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**Singh, Avtar**

**AUTOMATIC WAVEFORM DETECTION AND MODEL PARAMETER  
ESTIMATION FOR OPTOKINETIC NYSTAGMUS**

*City University of New York*

**Ph.D. 1982**

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AUTOMATIC WAVEFORM DETECTION AND MODEL PARAMETER ESTIMATION  
FOR OPTOKINETIC NYSTAGMUS

by

AVTAR SINGH

A dissertation submitted to the Graduate  
Faculty in Engineering in partial fulfillment of  
the requirements for the degree of Doctor of Philosophy  
The City University of New York

1982

This manuscript has been read and accepted by the Graduate Faculty  
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Abstract

AUTOMATIC WAVEFORM DETECTION AND PARAMETER ESTIMATION  
FOR  
OPTOKINETIC NYSTAGMUS

by

Avtar Singh

Adviser: Professor Frederick E. Thau

The purpose of this dissertation is to contribute to a precise understanding of the oculomotor system responsible for eye movements. The attempt to acquire this understanding is made through the signal processing of oculomotor responses and the parameter estimation of a model for the generation of slow eye movements. The slow eye movement system is important since it describes the tracking capability of the eye and thus gives clues to the pathological state of the neural system where these movements are generated.

In response to head rotation or to optokinetic stimulation, slow and rapid eye movements are made which together form nystagmus. The first step in the analysis of an eye movement record is to develop an algorithm that separates the slow and quick phase eye movements. These movements can then be related to the oculomotor system parameters and to the stimulus. The most commonly used technique for recording eye position, electrooculography (EOG), records muscle and skin artifacts along with changes in eye position. Thus one must identify and distinguish between waveforms in the presence of noise.

The detection algorithm presented in this dissertation compares a window of eye position samples to functional representations of quick and slow eye movements. Based upon minimizing the probability of error,

a decision function is formulated. Its value is then compared to a threshold to determine whether the latest sample in the window belongs to a slow or a rapid eye movement. Two kinds of errors can be made in the detection process. The first kind is: when all the samples in the window are from one kind of movement and it is detected as the other kind. This kind of error is due to the inherent noise on the samples. The second kind of error occurs when the data window consists of samples from both kinds of movements. This error is due to the frequency of transitions between movements, the temporal relations between movements and the window width used. An expression for the probability of error accounting for both kinds of errors is derived.

Once a quick phase or a saccade has been detected, it is removed by subtracting the saccadic jump and extrapolating the slow eye position during a saccade. This generates a cumulative slow phase position whose differentiation yields the slow phase eye velocity. The differentiator algorithm is based on least squares straight line fit to the data. The saccadic detection, the cumulative slow phase position, and slow phase velocity generation algorithms are implemented on a mini-computer for real-time signal processing. The implementation allows a sampling interval as small as 2msec and can be controlled from external inputs for optimal performance.

The slow phase velocity as obtained from the processing of an optokinetic nystagmus is utilized in the parameter estimation of a model for the system which generates optokinetic nystagmus (OKN) and optokinetic after-nystagmus (OKAN). The parameter estimation is based upon a least squares curve fitting technique which is implemented to generate recursively the model parameters. The parameter estimation obtained in this manner is used to evaluate the OKN and OKAN model. The estimation and evaluation programs are written in assembly language for optimization and on-line processing.

Contribution of this research lie in the application of detection theory, nonlinear digital filtering, and parameter estimation to the analysis of the oculomotor system. The implementation of various algorithms for the real-time signal processing and the on-line parameter estimation is another contribution of this dissertation. The direction chosen here has a great potential for further investigations.

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Avtar Singh

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## CHAPTER 1

## INTRODUCTION

1.1 Rationales and Motivation

This dissertation is concerned with the signal processing involved in detecting rapid eye movements during nystagmus induced by optokinetic and vestibular stimuli. The detection must be done in the presence of noise since the most commonly used eye movement recording techniques such as electrooculography (EOG) are noisy due to muscle and skin artifacts as well as electrode noise. The problem then becomes one of distinguishing between two waveforms i.e. the slow phase and quick phase in the presence of noise. In order to derive a slow phase eye velocity response waveform, the quick phase movements must be suppressed and the resulting position waveform be differentiated. Therefore, the signal processing involves extrapolation and differentiation of noisy signals.

A second problem addressed in this dissertation is the parameter identification of a model for the generation of optokinetic nystagmus and optokinetic-after nystagmus (OKN and OKAN). In the design of signal processing and parameter identification algorithms, an important consideration in this thesis is their implementation on a small general-purpose computer.

Recent studies on nystagmus generation have uncovered basic mechanisms underlying the generation of the slow phases of nystagmus. In addition, relationships have been found relating characteristics

of slow phase eye velocity of nystagmus to head velocity and surround velocity. It has thus become important to analyze slow phases of nystagmus in pathological states to determine which parameters of the slow eye movements are modified. Parametric models for the generation of nystagmus are important, since these models lead to a better understanding of functional aspects of brain structures controlling the oculomotor system response. In addition, parameters of a slow phase system model have the potential of being used in the diagnosis procedure. The computer implementation of signal processing and parameter identification techniques is important from the point of view of real-time and on-line analysis of oculomotor system responses.

The approach taken in this dissertation for the problem described above is as follows. As a first step, a technique based upon 'Baye's likelihood ratio detector' for the detection of quick phases/saccades is developed and implemented on a computer. 'Baye's likelihood ratio detector' which minimizes the probability of detection error is used to derive a sufficient statistic, the value of which leads to assign a window of data to one of the two processes namely quick phase or a slow phase. The implementation of this technique is easier and the detector equations can be used to compute the probability of error for given noise contents and other processing errors.

The next step of signal processing involves generation of a waveform which exclusively represents the slow phase system response. This is done by subtracting the saccadic jump and piecing together

slow phases of nystagmus. The gap left by the saccadic interval is bridged by an extrapolated waveform. The error introduced by extrapolation is likely to be negligible as the saccadic intervals are far smaller than the slow phase intervals. The waveform generated in this manner represents cumulative slow phase position which when differentiated yields slow phase eye velocity. The differentiator algorithm must satisfy the conditions that it is fast enough to keep the program cycle time small and be relatively immune to noise in the signal. The least squares straight line fit to the data yields such an algorithm for the digital differentiator.

The model for the neural mechanism generating slow phases of optokinetic and optokinetic-after nystagmus has been proposed by Raphan and Cohen [8]. The signal processing scheme described in this thesis yields the waveforms needed to carry out such an identification. A least squares curve fitting technique is considered to derive model parameters. This identification technique when implemented, recursively generates the model parameters fast enough so that the leading edge of the step response is appropriately utilized.

## 1.2 Historical Background

There are three aspects of the problem considered in this thesis. These are detection of quick/saccadic eye movement in an eye movement record, the generation of slow phase responses, and the parameter identification of a model for the generation of slow phase response.

Despite the fact that the detection theory provides basis for dealing with many signal processing problems [38], to-date it has not

been used to process oculomotor response signals. An old analog technique due to Henriksson [16] is still very popular, since it is easy to use. This technique along with other detection and slow phase response generation methods is discussed in detail in chapter 3. The newer saccadic detection and slow phase response generation methods known as MITNYS and MITNYS-II are from a group working at MIT [2], [37]. These are computer-oriented techniques and provide a variety of signal waveforms for the understanding of oculomotor system. These techniques are reviewed in chapter 3. The detection processes in both these techniques are cumbersome and do not provide any mathematical basis for predicting their performance. A microprocessor-oriented oculomotor response analysis scheme was presented by Michaels et al [22] which is a step in the direction of portable instruments for this purpose. This technique, however, needs to be perfected to reduce the error-rate in the detection of saccades. In order to obtain eye velocity a number of differentiator algorithms are available [18], [20], [23], [34]. Most of these algorithms implement higher order transfer functions and therefore need large processing times. A simpler algorithm is needed to obtain slow phase eye velocity so that the detection and the slow phase eye velocity generation may be implemented in real-time.

In the area of parameter identification of a model for the slow phase generation in an OKN and OKAN response, work that is available is due to Raphan and Cohen [26], [8], [27]. In their work, the parameters are obtained manually and no on-line computer method has been developed to estimate parameters of the model. A number of on-line parameter identification techniques are available in the literature [17],

[6], [19], [35]. Most of these techniques apply only in cases where the input is rich enough to excite all the modes of a system. Traditionally, only the step response is available to estimate parameters of an OKN and OKAN model. Thus one must develop an on-line technique to estimate parameters from a given step response. The nonlinear structure of OKN and OKAN model has further constraints on an identification technique that can be used to yield a unique parameter set [13].

The next section outlines the dissertation organization and gives a brief description of the contents of subsequent chapters.

### 1.3 Organization of Dissertation

The presentation of this research effort is organized into 6 chapters described below:

Chapter 1 introduces the problem addressed and the motivation behind it. A brief historical background is given and the dissertation organization is described.

Chapter 2 is a study of essential response signals of an oculomotor system. These signals consist of periods of fixation, slow eye movements, and fast or saccadic eye movements. The laboratory techniques for the measurements of eye movements are described and evaluated. The quantitative characteristics of saccadic and slow eye movements are studied so as to formulate functional descriptions for them. Next, nystagmus along with its constituents slow and quick phase eye movements is defined. Two experimentally generated nystagmus waveforms, the vestibular nystagmus and optokinetic nystagmus are described and their

characteristics are studied. The study of properties of oculomotor control system signals is essential to the design of signal analysis algorithms and for the parameter identification of oculomotor control system models.

In chapter 3, the saccadic detection algorithm is derived based on 'Baye's likelihood ratio criterion'. The application of the detection algorithm to an EOG waveform is discussed. In section 3.3 an expression for the probability of error is derived. The probability of error expression considers two types of detection errors - one due to the noise in signal and the other due to the finite window width which contributes to delay in the detection of on-coming movements. The detection algorithm is implemented on a PDP-8/E computer and is tested on simulated EOG-like waveforms. The chapter closes with application of the detection algorithm to real EOG waveforms that demonstrates its usefulness as a saccadic detector.

Chapter 4 describes algorithms which were developed to generate the signals related to the slow phase eye velocity. These include cumulative slow phase position (CSPP) and the slow phase velocity (SPV). The detector of chapter 3 is used to mark the beginning and the end of saccadic movements. Once saccades are detected, saccadic jump is subtracted and the slow phases are bridged together using extrapolated slow phase positions during saccades. The extrapolation and the CSPP generation algorithms are described and implemented. Next an algorithm for a simple digital differentiator based upon least squares straight line fit is described and implemented. The complete signal processing technique consisting of detection of saccades, generation of CSPP and

SPV along with input output routines is implemented on a PDP-8/E computer. Simulated EOG-like waveforms are tested to evaluate its applicability in real situations. The last section shows the performance of this scheme on real EOG waveforms and also compares the results with currently used analog technique.

In chapter 5, the parameter identification of the slow phase system of oculomotor system is considered. Practical constraints are described which influence the choice of an on-line identification technique. In this work, the identification technique is based on familiar 'least squares fit' over a finite data window which leads to simplicity in computation and works recursively to generate the model parameters. The technique is used to identify parameters of a slow phase model for optokinetic and optokinetic-after nystagmus (OKN and OKAN). The chapter ends with an evaluation of the parameter identification technique as applied to OKN and OKAN generation.

The last chapter gives a summary of research and discusses possible extensions to this work. The recommendations for future research include theoretical developments, implementation techniques and hardware realization of an instrument for automated analysis of oculomotor responses.

## CHAPTER 2

### THE OCULOMOTOR CONTROL SYSTEM

#### 2.1 Introduction

The function of the oculomotor system is to move the eyes. The visual system and the vestibular system are the two primary inputs to this system. The vestibular system provides a compensatory mechanism to stabilize the environments during head movements. The visual system drives the oculomotor system to make compensatory eye movements when the visual field moves. In response to visual and vestibular stimuli all animals make combinations of two basic types of movements; quick or saccadic movements and slow or smooth pursuit movements. Saccades shift the gaze of the eye from one point to another and have peak velocities up to  $600^{\circ}/\text{sec}$ . in man and  $1000^{\circ}/\text{sec}$ . in monkey [30]. The rapid movements bring an image from the periphery of the retina to the fovea, the high resolution region of the retina which is in the center of the visual field. Smooth pursuit movements are continuous movements of the eye and can be elicited when a target moves smoothly over the retina. These movements are generally slower than the saccadic movements; their velocities usually being less than  $45^{\circ}/\text{sec}$ . in man [31] and  $90^{\circ}/\text{sec}$ . in monkey [8].

Nystagmus is a combination of the saccadic and the slow phase eye movements. It consists of slow phases interspersed with rapid movements in the opposite direction. Nystagmus can be induced by stimulation of either the vestibular system by head turning or the

visual system when the environment turns. These stimuli induce vestibular nystagmus and optokinetic nystagmus (OKN) respectively. Perception of visual information occurs during the slow phases.

This chapter will review how eye movements are measured (sec. 2.2) to define the properties of the signals (sec. 2.3) that will be used to identify and separate saccades from nystagmus. After the saccades have been removed, the slow phase velocity of the resulting waveform will be used to automatically identify a model for optokinetic nystagmus and optokinetic after-nystagmus (Raphan et al, 1979, Cohen et al, 1977).

## 2.2 Eye Movement Measurement Methods

The three most widely used methods for measuring eye movements are the corneal reflection, contact lens and electrooculography (EOG). All of these eye movement measuring techniques generate voltage proportional to eye position differing in sensitivity and in the range of the eye movements being measured. This section reviews these measurement techniques with particular emphasis on the EOG measurement technique since it is a common technique used in animal and human studies. A review of these and other techniques can be found in [42].

### 2.2.1 Corneal Reflection Method

A beam of light is reflected from the surface of the cornea to form a bright spot on a screen. The angle of reflected light depends upon the angle between the incident light and the normal to the reflecting (corneal) surface. The normal to the cornea changes as the eye

rotates during a movement resulting in a corresponding movement of the spot. The reflected beam is photographed on a moving film to produce an eye movement record.

The corneal reflection method is suitable for untrained subjects, since it does not interfere with normal eye movements. The limitations of this method are: first, the linear range of the method is restricted to about  $\pm 12.5^\circ$  [42] due to nonspherical corneal surface; second, lateral head movements affect the measurements to a great extent. For instance a lateral displacement of 0.1 mm. introduces an error of about  $1^\circ$  in the measured eye position [41].

### 2.2.2 Contact Lens Methods

Contact lens methods involve fitting special lenses over the cornea. A small plane mirror mounted on the lens reflects the image of a light source. The reflected image is then photographed on a moving film to obtain a record of the eye movements. A modified method involves placing a small lamp at the end of a short aluminum tube attached to the contact lens. As the eye moves, the amount of light passing through two knife edges and falling on the sensitive surface of a photomultiplier, changes. The output voltage variations indicate the variation in eye position.

A nonoptical contact lens measuring method was introduced by Robinson [29]. Two small thin wire coils, oriented orthogonal to each other and embedded in the contact lens, pick up an induced voltage from two large orthogonal electromagnetic coils surrounding the head. The induced voltage in each coil varies with the sine of the angle of gaze relative to the magnetic field. Fuchs and Robinson [12] modified the

coil method for animal study by implanting the coil of wire on the globe under the insertion of extraocular recti muscles. This method measures both vertical and horizontal movements simultaneously, has a sensitivity of  $.25^\circ$  and can measure very large movements.

The contact lens methods are the most sensitive eye movement measurement methods and yield good records of miniature eye movements down to 5 seconds of arc [42]. The accurate range of such methods is limited to about  $5^\circ$ , since the lens slippage becomes important for larger eye movements. The other disadvantage of these methods is the necessity of placing a foreign object on the eye and thereby interfering with normal eye movements. The fitting of contact lenses is an exacting task and can't be used on all subjects. To avoid lens slippage, it has to fit tightly which causes discomfort. The contact lens methods are the most appropriate for the precise measurements of eye movements less than  $1^\circ$ .

### 2.3.3 Electrooculography (EOG)

The position of the eye can be measured by placing electrodes around the eye and recording potential differences. There exists a standing potential between the cornea and the retina, setting up an electrostatic field which rotates with the eye. The cornea is approximately 1mV positive with respect to the retina. The potential difference detected by a pair of electrodes placed lateral to an eye is zero with the gaze directed forward and varies sinusoidally when the eye moves to the left or to the right. Similar potential difference can be detected by the electrodes placed above and below the eye when the eye moves vertically. the voltage versus gaze angle relationship is approximately

linear for eye movements less than  $40^\circ$ , since the difference between  $\sin\theta$  and  $\theta$  is less than 10% for such movements. The recorded voltage falls in the range of 15-200uV with approximate sensitivity of 4uV/degree of movement [42].

The small potential difference corresponding to eye movement must be amplified by a DC amplifier in order to determine the eye position. The problem of drift in electrodes and DC amplifiers makes these recordings very difficult. Recent advances in skin electrodes such as silver-silver chloride electrodes coupled with high input impedance preamplifiers have eased the problem of drift. The electromagnetic pick ups can be reduced by using a high common-mode rejection ratio preamplifier close to the head, grounding through an ear electrode and using shielded cables. Fig. 2.1 shows the placement of electrodes when both horizontal and vertical recordings are performed. Conjugate horizontal eye movements are recorded between the electrodes at the outer canthi of the eyes. Separate recording of the horizontal movements of each eye can be performed by placing a third electrode over the bridge of the nose. The vertical eye movements are recorded from a set of 4-electrodes, the upper two and the lower two being tied together to reduce the coupling between horizontal and vertical movements. Surface electrodes are used for humans but suffer from problems such as muscle artifacts and drift.

The use of implanted, silver-silver chloride electrodes for animal recording [ 7 ] removes some of the problems with surface electrodes. These electrodes are permanently placed in holes in the bony orbit. The use of fine platinum needle electrodes in the skin around the orbit is also used for animal recording [42].

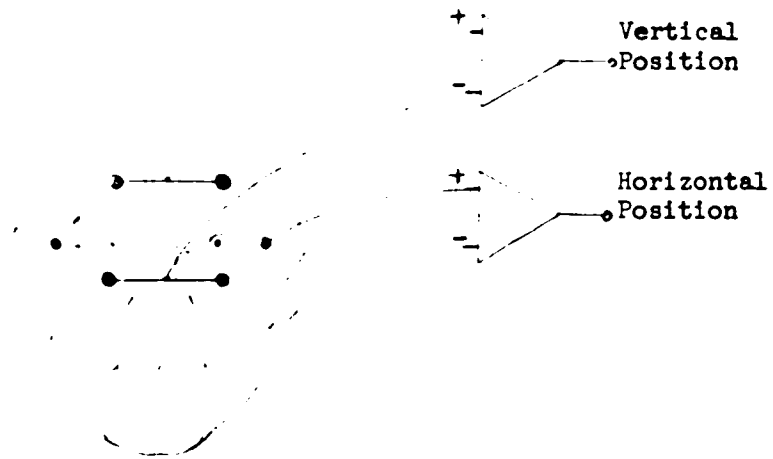


Fig. 2.1 Placement of skin electrodes in humans for the measurement of vertical and horizontal positions by electrooculography (From Young and Sheena [42])

The corneoretinal potential, the basis of EOG, tends to change with environmental and experimental changes, thereby affecting EOG gain. This may require frequent calibration to offset such changes [42].

Despite its limitations, electrooculography is a commonly used method to record eye position since it is easy to use especially for humans, has a wide range of eye movements that can be measured and has practically a linear relation for commonly occurring eye movements. Recordings using electrooculography are accurate to within  $2^\circ$  of eye movements [42] and therefore are suitable for measuring movements in the range of  $5-50^\circ$ . EOG is the technique used to obtain eye movement records analyzed in chapters 3, 4 and 5.

A detailed study of the properties of EOG noise has not been carried out. This is due to the many factors which contribute to the noise variations such as physiological changes, environmental changes and the specific instrumentation used in filtering, amplifying and recording signals. In order to facilitate the analysis in chapter 3, the noise in EOG will be assumed to be gaussian. Based on this assumption, a sufficient statistics is derived for the detection of rapid and slow eye movements. Other kinds of noise statistics should give different sufficient statistics and could be investigated as an extension of this thesis.

### 2.3 Properties of Eye Movements

The temporal characteristics distinguishing the two kinds of eye movements (the rapid and the slow movements) must be considered in the design of a technique for their separation. In this section, these

characteristics are studied. This leads to the formulation of a criterion for the detection of saccades in a record of eye movements.

### 2.3.1 Properties of Saccadic Eye Movements

Saccades are the rapid jumps by which we voluntarily divert our eyes from one fixation point to another. These are generally conjugate movements, i.e. both eyes move simultaneously in the same direction. Fig. 2.2A shows an electrooculogram (EOG) record of saccadic eye movements performed by a monkey looking around in an environment with no moving objects. When a monkey is presented with a random change in target position, his response typically starts after about 240msec [11]. The eye accelerates to a maximum speed, which is reached about midway in the total trajectory, and then decelerates to a stop (Fig. 2.2B). In response to target displacements greater than  $25^\circ$ , the eye often falls short of the target with its initial saccade, requiring a second saccade within about 250msec to correct the remaining error [11]. The duration of a saccadic eye movement depends upon its size and it is about 25msec for a saccade of  $10^\circ$ . The maximum velocity during a saccadic eye movement can be as high as  $1000^\circ/\text{sec}$  and depends upon the size of the saccade. The relations between the magnitude, duration and maximum eye velocity are shown in Fig. 2.3 (taken from Fuchs, 1967). The maximum saccadic velocity increases nonlinearly with the saccadic magnitude whereas the saccadic duration is approximately linearly related to the saccadic magnitude. The temporal (abduction) saccades have been found to be slightly slower than the nasal saccades. Duration vs magnitude plot has an approximate slope of 1msec/deg. for horizontal saccades.



Fig. 2.2. A. Horizontal saccadic eye movements of a monkey looking about the laboratory with no moving objects. B. Velocity corresponding to the eye movements in A. C. Time.

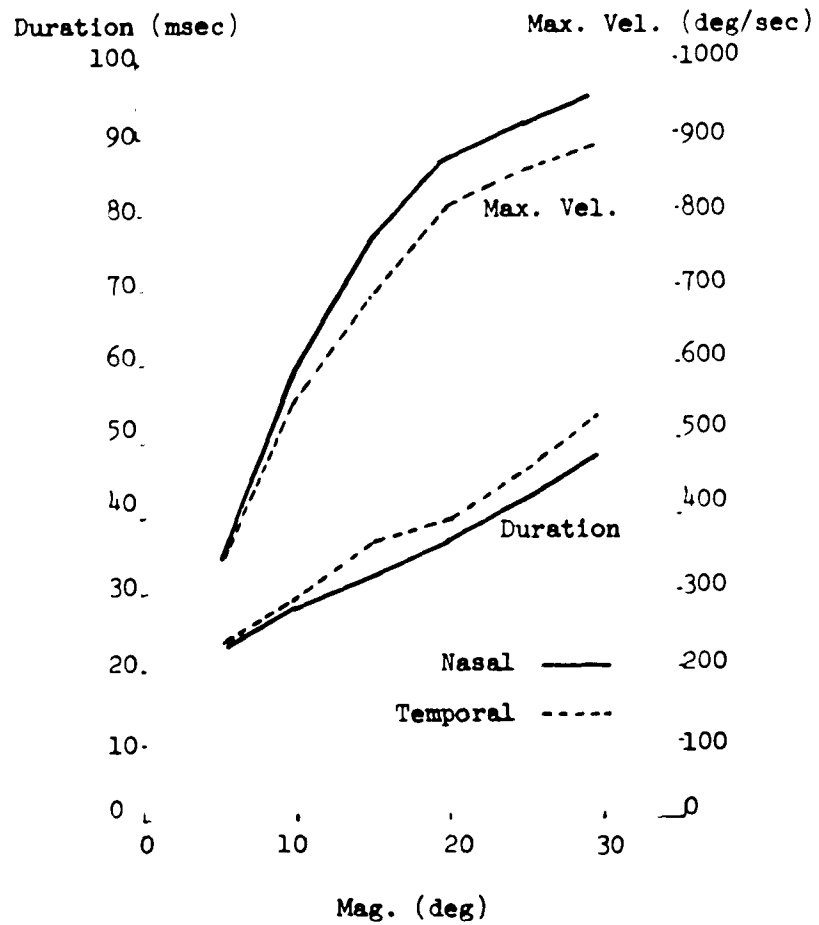


Fig. 2.3. Duration and maximum velocity of horizontal saccades of a monkey (taken from Fuchs [11])

Vertical saccadic response is qualitatively similar to the horizontal. Vertical saccades have an average latency of 235msec and duration vs magnitude plot is characterized by an approximate slope of 1.35msec/deg. [11].

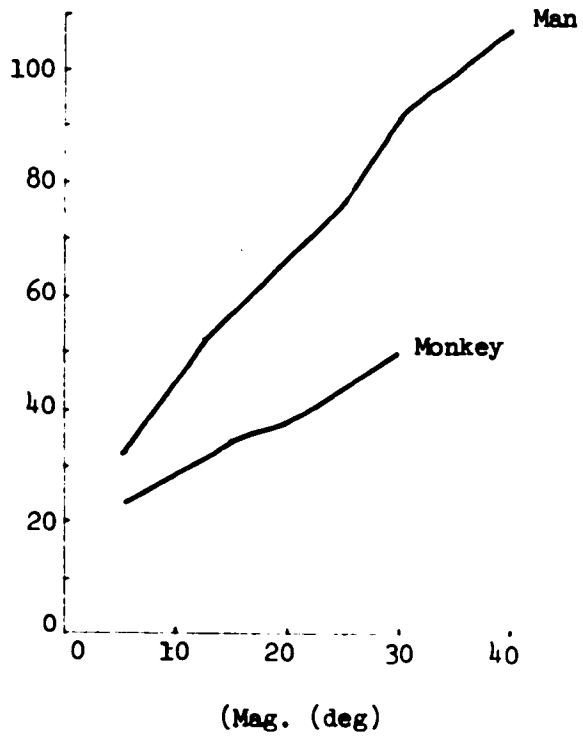
The saccadic movements of a monkey are not qualitatively different from those of man. Monkeys execute their saccades more rapidly than humans. The duration vs magnitude and maximum velocity vs magnitude plots for the two primates are compared in Fig. 2.4. As is apparent from these plots, humans perform a 30° saccade in about double the time than monkeys. The maximum velocity reached in monkeys is about 400°/sec faster than in humans. The saccadic latency both in man and monkey has been reported to be the same [11]. The human saccades were analyzed by Baloh et al [5] and Bahill et al [3]. Quantitative analysis as done by Baloh et al [5] indicates that saccadic duration and amplitude are linearly related with a mean slope of 2.7sec/°, whereas amplitude and velocity have a nonlinear relationship that is best fit by an exponential equation of the form

$$EV = K (1 - \exp [-A/L])$$

where EV = eye velocity, A = saccade amplitude,  $K = 551 \pm 65^\circ/\text{sec}$  and  $L = 14.0 \pm 1.7^\circ$ .

The mathematical characterization of saccades is an important first step for detecting them in an eye movement record. The time behavior (position vs time) of saccades will be used in chapter 3 to design a technique for their detection and then their removal to study the slow eye movement characteristics. Since saccades occur in conjunction with slow eye movements, the properties of the slow eye movements are reviewed in the next section.

Duration (msec)



Max. Vel. (deg/sec)

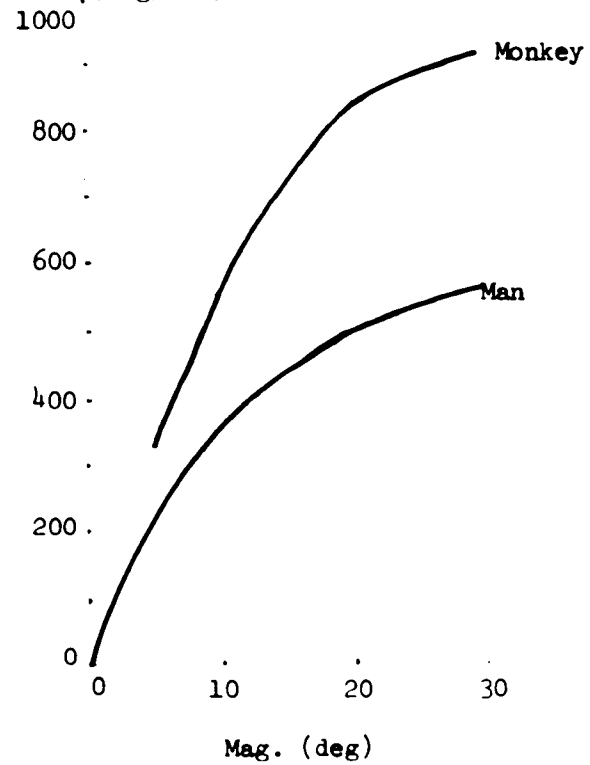


Fig. 2.4. Comparison of monkey and human saccadic eye movements (taken from Fuchs [11])

### 2.3.2 Slow Eye Movements

The eye performs slow tracking conjugate movements while following a slowly moving target or while compensating for movements of head or trunk. The function of compensatory and tracking eye movements is to stabilize the retinal image of an object during relative motion between the head and the object. These movements are characterized by low velocities relative to saccades and are presumed to be generated by different neuronal structure in the central nervous system (Raphan and Cohen, [25]). Fig. 2.5 shows a record of smooth pursuit eye movements of a monkey in response to moving objects in its field. It may be noted from Fig. 2.5 that the pure pursuit movements are difficult to excite; they are generally made in conjunction with saccades.

The characteristics of slow eye movements in man were studied by Robinson [31] and in monkey by Fuch [11]. Qualitatively the two primates perform similar smooth pursuit movements and are believed to possess similar mechanisms for their generation. Quantitatively, a monkey can attain a smooth pursuit velocity which is twice as fast as that of man. Fig. 2.6 shows the response of a monkey to ramp inputs from  $10^\circ/\text{s}$  to  $40^\circ/\text{s}$ . The response consists of a smooth component and a saccadic component. The latency in response varies with the target velocity and is approximately  $174$  msec for a  $10^\circ/\text{s}$  target velocity which is about  $50$  msec more than in humans as reported by Robinson [31]. The saccadic component appears after about  $250$  msec and the size of the saccade increases with the target velocity. After the saccade, the pursuit eye movement follows the target at its velocity for target velocities up to  $25^\circ/\text{s}$ . For higher target velocities, that is

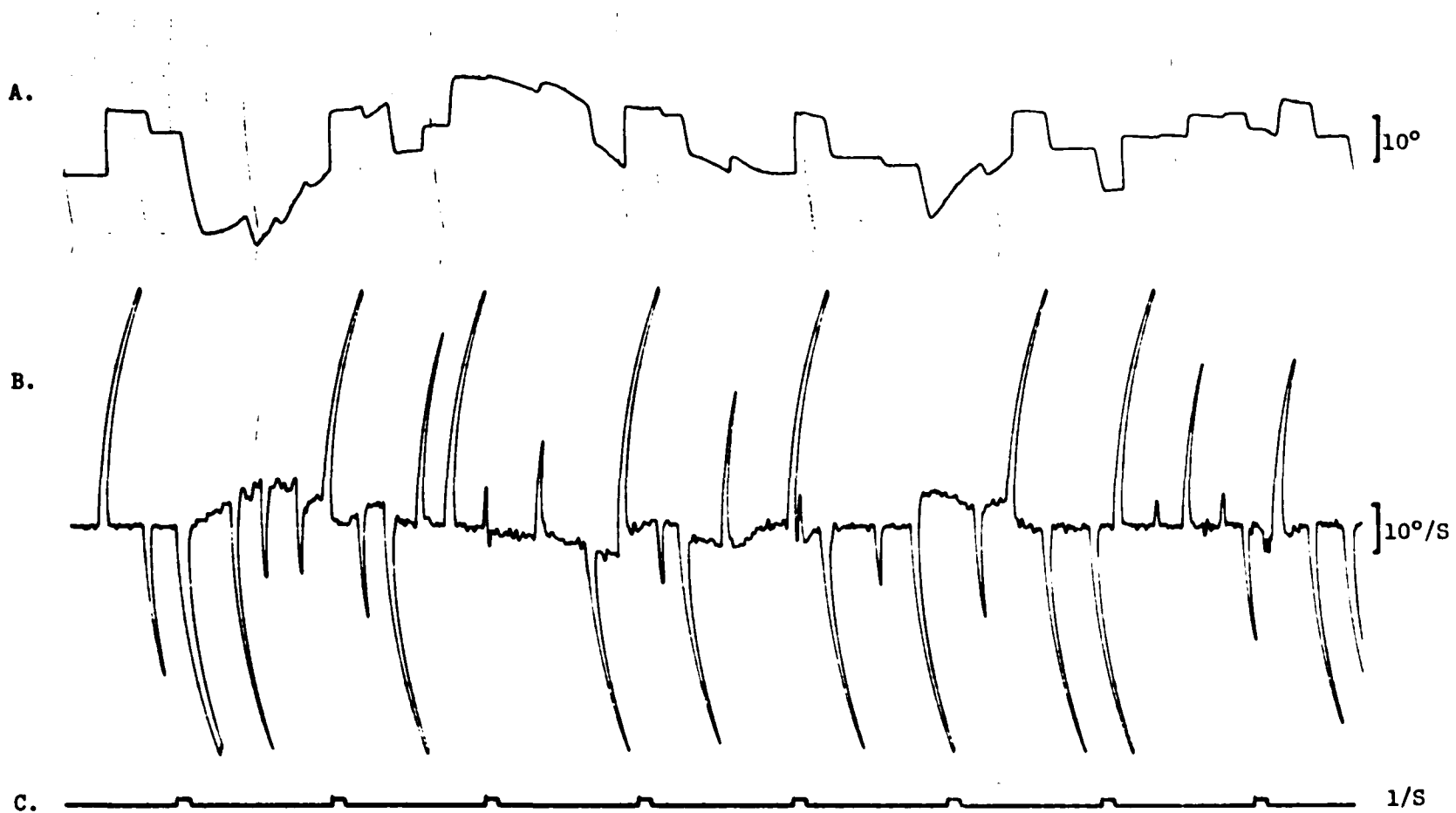


Fig. 2.5. A. Smooth pursuit eye movements of a monkey induced by moving objects in its environments. B. Velocity associated with the eye movements in A. C. Time

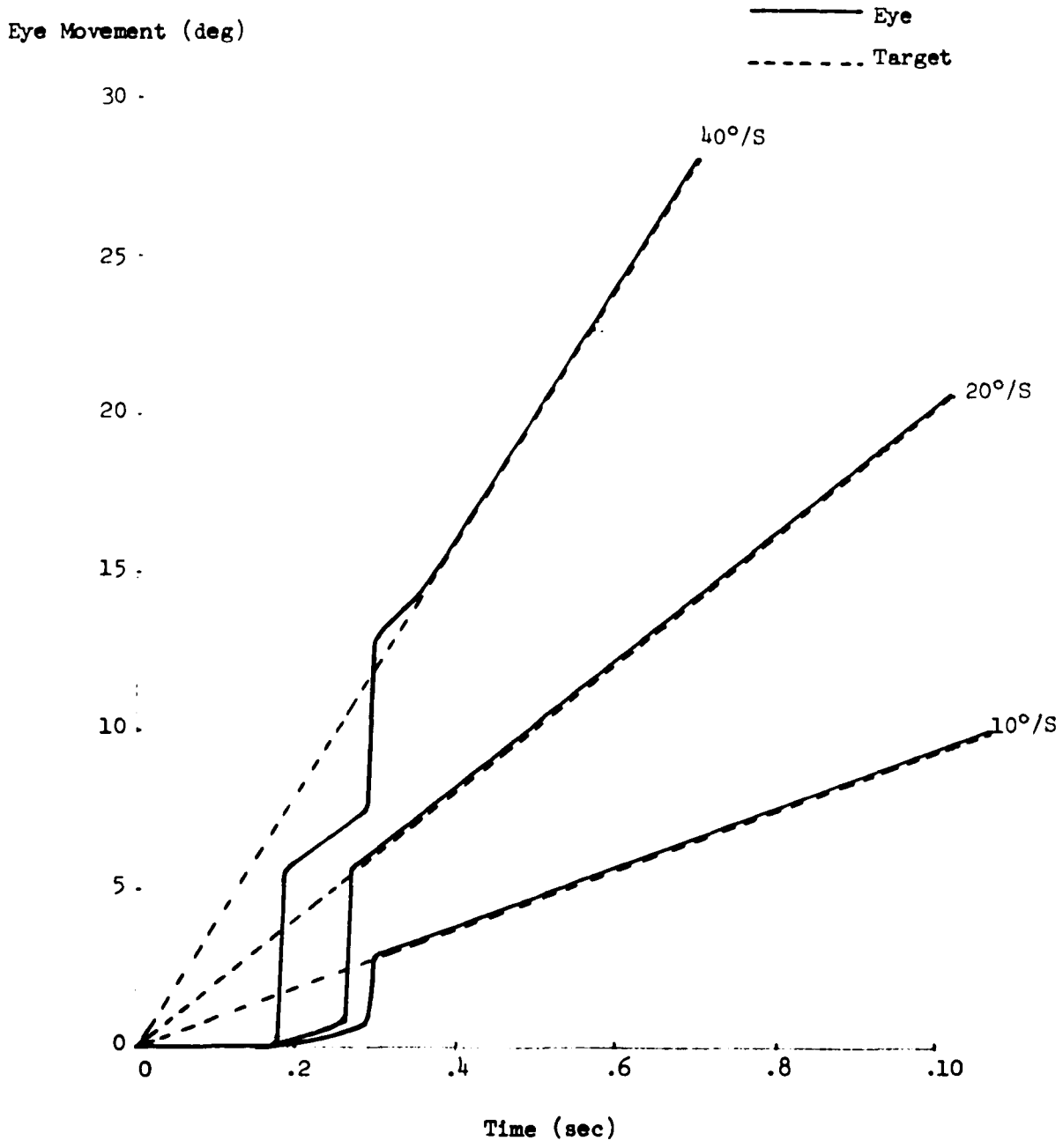


Fig. 2.6. Eye movement response of a monkey to target ramps (taken from Fuchs [11]).

velocities greater than  $25^{\circ}/s$ , the monkey displays many combinations of saccades and smooth pursuit movements. For instance to catch a target moving at  $40^{\circ}/s$ , the monkey makes two saccades (see Fig. 2.6). The second saccade is made either after about 250msec or earlier. The earlier saccades are generally accompanied by a small overshoot. Monkeys are capable of following target velocities up to about  $90^{\circ}/s$  [25] which is about twice the velocity that humans can turn their eyes to follow a ramp stimulus.

That the smooth component of the ramp response is elicited by the target velocity and not its position was demonstrated by Rashbash [28]. He presented a monkey with a step-ramp trajectory by first moving the target in one direction followed by a constant velocity in the opposite direction, after a delay, the response exhibits a smooth component which moves the eyes away from the target but in the direction of target motion. After one saccadic latency, the eye catches the target by performing a saccade in the opposite direction which shows the sample-data system nature of saccadic system.

The velocity attained by the eye during smooth pursuit movements is an important diagnostic tool [4] for brainstem dysfunction. In general, the smooth pursuit velocity decreases in patients having brainstem diseases [4]. The computation of smooth pursuit velocity from EOG records becomes a difficult task since the pursuit movements always have interspersed saccadic movements. One of the objects of this dissertation is to obtain pursuit eye velocity after removing saccadic movements from an EOG record.

The position vs time characteristics of slow eye movements are

required to design a detection scheme for saccadic movement. The performance of the detection scheme discussed in chapter 3 is a function of how accurately such characteristics are available.

#### 2.4 Nystagmus

A class of eye movements of an oscillatory or unstable nature are known as nystagmus. The most common types of nystagmus are vestibular and optokinetic nystagmus. Vestibular nystagmus occurs when a subject undergoes angular acceleration, and consists of slow compensatory eye movements opposite to the acceleration and fast movements for resetting the eyes. Optokinetic nystagmus occurs whenever a nonhomogeneous visual field is moved past an observer; the eyes move conjugately with the field, as with normal pursuit movements, and then rapidly return to a central position so as to continue to follow the motion of the visual field. The optokinetic nystagmus characteristics are described in section 2.4.1 and in many respects are similar to the characteristics of vestibular nystagmus described in section 2.4.2. A nystagmus waveform is shown in Fig. 2.7. There are two components which characterize a nystagmus waveform, first, a component having a smaller eye velocity which is called the slow phase of nystagmus and second, a component with larger eye velocity and this component is called a quick or fast phase of nystagmus. The velocity characteristics of the slow and quick phases of a nystagmus resemble those of pursuit and saccadic eye movements respectively. The velocity waveform can be obtained by differentiating the nystagmus waveform. The quick phases are of much shorter duration and of higher

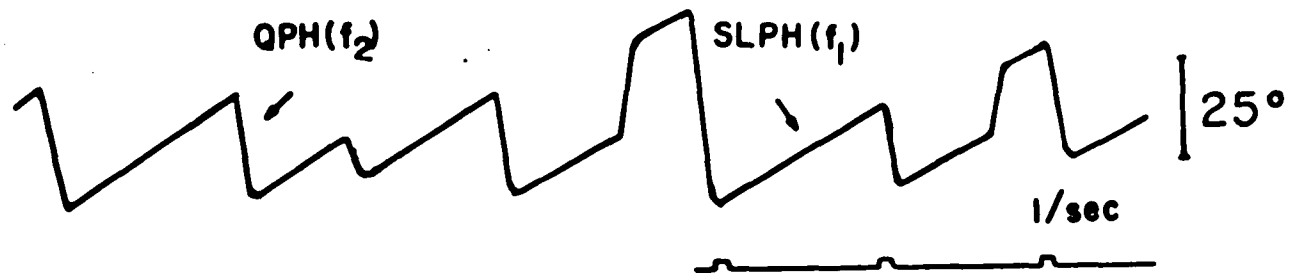


Fig. 2.7. A time-expanded view of a nystagmus waveform. The quick phase (QPH) and the slow phase (SLPH) movements can be described by functions  $f_2$  and  $f_1$  respectively. Note the relative durations and velocities associated with these eye movements.

eye velocities as compared to slow phases. Due to the shorter duration of a quick phase, the slow phase eye velocity just before and just after a quick phase is essentially the same. This fact will be used in chapter 4 to obtain slow phase eye velocity waveforms from EOG waveforms.

Thus, in both monkey and man, saccades and quick phases are approximately 2 to 3 times faster than normal slow phases or pursuit eye movements. It is these characteristics which will enable us to derive functional templates representations for these signals and derive a criterion for their separation.

The following sections describe the properties of Optokinetic nystagmus (OKN), optokinetic after-nystagmus (OKAN) and vestibular nystagmus. The waveforms are used as inputs to the detection program and to estimate parameters of the OKN and OKAN model.

#### 2.4.1 Optokinetic Nystagmus and Optokinetic After-Nystagmus Characteristics

Optokinetic nystagmus (OKN) is the nystagmus induced by continuous movement of the visual field, and it lasts as long as the stimulus continues. When the stimulus is terminated, if the animal is in darkness, there is a persistent after-reponse, known as optokinetic after-nystagmus (OKAN). The significance of OKN is that it stabilizes the retinal image of a moving environment by matching eye velocity to the stimulus velocity. OKAN is a motor response to a prolonged central excitatory state which is produced simply by viewing a moving visual field. Both these responses characterize the slow phase subsystem of the oculomotor system and are fundamental to modeling of this system.

Velocity characteristics of OKN and OKAN induced by constant velocity full field rotation were studied by Cohen et al [8] and Raphan et al [27]. In their studies, OKN was induced by an internally lit, servo-controlled, rotating drum 90 cm in diameter and 60 cm high. It surrounded the monkey and filled the field of vision. The drum wall was made of opalescent white plastic with 3° black stripes at 45°. A mirror was placed under the monkey's chin to reflect stripes on the roof of the visual field. Such a stimulation is known as full field rotation, since not only the stripes but the textured background also contributes to the response. Electrooculography (EOG) was used to record eye movements. The EOG was differentiated and rectified to obtain the velocity of slow phases of nystagmus. The velocity characteristics of OKN and OKAN are summarized as follows:

1. Slow phase velocity of OKN in response to a step in stimulus velocity is composed of two components, a rapid rise, followed by a slower rise to a steady state value. A typical response to a stimulus velocity of 45°/sec is shown in Fig. 2.8. For stimulus velocities up to 90°/sec, the rapid rise is found to be about 60% of the final steady state eye velocity. The slower rise has a time constant in the range of 2.6 to 3.3 sec. The steady-state velocity has a gain of 1 to about 180°/sec stimulus. This gain drops with increased stimulus velocity and saturates at about 240°/sec in monkeys. The saturation velocity in the monkey is 2-3 times as great as in humans.

