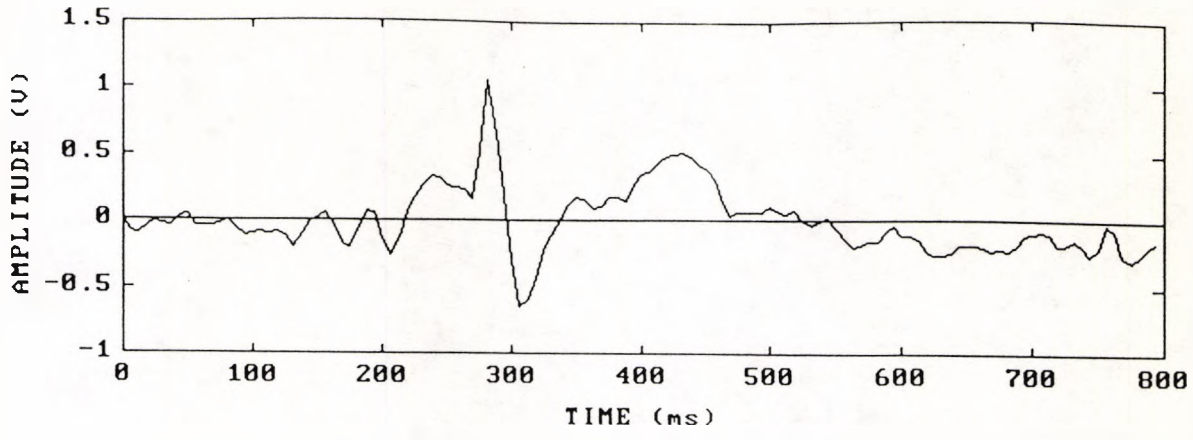


(a)

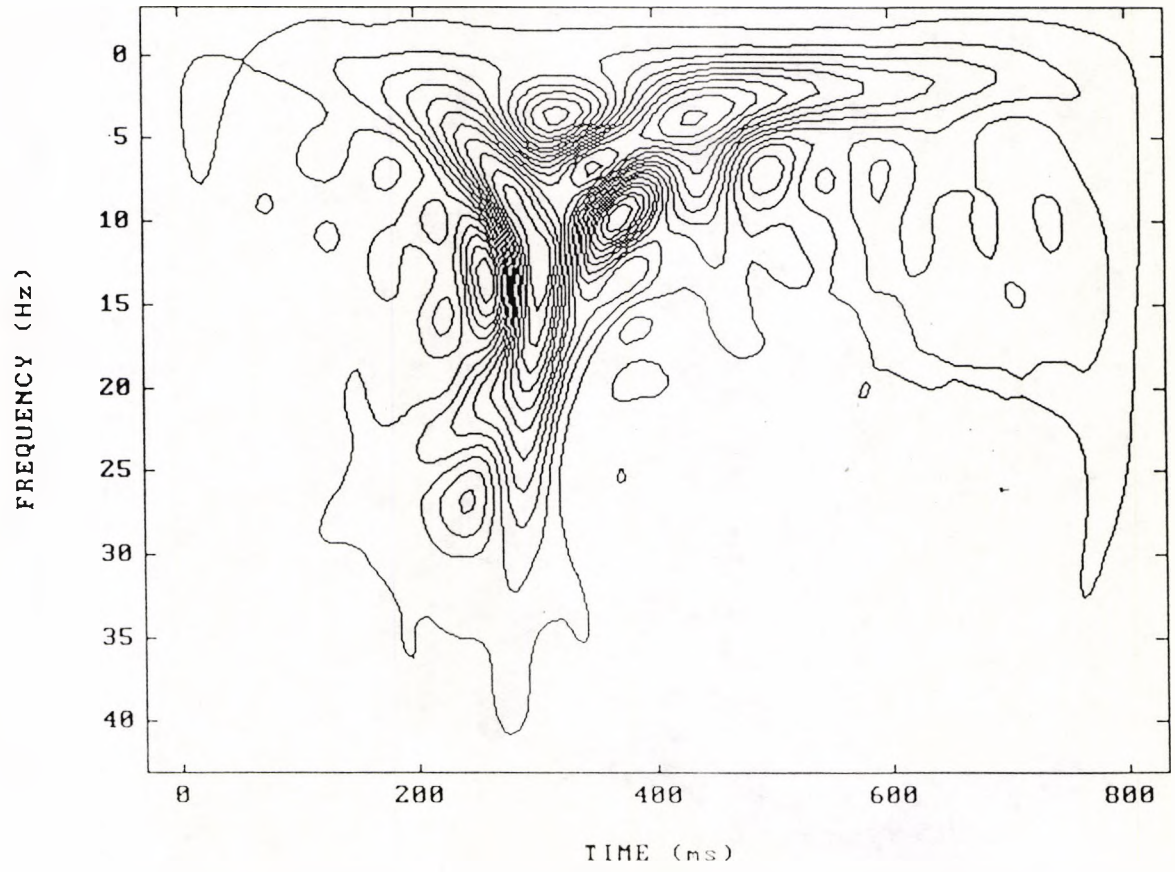


(b)

Figure 6.10-b - Smoothed WD of a SAWC. (a) The signal and (b) contour plot of its WD.

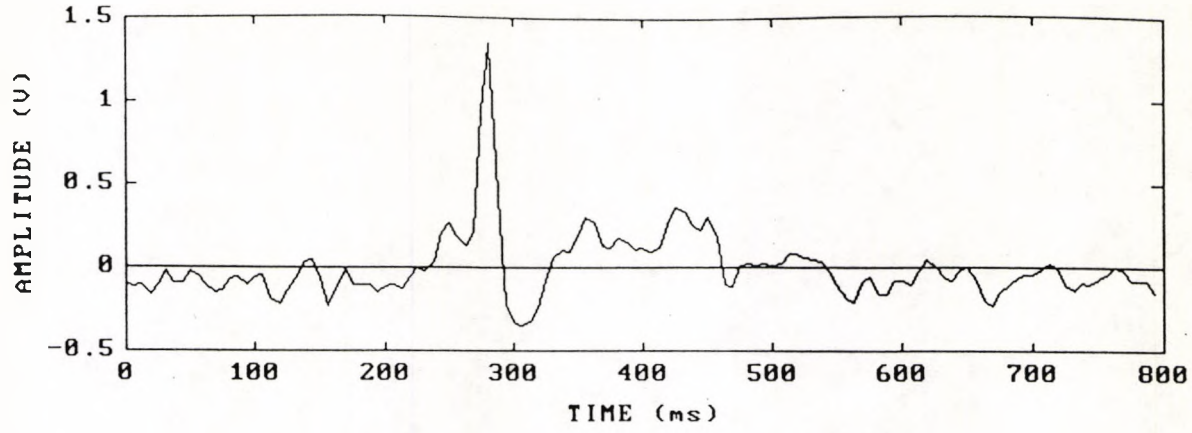


(a)

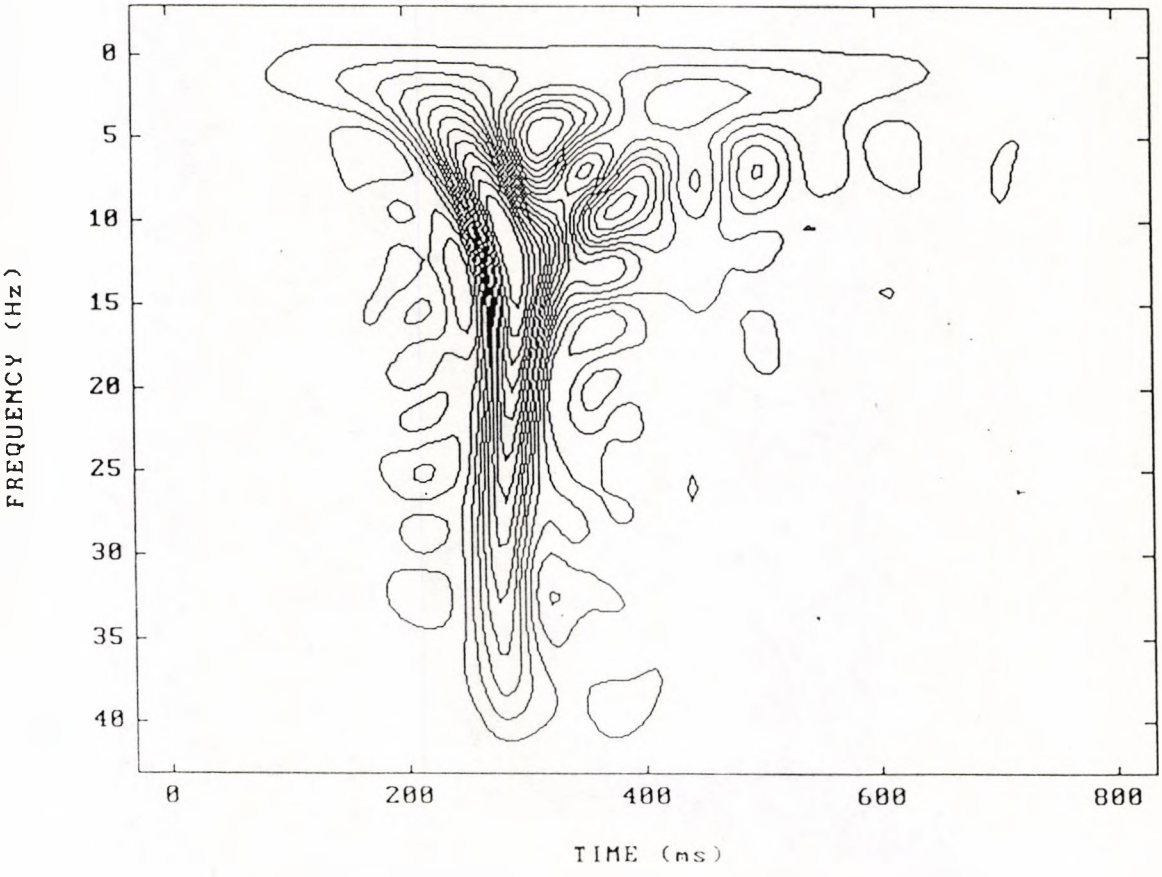


(b)

Figure 6.10-c - Smoothed WD of a SAWC. (a) The signal and (b) contour plot of its WD.

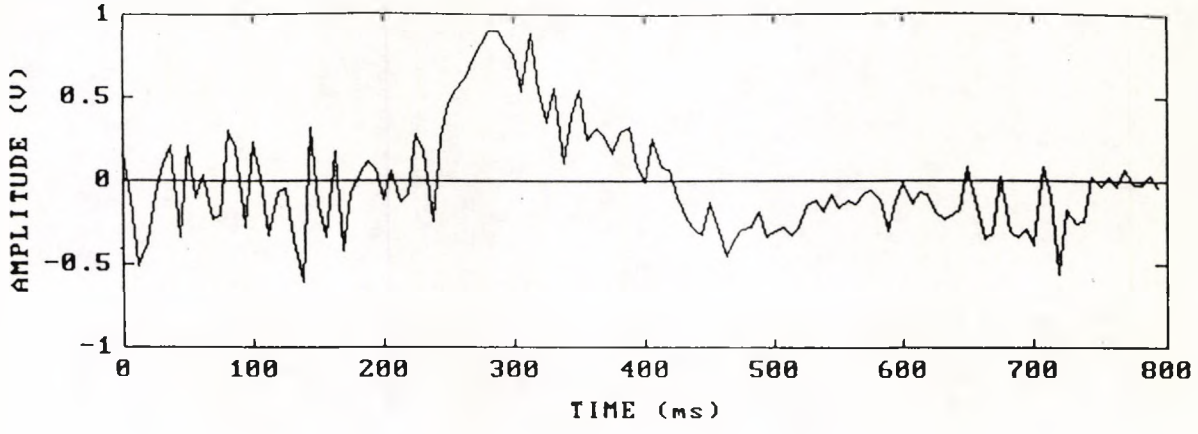


(a)

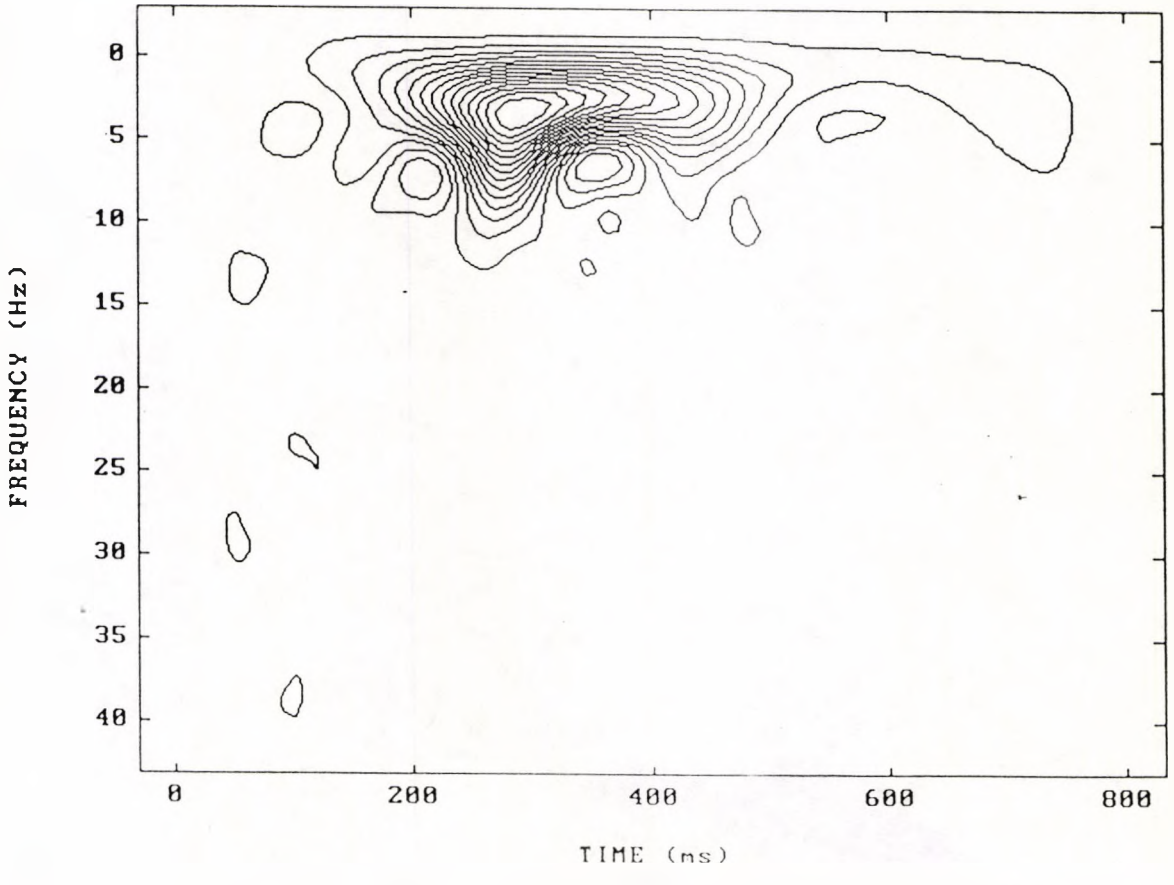


(b)

Figure 6.10-d - Smoothed WD of a SAWC. (a) The signal and (b) contour plot of its WD.

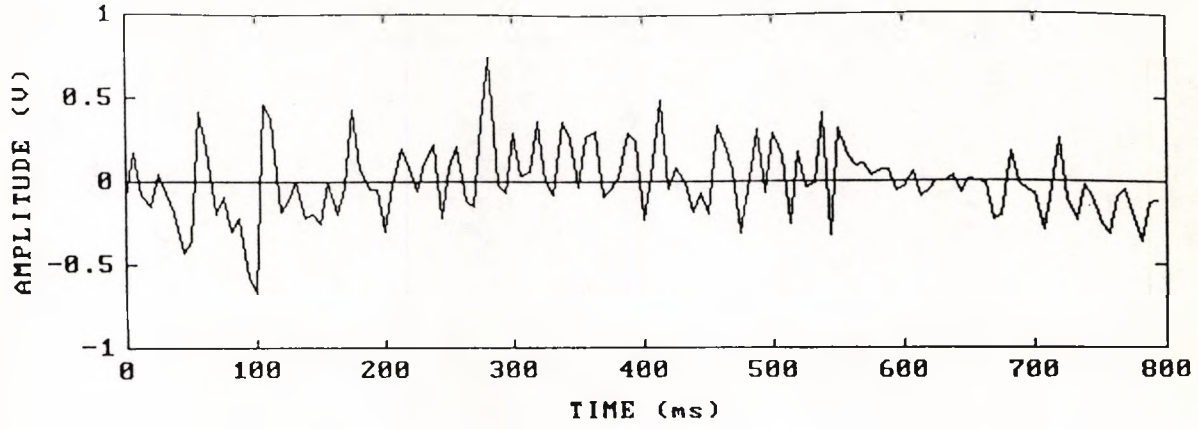


(a)

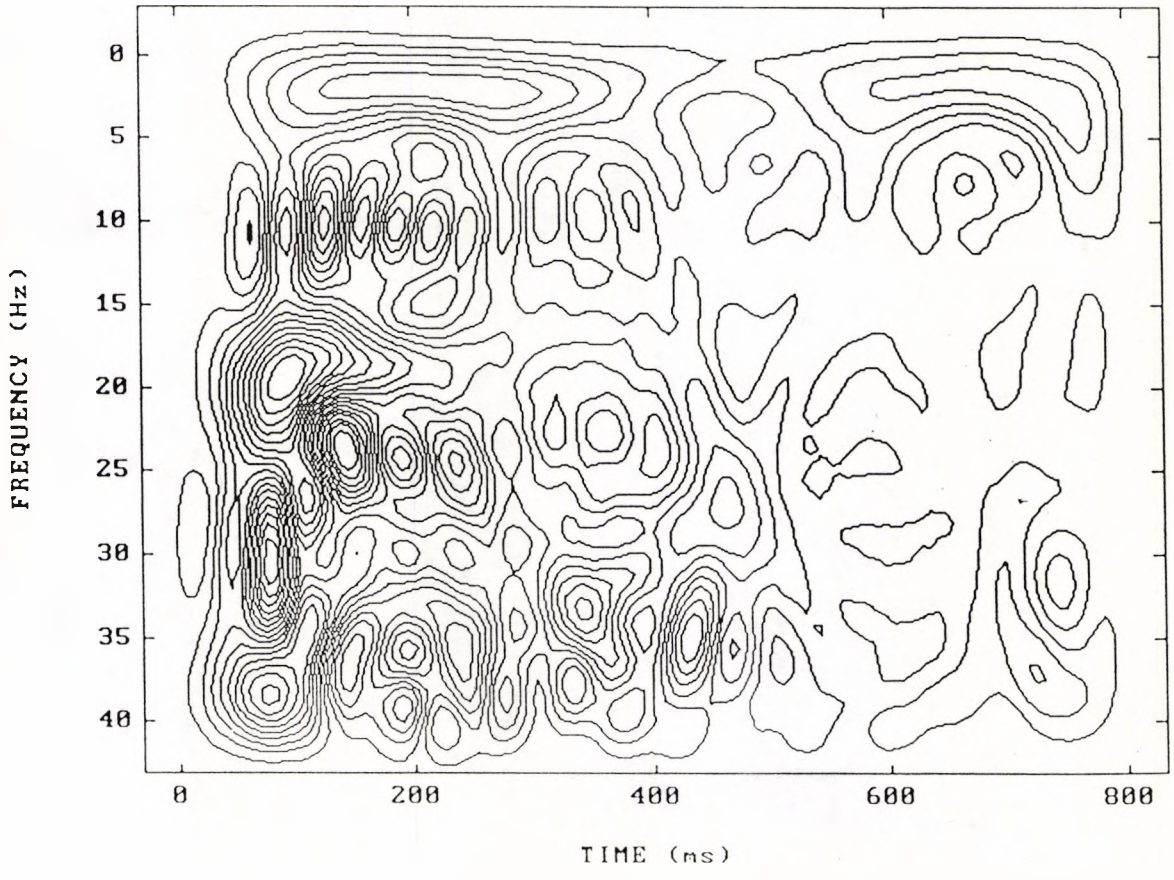


(b)

Figure 6.11-a - Smoothed WD of an artifact.
(a) The signal and (b) contour plot of its WD.