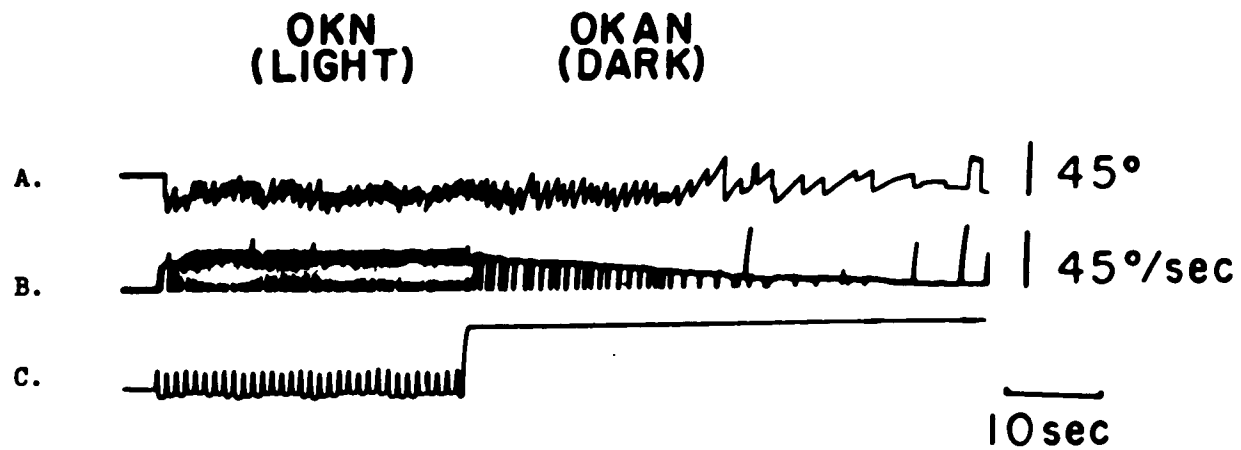


Fig. 2.8. A. The horizontal EOG during optokinetic and optokinetic-after-nystagmus of a monkey subjected to full field visual stimulation.

B. The eye velocity associated with the nystagmus in A.

C. The visual stimulus for the generation of OKN and OKAN.

2. At the onset of OKAN, slow phase velocity falls by about 10-20%, followed by a slower decline to zero. Peak OKAN velocities are linearly related to optokinetic stimulus velocities up to 90-120°/sec. Above 120°/sec OKAN slow phase velocity saturates. The optokinetic stimulus duration is important to the generation of OKAN, since if OKAN is initiated before reaching the steady state for OKN, the drop in the slow phase velocity is considerably larger than 10-20%. In other words, the system generating OKAN charges to its full value in about the same time that the OKN attains its steady state. The time constant for the slow decline ranges from 10 to 25 seconds and seems to depend upon the stimulus velocity; furthermore, it can be different for rightward and leftward beating nystagmus. Extended visual fixation (lights on) discharges the activity responsible for producing OKAN. Short fixations cause only partial discharge of OKAN mechanism. Following brief fixations, OKAN resumes but with decreased slow phase velocity.

A model which closely predicts the dominant characteristics of OKN and OKAN in normal monkeys was developed by Raphan (Cohen et al, 1977, Raphan et al, 1979). However, to relate the model parameters to pathological states associated with vestibular system lesions, automatic parameter identification techniques must be developed. This is the subject of chapter 5.

### 2.4.2 Vestibular Nystagmus Characteristics

Vestibular nystagmus is induced by head rotation. It is also a combination of rapid and slow eye movements whose relationship to stimulus velocity has been quantitatively described and modelled (Raphan et al, 1979). The relationship between stimulus velocity and peak eye velocity (of slow phases) during per and post-rotatory nystagmus is linear up to  $240^\circ/\text{sec}$  with a slope close to one. The per-rotatory nystagmus is the animal's response during rotation in darkness and the post-rotatory nystagmus is the response of the animal after the rotation is stopped. A typical vestibular nystagmus and the corresponding slow phase velocity response are shown in Fig. 2.9. The transient characteristics of vestibular nystagmus can be summarized as follows:

1. At the onset of stimulation slow phase velocity rises abruptly, peak velocity is maintained for several seconds and then it declines to zero with a dominant time constant of 15-28 sec. For higher stimulus velocities, peak velocity is held for a shorter time and the decline in slow phase velocity is more rapid.
2. The post-rotatory nystagmus slow phase velocity is set to zero after per-rotatory nystagmus has entirely disappeared, the characteristics of the per and post-rotatory nystagmus are approximately similar with opposite velocity sign.

The slow phase velocity characteristics of nystagmus are used in mathematical modeling of the neuronal structures responsible for their production. Such models are considered in chapter 5.

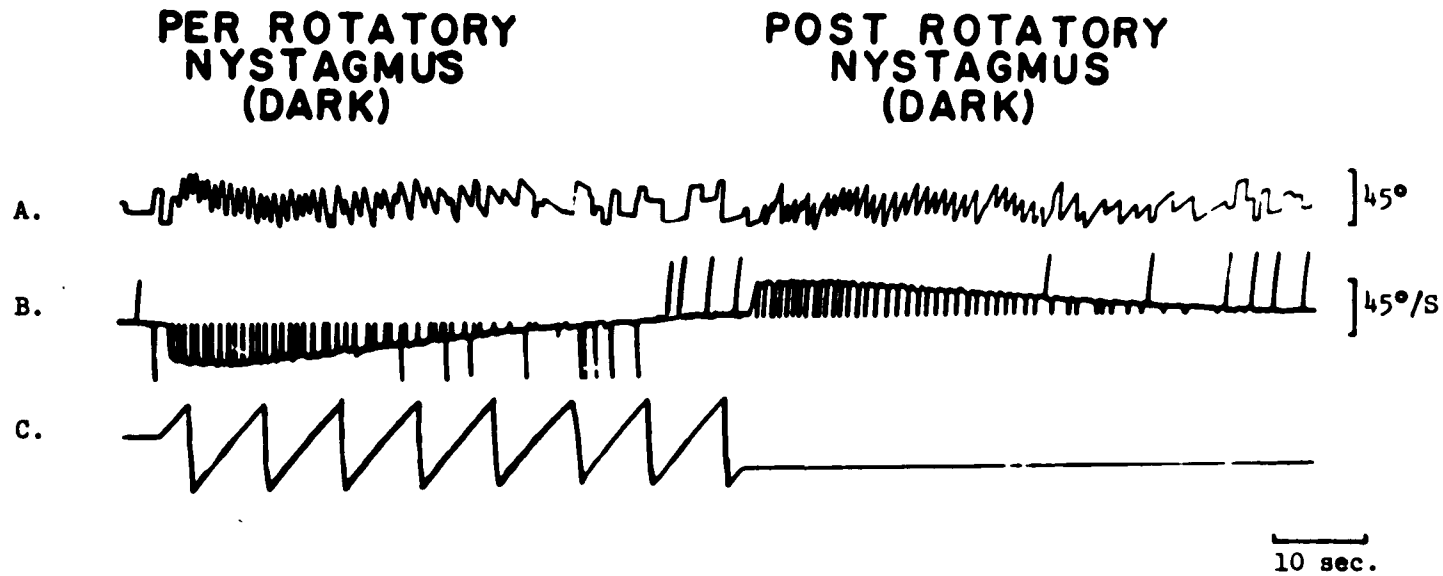


Fig. 2.9. A. The horizontal EOG during a per and post rotatory nystagmus.  
 B. The eye velocity associated with the nystagmus waveform in A.  
 C. The vestibular input to generate the vestibular nystagmus in A.

## CHAPTER 3

## AN ON-LINE SACCADE DETECTION PROGRAM

3.1 Introduction

Eye movement records in the form of electrooculographs (EOG) are analyzed [22] to extract diagnostically important information such as the relationships between the slow eye velocity characteristics and head velocity and surround velocity. Another important purpose of this analysis is to understand the brain mechanism responsible for generating various types of eye movements. The information usually needed includes time, duration and frequency of occurrence of quick phases and the velocity associated with slow phase eye movements.

Analog differentiators have been used and are still being used to detect quick phases in an EOG record [16]. However, an analog differentiating scheme introduces delay and performs poorly when operating on noisy data (see next chapter, section 4.2.2). For these reasons, in recent years, several researchers have developed computer programs to process EOG waveform on-line and generate the required information [37] [2]. These techniques involve cumbersome algorithms for the detection of quick phases and therefore are inappropriate for microprocessor implementation. A more recent technique based upon an acceleration sensitive detector [22] seems to be a step in the direction of dedicated portable instruments for the analysis of nystagmus. This technique is basically an implementation of a differentiating type digital filter and therefore is noise sensitive and has high detection errors [22]. Thus,

there is a need of a detection scheme which should be relatively immune to noise and implementable at microprocessor level to design portable diagnostic instruments.

The new technique presented in this chapter is based upon a 'likelihood ratio detector' [38]. A decision function is computed, the value of which reflects to the origin of the data used to compute it, i.e., whether the sample taken belongs to a slow phase or a quick phase. Once a quick phase is detected it can be suppressed to generate slow phase waveform. The technique to generate slow phase waveform is discussed in the next chapter. The detection technique is mathematically simple and is implementable using a microprocessor for on-line processing of EOG records.

Since a central problem to be treated is the on-line detection of quick phases, we first review the existing analysis techniques from this view point in section 3.2 and then the new technique is presented in section 3.3. The performance of the 'likelihood ratio detector technique' is studied in section 3.4 by computer simulations and by on-line processing of experimentally obtained eye movement records. This technique will be utilized in the next chapter to generate some diagnostically important waveforms, such as the slow phase velocity and the cumulative slow phase position waveforms.

### 3.2 The Current Status of Saccade Detection Methods

There has been appreciable interest in the processing of EOG waveform so that the nystagmus parameters could be used to understand the oculomotor control system and relate eye movement disorders to the

neuronal activity. The complication in the analysis procedures arises due to the presence of quick phases whose occurrence is random in both magnitude and time. Another problem arises due to the fact that one of the requirements of analysis [ 2 ] is to generate slow phase eye velocity which involves differentiation in noisy environments. Thus the techniques of analysis developed so far differ in the manner in which the quick phases are detected or in the manner in which the slow phases are differentiated to generate slow phase eye movement velocity.

The first on-line technique is due to Henriksson [16]. This technique is shown in Fig. 3.1 and involves differentiating the EOG waveform using an analog differentiator of the form  $S/(S+K)$ . The differentiated waveform is passed through a positive or a negative halfwave rectifier to extract positive or negative slow phase velocities respectively. Fig. 3.2 shows the results of processing an EOG waveform by Henriksson's method. The quick phases are indicated by large magnitude jumps and the rest of the waveform is that of slow phase velocity. This method though limited in information is used due to easier implementation. The analog differentiator used in the analysis introduces considerable time delay and therefore renders this method inappropriate for further on-line work.

The first attempt to use a computer for the process of on-line nystagmus analysis was made at MIT by Tole and Young [37]. They developed a hybrid technique : MITNYS, for on-line analysis of nystagmus. The algorithm used to detect quick phases depended upon the relative magnitude and the sign of the velocity associated with EOG waveform. The forward quick phases were detected due to the change in velocity magnitude and the reverse quick phases were detected due to the change in velocity sign or both. This technique had a number of limitations [ 2 ]

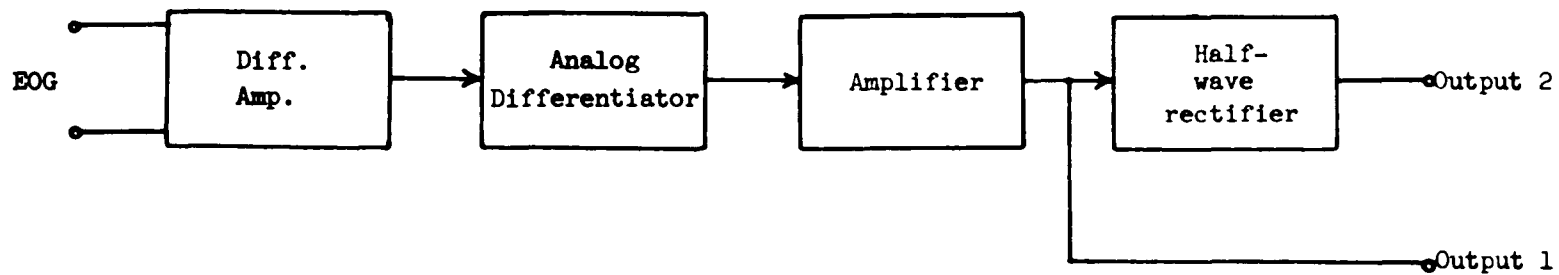


Fig. 3.1. Block diagram of Henriksson's method of EOG record analysis

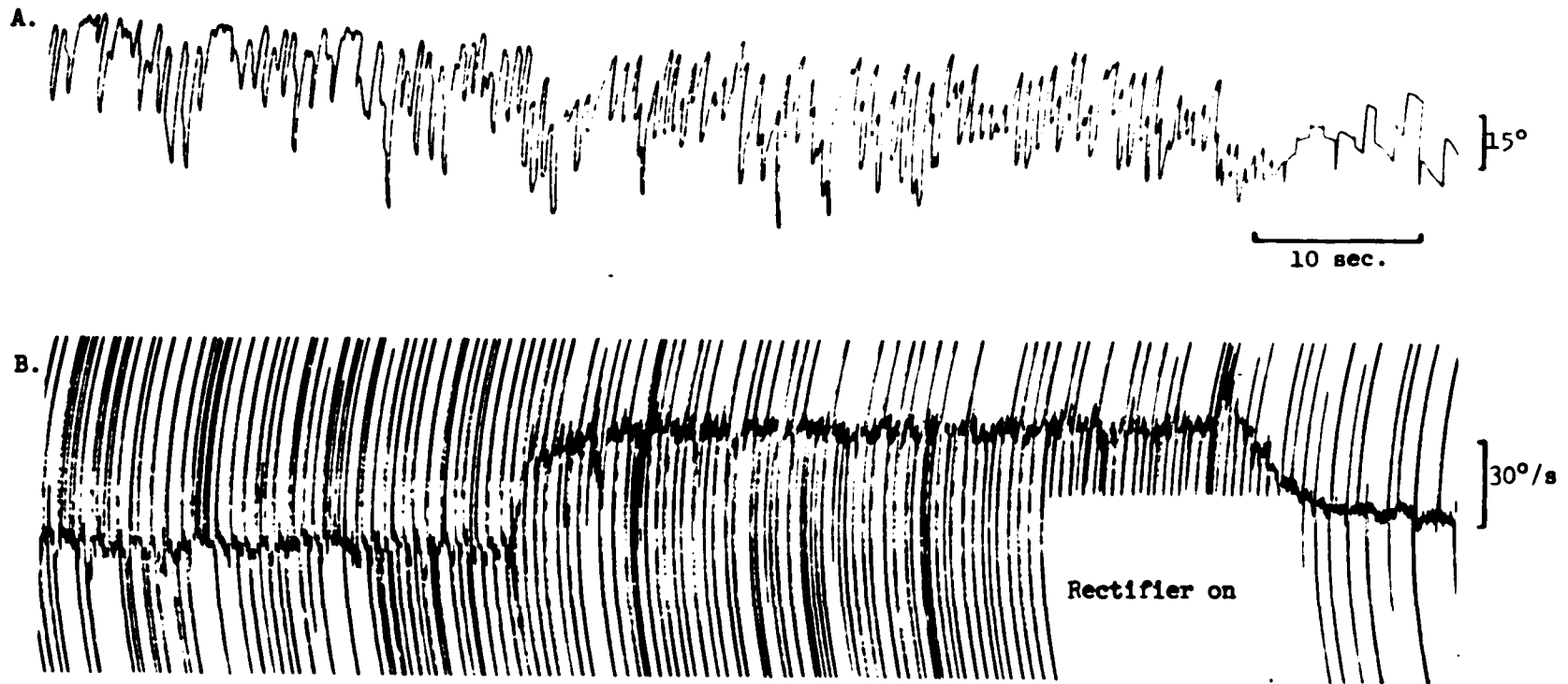


Fig. 3.2 A. EOG waveform. B. Differentiated EOG waveform. Note that the spikes in the differentiated waveform indicate saccades and trend of the waveform indicates slow phase eye velocity.

including high error rate in quick phase detection and limited stimulus frequency bandwidth. Low pass analog filters of the form  $K/(S+\tau)$  were used to smooth differentiator noise. The time constant  $\tau$  of these filters ran in seconds and therefore the technique was incapable of reproducing faithfully the transitions in EOG velocity.

Some of the problems of MITNYS were overcome by MITNYS-II, an all-digital program developed by Alum, Tole and Weiss [2]. Their technique of saccade detection involved three tests i.e., velocity test, slope-sense test and the minimum velocity test were used to mark quick (fast) phases. If the eye velocity magnitude as calculated by subtracting two successive eye position samples exceeded the estimated fast phase velocity (FPV), the fast phase was said to have occurred. FPV was estimated using fast phase estimator which was developed after studying the relation between slow phase velocity (SPV) obtained from a 33 point digital differentiator operating upon pieced together slow phase segments of eye position called cumulative slow phase position, and the FPV. The slope sense test involved estimating the SPV sign. The SPV sign was taken to be that of the slow phase velocity averaged over 9 samples ( $\overline{SPV}$ ) provided the SPV was greater than  $3^\circ/s$ . If SPV was  $< 3^\circ/s$ , the sign of slow phase velocity averaged over 80 samples (Ave SPV) was used as the estimate of SPV sign. In both cases  $|Ave\ SPV|$  must be  $> 2^\circ/s$  and  $|SPV| < 3^\circ/s$  for more than 0.3 seconds. If SPV criterion was not met, the test was not used. Estimated sign of SPV thus obtained was compared to the eye velocity sign provided the eye velocity was  $> 30^\circ/s$  and unequal signs indicated a fast phase. In the event the minimum SPV criterion was met, FPV was assumed to be at  $20^\circ/s$  and the minimum velocity test was applied. The

minimum velocity test involved using three successive eye positions and computing two successive velocities. If the magnitude of both of these velocities exceeded  $20^\circ/\text{s}$ , a fast phase was indicated. In the event two successive velocities of opposite signs were detected, the test was ignored. MITNYS-II though useful is simply too complex to be implemented at the microprocessor level [22]. Secondly the program uses so much smoothing that it is suitable only for very slow running nystagmus and is not capable of reproducing sharp transitions in the slow phase velocity.

The most recent technique of analysis has been developed by Michaels and Tole [22]. It involves convolving the EOG waveform with a finite impulse response digital filter of the type:

$$d(k) = -x(k-4) - x(k-3) + x(k-1) + 2x(k) + x(k+1) - x(k+3) - x(k+4)$$

where  $d(k)$  is the output of the filter and  $x(k)$  is the input. The important characteristic of this digital filter is its sensitivity to acceleration. The output after convolution contains peaks corresponding to quick phases and therefore can be detected using a threshold detector. This technique is simple and microprocessor implementable, but suffers from a high percentage of errors in quick phase detection. This technique when applied to EOG samples taken 16.7 ms apart on a filtered waveform which ensures high filter gain and reliable detection, still has an error of 3% in saccade detection [22]. These results were obtained by using the technique in conjunction with a spike elimination routine, because the filter itself is very sensitive to these spikes and produces false detections. In spite of its limitations this technique is a step in the direction of portable instruments for nystagmus analysis.

### 3.3 Likelihood Ratio Detector

Consider received data which has been produced by one of two subprocesses of a system. The outputs of these subprocesses are denoted by  $f_1(t)$  and  $f_2(t)$ . Let the corresponding hypotheses be denoted by  $H_1$  and  $H_2$  respectively, i.e.  $H_j$  denotes the hypothesis that the data is produced by subprocess  $f_j(t)$ ;  $j = 1, 2$ . For the analysis of nystagmus waveforms,  $f_1(t)$  will denote the slow phase subsystem response and  $f_2(t)$  the response of the quick phase generating subsystem.

The received data is scaled before processing. The scaling is done with respect to the first sample in the window of samples considered before making a decision. The scaled samples then are used to compute a scalar function called 'decision function'. The value of the 'decision function' leads to the assignment of the latest sample to either  $f_1(t)$  or  $f_2(t)$ . The 'decision function' evolves from the process of minimizing a probability of error, based upon the window of samples.

The input being noisy, there is a finite probability of error associated with each decision. Another kind of error which occurs during transitions from  $f_1(t)$  to  $f_2(t)$  or vice versa, arises since the decision concerning the latest sample is based upon all the samples in a window. A window comprising a large number of samples can reduce the probability of error when the decision is based on all the received samples, but a large window introduces detection delay during transitions. These are the topics considered in sections 3.3.3 and 3.3.4.

The theoretical background is based upon the Bayes likelihood ratio test [38]. In section 3.3.1 we consider 'the decision rule' for the detection process. The application of 'the decision rule' to EOG waveform analysis is considered in section 3.3.2 followed by the derivation

of the probability-of-error equation in section 3.3.3. The results of these sections are applied to a simulated EOG waveform in section 3.3.4. In section 3.4 laboratory results are presented for various types of simulated waveforms and experimentally obtained nystagmus waveforms.

### 3.3.1 The Decision Rule

In this section, the Bayes likelihood ratio test is used to derive an inequality which can be used to assign received data samples to one of two possible processes. The decision rule is optimum in the sense that the probability of error is minimized. A moving window of  $N$  samples is used to arrive at a decision. The fact that the received samples are noise contaminated is the motivation for using a window of samples to smooth out the effect of noise. Let  $N$  data samples be denoted by a vector  $R$  and the outputs of two processes by vectors  $F_1$  and  $F_2$ , i.e.

$$R = [r(1) \quad r(2) \quad r(3) \quad \text{-----} \quad r(N)]$$

$$F_j = [f_j(1) \quad f_j(2) \quad f_j(3) \quad \text{-----} \quad f_j(N)] ; j = 1,2$$

where

$$r(i) = f_j(i) + n(i) \text{ for } i = 1,2,3 \text{---} N \text{ and } j = 1,2 \quad (3.3.1)$$

$n(i)$  being the noise component of the received sample  $r(i)$ . Equation (3.3.1) assumes all samples come from either  $F_1$  or  $F_2$ . The noise samples  $n(i)$  are assumed to be zero mean Gaussian with variance  $\sigma_n^2$ . In other words, the probability density function of  $n(i)$  is given by

$$p(n(i)) = \frac{1}{\sqrt{2\pi} \sigma_n} \exp \left( - \frac{n(i)^2}{2\sigma_n^2} \right) \quad (3.3.2)$$

Let  $H_j$  be used to denote the hypothesis that the received data  $R$  is due to  $F_j$ ;  $j = 1, 2$ . The conditional probability density functions over the entire window, in the case of independent noise samples are given by

$$p(R/H_1) = \prod_{i=1}^N p(r(i)|f_1(i)) \quad (3.3.3)$$

and

$$p(R/H_2) = \prod_{i=1}^N p(r(i)|f_2(i)) \quad (3.3.4)$$

According to Bayes likelihood ratio test [38] (which minimizes the probability of error),  $H_1$  or  $H_2$  are accepted to be true as per the following inequality

$$\frac{\prod_{i=1}^N p(r(i)|f_1(i))}{\prod_{i=1}^N p(r(i)|f_2(i))} \underset{H_2}{\overset{H_1}{>}} \frac{P_2}{P_1} \quad (3.3.5)$$

where  $P_1$  and  $P_2$  are the a-priori probabilities associated with  $F_1$  and  $F_2$  respectively.

For a case of Gaussian noise we have

$$p(r(i)|f_j(i)) = \frac{1}{\sqrt{2\pi} \sigma_n} \cdot \exp(-\frac{(r(i)-f_j(i))^2}{2\sigma_n^2}) \quad (3.3.6)$$

Substituting (3.3.6) in (3.3.5) yields

$$\prod_{i=1}^N \exp \left[ \frac{(r(i)-f_2(i))^2}{2\sigma_n^2} - \frac{(r(i)-f_1(i))^2}{2\sigma_n^2} \right] \underset{H_2}{\overset{H_1}{>}} \frac{P_2}{P_1} \quad (3.3.7)$$

Alternatively, taking logarithms, we get

$$\sum_{i=1}^N \left[ [r(i) - f_2(i)]^2 - [r(i) - f_1(i)]^2 \right] \underset{H_2}{\overset{H_1}{>}} 2 \sigma_n^2 \ln \frac{P_2}{P_1}$$

or

$$\sum_{i=1}^N (2r(i) - f_2(i) - f_1(i))(f_1(i) - f_2(i)) \underset{H_2}{\underset{H_1}{\gtrless}} 2 \sigma_n^2 \ln \frac{P_2}{P_1} \quad (3.3.8)$$

or

$$\sum_{i=1}^N r(i)(f_1(i) - f_2(i)) \underset{H_2}{\underset{H_1}{\gtrless}} \frac{1}{2} \sum_{i=1}^N (f_1^2(i) - f_2^2(i)) + \sigma_n^2 \ln \frac{P_2}{P_1}$$

In vector form (3.3.8) can be written as

$$(\mathbf{F}_1 - \mathbf{F}_2)'_R \underset{H_2}{\underset{H_1}{\gtrless}} \frac{1}{2} \|\mathbf{F}_1\|^2 - \frac{1}{2} \|\mathbf{F}_2\|^2 + \sigma_n^2 \ln \frac{P_2}{P_1} \quad (3.3.9)$$

Inequality (3.3.8) or (3.3.9) can be used to determine if the received data samples  $R$  belong to  $F_1$  or  $F_2$ , the known vectors.

Now defining:

$$\Delta f_{12}(i) = f_1(i) - f_2(i) \quad (3.3.10)$$

and

$$\frac{1}{2} \sum_{i=1}^N (f_1^2(i) - f_2^2(i)) + \sigma_n^2 \ln \frac{P_2}{P_1} = K \quad (3.3.11)$$

(3.3.8) can be rewritten as

$$\sum_{i=1}^N r(i) \Delta f_{12}(i) \underset{H_2}{\underset{H_1}{\gtrless}} K \quad (3.3.12)$$

This decision rule is illustrated by Fig. 3.3. The threshold  $K$  is a function of noise and processes' statistics. By increasing  $N$ ,  $K$  can be made less dependent on  $\sigma_n$  (Eqn. (3.3.11)) which demonstrates the smoothing property of the decision rule.

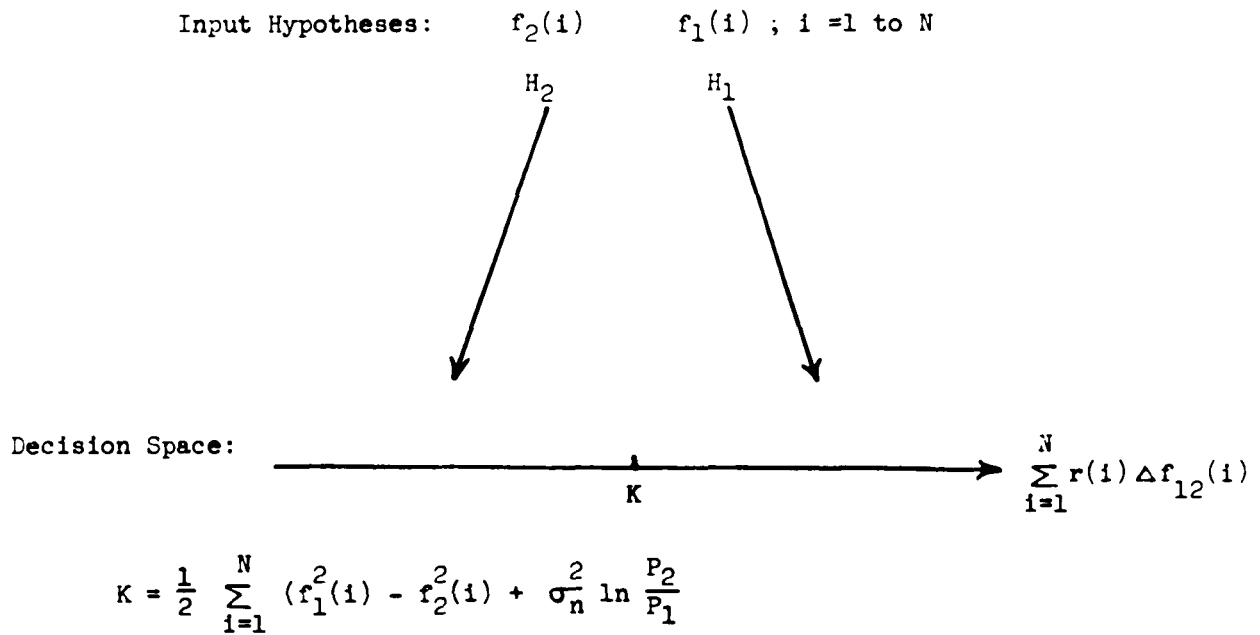


Fig. 3.3. Decision regions as determined by the decision rule of section 3.3.1.

### 3.3.2 The Decision Rule as applied to Nystagmus Waveform

A nystagmus waveform consists basically of two types of eye movements, the slow phase movements and the quick phase movements. For the purpose of their detection, these movements can be defined by vectors  $F_1$  and  $F_2$ . In general these vectors will not define the total time span of these movements, but will only be representative of the time functions defining them. With respect to a moving data window of  $(N+1)$  samples, where the first sample is subtracted from the rest of the samples, the vectors  $F_1$  and  $F_2$  are defined in Fig. 3.4.

In an on-line EOG data processing scheme one would like to associate each received sample to one of the two possible eye movements. If the decision rule of section 3.3.1 is used, the decision will be statistically correct if all the components of the received vector are due to either  $F_1$  or  $F_2$ . The decision may not be correct if the data window (or vector  $R$ ) is due partly to  $F_1$  and partly to  $F_2$ . Such is the case at the time of transition from  $F_1$  to  $F_2$  or  $F_2$  to  $F_1$ . This is illustrated in Fig. 3.5. for a window of 5 samples and will be pursued further in section 3.3.3.

The implementation of (3.3.8) or (3.3.9) requires the knowledge of  $P_1$  and  $P_2$ , which in the case of a nystagmus waveform, can be obtained as follows. Consider a typical cycle of nystagmus shown in Fig. 3.6,  $P_1$  and  $P_2$  are estimated by

$$P_1 = T_1 / (T_1 + T_2) \quad (3.3.13)$$

$$P_2 = T_2 / (T_1 + T_2) \quad (3.3.14)$$

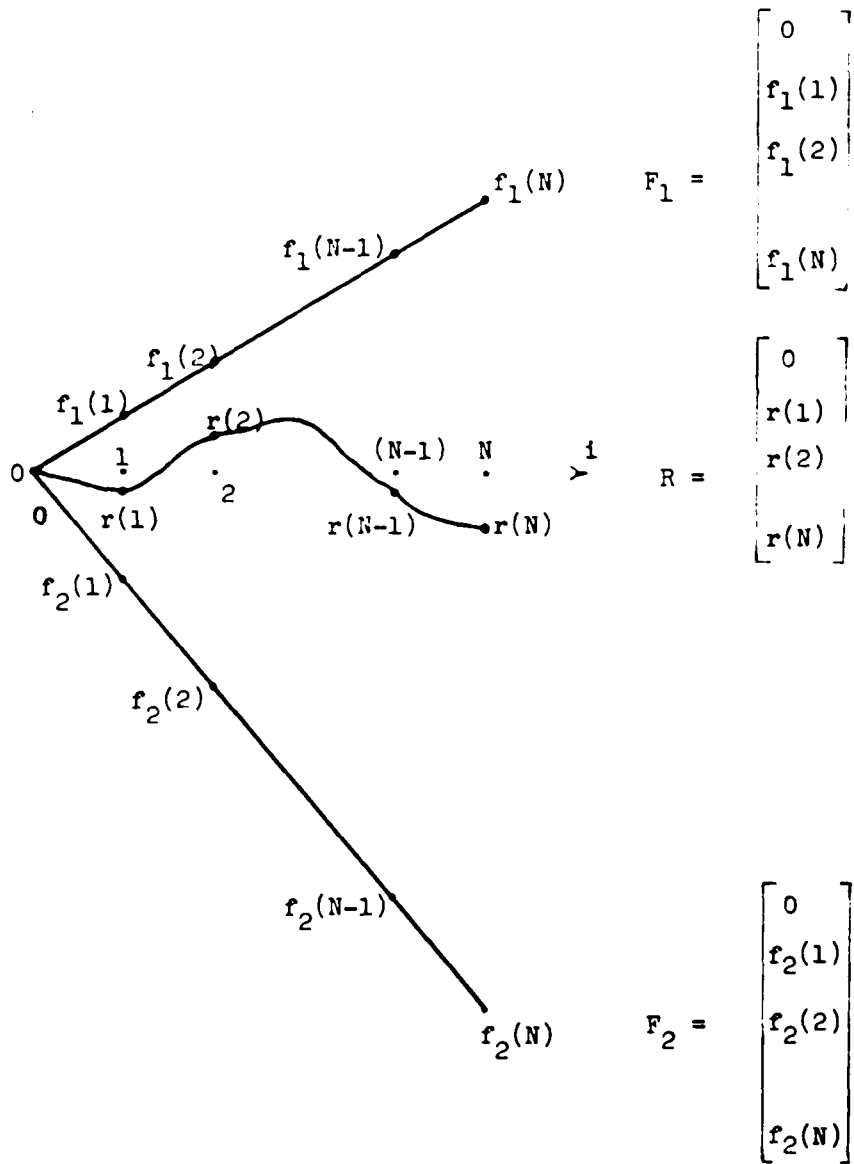
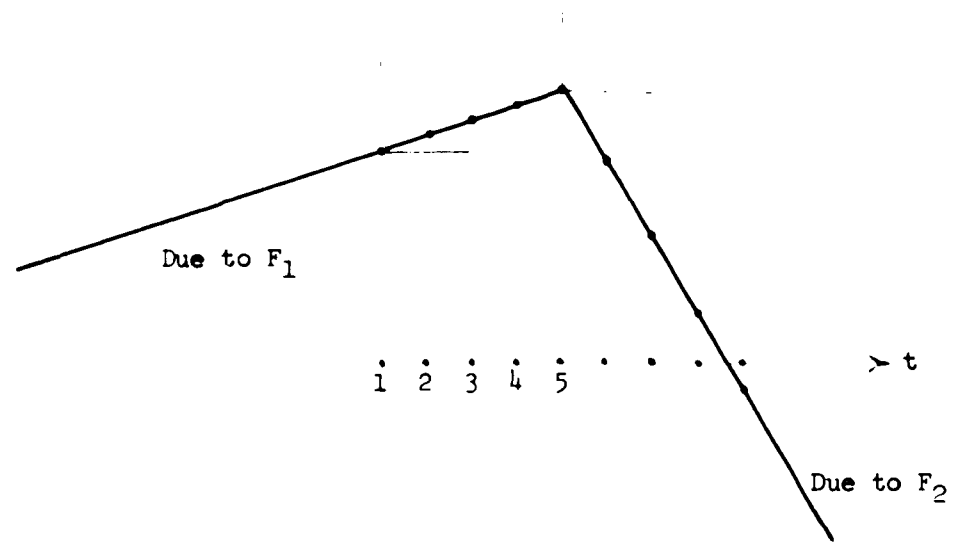


Fig. 3.4. Definitions of vectors  $F_1$  and  $F_2$  and the received data vector  $R$ .



Window Starting Time

t	Samples
1	0, $f_1(1)$ , $f_1(2)$ , $f_1(3)$ , $f_1(4)$ $\hat{=} F_1$
2	0, $f_1(1)$ , $f_1(2)$ , $f_1(3)$ , $f_1(3) + f_2(1)$
3	0, $f_1(1)$ , $f_1(2)$ , $f_1(2) + f_2(1)$ , $f_1(2) + f_2(2)$
4	0, $f_1(1)$ , $f_1(1) + f_2(1)$ , $f_1(1) + f_2(2)$ , $f_1(1) + f_2(3)$
5	0, $f_2(1)$ , $f_2(2)$ , $f_2(3)$ , $f_2(4)$ $\hat{=} F_2$

Fig. 3.5. For a moving window of 5 samples, the sample sequences during transition from  $F_1$  to  $F_2$ . Noise is assumed to be zero. Similar sequences arise during the transition from  $F_2$  to  $F_1$ .

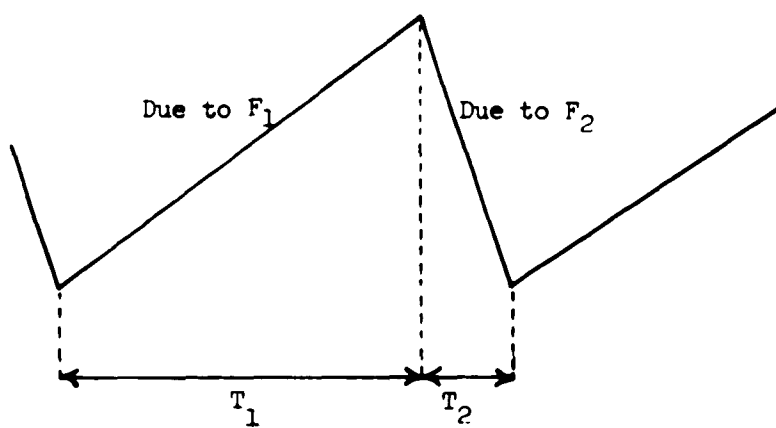


Fig. 3.6. A-priori probabilities  $P_1$  and  $P_2$  calculations use  $T_1$  and  $T_2$  intervals for a typical cycle of nystagmus.

A simplifying assumption that  $F_1$  and  $F_2$  represent two straight lines with different slopes will be made in the analysis. It is assumed that the slopes of these lines are correct enough to represent the entire spans of two types of eye movements. The justification of this assumption is that, within the window span the EOG is practically a straight line and over the entire span of one type of movement the slope change is small enough not to introduce any gross detection error.

### 3.3.3 The Probability of Error of the Detection Process

Each incoming data sample must either be assigned to  $f_1(i)$  or to  $f_2(i)$ . The decision rule of section 3.3.1 uses all the sample points in a window. Therefore, if at an instant, all the sample points received up to that time are due to one or the other process, the only error in the decision may be due to noise. In another case where the window samples are partly due to  $f_1(i)$  and partly due to  $f_2(i)$ , the decision about the latest sample is influenced by the samples before it. Here, we will derive expressions for the probability of error associated with the decision process where the decision rule of (3.3.12) is used and at each time the decision is either  $f_1(i)$  or  $f_2(i)$ .

The value of the expression  $\sum_{i=1}^N r(i)\Delta f_{12}(i)$  depends upon the data samples  $r(i)$  which may all be due to  $f_1(i)$  or all due to  $f_2(i)$  or partly due to  $f_1(i)$  and partly due to  $f_2(i)$ . Let us use the

following variables to denote the value of  $\sum_{i=1}^N r(i)\Delta f_{12}(i)$  for these different data sets:

$$\begin{aligned}
 \sum_{i=1}^N r(i)\Delta f_{12}(i) &= Z_{11N} \text{ when all } (N+1) \text{ samples are due to } f_1(i) \\
 &= Z_{22N} \text{ when all } (N+1) \text{ samples are due to } f_2(i) \\
 &= Z_{12x} \text{ when the last 'x' samples are due to} \\
 &\quad f_2(i) \text{ and the rest are due to } f_1(i) \\
 &= Z_{21x} \text{ when the last 'x' samples are due to} \\
 &\quad f_1(i) \text{ and the rest are due to } f_2(i)
 \end{aligned} \tag{3.3.15}$$

In terms of  $f_1(i)$  and  $f_2(i)$  (3.3.15) can be written as

$$Z_{11N} = \sum_{i=1}^N (f_1(i)+n(i)-n(0))\Delta f_{12}(i) \tag{3.3.16}$$

$$Z_{22N} = \sum_{i=1}^N (f_2(i)+n(i)-n(0))\Delta f_{12}(i) \tag{3.3.17}$$

$$\begin{aligned}
 Z_{12x} &= \sum_{i=1}^{N-x} (f_1(i)+n(i)-n(0))\Delta f_{12}(i) + \sum_{i=N-x+1}^N (f_1(N-x)+ \\
 &\quad f_2(i-N+x)+n(i)-n(0))\Delta f_{12}(i)
 \end{aligned} \tag{3.3.18}$$

$$\begin{aligned}
 Z_{21x} &= \sum_{i=1}^{N-x} (f_2(i)+n(i)-n(0))\Delta f_{12}(i) + \sum_{i=N-x+1}^N (f_2(N-x)+ \\
 &\quad f_1(i-N+x)+n(i)-n(0))\Delta f_{12}(i)
 \end{aligned} \tag{3.3.19}$$

where  $n(0)$  is the noise term with the reference sample  $r(0)$ .

Now an error in the decision will be made if  $Z_{11N} < K$  or  $Z_{21x} < K$  for all  $x$  or  $Z_{22N} > K$  or  $Z_{12x} > K$  for all  $x$ . The a-priori probabilities associated with the cases generating  $Z_{12x}$  and  $Z_{21x}$  depend upon the sampling interval and the average frequency of transitions in the

waveform. These will, though, be the same for all cases and let us denote them by  $P_t$ .  $P_1$  and  $P_2$  will also be slightly different from (3.3.13) and (3.3.14) if the window interval is accounted in calculations. Ignoring these minor differences, the probability of error is given by

$$\begin{aligned}
 P(E) = & P_1 P(Z_{11N} < K) + P_2 P(Z_{22N} > K) + P_t \sum_{x=1}^{N-1} P(Z_{21x} < K) + \\
 & + P_t \sum_{x=1}^{N-1} P(Z_{12x} > K) \quad (3.3.20)
 \end{aligned}$$

To compute  $P(E)$ , we need to determine the statistics of  $Z_{11N}$ ,  $Z_{22N}$ ,  $Z_{21x}$  and  $Z_{12x}$  for  $1 \leq x \leq N-1$ . For normally distributed noise, these are also normally distributed random variables with the following means and variances.

$$\bar{Z}_{11N} = \sum_{i=1}^N f_1(i) \Delta f_{12}(i) \quad (3.3.21)$$

$$\bar{Z}_{22N} = \sum_{i=1}^N f_2(i) \Delta f_{12}(i) \quad (3.3.22)$$

$$\bar{Z}_{21x} = \sum_{i=1}^{N-x} f_2(i) \Delta f_{12}(i) + \sum_{i=N-x+1}^N (f_2(N-x) + f_1(i-N+x)) \Delta f_{12}(i) \quad (3.3.23)$$

$$\bar{Z}_{12x} = \sum_{i=1}^{N-x} f_1(i) \Delta f_{12}(i) + \sum_{i=N-x+1}^N (f_1(N-x) + f_2(i-N+x)) \Delta f_{12}(i) \quad (3.3.24)$$

$$\sigma_{11N}^2 = \sigma_{22N}^2 = \sigma_{12x}^2 = \sigma_{21x}^2 = \sigma_n^2 \cdot \sum_{i=1}^N (\Delta f_{12}(i))^2 \quad (3.3.25)$$

These equations lead to the probability density functions as follows

$$P_{11N}(X) = \frac{1}{\sqrt{2\pi} \sigma_{11N}} \cdot \exp \frac{-(X - \bar{Z}_{11N})^2}{2 \sigma_{11N}^2} \quad (3.3.26)$$

$$P_{22N}(X) = \frac{1}{\sqrt{2\pi} \sigma_{22N}} \cdot \exp \frac{-(X - \bar{Z}_{11N})^2}{2 \sigma_{22N}^2} \quad (3.3.27)$$

$$P_{21x}(X) = \frac{1}{\sqrt{2\pi} \sigma_{21x}} \cdot \exp \frac{-(X - \bar{Z}_{21x})^2}{2 \sigma_{21x}^2} \quad (3.3.28)$$

$$P_{12x}(X) = \frac{1}{\sqrt{2\pi} \sigma_{12x}} \cdot \exp \frac{-(X - \bar{Z}_{12x})^2}{2 \sigma_{12x}^2} \quad (3.3.29)$$

Eqn. (3.3.20) when rewritten in terms of probability density functions is given by

$$P(E) = P_1 \cdot \int_{-\infty}^K P_{11N}(X) dX + P_2 \cdot \int_K^{\infty} P_{22N}(X) dX + P_t \cdot \sum_{x=1}^{N-1} \left[ \int_{-\infty}^K P_{21x}(X) dX \right] \\ + P_t \cdot \sum_{x=1}^{N-1} \left[ \int_K^{\infty} P_{12x}(X) dX \right] \quad (3.3.30)$$

Substituting (3.3.26) - (3.3.29) in (3.3.30) and further simplification yields

$$P(E) = \frac{P_1}{2} \cdot \operatorname{erf} \left( \frac{K - \bar{Z}_{11N}}{\sqrt{2} \sigma_{11N}} \right) + 1 + \frac{P_2}{2} \cdot \operatorname{erfc} \left( \frac{K - \bar{Z}_{22N}}{\sqrt{2} \sigma_{22N}} \right) + \frac{P_t}{2} \cdot \sum_{x=1}^{N-1} \\ \left( \operatorname{erf} \left( \frac{K - \bar{Z}_{21x}}{\sqrt{2} \sigma_{21x}} \right) + 1 \right) + \frac{P_t}{2} \cdot \sum_{x=1}^{N-1} \operatorname{erfc} \left( \frac{K - \bar{Z}_{12x}}{\sqrt{2} \sigma_{12x}} \right) \quad (3.3.31)$$

In most practical cases  $P_t \ll P_1$  and  $P_2$ . Thus (3.3.31) can be approximated by

$$P(E) \approx \frac{P_1}{2} \left[ \operatorname{erf} \left( \frac{K - \bar{Z}_{11N}}{\sqrt{2} \sigma_{11N}} \right) + 1 \right] + \frac{P_2}{2} \cdot \operatorname{erfc} \left( \frac{K - \bar{Z}_{22N}}{\sqrt{2} \sigma_{22N}} \right)$$

for small N (3.3.32)

In (3.3.31) and (3.3.32), error function and complementary error function are defined as

$$\operatorname{erf}(Z) = \frac{2}{\sqrt{\pi}} \int_0^Z e^{-t^2} dt \quad (3.3.33)$$

and  $\operatorname{erfc}(Z) = 1 - \operatorname{erf}(Z)$

The results of this section are illustrated in the next section by application to a simulation example.

#### 3.3.4 A Simulation Example

Let us construct an artificial example to illustrate the theory of section 3.3.3. Consider a case where  $f_1(t)$  and  $f_2(t)$  are given by

$$f_1(t) = .2t \quad (3.3.34)$$

$$f_2(t) = -1.6t \quad (3.3.35)$$

The associated a-priori probabilities are computed based upon the assumption that average time period for  $f_1(t)$  is 900 msec( $T_1$ ) and for  $f_2(t)$  is 100 msec( $T_2$ ). Let the sampling period be 2msec( $T$ ). The a-priori probabilities are obtained as follows:

$$P_1 = \frac{T_1 - (N-1)T}{T_1 + T_2} \approx \frac{T_1}{T_1 + T_2} = .9 \quad (3.3.36)$$

$$P_2 = \frac{T_2 - (N-1)T}{T_1 + T_2} \approx \frac{T_2}{T_1 + T_2} = .1 \quad (3.3.37)$$

$$P_t = \frac{T}{T_1 + T_2} = .002 \quad (3.3.38)$$

Where  $(N=1)$  are the number of samples in a window. Approximation in (3.3.36) and (3.3.37) assumes that the window width is relatively much smaller than  $T_1$  and  $T_2$ .

Substituting (3.3.36) - (3.3.38) in (3.3.31) and (3.3.32) yields

$$P(E) = .45 \left[ \operatorname{erf} \left( \frac{K - \bar{Z}_{11N}}{\sqrt{2} \sigma_{11N}} \right) + 1 \right] + .05 \operatorname{erfc} \left( \frac{K - \bar{Z}_{22N}}{\sqrt{2} \sigma_{22N}} \right) + .001 \sum_{x=1}^{N-1} \left( \operatorname{erf} \left( \frac{K - \bar{Z}_{21x}}{\sqrt{2} \sigma_{21x}} \right) + 1 \right) + .001 \sum_{x=1}^{N-1} \left( \operatorname{erfc} \left( \frac{K - \bar{Z}_{12x}}{\sqrt{2} \sigma_{12x}} \right) \right) \quad (3.3.39)$$

and

$$P(E) \approx .45 \left[ \operatorname{erf} \left( \frac{K - \bar{Z}_{11N}}{\sqrt{2} \sigma_{11N}} \right) + 1 \right] + .05 \operatorname{erfc} \left( \frac{K - \bar{Z}_{22N}}{\sqrt{2} \sigma_{22N}} \right) \text{ for small } N \quad (3.3.40)$$

Probabilities of error as obtained from (3.3.39) and (3.3.40) are plotted in Fig. 3.7 for  $N=2, 4$  and  $6$ ; and  $\sigma_n = 0.0$  to  $3.5$ . Observe that for small  $N$  (say  $N=2$ ), equations (3.3.39) and (3.3.40) yield about the same probability of error and it increases with  $\sigma_n$ . For larger values of  $N$  (say  $N=6$ ), the error probability is mainly due to the transitional error and is approximately constant for small  $\sigma_n$  ( $< 2.5$ ). For larger  $\sigma_n$  values, the error probability is due to both the transition and the noise and it increases with  $\sigma_n$ . The probability of error conditioned on the latest sample during the transition from  $f_1(t)$  to  $f_2(t)$  varies from

$$\left[ \operatorname{erf} \left( \frac{K - \bar{Z}_{11N}}{\sqrt{2} \sigma_{11N}} \right) + 1 \right] \text{ to } \left[ \operatorname{erfc} \left( \frac{K - \bar{Z}_{12x}}{\sqrt{2} \sigma_{12x}} \right), x=1 \text{ to } (N-1) \right]$$

$$\left[ \text{to } \operatorname{erfc} \left( \frac{K - \bar{Z}_{22N}}{\sqrt{2} \sigma_{22N}} \right) \right]. \text{ Similarly for the transition from } f_2(t) \text{ to } f_1(t) \text{ it varies from}$$

$$\left[ \operatorname{erfc} \left( \frac{K - \bar{Z}_{22N}}{\sqrt{2} \sigma_{22N}} \right) \right] \text{ to } \left[ \operatorname{erf} \left( \frac{K - \bar{Z}_{21x}}{\sqrt{2} \sigma_{21x}} \right) + 1, x=1 \text{ to } (N-1) \right]$$

$$\text{to } \left[ \operatorname{erf} \left( \frac{K - \bar{Z}_{11N}}{\sqrt{2} \sigma_{11N}} \right) + 1 \right].$$

The probability of error conditioned on each new received sample during the transition from  $f_1(t)$  to  $f_2(t)$  is plotted in Fig. 3.8a. Observe that as the number of samples in a window are increased, a larger number of samples are needed from  $f_2(t)$  before it can be detected. For instance for  $N=4$ , we must receive at least 3 samples from  $f_2(t)$  before it is detected. Similar results are plotted for the transition from  $f_2(t)$  to  $f_1(t)$  in Fig. 3.8b. The plots of Fig. 3.8a and 3.8b lead to the conclusion that there is a definite amount of delay in the detection of an on-coming process and it depends upon the window width.

In Fig. 3.8c, the error probability associated with each sample for the transition  $f_1(t)$  to  $f_2(t)$  for  $N=6$  is plotted for various  $\sigma_n$  values. Observe that increasing  $\sigma_n$  increases the error probability when a larger number of samples are contributed by the on-coming process. However, this probability of error is decreased for smaller number of samples contributed by the on-coming process. Similar results are shown for the transition  $f_2(t)$  to  $f_1(t)$  in Fig. 3.8d. The two transitions are compared in Fig. 3.8e for a case of  $\sigma_n = 3.0$

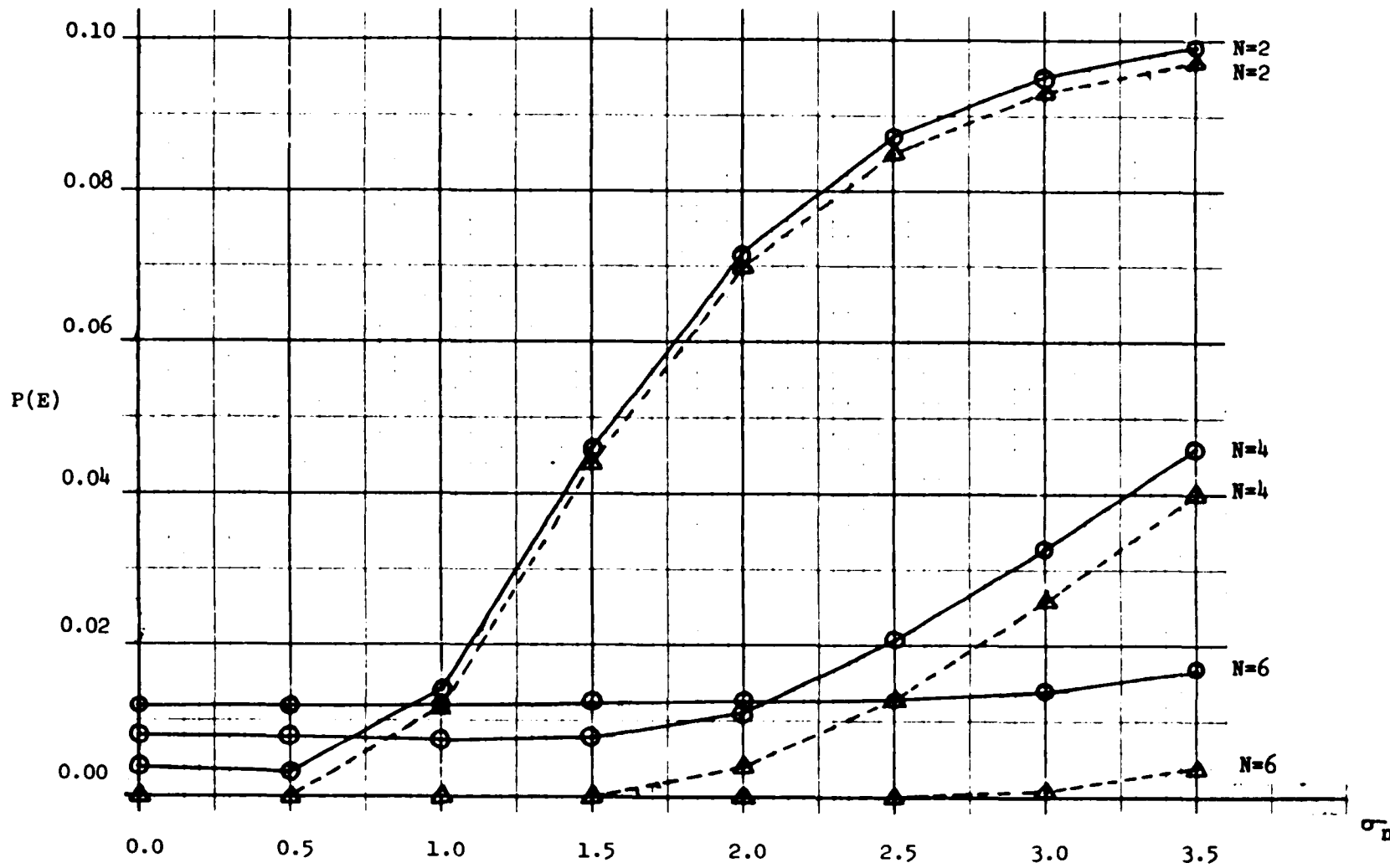


Fig. 3.7 . Total probability of error for the detection of example in section 3.3.4.  
 ○—○ Eqn. 3.3.39, △-----△ Eqn. 3.3.40.

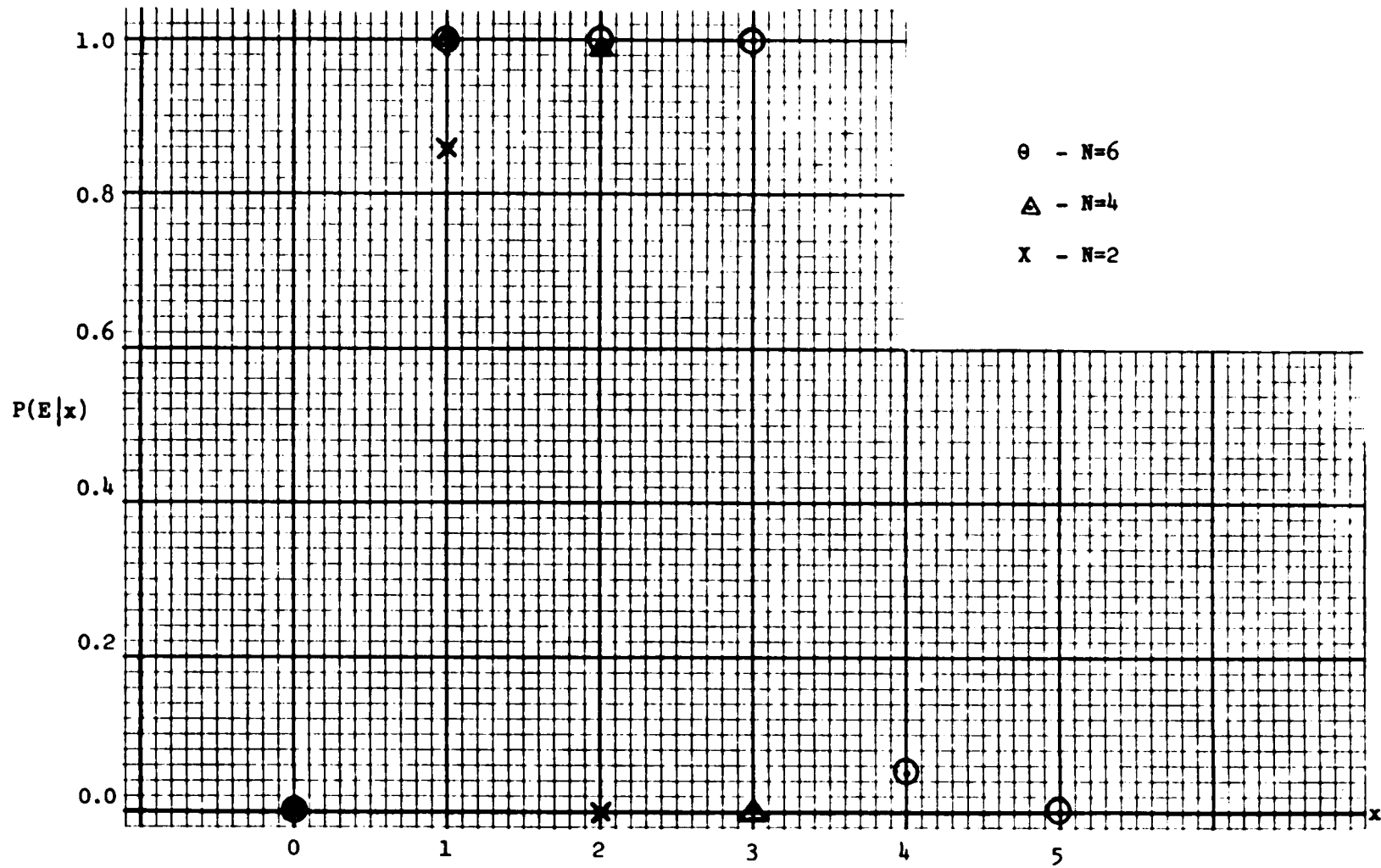


Fig. 3.8a. Conditional probability of error during the transition from  $f_1(t)$  to  $f_2(t)$ .  
 $\sigma_n = 0.5$  for all the cases.

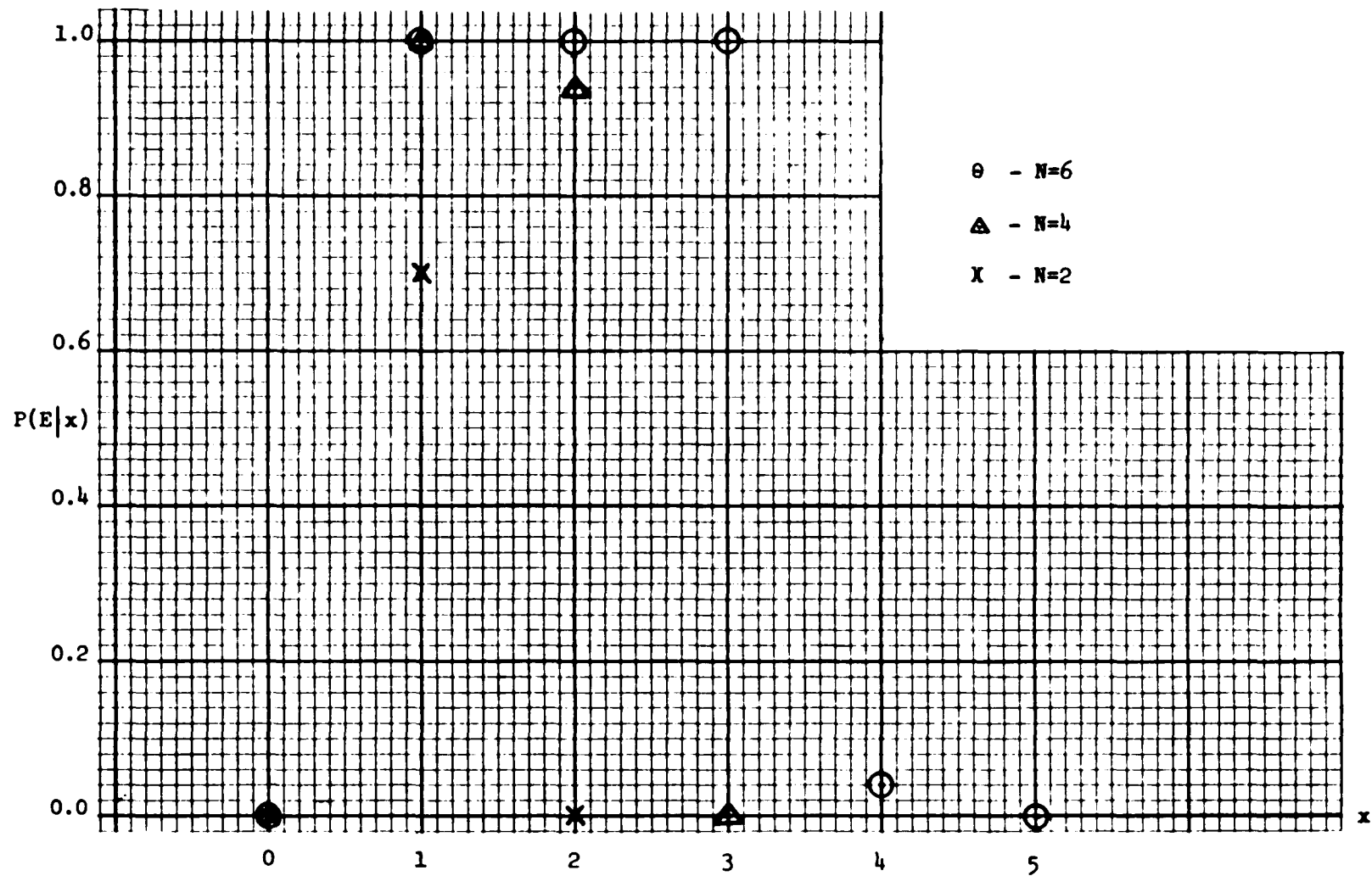


Fig. 3.8b. Conditional probability of error during the transition from  $f_2(t)$  to  $f_1(t)$ .  
 $\sigma_n = 0.5$  for all the cases.

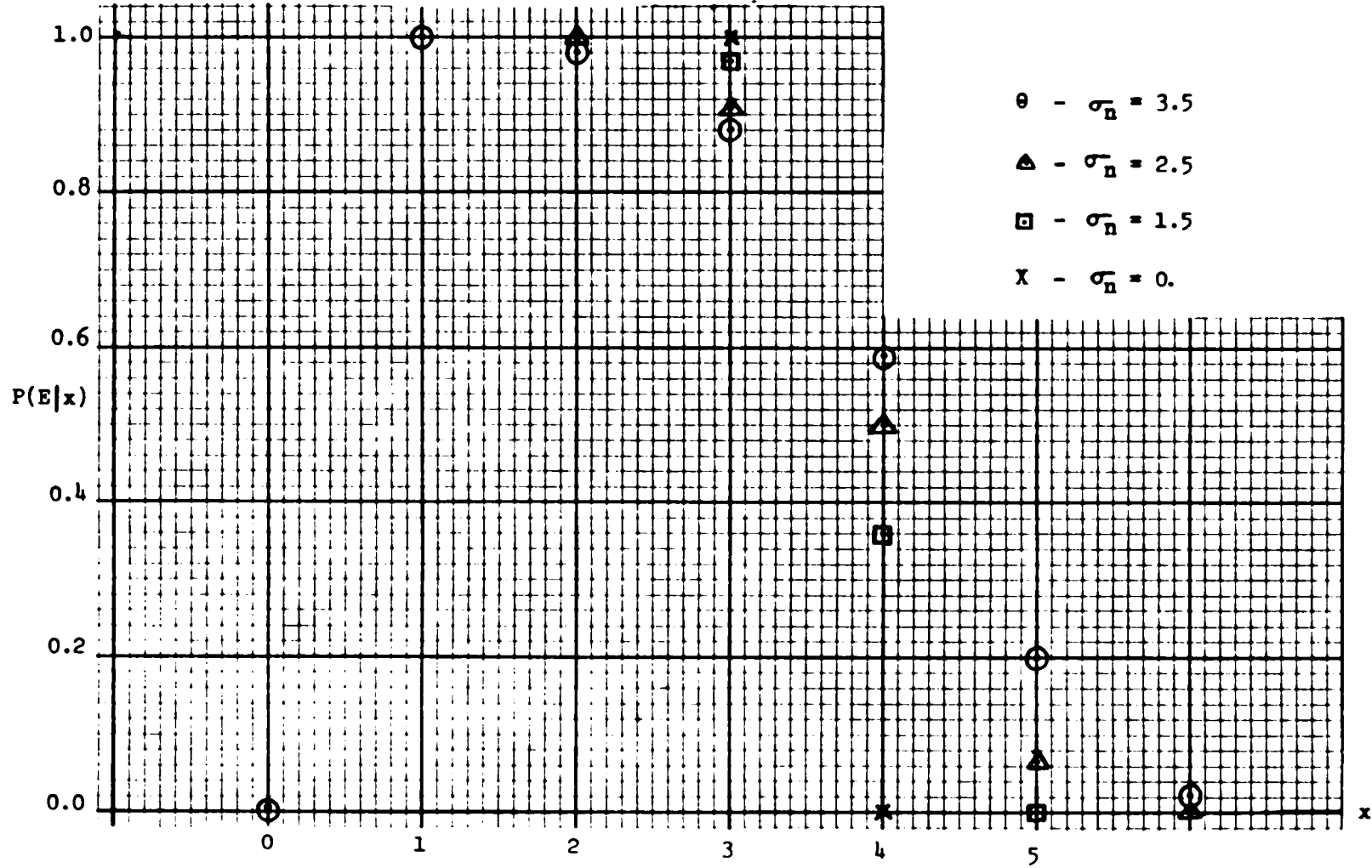


Fig. 3.8c. Conditional probability of error for the transition from  $f_1(t)$  to  $f_2(t)$  for  $N=6$  and  $\sigma_n = 0.0, 1.5, 2.5$  and  $3.5$ .

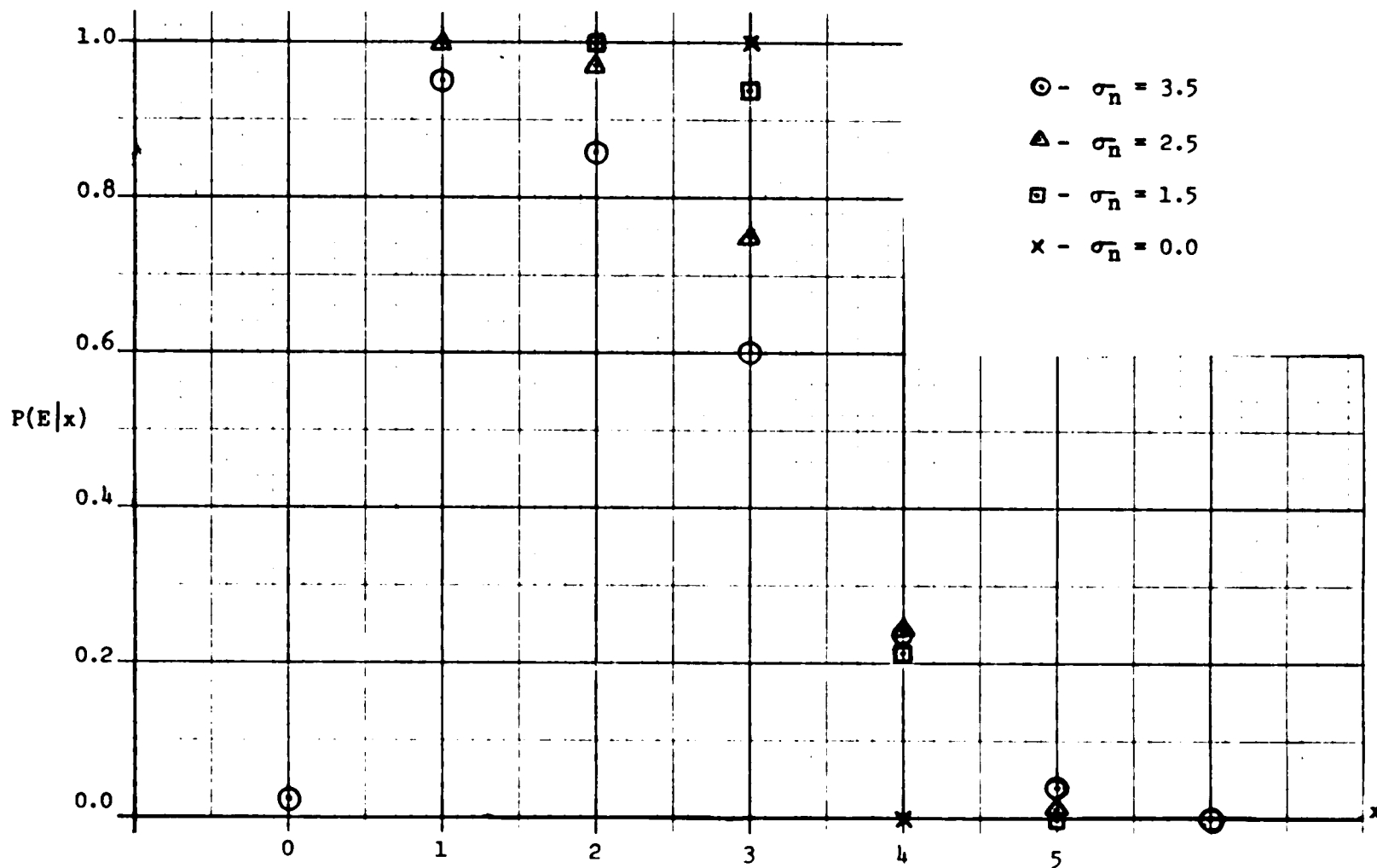


Fig. 3.8d. Conditional probability of error for the transition from  $f_2(t)$  to  $f_1(t)$  for  $N=6$  and  $\sigma_n = 0.0, 1.5, 2.5$  and  $3.5$ .

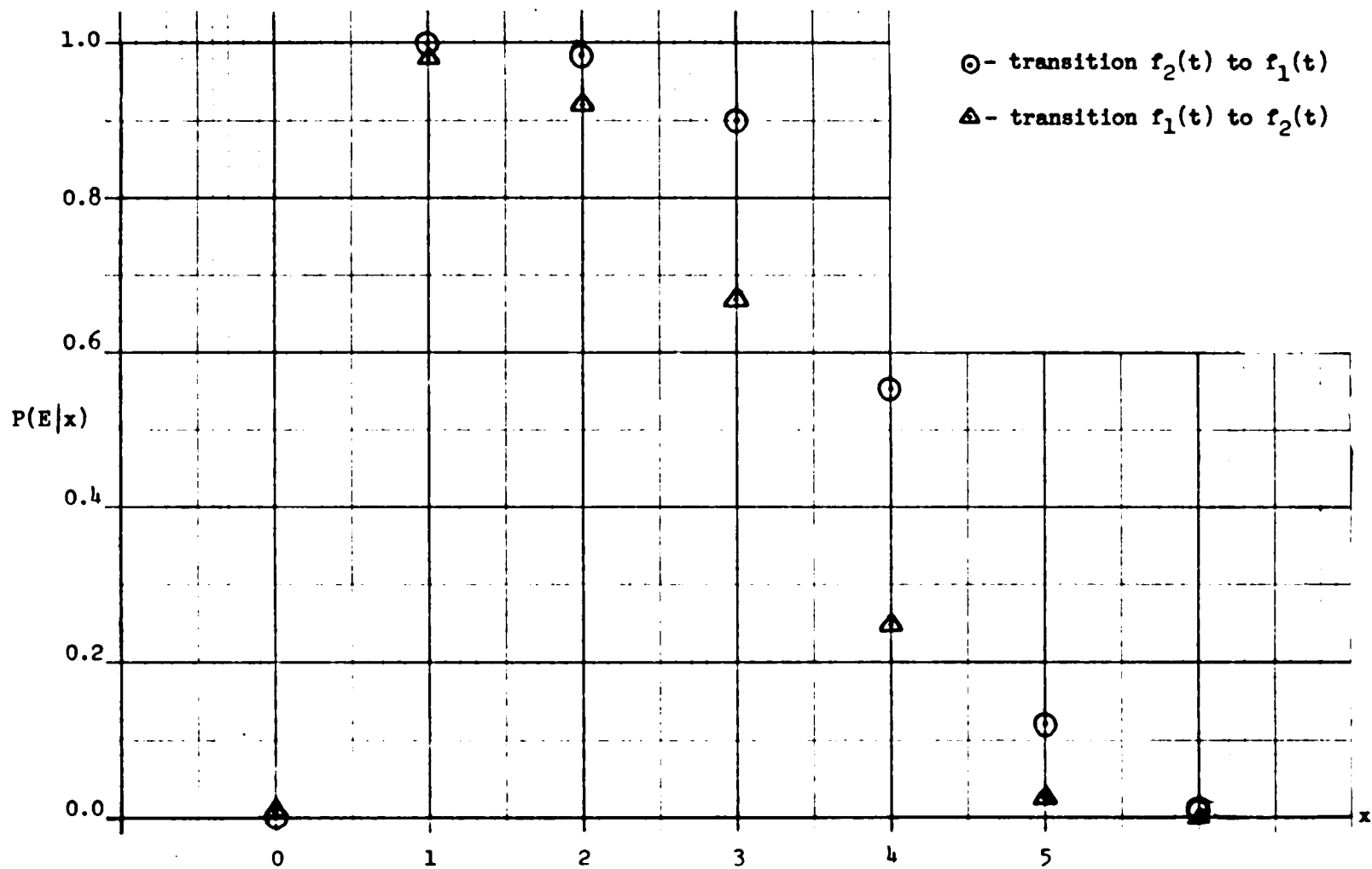


Fig. 3.8e. Conditional probability of error comparison for the two transitions  $f_1(t)$  to  $f_2(t)$  and  $f_2(t)$  to  $f_1(t)$ .

and  $N=6$ . Observe that the transition  $f_1(t)$  to  $f_2(t)$  is accompanied by larger error probability as compared to the transition  $f_2(t)$  to  $f_1(t)$ . When all the samples belong to one or the other process, the error associated with  $f_2(t)$  is larger than the error associated with  $f_1(t)$ .

The program used to obtain the results of Fig. 3.7 & Fig. 3.8 is in Appendix A.

### 3.4 Experimental Results

The theory presented in the previous sections was tested in the laboratory on simulated and real data. The following sections are organized to present the experimental hardware configuration, software implementation, the simulation results, and the real EOG saccade detection results.

#### 3.4.1 EOG Data Processing Hardware Configuration

Fig. 3.9 is a simplified block diagram of EOG data processing system as used in our laboratory. Eye movements are recorded by electrooculography using implanted Ag-AgCl electrodes [7]. The EOG so obtained is filtered and amplified. For later processing it can be stored on FM magnetic tape. For on-line processing it is fed directly into the computer system.

A 10-bit successive approximation type analog to digital converter AD8-EA [10] with sample and hold circuits, conversion circuits, an input buffer, and control logic is used to convert analog EOG to

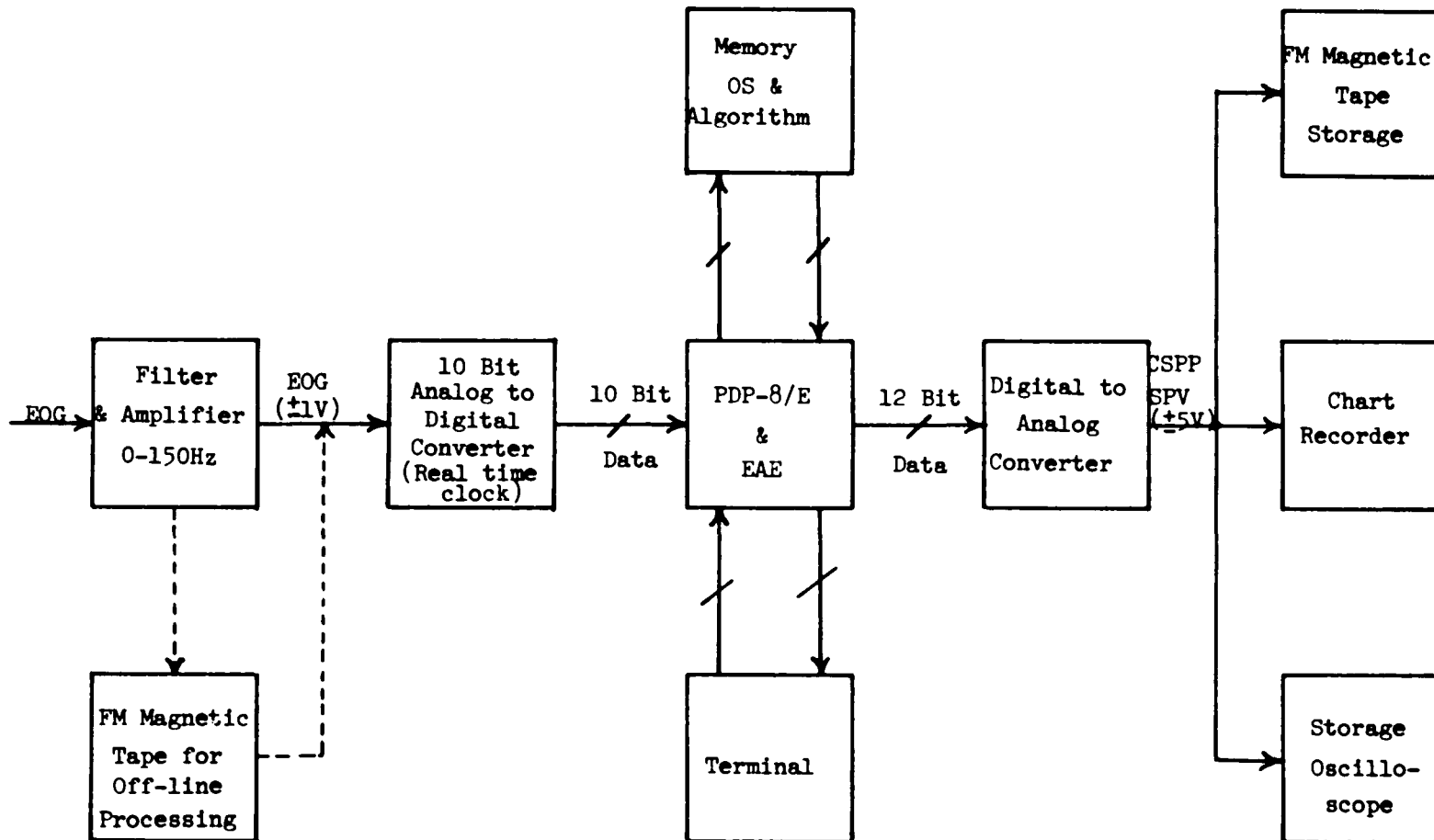


Fig. 3.9. A simplified block diagram of EOG data processing system as used in this study.

digital signal. The analog EOG must be limited between  $\pm 1$  volt to avoid overdriving the converter. The conversion is initiated by the Real Time Clock DK8-EP [10]. When the conversion is complete, A/D Done Flag is set. This is sensed by the processor and the 10-bit digital word is transferred to 10 least significant bits of the accumulator. Since the 10-bit word is in two's complement form, the sign bit is extended to the two most significant bits of the accumulator. Thus all further processing can be done on 12-bit words. The data so gathered is stored in the memory.

The computer used to process the data is the Digital Equipment Corporation's PDP-8/E a 12-bit machine [10]. It is a single-address, fixed word length, parallel transfer computer using two's complement arithmetic. It has a cycle time of 1.2/1.4 usec. Apart from a 12-bit accumulator (AC) it also has another 12-bit register called multiplier-quotient (MQ) register. MQ acts as an extension of the AC during extended arithmetic operations. For extended operations a KE8-E Extended Arithmetic Element (EAE) is installed [10]. EAE allows implementation of 24-bit arithmetic operation for more accuracy. The computer used in this study is equipped with 28K memory. The memory is divided into fields each of 4K for addressing purposes. Each field is further subdivided into 32 pages each page having space for 128 12-bit words.

The processed digital data is converted back to an analog signal by a digital to analog (D-A) converter. The D-A converter used has 12-bits equivalent to  $\pm 5$  volts. Thus the computed information can be directly fed to the D-A converter without any modification. The analog waveforms obtained from the converter can be displayed on a storage

oscilloscope or recorded on a chart recorder or stored on a magnetic tape for further processing at a later time.

#### 3.4.2 EOG Saccade Detection Algorithm

The 'Likelihood Ratio Detector' of the last section is implemented on the PDP-8/E computer for the detection of saccades in an EOG waveform. The functional description of saccades and slow phases was obtained by examining records of typical EOG waveforms. Then tables were prepared describing their time vs. functional value plots. If  $f_1(t)$  designates slow phase and  $f_2(t)$  designates quick phase, then further tables of  $f_1(t) + f_2(t)$  and  $f_1(t) - f_2(t)$  were prepared to be used in the implementation of the left side of inequality (3.3.8). The right side of (3.3.8) was evaluated examining previously obtained EOG records and in most cases it turned out to be a very small number in comparison with the left side.

Actual implementation of the left side in (3.3.8) is shown in Fig. 3.10. In the flow chart 'DFN', the decision function is the negative of the left hand side of inequality (3.3.8). A decision window width of 'N+1' is assumed which may be increased to reduce noise effect but must be decreased to detect the transitions appropriately and at the right time. A value of  $N=5$  was found to be a compromise for the detection of transitions and in minimizing false detections due to noise. In order to detect both left going and right going saccades, the absolute value of the scaled signal is used in the computation of 'DFN'. The value of 'DFN' calculated leads to the origin of the data, i.e. whether the received signal is

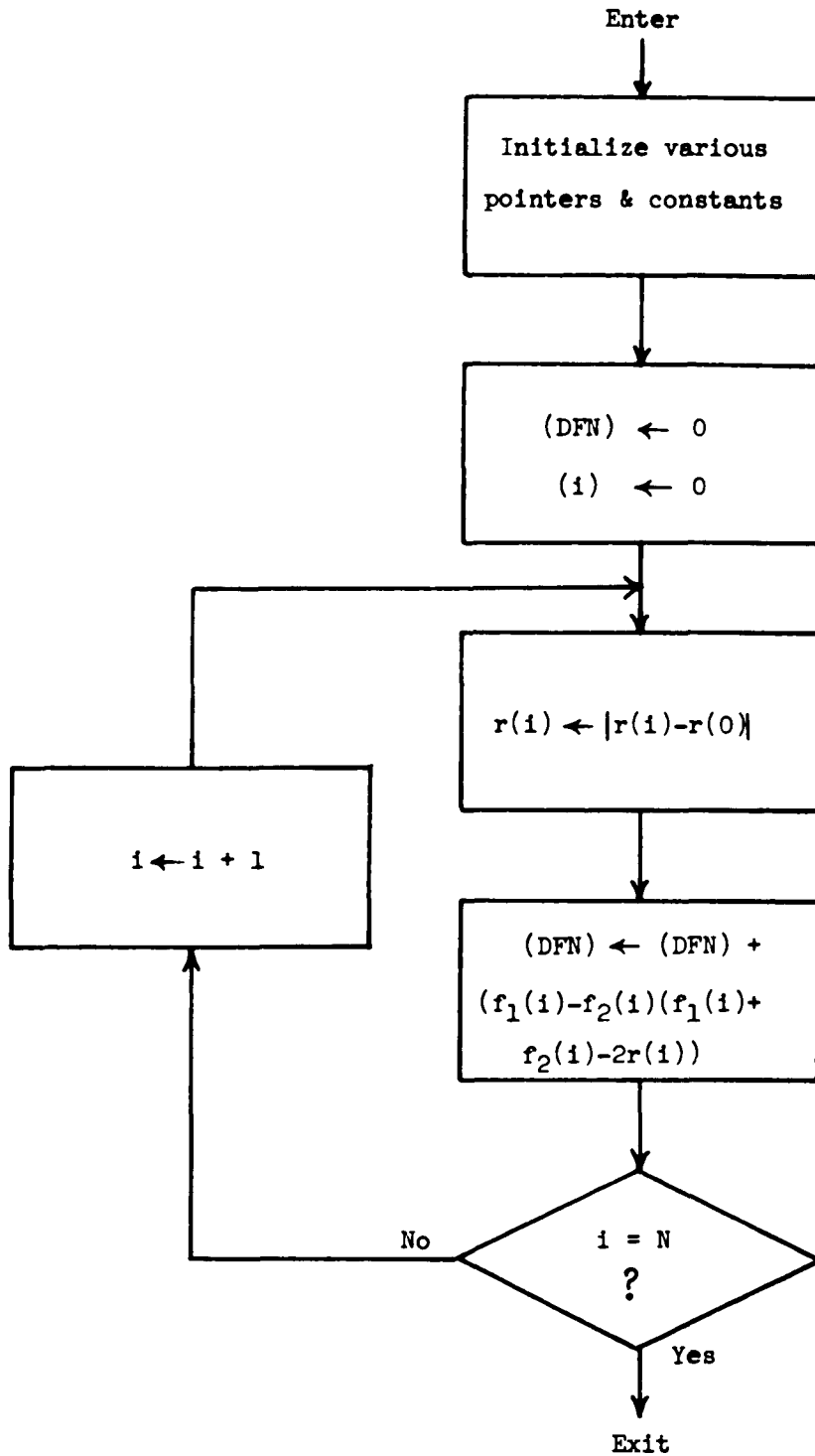


Fig. 3.10. Flow chart of DETECT subroutine for computing a decision function (DFN). Window width =  $N+1$ .

from saccadic process or from the slow phase system. The following criterion was used to detect saccades in the EOG waveform

$$\text{DFN} > 2 \sigma_n^2 \ln (P_2/P_1) \text{ implies saccade}$$

and  $\text{DFN} < 2 \sigma_n^2 \ln (P_2/P_1)$  implies slow phase

The program for the implementation of saccade detection algorithm appears in Appendix B along with the rest of the program used in Chapter 4. The saccadic detection part of that program is tested in the next section on simulated and experimentally obtained EOG waveforms.