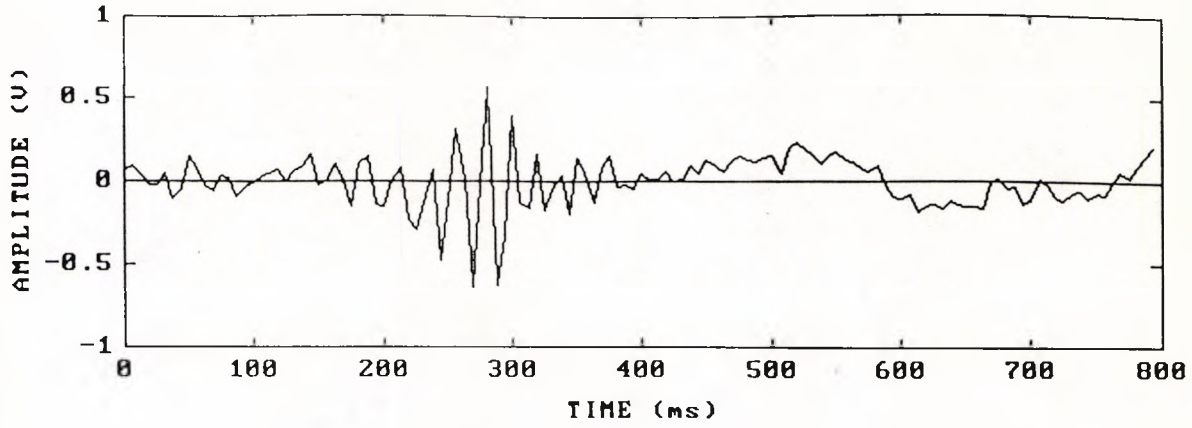


(a)

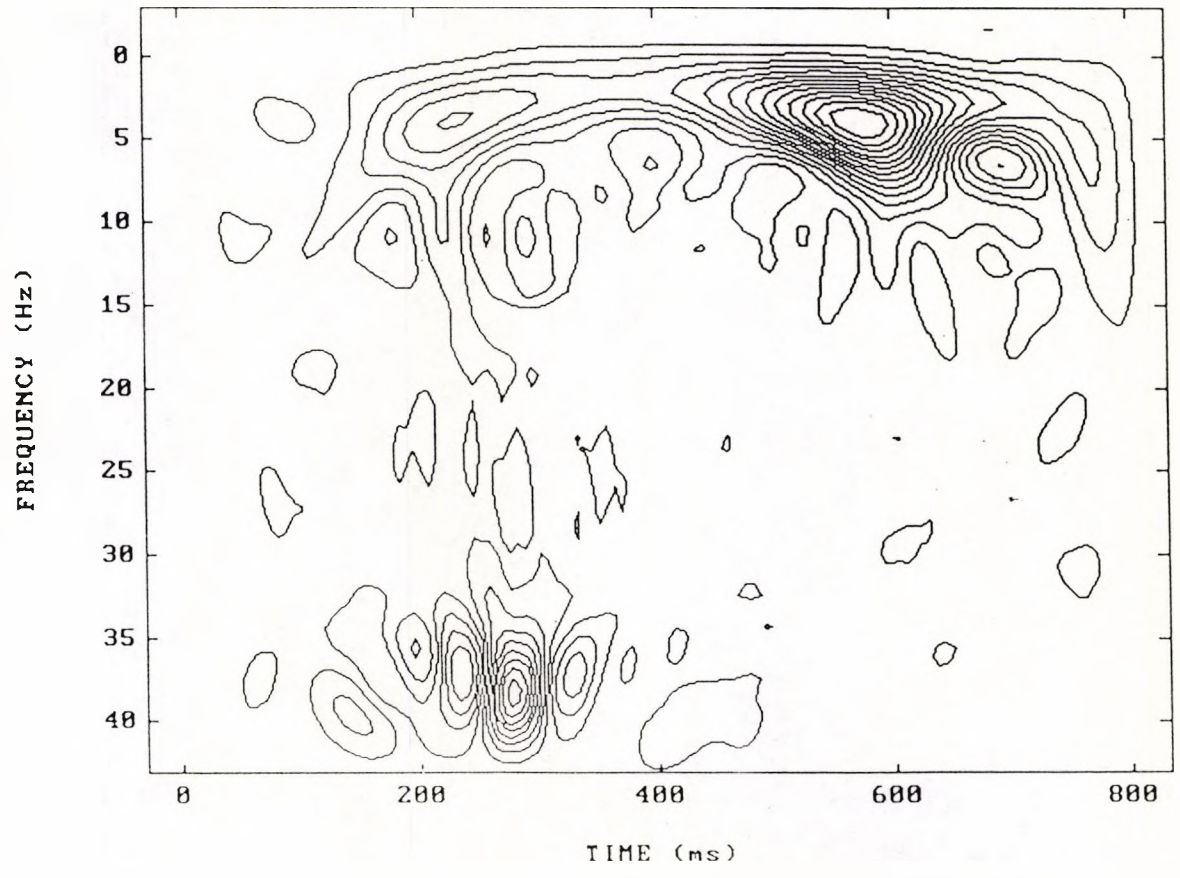


(b)

Figure 6.11-b - Smoothed WD of an artifact. (a) The signal and (b) contour plot of its WD.

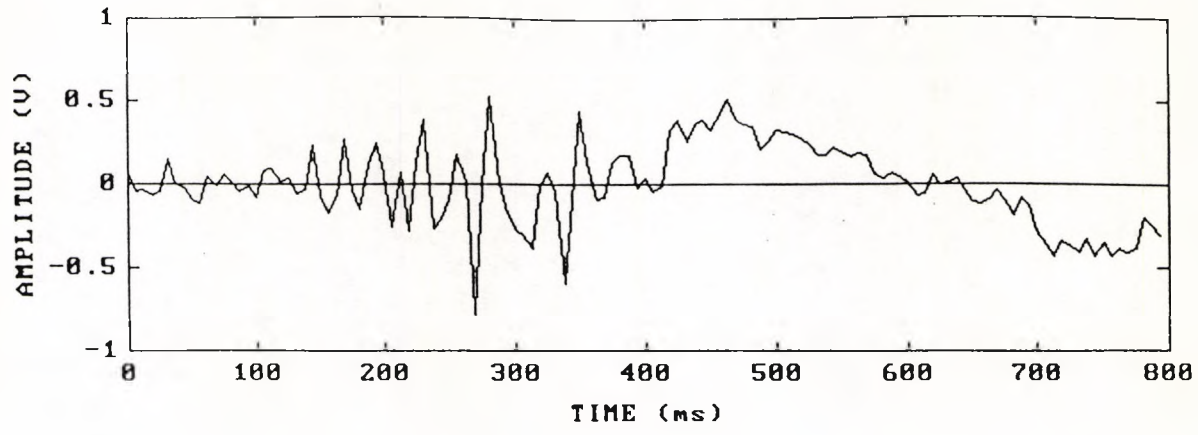


(a)

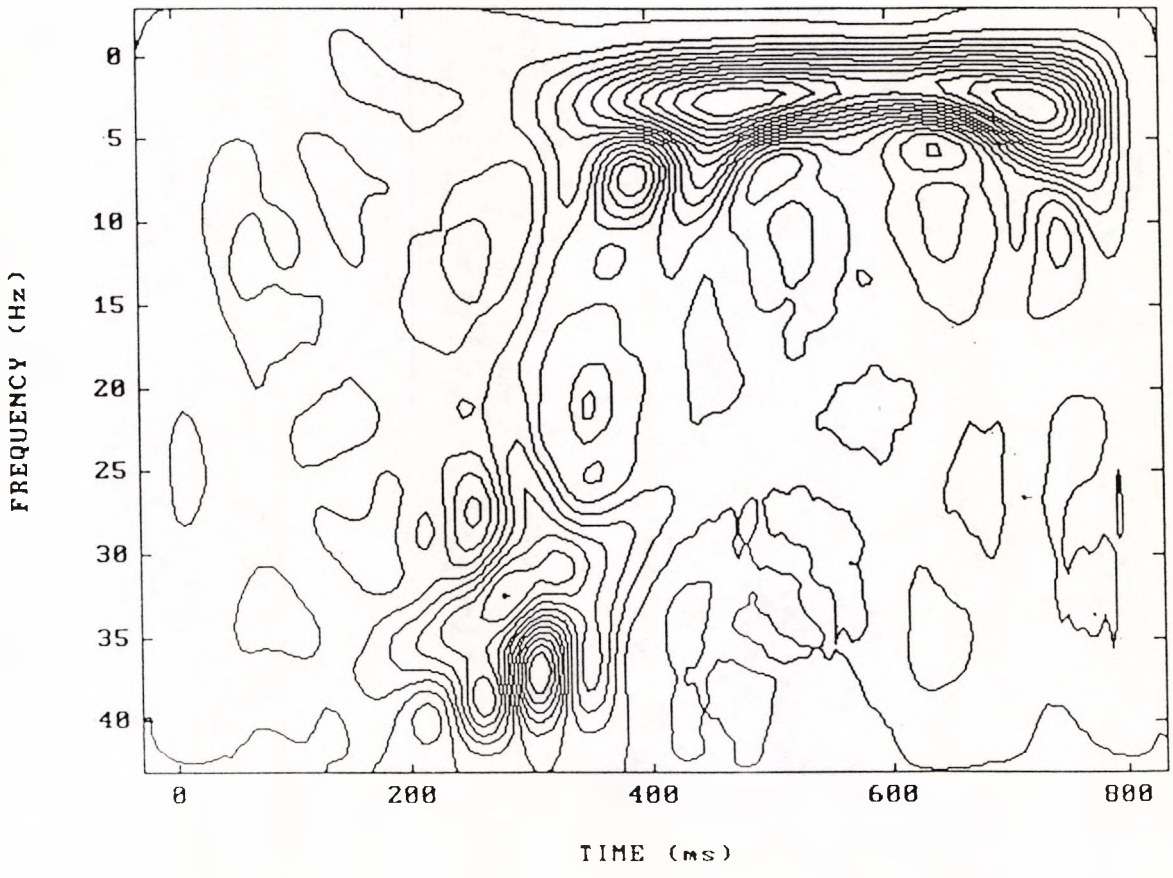


(b)

Figure 6.11-c - Smoothed WD of an artifact.
(a) The signal and (b) contour plot of its WD.

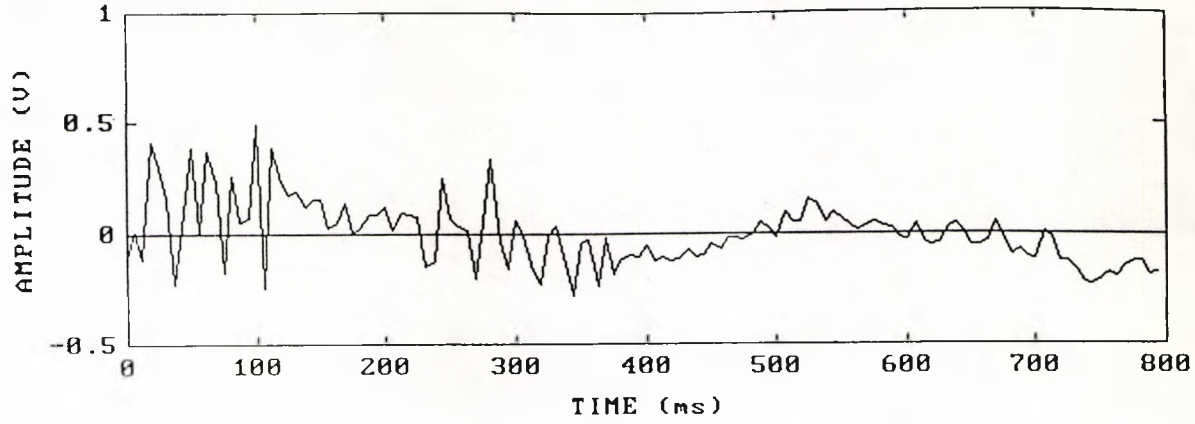


(a)

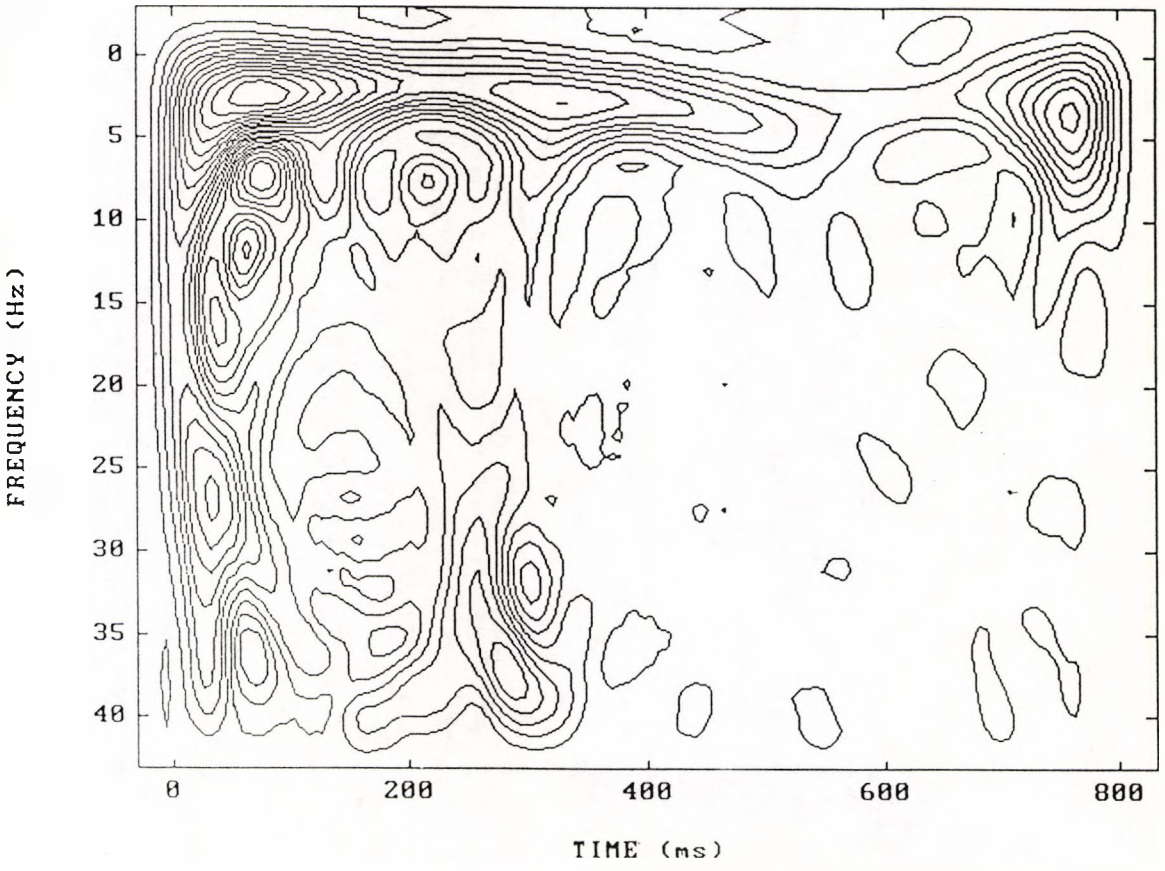


(b)

Figure 6.11-d - Smoothed WD of an artifact. (a) The signal and (b) contour plot of its WD.

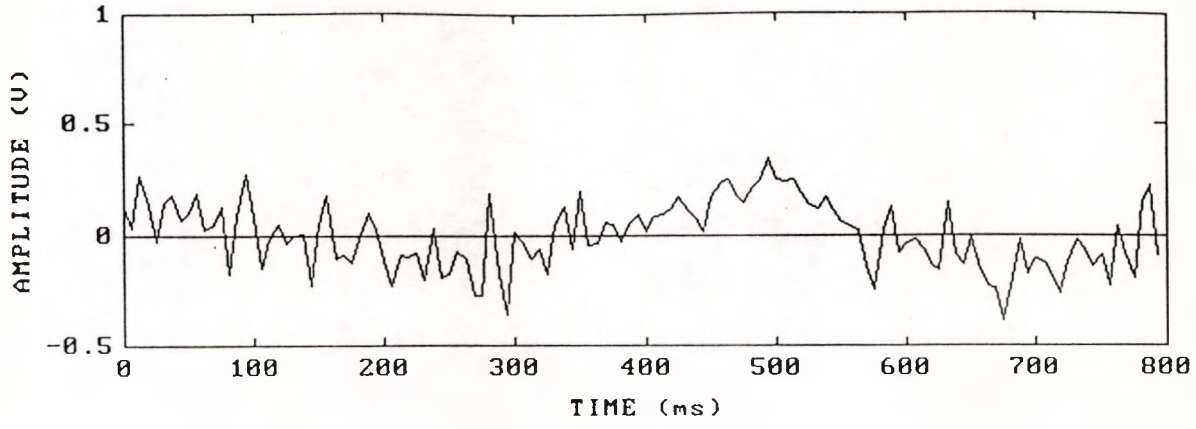


(a)

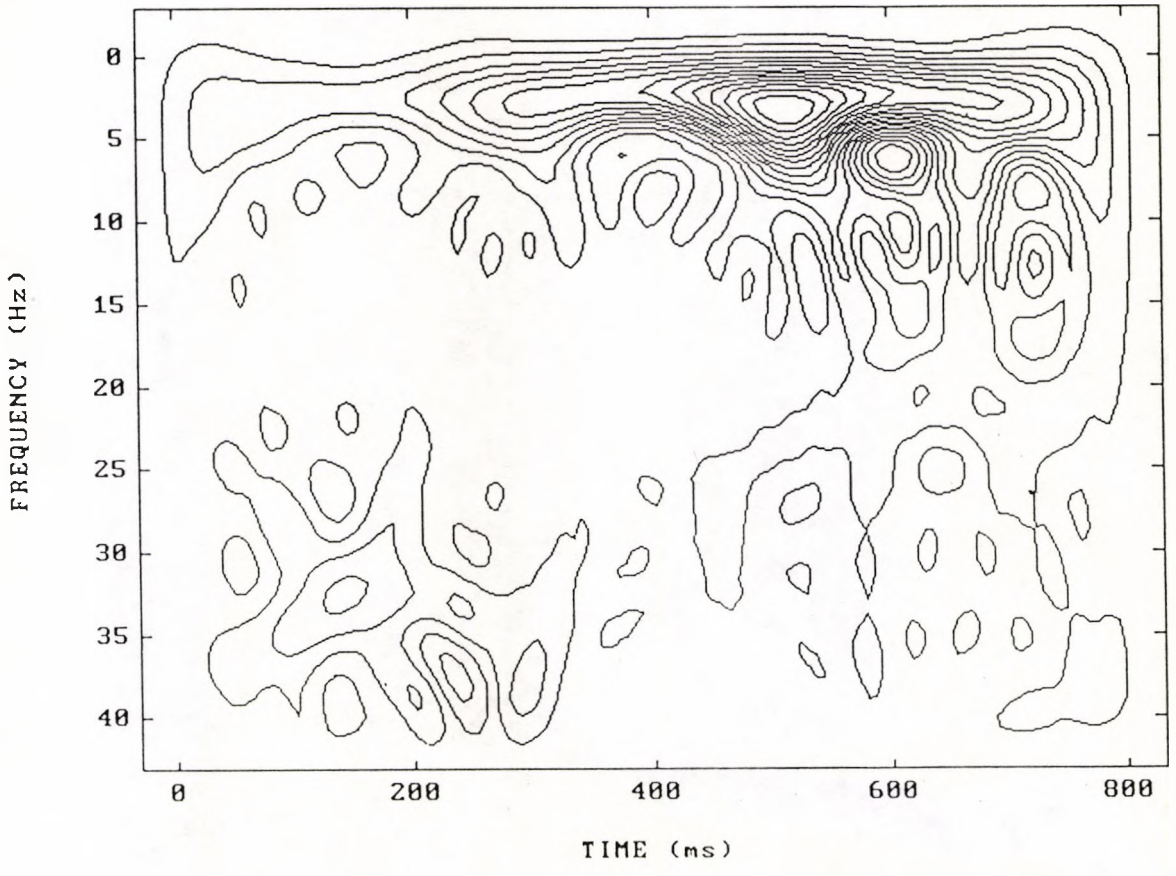


(b)

Figure 6.12-a - Smoothed WD of a false-alarm SAWC. (a) The signal and (b) contour plot of its WD.

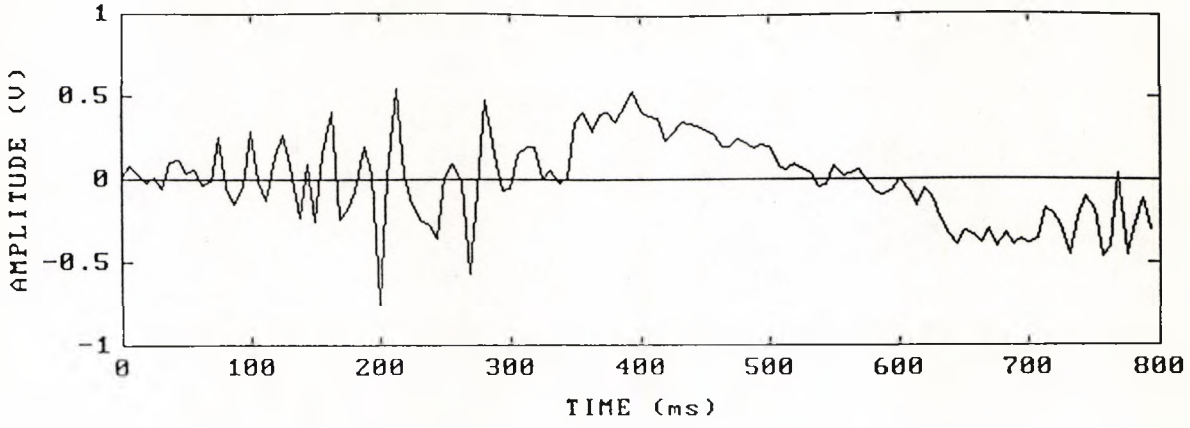


(a)



(b)

Figure 6.12-b - Smoothed WD of a false-alarm SAWC. (a) The signal and (b) contour plot of its WD.