### 3.4.3 Simulated and Real Saccadic Detection Examples

The saccadic detection algorithm of the last section was used to compute the decision function for an EOG-like waveform. The result is shown in Fig. 3.11. It is obvious from the 'DFN' waveform that 'DFN' changes in accordance with the slope of the simulated EOG waveform. To indicate saccades, an appropriate threshold function may be used. In Fig. 3.12a and 3.12b, the saccade indications are obtained from the sign of 'DFN' (which is equivalent to ignoring  $2 \sigma_n^2 \ln (P_2/P_1)$ ), positive value of 'DFN' indicates a saccade and a negative value indicates a slow phase. Various types of saccade-like waveforms are processed to generate saccade indication waveform. There is no miss or false detection indication in the case of the simulated waveforms.

In Fig. 3.13, an experimentally obtained EOG waveform is used to generate the corresponding 'DFN' waveform. The threshold value to

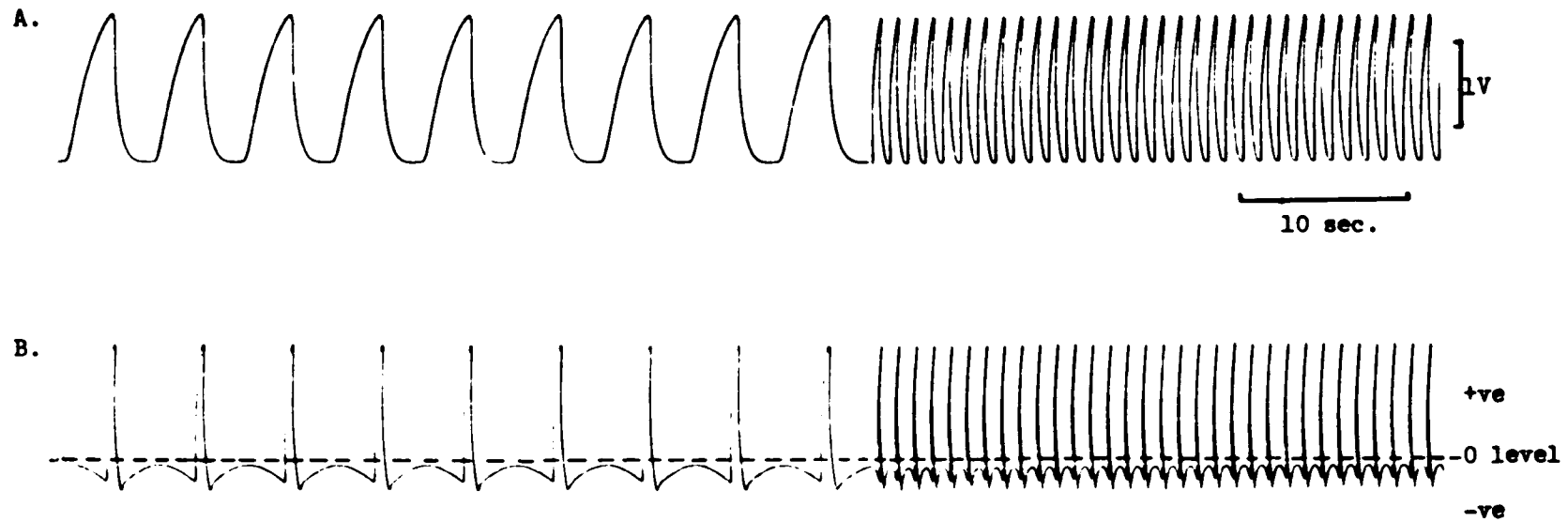


Fig. 3.11. Simulated EOG and its decision function. A. Simulated EOG.  
 B. Decision function as computed by 'likelihood ratio detector' subroutine.

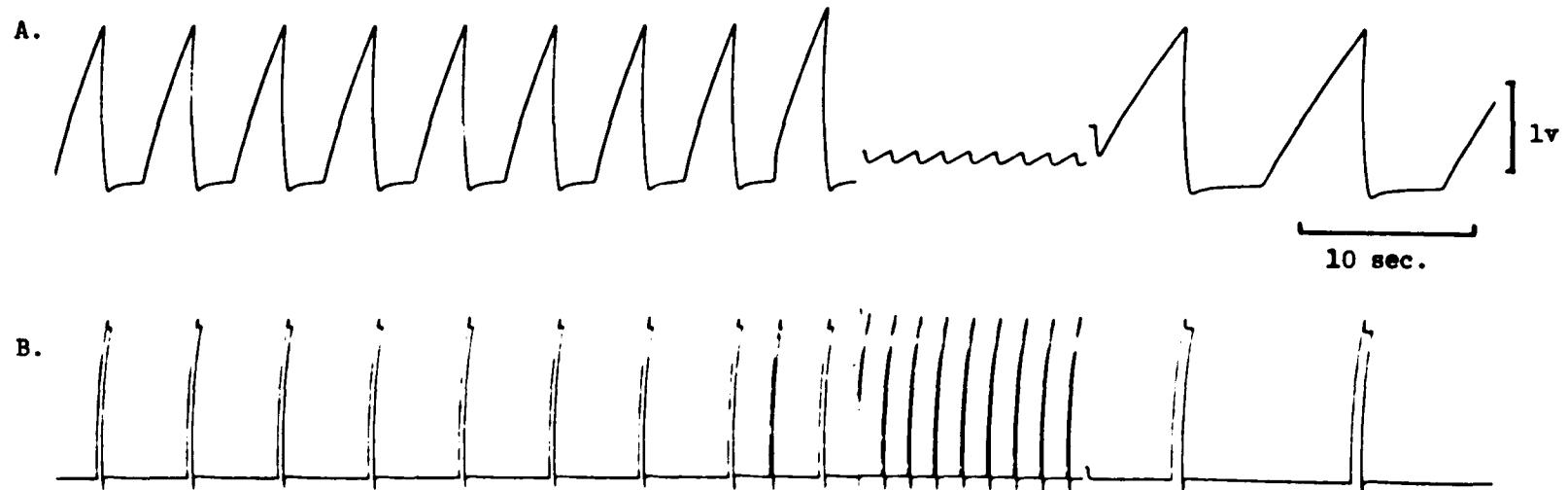


Fig. 3.12a. Saccade indications for simulated EOG waveforms. A. Simulated EOG waveforms. B. Saccade indication as determined by 'likelihood ratio detector' subroutine.

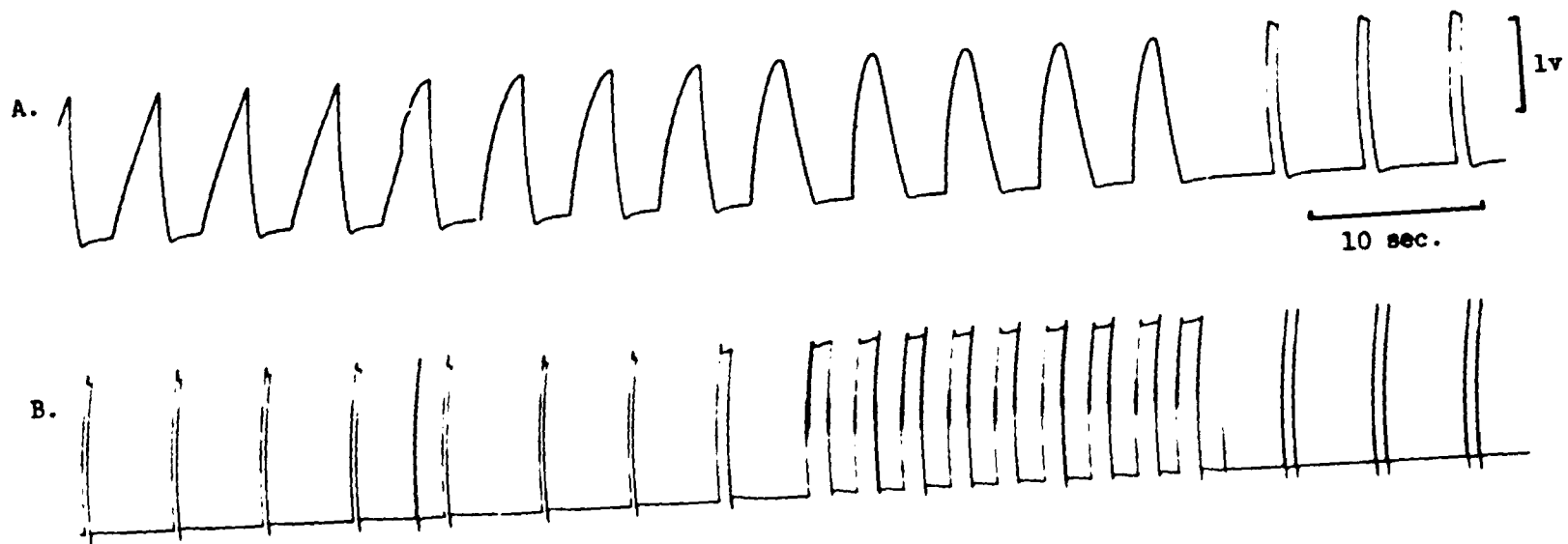


Fig. 3.12b. Saccade indications for various shapes of simulated EOG waveforms.  
 A. Various simulated EOG shapes. B. Saccade indication as determined by 'likelihood ratio detector' subroutine.

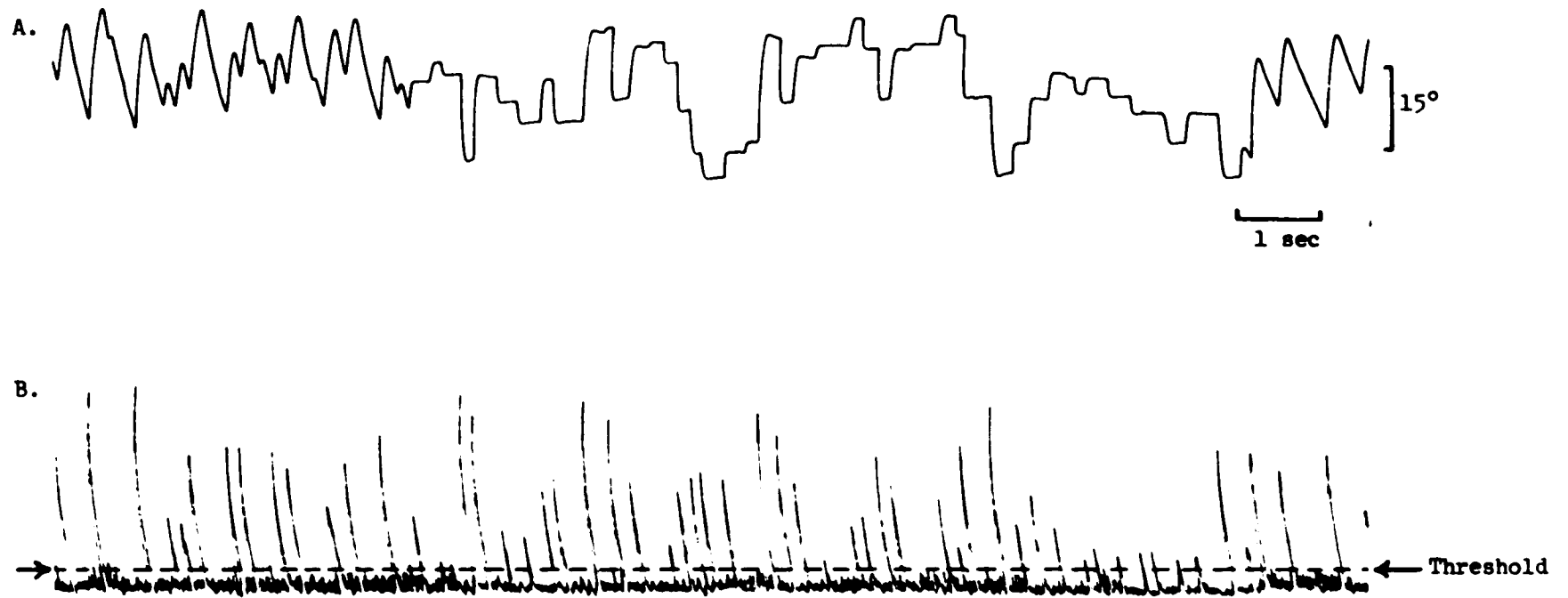


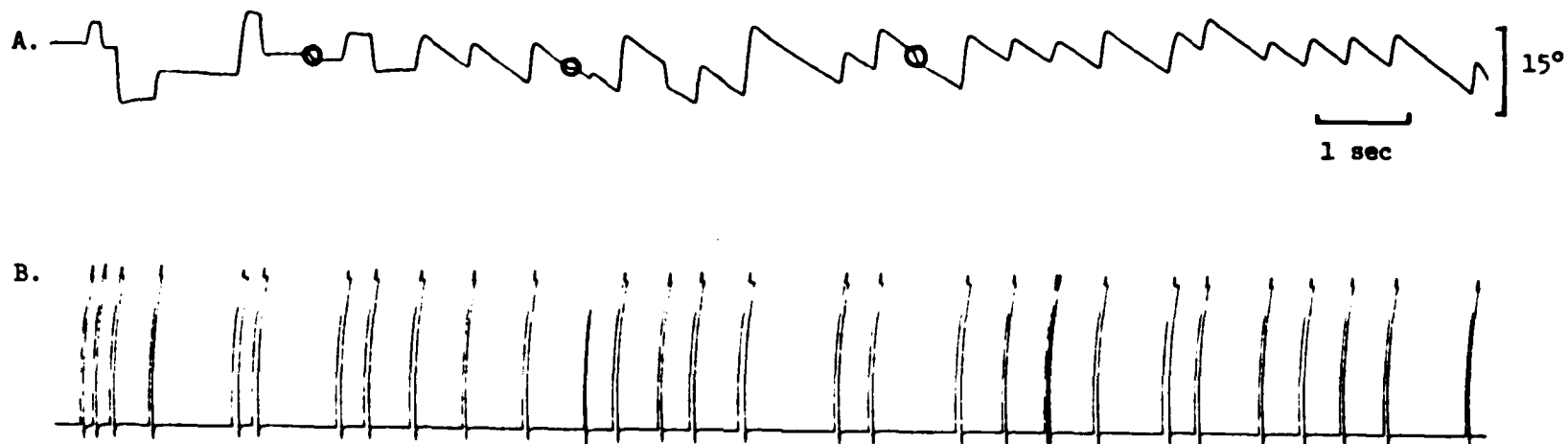
Fig. 3.13. Experimentally obtained EOG and its decision function.  
A. Experimentally obtained EOG waveform containing nystagmus.  
B. Decision function computed by 'likelihood ratio detector' technique.

make distinction between a saccade and a slow phase might be crucial not to miss saccade or not to produce false detections. In Fig. 3.14, the saccade indications are derived using the same rule as in the case of simulated waveforms, i.e., positive value of 'DFN' implies saccade and a negative value implies a slow phase. The result obtained seems to be acceptable as only a few tiny saccades have been missed. The analysis of Fig. 3.14 yields that less than 10% saccades were missed and no false detection occurred. The missed saccades are circled in A. of Fig. 3.14. Now if threshold is changed to include the noise term (the right hand side of (3.3.8)), the new threshold being shown by two arrows in B. of Fig. 3.13, the indication analysis yields missed saccades  $< 1\%$  and false detection  $< .5\%$ . Obviously it is possible to bias the saccade detection to reduce misses to as low as possible by lowering the threshold, but it would mean accepting some false detections. Increasing the number of samples will lower the false detections but will increase misses of tiny saccades. These misses may be avoided by using a smaller sampling interval. The detection scheme allows sampling intervals as small as 1 msec which are adequate for many kinds of saccades.

Functional descriptions for the slow and the quick phases is very crucial to the process of detection. A set of function templates that is optimal for a specific nystagmus velocity may not be suitable for another nystagmus velocity. However, it was discovered by experimentation that for a sampling interval of 2 msec, the detection scheme

optimized for a specific nystagmus velocity works well (with no added misses) over an approximate range of 75% to 125% of that velocity. Since straight-line function templates were used in the implementation, the slopes of these lines were supplied to the program from a switch register. This gave a convenient control for optimization of the detection process for various nystagmus velocities.

The saccade detection of this chapter will be utilized in the next chapter to generate slow phase system responses.



**Fig. 3.14. Saccade indications for an experimentally obtained EOG waveform.**  
**A. Experimentally obtained EOG waveform.**  
**B. Saccade indications as determined by 'likelihood ratio detector' technique. Note the missed saccades due to low gain on EOG waveform. The saccade indications waveform was obtained using the same threshold and slow and quick phase definitions as for Fig. 3.13 where the EOG gain is relatively higher.**

## CHAPTER 4

## ON-LINE ANALYSIS OF SLOW PHASE GENERATING SYSTEM RESPONSES

4.1 Introduction

The electrooculograph representing response of the oculomotor control system to optokinetic or vestibular inputs, consists of two types of responses - the saccadic eye movements and the slow phase eye movements. In the last chapter, an on-line saccade detection scheme was described. The present chapter deals with the problem of obtaining slow phase system response characteristics. The characterization of the slow phase system response leads to mathematical modeling of the slow phase system. The slow phase system modeling is the subject of the next chapter.

The basic assumption of analysis done in this chapter is that the two types of eye movements are generated internally by two separate systems - the saccadic system and the slow phase system [25]. A further assumption used in the design of the on-line data reduction technique is that the slow phase system velocity response remains essentially the same during a saccade. This assumption is validated by the fact that the saccadic eye movements are much faster and of smaller duration compared to slow phase eye movements. The experimental results further support this assumption [8].

The saccadic detection technique of the last chapter marks the beginning and the end of a saccade. Once a saccade is detected, it is suppressed in the on-line processing program by subtracting the saccadic

jump from the original position waveform. The slow phase movements are then pieced together to generate cumulative slow phase position (CSPP) waveform. The cumulative slow phase position when differentiated yields slow phase velocity (SPV) waveform. The slow phase velocity is the primary output of the slow phase system and therefore it will be utilized in the next chapter to identify parameters of this system. The slow phase velocity is also a diagnostically important response of the slow phase system [ 9 ].

The next section describes the fundamental components of the EOG data processing algorithm which is described in the subsequent section. The results of the algorithm are demonstrated by applying it to the simulated and the experimentally obtained EOG waveforms.

#### 4.2 Components of EOG Data Processing Algorithm

The EOG data processing algorithm has three fundamental components: first the extrapolation, which computes the slow phase eye position during saccadic eye movements; second the differentiator, which computes slow phase velocity from cumulative slow phase position; and third the data smoothing routine, which can be used to smooth or low pass filter the EOG waveform, the cumulative slow phase position waveform and/or the slow phase velocity waveform. These components are described in the next three sections. The performance of each is studied on simulated and experimentally obtained EOG waveforms.

#### 4.2.1 The Approximate Cumulative Slow Phase Position During a Saccade (Extrapolation)

The slow phase velocity during a saccade is assumed to be the velocity just prior to the beginning of a saccade. The truth of this assumption lies in the fact that the saccadic duration is relatively small and the slow phase system remains practically in the same state during a saccade. This fact is used here to derive an equation to be used to extrapolate cumulative slow phase position during a saccade.

Consider a window of  $(2n+1)$  EOG position samples  $y_0, y_1, y_2, \dots, y_{2n}$  all of which are assumed to be from slow phase movement (see Fig. 4.1). Passing a least square error straight line through these points and calculating its slope to represent slow phase velocity at the  $n$ th time, we obtain (see section 4.2.2)

$$u_n = n(y_{2n} - y_0) + (n-1)(y_{2n-1} - y_1) + (n-2)(y_{2n-2} - y_2) + \dots + 2(y_{n+2} - y_{n-2}) + (y_{n+1} - y_{n-1}) \quad (4.2.1)$$

where  $u_n$  denotes the slow phase velocity at the  $n$ th time. Assume that the next sample  $y_{2n+1}$  at  $(2n+1)$ th time belongs to a saccade. At this point we need to extrapolate the slow phase position. Let  $\hat{y}_{2n+1}$  denote the extrapolated slow phase position. To keep the window width constant at  $(2n+1)$  samples, we will drop  $y_0$  to include  $\hat{y}_{2n+1}$ . The slow phase velocity computed from this new window using the least square error straight line fit is given by

$$u_{n+1} = n(\hat{y}_{2n+1} - y_1) + (n-1)(y_{2n} - y_2) + (n-2)(y_{2n-1} - y_3) + \dots + 2(y_{n+3} - y_{n-1}) + (y_{n+2} - y_n) \quad (4.2.2)$$

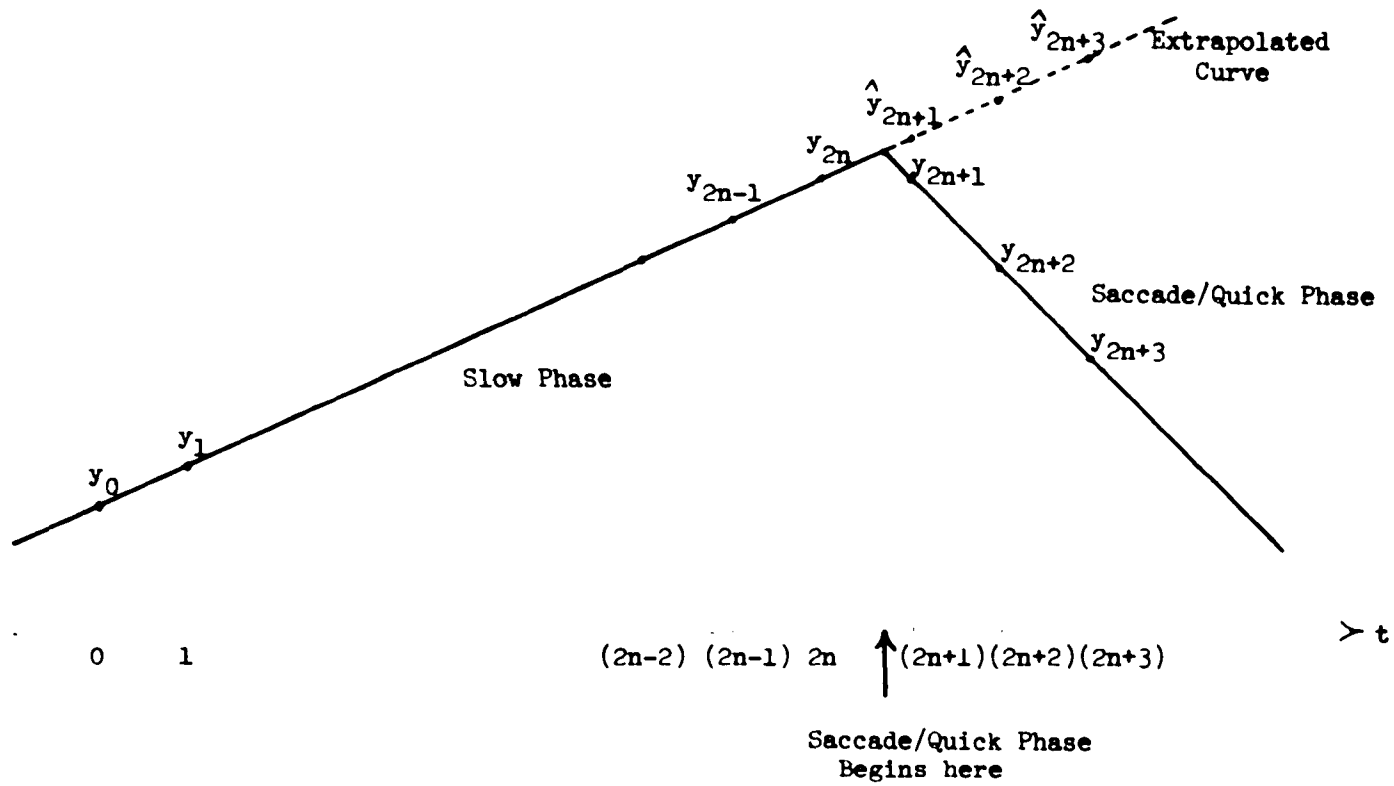


Fig. 4.1. Extrapolation of slow phase position during a saccade/quick phase.

By assumption as stated above, we have

$$u_{n+1} = u_n \quad (4.2.3)$$

From (4.2.1), (4.2.2) and (4.2.3), one can obtain

$$\hat{y}_{2n+1} = \frac{1}{n} \sum_{i=1}^{2n} y_i - y_0 \quad (4.2.4)$$

To estimate  $\hat{y}_{2n+2}$ , the already computed  $\hat{y}_{2n+1}$  is used to give

$$\hat{y}_{2n+2} = \frac{1}{n} \left( \sum_{i=2}^{2n} y_i + \hat{y}_{2n+1} \right) - y_1 \quad (4.2.5)$$

Similarly  $\hat{y}_{2n+3}$  is estimated using previous estimates  $\hat{y}_{2n+2}$  and  $\hat{y}_{2n+1}$  as follows

$$\hat{y}_{2n+3} = \frac{1}{n} \left( \sum_{i=3}^{2n} y_i + \sum_{j=2n+1}^{2n+2} \hat{y}_j \right) - y_2 \quad (4.2.6)$$

or in general we can write

$$\begin{aligned} \hat{y}_{2n+k} &= \frac{1}{n} \left( \sum_{i=k}^{2n} y_i + \sum_{j=2n+1}^{2n+k-1} \hat{y}_j \right) - y_{k-1} \quad \text{for } k \leq 2n \\ &= \frac{1}{n} \sum_{j=k}^{2n+k-1} \hat{y}_j - \hat{y}_{k-1} \quad \text{for } k > 2n+1 \end{aligned} \quad (4.2.7)$$

The equations (4.2.4) and (4.2.5) can also be used to derive recursive formula as follows: substituting (4.2.4) in (4.2.5) and simplifying, we will get

$$\hat{y}_{2n+2} = \hat{y}_{2n+1} + \frac{1}{n} (\hat{y}_{2n+1} - y_1) + (y_0 - y_1) \quad (4.2.8)$$

or in general we can write

$$\begin{aligned} \hat{y}_{2n+k} &= \hat{y}_{2n+k-1} + \frac{1}{n} (\hat{y}_{2n+k-1} - y_{k-1}) + (y_{k-2} - y_{k-1}) \quad \text{for } k \leq 2n+1 \\ &= \hat{y}_{2n+k-1} + \frac{1}{n} (\hat{y}_{2n+k-1} - \hat{y}_{k-1}) + (y_{k-2} - \hat{y}_{k-1}) \quad \text{for } k = 2n+2 \end{aligned}$$

$$= \hat{y}_{2n+k-1} + \frac{1}{n} (\hat{y}_{2n+k-1} - \hat{y}_{k-1}) + (\hat{y}_{k-2} - \hat{y}_{k-1}) \text{ for } k > 2n+2 \quad (4.2.9)$$

If an equation for  $\hat{y}_{2n+1}$  is written using (4.2.8), it involves  $\hat{y}_{2n}$ ,  $y_0$  and  $y_{-1}$ . Now if  $(2n+1)$  represents the first time in the quick phase,  $y_{2n}$  is available in place of  $\hat{y}_{2n}$ . Thus using  $y_{2n}$  for  $\hat{y}_{2n}$ , the equation for  $\hat{y}_{2n+1}$  is written as

$$\hat{y}_{2n+1} = y_{2n} + \frac{1}{n} (y_{2n} - y_0) + (-y_0 + y_{-1}) \quad (4.2.10)$$

$$\text{Now let us define } \Delta = \frac{1}{n} (y_{2n} - y_0) + (-y_0 + y_{-1}) \quad (4.2.11)$$

where ' $\Delta$ ' represents the change in position from the time  $2n$  to the time  $2n+1$ , and the position samples prior to the beginning of a quick phase determine its value. In view of (4.2.11), (4.2.10) can be written as

$$\hat{y}_{2n+1} = y_{2n} + \Delta \quad (4.2.12)$$

Now if  $\Delta$  is used to estimate each position sample during a quick phase, i.e.

$$\hat{y}_{2n+j} = \hat{y}_{2n+j-1} + \Delta \quad (4.2.13)$$

then we are basing all our estimates  $\hat{y}_{2n+1}$ ,  $\hat{y}_{2n+2}$  ----- etc. on just three positions  $y_0$ ,  $y_{-1}$  and  $y_{2n}$  used to calculate  $\Delta$ . It gives us a computational advantage, but introduces inaccuracy by the amount the samples prior to the quick phase define other than a perfect straight line. The implementation of (4.2.9) was compared with this simplified implementation and no difference was found for extrapolation window width of 100 msec or less. Thus this simplified extrapolation will be used in the subsequent sections unless the window width is increased over this limit.

#### 4.2.2 A Least Square Error Digital Differentiator

A digital differentiator is needed in order to generate velocity from position samples. A number of algorithms [1], [20], [23], [34] have been developed primarily for use on general-purpose computers. The complexity and timing requirement of these algorithms inhibits their use on microprocessor-based systems. In this section a simple digital differentiator algorithm is derived on the basis of using a least-squares approach to fit a straight line to the data. The frequency response of such a differentiator is studied to evaluate its performance when used on EOG signals.

Let us consider  $(2n+1)$  position samples  $y_0, y_1, y_2, \dots, y_{2n}$ . Assume that these samples are uniformly spaced at  $\Delta t$  intervals of time. Let the straight line used to represent this data be given by

$$y(t) = \hat{a} + \hat{b}t \quad (4.2.14)$$

so that

$$u(t) = \frac{dy}{dt} = \hat{b} \quad (4.2.15)$$

$u(t)$  or  $\hat{b}$  will be estimated by minimizing

$$I = \sum_{i=0}^{2n} (a + bt_i - y_i)^2 \quad (4.2.16)$$

where  $t_i = i \cdot \Delta t$

To minimize  $I$  we set its partial derivatives with respect to  $\hat{a}$  and  $\hat{b}$  = 0. That is

$$\frac{\partial I}{\partial \hat{a}} = 2 \sum_{i=0}^{2n} (\hat{a} + \hat{b}t_i - y_i) = 0 \quad (4.2.17)$$

$$\frac{\partial I}{\partial \hat{b}} = 2 \sum_{i=0}^{2n} (\hat{a} + \hat{b}t_i - y_i) t_i = 0 \quad (4.2.18)$$

Rewriting (4.2.17) and (4.2.18) in matrix form yields

$$\begin{bmatrix} \sum_{i=0}^{2n} 1 & \sum_{i=0}^{2n} t_i \\ \sum_{i=0}^{2n} t_i & \sum_{i=0}^{2n} t_i^2 \end{bmatrix} \begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = \begin{bmatrix} \sum_{i=0}^{2n} y_i \\ \sum_{i=0}^{2n} y_i t_i \end{bmatrix} \quad (4.2.19)$$

solving (4.2.19) for  $\hat{b}$  yields

$$\hat{b} = \frac{\sum_{i=0}^{2n} 1 \sum_{i=0}^{2n} y_i t_i - \sum_{i=0}^{2n} t_i \sum_{i=0}^{2n} y_i}{\sum_{i=0}^{2n} 1 \sum_{i=0}^{2n} t_i^2 - \sum_{i=0}^{2n} t_i \sum_{i=0}^{2n} t_i} \quad (4.2.20)$$

Using summation formulae, it can be shown that

$$\sum_{i=0}^{2n} 1 = (2n+1) \quad (4.2.21)$$

$$\sum_{i=0}^{2n} t_i = n(2n+1) \Delta t \quad (4.2.22)$$

$$\sum_{i=0}^{2n} t_i^2 = \frac{1}{3} n(2n+1)(4n+1) (\Delta t)^2 \quad (4.2.23)$$

Substituting (4.2.21), (4.2.22) and (4.2.23) in (4.2.20) and subsequent simplification yields

$$\hat{b} = \frac{3 \sum_{i=0}^{n-1} (n-1) (y_{2n-i} - y_i)}{n(n+1)(2n+1) \Delta t} \quad (4.2.24)$$

The  $\hat{b}$  in (4.2.24) represents the velocity associated with the straight line fit to samples  $y_0, y_1, y_2, \dots, y_{2n}$ . In order to give equal emphasis to the points around the point for which the velocity is being estimated,  $\hat{b}$  will be assigned to be the velocity at the midpoint of the data window. Thus

$$u_n = \frac{3 \sum_{i=0}^{n-1} (n-i)(y_{2n-i} - y_i)}{n(n+1)(2n+1) \Delta t} \quad (4.2.25)$$

or

$$u_n = K(n, \Delta t) \sum_{i=0}^{n-1} (n-i)(y_{2n-i} - y_i) \quad (4.2.26)$$

where

$$K(n, \Delta t) = \frac{3}{n(n+1)(2n+1) \Delta t} \quad (4.2.27)$$

As an example let us consider a window width of 9 so that  $n=4$ . From (4.2.25) and (4.2.24) we get

$$K(4, \Delta t) = \frac{3}{4 \cdot 5 \cdot 9 \cdot \Delta t} = \frac{1}{60 \Delta t} \quad (4.2.28)$$

and

$$u_4 = \frac{1}{60 \Delta t} \sum_{i=0}^3 (4-i)(y_{8-i} - y_i) \quad (4.2.29)$$

or

$$u_4 = \frac{1}{60 \Delta t} \left[ 4(y_8 - y_0) + 3(y_7 - y_1) + 2(y_6 - y_2) + (y_5 - y_3) \right] \quad (4.2.30)$$

When (4.2.26) is applied to a window of samples  $y_{-n}, y_{-n+1}, y_{-n+2}, \dots, y_0, y_1, \dots, y_{n-1}, y_n$  so that the midpoint sample is  $y_0$ , the associated velocity is given by

$$u_0 = K(n, \Delta t) \left[ \sum_{i=1}^n i (y_i - y_{-i}) \right] \quad (4.2.31)$$

For  $y_i = e^{j\omega i \Delta t}$  where  $j = \sqrt{-1}$ ,  $u_0$  becomes the transfer function of the differentiator. Denoting the transfer function by  $H(\omega)$ , we have

$$H(\omega) = K(n, \Delta t) \cdot 2j \sum_{i=1}^n i \sin i \omega \Delta t \quad (4.2.32)$$

For  $n=4$ , we get

$$H(\omega) = \frac{J}{30 \Delta t} \left[ 4 \sin 4 \omega \Delta t + 3 \sin 3 \omega \Delta t + 2 \sin 2 \omega \Delta t + \sin \omega \Delta t \right] \quad (4.2.33)$$

The non-recursive differentiator of equation (4.2.26) can be realized as recursive filter as follows: the velocities  $u_n$ ,  $u_{n+1}$  and  $u_{n+2}$  as determined from (4.2.26) are given by

$$u_n = K(n, \Delta t) \sum_{i=0}^{n-1} (n-1) (y_{2n-i} - y_i) \quad (4.2.34)$$

$$u_{n+1} = K(n, \Delta t) \sum_{i=1}^n (n+1-i) (y_{2n+2-i} - y_i) \quad (4.2.35)$$

$$u_{n+2} = K(n, \Delta t) \sum_{i=2}^{n+1} (n+2-i) (y_{2n+4-i} - y_i) \quad (4.2.36)$$

Combining (4.2.34) and (4.2.35) we can obtain

$$u_{n+1} = u_n + K(n, \Delta t) \left[ n(y_{2n+1} + y_0) - \sum_{i=1}^{2n} y_i \right] \quad (4.2.37)$$

Similarly combining (4.2.35) and (4.2.36) we can obtain

$$u_{n+2} = u_{n+1} + K(n, \Delta t) \left[ n(y_{2n+2} + y_1) - \sum_{i=2}^{2n+1} y_i \right] \quad (4.2.38)$$

and now we can combine (4.2.37) and (4.2.38) to give

$$u_{n+2} = 2u_{n+1} - u_n + K(n, \Delta t) \left[ n(y_{2n+2} - y_{2n+1}) + n(y_1 - y_0) + (y_1 - y_{2n+1}) \right] \quad (4.2.39)$$

Equation (4.2.39) can be realized as a second order digital filter [15], [18]. It may be noted that the output of such a filter lags the latest input by  $n$  sampling intervals for a differentiator based on  $(2n+1)$  data samples.

The frequency response of the above differentiator is plotted in Fig. 4.2 for  $n = 2, 3$  and  $4$ . It is obvious from these plots that as the number of samples are increased, the response approximates a differentiator frequency response. The cut-off frequency though decreases for the same sampling interval. This will not pose any problem for processing slow phase EOG data as its frequency spectrum is less than  $1$  Hz [25]. Fig. 4.3 shows the pass band of a 17 point (i.e.  $n=8$ ) digital differentiator operating on a waveform sampled at  $1$  msec. sampling interval. The plot in Fig. 4.3 was obtained by applying a constant sinusoidal input to the differentiator and recording its output as the frequency was varied from  $0$ Hz to  $50$ Hz. When compared with an ideal differentiator, this response fairly matches with the latter.

In order to evaluate the performance of the digital differentiator with an analog differentiator, a simulated EOG waveform was applied simultaneously to these devices and their outputs are shown in Fig. 4.4. The digital device seems to have about the same performance as the analog one. To obtain a closer view of this, Fig. 4.5 shows the outputs of two differentiators on an expanded time scale. It is obvious from this figure that a digital differentiator response is superior to that of an analog one. There is not only shape distortion, but definite time delay in the response of analog device. This problem may be serious when observing exact transitions in EOG velocity waveforms. The fact that analog differentiator's output is delayed is further demonstrated by studying the phase relationship between the two outputs. The two outputs are shown for a  $10$ Hz sine wave input and it can be seen from Fig. 4.6

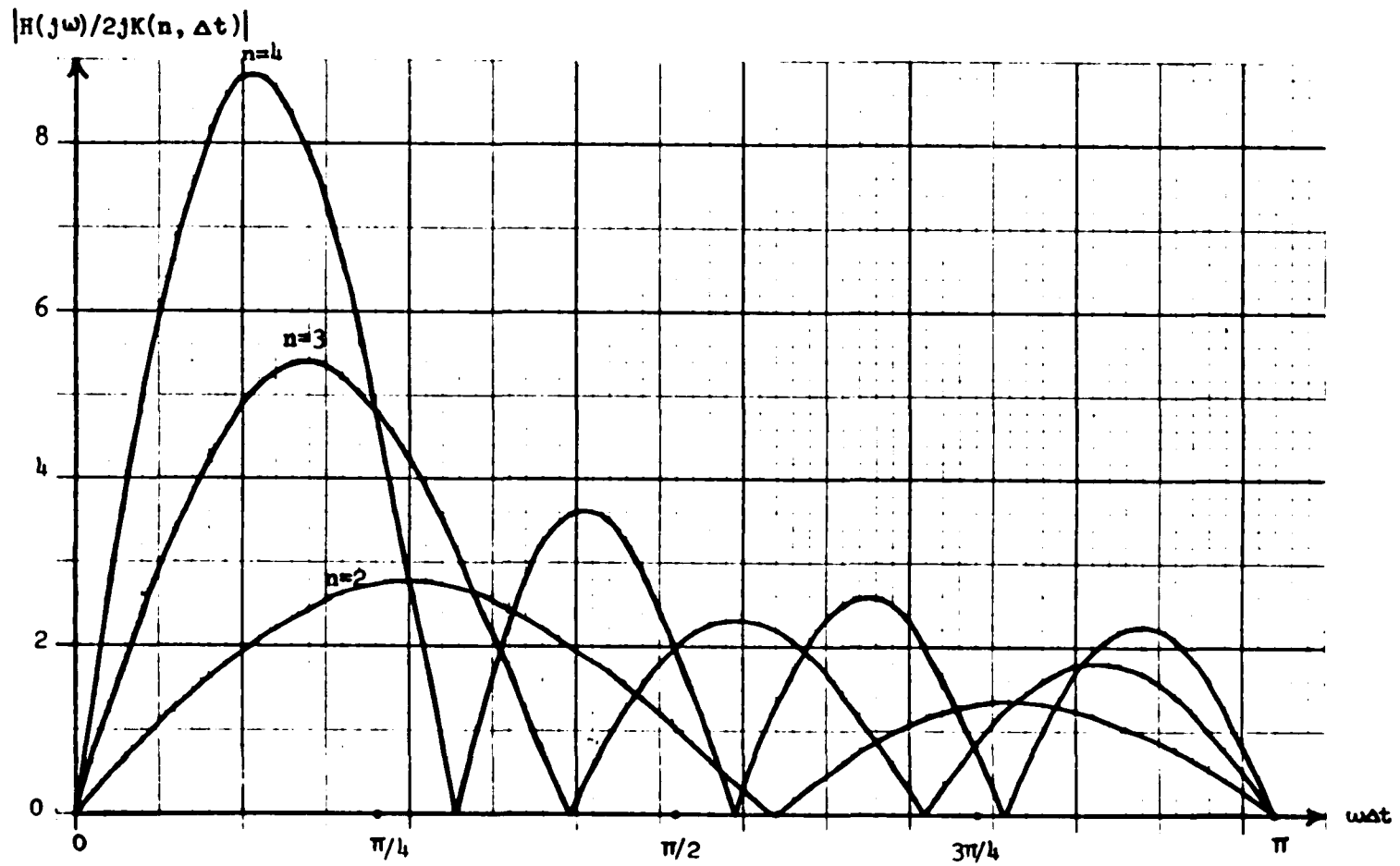


Fig. 4.2. Frequency response of the digital differentiators designed by least squares error straight line fit.

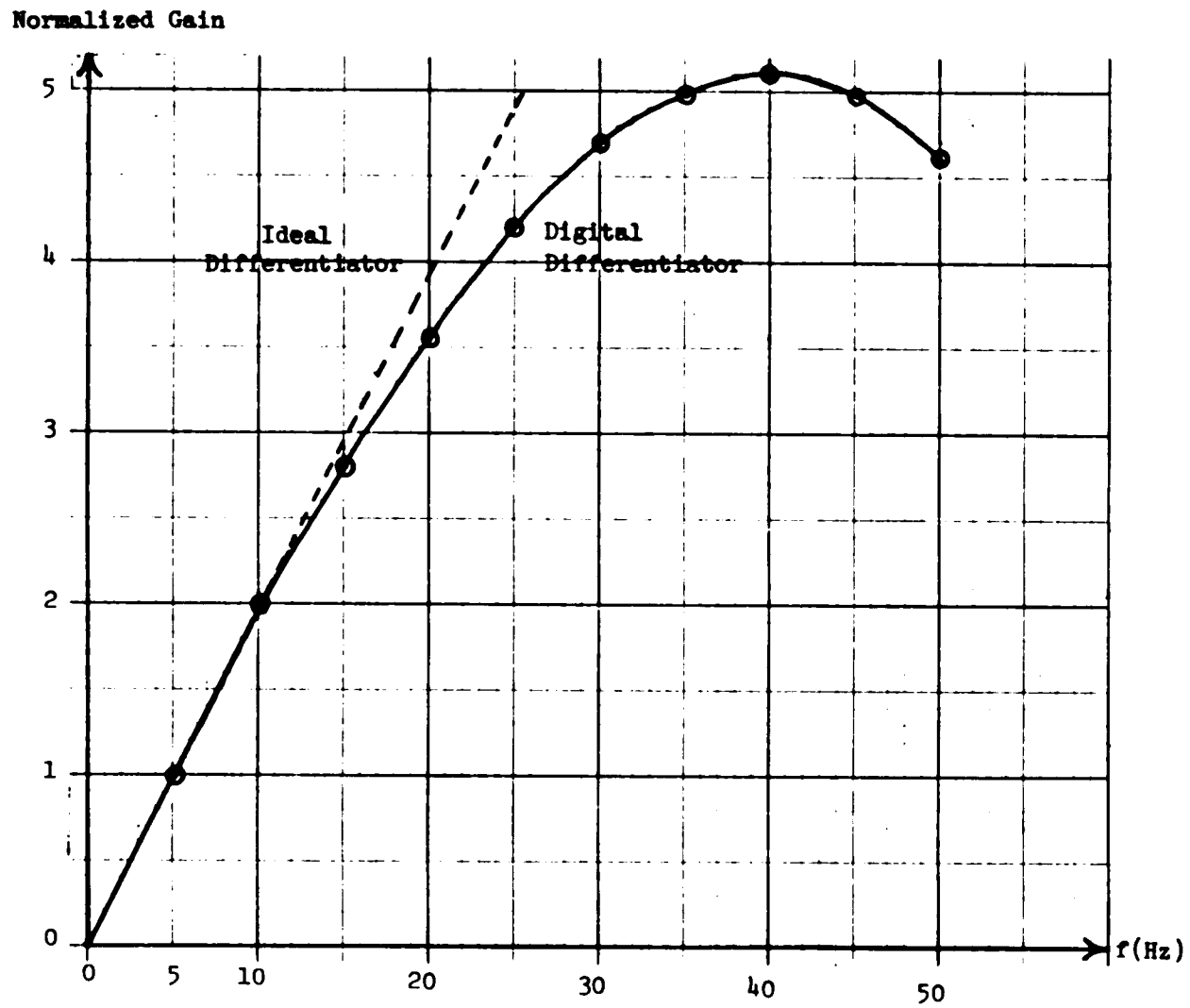


Fig. 4.3. Pass band of a 17-point digital differentiator. Input was sampled at 1 msec interval.

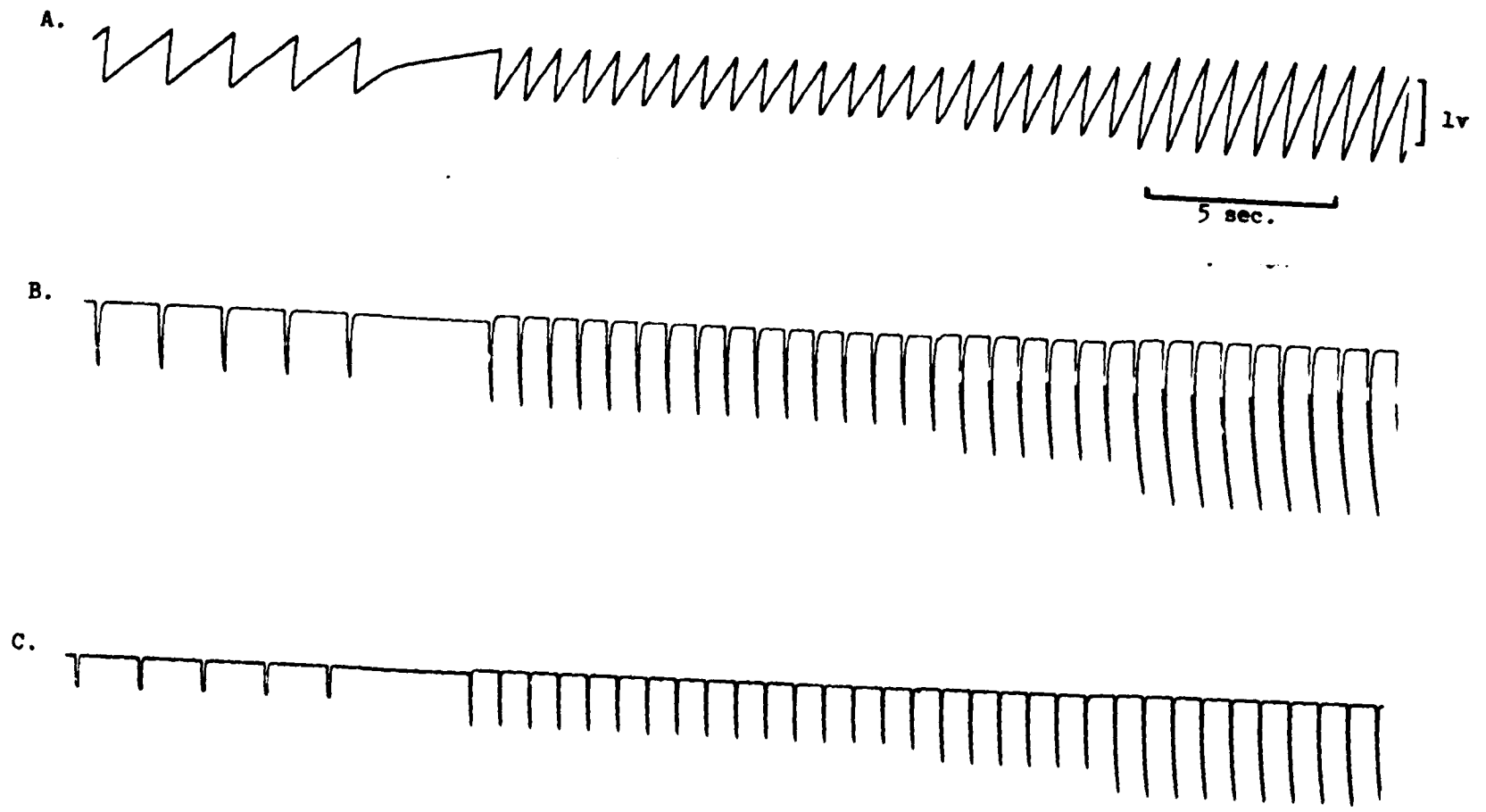


Fig. 4.4. Analog vs. digital differentiation of simulated data. A. Simulated waveform. B. Analog differentiation. C. Digital differentiation.

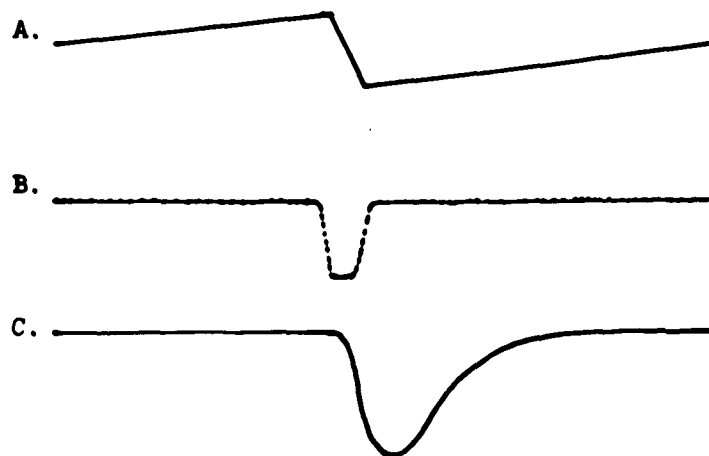


Fig. 4.5. Shape distortion in analog differentiation. A. Simulated waveform. B. Digital differentiation (1 msec. sampling). C. Analog differentiation

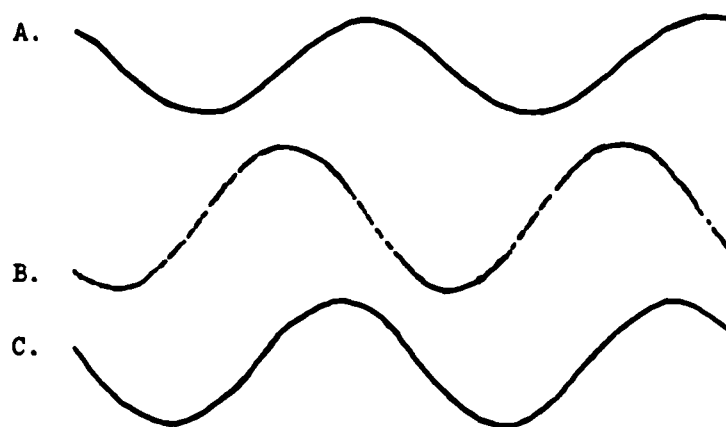


Fig. 4.6 Phase distortion in analog differentiation. A. Simulated waveform (10Hz). B. Digital differentiation (1 msec. sampling). C. Analog differentiation.

that the analog output is delayed by as much as  $70^\circ$ .

In the laboratory processing of EOG data, a differentiator is commonly used to obtain slow phase velocity waveform. Fig. 4.7 compares the performance of digital and analog differentiators as they operate upon an experimentally obtained EOG waveform. The differentiated outputs are just about the same from both devices. The only difference seems that the digital differentiator is noisier compared to an analog differentiator. This is even more obvious from Fig. 4.8C where a digital differentiator of 17 point window length was used to differentiate. This is really not a problem as a digital differentiator can produce smoother response when larger number of points are used. Thus, a digital differentiator response is easily controllable and does not suffer from the problem of delay in response.

#### 4.2.3 Digital Filters for EOG Waveforms

The bandwidth of nystagmus may be well over 100Hz, but most of the spectral power has been reported to be below 30Hz for most applications [22]. The noise above this frequency may be filtered before any processing is done. The processed waveforms may also need to be filtered. This can be done by employing appropriate analog or digital filters. To design an all digital processing scheme running in real time, appropriate digital filters should be considered. In this section, we consider two approaches, one which is based upon the least square error straight line fit of the last section and the

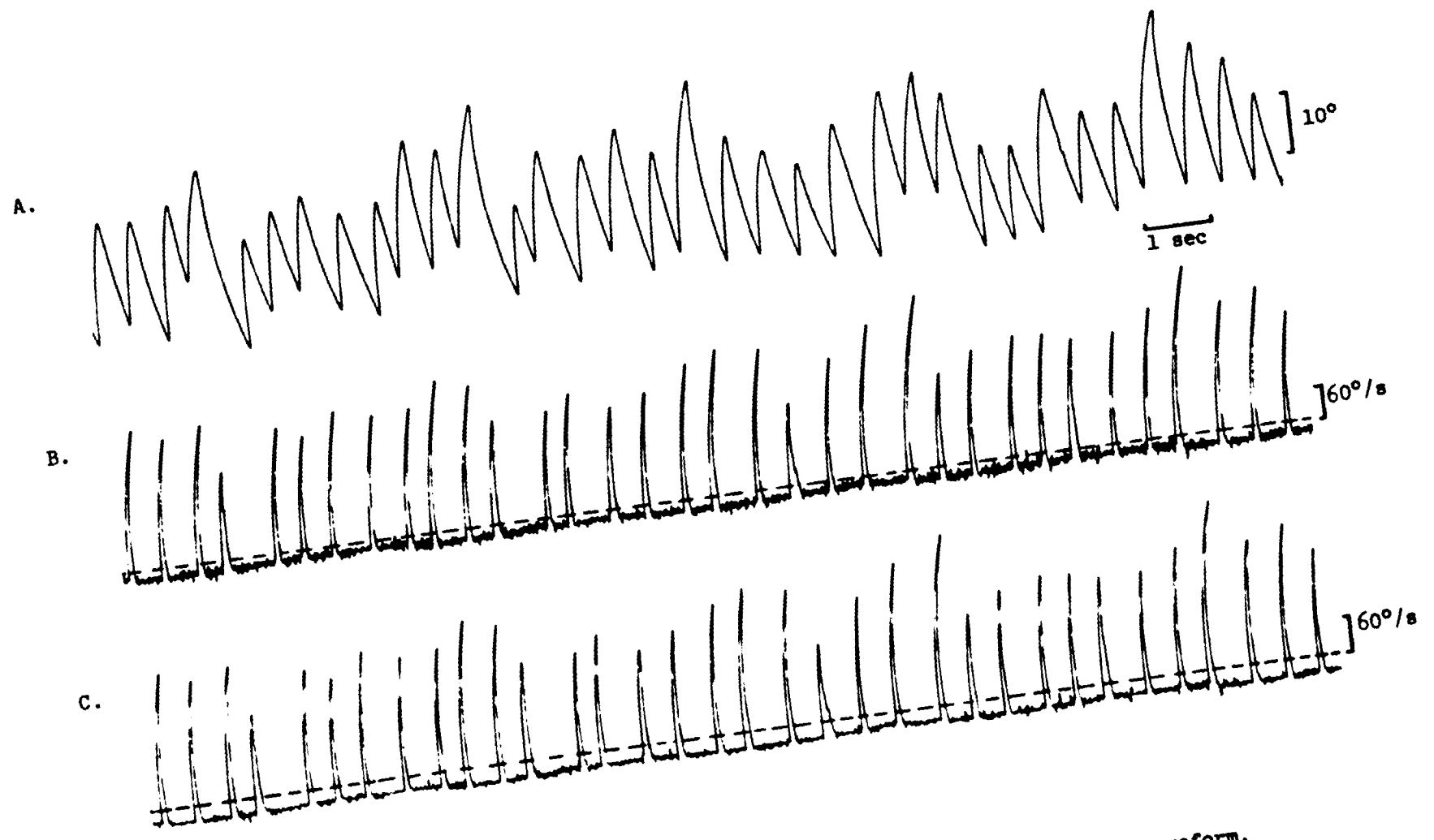


Fig. 4.7. Digital vs. analog differentiation of an ECG waveform. A. An ECG waveform. B. Digitally differentiated ECG waveform. C. Analog differentiation of ECG waveform.

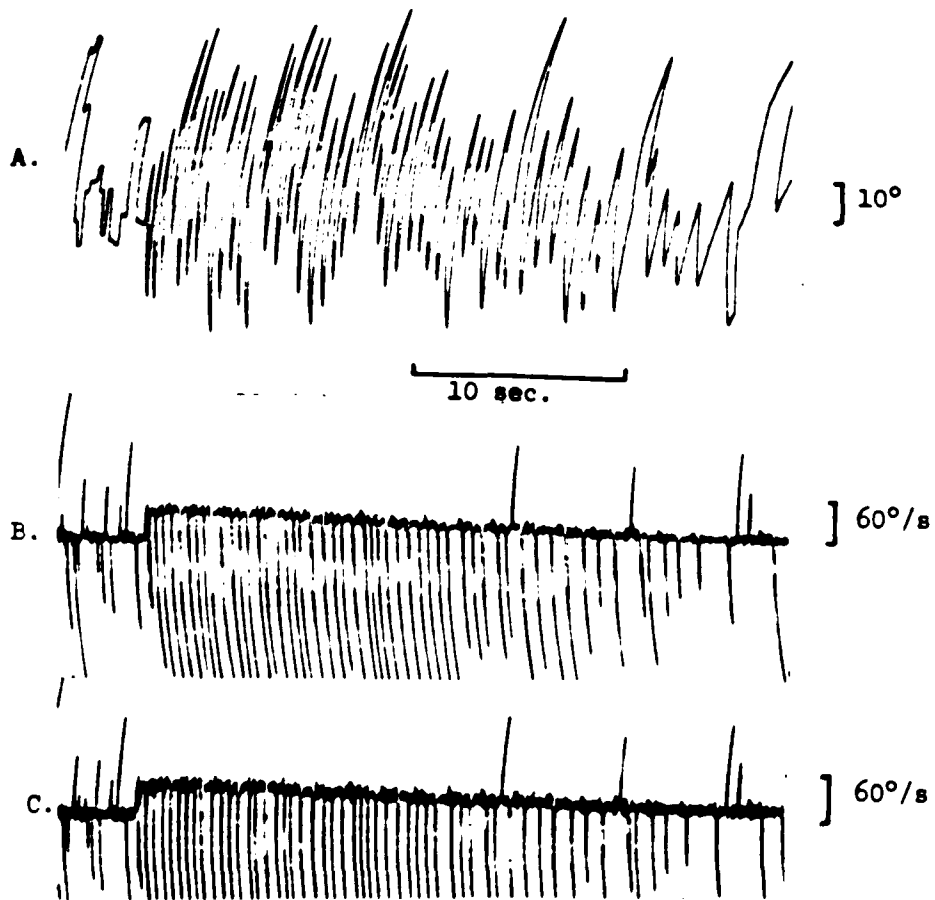


Fig. 4.8. Analog vs digital differentiation.

A. ECG waveform. B. Slow phase velocity from analog differentiator. C. Slow phase velocity from digital differentiator.

other based upon the idea of 'median' of a window of data.

If a least square error straight line  $\hat{a} + \hat{b}t$  is fitted to  $(2n+1)$  data points  $y_{-n}, y_{-n+1}, \dots, y_0, \dots, y_{n-1}, y_n$  and the estimated  $\hat{a}$  is used to represent the smoothed value of  $y_0$  denoted by  $\hat{y}_0$ , then it is given by [14]

$$\hat{y}_0 = \frac{1}{(2n+1)} \sum_{i=-n}^n y_{n+i} \quad (4.2.40)$$

the corresponding transfer function being [14]

$$H(\omega) = \frac{\sin\left(\left(n+\frac{1}{2}\right)\omega\Delta t\right)}{(2n+1)\sin(\omega\Delta t/2)} \quad (4.2.41)$$

The well-known problem with this filter is that a single point in error affects all the subsequent points within the range of smoothing window width. Thus this filter is suitable where high frequency spikes are non-existent such as cumulative slow phase position.

The 'spiky' data such as the slow phase velocity may be better filtered by a 'median filter'. A median filter considers the median of a window of data to represent the middle point in the window, thereby ignoring points in gross error. This type of filter was found to be a slightly better filter when used on slow phase velocity waveform. However, there is no direct way to compare the two filters, since a smoothing filter is a linear device and a median filter is a non-linear device.

#### 4.3 Cumulative Slow Phase Position (CSPP) and Slow Phase Velocity (SPV) Algorithm

The saccadic detection of the last chapter, the extrapolation and differentiation of the previous section are put together to design an

algorithm which generates the cumulative slow phase position and the slow phase velocity along with other useful waveforms. The hardware configuration is exactly the same as of saccadic detection of the last chapter, i.e., the PDP-8/E computer is interfaced to the experimental process producing data and also to the monitoring devices to generate resulting waveforms. The algorithm is described in this section and the experimental results are the subject of section 4.4.

The experimentally generated EOG waveform is sampled and the samples are stored in a buffer. The conversion is done by a 10-bit analog to digital converter. The sampling interval can be controlled from a programmable real-time clock. The 10-bit digital word is sign extended to adapt to the 12-bit accumulator of PDP-8/E computer. The data processing of the experimentally generated position data is described in flow chart of Fig. 4.9 and in software block diagram of Fig. 4.10.

The first step of processing is to detect the presence of saccades. The 'likelihood ratio detector' of the last chapter is used for this purpose. The saccadic detection program generates a value for a function called the decision function (DFN). The sign of DFN is used to indicate the origin of sampled data point. The positive sign of DFN indicates the presence of a saccade and the negative sign indicates the absence of one. This way the beginning and the end of a saccadic movement is marked.

The second step of processing involves generating cumulative slow phase position. Fig. 4.11 shows the schematic for the generation of the cumulative slow phase position waveform. When a first saccade is

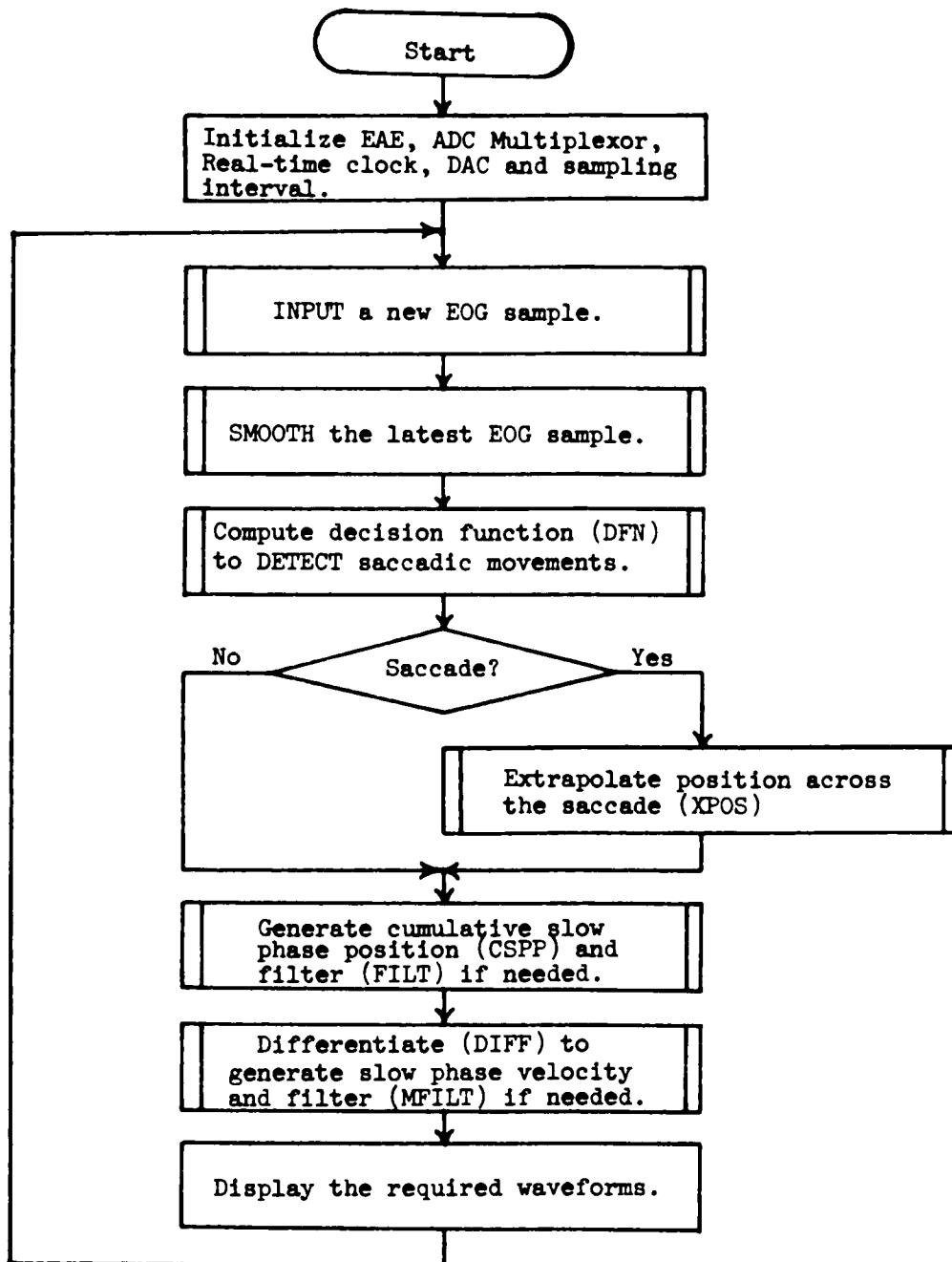


Fig. 4.9. Main program flow chart of EOG data processing for saccadic detection and slow phase velocity generation.

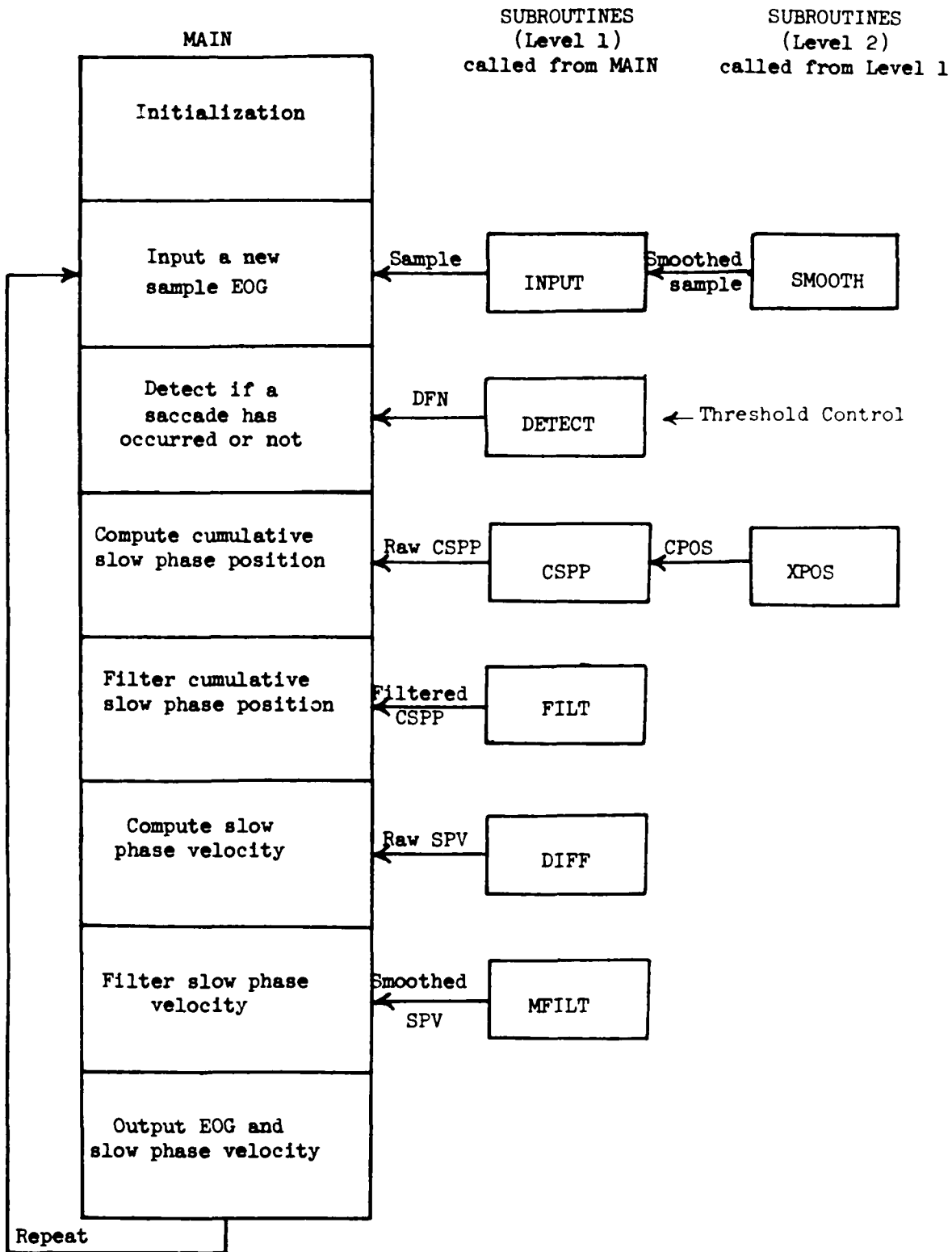


Fig. 4.10. Software components of saccadic detection and slow phase velocity and cumulative position generation program.

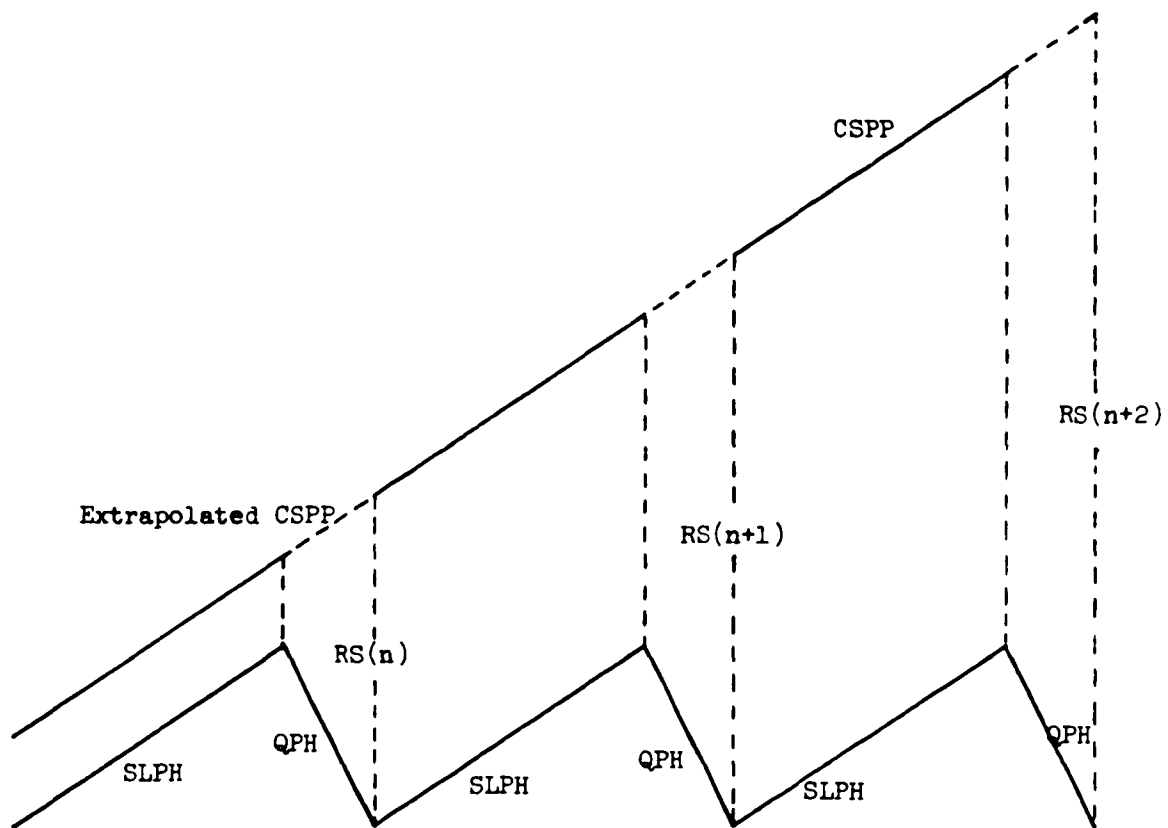


Fig. 4.11. Cumulative slow phase position (CSPP) generation schematic.

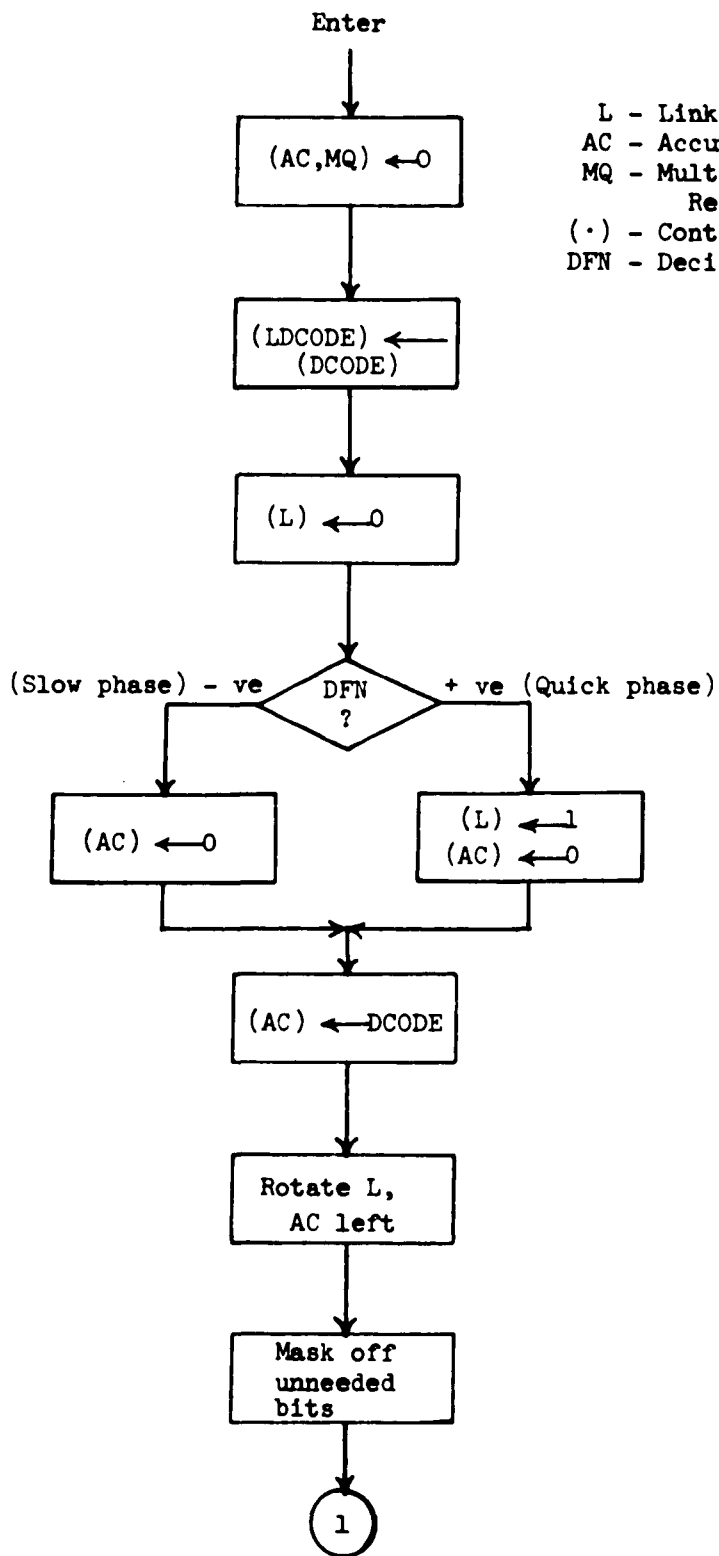
first detected, a few samples (2 or 3 for a window of 5 samples) before the first detected saccadic point are replaced by the extrapolated points. This is done to overcome any detection-delay, since a quick phase is not detected unless the detection window consists of sufficient points from the oncoming quick phase to turn DFN positive (see Chapter 3 for details). The extrapolation is done using EOG samples before the points to be replaced which belong to the slow phase eye movement. During the saccadic movement, the extrapolation is continuously repeated on the previously extrapolated and the actual slow phase points to generate new extrapolated positions (see section 4.2.1 for details). This way, the slow phase waveform is extended through the saccade using a line with the same slope as the slope at the end of the slow phase. When an end of the quick phase is detected, the saccadic jump for the immediate past saccade is computed by subtracting the measured EOG value from the extrapolated value. The negative of the saccadic jump is added to all the points on the oncoming slow phase movement. This process removes the saccadic movement and pieces together the two slow phase movement, generating a cumulative slow phase position (CSPP) waveform. For the next saccade, the extrapolation is done using the points on the CSPP waveform preceding it. Now when the next saccadic jump is computed using the extrapolated position at the end of the saccade and the first measured slow phase position from the on-coming slow phase it is representative of accumulated sum of the past two saccades. This sum is called the running sum denoted by RS in Fig. 4.11.  $RS(n)$  in the figure is the running sum generated by all the previous 'n'

saccades and is the amount by which the points on the on-coming slow phase, after having encountered  $n$  saccades, are offset to compute the corresponding cumulative slow phase position.

It is obvious that the above process of generating cumulative slow phase position can generate values which cannot be accommodated by the 12-bit arithmetic capability of the machine. This does not pose any problem as long as only addition of RS is done to slow phase positions to generate CSPP. However when the extrapolation itself involves points after the 12-bit overflow along with some points before it, the process of extrapolation runs into arithmetic overflow problem. This problem can be overcome by extrapolating only on the EOG slow phase position waveform which precedes the saccade. However, overflow may still occur due to the uncertainty of the type of eye movement preceding the saccade. A solution to this problem is to reformulate the extrapolation process so as to avoid arithmetic overflow condition by scaling the numbers whenever operating near ends and rescaling the results.

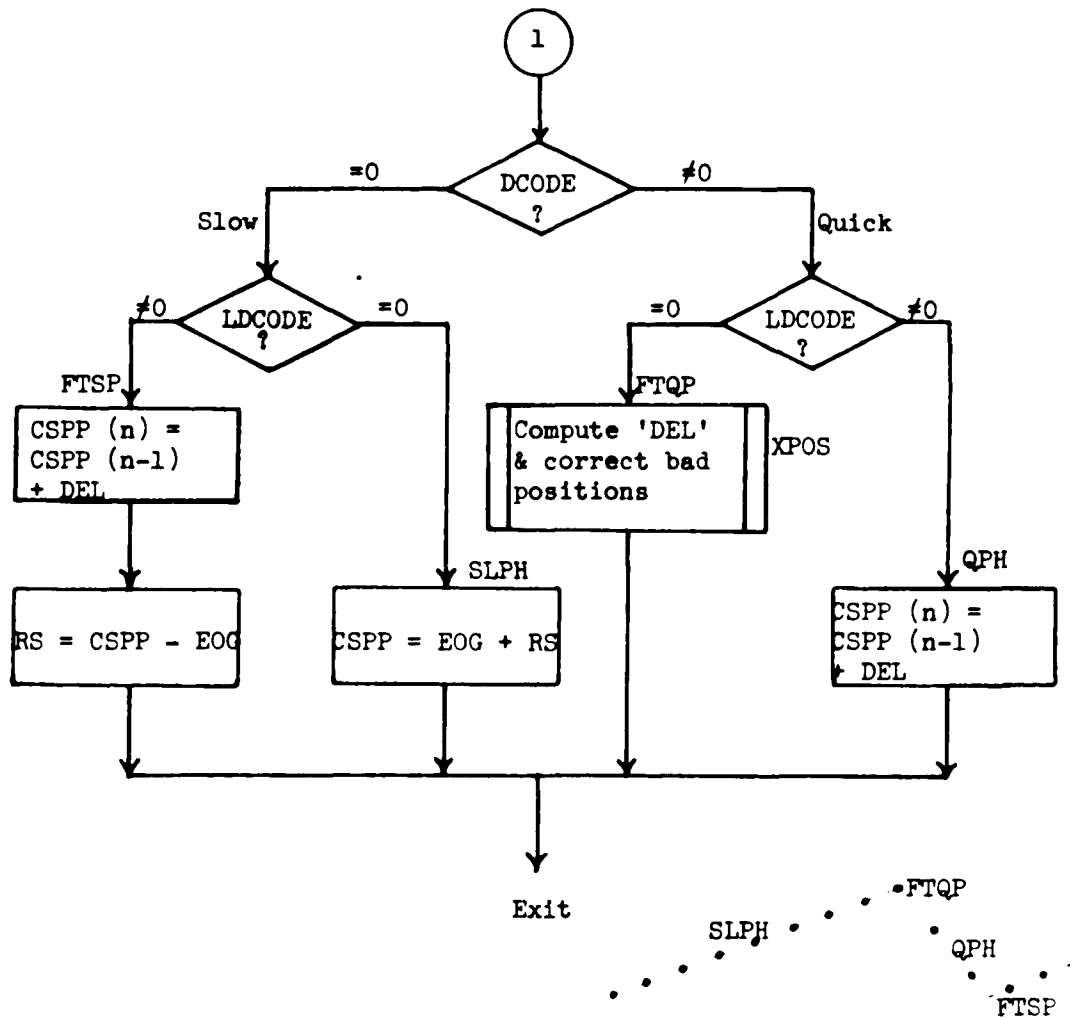
The details of marking the beginning and the end of a saccade, extending the saccadic interval on both sides to overcome detection errors, computing the cumulative slow phase position waveform are all described in a flow chart of Fig. 4.12. The flow chart is based upon the assumption that the extrapolation is done only once and its information used for all saccadic points. The symbols used in the flow chart are described below it.

The cumulative slow phase position thus obtained may be filtered if needed. The filtering can be done by an averaging type of smoothing



L - Link (1-bit)  
 AC - Accumulator (12-bit)  
 MQ - Multiplier quotient  
     Reg. (12-bit)  
 (·) - Contents of ·  
 DFN - Decision Function

continued on next page



CSPP - Cumulative Slow Phase Position  
 DCODE - Decision Code  
 LDCODE - Last Value of DCODE  
 FTSP - First Time Slow Phase  
 SLPH - Slow Phase (continuation)  
 FTQP - First Time Quick Phase  
 QPH - Quick Phase (continuation)  
 RS - Running Sum (Accumulated quick phases)  
 DEL - Delta Change in Slow Phase Position (or CSPP)

Fig. 4.12. Flow chart of Cumulative Slow Phase Position subroutine.

filter or by any other low pass filter which can be implemented without adding too much to the timing requirements. In most cases filtering may not be needed at all.

The last major step of processing is to generate the slow phase velocity. Obviously, the slow phase velocity accuracy will depend on how accurately the cumulative slow phase position represents the slow phases in EOG. The slow phase velocity is obtained by differentiating the cumulative slow phase position; the digital differentiator used for the purpose was described in the last section. Filtering of the resulting velocity waveform may be required. The filtering may be done using the filter of the last section or any such algorithm implementable without jeopardizing on-line processing requirements.

The next section describes the implementation results of the algorithm described above. The results are shown using simulated data and actual experimental data.

#### 4.4 Experimental Results

The algorithm described in the last section was implemented on PDP-8/E computer in assembly language. The incoming EOG data was stored in a full field of  $4000_8$  words. The cumulative slow phase position values as generated are stored in another field of  $4000_8$  words and the slow phase velocity in a third field. Even though not all  $4000_8$  points will be used at any time in any computation, it generates self-wrap-around for the pointer used to store a sample or a computed value into the memory. The algorithm program is stored in field zero of the computer memory. The listing of this program appears in Appendix B.

Fig. 4.13 shows the performance of algorithm in generating the cumulative slow phase position and the slow phase velocity waveform for a simulated waveform containing all types of saccades. The frequency of the saccade varies over a range of 1 to 15Hz for saccades to the left and to the right. The cumulative slow phase position and the corresponding slow phase velocity waveforms are as expected. The last part of Fig. 4.13 shows occurrence of pure saccades with no nystagmus. Those saccades are seen to be removed perfectly and no trace of saccades appear in the CSPP and the SPV. The program is run without any kind of filtering at any stage and it produces very smooth waveforms. The run time for these waveforms is less than 2msec and therefore a sampling of 2msec can be used without running into any real-time problems.

Fig. 4.14 shows how well the algorithm performs on an experimental EOG waveform to generate the cumulative slow phase position waveform and a waveform showing accumulation of quick phase jumps. The accumulated quick phases waveform also shows indirectly if a particular saccade was detected or missed. The waveform C in Fig. 4.14 is the CSPP waveform which is seen to be in accordance with the expected results. The run-time to generate these two waveforms is even less than that required to generate the waveforms in Fig. 4.13 since, in this case, differentiation is not done.

Fig. 4.15 shows the results of algorithm processing of a real EOG waveform. B is a waveform generated by the analog system, the nystagmus velocity coupler which differentiates the waveform and clips positive half or negative half as may be required. D is the cumulative

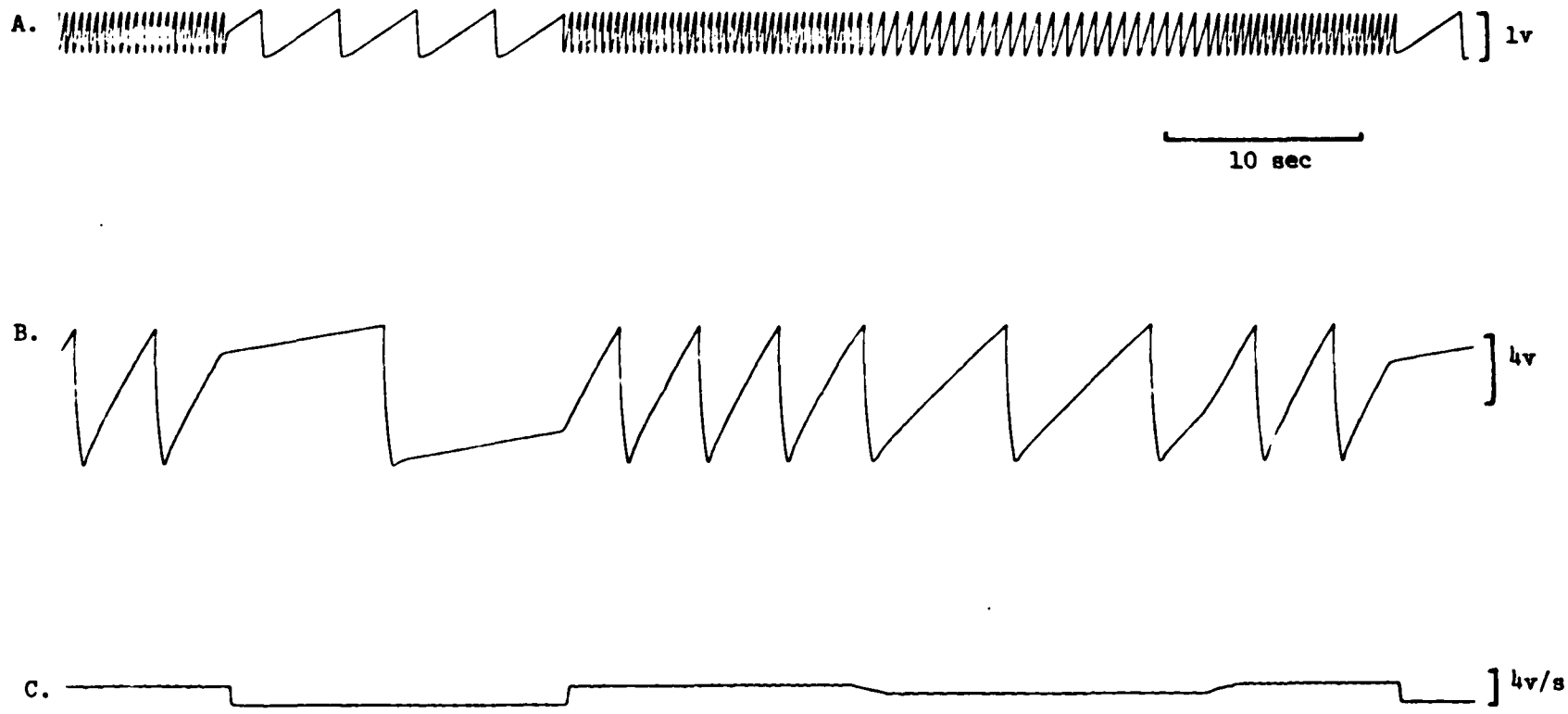


Fig. 4.13. Cumulative slow phase position and slow phase velocity for simulated waveform. A. Simulated waveform. B. Cumulative slow phase position. C. Slow phase velocity. (continued on next page.)