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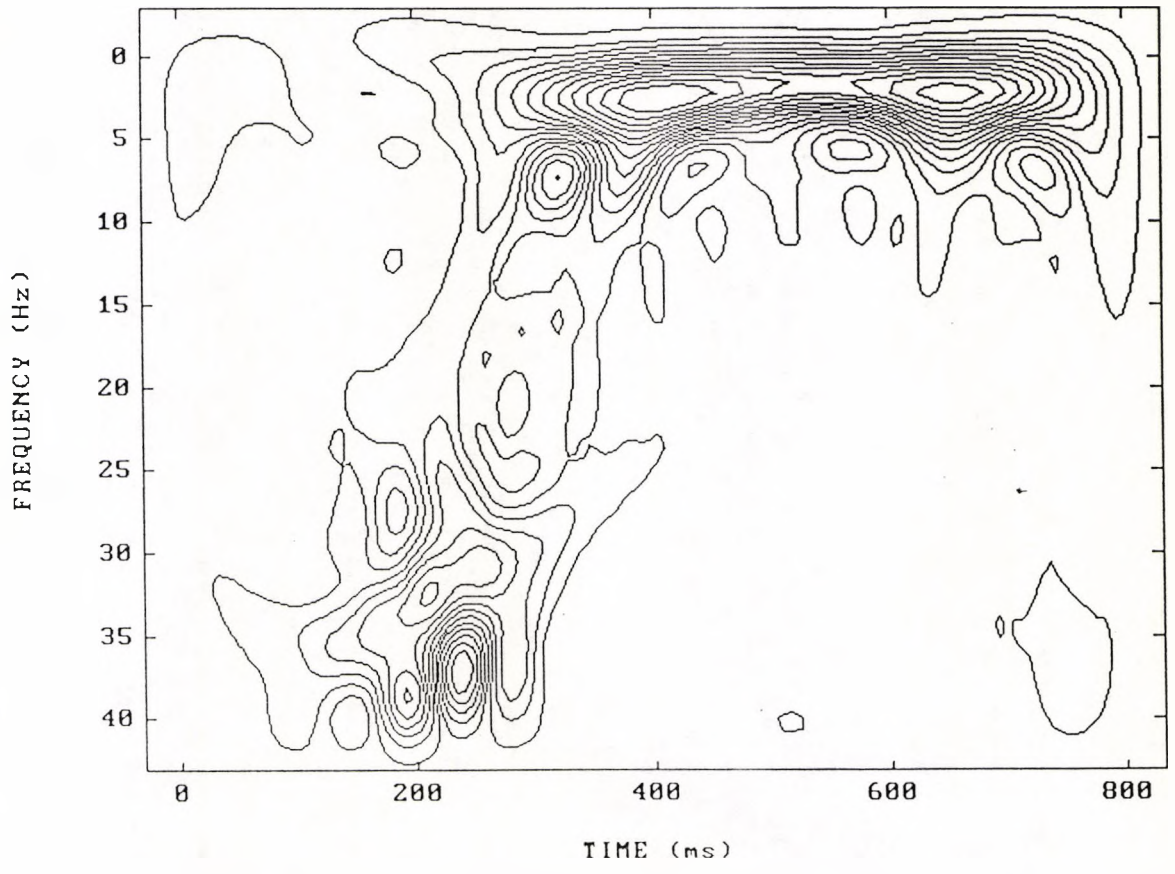
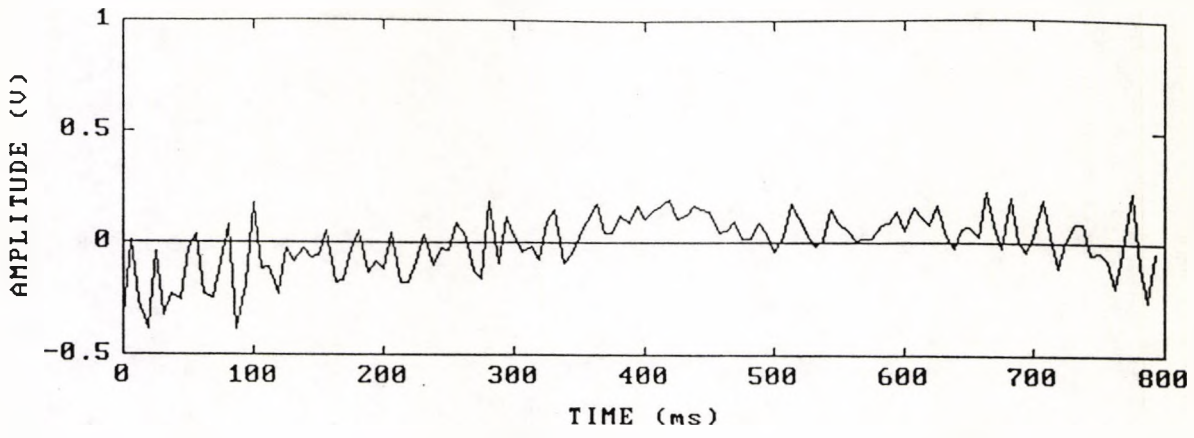
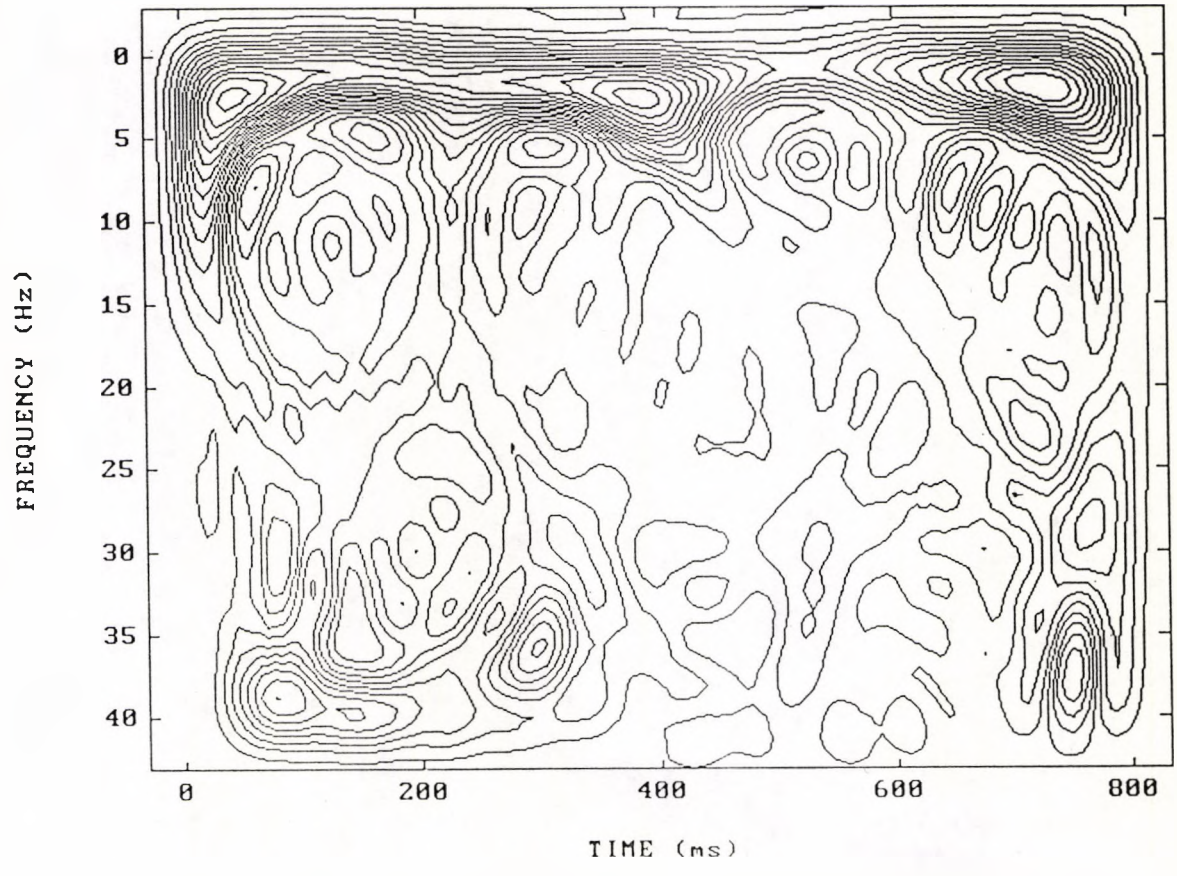


(b)

Figure 6.12-c - Smoothed WD of a false-alarm SAWC. (a) The signal and (b) contour plot of its WD.



(a)



(b)

Figure 6.12-d - Smoothed WD of a false-alarm SAWC. (a) The signal and (b) contour plot of its WD.

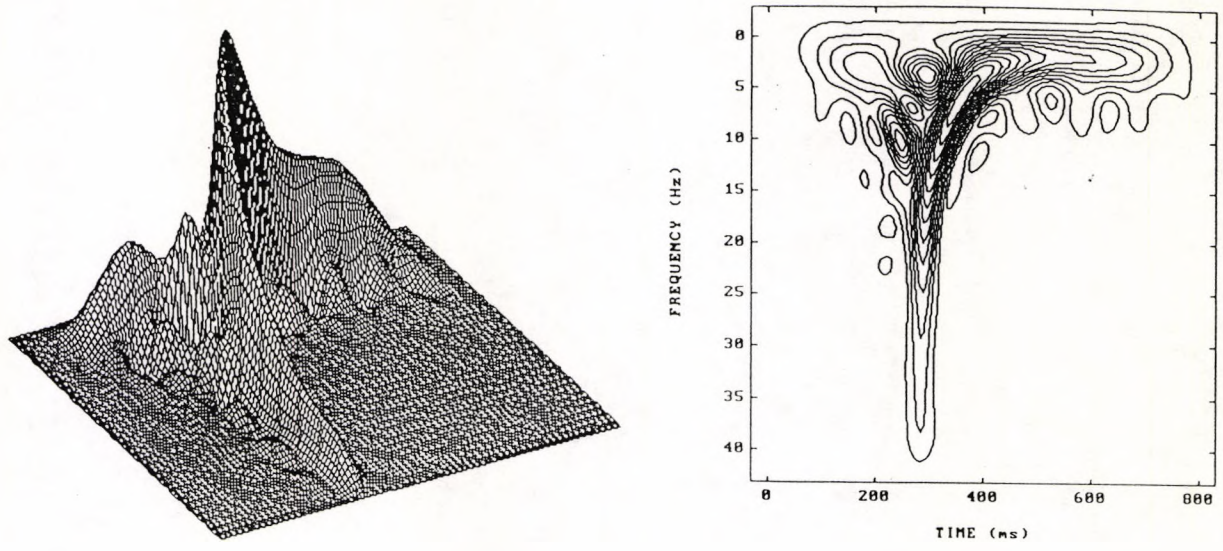
a standard SAWC.

The description of a more basic algorithm follows below.

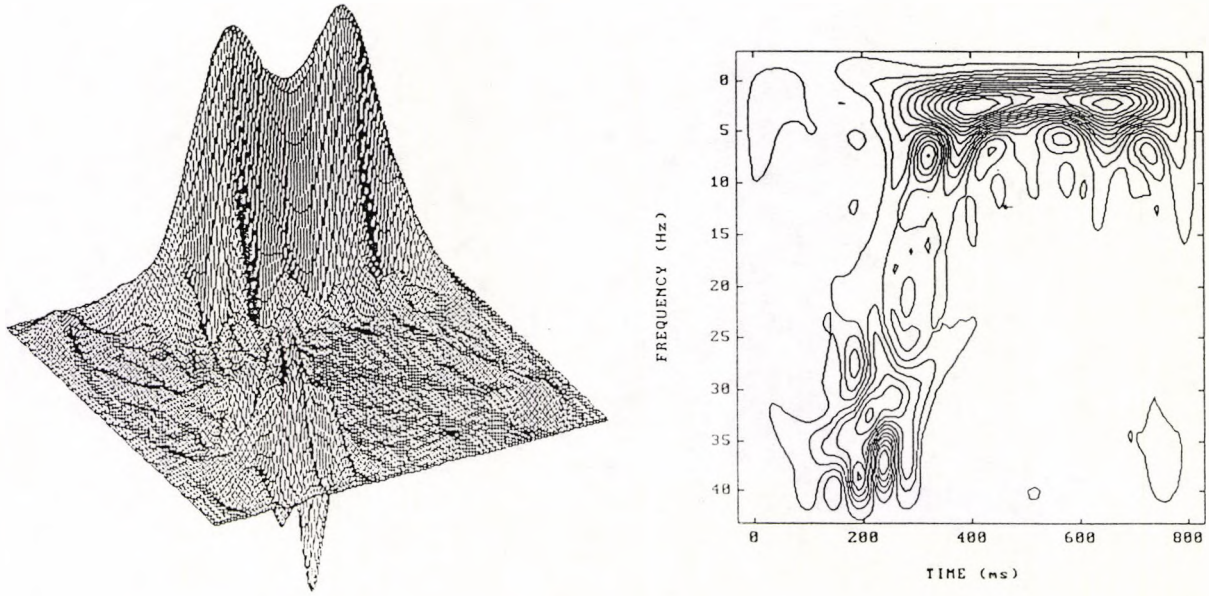
6.3.3 - False-alarm-rejection algorithm

The false alarms that occurred during the tests arose mainly as a consequence of lowering the detection levels. They were provoked by very sharp spikes mixed with slow waves, which were normally contaminated with spiky signals (in general, it is expected that the false alarms will be caused by artifacts). Consequently, high-frequency components will cover the respective WDs not only in the region corresponding to the spike (from 200 ms to 350 ms in the smoothed WD) but also in the region corresponding to the slow wave (from 350 ms to 800 ms). This phenomenon can be observed in figure 6.13, which shows as an example the perspective view and the contour plots of the WDs of a standard SAWC and of a typical false alarm. It can also be observed that in figure 6.13-b, the region corresponding to the spike shows more activity in the high frequencies when compared to figure 6.13-a and that such activity is dispersed around with positive and negative values. This is due to the fact that the artifact spikes are sharper than a normal spike and appear in groups, causing more crossterms to be generated by the high-frequency components, spread over a wider area.

Based on the facts discussed above and on a consideration of the signals that were being analyzed (the artifacts had low amplitude), the first idea was simply to measure the



(a)



(b)

Figure 6.13 - (a) WD of a standard SAWC. (b) WD of a typical false alarm.

mean value of the region of the WD that corresponds to the spike and to set a threshold. The mean value of the region that corresponds to the slow wave varies significantly as the slow waves may have a low amplitude in a normal SAWC and very high amplitude in an artifact; consequently, the total mean was not considered to be a good reference either from which to set a threshold. For this reason, an algorithm that depended mainly on the shape of the WD and not on the magnitude of the values had to be obtained.

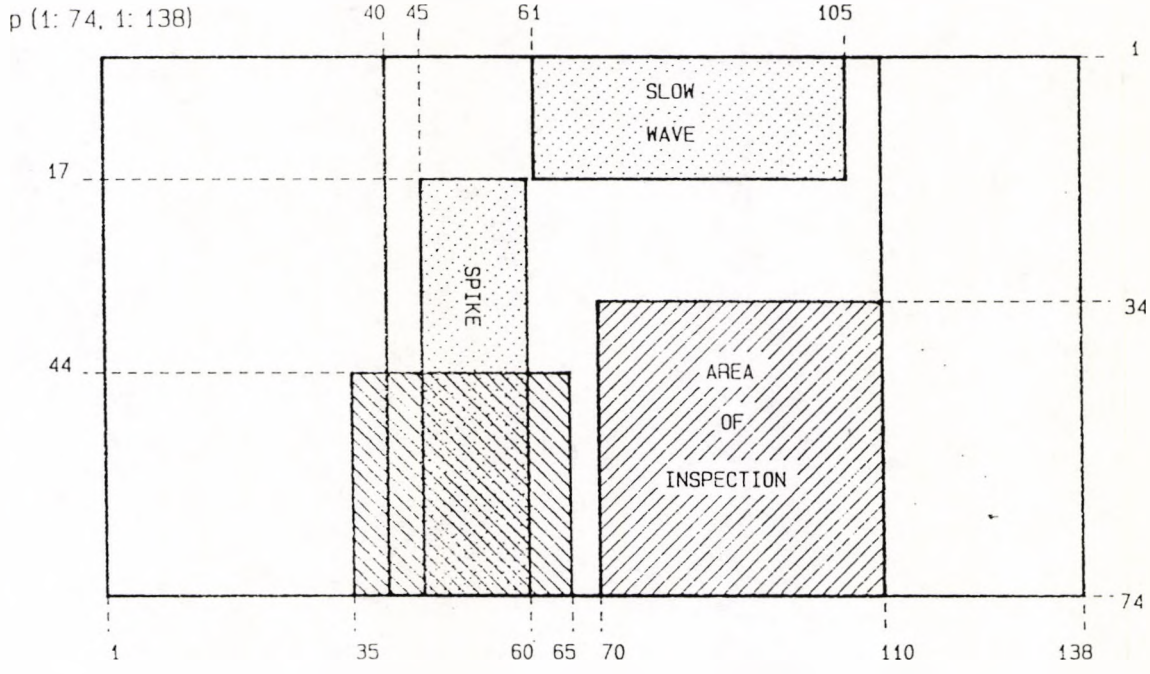


Figure 6.14 - Feature areas of the WD.

At the beginning of the experiments, all the segments of EEGs whose WDs were to be calculated were aligned either according to the maximum value of a spike (SAWCs, false-alarm

SAWCs and artifacts), i.e. as if the spikes had been previously detected, or according to the maximum value of the segment (normal EEG or non-spiky artifacts). Now, having figure 6.14 as a reference, the area of inspection (Ai) was determined as the region were the "energy" of the WD of a normal SAWC should be minimum. A general-purpose coefficient, that may be used as a decision point, can be obtained for this area. The algorithm that determines such a coefficient follows below; it has been assumed that the precalculated smoothed Wigner Distribution contains 74 lines (frequency) and 138 columns (time).

6.3.3.1 - The algorithm

1) Load the precalculated smoothed WD
   WD(1:74,1:138). **% WD(lines,columns)**

2) Select the area corresponding to SAWCs.
   Asawc(l1,c1) = WD(1:74,40:110)

3) Select the area of high frequencies around the spike region.
   Ahf(l2,c2) = WD(44:74,35:65)

4) Select the area of inspection.
   Ai(l3,c3) = WD(34:74,70:110)

5) Enhance the high-frequency variations in Ahf(l2,c2) by differentiation.
   X1(l4,c4) = diff(Ahf(l2,c2))

6) Calculate both the standard deviation, that is a function of the variance, and the mean value of X1(l4,c4) and divide the first by the second so that the result be independent of the amplitude of the WD.
   K1 = std(X1(l4,c4))/mean(X1(l4,c4)) **% constant 1**

7) Calculate the maximum value of the WD in the region of interest (corresponding to the SAWC).
   K2 = max(Asawc) **% constant 2**

8) In the area of inspection Ai(l3,c3), make constant K3 equal to the line number (proportional to frequency) **% constant 3**

9) Calculate the coefficient Y(l,c) for each point. (K1 and K3 are independent of the amplitude; K2 and Ai(l,c) cancel such dependence).
Y(l,c) = abs[Ai(l,c)/K2].K1.K3

10) If Y(l,c) is above a preselected threshold (K4), make the variable Z(l,c) equal to one, otherwise make it nil.
if Z(l,c) > K4, Z(l,c)=1 **% constant 4**
otherwise, Z(l,c)=0

11) The final false-alarm rejection coefficient is the mean value of the matrix Z(l3,c3).
FARC = mean[Z(l3,c3)]

This way, the final coefficient has been made proportional to three main variables, which are:

1) the relative amplitude [Ai(l,c)/K2] of the WD in the area of inspection (it is independent of the polarity),

2) the relative variation of amplitude (standard deviation/mean value) of the WD in the region of high frequencies near the spike (it tends to be higher for artifacts) and

3) the point, in terms of frequency, of the area of inspection where the coefficient is calculated. (The higher the value of the frequency component, the higher is the line number).

As can be observed from Table 6.1, the value of the coefficient will be very low (tending to zero) in the case of normal SAWCs and have a relatively high value for other kinds of signals. These results were obtained for a threshold (K4) equal to 10. The most important fact is that the coefficient does not depend on the real amplitude of the Wigner Distribu-

tion, but on its shape.

Table 6.1 - Variation of the false-alarm rejection coefficient as a function of the signal (threshold = 10).