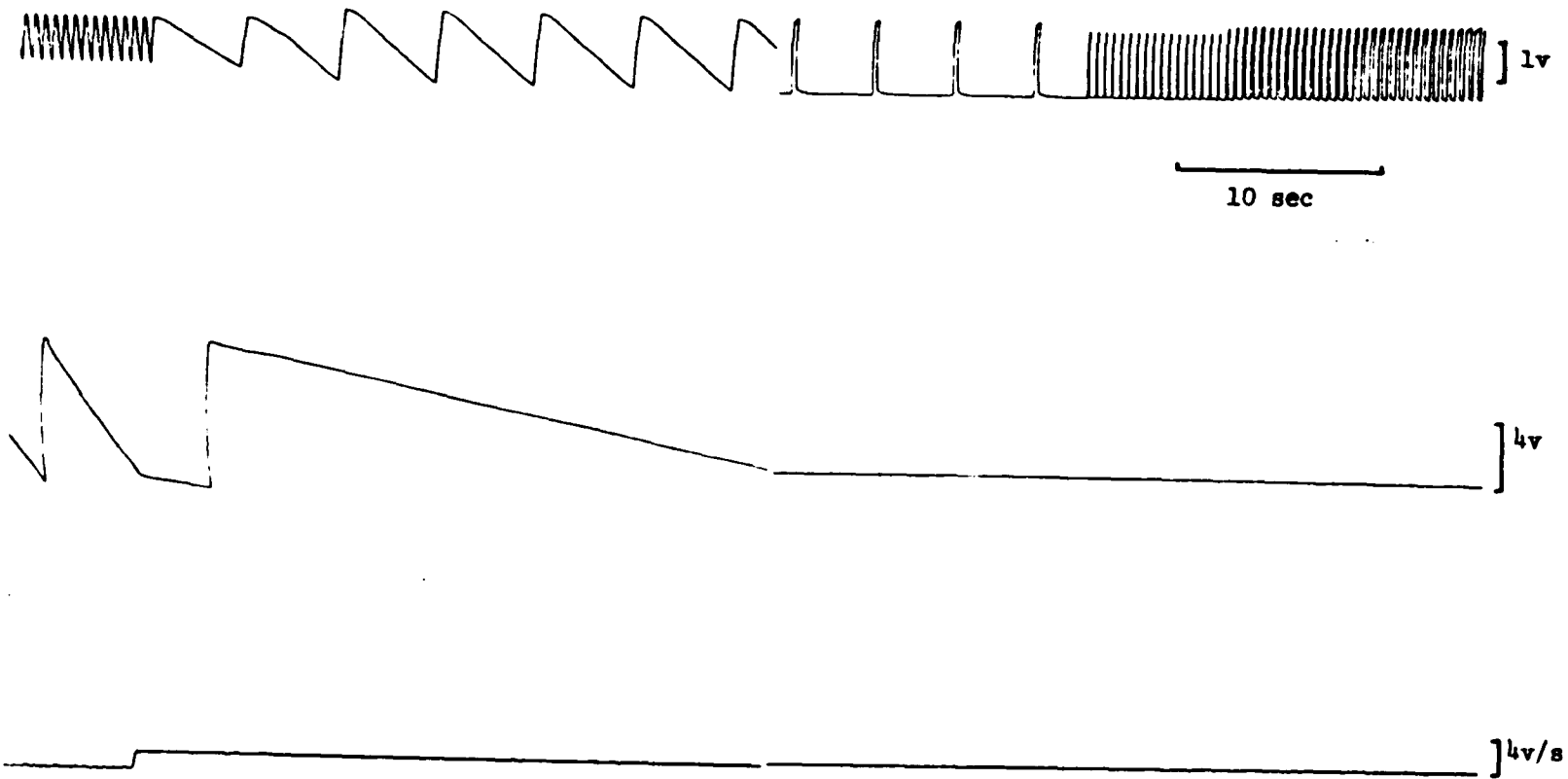


Fig. 4.13. Continued from last page.

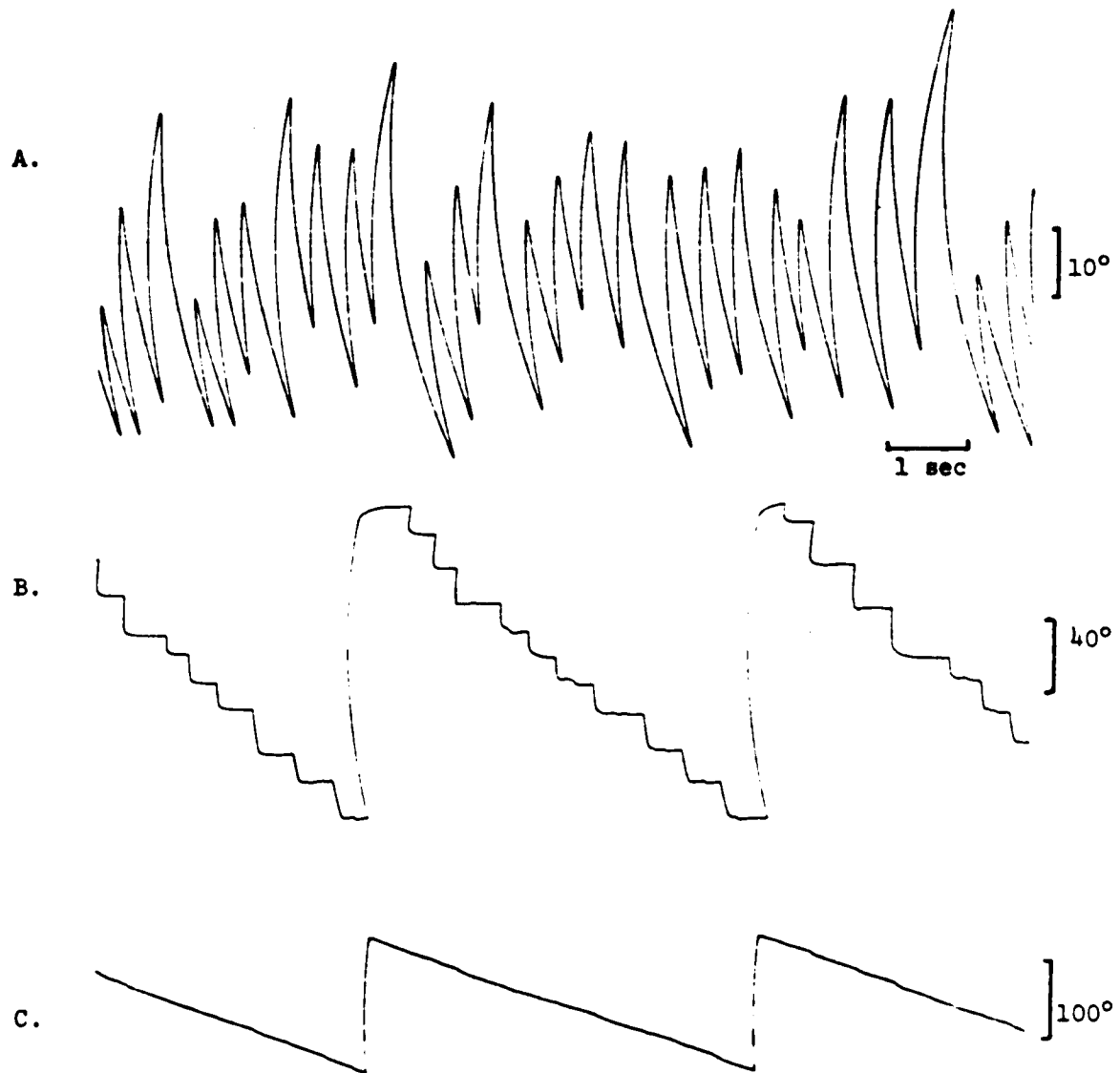


Fig. 4.14. A. EOG waveform. B. Accumulated quick phases waveform.  
C. Cumulative slow phase position (CSPP) waveform.

position waveform which follows the slow phases fairly well. The jumps are due to the wrap-around feature and therefore do not affect when differentiation is done. The waveform C is obtained after differentiation of the waveform D, and, therefore, represents the slow phase velocity waveform. The occasional kinks in the slow phase velocity waveform are the real manner in which the slow phases change. This is clear when one looks at the cumulative slow phase position, there is no jump which can be considered due to any quick phase eye movement. Secondly the velocity associated with these small kinks (Fig. 4.15 C) and comparing it with the velocity associated with the saccades (Fig. 4.15 B), one can come to the conclusion that these small variations in the slow phase velocity are primarily due to the real variations in the slow phase eye velocity. However, these kinks could have been tiny saccades which were undetected due to their time period being smaller than the width of the decision window (see Chapter 3 for details). This, however, leads us to redefine a saccadic movement based upon its time duration which will not be done here since it needs extremely small decision window and extremely fast computer to run the program on-line. All the waveforms generated in Fig. 4.15 are generated without any filtering at any stage of the processing. The low pass filtering on the SPV waveform may generate a smoother waveform, but will affect the transitions in the slow phase velocity and may not faithfully represent SPV during the time interval of a slow phase.

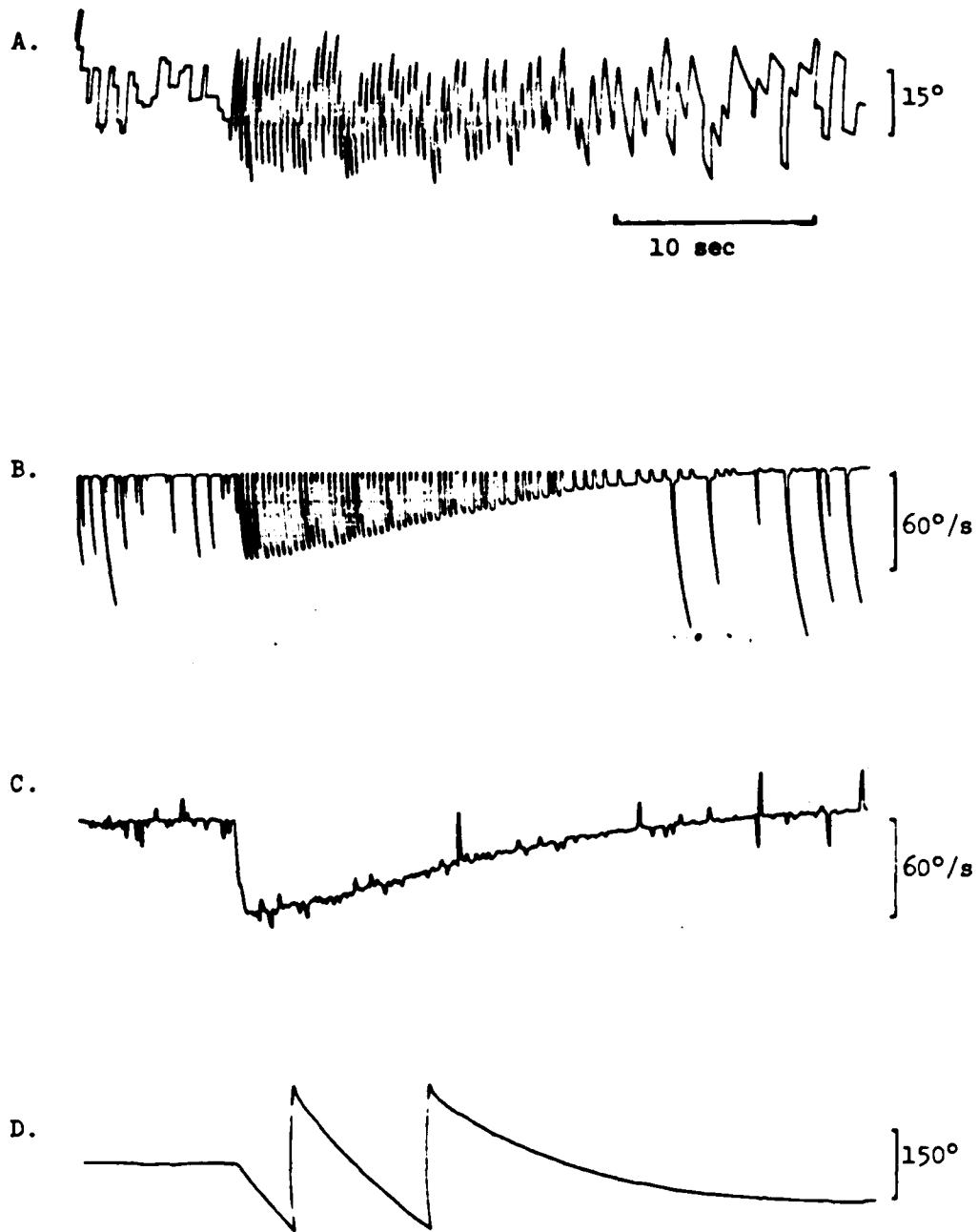


Fig. 4.15. Cumulative slow phase position and slow phase velocity as obtained by analog and computerized methods. A. EOG waveform. B. Differentiated EOG waveform - analog technique. C. Slow phase velocity waveform - computerized technique. D. Cumulative slow phase position waveform - computerized technique.

The precision with which the beginning and the end of a saccade are marked depends on how a slow phase turns into a quick phase and how a quick phase turns into a slow phase. Thus the extrapolated part of a waveform may not be an exact replacement for the saccadic interval. Secondly, since the extrapolation is based upon the slow phase portion just prior to the quick phase, the extrapolated waveform may not represent an accurate bridge between two slow phases. These processing errors affect the accuracy of a cumulative slow phase position waveform and the slow phase velocity waveform. If this poses a real problem, one may look into higher order function templates to define slow and quick phases for the detection scheme.

The next chapter will utilize the waveforms generated in this chapter to identify the parameters of a slow-phase-generating system model.

## CHAPTER 5

PARAMETER IDENTIFICATION FOR A MODEL OF  
SLOW PHASES OF OPTOKINETIC NYSTAGMUS5.1 Introduction

This chapter considers the parameter identification of a model for slow phase eye velocity in response to full-field optokinetic stimuli. The specific model taken for identification is a subset of the one developed by Raphan and Cohen (Cohen et al, 1977; Raphan et al, 1979). The identification scheme uses the slow phase eye velocity of a monkey in response to a step. The model parameters are generated using a least squares error criterion.

The next section describes the slow phase model. The least squares parameter identification technique is described in section 5.3. The application of the technique to estimate the parameters of a slow phase model is the subject of section 5.4.

5.2 A Model for Slow Phase Generation

The model which will be utilized to demonstrate the behavior of the parameter identification algorithm is shown in Fig. 5.1 (Cohen et al, 1977). The response to a pulse input is shown in Fig. 5.2 and simulates the dominant characteristics of optokinetic nystagmus (OKN) and optokinetic after-nystagmus (OKAN) in response to a pulse (see Chapter 2).

Integration is assumed to be the basic element of OKN and OKAN system. The integrator stores activity during full-field optokinetic

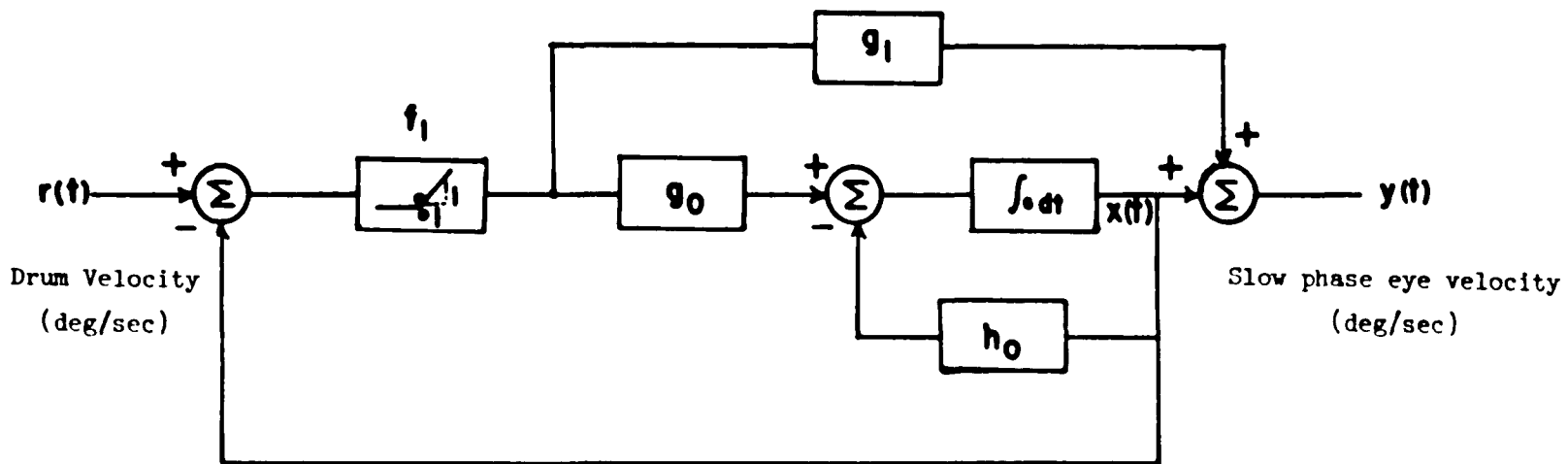


Fig. 5.1. Raphan-Cohen model of the neural mechanism responsible for producing OKN and OKAN.

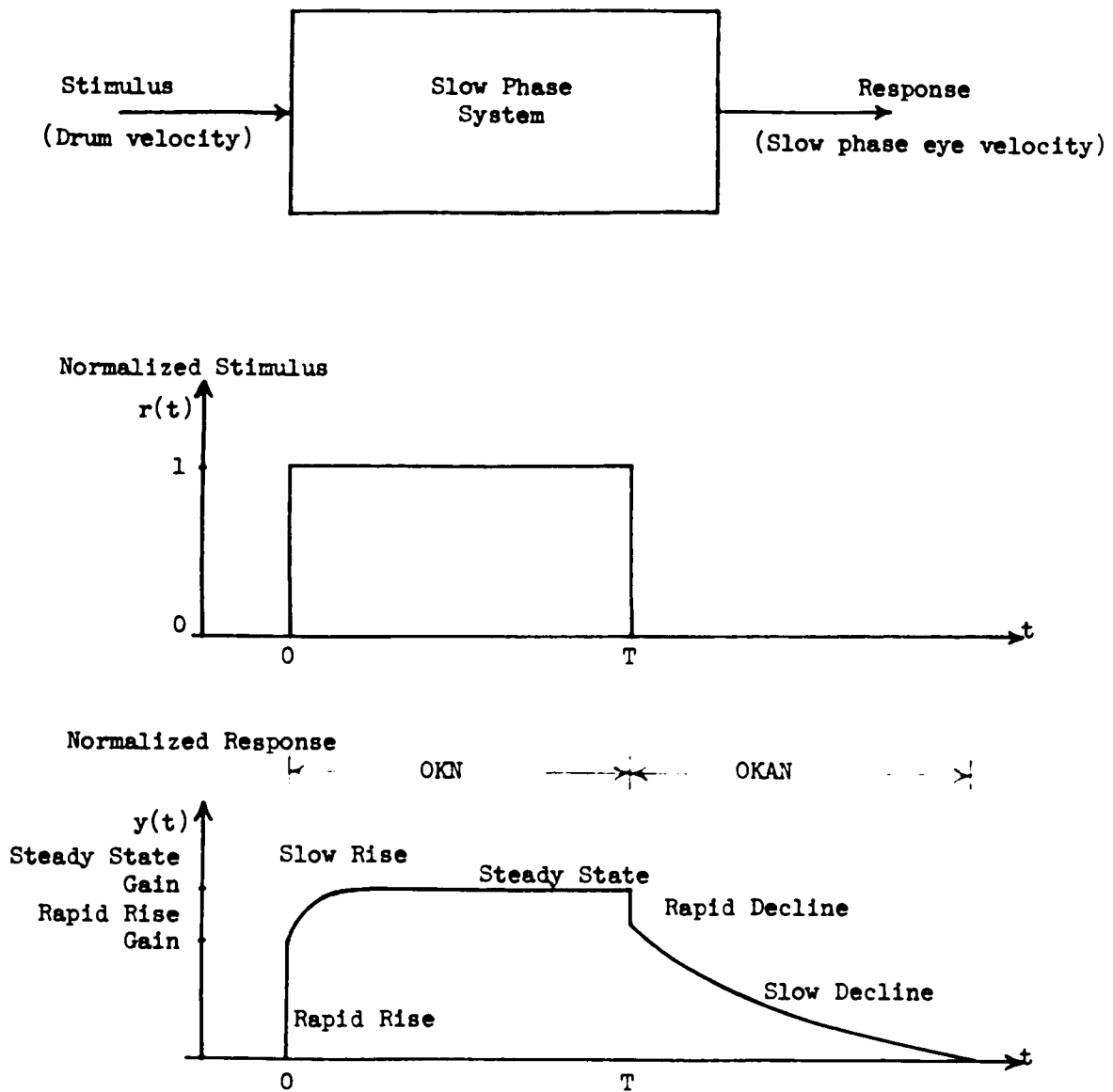


Fig. 5.2. An idealized pulse response of a slow phase system.

stimulation (OKN) which is later used to drive the eyes during OKAN. During OKN,  $r$  is assumed to be equal to the drum velocity and during OKAN  $r = 0$ . The nonlinear element  $f_1$  allows transmission during OKN and shuts off during OKAN. The forward gain parameters  $g_0$  and  $g_1$  along with the feedback parameter  $h_0$  determine the OKN characteristics like the rapid rise, slow rise and the steady state value. The feedback parameter  $h_0$  determines the slow decline characteristics of OKAN. It is these parameters which will be identified.

The differential equation for the model in Fig. 5.2 is given by

$$\dot{x} = -h_0 x + g_0(r-x) u(r-x) \quad (5.2.1)$$

$$y = x + g_1(r-x) u(r-x)$$

where  $u(z) = 1$  for  $z \geq 0$

$= 0$  for  $z < 0$

The OKN response ( $r > x$ ) of this model to an input similar to the one in Fig. 5.1B is given by

$$x(t) = \frac{g_0 V}{h_0 + g_0} (1 - \exp(-(h_0 + g_0)t)) \quad (5.2.2)$$

$$y(t) = g_1 V + (1 - g_1) \frac{g_0 V}{h_0 + g_0} [1 - \exp(-(h_0 + g_0)t)]$$

where  $V$  is the amplitude of the step input. From (5.2.2), one can obtain the following results relating the model parameters to the response parameters:

$$\text{Rapid rise} = g_1 V$$

$$\text{Slow rise time constant} = 1/(g_0 + h_0)$$

$$\text{Steady state value } y_s = (g_1 h_0 + g_0) V / (h_0 + g_0)$$

$$\text{Steady state value } x_s = g_0 V / (h_0 + g_0)$$

At  $t=T$ , when the stimulus is set to zero ( $r \leftarrow x$ ), the OKAN response as obtained from (5.2.1) is given by

$$x(t) = x_s \exp(-h_0(t - T)) \quad (5.2.3)$$

$$y(t) = x(t)$$

From (5.2.3) one can obtain the following relations

$$\text{Rapid decline} = g_1 h_0 V / (h_0 + g_0)$$

$$\text{Slow decline time constant} = 1/h_0$$

The model is an approximation to a complex neural mechanism responsible for producing OKN and OKAN. The usefulness of this model lies in its simplicity coupled with reasonably good predictions [8]. This is explored in more detail when the model parameter identification is done in section 5.4 utilizing an actual experimental response of a monkey.

### 5.3 Identification of the Model Parameters

The parameter identification of the model is considered in this section. The nonlinear model structure imposes a constraint that separate identification must be done for the rising portion of the step response (when input is applied) and for

the decaying portion (when the input has been removed). This is because the system response in the two regions is not dependent upon the same parameters of the model. During OKN all the parameters  $g_1$ ,  $g_0$  and  $h_0$  determine the response. During OKAN only  $h_0$  determines the response.

The model state equation for  $r(t) > x(t)$  is given by

$$\dot{x}(t) = -(h_0 + g_0) x(t) + g_0 r(t) \quad (5.3.1)$$

$$z(t) = (1 - g_1) x(t) + g_1 r(t) + n(t)$$

where  $n(t)$  accounts for the measurement noise. The discrete equivalent of (5.3.1) is given by

$$x(k+1) = \exp(-(h_0 + g_0)T) x(k) + \int_{kT}^{(k+1)T} \exp[-(h_0 + g_0)[(k+1)T - \tau]] \cdot g_0 d\tau r(k) \quad (5.3.2)$$

$$z(k+1) = (1 - g_1) x(k+1) + g_1 r(k+1) + n(k+1)$$

Eliminating the state variable  $x(k+1)$  in (5.3.2) yields

$$z(k+1) = a z(k) + b r(k) + c r(k+1) + n(k+1) - a n(k) \quad (5.3.3)$$

where

$$a = \exp(-(h_0 + g_0)T) \quad (5.3.4)$$

$$b = (1 - g_1)g_0 / (h_0 + g_0) \cdot [1 - \exp(-(h_0 + g_0)T)] - g_1 \exp(-(h_0 + g_0)T) \quad (5.3.5)$$

$$c = g_1 \quad (5.3.6)$$

Let the step input be defined by

$$r(k) = V u(k) \quad (5.3.7)$$

where  $V$  is the magnitude of the step input.

Substituting (5.3.7) in (5.3.3) yields

$$z(k+1) = a z(k) + b V u(k) + c V u(k+1) + n(k+1) - a n(k) \quad (5.3.8)$$

For  $k \geq 0$  (5.3.8) becomes

$$z(k+1) = a z(k) + b V + c V + n(k+1) - a n(k) \quad (5.3.9)$$

Equation (5.3.9) fails to satisfy output distinguishability conditions [13] and therefore can't be used to estimate all three parameters.

One method to circumvent this problem is to use the initial response  $y(0)$  to estimate parameter  $c$ . This is accomplished by substituting  $k = -1$  in (5.3.8) which yields

$$z(0) = c V u(0) + n(0) \quad (5.3.10)$$

It is possible to derive least square estimate [19] of  $c$  if a number of step responses for different magnitudes of step inputs are available. In such a case (5.3.10) can be written as

$$z_i(0) = c V_i u(0) + n_i(0) \quad (5.3.11)$$

where  $i$  denotes the particular experiment in each  $V_i u(0)$  is the input and  $z_i(0)$  is the output at  $t=0$  (or  $k=0$ ). The least square estimate of  $c$  as obtained from (5.3.11) is given by

$$\hat{c} = (\phi^T \phi)^{-1} \phi^T z(0) \quad (5.3.12)$$

$$\text{where } \phi = [V_1 \ V_2 \ \dots \ V_N]^T \quad (5.3.13)$$

$$\text{and } z(0) = [z_1(0) \ z_2(0) \ \dots \ z_N(0)]^T$$

where  $N$  denotes the number of experiments used to estimate  $c$ .

To estimate parameters  $a$  and  $b$ , (5.3.8) is written as

$$\begin{aligned} z(k+1) &= a z(k) + b V + z(0) - n(0) + n(k+1) - a n(k) \\ &= a z(k) + \beta + w(k+1) \quad k \geq 0 \end{aligned} \quad (5.3.14)$$

$$\text{where } \beta = bV + (z(0) - n(0)) = (b + c) V \quad (5.3.15)$$

$$\text{and } w(k+1) = n(k+1) - a n(k) \quad (5.3.16)$$

Least squares estimation [19] as applied to (5.3.14) yields  $a$  and  $\beta$ .

These estimates are given by

$$\begin{bmatrix} \hat{\mathbf{a}}(m) \\ \hat{\boldsymbol{\beta}}(m) \end{bmatrix} = [\Phi^T \Phi]^{-1} \cdot \Phi^T \mathbf{z} \quad (5.3.17)$$

where  $m$  denotes the number of measurements (in addition to initial  $z(0)$ ) used to estimate  $\mathbf{a}$  and  $\boldsymbol{\beta}$ .

$$\mathbf{z} = [z(1) \quad z(2) \quad \dots \quad z(m)]^T \quad (5.3.18)$$

$$\Phi = \begin{bmatrix} z(0) & 1 \\ z(1) & 1 \\ z(2) & 1 \\ \vdots & \vdots \\ z(m-1) & 1 \end{bmatrix} \quad (5.3.19)$$

Equation (5.3.17) when expanded yields

$$\hat{\mathbf{a}}(m) = \frac{m \sum z(i) \cdot z(i+1) - \sum z(i) \sum (z(i+1))}{m \sum z^2(i) - (\sum z(i))^2} \quad (5.3.20)$$

$$\hat{\boldsymbol{\beta}}(m) = \frac{-\sum z(i) \sum z(i) \cdot z(i+1) + \sum z^2(i) \sum z(i+1)}{m \sum z^2(i) - (\sum z(i))^2} \quad (5.3.21)$$

where all summations  $\sum$  s are taken from  $i = 0$  to  $(m-1)$ . The recursive realization of (5.3.20) and (5.3.21) can be carried out by defining intermediate variables as follows:

$$\begin{aligned} \text{SZ}(m) &= \sum_0^{m-1} z(i) = \sum_0^{m-2} z(i) + z(m-1) \\ &= \text{SZ}(m-1) + z(m-1) \end{aligned} \quad (5.3.22)$$

$$\begin{aligned} \text{SSZ}(m) &= \sum_0^{m-1} z^2(i) = \sum_0^{m-2} z^2(i) + z^2(m-1) \\ &= \text{SSZ}(m-1) + z^2(m-1) \end{aligned} \quad (5.3.23)$$

$$\begin{aligned} \text{SZ1}(m) &= \sum_0^{m-1} z(i+1) = \sum_0^{m-2} z(i+1) + z(m) \\ &+ \text{SZ1}(m-1) + z(m) \end{aligned} \quad (5.3.24)$$

$$\begin{aligned}
\text{SZZ1}(m) &= \sum_0^{m-1} z(i).z(i+1) \\
&= \sum_0^{m-2} z(i).z(i+1) + z(m-1).z(m) \\
&= \text{SZZ1}(m-1) + z(m-1).z(m)
\end{aligned} \tag{5.3.25}$$

Parameter estimation must begin with at least two measurements for two parameters. Alternatively the initial values (for  $m=1$ ) for the variables defined in (5.3.22) to (5.3.25) are given by

$$\begin{aligned}
\text{SZ}(1) &= z(0) \\
\text{SSZ}(1) &= z^2(0) \\
\text{SZ1}(1) &= z(1) \\
\text{SZZ1}(1) &= z(1).z(0)
\end{aligned} \tag{5.3.26}$$

In view of (5.3.22) to (5.3.25), (5.3.20) and (5.3.21) can be written as

$$\hat{a}(m) = \frac{m \cdot \text{SZZ1}(m) - \text{SZ}(m) \cdot \text{SZ1}(m)}{m \cdot \text{SSZ}(m) - (\text{SZ}(m))^2} \tag{5.3.27}$$

$$\hat{\beta}(m) = \frac{\text{SZ}(m) \cdot \text{SZZ1}(m) + \text{SSZ}(m) \cdot \text{SZ1}(m)}{m \cdot \text{SSZ}(m) - (\text{SZ}(m))^2} \tag{5.3.28}$$

Thus equations (5.3.22) - (5.3.25) along with (5.3.27) and (5.3.28) can be implemented for recursive estimation of parameters  $a$  and  $\beta$ . The identification process may be stopped when the parameters settle with required accuracy.

The estimates of  $h_0$ ,  $g_0$  and  $g_1$  can be obtained from the estimates of  $a$ ,  $\beta$ ,  $c$  and equations (5.3.4) - (5.3.6), (5.3.15). These estimates are given by

$$\begin{aligned}\hat{g}_0 &= \ln[\hat{a}](\hat{b} + \hat{a}\hat{c}) / [(-T)(1-\hat{a})(1-\hat{c})] \\ \hat{h}_0 &= \ln[\hat{a}](\hat{a} + \hat{b} + \hat{c}-1) / [T(1-\hat{a})(1-\hat{c})]\end{aligned}\quad (5.3.29)$$

$$\hat{g}_1 = \hat{c}$$

where  $\hat{b} = \hat{\beta}/V - \hat{c}$

When  $r(t) = 0$ , the differential equation generating output (OKAN velocity) is given by

$$\dot{x}(t) = -h_0 x(t) \quad (5.3.30)$$

$$z(t) = x(t) + n(t)$$

Discrete equivalent of (5.3.30) is given by

$$x(k+1) = \exp(-h_0 T) x(k) \quad (5.3.31)$$

$$z(k+1) = x(k+1) + n(k+1)$$

Eliminating  $x(k+1)$  in (5.3.31) yields

$$z(k+1) = \alpha z(k) + w(k+1) \quad (5.3.32)$$

where

$$\alpha = \exp(-h_0 T) \quad (5.3.33)$$

$$\text{and } w(k+1) = n(k+1) - \alpha n(k) \quad (5.3.34)$$

Least square estimation of  $\alpha$  from (5.3.32) gives

$$\hat{\alpha} = (\phi^T \phi)^{-1} \phi^T z \quad (5.3.35)$$

$$\text{where } z = [z(1) \quad z(2) \quad \dots \quad z(m)]^T \quad (5.3.36)$$

$$\text{and } \phi = [z(0) \quad z(1) \quad \dots \quad z(m-1)]^T$$

The estimation of  $\alpha$  leads to the estimation of  $h_0$  from eqn. (5.3.33),

i.e.

$$\hat{h}_0 = -\ln(\hat{\alpha})/T \quad (5.3.37)$$

The least square parameter estimates are known to be biased [19]. The amount of bias can be estimated as follows. In general the estimate for the parameter vector  $\Theta$  is given by

$$\hat{\Theta} = (\Phi^T \Phi)^{-1} \Phi^T z \quad (5.3.38)$$

where  $\Phi$  is a matrix of past outputs and  $z$  is a vector of outputs given by

$$z = \Phi \Theta + w \quad (5.3.39)$$

where  $w$  is a noise vector.

Substituting (5.3.39) in (5.3.38) yields

$$\hat{\Theta} = \Theta + (\Phi^T \Phi)^{-1} \Phi^T w \quad (5.3.40)$$

From (5.3.40) bias on  $\Theta$  is given by

$$\hat{\Theta}_{\text{bias}} = E [(\Phi^T \Phi)^{-1} \Phi^T w] \quad (5.3.41)$$

The bias is due to the reason that the system outputs are correlated with the past noises. If we assume that each output has significant correlation only with the finite past and then take data far enough apart in time such that each new equation is essentially independent of the past noises, we can minimize  $\hat{\Theta}_{\text{bias}}$ .

#### 5.4 Experimental Results

The least square error parameter identification of the slow phase model described in section 5.3 was applied to the experimentally obtained OKN and OKAN responses of a monkey. The results of the identification are described in section 5.4.2. However, first the scheme used in collecting needed data for the identification is considered in section 5.4.1.

#### 5.4.1 Data Acquisition for the Parameter Identification Program

The schematic which describes the steps used to generate the slow phase eye velocity and the identification of parameters is shown in Fig. 5.3. The EOG representing eye position and stimulus velocity were obtained from an analog tape (Honeywell). The eye velocity of the slow phases was estimated from the EOG waveform using the saccade detection program.

The saccades were detected (see chapter 3) and removed (see chapter 4) to generate cumulative slow phase position whose differentiation using one PDP-8/E computer yielded the slow phase velocity. A second computer (PDP-8/E) was used to smooth and store this velocity along with the stimulus velocity on a DEC tape. The various amplifiers used in the schematic were needed to scale the signals to proper amplitudes for the A/D converters. The data tape so prepared was then used to obtain the model parameters by running the parameter identification program off-line on a PDP-8/E computer. The identification program is shown in Appendix C.

#### 5.4.2 Parameter Identification Results

The slow phase system response to a stimulus velocity pulse of  $90^\circ/\text{sec}$  to the right is considered for the parameter identification. The response along with the stimulus is shown in Fig. 5.4. The approximate response parameters as obtained graphically from Fig. 5.4B are also given in the figure. These parameters can be compared with the ones obtained by the least squares identification technique.

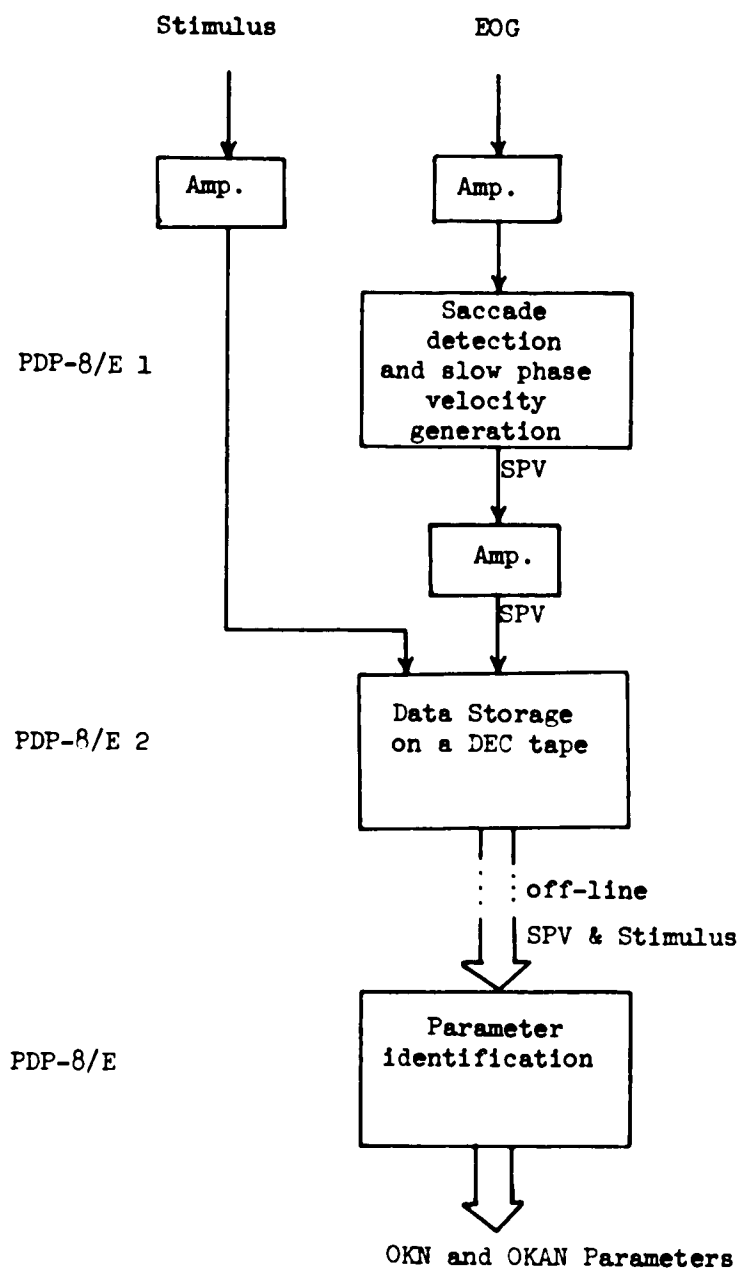


Fig. 5.3. The data-acquisition system for the parameter identification of OKN and OKAN model.

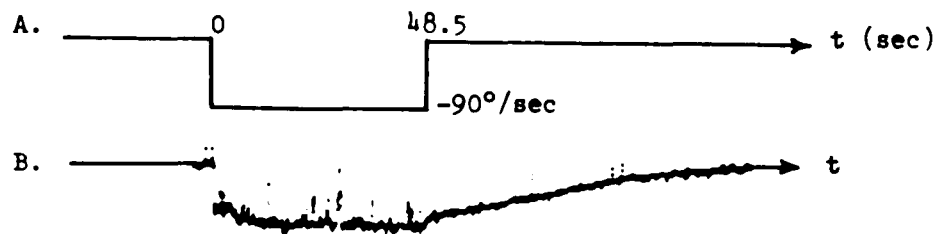


Fig. 5.4. OKN and OKAN response to a pulse input.

- A. Stimulus velocity is  $-90^\circ/\text{sec}$
- B. Eye velocity as obtained by the method discussed in Chapter 4. Graphical estimates of response parameters are as follows:
- Rapid rise gain  $\approx .65$
  - Slow rise time constant  $\approx 3 \text{ sec}$
  - Steady state gain  $\approx 1$
  - Rapid decline gain  $\approx .15$
  - Slow decline time constant  $\approx 27 \text{ sec.}$

The least squares estimates for the OKN parameters  $c$ ,  $a$  and  $\beta$ , for a  $-90^\circ/\text{sec}$  nystagmus velocity, and a sampling interval of .2048 sec. are plotted in Fig. 5.5. Under these conditions

$\hat{c} = .575$ ,  $\hat{a} = .94$  and  $\hat{\beta}/V = .05$  which correspond to  $\hat{g}_1 = .575$ ,  $\hat{h}_0 = .13$  and  $\hat{g}_0 = .16$ . The identification was repeated for various sampling intervals and the results are shown in Appendix D and summarized in Table 5.1. The mean of the estimates of  $g_1$ ,  $h_0$  and  $g_0$  are .575, .18, .25 respectively. These results can be used to compute the response parameters for comparison with the graphical measurements.

The least squares estimate for the OKAN parameter  $\alpha$ , for a sampling interval of 1.536 sec. is plotted in Fig. 5.6. It can be observed that  $\hat{\alpha} = .94$  which corresponds to the OKAN model parameter  $\hat{h}_0 = .0388$ . The identification was repeated for various sampling intervals and the results are shown in Appendix D and summarized in Table 5.2. The mean of the  $h_0$  estimate is .03942, corresponding to an OKAN time constant of 25.38 seconds. These results are consistent with the graphical measurements from Fig. 5.4B. It seems that  $h_0$  as obtained from OKAN is closer to the real value of  $h_0$  when compared to the one obtained from OKN. The reason seems to be that response waveform during OKN is not an exponential rise. The OKAN response, however is closer to an exponential as implicitly assumed by the model. This fact has already been noted by Raphan et al, (1979).

The response parameters as computed from the model parameters are presented in Table 5.3 and they compare reasonably well to the ones determined graphically. This supports the contention that  $h_0$  as obtained from OKAN is a better estimate of  $h_0$ .