SIGNAL	FARC
SAWC 1	0
SAWC 2	0
SAWC 3	0
SAWC 4	0
SAWC 5	0
SAWC 6	0
SAWC 7	0
SAWC 8	0
SAWC 9	0
SAWC 10	0
SAWC 11	0
SAWC 12	0
SAWC 13	0
SAWC 14	0
SAWC 15	0
SAWC 16	0
SAWC 17	0
SAWC 18	0
SAWC 19	0
SAWC 20	0
ARTIFACT 1	14
ARTIFACT 2	22
ARTIFACT 3	1476
ARTIFACT 4	468
ARTIFACT 5	1232
EEG 1	774
EEG 2	110
EEG 3	986
EEG 4	625
EEG 5	675
FALSE SAWC 1	270
FALSE SAWC 2	381
FALSE SAWC 3	1129
FALSE SAWC 4	1538
FALSE SAWC 5	479

6.4 - Discussion

The processing time was too high during the experiments for the technique to be considered for any real-time analysis, although it may be reduced significantly if more appropriate software is developed. The first idea is to use the WD to post-process records previously selected by the SAWC detector in order to confirm or not the detections made by this, so as to improve the quality of the analysis. (As discussed in the previous chapters, it is always the patient who suffers the consequences of a low-quality EEG analysis).

The real-time implementation of the WD has already been investigated in 1987 by Boashash and Black. During the last decade, researchers have tried to obtain more efficient algorithms for its computation. With the constant progress in microelectronics, the possibility of applying this technique to real-time analysis of signals in a few years time exists, leaving the hope that more precise EEG analizers will be made possible. For example, one possibility would be a portable unit constituted of a WD analizer that would detect SAWCs by itself based on the shape of the computed WD.

6.5 - Conclusion

Originally developed by Wigner in 1932 to be used in the field of quantum mechanics, the Wigner Distribution was used for the first time in signal analysis by Ville in 1948, who redefined it making use of the analytic signal instead of the

real signal. It is for this reason that it is also known as Wigner-Ville Distribution. Since 1980, when it was reintroduced by Claasen and Mecklenbrauker, it has been investigated as a time-frequency distribution that is of particular use in the analysis of nonstationary signals.

Having several desirable properties, its main drawback is the creation of artifacts, also known as crossterms, which corrupt the real spectrum, mainly when the signal contains several components. The crossterms that are a consequence of negative frequencies (aliasing) are eliminated by making use of a unilateral spectrum or, in other words, of the analytical signal; this also reduces significantly the required amount of memory. In order to reduce the amplitude of those artifacts that are caused by interference between the positive components, the original WD has to be smoothed with the use of time windows introduced into the general formula (Pseudo Wigner Distribution) or commonly by convolving the original WD with a two-dimensional Gaussian function (which is in fact a lowpass-filtering process). The different smoothing methods always cause some smearing in one or in both dimensions.

The possibility of application of the WD to the analysis of EEG signals, which are highly nonstationary, has been demonstrated. With the obtained results, it seems that the Wigner Distribution could prove to be a very powerful technique for the identification of spike-and-slow-wave complexes, which have a characteristic T-shape WD, in contrast to normal records of EEGs or artifacts, which have no particular form.

The main problem lies in its computation. During the experiments, the processing time, especially for smoothing, was quite long and much attention had to be given to memory capacity. Part of the problem was due to the chosen test setup and not of the technique itself.

In 1989, H. Choi and W. Williams introduced another form of distribution known as the Exponential Distribution (ED) owing to its exponential kernel function. They applied it to the analysis of multicomponent signals such as brain waves evoked by words (evoked potentials).

The ED, like the WD, is also a member of the Cohens's class of time-frequency distributions and, due to its bilinear structure it also has crossterms. The main difference is that, with its more complex mathematical representation, the process of smoothing is inherent to the distribution. This way, by altering the kernel (in the WD, the kernel is equal to one), it is possible to smooth the distribution, controlling the amplitude of the interference caused by the crossterms. As with the WD, the price paid for the elimination of the crossterms is the spreading of the autoterms, which leads to a poorer resolution.

CHAPTER 7

DISCUSSION AND CONCLUSIONS

7.1 - Discussion

This thesis has been concerned with the application of computer aided measurement techniques to assist in the diagnosis of medical conditions. In particular, it has addressed the problem of the reliable detection of epilepsy based on signals derived from the surface of the scalp (i.e. the electroencephalogram).

The importance of a very accurate diagnosis of epilepsy was identified very early in the thesis. The need for an accurate positive indication is obvious, in order that suitable treatment may be prescribed. Also, it is important to the patient to be aware of their condition in order that they may take appropriate precautions to minimize the possible risk of personal injury in the event of an attack.

A negative result, while it may not bring very serious problems to an epileptic patient (the patient will just go on having some seizures while more tests are carried out), a positive result for a person who is not epileptic may have very serious consequences. These may include the side effects of the drug(s), loss of job or difficulties in getting a job (e.g. a person who suffers from epilepsy cannot be a pilot, fireman, etc)

and others, based on human prejudice, which may result in isolation from society.

In order to improve the degree of accuracy in the diagnoses of brain diseases often related to epilepsy, the long-term EEG has been adopted in cases where the normal EEG does not show significant results. With the long-term EEG, it is possible to capture and to quantify very rare and unpredictable events, which may appear in a space of hours or even days and not in 30 or 40 minutes, that is the duration of a normal EEG recording.

The problem posed by the long-term EEG is the sheer volume of data that is obtained, which cannot be analysed by an human interpreter in a simple way. A fast review of the signal on an oscilloscope may be a convenient procedure in just a few cases. For this reason, it is necessary to reduce the dimensionality of the data set or, in other words, to compress the data. The approach taken to the problem in this thesis was to develop a computer aided technique based on a real-time feature extractor that could identify portions of the EEG record which appeared to be abnormal, in particular, the spike-and-slow-wave complex.

The problem with these sorts of models is the difficulty in defining an accurate model because of:

(a) the nature of the signal (low amplitude, distorted and non-stationary)

(b) the differences between various records and

(c) the different criterions used by different people to define what is abnormal in an EEG record and what is not.

A reasonably comprehensive survey of previous models was carried out, all of which offered various advantages and disadvantages. From these, a one-dimensional real time model, constituted of a spike detector, a slow-wave detector and an artifact rejection algorithm, was developed. It offered good results, but, in the face of the above and in common with previous attempts, it was practically impossible to define a set of criteria with which there was neither missed features nor false alarms, as demonstrated in Chapter 5. This approach was clearly not going to prove suitable as a means of achieving the stated aims and objectives in terms of reliability.

Another model, based on the Wigner Distribution, was then developed. The WD offers simultaneous analysis of the signal in both the time and frequency domains and a more sophisticated set of criteria could be used. Also, it is felt that a two-dimensional analysis represents the method used by human observers more closely, where the words "sharp" and "high frequency" are frequently interchanged (often in the same sentence!). It was possible, with the WD, both to confirm SAWCs and to reject false-alarms that had been previously detected by the one-dimensional model. In clinical terms, it will lead to a more accurate and, consequently, to a more reliable diagnosis.

The major problem with the WD was concerned with the time taken to analyse a segment of signal. Some authors have claimed that they have obtained some algorithms that permit the Wigner Distribution to be obtained in real time (Boashash and Black, 1987; Sun and others, 1989) but these have not been fully investigated. An initial study suggests that the compromises

necessary to compute the WD in real time lead to a significant loss of accuracy and so would probably prove unsuitable.

This problem, however, is likely to be resolved in the not too distant future, as advances in VLSI technology provide even more powerful microprocessors and specialist digital signal processing (DSP) chips.

In the meantime, an hybrid solution is suggested which makes use of both the techniques described. The one-dimensional model would form the basis of the portable real-time unit, which would act as an "intelligent data compressor".

It would in fact be a very good data compressor because what it does is to select only portions of the record that contain abnormalities. By using a portable cassette recorder as a back-up store, long-term records may be saved for subsequent analysis. The feature extractor would be capable of reliable results, but, with a relaxed set of criteria, a number of false-alarms will occur. If a tight set of criteria is defined, there would be a possibility that features would be missed.

The output from the cassette recorder would then be subjected to a post-processing phase in which the one-dimensional model would again be used, but this time defined to a tighter criteria. Any feature rejected by this step would then be analysed using the WD, from which an accurate result could be expected.

7.2 - Conclusions

The WD appears to offer the basis for a very reliable

detection technique for the SAWC. At present, the available microprocessors are not powerful enough to permit its use in real- time , but this is likely to change. The suggestions for an interim "hybrid" solution would appear to meet the two objectives of a portable real-time analyser that may be conveniently carried by a patient, but that also offers high reliability in terms of accurate identification.

Neither of the models has undergone clinical trials. As the EEG signals that were used during the experiments were pre-recorded signals which, by their nature, could be considered good since they had very distinctive SAWCs and obvious plots of artifacts. No major problems were encountered during the experiments.

Clearly, there is much work still to be done before an instrument suitable for clinical use can be produced. The application of the Wigner Distribution could however prove to be a very significant step towards achieving this goal.

APPENDIX A-1

PORTABLE ANALYSER FOR REAL-TIME DETECTION OF THE EPILEPTIC PRE-CURSOR

PORTABLE ANALYSER FOR REAL-TIME DETECTION OF THE EPILEPTIC PRE-CURSOR

A. L. Stelle R. A. Comley

ABSTRACT -- The application of a portable microcomputer system to the problem of the long term monitoring of clinical EEGs is described. A detection algorithm is developed to identify a feature associated with the onset of an epiletpic attack in real-time. The results of practical tests are presented.

INTRODUCTION

The prospect of determining the underlying activity of the brain through the use of monitoring electrodes attached to the surface of the scalp has aroused varying degrees of interest for a number of years. Some researchers have reported significant results in this area, while others [Stowell, 1970] have been of the opinion that no meaningful information may be obtained from such a complex and distorted signal. Research has progressed rapidly to provide an understanding of the structure and functioning of the brain, largely through invasive techniques. Non-invasive monitoring, the subject of this paper, has concentrated largely on the identification of abnormalities in the EEG record, an has not enjoyed such rapid advances.

A number of factors contribute to this slow rate of progress, not least of which is the abscence of any clear definition or agreement as to what constitutes 'abnormal activity'. Many human analyses would appear to be based more on acquired, intuitive skills rather than any formal criteria. Also, what may be considered abnormal in an EEG record from one patient may be regarded as not unusual in that from another individual.

It has become increasingly apparent in recent years that in order for any degree of confidence to be placed on the results obtained from an EEG record, long term monitoring is required [Binnie, 1988]. This places an unpractical burden on the traditional techniques of hard-copy and manual interpretation owing to the potentially large amounts of data that must be recorded. A further obstacle concerns the amount of freedom a patient is to be allowed. It is clearly not reasonable to expect the patient to remain imobilised or within the confines of the EEG laboratory for considerable periods of time. Idealy, the monitoring system should allow as much freedom

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as possible. This implies some form of portable unit that is small enough to be carried easily by the patient.

In order to overcome the problems of the volume of data associated with long term monitoring and the need for portability, it was decided that a microprocessor based, real-time detection system was required. The power of modern microprocessors makes real-time analysis a practical proposition and current levels of integration make a portable unit feasible.

The unit developed is based on the Motorola 68000 microprocessor equipped with 8k words of non-volatile read-write memory and a ten-channel, ten-bit analogue-to-digital converter. A dual channel, eight-bit digital-to-analogue converter was also included in the prototype to allow the output of resutls as the detection algorithm was developed. This facility will probably be retained in the final version with a portable FM tape recorder made available as an optional back-up store onto which the abnormal segments of the EEG record may be saved for subsequent visual inspection.

The monitor unit has no standard peripheral channels but is connected to a host computer (Motorola SYS133) for program downloading and the dumping of results for display or further analysis. This computer aided measurement technique was developed some time ago and has been reported in an earlier publication [Brignell, Comley & Young, 1976].

The development of a suitable detection algorithm poses the major problem for any such monitoring system. The specific abnormality of interest in the current research is the spike-and-wave complex which is associated with the onset of a petit-mal epileptic attack (Fig. 1). The requirement for real-time operation rules out the use of the more elaborate detection techniques and so leaves us to consider the simpler methods. Spike detectors are probably the simplest algorithms in this class and are usually based on some form of differentiator [Comley and Brignell, 1981].

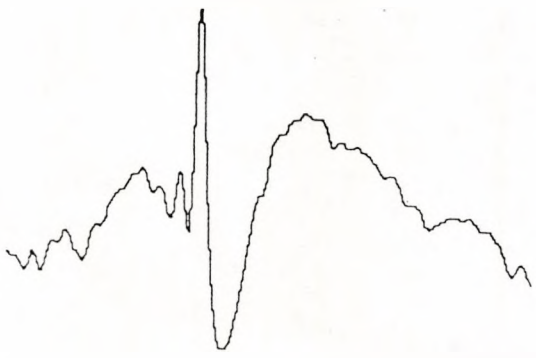
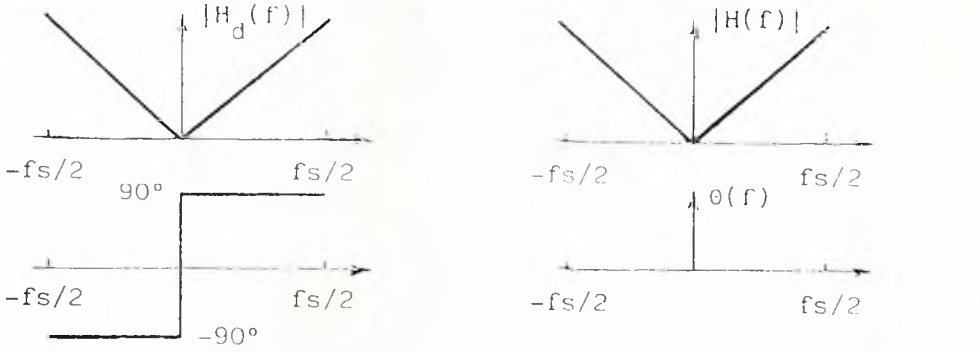


Figure 1. Spike-and-wave complex.

THE BASIC DETECTOR

The differentiation process is an odd function producing a bipolar output. If a simple level checking method is employed to identify the spike features then two detection thresholds are required, (Fig. 3). Since, in general, the output from the differentiator will not be symmetrical, this can present serious problems for reliable detection. If however an even function is chosen, the above problems can be significantly reduced.

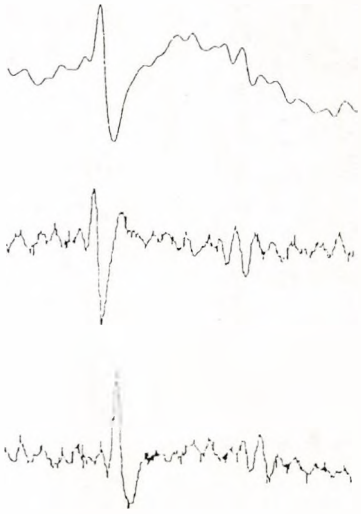
The transfer functions for the differentiator and the desired system response are shown in Figure 2. As can be seen, the degree of enhancement to high frequencies is the same in both cases, but the phase components are all nil for the even function. In other words, the system is equivalent to a differentiator in series with a Hilbert transformer (quadrature phase shifter).



a) Differentiator

b) Differentiator + Hilbert Transformer

Figure 2. System frequency and phase characteristics.



Spike-and-wave

Differential

Differential + Hilbert Transformer

Figure 3. Spike detector algorithm output.

The output from this algorithm has the very desirable property of being unipolar, i.e. the whole signal due to the spike is contained in a single positive pulse. Only one threshold comparison is now required which is immune to the asymmetry problems of the simpler differentiator (Fig. 3). The price paid for this significant improvement is an increase in the computational load. This however is not excessive and the algorithm has proved to be very effective as the basis of a real-time detection system.

DETERMINATION OF THE TRANSFER FUNCTION

To perform the operation illustrated in Figure 2b it is necessary to convolve the input signal with the discrete impulse response, h(n). This may be derived as indicated in Figure 4. Comparing Figure 2b with Figure 4c, it can be seen that the slopes located between - fs/2 and fs/2 correspond respectively to the slopes located between -fo and fo. So, by making t = nTs = n and fo = fs/2 = 1/2, the normalised discrete impulse response is obtained:

$$h(n.T_s) = h(n) = A.\text{sinc}^2(n/2) \cdot \cos(n.\pi)$$

The number of coefficients required for the computation of h(n) can be kept quite low since:

$h(n) = 0$ for even values of n

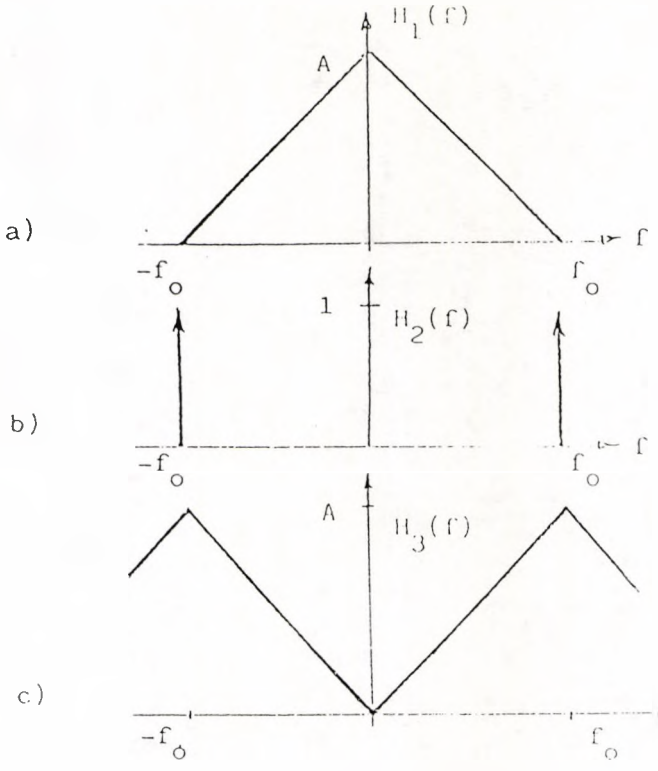
$h(n) = A$ for $n = 0$

and since $h(n) \propto \text{sinc}^2(n/2)$, it decreases rapidly for increasing n (e.g. for $n = 5$, $\text{sinc}^2(n/2) = 0.016$ and for $n = 15$, $\text{sinc}^2(n/2) = 0.0018$).

A value of n = 17 was chosen for the preliminary studies as this represented a good compromise between accuracy and speed of computation.

Normally the output from the spike enhancer process would be followed with a low-pass filter (second order min.) and then a level comparison would be employed to identify the spikes. A serious disadvantage of this method is that while the filter reduces the 'noise' output from the enhancement process, it also reduces the amplitude of the spike feature, making level detection less reliable and very sensitive to the threshold setting.

An alternative algorithm has been developed in which the output from the enhancer is raised to the power of three and scaled appropriately. This has the effect of amplifying the features of interest whilst reducing the 'noise' level (Fig. 5).



$$H_1(f) = \Lambda.\mathrm{tri}\left(\frac{f}{f_o}\right)$$

$$h_1(t) = \Lambda.f_o.\mathrm{sinc}^2(f_o.t)$$

$$H_2(f) = \delta(f-f_o) + \delta(f+f_o)$$

$$h_2(t) = 2.\cos(2.\Pi.f_o.t)$$

$$H_3(f) = H_1(f) * H_2(f)$$

$$H_3(f) = \Lambda.\left[\mathrm{tri}\left(\frac{f-f_o}{f_o}\right) + \mathrm{tri}\left(\frac{f+f_o}{f_o}\right)\right]$$

$$h_3(t) = h_1(t).h_2(t)$$

$$h_3(t) = 2.\Lambda.f_o\mathrm{sinc}^2(f_o.t) .$$

$$\cos(2.\Pi.f_o.t)$$

Figure 4. The discrete impulse response of the spike detector.

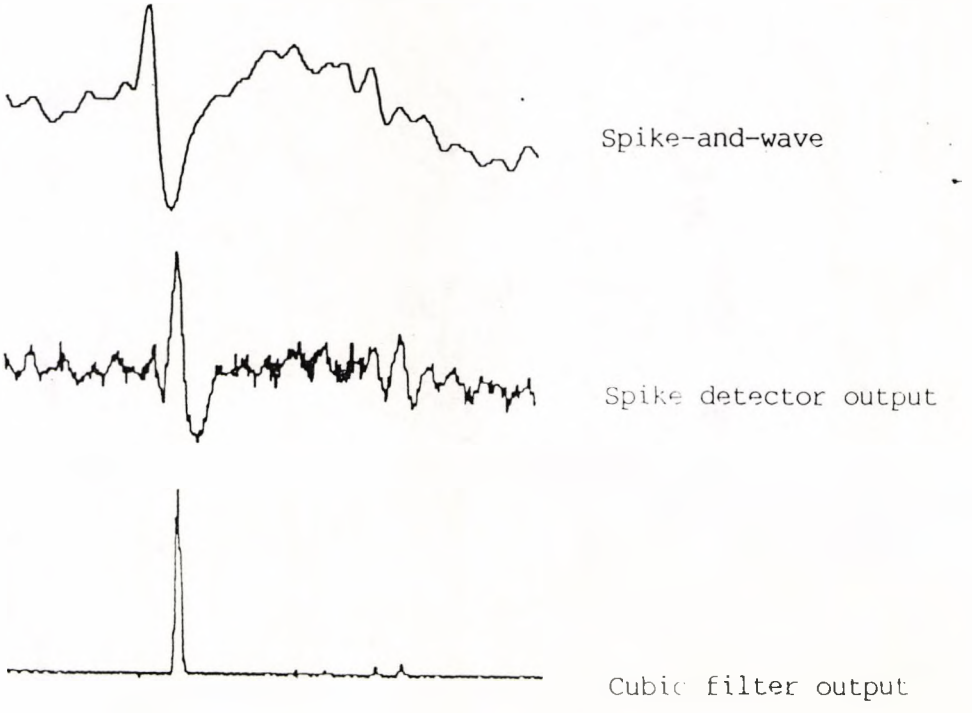


Figure 5. Operation of the complete spike detector.

SLOW WAVE DETECTOR

The spike detector alone can only be considered a reliable means of detection of the onset of an epileptic attack for noise free EEG signals. A major source of corruption of the EEG arises as the result of muscle artifact and generally takes the form shown in Figure 6. This is a particular problem for any portable system where a large amount of muscle activity is to be expected. The addition of a slow-wave detector can provide a significant improvement. This has been implemented in the form of a fourth-order Butterworth low-pass filter with a 7Hz cut-off frequency followed by a level discriminator. The above values were selected as offering the best performance following extensive experimentation on pre-recorded data.

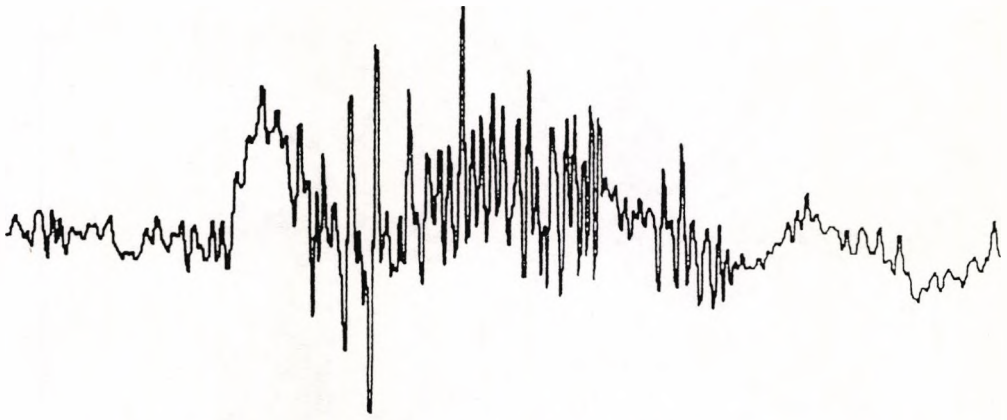


Figure 6. Example of muscle artifact corruption.

EXPERIMENTAL RESULTS

The complete detection algorithm has been tested on the Motorola SYS133 using pre-recorded EEG data. These records were band-limited to 70Hz and played back at normal speed to simulate real-time operation. A sampling frequency of 600Hz has been used throughout the tests but it is planned to reduce this before trials begin using the portable unit.

Initial results have been very encouraging, with a high detection and low false alarm rate being achieved. Artifact rejection however does still pose considerable problems, as can be seen from Figure 6. The basic algorithm has been modified in an attempt to improve this situation. It involves the use of 350ms wide window during which a count is accumulated of the number of spike detections. If more than two spikes are encountered within the window period, then the record is judged to contain artifacts and so any detections are rejected. This improves the performance of the algorithm considerably in terms of artifact rejection without any loss in true spike and wave identification for the test records.

CONCLUSIONS

The ability of a modern microprocessor to analyse a complex signal and to detect specific features in real-time has been demonstrated. Testing of the portable version of the system is about to commence and it is hoped that full clinical trials will be possible in the near future. Major areas of interest to us are the potential for conducting long term analyses on patients for whom there is considerable doubt as to whether they suffer from epilepsy and for such activities as the screening of various drug regimes in order to provide a quantitative measure of their effectiveness.

Our work has to date concentrated on the analysis of EEG records with particular reference to the spike-and-wave complex. Since, however, the functioning of the hardware monitor unit is defined entirely in software, we can foresee numerous other potential applications for the techniques we have developed.

Our future plans include the expansion of the detection algorithm to deal with up to five input channels in real-time. This should allow for a much more reliable artifact rejection routine to be developed. Further, we also plan to investigate the possibility of assigning one or more of the available input channels to monitor muscle movements as we feel that this may be able to provide valuable additional information during the onset of an epileptic attack.

ACKNOWLEDGEMENTS

One of the authors, Mr. A.L. Stelle, would like to thank the British Council and CAPES (Coordenacao de Aperfeicoamento de Pessoal de Nivel Superior) of the Brazilian Ministry of Education for the provision of financial assistance and the CEFET-PR (Centro Federal De Educacao Tecnologica Do Parana) for the provision of both study leave and financial support.

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APPENDIX A-2

THE APPLICATION OF THE WIGNER DISTRIBUTION TO THE ANALYSIS OF EEG SIGNALS

THE APPLICATION OF THE WIGNER DISTRIBUTION TO THE ANALYSIS OF EEG SIGNALS

A.L. Stelle* R.A. Comley**

ABSTRACT -- The need for a two-dimentional approach to the analysis of EEG signals is identified. The Wigner Distribution is proposed as a suitable candidate and a brief review of its major features is presented. The application of this algorithm to EEG records is described both in terms of the practical implications and the results obtained.

INTRODUCTION

The application of computer aided techniques to the analysis of EEG records poses many problems. The signal itself is low-level (150μV typ.), non-stationary and subject to significant corruption (usually in the form of muscle artifact). Further, considerable variations exist between different patients and within a record from a single individual.

Computer Assisted Diagnostic Systems (CADS) have been developed to help the electroencephalographer particularly in the analysis of long-term EEG recordings of a large population of epileptic patients. These involve elements of quantitative analysis and pattern recognition, or both. The three main goals of such CADS are the detection of interictal epileptiform events, the detection of epileptic seizures, especially petit mal absences, and the localization of epileptogenic areas of the brain [Niedermeyer & Lopes da Silva, 1987].

A good example of pattern recognition is in the detection of the epileptiform event known as a spike-and-wave complex (SAWC), which characterizes attacks of petit mal epilepsy. Many methods have been proposed for such kinds of detection [E.g. Gotman & Gloor, 1976; Comley & Brignell 1981; Stelle & Comley 1989], which have met with varying degrees of success, but all suffer from the recurrent problem relating to the difficulty in defining a suitable model with which to describe the features of interest. These problems are compounded by the fact that trained electroencephalographers find it difficult to describe in any formal way, the processes and criteria they employ in their manual analyses.

One fact which has become increasingly apparent to us is that human interpretation is based on some form of simultaneous time and frequency analysis. The above examples of computer aided methods are based on both the waveform and the spectrum of the signal, but considered separately (i.e. in one dimension).

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The above would suggest that a much more reliable EEG analysis may be obtained from a consideration of both the time-domain and the frequency-domain features of the signal simultaneously, in a two-dimensional way. The most basic tool that permits such kinds of analysis is the spectrogram. This is most appropriate for analysing long segments of EEG (quasistationary signals) but is not particularly useful for the analysis of a single epileptiform event such as a SAWC, mainly because of the low number of samples and the necessity of using windows that corrupt the original signal. Another special tool that shows the variations of the signal in both the time and frequency domains is the Wigner Distribution (WD). This has already been applied successfully in such areas as the analysis of ultrasound signals [Costa & Leeman, 1989]. It is particularly efficient in the analysis of non-stationary signals, as is the case of epileptiform events. Some examples of the application of the Wigner Distribution to the analysis of EEG signals will be shown in this paper.

THE WIGNER DISTRIBUTION

The Wigner Distribution, defined by (1), was introduced by Wigner in the area of Quantum Mechanics in 1932 and applied in signal analysis by Ville in 1948. It remained in obscurity until 1980, when Claasen and Mecklenbrauker gave it a new lease of life.

$$W_x(t,w) = \int_{-\infty}^{+\infty} x(t + \tau/2).x^*(t - \tau/2).\exp(-jw\tau).d\tau \qquad (1)$$

where: a) "t" represents time,
b) "w" represents frequency and
c) "$x^*(t)$" represents the complex conjugate of x(t).

The WD offers several interesting properties, four of the more important are listed below. Properties 3) and 4) are of particular importance in this work. Property 3) permits flexibility as to where the feature to be identified is positioned within the time window. The significance of property 4) is that it represents a corruption of the output, the consequences of which will be seen later.

1) The WD of any signal (real or complex) is real.
2) The WD of a real signal is an even function of the frequency.
3) If the signal is shifted in time, the WD is also shifted in time.
4) The WD of the sum of two signals "f" and "g" is a bilinear function of "f" and "g" , or

As with the Fourier Transform, the definition given by (1) is not useful in practical terms. In order to apply the WD to discrete-time signal processing and to calculate it via FFT techniques, equation (3), that represents the Discrete Time Wigner Distribution and (4), the Pseudo Wigner Distribution, may be used. In equation (4), due to the side effect provoked by the time window "h(m)" [Hamming, Hanning, etc], some blurring occurs in the frequency domain.

$$W_x(n,w) = 2\sum_{m=-\infty}^{\infty} x(n+m).x^*(n-m).\exp(-j2wm) \qquad (3)$$

$$W_x(n,w) = 2\sum_{m=-\infty}^{\infty} x(n+m).x^*(n-m).h(m).h^*(-m).\exp(-j2wm) \qquad (4)$$

As expected, aliasing is caused by the sampled signal, but, as can be seen from (3) and (4), the repetition period is "π" rather than the "2π" that all spectra of the discrete-time signals have. For this reason, the signal should be sampled at least, at twice the Nyquist rate ($fs \geq 4.fmax$). This, however, is not a good idea in practical terms, mainly because of memory limitations and a considerable increase in processing time. The best solution is to make use of the analytic signal associated with "x(n)" because it has a unilateral spectrum.

The main drawback of the WD is the appearance of artifacts for any signal that is not a single Gaussian function (no artifacts appear if the Gaussian function is modulating a sinusoidal signal) , as shown by equation (2). Such artifacts are composed of relatively high frequency spikes that assume positive and negative values. In order to eliminate them, the original version of the WD must be passed through a two-dimensional lowpass filter. The process is popularly known as "smoothing" and is commonly done by convolving the impure WD with a two-dimensional Gaussian function given by (5), where $\alpha\beta \geq 1$ [Cohen, 1989].

$$L(k,l) = 1/(\alpha\beta).\exp(-k^2/\alpha - l^2/\beta) \qquad (5)$$

As an example, both the impure WD and the smoothed WD of the signal represented by (6) are shown in Figure 1.

$$x(n) = \exp(-a((n-n_1)/N)^2).\cos(2\pi f_1 n/N) + \exp(-a((n-n2)/N)^2).\cos(2\pi f_2 n/N) \qquad (6)$$

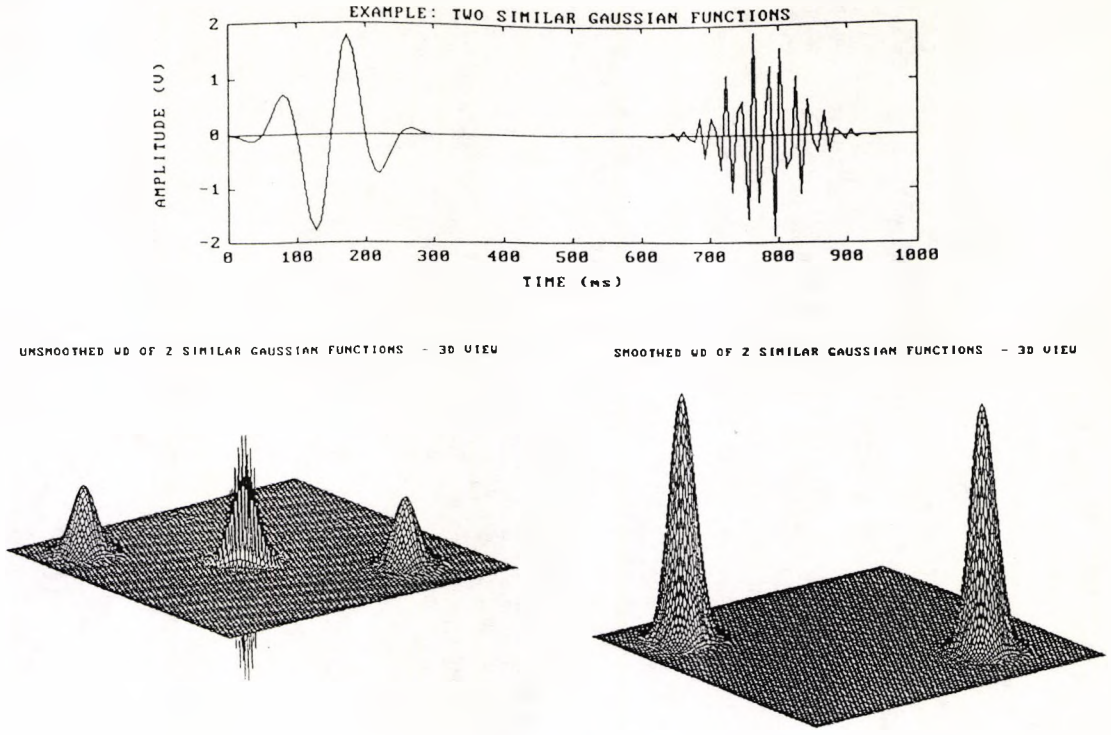

Figure 1.Application of the Wigner Distribution to a test waveform. (All WDs are normalised).

EXPERIMENTAL SETUP

For the implementation of the algorithm, the commercially available MATLAB-386 package was used. The program was run on a 386 IBM-compatible personal computer that has a memory capacity of 7 Mbytes and a clock frequency of 36 MHz.

The EEG signal, band-limited to 70 Hz and pre-recorded on magnetic tape, was digitized at a frequency (fs) of 160 Hz and stored in ASCII-format files. Given x(n) with a total of N samples, the respective WD original matrix has N^2 samples, with a time scale and a frequency scale that go from 0 to (N - 1) and from 0 to fs/2, respectively .

The total processing time depends on two factors: a) the value of N and b) the total number of samples (A.B) that compose the two-dimensional smoothing function L(k,l), where A=kmax-kmin+1 and B=lmax-lmin+1. During the experiments, the total processing time was checked for two distinct cases. First, for N=128 and A=B=11, it took 5 minutes for the final smoothed WD matrix to be obtained. Second, for N=256 and A=B=11, 40 minutes were necessary. Most of the processing time is spent on the smoothing process.

From the results obtained, it was noted that most of the energy of the EEG signal was concentrated below 40 Hz, and a decision was taken to smooth only the lower frequency half of the original WD matrix. In this way, a considerable decrease in the processing time was obtained without the necessity of changing the resolution of the signal in the time domain.

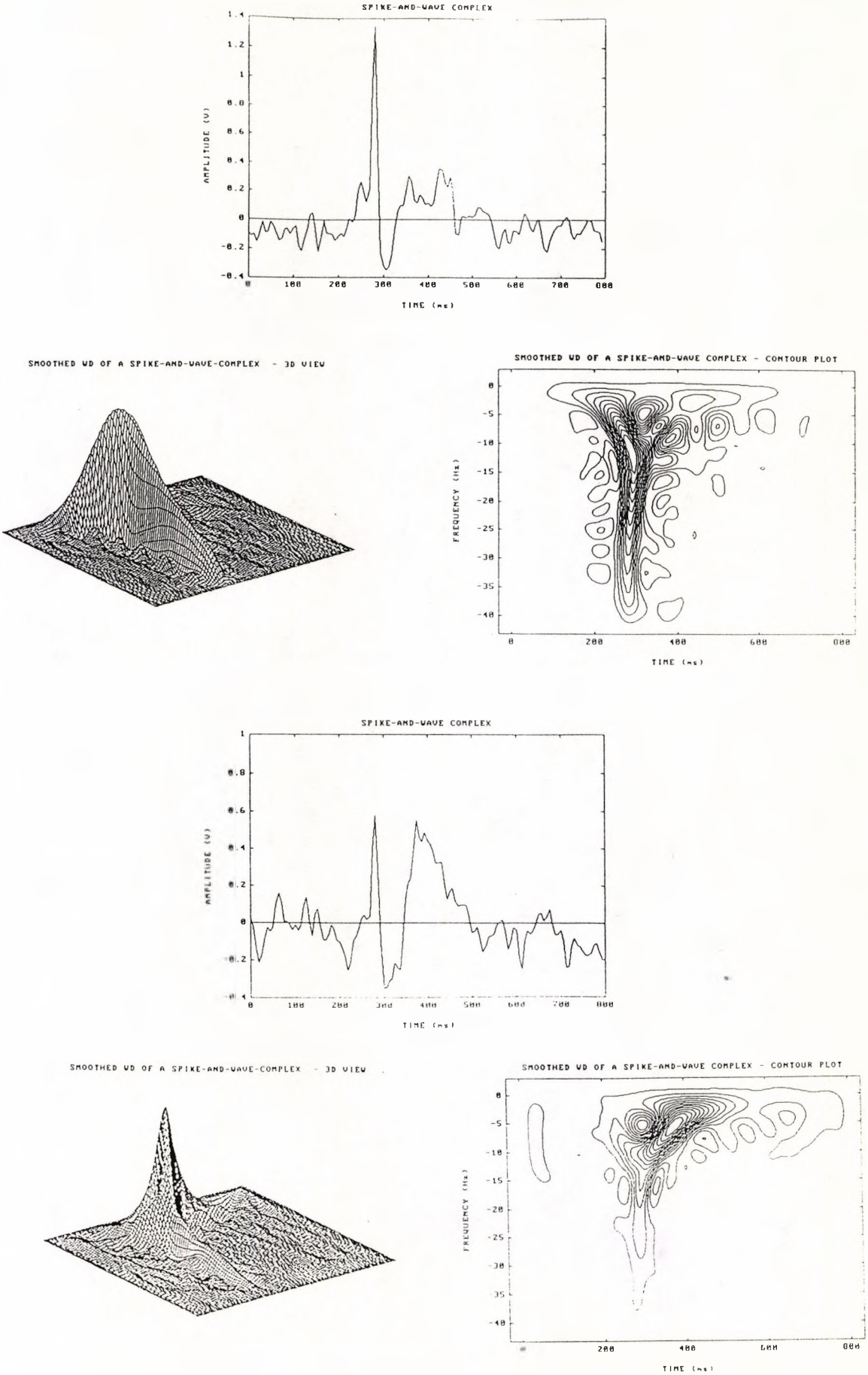

Figure 2. Examples of the application of the Wigner Distribution to spike-and-wave complexes. (All WDs are normalised).

DISCUSSION OF RESULTS

Initial results obtained with the WD are very encouraging. From the two examples given it can be seen that the basic form of the contour plot outputs are very similar for quite different spike-and-wave complexes: both exhibit a characteristic "T" shape. This has been repeated for all the SAWC inputs we have tried and shows a marked contrast to segments of normal records, for which no particular form is obtained, and for records containing artifacts. The processing time involved on our test setup is quite long and memory capacity can quickly give rise to problems. Various techniques aimed at overcoming these problems are being considered [Boashash & Black, 1987].

CONCLUSIONS

The application of the Wigner Distribution to the analysis of EEG records has been demonstrated. From our initial results it would appear that the technique is capable of offering a very reliable means of identifying spike-and-wave complexes from the EEG record, which is our primary area of interest. Further, preliminary studies with records containing artifacts suggest that a high degree of rejection would appear to be possible, although more work is required in this area before any firm conclusions may be drawn.

ACKNOWLEDGEMENTS

One of the authors, Mr. A.L. Stelle, would like to thank the British Council and CAPES (Coordenacao de Aperfeicoamento de Pessoal de Nivel Superior) of the Brazilian Ministry of Education for the provision of financial assistance and the CEFET-PR (Centro Federal De Educacao Tecnologica Do Parana) for the provision of both study leave and financial support. Also, the authors would like to thank Dr. E.T. Costa from CEB-UNICAMP (Universidade Estadual de Campinas - SP - Brazil) for his help with this work.