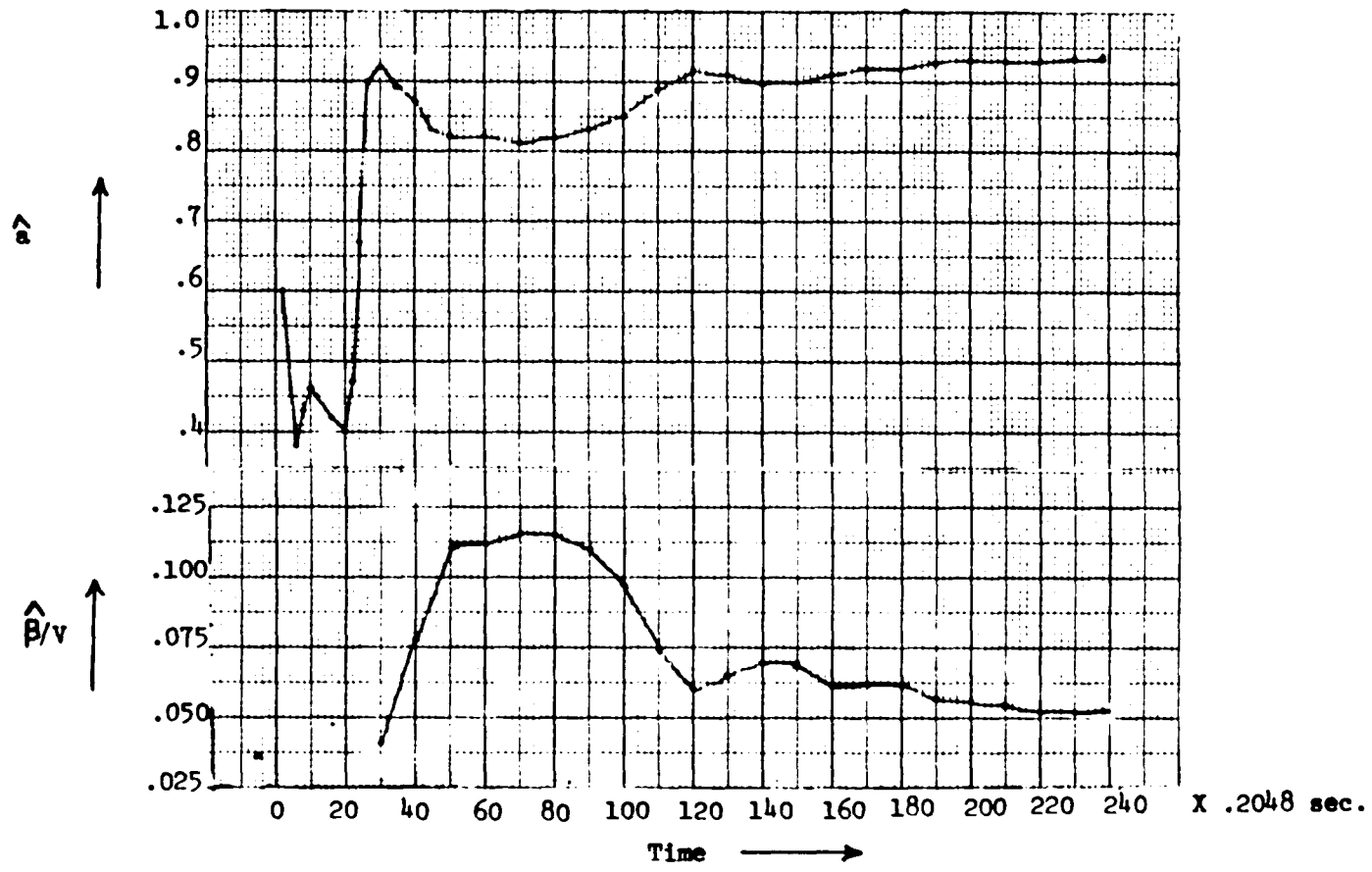


Fig. 5.5. OKN parameter identification. Sampling interval = .2048 sec.

Table 5.1. OKN parameter identification for various sampling intervals.

$T$ (sec.)	$\hat{c}$	$\hat{a}$	$\hat{\beta}/v$	$\hat{g}_1$	$\hat{h}_0$	$\hat{g}_0$
.2048	.575	.94	.05	.575	.13	.16
.512	.575	.85	.12	.575	.15	.17
1.024	.575	.52	.40	.575	.24	.38
2.048	.575	.38	.52	.575	.18	.29

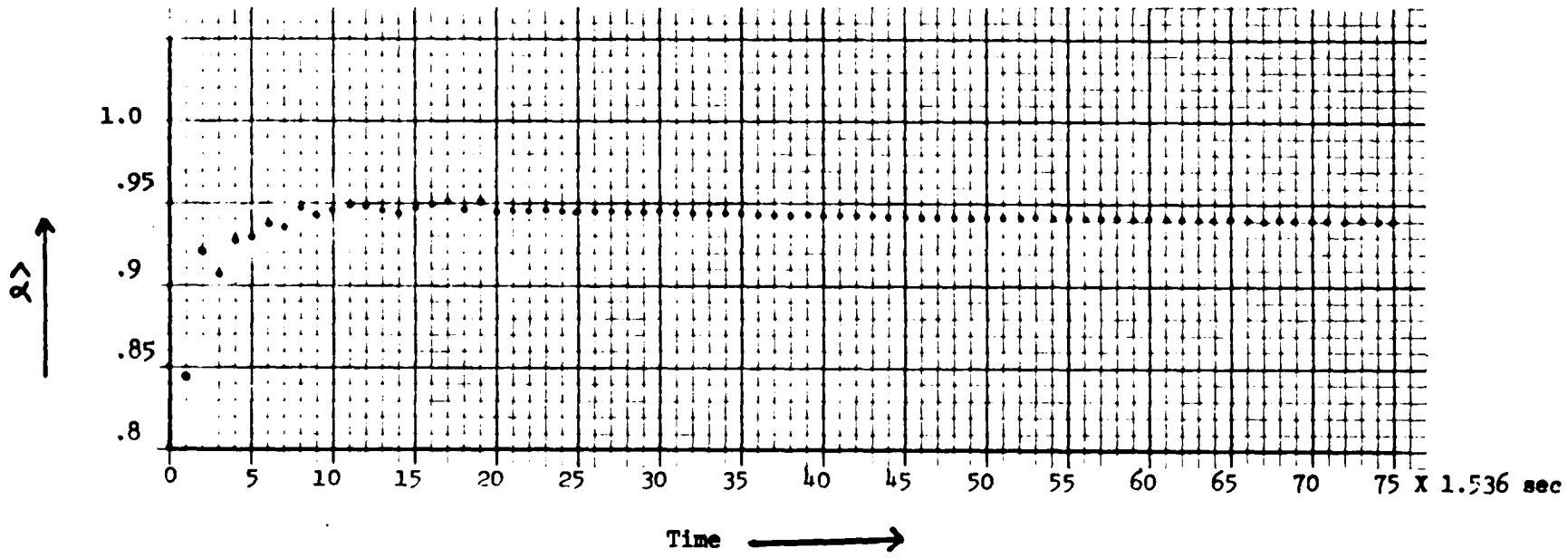


Fig. 5.6. OKAN parameter  $\alpha$  identification.  $T = 1.536$  sec.

Table 5.2. OKAN parameter identification for various sampling intervals.

T (sec.)	$\hat{\alpha}$	$\hat{h}_0$
.0512	.9975	.0391
.256	.9885	.0452
.512	.980	.0395
1.024	.961	.0388
1.536	.940	.0403
2.56	.902	.0394

Table 5.3. Response parameters as obtained from the OKN and OKAN model parameters.

Response parameter	Graphically from Fig. 5.4B	From identified model parameters
Rapid rise gain	.65	.575
Slow rise time constant	3 sec	3.45 sec ** (2.33 sec) *
Steady state gain	1	.94 ** (.82) *
Rapid decline gain	.15	.08 ** (.24) *
Slow decline time constant	27 sec	25.37 ** sec (5.6 sec) *

\*  $h_o = .18$  used in calculations (OKN identification)

\*\*  $h_o = .04$  used in calculations (OKAN identification)

To compare the parameter estimation of  $h_0$  from OKN data with the parameter estimation from the OKAN data, the model outputs were generated using  $h_0$  as estimated from these data. The simulated outputs were compared with the system outputs by defining a model error  $e(k)$  and the integral square error  $ISE(k)$  as follows:

$$e(k) = z(k) - \hat{z}(k)$$

$$ISE(k) = \sum_{i=k-1}^k e^2(i)$$

where  $z(k)$  is the system output and  $\hat{z}(k)$  is the simulated model output. The '1' defines the length of the moving window for computing  $ISE(k)$ .

The simulation program for this purpose is shown in Appendix E. The signal processing results are shown in Fig. 5.7. The traces in Fig. 5.7 show the model output, the model error and the integral square error for three cases: one, when the OKN parameter estimation was used to simulate the OKN model output and the OKAN parameter the OKAN model output; two, when  $\hat{h}_0$  from OKAN was used to simulate the model output; and three, when  $\hat{h}_0$  from OKN was used to simulate the model output. These traces for various  $z(t)$ ,  $e(t)$  and  $ISE(t)$  show that the estimate of  $h_0$  parameter of the OKN is not reliable and the OKAN must be used to estimate it. The parts which show OKN simulation in these traces demonstrate the fact that the value of  $h_0$  is not a crucial factor in the OKN generation.

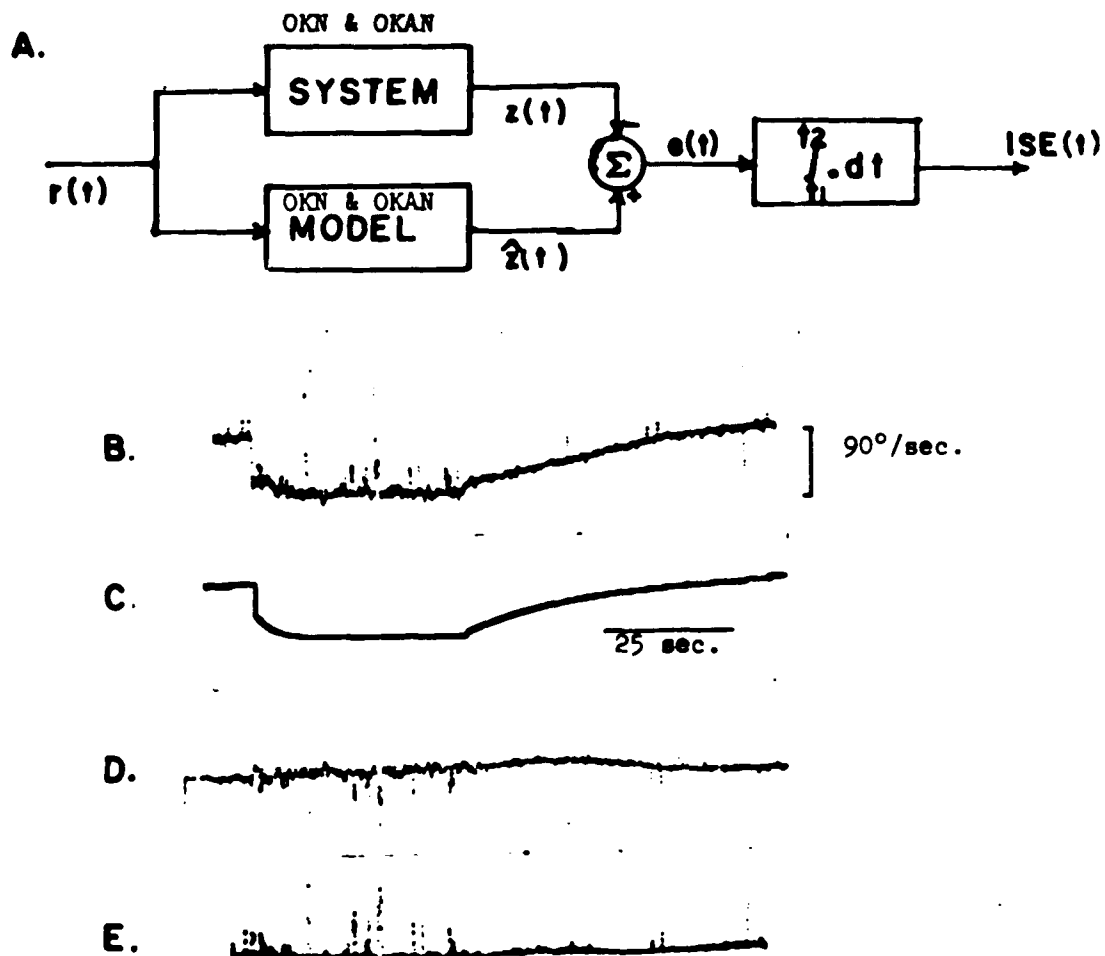


Fig. 5.7. The OKN & OKAN system response vs the OKN & OKAN model response.

- A. Block diagram of the OKN & OKAN system vs model for comparison. Stimulus used was  $-90^\circ/\text{sec}$  (Fig. 4B)
- B. The OKN & OKAN system output  $z(t)$ .
- C. The OKN & OKAN model output  $\hat{z}(t)$ . The OKN was simulated using OKN parameter estimation and the OKAN using the OKAN parameter estimation.
- D. The model error  $e(t)$  for the system output of B. and the model output of C.
- E. The integral square error  $ISE(t)$  for the system output of B. and the model output of C.

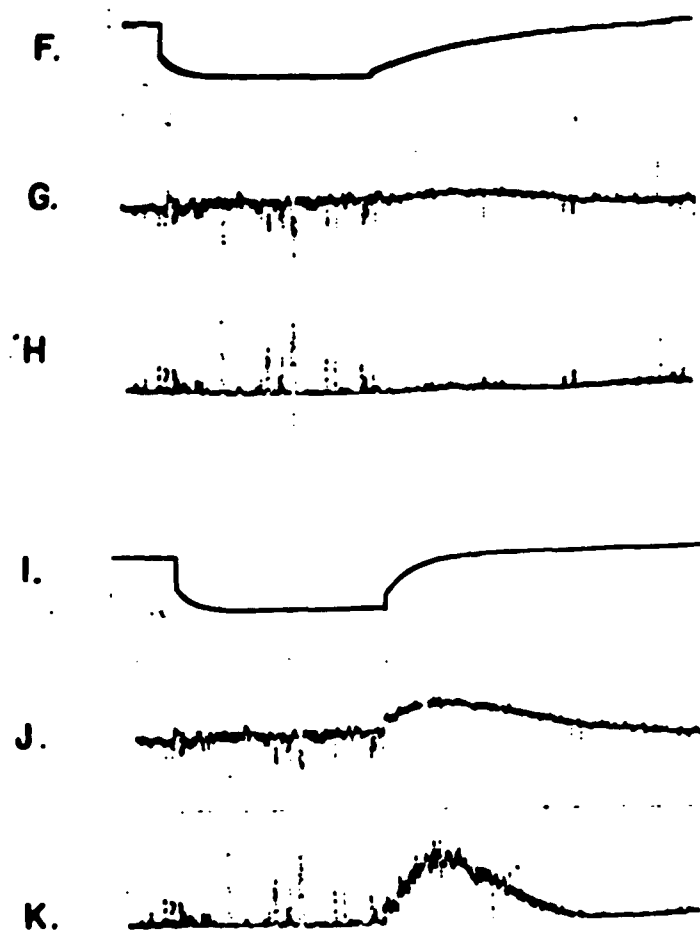


Fig. 5.7. Continued.

- F. The OKN & OKAN model output  $\hat{z}(t)$ . Both OKN and OKAN were simulated using  $h_0$  as estimated from OKAN parameter estimation.
- G. The model error  $e(t)$  for the system output of B. and the model output of F.
- H. The integral square error  $ISE(t)$  for the system output of B. and the model output of F.
- I. The OKN & OKAN model output  $\hat{z}(t)$ . Both OKN and OKAN were simulated using  $h_0$  as estimated from OKN parameter estimation.
- J. The model error  $e(t)$  for the system output of B. and the model output of I.
- K. The integral square error  $ISE(t)$  for the system output of B. and the model output of I.

## CHAPTER 6

## SUMMARY AND CONCLUSIONS

6.1 Summary

In this dissertation, an on-line digital signal processing technique has been developed to analyze the response of an oculomotor system subjected to an optokinetic stimulus or to a vestibular stimulus. The analyzed response is then utilized in the parameter identification of a slow phase subsystem model of the oculomotor system. Thus a technique has been developed which leads to the parameterization of the oculomotor system response. The response waveforms and the model parameters generated in this manner has the potential of being used in the diagnosis of oculomotor system problems and in the understanding of its functional behavior.

An important assumption on which the signal processing technique is based is that the two parts of the response (the slow phase and the quick phase or a saccade) are generated internally by two separate subsystems. This assumption allow treatment of a slow phase subsystem and its response independent of the quick phase or saccadic subsystem. Another assumption is that the quick phase saccadic duration is relatively much smaller than the slow phase duration. This leads to the assumption that during a quick/saccadic phase, the slow phase system state remains essentially unchanged. Still another assumption is that the slow phase response can be approximated by a straight line; this simplifies the implementation and reduces the timing requirements

of the on-line signal processing system.

An important feature of the signal processing developed in this work is that it lends itself to a microprocessor implementation for real-time analysis of waveforms. Special consideration was given in chapter 4 to the implementation in terms of its timing requirements and the complexity of algorithms. Thus the results of this work serve as the foundation for the development of a microprocessor-based instrument for on-line oculomotor system analysis. The parameter identification of the slow phase system model replaces a cumbersome manual operation by an automatic identification procedure.

A crucial part of the signal processing technique is the detection of saccades and quick phases in an EOG waveform. This was achieved using 'Baye's Likelihood Ratio Criterion', which minimizes the probability of a detection error. It leads to a detection technique with predictable performance and the control elements for adaptation to various experimental situations. The detection technique was described in section 3.3.1 and its probability of error was computed in section 3.3.3. The technique was tested on simulated waveforms in section 3.3.4 and on experimental waveforms in section 3.4. The results of these tests lead to the conclusion that it is an appropriate way to detect quick phases/saccade and the process of detection can be controlled by varying detection technique parameters, such as the number of samples used for detection, sampling interval and the functional description of the waveform sections.

Once saccades/quick phases are detected, the next step is to remove them to obtain a purely slow phase system response. The technique was based upon describing a slow phase by a straight line

and assuming that saccades/quick phases are much faster than the slow phases. The description of the technique which generates cumulative slow phase position (CSPP) is contained in section 4.2.1. The slow phase velocity (SPV) is obtained by differentiating CSPP. A least squares error digital differentiator for this purpose was described in section 4.2.2. The applicability of this type of digital differentiator to EOG waveforms was tested mathematically by evaluating its frequency response and experimentally by applying it to real EOG waveforms. The digital differentiator has advantages over an analog differentiator most commonly used for obtaining SPV waveforms. The combined detection, CSPP and SPV generation program is presented in section 4.4 where a vestibular nystagmus was processed to detect/suppress quick phases and generate cumulative slow phase position and the slow phase velocity. The slow phase velocity generated in this manner is compared to an analog differentiator output. The conclusion is that the type of signal processing technique developed in this dissertation is capable of producing predictable performance and has a number of advantages over the ones which have been developed so far. These advantages include the detection of forward as well as reverse saccades, reproduction of slow phase velocity transitions, and control over detection parameters for optimal processing.

A state space model due to Raphan and Cohen [8] was considered to represent the slow phase subsystem responsible for producing OKN and OKAN response. The model is an approximation to a more complex and nonlinear system but is adequate to predict salient features of a step (or a long pulse) response. For this model, the parameter identification had to be carried using a step response and the response itself was very

noisy. A least square error technique which has a smoothing effect on the noise was considered for the parameter identification. The technique was described in section 5.3 and was applied to a 90°/sec nystagmus in section 5.4.2. The estimated parameters compare favorably to the ones measured manually. The bias in the least square estimation technique was minimized by using data samples sufficiently apart so as to reduce the noise correlation between them.

Control over the signal processing parameters allows one to adapt the technique described in this work to various experimental situations. The predictability of the technique leads to the pre-evaluation of its applicability to an experimental response. This initial step in the understanding of oculomotor system through signal processing has a potential in analyzing various kinds of oculomotor system responses and in evolving an optimal and adaptive technique for this purpose.

## 6.2 Recommendations for Future Research

Theoretical and practical future extensions of this research are listed below. A sound understanding of the measurement noise statistics should be obtained so that possibly a new detection scheme could be achieved. Specifically the following recommendations are made for further investigation in line with this thesis.

1. Consider the other forms of EOG noise statistics and derive other forms of saccade/quick phase detectors and the associated probabilities of detection error.

2. Change the functional descriptions of the quick and the slow phases of nystagmus to higher order functions. Specifically, higher order functions are needed to describe the beginning and the end of these movements. This may lead to a multiple-hypotheses detection problem. The detection based upon the solution to the multiple-hypothesis problem may lead to lower probability of detection error.
3. Optimize the functional descriptions for the slow and the quick phases for various nystagmus velocities and fit them into a functional so that the process of detection may be made self-adaptive.
4. Obtain noise vs time trade-off for the digital differentiator used to obtain slow phase velocities. Also consider other forms of digital differentiators to find an optimal one for the slow phase velocity generation.
5. Consider other forms of experiments for the on-line parameter identification of the slow phase system. This is to circumvent the difficulties associated with an on-line parameter identification from a step response.
6. Integrate the saccadic detector and the parameter identification so that these two schemes run simultaneously in an on-line manner. This will generate a system of results valuable for the real-time analysis of oculomotor system.
7. Implement the detection and the identification of a slow phase system on a microprocessor system. Such an implementation will lead to a portable instrument for the oculomotor system diagnosis.

APPENDIX A

COMPUTER PROGRAM FOR ERROR ANALYSIS OF EXAMPLE IN SECTION 3.3.4

TYPE ERROR1 FORTRAN		
C	ERROR ANALYSIS OF DETECTION SYSTEM	ERR00010
	REAL K	ERR00020
	INTEGER X	ERR00030
	DIMENSION F(10),G(10),Z(2),Y(2,10)	ERR00040
	WRITE(6,1)	ERR00050
1	<del>FORMAT(//,5X,'N',10X,'S',10X,'Z11N',7X,'Z22N',7X,'X',4X,'Z21X',</del>	<del>ERR00060</del>
	A7X,'Z12X',//)	ERR00070
	DO 500 N=2,6,2	ERR00080
	S=0.5	ERR00090
	DO 400 M=1,7	FRR00100
	K=0.	ERR00110
	<del>Z(1)=0.</del>	<del>ERR00120</del>
	Z(2)=0.	ERR00130
	S1=0.	ERR00140
	DO 100 I=1,N	ERR00150
	F(I)=.2*I	FRR00160
	G(I)=-1.6*I	ERR00170
	<del>Z(1)=Z(1)+F(I)*(F(I)-G(I))</del>	<del>ERR00180</del>
	Z(2)=Z(2)+G(I)*(F(I)-G(I))	ERR00190
	K=K+F(I)**2-G(I)**2	ERR00200
100	S1=S1+(F(I)-G(I))**2	ERR00210
	K=K/2+S**2*ALOG(.1)	ERR00220
	S1=S1**.5*S	LKR00230
	<del>Z(1)=.5*ERF((K-Z(1))/(1.414*S1))+.5</del>	<del>ERR00240</del>
	Z(2)=.5*ERFC((K-Z(2))/(1.414*S1))	ERR00250
	N1=N-1	FRR00260
	YX=0.	LKR00270
	DO 300 X=1,N1	FRR00280
	Y(2,X)=0.	ERR00290
	Y(1,X)=0.	LRR00300
	N2=N-X	ERR00310

	DO 200 I=1,N2	ERR00320
	Y(2,X)=Y(2,X)+G(I)*(F(I)-G(I))	ERR00330
200	Y(1,X)=Y(1,X)+F(I)*(F(I)-G(I))	ERR00340
	N3=N-X+1	ERR00350
	DO 250 I=N3,N	ERR00360
	Y(2,X)=Y(2,X)+(G(N2)+F(I-N2))*(F(I)-G(I))	ERR00370
250	Y(1,X)=Y(1,X)+(F(N2)+G(I-N2))*(F(I)-G(I))	ERR00380
	Y(2,X)=.5*ERF((K-Y(2,X))/(S1*1.414))+.5	ERR00390
	Y(1,X)=.5*ERFC((K-Y(1,X))/(S1*1.414))	ERR00400
	WRITE(6,2) N,S,Z(1),Z(2),X,Y(2,X),Y(1,X)	ERR00410
2	FORMAT(5X,I3,8X,F6.3,5X,F6.4,5X,F6.4,5X,I2,3X,F6.4,5X,F6.4)	ERR00420
300	YX=YX+Y(2,X)+Y(1,X)	ERR00430
	TOTEA=.9*Z(1)+.1*Z(2)	ERR00440
	TOTE=TOTEA+.002*YX	ERR00450
	WRITE(6,3)TOTEA,TOTE	ERR00460
3	FORMAT(/,20X,'TOTEA=',F6.4,/,20X'TOTE=',F6.4,//)	ERR00470
400	S=S+.5	ERR00480
500	CONTINUE	ERR00490
	STOP	ERR00500
	END	ERR00510

## APPENDIX B

## A PROGRAM FOR PROCESSING EOG WAVEFORMS

The following pages contain listing of an assembly language program developed on PDP-8/E minicomputer to process raw EOG data and generate any combination of following waveforms.

- i) Smoothed EOG waveform where smoothing is done by means of a 4-point averaging filter.
- ii) A waveform indicating occurrences of saccades or quick phases in EOG waveform. The saccade detection algorithm is based upon the 'likelihood ratio detector' of Chapter 3.
- iii) Cumulative slow phase position (CSPP) waveform. The algorithm is discussed in Chapter 4.
- iv) Cumulative quick phases/saccades waveform. The algorithm is discussed in Chapter 4.
- v) EOG velocity waveform. The digital differentiator used is designed using least square error straight line fit to EOG data. The slope of the line indicates velocity.
- vi) EOG slow phase velocity waveform. Cumulative slow phase position and digital differentiator are used to generate slow phase velocity.

-----  
/ON-LINE SACCADIC DETECTION AND SLOW PHASE VELOCITY GENERATION PROGRAM.  
-----

/REM: THIS PROGRAM SAMPLES EOG WAVEFORM ON CHANNEL 0 AND GENERATES  
/SLOW-PHASE VELOCITY WAVEFORM ON CHANNEL X  
/AND CUMULATIVE POSITION WAVEFORM ON CHANNEL Y  
/SWITCH REGISTER SETTING: BITS 0-5 ABS(F1-F2),BITS 6-11 (F1+F2)  
/F1 DENOTES SLOW PHASE (1ST QUAD), F2 DENOTES QUICK PHASE (4TH QUAD)  
-----

/LABORATORY PERIPHERALS DEFINITIONS

/DK-8/EP CLOCK DEFINITIONS

6130            CLZE=    6130            /ZEROS TO CLOCK ENABLE  
6132            CLOE=    6132            /ONES TO CLOCK ENABLE  
6133            CLAB=    6133            /LOAD BUFFER PRESET REGISTER

/AD-8/cA A-D CONVERTOR DEFINITIONS

6531            ADLM=    6531            /LOAD A-D MUX REGISTER  
6532            ADST=    6532            /START A-D CONVERTER  
6533            ADRB=    6533            /READ A-D BUFFER  
6534            ADSK=    6534            /SKIP UN A-D FLAG  
6536            ADLE=    6536            /LOAD A-D ENABLE REGISTER

/D-A CONVERTOR DEFINITIONS

6551            DALX=    6551            /LOAD X  
6552            DALY=    6552            /LOAD Y  
6553            DASK=    6553            /SKIP ON D-A FLAG  
6554            DINT=    6554            /INTENSIFY DISPLAY

/GENERAL EQUIVALENCES

0177            PROTMK=0177            /ROTATING MASK FOR PROTECTING TRAILING EDGE  
0004            SAMINT=4            /SAMPLING INTERVAL IN MSEC.

## /NUMERICAL CONSTANTS

7300	NL0000=	CLA CLL	/GET 0
7301	NL0001=	CLA CLL IAC	/GET 1
7305	NL0002=	CLA CLL IAC RAL	/GET 2
7325	NL0003=	CLA CLL CML IAC RAL	/GET 3
7307	NL0004=	CLA CLL IAC RTL	/GET 4
7327	NL0006=	CLA CLL CML IAC RTL	/GET 6
7340	NL7777=	CLA CLL CMA	/GET -1
7344	NL7776=	CLA CLL CMA RAL	/GET -2

## /PAGE ZERO LOCATIONS

*0010	*10		
00010	0367	XR,	BUFF-1
00011	7777	XRE,	EBUFF-1
00012	0020	XR1,	F1MF2
00013	0021	XR2,	F1PF2
			/AUTO-INDEX FOR RAW EOG SAMPLES
			/AUTO-INDEX FOR SMOOTHED EOG SAMPLES
			/AUTO-INDEX FOR F1-F2
			/AUTO-INDEX FOR F1+F2
*0020	*20		
00020	0512	F1MF2,	F1MF2T
00021	0505	F1PF2,	F1PF2T
00022	0400	PDETECT,	DETECT
00023	0600	PCSPP,	CSPP
00024	1200	PDIFF,	DIFF
00025	0000	PB1,	0
00026	0000	PB2,	0
00027	0000	CNT1,	0
00030	0004	DWNWTH,	4
00031	0000	DREF,	0
			/F1-F2 TABLE ADDRESS POINTER
			/F1+F2 TABLE ADDRESS POINTER
			/POINTER TO DETECT SUBROUTINE
			/POINTER TO CUMULATIVE SLOW PHASE POSITION ROUTINE
			/POINTER TO DIFF. FILTER ROUTINE
			/POINTER1
			/POINTER2
			/INITIALIZING COUNTER
			/DECISION WINDOW WIDTH-1
			/MOVING REFERENCE TO SCALE INPUT SAMPLES

00032	0000	DFN,	0	/DECISION FUNCTION
00033	0000		0	/DOUBLE PRECISION
00034	0000	DCODE,	0	/DECISION CODE TO PROTECT TRAILING EDGE
00035	0000	LDCODE,	0	/LAST VALUE OF DCODE
00036	0000	RS,	0	/RUNNING SUM
00037	0000	SIGN,	0	/SIGN SWITCH
00040	0000	DEL,	0	/DELTA CHANGE IN CUM. POS.
00041	0000	VEL,	0	/SLOW PHASE VELOCITY
00042	0000		0	/DOUBLE PRECISION
00043	0000	VELDIS,	0	/VELOCITY TO BE DISPLAYED
00044	0000	TEMP1,	0	/TEMPORARY LOCATION
00045	0000	TEMP2,	0	/DOUBLE-PRECISION
00046	0000		0	/TEMPORARY LOCATION
00047	0000	TEMP3,	0	/TEMPORARY LOCATION
00050	0000	TEMP4,	0	/TEMPORARY LOCATION
00051	0000	TEMP5,	0	/TEMPORARY LOCATION
00052	0000	TEMP6,	0	/TEMPORARY LOCATION
00053	0000		0	/DOUBLE PRECISION
	0000	EBUFF=	0	/EOG BUFFER INITIALIZATION
00054	0000	EBUFDL,	EBUFF	/EOG DISPLAY POINT POINTER
00055	0104	YM1,	CBUFF+104	/Y(-1) POINTER
00056	0105	YO,	CBUFF+105	/Y(0) POINTER
00057	0125	Y2N,	CBUFF+125	/Y(2N) POINTER
	0003	XDIVN=	3	/DIVISION BY 'N' IN EXTRAPOLATION
	0010	DELWN=	10	
	0001	DELN=	1	/DIVISION CONSTANT FOR DEL AVERAGING
00060	0061	EBUFDS,	EBUFF+61	/START OF DECISION WINDOW POINTER
00061	0063	EBUFDL,	EBUFF+63	/DECISION WINDOW MID POINT POINTER
00062	0065	EBUFLP,	EBUFF+65	/LATEST EOG POINT POINTER
	0000	CBUFF=	0	/CUM. POS. BUFFER INITIALIZATION

00063	0057	CBUFD <sub>P</sub> , CBUFF+57	/CUMULATIVE POS. DISPLAY POINT POINTER
00064	0060	DIFMM1, CBUFF+60	/DIFF. MID POINT-1
00065	0061	CDIFMP, CBUFF+61	/DIFF. MID POINT POINTER
00066	0062	DIFMP1, CBUFF+62	/DIFF. MID POINT+1
	0030	NM1B2= 30	/(TOTAL DIFF.PTS.-1)/2
00067	0131	CBUFN, CBUFF+131	/FIRST POINT REPLACED-4 POINT POINTER
00070	0135	CBFN <sub>P</sub> 1, CBUFF+135	/FIRST POINT REPLACED POINTER
	0006	CBUFRP= 6	/CBUFF POINTS TO BE REPLACED
00071	0136	CBLPM1, CBUFF+136	/LATEST POINT-4 POINTER
00072	0142	CBUFLP, CBUFF+142	/LATEST CUMULATIVE POINT POINTER
00073	1464	DFILTS, DBUFF+64	/DIFF. FILTER START POINTER
00074	1500	DBLP, DBUFF+100	/DIFF. BUFFER LATEST POINT POINTER
	0004	VGAIN= 4	/VELOCITY GAIN CONTROL

\*0200

PAGE

## /MAIN PROGRAM

```

00200 6007 START, CAF /CLEAN UP
00201 6201 CDF 00 /MAKE SURE DATA FIELD 0
00202 7431 SWAB /FORCE MODE 8 EAE
00203 7300 NL0000 /GET A/D 0
00204 6531 ADLM /LOAD MUX REG
00205 1377 TAD (200 /ENABLE A-D BY CLOCK
00206 6536 ADLE /FOR INPUT ROUTINE
00207 6551 DALX /CENTER X, RAISING DONE FLAG
00210 6552 DALY /CENTER Y, RAISING DONE FLAG
00211 1177 TAD (-SAMINT) /SET SAMPLING INTERVAL
00212 6133 CLAB /PRESET CLOCK BUFFER
00213 7240 STA /-1
00214 6130 CLZE /CLEAR CLOCK
00215 0376 AND (1340 /MODE 01, 1KHZ, A-D START
00216 6132 CLOE /LOAD CLUCK ENABLE
00217 4336 FEED, JMS SMOOTH /OBTAIN A SMOOTHED EOG SAMPLE
00220 6211 CDF 10 /SAVE IN DATA FIELD 1
00221 3462 DCA I EBUFLP /THE LATEST SAMPLE
00222 6201 CDF 00 /RESTORE DATA FIELD
00223 1021 TAD F1PF2 /INITILIZE POINTERS FOR TABLES
00224 3012 DCA XR1
00225 1020 TAD F1MF2
00226 3013 DCA XR2
00227 7307 NL0004 /INITILIZE COUNTER
00230 7041 CIA
00231 3045 DCA TEMP2
00232 3044 DCA TEMP1 /CLEAN UP TEMP1
00233 7604 TABUP1, LAS /READ IN SWITCH REGISTER
00234 0375 AND (77 /MASK LEFT BITS
00235 1044 TAD TEMP1 /ADD ON OLD SUM
00236 3044 DCA TEMP1 /AND SAVE
00237 1044 TAD TEMP1 /GET BACK SUM
00240 3412 DCA I XR1 /UPDATE TABLE

```

00241	2045		ISZ	TEMP2	/DONE?
00242	5233		JMP	TABUP1	/NO
00243	3044		DCA	TEMP1	/CLEAN UP TEMP1
00244	7307		NL0004		/INITIALIZE COUNTER
00245	7041		CIA		
00246	3045		DCA	TEMP2	
00247	7604	TABUP2,	LAS		/READ IN SWITCH REGISTER
00250	7002		DSW		/SWAP
00251	0375		AND	(77	/CLEAN UP LEFT BITS
00252	7041		CIA		/NEGATE IT
00253	1044		TAD	TEMP1	/ADD ON OLD SUM
00254	3044		DCA	TEMP1	/AND SAVE
00255	1044		TAD	TEMP1	/GET IT BACK
00256	3413		DCA I	XR2	/UPDATE TABLE
00257	2045		ISZ	TEMP2	/DONE?
00260	5247		JMP	TABUP2	/NO
00261	4422		JMS I	PDETECT	/DETECT ROUTINE
00262	4423		JMS I	PCSP	/COMPUTE CUMULATIVE SLOW PHASE POSITION
00263	4424		JMS I	PDIFF	/COMPUTE VELOCITY
00264	7621		CAM		/CLEAN UP
00265	6221		CDF	20	/OBTAIN FROM DATA FIELD 2
00266	1463		TAD I	CBUFOP	/THE CUMULATIVE POSITION DISPLAY POINT
00267	6201		CDF	00	/RESTORE DATA FIELD 0
00270	6552		DALY		/DISPLAY
00271	7621		CAM		/CLEAR AC AND HQ
00272	1043		TAD	VELDIS	/OBTAIN VELOCITY FOR DISPLAY
00273	6551		DALX		/DISPLAY
00274	6553		DASK		/D-A DONE?
00275	5274		JMP	.-1	/NO, WAIT
00276	6554		DINT		/YES OUTPUT INTENSITY

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-----
/UPDATE VARIOUS POINTERS:
00277 2054 ISZ EBU FDP /EOG DISPLAY POINT POINTER
00300 7000 NOP
00301 2055 ISZ YM1 /Y(-1) POINTER
00302 7000 NOP
00303 2056 ISZ YO /Y(0) POINTER
00304 7000 NOP
00305 2057 ISZ Y2N /Y(2N) POINTER
00306 7000 NOP
00307 2060 ISZ EBU FDS /DECISION WINDOW START POINTER
00310 7000 NOP
00311 2061 ISZ EBU FDM /DECISION WINDOW MID POINT POINTER
00312 7000 NOP
00313 2062 ISZ EBU FL P /LATEST EOG POINT POINTER
00314 7000 NOP
00315 2063 ISZ CBU FDP /CUM. POS. DISPLAY POINT POINTER
00316 7000 NOP
00317 2064 ISZ DIF M M1 /DIFF. MID PT.-1
00320 7000 NOP
00321 2065 ISZ CDIF M P /DIFF. MID POINT POINTER
00322 7000 NOP
00323 2066 ISZ DIF M P1 /DIFF. MID PT.+1
00324 7000 NOP
00325 2067 ISZ CBU FN /FIRST REPLACED-1 POINT POINTER
00326 7000 NOP
00327 2070 ISZ CBU FN P1 /FIRST REPLACED POINT POINTER
00330 7000 NOP
00331 2071 ISZ CBL P M1 /LATEST POINT-1 POINTER
00332 7000 NOP
00333 2072 ISZ CBU FL P /LATEST CUM. POS. POINT POINTER
00334 7000 NOP
00335 5217 JMP FEED /GO DO IT AGAIN
-----
```

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00336 0000 SMOOTH, 0 /AVERAGING INPUT ROUTINE
00337 7344 NL7776 /-2
00340 3037 DCA SIGN /TO SIGN SWITCH
00341 1371 TAD BUFF+1 /\
00342 3370 DCA BUFF / \
00343 1372 TAD BUFF+2 / \MOVE BACK
00344 3371 DCA BUFF+1 / /ONE PLACE
00345 1373 TAD BUFF+3 / /
00346 3372 DCA BUFF+2 //
00347 6534 ADSK /A-D READY?
00350 5347 JMP .-1 /NO, WAIT FOR IT
00351 6533 ADRB /READ IT IN
00352 3373 DCA BUFF+3 /STASH IT
00353 1370 TAD BUFF /\
00354 1371 TAD BUFF+1 / \ADD UP
00355 1372 TAD BUFF+2 / /FOUR POINTS
00356 1373 TAD BUFF+3 //
00357 7500 SMA /NEGATIVE?
00360 2037 ISZ SIGN /NO, BUMP SIGN SWITCH
00361 7510 SPA /POSITIVE?
00362 7041 CIA /NO, TAKE ABSOLUTE VALUE
00363 7110 CLL RAR /DIVIDE BY 2
00364 7110 CLL RAR /DIVIDE BY 2
00365 2037 ISZ SIGN /INVERT BACK?
00366 7041 CIA /YES
00367 5736 JMP I SMOOTH /RETURN TO CALLER

00370 0000 BUFF, ZBLOCK 4 /RAW EOG BUFFER

*0375
00375 0077
00376 1340
00377 0200
*0400 PAGE

```

## /LIKELIHOOD RATIO DETECTOR SUBROUTINE

```

00400 0000 DETECT, 0
00401 7621          CAM          /CLEAN UP
00402 1377          TAD          (SBUFF /RESTORE XRE TO
00403 3011          DCA          XRE   /START OF DATA WINDOW
00404 1020          TAD          F1MF2 /RESTORE XR1 TO
00405 3012          DCA          XR1   /START OF F1-F2
00406 1021          TAD          F1PF2 /RESTORE XR2 TO
00407 3013          DCA          XR2   /START OF F1+F2
00410 7421          MQL          /ZERO LSPART OF DFM
00411 7445          DST;        DFN   /ZERO DFN
00412 0032
00413 1060          TAD          EBUFDS /RESET PB1 TO
00414 3025          DCA          PB1   /FIRST SMOOTHED SAMPLE
00415 1377          TAD          (SBUFF /RESET PB2 TO
00416 3026          DCA          PB2   /FIRST SCALED SAMPLE
00417 1030          TAD          DWNWTH /RESTORE WINDOW COUNTER
00420 7041          CIA
00421 3027          DCA          CNT1  /TO -(DECISION WINDOW WIDTH-1)
00422 6211          CDF          10   /FROM DATA FIELD 1,
00423 1425          TAD I       PB1   /GET FIRST POINT
00424 6201          CDF          00   /RESTORE DATA FIELD 0
00425 7041          CIA          /NEGATE IT
00426 3031          DCA          DREF  /SAVE IN DREF
00427 3426          DCA I       PB2   /ZERO IPO FIRST POINT
00430 2025 BACK1,   ISZ          PB1   /INCREMENT PB1
00431 7000          NOP
00432 2026          ISZ          PB2   /INCREMENT PB2
00433 6211          CDF          10   /FROM DATA FIELD 1
00434 1425          TAD I       PB1   /GET NEXT POINT
00435 6201          CDF          00   /RESTORE DATA FIELD 0
00436 1031          TAD          DREF  /ADD -FIRST POINT
00437 7510          SPA          /POSITIVE?
00440 7041          CIA          /NO, NEGATE
00441 3426          DCA I       PB2   /SAVE IT
00442 2027          ISZ          CNT1  /DONE?
00443 5230          JMP          BACK1 /NO, DO IT AGAIN

```

## /DECISION FUNCTION "DFN" CALCULATIONS

00444	1030		TAD	DWNWTH	/SET COUNTER
00445	7041		CIA		/TO
00446	3027		DCA	CNT1	/-(DECISION WINDOW WIDTH-1)
00447	7340	DECSN,	NL7777		/-1
00450	3037		DCA	SIGN	/TO SIGN SWITCH
00451	1412		TAD I	XR1	/GET F1-F2
00452	7041		CIA		/NEGATE
00453	7421		MOL		/SAVE IN MQ
00454	1411		TAD I	XRE	/GET DATA SAMPLE R
00455	7104		CLL	RAL	/R*2
00456	7041		CIA		/-R*2
00457	1413		TAD I	XR2	/FORM F1+F2-2R
00460	3044		DCA	TEMP1	/SAVE IN TEMP1
00461	1044		TAD	TEMP1	/GET F1+F2-2R
00462	7510		SPA		/POSITIVE?
00463	7410		SKP		/NO, SKIP TO INVERT
00464	5270		JMP	POSMUL	/YES, SKIP TO MULTIPLY
00465	7041		CIA		/INVERT
00466	3044		DCA	TEMP1	/SAVE IN TEMP1
00467	2037		ISZ	SIGN	/SIGN=0 IF F1+F2-2R IS NEGATIVE
00470	7200	POSMUL,	CLA		/CLEAR AC
00471	7405		MUY;	TEMP1	/(F1-F2)(F1+F2-2R)
00472	0044				
00473	2037		ISZ	SIGN	/WAS NEGATIVE?
00474	7410		SKP		/NO, SKIP TO SAVE
00475	7575		DCM		/YES, ATTACH SIGN
00476	7443		DAD;	DFN	/ADD TO LAST DFN VALUE
00477	0032				
00500	7445		DST;	DFN	/AND SAVE
00501	0032				
00502	2027		ISZ	CNT1	/DONE?
00503	5247		JMP	DECSN	/NO, DO NEXT PT.
00504	5600		JMP I	DETECT	/RETURN

/FUNCTION TABLES

00505	0000	F1PF2T, 0	/F1+F2 TABLE
00506	0010	10	
00507	0020	20	
00510	0030	30	
00511	0040	40	

00512	0000	F1MF2T, 0	/F1-F2 TABLE
00513	7772	7772	
00514	7764	7764	
00515	7756	7756	
00516	7750	7750	

00517	0000	SBUFF, ZBLOCK 5	/SCALED EOG BUFFER
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	*0577	
00577	0517	
	*0600	PAGE