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APPENDIX B

SAWC DETECTION ALGORITHM

```
*****************************************************************************
*                                                                           *
*          SPIKE-AND-SLOW-WAVE-COMPLEX (SAWC) DETECTOR          OCTOBER/1989 *
*                                                                           *
*****************************************************************************

* BOTH THE SPIKE AND THE SLOW WAVE DETECTORS ARE ALWAYS ACTIVE.

* THE SAMPLING FREQUENCY (fs) FOR THE SPIKE DETECTOR IS 600 Hz.
* FOR THE LOWPASS FILTER AND FOR THE DC AVERAGER (RUNNING MEAN), IT IS 200 Hz
* (fs/3), WHICH IS CONTROLLED BY THE "LPFCLOCK" COUNTER.
* (LPFCLOCK = 3 ==> CLOCKFLG = 1 ==> SAMPLE IS PROCESSED)

* MAXIMUM INPUT LEVEL = MAXLEVEL = $200 ($150 ==> HIGH-AMPLITUDE SPIKE)
* SPIKE-DET LEVEL = SPLEVEL = DCLEVEL/4
* MAXIMUM SLOW-WAVE LEVEL = MAXSWLEV = 2 * DCLEVEL
* SLOW WAVE DETECTION LEVEL = SWLEVEL = 1.125 * DCLEVEL  (DC+DC/8)

* IF A HIGH-AMPLITUDE LOW-FREQUENCY ARTIFACT IS DETECTED (VLPF > MAXSWLEV),
* ARTFLAG IS SET AND Vin=PRESETDC (ESTIMATED DC LEVEL) DURING THE NEXT 1000 ms
* (TIME CONTROLLED BY "T" COUNTER)

*****************************************************************************
****************************  SPIKE DETECTOR  ********************************

* H(f) = A * (tri ((f-fo)/fo) + tri ((f-fo)/fo)); WHERE fo=fs/2=1/2

* h(n)= A * (sinc(n/2))^2 * cos(n.pi),   WHERE A=1000 ($3E8) (fs = 1)

* THE CONVOLUTION IS CALCULATED MAKING USE OF THE PROPERTY OF SYMMETRY FOR
* LINEAR FILTERS (y(0)=x(0).h(0) + (x(-1)+x(1)).h(1) + (x(-2)+x(2).h(2) + ...)
* WHEN h(n) = 0, THERE IS NO COMPUTATION (IF h(n) IS NIL, IT IS NOT STORED
* IN MEMORY).

* TOTAL NUMBER OF SAMPLES TO BE CONVOLUTED = &36 ($24)

*****************************************************************************
************************  AVERAGER - DC LEVEL  ******************************

* THE MEAN VALUE IS CALCULATED OVER 1360 ($550) SAMPLES (L=1359) ==> 1360/200
* SECONDS TO OBTAIN THE DC VALUE (fzeroes = k*200/1360).
* THE DC LEVEL IS CALCULATED USING THE RUNNING-MEAN METHOD. THE BASIC IDEA IS
* MEAN = [K.MEAN + (NEW SAMPLE - OLDEST SAMPLE)]/K, WHERE K IS THE NUMBER OF
* SAMPLES.

*****************************************************************************
************************  LOWPASS FILTER  ******************************

* THE LOWPASS FILTER IS AN AVERAGER (fzeroes = k*200/13) ==> 13 SAMPLES (13)
* FOLLOWED BY A 1ST. ORDER BUTTERWORTH FILTER (fc = 11 Hz)
* IN ORDER TO OBTAIN CUTOFF FREQUENCY = 5 Hz (approximately).

*****************************************************************************
```

```
**********************************************************************************

*********************************  PROGRAM  ***************************************

PROGRAM   EQU       $20000
DATA1     EQU       $25000          *GENERAL DATA
DATA2     EQU       $26000          *LOWPASS FILTER
DATA3     EQU       $30000          *WINDOW IMPULSE RESPONSE AND SPIKE DET.
SAMPLE    EQU       $30146          *X(n) WITHOUT DC LEVEL (SPIKE DETECTOR)
DCLEVEL   EQU       $30CA0          *MEAN VALUE

          ORG       DATA1           *GENERAL

SPK_BEGP  DC.L      $30200          *BEGINNING POINTER (DC LEVEL)
SPK_ENDP  DC.L      $30CA0          *END POINTER (30200+2*550)
K1        DC.W      $550            *USED TO CALCULATE THE MEAN VALUE   360)
K_SPMEAN  DS.L      1               * K.MEAN (TO IMPROVE PRECISION)
SPK_PTER  DS.L      1               *INDICATES THE OLDEST SAMPLE ADDRESS

PRESETDC  DC.W      $60             *ESTIMATED DC LEVEL
MAXLEVEL  DC.W      $200            *MAX. INPUT LEVEL (2.5 V)

SPIKEMIN  DC.W      $C              *NUMBER OF SAMPLES FOR THE SPIKE (0.5,6
M_MIN     DC.W      $1E             *50ms.600Hz (INTERVAL FROM SPIKE TO SW
M_MED     DC.W      $96             *250ms.600Hz (    " TO CONFIRM THE SPIKE
M_MAX     DC.W      $96             *$96=$150 => 250 ms . 600 Hz

M         DS.W      1               *GENERAL SAMPLE-COUNTER

T         DS.W      1               *TIME-INTERVAL  COUNTER

          ORG       DATA2           *SLOW-WAVE DETECTOR

LPF_BEGP  DC.L      $33000          *BEGINNING POINTER (LOWPASS FILTER)
ENDPOIN2  DC.L      $3301A          *END POINTER (33000+2*D)
K2        DC.W      $D              *USED TO CALCULATE THE MEAN VALUE (&13)
K_LPMEAN  DS.L      1               * K.MEAN (TO IMPROVE PRECISION)
LPF_PTER  DS.L      1               *INDICATES THE OLDEST-SAMPLE ADDRESS

*BUTTERWORTH 1ST-ORDER FILTER

COEF1     DC.W      $5BF            *COEF1*(x(n) + x(n-1)) + COEF2 * (y(n-1)
COEF2     DC.W      $1B91
COEF3     DC.W      $2710           *(MAY BE ELIMINATED; USE ASR #1 , Dn)
XN        DS.W      1
XN_1      DS.W      1
YN_1      DS.W      1

MAXSWLEV  DS.W      1               *MAX SLOW WAVE  LEVEL (COEF1*(x(n)+x(n
SWLEVEL   DS.W      1               *SLOW-WAVE DETECTION LEVEL (AT THE
DCSAMPL   DS.W      1               *X(n) WITH DC LEVEL FOR THE LP FILTER
LPFMEM    DS.W      1               *LOWPASS FILTER OUTPUT LEVEL
LPFLOW1   DS.W      1               *                 (END POINT)
```

```
PAGE    3    (IST V05  [02004 4    ]  5/21  17:41:57  SYS:0001  .SAWSPKT.SA

        ORG         DATA3                   *SPIKE DETECTOR + FLAGS

S1      DC.L        $FFFFFFFE               *h(-17)=h(17)=-1;   h(-15)=h(15)=-2
S2      DC.L        $FFFEFFFD               *h(-13)=h(13)=-2;   h(-11)=h(11)=-3
S3      DC.L        $FFFBFFF8               *h(-9)=h(9)=-5;     h(-7)=h(7)=-8
S4      DC.L        $FFF6FFD3               *h(-5)=h(5)=-16;    h(-3)=h(3)=-45
S5      DC.L        $FE6B03EB               *h(-1)=h(1)=-405;   h(0)=1000
*                                            2 BYTES/SAMPLE --> $46 BYTES FOR x(n)
*                                            COMPARISONS:  $30010 TO CONVOLUTE
*                                            AND           $30146 TO SHIFT x(n)

ADRW    DC.L        $30000                  *FIRST WINDOW-ADDRESS  ---> h(0)
ADR1    DC.L        $30100                  *1st.-ACQUIRED-SAMPLE (x(0))  ADDRESS
ADR35   DC.L        $30146                  *LAST-ACQUIRED-SAMPLE (x(35)) ADDRESS
ATTEN1  DC.W        $A                      *ATTEN. Vo FROM FIR FILTER yspk(m)
ATTEN2  DC.W        $850                    *ATTEN. Vo FROM CUBIC FILTER (yspk)^3
N       DC.W        $24                     *NUMBER OF SAMPLES (&36=$24) ---> h(n)

SPLEVEL DS.W        1                       *SPIKE DETECTION LEVEL (DC LEVEL/4)
SPLIM17 DS.W        1                       *SPIKE AMPLITUDE LIMITER (1.75 * DC LEVEL)
SPCOUN1 DS.W        1                       *SPIKE COUNTER
SPIKSAMP DS.W       1                       *SPIKE SAMPLES COUNTER
SPFLAG  DS.W        1                       *SPIKE FLAG

SAWFLAG DS.W        1                       *SPIKE AND-WAVE FLAG

OUTFLAG DS.W        1                       *OUTPUT-PULSE FLAG

ARTIFLAG DS.W       1                       *ARTIFACT FLAG

CLOCKFLG DS.W       1                       *CLOCK FLAG ==> fs = 200 Hz (LPF/DC)

        ORG         PROGRAM

SAWCDET JSR.L       RESET                   *CLEAR FLAGS/COUNTERS (EXCEPT LPFCLOCK
        CLR.W       LPFCLOCK                *AND CLOCKFLG)

        MOVE.L      £$FEFFE0,A3             *STATUS INPUT
        MOVE.L      £$FEFFD0,A4             *SIGNAL INPUT
        MOVE.L      £$FEFF80,A5             *SIGNAL OUTPUT £1
        MOVE.L      £$FEFF82,A6             *SIGNAL OUTPUT £2

        MOVE.L      SPK_BEGP,SPK_PTER       *POINT AT THE BEGINNING OF STACK1 (MEAN)
        MOVE.L      LPF_BEGP,LPF_PTER       *POINT AT THE BEGINNING OF STACK2 (LPF)

STATUSLO MOVE.W     (A3),D7                 *WAIT UNTIL STATUS GOES HIGH (IT IS LOW)
        AND.W       £$1,D7                  *SAVE BIT "0"
        BEQ.S       STATUSLO                *IF D7 = 0, GO STATLO

        ADDQ.W      £$1,LPFCLOCK            *IF LPFCLOCK=3, CLOCKFLAG IS SET
        MOVE.W      LPFCLOCK,D6             *LPFCLOCK = 3 ==> fs = 200 Hz
        CMP.W       CF3,D7                  *SO THE SAMPLE WILL BE PROCESSED BY
        BNE.S       INPUT                   *BOTH THE MEAN_AVERAGER AND THE LPF
        BSET.B      £$1,CLOCKFLG            *FILTER
        CLR.W       LPFCLOCK                *LPFCLOCK = 0
```

```
*SIGNAL INPUT

INPUT     MOVE.W    (A4),D6              *COLLECT SAMPLE
          AND.L     £$3FF,D6
          NOP                            *x(n) OUTPUT [MOVE.B D6,(A5)]
          NOP

*CHECK ARTIFACT FLAG

          BTST.B    £$1,ARTFLAG          *CHECK IF THERE HAS BEEN AN ARTIFACT
          BEQ.S     BEGIN                *IF ARTFLAG IS NOT SET, GO AHEAD
          MOVE.W    PRESETDC,D6          *OTHERWISE, Vin=DCLEVEL

*AMPLITUDE LIMITER

BEGIN     CMP.W     MAXLEVEL,D6          *COMPARE MAXLEVEL WITH SAMPLE
          BLE.S     SAVESAMP             *IF XN  = MAXLEVEL, START CALCULATIONS
          MOVE.W    MAXLEVEL,D6          *OTHERWISE  XN = MAXLEVEL
SAVESAMP  MOVE.W    D6,DCSAMPL           *x(n) WITH DC LEVEL FOR THE LP FILTER
          NOP                            *Vin OUTPUT
          NOP

*CALCULATES THE RUNNING MEAN VALUE    (f&  200 Hz)

          BTST.B    £$1,CLOCKFLG         *IF CLOCK_FLAG IS SET, THE SAMPLE IS
          BNE.S     BEG_MEAN             *PROCESSED. OTHERWISE KEEP THE LAST
          MOVE.W    DCLEVEL,D1           *DCLEVEL VALUE AND SKIP THE "MEAN"
          JMP       MEAN_OUT             *SUBROUTINE

BEG_MEAN  MOVE.L    SPK_PTER,A0          *A0 POINTS TO THE OLDEST-SAMPLE ADDRESS.
          CMP.L     SPK_ENDP,A0          *IS THIS THE LAST MEM LOCATION IN STACK?
          BLT.S     MEAN                 *IF NOT, CALCULATE THE MEAN VALUE
          MOVE.L    SPK_BEGP,SPK_PTER    *OTHERWISE, POINT TO THE FIRST MEMORY
MEAN      MOVE.L    SPK_PTER,A0          *LOCATION
          CLR.L     D0
          CLR.L     D1
          MOVE.W    D6,D0                *x(n) --> D0
          MOVE.L    K_SPMEAN,D1          *K.MEAN --> D1
          MOVE.W    (A0),D2
          AND.L     £$FFFF,D2            *D2=0000.XXXX
          SUB.L     D2,D1                *K.MEAN   OLDEST SAMPLE = D1
          ADD.L     D0,D1                *D1 = D1 + NEW SAMPLE
          MOVE.W    D0,(A0)+             *OLDEST SAMPLE IS REPLACED BY NEW.
          MOVE.L    A0,SPK_PTER          *AND POINTER = A0 = former A0   +   2
          MOVE.L    D1,K_SPMEAN          *STORE K.MEAN
          DIVS.W    K1,D1                *FIRST MEAN VALUE
          AND.L     £$3FF,D1             *MAXIMUM  NPUT VALUE = 3FF ---> 5 V
          MOVE.W    D1,DCLEVEL

*[illegible] HAS BEEN DETERMINED

MEAN OUT NOP
```

```
*SPLEVEL, SWLEVEL AND MAXSWLEVEL ARE DETERMINED NOW

        MOVE.W    D1,D7                 *SPLEVEL = DCLEVEL/4
        ASR.W     £$2,D7
        MOVE.W    D7,SPLEVEL
        MULS.W    £$7,D7
        MOVE.W    D7,SPLIMIT            *SPLIMIT=7*SPLEVEL= 1.75 * DCLEVEL
        NOP
        NOP
        MOVE.W    D1,D7
        ASR.W     £$3,D7
        ADD.W     D1,D7
        MOVE.W    D7,SWLEVEL            *SW DETECTION LEVEL = DC + DC/8

        ASL.W     £$1,D1                *MAX SW-LEVEL = DC LEVEL * 2,00
        MOVE.W    D1,MAXSWLEV           *(HIGH-AMPLIT. SPIKES ALSO CAUSE
        NOP                             *HIGH-AMPLIT. SIGNALS AT THE LPFIL OUT)
        NOP
        SUB.W     DCLEVEL,D6
        MOVE.W    D6,SAMPLE             *STORE [illegible] SAMPLE

*[illegible] DETECTOR STARTS HERE (FIR FILTER)

        MOVE.L    ADR1,A0               *(A0) --- x(0)
        MOVE.L    ADR35,A1              *(A1) --- x(n-(N-1))
        MOVE.L    ADRW,A2               *(A2) --- h(0)
        CLR.L     D2                    *R[illegible] (M) IS STORED IN D2

[illegible]     CLR.L     D0
        CLR.L     D1
        MOVE.W    (A0)+,D0              *D0 = x(n)     &     A0 = A0 + 2
        ADD.W     -(A1),D0              *A1 = A1 - 2   &   D0 = x(n) + x(n-(N-1))
        MOVE.W    (A2)+,D1              *D1 = h(n)     &     A2 = A2 + 2
        MULS.W    D1,D0                 *x(n).h(n)
        ADD.L     D0,D2                 *SUMMATION
        CMP.L     £$30010,A2            *IS h(n) = h((N-1)/2 -1) ?
        BGT.S     LASTSUM               *IF GREATER, SUM THE LAST TERM. OTHERWI-
        ADDQ.W    £$2,A0                *SE, A0 = A0 + 2 (equivalent to h(n)=0)
        SUBQ.W    £$2,A1                *A1 = A1 - 2
        JMP       SUM
LASTSUM MOVE.W    (A0),D0               *D0 = x(n - (N-1)/2)
        MOVE.W    (A2),D1               *D1 = h((N-1)/2)
        MULS.W    D1,D0
        ADD.L     D0,D2

*SHIFT DATA  X(1) <== X(2) <== X(3)...x(n) <== INPUT SAMPLE

        MOVE.L    ADR1,A0               *A0=$[illegible]
        MOVE.L    A0,A1                 *A1=$[illegible]
        ADDQ.L    £$2,A1                *A1 [illegible] (n+1) ADDRESS [illegible]

        [illegible].W    (A1)+,(A0)+          *[illegible] (n) (WITH AUTOINCREMENT
        CMP.L     £$30148,A0            *[illegible] SAMPLES TO BE SHIFTED
        [illegible]     SHIFT                 *[illegible] (NUMBER OF ADDRESSES)
```

```
*CUBIC FILTER

          DIVS.W    N,D2                *SUMMATION/N = yspk(m)
          EXT.L     D2                  *EXTEND THE MSB FROM WORD TO LONGWORD
          DIVS.W    ATTEN1,D2           *ATTENUATE yspk(m)   IF NECESSARY
          AND.L     £$FFFF,D2           *D2 = y(n) = yspk(m)  (ATTENUATED)

          MOVE.W    D2,D7               *SAVE y(n)
          MULS.W    D7,D2               *y(n)^3 ==>SMALL VALUES TEND TO ZERO
          MULS.W    D7,D2               *AND NEG. VALUES ARE KEPT NEGATIVE
          DIVS.W    ATTEN2,D2           *ATTENUATE OUTPUT

          NOP                           *BOTH SPIKE DETECTOR OUTPUT (D7) AND THE
          NOP                           *CUBIC FILTER OUTPUT MUST BE ADDED TO
          NOP                           *A CONSTANT LEVEL BEFORE BEING SENT TO
          NOP                           *THE OUTPUT [ADD.W £$50,D7;ADD.W £$10,D2]
          NOP                           *
          NOP

* ILL AMPLITUDE COMPARATOR    (AMPLITUDE LIMITING)

          CMP.W     SPLEVEL,D2          *IF yspk(m)^3 >   SPLEV., CLEAR D2
          BLT.S     CLEAR_D2            *OTHERWISE, MAKE D2 = SPLIMIT  AND
          MOVE.W    SPLIMIT,D2          *JUMP TO SPIKOUT
          BRA.S     SPIKOUT

CLEAR_D2  CLR.L     D2

*SPIKE-DETECTOR OUTPUT AFTER COMPARISONS (CUBIC FILTER OUTPUT = SPLIMIT OR 0)

SPIKOUT   MOVE.W    DCSAMPL,D6          *INPUT-SIGNAL SAMPLE
          NOP                           *INPUT SIGNAL
          NOP
          NOP
          NOP
          NOP
          MOVE.B    D2,(A5)             *z(n) ---> yspk(m)^3 AFTER COMPARISON

*FROM THIS POINT ON, THE SPFLAG IS SET, THE COUNTERS AND THE LOWPASS FILTER ARE
*ACTIVATED, ETC.

          BNE.S     ADDSAMP             *IF D2=0, CHECK THE VALUE OF SPIKSAMP.
*                                       *OTHERWISE, ADD £1 TO SPIKSAMP

SAMPCHEC  MOVE.W    SPIKSAMP,D7         *IF THE NUMBER OF SIGNIF. SPIKE-SAMPLES
          BEQ.S     LPFIL               *IS = 0, GOTO LPFIL (NO SPIKE HAS BEEN
          CMP.W     SPIKEMIN,D7         *DETECTED YET). IF IT IS > SPIKEMIN,
          BHI.S     SETSPFLG            *INCREASE SPIKSAMP (SPIKE IS BEING PROC.)
*                                       *OTHERWISE, A SPIKE HAS BEEN DETECTED.
*                                       *THEN, SET THE SPIKE FLAG (SETSPFLG)

ADDSAMP   ADD.W     £$1,SPIKSAMP        *ADD £1 TO SPIKE-SAMPLE COUNTER AND
          BRA.S     LPFIL               *BRANCH TO LPFIL.

SETSPFLG  BSET.B    £$1,SPFLAG          *SET THE SPIKE FLAG
          ADDQ.W    #1,SPIKSAMP         *INCREMENT THE SPIKE COUNT
```

```
          CLR.W     M                    *CLEAR M_COUNTER, SAWFLAG AND SPIKSAMP
          CLR.W     SAWFLAG
          CLR.W     SPIKSAMP

*LOWPASS FILTER (SAMPLING FREQUENCY = 200 Hz  ===> LPFCLOCK MUST BE = 3)

LPFIL     BTST.B    #1,CLOCKFLG          *IF LPFCLOCK=3 (CLOCK_FLAG IS SET), THE
          BNE.S     LPF_INP              *SAMPLE IS PROCESSED. OTHERWISE, KEEP
          MOVE.W    LPFMEM,D0            *THE LAST LPF-OUTPUT VALUE AND SKIP
          JMP       LPF_OUT              *THE LPF ROUTINE

LPF_INP   CLR.W     CLOCKFLG             *CLEAR THE CLOCK_FLAG
          MOVE.W    DCSAMPL,D6           *INPUT SAMPLE

*LOWPASS FILTER  SUBROUTINE

*CALCULATES THE RUNNING-MEAN VALUE

          MOVE.L    LPF_PTER,A0          *A0 POINTS TO THE OLDEST-SAMPLE ADDRESS.
          CMP.L     ENDPOIN2,A0          *IS THIS THE LAST MEM LOCATION IN STACK?
          BLS.S     MEAN1                *IF NOT, CALCULATE THE MEAN VALUE
          MOVE.L    LPF_BEGP,LPF_PTER    *OTHERWISE, GOTO TO THE FIRST MEMOR
MEAN1     MOVE.L    LPF_PTER,A0          *LOCATION
          CLR.L     D0
          CLR.L     D1
          MOVE.W    D6,D0                *x(n)
          MOVE.L    K_LPMEAN,D1          *K.MEAN
          MOVE.W    (A0),D2
          AND.L     #$FFFF,D2            *D2=OOOx
          SUB.L     D2,D1                *K.MEAN - OLDEST SAMPLE = D1
          ADD.L     D0,D1                *D1 = D1 + NEW SAMPLE
          MOVE.W    D0,(A0)+             *OLDEST SAMPLE IS REPLACED BY NEW.
          MOVE.L    A0,LPF_PTER          *AND POINTER = A0 = former A0    +    2
          MOVE.L    D1,K_LPMEAN          *STORE K.MEAN
          DIVS.W    K2,D1                *FIRST MEAN VALUE
          AND.L     #$3FF,D1             *MAXIMUM INPUT VALUE = 3FF ---> 5 V
          CLR.L     D0
*BUTTERWORTH 1ST-ORDER
          MOVE.W    D1,XN                *STORE x(n)
          MOVE.W    D1,D0                *
          ADD.W     XN_1,D0              *x(n) + x(n-1)
          MULS.W    COEF1,D0             *COEF1*(x(n) + x(n-1))
          MOVE.W    YN_1,D1
          MULS.W    COEF2,D1
          ADD.L     D1,D0
          DIVS.W    COEF3,D0             *ASR #..,D0 MAY BE USED (BEFORE, THE USER
          AND.L     #$FFFF,D0            *SHALL CALCULATE THE OTHER COEFFICIENTS)

          MOVE.W    D0,YN_1
          MOVE.W    XN,XN_1
          MOVE.W    D0,LPFMEM            *LPF-OUTPUT

*LOWPASS FILTER OUTPUT
```

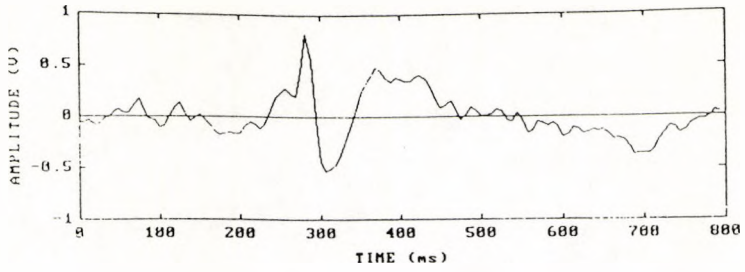
```
        NOP

*CHECK OUTPULSE FLAG

        BTST.B    £#1,OUTFLAG          *IF OUTPULSE IS SET, THEN THE OUTPUT
        BNE.L     PULSOUT              *IS ACTIVE (SAWC HAS BEEN DETECTED).

*CHECK ARTIFACT FLAG

        BTST.B    £#1,ARTFLAG          *IF ARTFLAG IS SET, Vin = DCLEVEL DURING
        BEQ.S     CHECSPFL             *THE NEXT 1000 ms (600 SAMPLES)
        ADDQ.W    £#1,T
        MOVE.W    T,D7
        CMP.W     £#258,D7             *IS T = 1s (&600)
        BLT.L     OUTNIL
        JMP       RESET1


*CHECK SPFLAG

CHECSPFL BTST.B   £#1,SPFLAG           *IF SPFLAG IS NOT SET (ZERO FLAG IS SET)
        BEQ.S     OUTNIL               *THEN Vo = 0

*LPF OUTPUT LEVEL IS COMPARED WITH MAXSWLEV

        CMP.W     MAXSWLEV,D0          *IF LPF OUT-LEVEL > MAXSWLEV,THEN IT
        BLE.S     CHECKMIN             *MUST BE AN ARTIFACT (SET ARTFLAG)
*                                      *OTHERWISE, CHECK M_MIN (75 ms)
SETARTFL BSET.B   £#1,ARTFLAG
        JMP       OUTNIL

*M_MIN IS CHECKED

CHECKMIN MOVE.W   M,D7
        CMP.W     M_MIN,D7             *THE LPF OUT-LEVEL STARTS TO BE CHECKED
        BLE.S     COUNTERS             *75 ms AFTER THE SPIKE DETECTION.

*SAWFLAG IS CHECKED

        BTST.B    £#1,SAWFLAG          *IF SAWFLAG IS SET, THEN CHECK M.
        BNE.S     CHECK_M              *OTHERWISE, CHECK THE LPF OUT-LEVEL.

*LPF OUTPUT LEVEL IS COMPARED WITH SLOW-WAVE DETECTION LEVEL

        CMP.W     SWLEVEL,D0           *IF LPF OUT LEVEL > SWLEVEL, THEN GOTO
        BLT.S     COUNTERS             *COUNTERS.
        BSET.B    £#1,SAWFLAG          *OTHERWISE, SET SAWFLAG AND CHECK M.

*OBS: SPCOUNT MAY BE CHECKED EARLIER, IMMEDIATELY AFTER THE ADDITION (SPCOUNT
*     [illegible] IN "SETSPFLAG". IF SPCOUNT > 2, SETARTFL WITHOUT WAITING FOR M [illegible]
*     [illegible] BLACKIMMED.


CHECK M [illegible]  M,D0                 *IF M [illegible] MED, COUNTER IS INCREASED.
        [illegible]  M_MED,D0             *OTHERWISE, CHECK THE NUMBER OF SPIKES.
        [illegible]  COUNTERS             *IF [illegible] BEEN DETECTED, [illegible]
```

```
          MOVE.W    SPCOUNT,D0          *OTHERWISE, RESET COUNTERS AND FLAGS
          CMP.W     #$2,D0              *AND MAKE Vo = 0 (RESET1)
          BGT.S     RESET1              ***(IT MAY BE   BGT.S SETARTFL)
          BSET.B    #$1,OUTFLAG         *SET OUTFLAG (OUTPUT PULSE)
          BRA.S     PULSOUT

COUNTERS  ADDQ.W    #$1,M               *M = M + 1
          MOVE.W    M,D0                *IF T < = TMAX, Vo = 0
          CMP.W     M_MAX,D0            *OTHERWISE, RESET COUNTERS AND FLAGS
          BLE.S     OUTNIL              *(IT WAS JUST A SPIKE. PS: SAWFLAG
RESET1    BSR.S     RESET

OUTNIL    MOVE.W    LPFMEM,D7           *Vo = LPFIL OUTPUT
          MOVE.B    D7,(A6)

STATUSHI  MOVE.W    (A3),D7             *WAIT UNTIL STATUS GOES LOW
          AND.W     #$1,D7              *SAVE BIT "0"
          BNE.S     STATUSHI            *IF NOT = 0, GO STATHI

          BRA       STATUSLO            *NEXT SAMPLE - NOW, wait Lo

*SPIKE-AND-WAVE HAS BEEN DETECTED

PULSOUT   MOVE.B    #$E0,(A6)           *Vo = 1A
          MOVE.W    M_MED,D0            *OUTPUT PULSE IS ACTIVE WHILE COUNTER
          ADDI.W    #$16,D0             *(INCREASES FROM M_MED TO "M_MED+#$16"
          CMP.W     M,D0                *IF M = M_MED + $16, RESET COUNTERS AND
          BEQ.S     RESET1              *FLAGS AND MAKE Vo = 0 (RESET1).
ADD1      ADDQ.W    #$1,M               *OTHERWISE, INCREASE COUNTER AND GOTO
          BRA.S     STATUSHI            *STATUSHI

*RESET SUBROUTINES

RESET     CLR.W     SPFLAG              *SPIKE FLAG
          CLR.W     SPCOUNT             *SPIKE COUNTER
          CLR.W     SPIKSAMP            *SPIKE-SAMPLES COUNTER
          CLR.W     T                   *TIME-INTERVAL COUNTER
          CLR.W     M                   *SAMPLE COUNTER
          CLR.W     SAWFLAG             *SPIKE-AND-WAVE FLAG
          CLR.W     OUTFLAG             *OUTPUT-PULSE FLAG (Vo = 1)
          CLR.W     ARTFLAG
          RTS

          END
```

APPENDIX C

ADDITIONAL EXAMPLES OF

THE WIGNER DISTRIBUTION OF SAWCs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-0.5
-1
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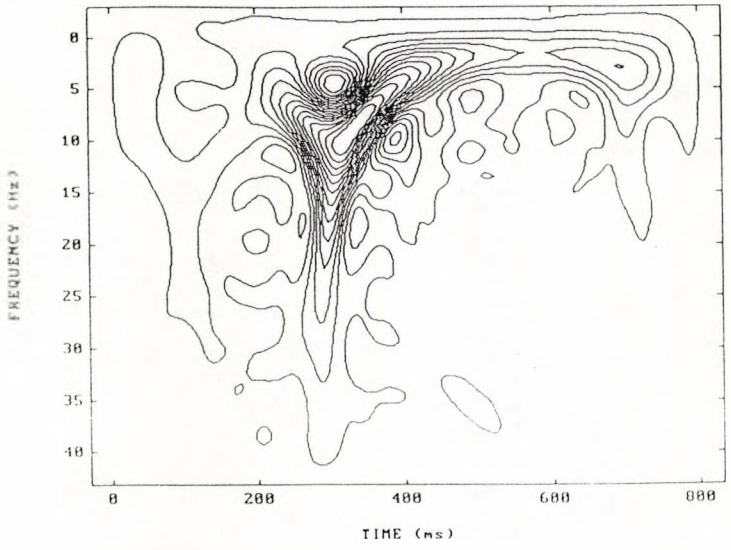
400
500
600
700
800
TIME (ms)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400
600
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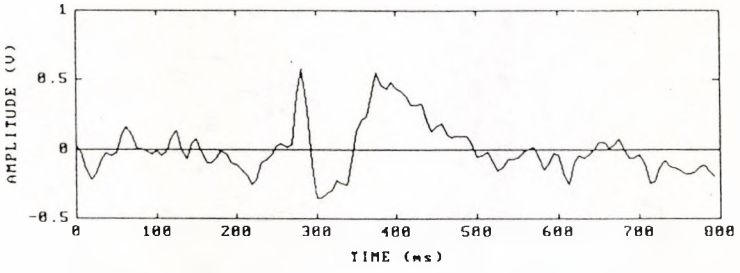
TIME (ms)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-0.5
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100
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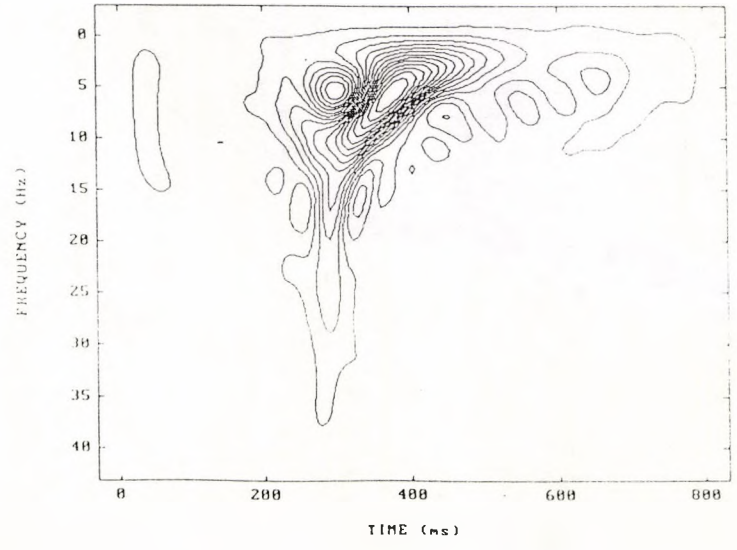
400
500
600
700
800
TIME (ms)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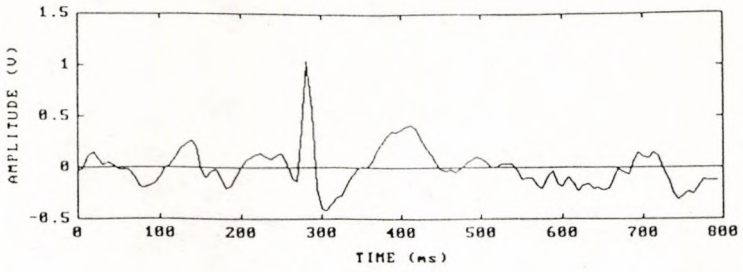
TIME (ms)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-0.5
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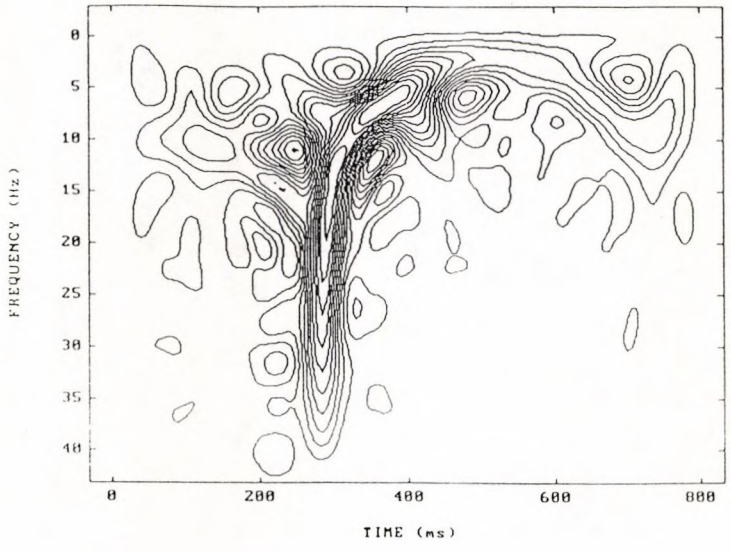
TIME (ms)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600
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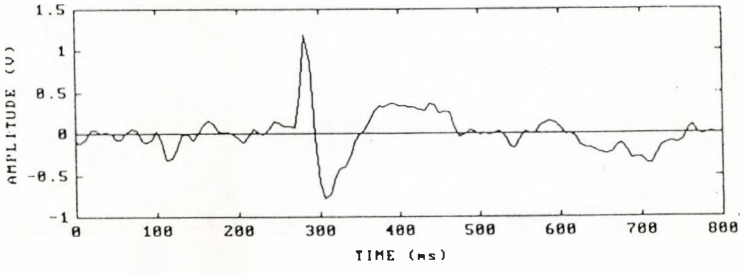
TIME (ms)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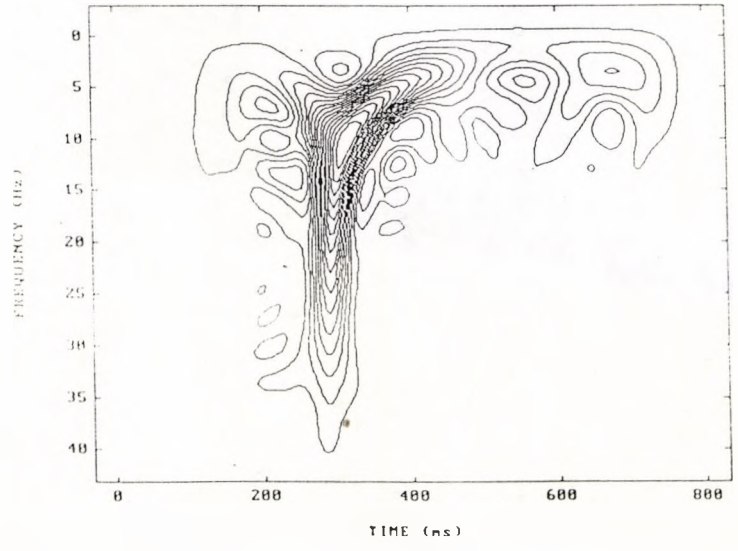
TIME (ms)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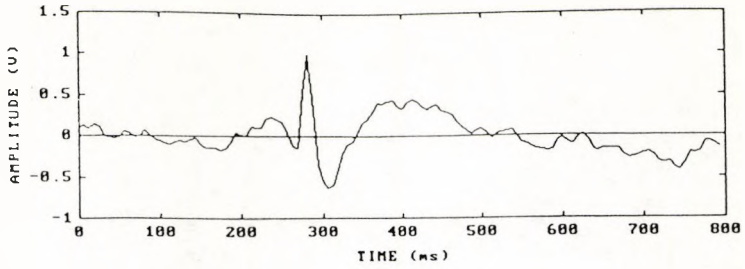
TIME (ms)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-0.5
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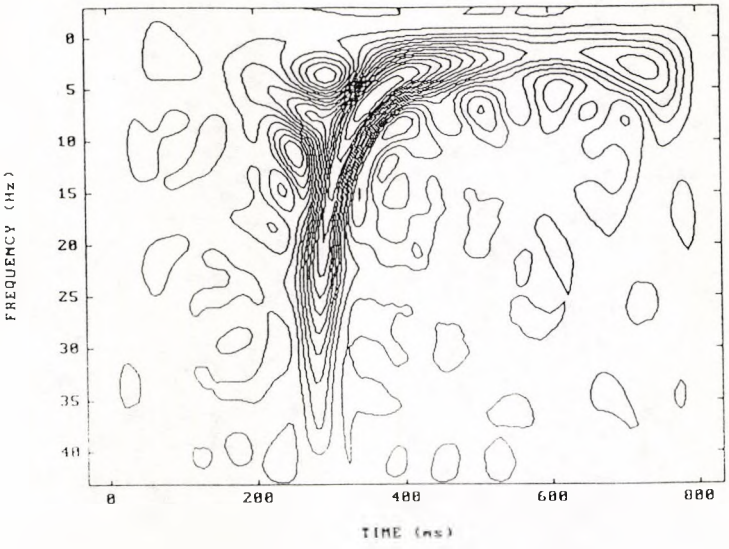
TIME (ms)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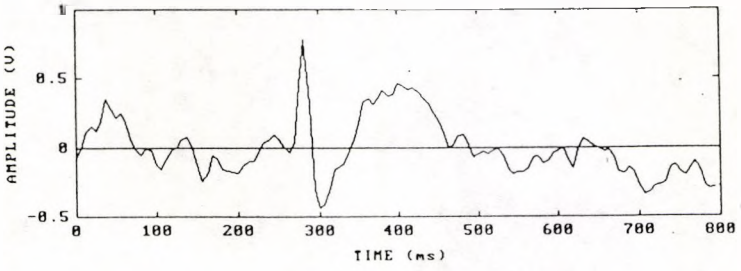
TIME (ms)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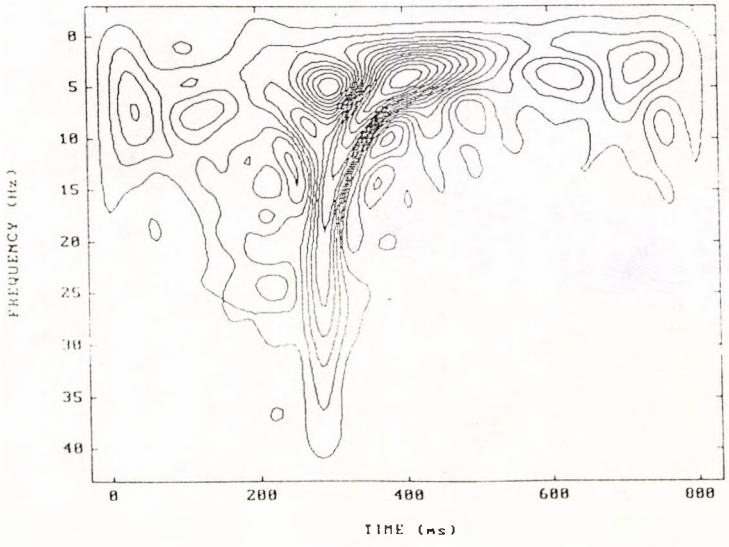
TIME (ms)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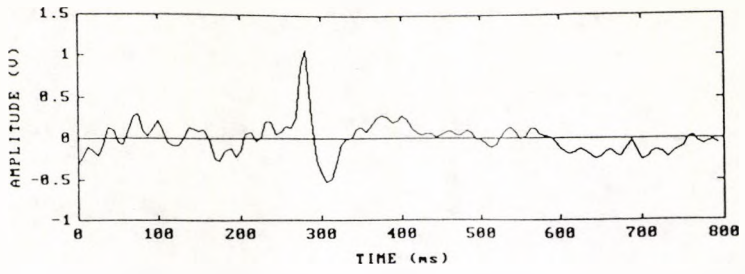
800
TIME (ms)


AMPLITUDE (V)
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0.5
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-0.5
-1
0
100
200
300
400
500
600
700
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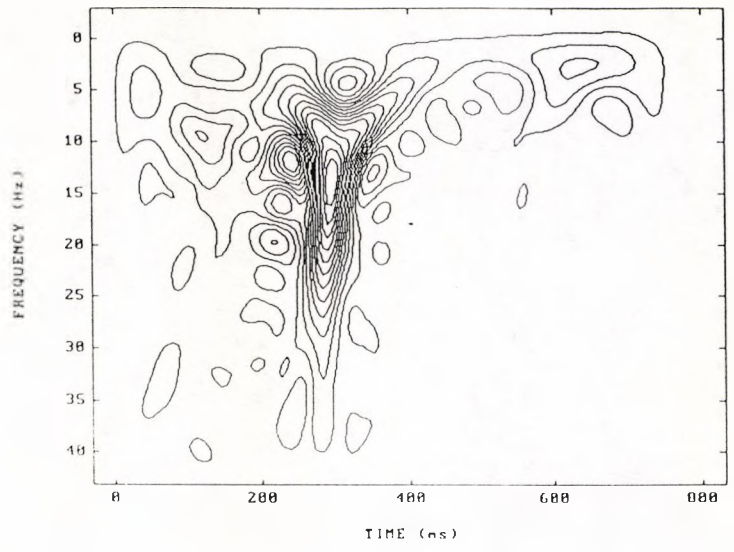
TIME (ms)


FREQUENCY (Hz)
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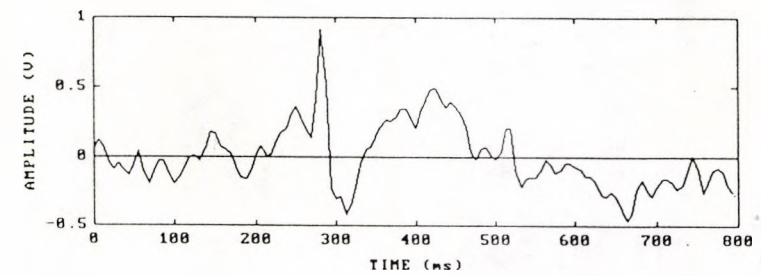
200
400
600
800
TIME (ms)


AMPLITUDE (V)
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0.5
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-0.5
0
100
200
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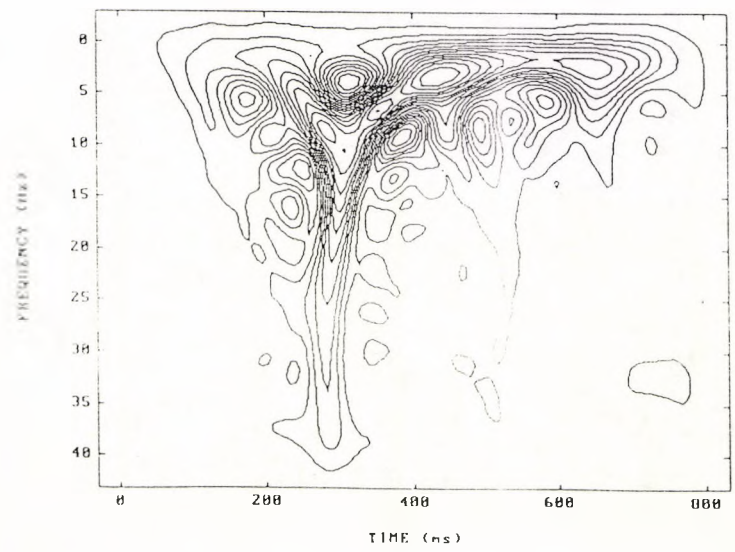
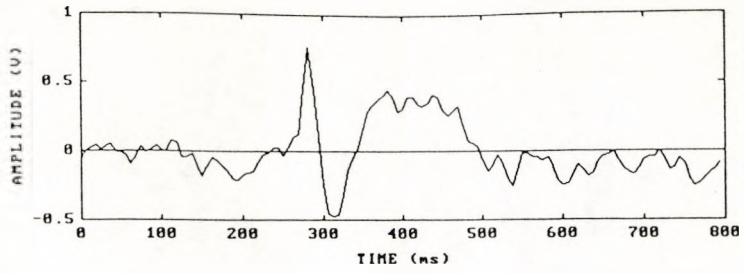
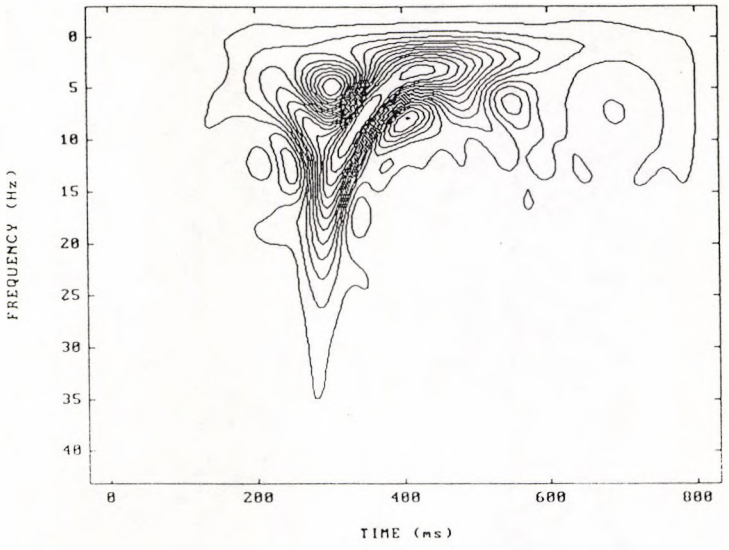
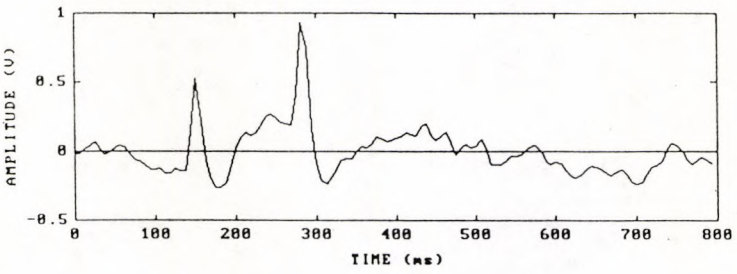
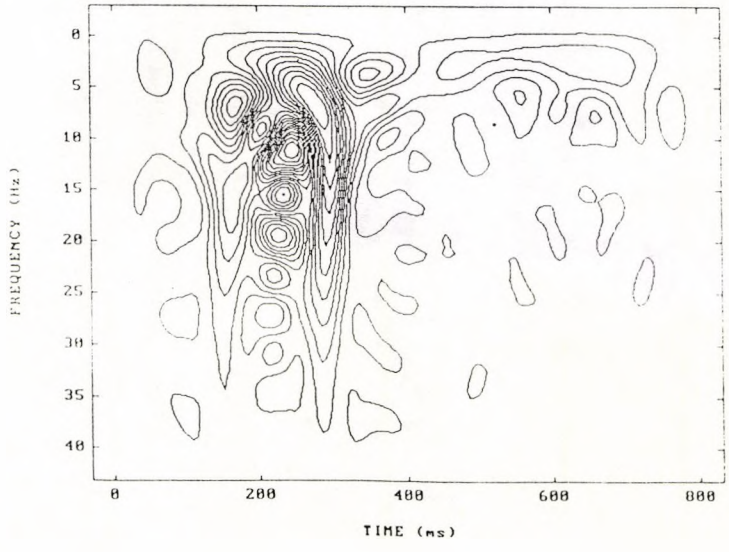
500
600
700
800
TIME (ms)


FREQUENCY (Hz)
0
5
10
15
20
25
30
35
40
0
200
400
600
800
TIME (ms)


AMPLITUDE (V)
1
0.5
0
-0.5
0
100
200
300
400
500
600
700
800
TIME (ms)


FREQUENCY (Hz)
0
5
10
15
20
25
30
35
40
0
200
400
600
800
TIME (ms)


AMPLITUDE (V)
1
0.5
0
-0.5
0
100
200
300
400
500
600
700
800
TIME (ms)


FREQUENCY (Hz)
0
5
10
15
20
25
30
35
40
0
200
400
600
800
TIME (ms)

APPENDIX D

WIGNER DISTRIBUTION ALGORITHM

```
%     WIGNER DISTRIBUTION
%
%     NECESSARY VARIABLES IN WORKSPACE:
%
%     x ---> vector with a maximum number of 256 elements
%
%     RESERVED VARIABLE NAMES:
%
%     y1  y2  y3  y4  p  q  q1  t w zero
%
%
%    The parts of the  program that  precede and  follow  the
%    calculation of the unsmoothed WD were added to the original
%    program written by E. T. COSTA (1989).

clear

load eg7r.mat;                  % Load data file or write equation
x=eg7-mean(eg7);                % "x" is the time variable.
clear eg7

clc;home
K=max(size(x));
k=0:K-1;
zero=0*k;
fs=160;                         % Sampling frequency=160 Hz.
t=k*1000/fs;
plot(t,x,t,zero);               % Time in "ms".
title('INPUT SIGNAL')
xlabel('TIME (ms)')
ylabel('AMPLITUDE (V)')
pause

%       WIGNER DISTRIBUTION (unsmoothed)

n=max(size(x));
[y1,y2]=analytic(x);
[y3,y4]=resize(y1,y2,n);
clear y1 y2
pack
w=slide1(y3,y4,n);
clear y3 y4
pack
p=wigfft(w);
clear w
pack
mesh(p)
title('UNSMOOTHED WD')
pause
contour(p,17)
title('UNSMOOTHED WD')
xlabel('TIME ')
ylabel('FREQUENCY ')
pause
```

```
%    SMOOTHING PROCESS AND GRAPH DISPLAY

clg
p=p(1:n/2,:);                  % Smooth only a half of the
                               % original WD.
a=5;b=5;alpha=12;beta=12;      % Coefficients used to determine the
q=smooth(p,a,b,alpha,beta);    % the 2-D Gaussian function.
pack

%    CONTOUR PLOT WITH REAL SCALES

% time (ms)        --->  left to right
% frequency (Hz)   --->  bottom to top

[linefreq,colutime]=size(q);
N=colutime-2*a;
J=N/(linefreq-2*b);

tmin=0;
tmax=max(size(x))*1000/fs;
fmin=0;
fmax=fs/2;

dt=(tmax-tmin)/(N-1);
df=(fmax-fmin)/(N-1);

t=(tmin-a*dt:dt:tmax+a*dt);
f=(fmin-b*df:df:fmax/J+b*df);

mesh(q)                        % The original matrix is displayed
title('SMOOTHED WD')           % in three dimensions
pause
clg

contour(q,17,t,-fs/(2*J)+f)    % The "-" signals, which appear
xlabel('TIME (ms)')            % in the frequency axis, shall
ylabel('FREQUENCY (Hz)')       % be eliminated manually.
title('SMOOTHED WD (eliminate the "-" signals manually)')
pause
clg

%    ROTATE THE ORIGINAL MATRIX

q1=rot90(q');                  % The original matrix is rotated
mesh(q1)                       % 180° and displayed in three
title('SMOOTHED WD')           % dimensions.
pause
clg

contour(q1,17,t,f)
title('SMOOTHED WD')
xlabel('TIME (ms)')
ylabel('FREQUENCY (Hz)')

end
```

```
%    SUBROUTINES

% The function ANALYTIC(X) determines the analytic signal
% associated with the sampled signal x(t).
%
% It implements the following algorithm:
%
%      1) find y=fft(x);
%      2) zero out the "negative frequencies"
%      3) multiply all elements by 2, except the first one (DC);
%      4) find y1=ifft(y);
%      5) y2=complex conjugate of y1
%
%  Calling: [y1,y2]=analytic(x).
%

function [y1,y2]=analytic(x)
n=max(size(x));
y=fft(x);
y=y(1:n/2);
y(n)=0;
y=2.*y;
y(1)=y(1)./2;
y1=ifft(y);
y2=conj(y1);
end

%    The function RESIZE(y1,y2,n) creates two new vectors
%    y3 and y4 so that:
%    1) y3 has its last "n" elements equal to zero and the first
%       elements equal to the elements of y1. If y1 has "n"
%       elements, y3 will have "2*n" elements;
%    2) y4 has its first "n" elements equal to zero and the
%       remaining elements equal to the elements of y2. If y2
%       has "n' elements, y4 will have "2*n" elements.
%
%    CALLING: [y3,y4]=resize(y1,y2,n)
%

function [y3,y4]=resize(y1,y2,n);
m=length(y1);
l=length(y2);
n1=0:n-1;
y3(m+1:m+n)=0*n1;
y3(1:m)=y1;
y4(l+1:l+n)=y2;
end
```

```
%     The function SLIDE1(y3,y4,n) performs the point by point
%     multiplication of y3 by y4 such that:
%
%     1) the 1st row contains y3(1:n).*y4(1:n)
%     2) the 2nd row contains y3(2:n+1).*y4(0:n-1)
%     3) the nth row contains y3(n:2*n-1).*y4(-n+1,1)
%     4) the 1st row is divided by 2;
%
%     To improve speed performance, the matrix is created in
%     blocks (smaller matrices) with n/16 columns by 1 row.
%
%     CALLING: a=slide1(y3,y4,n)
%

function a=slide1(y3,y4,n);
clc
j=n-1;
k=n+2;
m=2*n+1;
for i=1:n/16
     a(i,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
a(1,:)=a(1,:)./2;
for i=n/16+1:2*n/16
     a1(i-n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=2*n/16+1:3*n/16
     a2(i-2*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=3*n/16+1:4*n/16
     a3(i-3*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=4*n/16+1:5*n/16
     a4(i-4*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=5*n/16+1:6*n/16
     a5(i-5*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=6*n/16+1:7*n/16
     a6(i-6*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=7*n/16+1:8*n/16
     a7(i-7*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=8*n/16+1:9*n/16
     a8(i-8*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
```

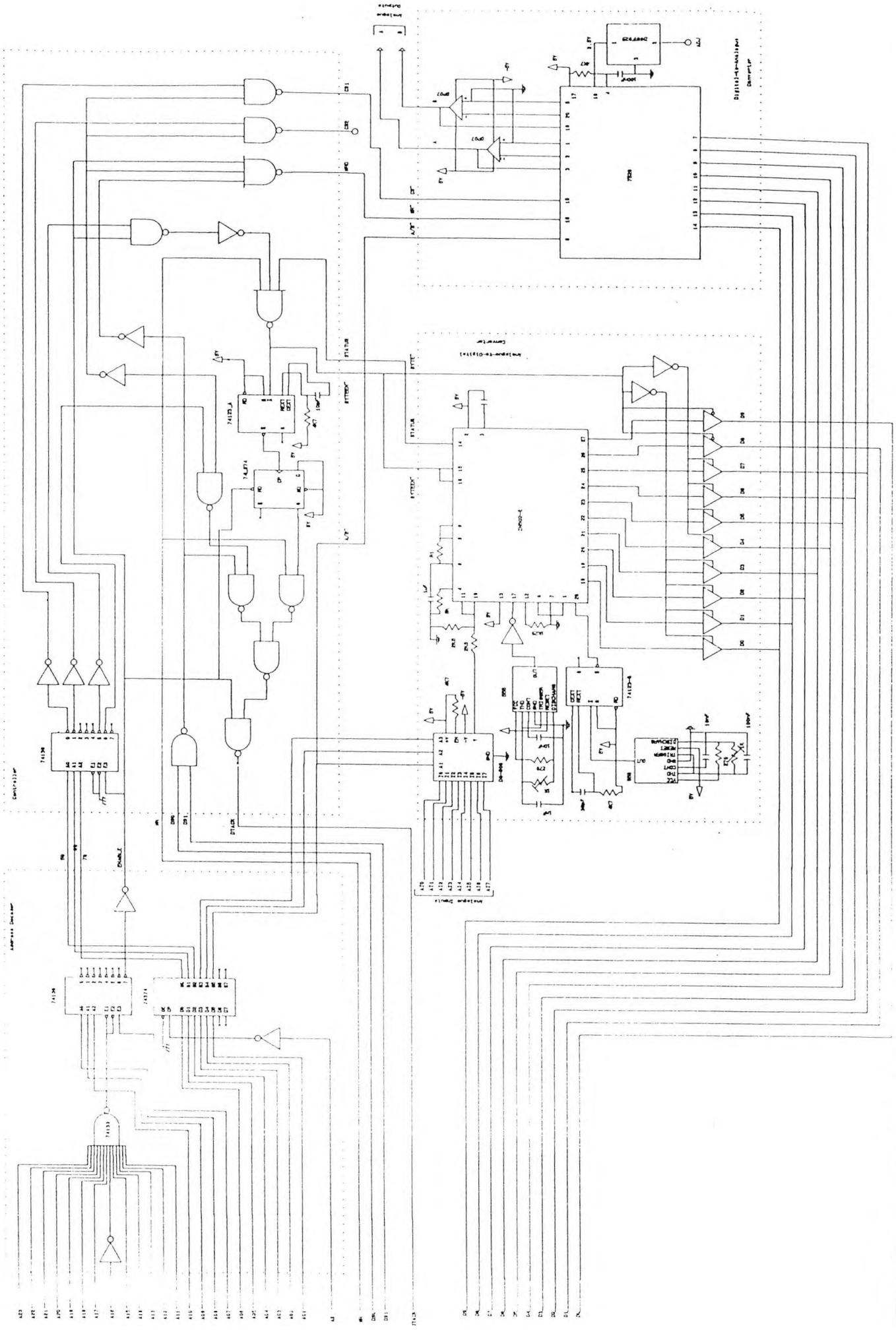
```
for i=9*n/16+1:10*n/16
     a9(i-9*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=10*n/16+1:11*n/16
     a10(i-10*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=11*n/16+1:12*n/16
     a11(i-11*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=12*n/16+1:13*n/16
     a12(i-12*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=13*n/16+1:14*n/16
     a13(i-13*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=14*n/16+1:15*n/16
     a14(i-14*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end
for i=15*n/16+1:n                                          % :16*n/16
     a15(i-15*n/16,:)=y3(i:j+i).*y4(k-i:m-i);
home;i
end


%    CREATING THE FINAL MATRIX

a(n/16+1:2*n/16,:)=a1;
a(2*n/16+1:3*n/16,:)=a2;
a(3*n/16+1:4*n/16,:)=a3;
a(4*n/16+1:5*n/16,:)=a4;
a(5*n/16+1:6*n/16,:)=a5;
a(6*n/16+1:7*n/16,:)=a6;
a(7*n/16+1:8*n/16,:)=a7;
a(8*n/16+1:9*n/16,:)=a8;
a(9*n/16+1:10*n/16,:)=a9;
a(10*n/16+1:11*n/16,:)=a10;
a(11*n/16+1:12*n/16,:)=a11;
a(12*n/16+1:13*n/16,:)=a12;
a(13*n/16+1:14*n/16,:)=a13;
a(14*n/16+1:15*n/16,:)=a14;
a(15*n/16+1:n,:)=a15;
end
```

```
%     The function WIGFFT(b) performs the Fourier Transformation
%     on the matrix formed by the sliding function. Only the real
%     part of FFT is required and, to improve speed, smaller
%     matrices (n X n/16) are formed before the final result is
%     obtained.
%
%     CALLING: a=wigfft(b);
%

function a=wigfft(b);
clc
n=length(b);
a1=real(fft(b(:,1:n/16)));home;i=1
a2=real(fft(b(:,n/16+1:2*n/16)));home;i=2
a3=real(fft(b(:,2*n/16+1:3*n/16)));home;i=3
a4=real(fft(b(:,3*n/16+1:4*n/16)));home;i=4
a5=real(fft(b(:,4*n/16+1:5*n/16)));home;i=5
a6=real(fft(b(:,5*n/16+1:6*n/16)));home;i=6
a7=real(fft(b(:,6*n/16+1:7*n/16)));home;i=7
a8=real(fft(b(:,7*n/16+1:8*n/16)));home;i=8
a9=real(fft(b(:,8*n/16+1:9*n/16)));home;i=9
a10=real(fft(b(:,9*n/16+1:10*n/16)));home;i=10
a11=real(fft(b(:,10*n/16+1:11*n/16)));home;i=11
a12=real(fft(b(:,11*n/16+1:12*n/16)));home;i=12
a13=real(fft(b(:,12*n/16+1:13*n/16)));home;i=13
a14=real(fft(b(:,13*n/16+1:14*n/16)));home;i=14
a15=real(fft(b(:,14*n/16+1:15*n/16)));home;i=15
a16=real(fft(b(:,15*n/16+1:n)));home;i=16          % :16*n/16

a=[a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 a13 a14 a15 a16];

clear a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 a13 a15 a16

a=2*a/n;
end
```

```
%     SMOOTH.M


%     The function SMOOTH(p) filters the original Wigner
%     Distribution in order to remove the artifacts caused by
%     crossterms.
%     It convolves the unsmoothed WD (p) with a two-dimensional
%     Gaussian function determined by "a", "b", "alpha" and
%      "beta".

%     The values of "a", "b", "alpha" and "beta" may be changed

%     CALLING: q=smooth(p,a,b,alpha,beta);

function q=smooth(p,a,b,alpha,beta);
j=-a:1:a;
k=-b:1:b;
[x,y]=meshdom(j,k);
l=exp(-x.^2/alpha-y.^2/beta)/(alpha*beta);  % Gaussian function
clc;home
s='SMOOTHING'
q=conv2(l,p);
clc;home
end
```

APPENDIX E

68000-SYSTEM DATA ACQUISITION UNIT



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