## /CUMULATIVE SLOW PHASE POSITION "CSPP" LOGIC AND CALCULATIONS SUBROUTINE

```

00600 0000 CSPP, 0
00601 7621 CAM /CLEAN UP
00602 1034 TAD DCODE /REPLACE LDCODE
00603 3035 DCA LDCODE /BY DCODE
00604 7100 CLL /CLEAR LINK
00605 7443 DAD; JFN /GET DFN
00606 0032
00607 7700 SMA CLA /NEGATIVE?
00610 7120 STL /NO, SET LINK=1
00611 1034 TAD DCODE /GET LAST DECISION CODE
00612 7004 RAL /ROTATE LEFT
00613 0176 AND [PROTMK] /CLEAN LEFT OF DECISION-CODE
00614 3034 DCA DCODE /SAVE NEW DECISION-CODE
00615 1034 TAD UCODE /GET DECISION -CODE
00616 7450 SNA /NON-ZERO?
00617 5237 JMP SLOW /NO, SLOW-PHASE!
00620 7300 QUICK, CLA CLL /CLEAN UP
00621 1035 TAD LDCODE /WAS LAST POINT QUICK PHASE
00622 7440 SZA /NO
00623 5226 JMP UPH /YES
00624 4673 FTOP, JMS I PXPOS /EXTRAPOLATE CORRECTION FACTOR "DEL" AND
00625 5272 JMP NEXT /CORRECT BAD CUM.POSITIONS
00626 7621 QPH, CAM
00627 6221 CDF 20 /FROM DATA FIELD 2
00630 1471 TAD I CBLPM1 /GET LAST CUM. POS.
00631 6201 CDF 00 /RESTORE DATA FIELD 0
00632 1040 TAD UEL /ADD ON DEL. CHANGE
00633 6221 CDF 20 /SAVE IN DATA FIELD 2 THE
00634 3472 DCA I CBUFLP /EXTRAPOLATED CUMULATIVE POSITION
00635 6201 CDF 00 /RESTORE DATA FIELD 0
00636 5272 JMP NEXT /DD NEXT POINT

```

00637	1035	SLOW,	TAD	LDCODE	/GET LAST DCODE
00640	7450		SNA		/BEGINNING OR CONTINUATION
00641	5262		JMP	SLPH	
00642	7621	FTSP,	CAM		
00643	6221		CDF	20	/FROM DATA FIELD 2
00644	1471		TAD I	CBLPM1	/GET LAST CUM. POS.
00645	6201		CDF	00	/RESTORE DATA FIELD 0
00646	1040		TAD	DEL	/ADD ON DEL CHANGE
00647	3045		DCA	TEMP2	/SAVE TEMPORARILY
00650	1045		TAD	TEMP2	/GET CUM. POS. BACK
00651	6221		CDF	20	/SAVE IN DATA FIELD 2 THE
00652	3472		DCA I	CBUFLP	/EXTRAPOLATED CUMULATIVE POSITION
00653	6211		CDF	10	/FROM DATA FIELD 1
00654	1462		TAD I	EBUFLP	/GET DECISION WINDOW MID POINT
00655	6201		CDF	00	/RESTORE DATA FIELD 0
00656	7041		CIA		/NEGATE IT
00657	1045		TAD	TEMP2	/ADD ON CUM. POS.
00660	3036		DCA	RS	/AND SAVE RUNNING SUM
00661	5272		JMP	NEXT	
00662	7621	SLPH,	CAM		
00663	6211		CDF	10	/FROM DATA FIELD 1
00664	1462		TAD I	EBUFLP	/GET DECISION WINDOW MID POINT
00665	6201		CDF	00	/RESTORE DATA FIELD 0
00666	1036		TAD	RS	/ADD ON RUNNING SUM
00667	6221		CDF	20	/IN DATA FIELD 2
00670	3472		DCA I	CBUFLP	/SAVE CUM. POS.
00671	6201		CDF	00	/RESTORE DATA FIELD 0
00672	5600	NEXT,	JMP I	LSPP	/RETURN
00673	1000	PXPOS,	XPOS		/POINTER TO EXTRAPOLATE CUMULATIVE POSITION
	*1000		PAGE		

## /SUBROUTINE TO EXTRAPOLATE CUMULATIVE POSITION ACROSS SACCADES

```

01000 0000 XPOS, 0
01001 7621 CAM /CLEAN UP
01002 1377 TAD (-DELMN /SET COUNTER TO - OF
01003 3027 DCA CNT1 /DELTA'S FOR AVERAGING
01004 7445 DST; TEMP6 /ZERO TEMP. LOCATION
01005 0052
01006 7621 LOOP, CAM /CLEAR AC AND MQ
01007 6221 CDF 20 /FROM DATA FIELD 2
01010 1456 TAD I Y0 /GET Y(0)
01011 7041 CIA /-Y(0)
01012 1457 TAD I Y2N /GET Y(2N)
01013 6201 CDF 00 /RESTORE DATA FIELD 0
01014 7415 ASR; XDIVN /DIVIDE BY N
01015 0003
01016 7443 DAD; TEMP6 /ADD ON PREVIOUS SUM
01017 0052
01020 7445 DST; TEMP6 /AND SAVE
01021 0052
01022 2056 ISZ Y0 /UPDATE POINTERS Y0 & Y2N
01023 7000 NOP
01024 2057 ISZ Y2N
01025 7000 NOP
01026 2027 ISZ CNT1 /DONE?
01027 5206 JMP LOOP /NO, DO NEXT POINT
01030 7621 CAM /ZERO AC AND MQ
01031 7340 NL7777 /DECREMENT POINTER Y0
01032 1056 TAD Y0
01033 3056 DCA Y0
01034 6221 CDF 20 /FROM DATA FIELD 2
01035 1456 TAD I Y0 /GET Y(0)
01036 7041 CIA /-Y(0)
01037 1455 TAD I YM1 /ADD ON Y(-1)
01040 6201 CDF 00 /RESTORE DATA FIELD 0

```

01041	7443	DAD;	TEMP6	/ADD ON SAVED SUM
01042	0052			
01043	7415	ASK;	DELN	/AVERAGE OVER DELTAS
01044	0001			
01045	3040	DCA	DEL	/SAVE DEL CHANGE IN CUMULATIVE POSITION
01046	7621	CAM		
01047	1377	TAD	(-DELWN	/RESTORE POINTERS YO & YZN
01050	1056	TAD	YO	
01051	7001	IAC		
01052	3056	DCA	YO	
01053	1377	TAD	(-DELWN	
01054	1057	TAD	YZN	
01055	3057	DCA	YZN	
01056	1376	TAD	(-CBUFRP	/- OF NO. OF POINTS TO BE REPLACED
01057	3027	DCA	CNT1	
01060	1070	TAD	CBFNP1	/FIRST POINT TO BE REPLACED
01061	3050	DCA	TEMP4	
01062	1067	TAD	CBUFN	/LAST SLOW PHASE POINT
01063	3051	DCA	TEMP5	
01064	6221	HERE, CDF	20	/FROM DATA FIELD 2
01065	1451	TAD I	TEMP5	/GET LAST CUM. POS.
01066	6201	CDF	00	/RESTORE DATA FIELD 0
01067	1040	TAD	DEL	/ADD ON DEL CHANGE
01070	6221	CDF	20	/IN DATA FIELD 2
01071	3450	DCA I	TEMP4	/SAVE EXTRAPOLATED CUM. POS.
01072	6201	CDF	00	/RESTORE DATA FIELD 0
01073	2050	ISZ	TEMP4	/UPDATE POINTERS
01074	7000	NOP		
01075	2051	ISZ	TEMP5	
01076	7000	NOP		
01077	2027	ISZ	CNT1	/DONE?
01100	5264	JMP	HERE	/NO, DO NEXT POINT
01101	5600	JMP I	XPOS	/RETURN

\*1176

01176 7772

01177 7770

\*1200

PAGE

## /DIFFERENTIATING FILTER SUBROUTINE

```

01200 0000 DIFF, 0
01201 7301 NL0001 /SET TEMPI=1
01202 3044 DCA TEMPI
01203 1064 TAD DIFMM1 /SET PB2 TO DIFF. MID PT.-1
01204 3026 DCA PB2
01205 1377 TAD (-NM1B2 /((TOTAL DIFF. PTS.-1)/2
01206 3027 DCA CNT1
01207 1066 TAD DIFMP1 /SET PB1 TO DIFF. MID PT.+1
01210 3025 UCA PB1
01211 7421 MQL /CLEAR MQ
01212 7445 DST; VEL /CLEAR VEL
01213 0041
01214 7344 BACK2, NL7776 /-2
01215 3037 DCA SIGN /TO SIGN
01216 6221 CDF 20
01217 1426 TAD I PB2 /FORM F(K+J)-F(K-J)
01220 7041 CIA
01221 1425 TAD I PB1
01222 6201 CDF 00
01223 7500 SMA /NEGATIVE?
01224 5227 JMP .+3 /NO, SKIP TO SAVE
01225 7041 CIA /YES,MAKE IT POSITIVE
01226 2037 ISZ SIGN /SIGN=1 ON NEGATIVE
01227 7421 MQL /SAVE
01230 2025 ISZ PB1 /INCREMENT PB1
01231 7000 NOP
01232 7340 NL7777 /DECREMENT PB2
01233 1026 TAD PB2
01234 3026 DCA PB2
01235 7405 MUY; TEMPI /MULTIPLY WITH J
01236 0044
01237 2037 ISZ SIGN /INVERT BACK?
01240 7410 SKP /NO

```

01241	7575	DCM		/YES
01242	7443	DAD;	VEL	/ADD ON PREVIOUS SUM
01243	0041			
01244	7445	DST;	VEL	/AND SAVE
01245	0041			
01246	2044	ISZ	TEMP1	/INCREMENT J
01247	2027	ISZ	CNT1	/DONE?
01250	5214	JMP	BACK2	/NO, DO NEXT POINT
01251	7413	SHL;	VGAIN	/ADJUST GAIN
01252	0004			
01253	3043	DCA	VELDIS	/VELOCITY TO BE DISPLAYED
01254	3474	DCA I	DBLP	/PUT ON TOP
01255	1074	TAD	DBLP	/UPDATE POINTER
01256	7001	IAC		
01257	0376	AND	(0177	/LIMIT TO 1 PAGE
01260	1375	TAD	(DBUFF	
01261	3074	DCA	DBLP	/PUT AWAY
01262	5600	JMP I	DIFF	/RETURN

\*1375

01375 1400

01376 0177

01377 7750

\*1400

PAGE

01400 0000 DBUFF, ZBLOCK 177

/DIFF. BUFFER

\*1600

PAGE

\*0176

00176 0177

00177 7774

/ON-LINE SACCADIC DETECTION AND SLOW PHASE VEL  
ASSEMBLY STATISTICS

P?S PAL V08K

TUE 07-OCT-80 PAGE 18

NO ERRORS DETECTED

NO LINKS GENERATED

5K MEMORY UTILIZED

1 FILE CREATED

103 SYMBOLS

## APPENDIX C

## OKN AND OKAN MODEL PARAMETER ESTIMATION PROGRAM

The following pages present the main part of an assembly program for the PDP-8/E computer. This program estimates the parameters of OKN and OKAN model from a given step response. The model, the parameter estimation technique and the relations between the estimated parameters and the model parameters are described in chapter 5.

/PARAMETER IDENTIFICATION PROGRAM

/THIS PROGRAM ESTIMATES THE PARAMETERS OF UKN AND UKAN MODEL.  
 /STIMULUS VELOCITY IS STORED IN FIELD 2 STARTING AT 400  
 /RESPONSE VELOCITY IS STORED IN FIELD 1 STARTING AT 400  
 /SET SWITCH REGISTER POSITIVE FOR UKAN MODEL IDENTIFICATION AND  
 /NEGATIVE STIMULUS VALUE FOR UKN MODEL IDENTIFICATION

```

*0770
000770 1170
000771 0171
000772 0467
000773 0466
000774 0001
000775 0465
000776 7000
000777 0430
*0014          *14
000014 0417 PTRDAT, 417          /DATA POINTER(AUTO-INDEX)
000015 0417 PARPTR, 417        /PARAMETER POINTER(AUTO-INDEX)

*0070          *70
000070 0000 Y0,      ZBLUCK 3          /Y(0)
000073 0000 M,      ZBLUCK 3          /NO. OF MEASUREMENTS
000076 0000 YMM1,   ZBLUCK 3          /Y(M-1)
000101 0000 YM,     ZBLUCK 3          /Y(M)
000104 0000 SY,     ZBLUCK 3          /Y(0)+Y(1)+.....+Y(M-1)
000107 0000 SSY,    ZBLUCK 3          /Y(0)**2+.....+Y(M-1)**2
000112 0000 SY1,    ZBLUCK 3          /Y(1)+Y(2)+.....+Y(M)
000115 0000 SYY1,   ZBLUCK 3          /Y(0)Y(1)+.....+Y(M-1)Y(M)
000120 0000 TEMP1,  ZBLUCK 3          /TEMPORARY STORAGE
000123 0000 TEMP2,  ZBLUCK 3          /TEMPORARY STORAGE
000126 0001 ONE,    1                /NUMERICAL 1
000127 2000         2000
000130 0000         0
000131 0000 MDIST,  0                /MEASUREMENTS DISTANCE-1
000132 1000 PLOUP,  LOOP              /CHANGE IT TO DEAL WITH CORRELATED NOISE
                                        /POINTER TO LOOP
    
```

000133	1105	PSPACE, PRSPACE		/POINTER TO PRINT SPACE ROUTINE
000134	1125	PCRSUPP, CRSUPP		/POINTER TO CR SUPPRESS ROUTINE
000135	1117	PCRREST, CRREST		/POINTER TO CR RESTORE ROUTINE
000136	1200	POKANID, OKANID		/POINTER TO OKAN PARAMETER IDENTIFICATION
000137	0000	R, ZBLUCK	3	/INPUT STIMULUS
000142	0000	A, ZBLUCK	3	/PARAMETER A
000145	0000	B, ZBLUCK	3	/PARAMETER B
000150	0000	C, ZBLUCK	3	/PARAMETER C
000153	6000	PARCTR, 6J00		/-2000 UCTAL
	*0651	*CONTIN		
000651	0000	FRQAN, 0-0		/ANALIZE
000652	6221	CDF	20	/SET DATA FIELD =2
000653	7300	BEGIN, CLA CLL		/CLEAN UP AC & LINK
000654	1367	TAD	(7720	/-60 UCTAL
000655	1414	TAD I	PTRDAT	/ADD UN STIMULUS
000656	7510	SPA		/STIMULUS ON?
000657	5253	JMP	BEGIN	/NO, SEARCH FOR IT
000660	6032	KCC		/INITIALIZE KEYBOARD
000661	6046	TLS		/AND TELEPRINTER
000662	7300	CLA CLL		/CLEAN UP
000663	7604	LAS		/READ IN SWITCH REGISTER
000664	7500	SMA		/OKN?
000665	5347	JMP	OKAN	/NO, OKAN
000666	6201	OKN, CDF	00	/SET TO FIELD 0
000667	7604	LAS		/READ IN SWITCH REG FOR STIMULUS R
000670	3044	DCA	FLAC	/R IN FLOATING AC
000671	4407	F=NT		/ENTER FPP
000672	0014	FLOT		/CONVERT TO FLOATING POINT NUMBER
000673	6137	FPUT	R	/SAVE IN R
000674	0000	FLXT		/LEAVE FPP
000675	2014	ISZ	PTRDAT	/GET PAST DELAY IN OKN RESPONSE
000676	2014	ISZ	PTRDAT	
000677	2014	ISZ	PTRDAT	
000700	2014	ISZ	PTRDAT	

000701	6211	10	10	/SET DATA FIELD =1
000702	1414	PKROAT		/SET Y(I0)
000703	6201	00		/SET DATA FIELD=0
000704	3044	FLAG		/SAVE IN FLOATING AC
000705	4407	FENT		/ENTER INTERPRETER
000706	0014	FLOT		/CONVERT TO FLOATING POINT NUMBER
000707	6070	FPUT	Y0	/SAVE Y(I0)
000710	0012	FOUT		
000711	5126	FGET	ONE	/M=1
000712	6073	FPUT	M	
000713	0000	FEXT		/EXIT FPP
000714	7300	CLA CLL		/CLEAN UP AC
000715	1014	TAD	PKROAT	/COMPUTE MEASUREMENT SPACING
000716	1131	TAD	MUJST	
000717	3014	DCA	PKROAT	
000720	6211	CDF	10	/SET DATA FIELD=1
000721	1414	TAD I	PKROAT	/GET Y(I1)
000722	6201	CDF	00	/SET DATA FIELD =0
000723	3044	UCA	FLAG	/IN FLOATING AC
000724	4407	FENT		/ENTER INTERPRETER
000725	0014	FLOT		/CONVERT TO FLOATING POINT NUMBER
000726	6101	FPUT	YM	/AND SAVE
000727	0012	FOUT		
000730	5070	FGET	Y0	/SY(I1)=Y0
000731	6104	FPUT	SY	
000732	5070	FGET	Y0	/SSY(I1)=Y(I0)**2
000733	3070	FMPY	Y0	
000734	6107	FPUT	SSY	
000735	5101	FGET	YM	/SY(I1)=Y(I1)
000736	6112	FPUT	SY1	
000737	5101	FGET	YM	
000740	3070	FMPY	Y0	/SY1(I1)=Y(I0)Y(I1)
000741	6115	FPUT	SY11	

000742	5070		FGET	Y0	/C=Y(0)/R
000743	4137		FJIV	R	
000744	6150		FPUT	C	
000745	0012		FJUT		/PRINT C
000746	0532		FJMP I	PLOOP	/NEXT FILE
000747	7300	OKAN,	CLA	CLL	
000750	1414		TAD I	PTRDAT	/GET STIMULUS
000751	7500		SMA		/OKAN?
000752	5347		JMP	OKAN	/NO, SEARCH FOR IT
000753	6211		CDF	10	/SET DATA FIELD =1
000754	7300		CLA	CLL	/CLEAN UP
000755	1414		TAD I	PTRDAT	/GET Y(0)
000756	6201		CDF	00	/SET DATA FIELD =0
000757	3044		DCA	FLAC	/IN FPP AC
000760	4407		FENT		/ENTER FPP
000761	0014		FLOT		/FLOATING POINT NUMBER
000762	6101		FPUT	YM	/SAVE Y(0)
000763	0012		FJUT		/PRINT Y(0)
000764	0536		FJMP I	POKANID	/IDENTIFY OKAN PARAMETERS
	*0767				
000767	7720				
	*1000		PAGE		

```

*1000          PAGE
/IDENTIFICATION OF PARAMETERS A AND B

001000  5073  LOOP,  FGET  M          /M=M+1
001001  1126          FADD  ONE
001002  6073          FPUT  M
001003  0012          FOUT  M          /PRINT M
001004  7325          FJMS  CRSUPP
001005  5101          FGET  YM        /SHIFT BACK ONE PLACE
001006  6076          FPUT  YMM1
001007  0000          FEXT
001010  7300          CLA  CLL        /CLEAN UP
001011  1014          TAD   PTRDAT    /COMPUTE MEASUREMENT SPACING
001012  1131          TAD   MJIST
001013  3014          DCA   PTRDAT
001014  6211          CDF   10        /SET DATA FIELD=1
001015  1414          TAD  I  PTRDAT    /GET Y(M)
001016  6201          CDF   00        /SET DATA FIELD=0
001017  3044          DCA   FLAC      /IN FLUATING AC
001020  4407          FENT
001021  0014          FLOT          /ENTER INTERPRETER
001022  6101          FPUT  YM        /CONVERT TO FLOATING POINT NUMBER
001023  0012          FJUT
001024  5076          FGET  YMM1      /AND SAVE
001025  1104          FADD  SY
001026  6104          FPUT  SY
001027  5076          FGET  YMM1      /SY=SY+Y(M-1)
001030  3076          FHPY  YMM1
001031  1107          FADD  SSY
001032  6107          FPUT  SSY
001033  5101          FGET  YM        /SSY=SSY+Y(M-1)**2
001034  1112          FADD  SY1
001035  6112          FPUT  SY1      /SY1=SY1+Y(M)

```

001036	5101	FGET	YM	
001037	3076	FMPY	YH11	/SY1=SY1+Y(M-1)Y(M)
001040	1115	FADD	SY11	
001041	6115	FPUT	SY11	
001042	5073	FGET	M	
001043	3115	FMPY	SY11	/M*SY1-SY*SY1
001044	6120	FPUT	TEMP1	
001045	5104	FGET	SY	
001046	3112	FMPY	SY1	
001047	0010	FNEG		
001050	1120	FADD	TEMP1	
001051	6120	FPUT	TEMP1	
001052	5104	FGET	SY	
001053	3104	FMPY	SY	/M*SSY-SY**2
001054	0010	FNEG		
001055	6123	FPUT	TEMP2	
001056	5073	FGET	M	
001057	3107	FMPY	SSY	
001060	1123	FADD	TEMP2	
001061	6123	FPUT	TEMP2	
001062	5120	FGET	TEMP1	/PARAMETER A
001063	4123	FDIV	TEMP2	
001064	7305	FJMS	PRSPACE	/PRINT SPACE
001065	6142	FPUT	A	
001066	0012	FPUT		
001067	5115	FGET	SY11	/TYPE OUT A
001070	3104	FMPY	SY	/-SY*SY1+SSY*SY1
001071	0010	FNEG		
001072	6120	FPUT	TEMP1	
001073	5107	FGET	SSY	
001074	3112	FMPY	SY1	
001075	1120	FADD	TEMP1	
001076	4123	FUIV	TEMP2	
001077	4137	FUIV	K	/PARAMETER B
001100	7305	FJMS	PRSPACE	/PRINT SPACE
001101	6145	FPUT	B	
001102	7317	FJMS	CRKEST	/RESTORE CR AND LF
001103	0012	FPUT		/TYPE OUT B
001104	0200	FJMP	LOOP	/CU IT AGAIN

```

001105 0000 PRSPACE,0          /PRINT SPACE SUBROUTINE
001106 0000          FEXT      /EXIT FPP
001107 7200          CLA       /CLEAR AC
001110 1377          TAD        (240) /ASCII FOR SPACE
001111 6041          TSF       /READY?
001112 5311          JMP        .-1  /NO
001113 6046          TLS       /PRINT
001114 7300          CLA CLL    /CLEAN UP
001115 4407          FENT      /ENTER FPP
001116 0705          FJMP I PRSPACE /RETURN

001117 0000 CRREST, 0        /CR,LF RESTORE ROUTINE
001120 0000          FEXT      /LEAVE FPP
001121 7203          CLA IAC BSW /NON-ZERO IN AC
001122 3055          DCA        R55 /R55 IS NON-ZERO
001123 4407          FENT      /ENTER FPP
001124 0717          FJMP I CRREST /RETURN

001125 0000 CRSUPP, 0       /CR,LF SUPPRESS ROUTINE
001126 0000          FEXT      /LEAVE FPP
001127 7200          CLA       /ZERO IN AC
001130 3055          DCA        R55 /R55 IS ZERO
001131 4407          FENT      /ENTER FPP
001132 0725          FJMP I CRSUPP /RETURN

*1177
001177 0240
*1200          PAGE

```

## / OKAN PARAMETER IDENTIFICATION

001200	0000	OKANID,	FEXT		/LEAVE FPP
001201	1377		TAD	(400	/INITIALIZE PARAMETER POINTER
001202	3015		DCA	PARPTR	
001203	4407		FENT		/ENTER FPP
001204	5073	REPET,	FGET	M	/M=M+1
001205	1126		FADD	ONE	
001206	6073		FPUT	M	
		/	FOUT		/PRINT M
		/	FJMS I	PCRSUPP	
001207	5101		FGET	YM	/SHIFT BACK ONE PLACE
001210	6076		FPUT	YMM1	
001211	0000		FEXT		/EXIT FPP
001212	7300		CLA	CLL	/CLEAN UP
001213	1014		TAD	PTRDAT	/COMPUTE MEASUREMENT SPACING
001214	1131		TAD	MU1ST	
001215	3014		DCA	PTRDAT	
001216	6211		CUF	10	/SET DATA FIELD =1
001217	1414		TAD I	PTRDAT	/GET Y(M)
001220	0201		CUF	00	/SET DATA FIELD =0
001221	3044		DCA	FLAC	/IN FLUATING AC
001222	4407		FENT		/ENTER FPP
001223	0014		FLOT		/CONVERT TO FLOATING POINT NUMBER
001224	6101		FPUT	YM	/AND SAVE
		/	FOUT		/PRINT IT OUT
001225	5076		FGET	YMM1	/SSY=SSY+Y(M-1)**2
001226	3076		FMPY	YMM1	
001227	1107		FADD	SSY	
001230	6107		FPUT	SSY	
001231	5101		FGET	YM	/SYY1=SYY1+Y(M-1)Y(M)
001232	3076		FMPY	YMM1	
001233	1115		FADD	SYY1	
001234	6115		FPUT	SYY1	
001235	4107		FUIV	SSY	/ALPHA=SYY1/SSY
		/	FJMS I	PSPACE	
		/	FJMS I	PCRRST	
001236	0000		FEXT		/EXIT FPP
001237	4250		JMS	DNORM	/TO 12-BIT NUMBER
001240	6221		CUF	20	

001241	3415		DCA I	PARPTR	/SAVE IN FIELD 2
001242	6201		CUF	00	
001243	4407		FENT		/ENTER FPP
001244	0153		FISZ	PARCTR	/PARAMETER FIELD FULL?
001245	0204		FJMP	REPET	/DO IT AGAIN
001246	0000		FEXT		/LEAVE FPP
001247	4267		JMS	PLOT	/GO DISPLAY
001250	0000	DNORM,	.-.		/CONVERT FP NUMBER TO 12 BIT NUMBER ROUTINE
001251	7200		CLA		
001252	1044		TAD	44	/GET EXPONENT
001253	7500		SMA		/NEGATIVE?
001254	5257		JMP	.-3	/NO
001255	7200		CLA		/YES, INTEGER VALUE =0
001256	5266		JMP	GG	
001257	7041		CIA		
001260	1376		TAD	14	/COMPUTE SHIFTS NEEDED TO MAKE IT INTEGER
001261	3265		DCA	SHFTCNT	
001262	7431		SWAB		/MODE 3 EAE
001263	1045		TAD	45	/GET MANTISSA
001264	7415		ASR		/SHIFT TO MAKE IT INTEGER
001265	0000	SHFTCNT,000			
001266	5650	GG,	JMP I	DNORM	/RETURN
001267	0000	PLOT,	.-.		/DATA PLOT ROUTINE
001270	6201	FF,	CUF	00	/DATA FIELD=0
001271	7300		CLA	CLL	/CLEAN UP
001272	1375		TAD	1320	/POINTS TO BE DISPLAYED
001273	3325		DCA	CUUNT1	
001274	1374		TAD	1477	/FIRST DATA POINT
001275	3014		DCA	PTRDAT	
001276	1014		TAD	PTRDAT	/FIRST PARAMETER POINT
001277	3015		DCA	PARPTR	
001300	3120		DCA	TEMP1	/DELAY FOR DISPLAY
001301	7021	EE,	CAM		/CLEAN UP
001302	6221		CUF	20	/DATA FIELD =2
001303	1414		TAD I	PTRDAT	/GET POINT TO BE PLOTTED
001304	6201		CUF	00	
001305	7413		SML;	4	/GAIN CONTROL
001306	0004				

001307	7000		NDP		
001310	6551		6551		/DISPLAY IT
001311	7621		CAM		
001312	6211		CDF	10	/FIELD 1
001313	1415		TAD I	PARPTR	/GET DISPLAY POINT
001314	6201		CDF	00	/FIELD 0
001315	7413		SHL;	4	/GAIN CONTROL
001316	0004				
001317	6552		6552		/DISPLAY ON Y CHANNEL
001320	2120	DELY,	ISZ	TEMP1	/DELAY LOUP
001321	5320		JMP	DELY	
001322	2325		ISZ	COUNT1	/COUNT UP
001323	5301		JMP	EE	
001324	5270		JMP	FF	/REPLOTT
001325	0000	COUNT1, 0			/DELAY COUNTER
	*1374				
001374	0477				
001375	3220				
001376	0004				
001377	0400				
	*0156				
000156	1000				
000157	0613				
000160	0634				
000161	0334				
000162	0200				
000163	0324				
000164	7000				
000165	0537				
000166	7774				
000167	0177				
000170	4000				
000171	3777				
000172	0077				
000173	7700				
000174	0600				
000175	0377				
000176	7777				
000177	7000				

/OKN AND UKAN MODEL PARAMETER ESTIMATION PRGR  
ASSEMBLY STATISTICS

P?S PAL V08M

TUE 28-JUL-81 PAGE 16

NO ERRORS DETECTED

NO LINKS GENERATED

6K MEMORY UTILIZED

1 FILE CREATED

209 SYMBOLS

## APPENDIX D

## OKN AND OKAN PARAMETER IDENTIFICATION

The following pages contain the results of the least square parameter identification as applied to a nystagmus of  $-90^\circ/\text{sec}$ . The results are printed in the following formats for the various sampling intervals.

OKN identification:

$z(0)$		
$z(1)$		
2		
$z(2)$	$\hat{a}(2)$	$\hat{\beta}(2)/v$
3		
.	.	.
.	.	.
.	.	.
.	.	.
$m$		
$z(m)$	$\hat{a}(m)$	$\hat{\beta}(m)/v$
.	.	.
.	.	.
.	.	.

OKAN identification:

$z(0)$	
1	
$z(1)$	$\hat{\alpha}(1)$
2	
.	
.	
.	
.	
$m$	
$z(m)$	$\hat{\alpha}(m)$
.	.
.	.
.	.
.	.

OKN Model Identification, sampling interval = .2048 sec.

BLOCK NO: 600			+25.000		
-23.000			-12.000	+1.041	-0.038
-28.000			+26.000		
+0.575			-15.000	+0.903	+0.055
+2.000			+27.000		
-31.000	+0.600	+0.355	-16.000	+0.898	+0.059
+3.000			+28.000		
-29.000	+0.173	+0.615	-15.000	+0.923	+0.041
+4.000			+29.000		
-26.000	+0.043	+0.683	-15.000	+0.930	+0.036
+5.000			+30.000		
-24.000	+0.210	+0.546	-16.000	+0.923	+0.041
+6.000			+31.000		
-24.000	+0.384	+0.417	-18.000	+0.908	+0.051
+7.000			+32.000		
-25.000	+0.426	+0.387	-19.000	+0.904	+0.054
+8.000			+33.000		
-26.000	+0.428	+0.385	-22.000	+0.890	+0.065
+9.000			+34.000		
-28.000	+0.422	+0.393	-25.000	+0.885	+0.070
+10.000			+35.000		
-29.000	+0.462	+0.370	-28.000	+0.889	+0.070
+11.000			+36.000		
-27.000	+0.418	+0.396	-28.000	+0.890	+0.069
+12.000			+37.000		
-26.000	+0.412	+0.398	-29.000	+0.896	+0.067
+13.000			+38.000		
-26.000	+0.418	+0.393	-30.000	+0.902	+0.064
+14.000			+39.000		
-27.000	+0.415	+0.396	-27.000	+0.888	+0.071
+15.000			+40.000		
-27.000	+0.415	+0.396	-19.000	+0.868	+0.078
+16.000			+41.000		
-28.000	+0.420	+0.394	-17.000	+0.881	+0.069
+17.000			+42.000		
-26.000	+0.391	+0.411	-23.000	+0.847	+0.092
+18.000			+43.000		
-26.000	+0.397	+0.406	-32.000	+0.839	+0.102
+19.000			+44.000		
-27.000	+0.393	+0.409	-32.000	+0.846	+0.098
+20.000			+45.000		
-29.000	+0.403	+0.405	-29.000	+0.833	+0.105
+21.000			+46.000		
-29.000	+0.437	+0.384	-25.000	+0.821	+0.111
+22.000			+47.000		
-29.000	+0.463	+0.367	-23.000	+0.820	+0.110
+23.000			+48.000		
-24.000	+0.362	+0.431	-24.000	+0.820	+0.111
+24.000			+49.000		
-16.000	+0.670	+0.214	-25.000	+0.819	+0.112
			+50.000		
			-24.000	+0.819	+0.111

OKN Model Identification, sampling interval = .2048 sec.

+51.000			+76.000		
-24.000	+0.819	+0.111	-26.000	+0.812	+0.118
+52.000			+77.000		
-24.000	+0.819	+0.111	-27.000	+0.813	+0.117
+53.000			+78.000		
-26.000	+0.818	+0.113	-27.000	+0.813	+0.117
+54.000			+79.000		
-27.000	+0.820	+0.112	-29.000	+0.817	+0.116
+55.000			+80.000		
-29.000	+0.824	+0.110	-29.000	+0.819	+0.115
+56.000			+81.000		
-29.000	+0.827	+0.109	-29.000	+0.821	+0.114
+57.000			+82.000		
-27.000	+0.822	+0.111	-31.000	+0.829	+0.110
+58.000			+83.000		
-26.000	+0.821	+0.112	-30.000	+0.828	+0.110
+59.000			+84.000		
-24.000	+0.819	+0.112	-28.000	+0.824	+0.112
+60.000			+85.000		
-24.000	+0.819	+0.112	-28.000	+0.825	+0.112
+61.000			+86.000		
-25.000	+0.819	+0.113	-29.000	+0.828	+0.110
+62.000			+87.000		
-28.000	+0.820	+0.114	-31.000	+0.834	+0.107
+63.000			+88.000		
-27.000	+0.818	+0.114	-29.000	+0.830	+0.109
+64.000			+89.000		
-25.000	+0.816	+0.115	-27.000	+0.827	+0.111
+65.000			+90.000		
-23.000	+0.815	+0.115	-27.000	+0.827	+0.111
+66.000			+91.000		
-23.000	+0.816	+0.114	-29.000	+0.829	+0.110
+67.000			+92.000		
-25.000	+0.814	+0.116	-30.000	+0.833	+0.108
+68.000			+93.000		
-26.000	+0.814	+0.116	-29.000	+0.832	+0.109
+69.000			+94.000		
-26.000	+0.814	+0.116	-28.000	+0.831	+0.109
+70.000			+95.000		
-26.000	+0.814	+0.116	-30.000	+0.834	+0.108
+71.000			+96.000		
-25.000	+0.813	+0.116	-32.000	+0.842	+0.104
+72.000			+97.000		
-23.000	+0.813	+0.116	-33.000	+0.849	+0.099
+73.000			+98.000		
-23.000	+0.814	+0.116	-33.000	+0.853	+0.097
+74.000			+99.000		
-25.000	+0.811	+0.117	-32.000	+0.853	+0.097
+75.000			+100.000		
-26.000	+0.812	+0.118	-31.000	+0.853	+0.097

## OKN Model Identification, sampling interval = .2048 sec.

+101.000			+126.000		
-32.000	+0.857	+0.095	-26.000	+0.908	+0.064
+102.000			+127.000		
-34.000	+0.866	+0.090	-25.000	+0.909	+0.063
+103.000			+128.000		
-36.000	+0.875	+0.082	-26.000	+0.908	+0.064
+104.000			+129.000		
-36.000	+0.884	+0.079	-26.000	+0.908	+0.064
+105.000			+130.000		
-35.000	+0.884	+0.079	-29.000	+0.907	+0.065
+106.000			+131.000		
-33.000	+0.880	+0.082	-31.000	+0.908	+0.065
+107.000			+132.000		
-32.000	+0.879	+0.082	-29.000	+0.906	+0.066
+108.000			+133.000		
-33.000	+0.883	+0.080	-24.000	+0.904	+0.066
+109.000			+134.000		
-34.000	+0.887	+0.077	-24.000	+0.904	+0.066
+110.000			+135.000		
-35.000	+0.893	+0.074	-32.000	+0.896	+0.073
+111.000			+136.000		
-35.000	+0.895	+0.072	-35.000	+0.901	+0.071
+112.000			+137.000		
-36.000	+0.901	+0.069	-35.000	+0.902	+0.070
+113.000			+138.000		
-36.000	+0.904	+0.067	-33.000	+0.899	+0.071
+114.000			+139.000		
-35.000	+0.903	+0.068	-32.000	+0.898	+0.072
+115.000			+140.000		
-36.000	+0.908	+0.065	-33.000	+0.900	+0.071
+116.000			+141.000		
-38.000	+0.917	+0.059	-34.000	+0.902	+0.070
+117.000			+142.000		
-37.000	+0.916	+0.060	-35.000	+0.905	+0.068
+118.000			+143.000		
-36.000	+0.915	+0.060	-34.000	+0.904	+0.069
+119.000			+144.000		
-35.000	+0.914	+0.061	-33.000	+0.903	+0.069
+120.000			+145.000		
-35.000	+0.915	+0.060	-33.000	+0.904	+0.069
+121.000			+146.000		
-34.000	+0.914	+0.061	-32.000	+0.903	+0.069
+122.000			+147.000		
-32.000	+0.911	+0.063	-33.000	+0.905	+0.068
+123.000			+148.000		
-31.000	+0.910	+0.063	-32.000	+0.904	+0.069
+124.000			+149.000		
-30.000	+0.910	+0.064	-29.000	+0.901	+0.070
+125.000			+150.000		
-28.000	+0.908	+0.064	-26.000	+0.900	+0.070

OKN Model Identification, sampling interval = .2048 sec.

+151.000			+176.000		
-27.000	+0.900	+0.071	-30.000	+0.913	+0.063
+152.000			+177.000		
-27.000	+0.900	+0.071	-32.000	+0.914	+0.063
+153.000			+178.000		
-26.000	+0.900	+0.070	-35.000	+0.916	+0.062
+154.000			+179.000		
-30.000	+0.898	+0.072	-36.000	+0.918	+0.061
+155.000			+180.000		
-34.000	+0.900	+0.072	-35.000	+0.917	+0.062
+156.000			+181.000		
-35.000	+0.903	+0.070	-33.000	+0.915	+0.063
+157.000			+182.000		
-37.000	+0.907	+0.067	-33.000	+0.916	+0.063
+158.000			+183.000		
-38.000	+0.911	+0.065	-35.000	+0.917	+0.062
+159.000			+184.000		
-38.000	+0.913	+0.064	-36.000	+0.919	+0.060
+160.000			+185.000		
-37.000	+0.912	+0.064	-36.000	+0.920	+0.060
+161.000			+186.000		
-36.000	+0.912	+0.065	-36.000	+0.920	+0.060
+162.000			+187.000		
-35.000	+0.911	+0.065	-38.000	+0.924	+0.058
+163.000			+188.000		
-35.000	+0.912	+0.064	-37.000	+0.923	+0.058
+164.000			+189.000		
-36.000	+0.914	+0.063	-37.000	+0.924	+0.057
+165.000			+190.000		
-36.000	+0.915	+0.063	-37.000	+0.925	+0.057
+166.000			+191.000		
-36.000	+0.916	+0.062	-36.000	+0.924	+0.057
+167.000			+192.000		
-37.000	+0.918	+0.060	-36.000	+0.924	+0.057
+168.000			+193.000		
-35.000	+0.916	+0.062	-35.000	+0.924	+0.058
+169.000			+194.000		
-34.000	+0.915	+0.062	-35.000	+0.924	+0.057
+170.000			+195.000		
-34.000	+0.916	+0.062	-36.000	+0.925	+0.056
+171.000			+196.000		
-33.000	+0.915	+0.063	-36.000	+0.926	+0.056
+172.000			+197.000		
-32.000	+0.914	+0.063	-36.000	+0.926	+0.056
+173.000			+198.000		
-31.000	+0.914	+0.063	-36.000	+0.927	+0.056
+174.000			+199.000		
-30.000	+0.913	+0.063	-35.000	+0.926	+0.056
+175.000			+200.000		
-30.000	+0.913	+0.063	-35.000	+0.927	+0.056

## OKN Model Identification, sampling interval = .2048 sec.

+201.000			+226.000		
-34.000	+0.926	+0.056	-40.000	+0.938	+0.049
+202.000			+227.000		
-36.000	+0.928	+0.055	-37.000	+0.935	+0.051
+203.000			+228.000		
-38.000	+0.930	+0.054	-34.000	+0.932	+0.053
+204.000			+229.000		
-38.000	+0.931	+0.053	-34.000	+0.932	+0.053
+205.000			+230.000		
-36.000	+0.929	+0.054	-37.000	+0.934	+0.052
+206.000			+231.000		
-34.000	+0.927	+0.056	-39.000	+0.936	+0.050
+207.000			+232.000		
-33.000	+0.927	+0.056	-38.000	+0.935	+0.051
+208.000			+233.000		
-33.000	+0.927	+0.056	-38.000	+0.936	+0.051
+209.000			+234.000		
-34.000	+0.927	+0.055	-37.000	+0.935	+0.051
+210.000			+235.000		
-36.000	+0.929	+0.055	-36.000	+0.935	+0.051
+211.000			+236.000		
-36.000	+0.929	+0.054	-37.000	+0.936	+0.051
+212.000			+237.000		
-38.000	+0.932	+0.053	-36.000	+0.935	+0.051
+213.000			+238.000		
-38.000	+0.932	+0.052	-35.000	+0.935	+0.051
+214.000					
-38.000	+0.933	+0.052			
+215.000					
-38.000	+0.934	+0.052			
+216.000					
-37.000	+0.933	+0.052			
+217.000					
-36.000	+0.932	+0.052			
+218.000					
-35.000	+0.932	+0.053			
+219.000					
-35.000	+0.932	+0.053			
+220.000					
-34.000	+0.931	+0.053			
+221.000					
-33.000	+0.931	+0.053			
+222.000					
-34.000	+0.931	+0.053			
+223.000					
-35.000	+0.932	+0.053			
+224.000					
-37.000	+0.934	+0.052			
+225.000					
-39.000	+0.936	+0.050			

OKN Model Identification, sampling interval = .512 sec.

BLOCK NO:600

-23.000					
-24.000			-35.000	+0.899	+0.069
+0.575			+25.000		
+2.000			-28.000	+0.877	+0.076
-29.000	+1.130	-0.001	+26.000		
+3.000			-29.000	+0.878	+0.076
-27.000	+1.037	+0.004	+27.000		
+4.000			-32.000	+0.884	+0.076
-29.000	+1.046	+0.004	+28.000		
+5.000			-33.000	+0.888	+0.074
-12.000	+0.878	+0.014	+29.000		
+6.000			-33.000	+0.890	+0.074
-16.000	+0.871	+0.029	+30.000		
+7.000			-26.000	+0.875	+0.079
-28.000	+0.882	+0.054	+31.000		
+8.000			-34.000	+0.878	+0.082
-19.000	+0.827	+0.059	+32.000		
+9.000			-37.000	+0.888	+0.079
-29.000	+0.846	+0.073	+33.000		
+10.000			-36.000	+0.888	+0.079
-24.000	+0.824	+0.076	+34.000		
+11.000			-34.000	+0.885	+0.080
-29.000	+0.845	+0.077	+35.000		
+12.000			-30.000	+0.878	+0.082
-24.000	+0.827	+0.080	+36.000		
+13.000			-35.000	+0.884	+0.082
-23.000	+0.826	+0.080	+37.000		
+14.000			-36.000	+0.888	+0.081
-26.000	+0.834	+0.082	+38.000		
+15.000			-37.000	+0.892	+0.079
-26.000	+0.837	+0.081	+39.000		
+16.000			-36.000	+0.892	+0.079
-29.000	+0.849	+0.081	+40.000		
+17.000			-35.000	+0.891	+0.079
-28.000	+0.850	+0.081	+41.000		
+18.000			-36.000	+0.894	+0.078
-27.000	+0.850	+0.081	+42.000		
+19.000			-36.000	+0.895	+0.078
-30.000	+0.860	+0.080	+43.000		
+20.000			-38.000	+0.901	+0.076
-31.000	+0.867	+0.078	+44.000		
+21.000			-34.000	+0.893	+0.079
-35.000	+0.886	+0.073	+45.000		
+22.000			-39.000	+0.901	+0.077
-35.000	+0.891	+0.071	+46.000		
+23.000			-37.000	+0.898	+0.078
-36.000	+0.899	+0.068	+47.000		
+24.000			-36.000	+0.897	+0.078

OKN Model Identification, sampling interval = .512 sec.

+48.000			+73.000		
-21.000	+0.875	+0.087	-37.000	+0.852	+0.118
+49.000			+74.000		
-13.000	+0.887	+0.074	-38.000	+0.853	+0.117
+50.000			+75.000		
-36.000	+0.828	+0.125	-38.000	+0.854	+0.116
+51.000			+76.000		
-35.000	+0.828	+0.125	-34.000	+0.851	+0.118
+52.000			+77.000		
-36.000	+0.831	+0.124	-37.000	+0.853	+0.118
+53.000			+78.000		
-38.000	+0.835	+0.122	-37.000	+0.853	+0.117
+54.000			+79.000		
-36.000	+0.834	+0.123	-36.000	+0.853	+0.118
+55.000			+80.000		
-34.000	+0.833	+0.123	-30.000	+0.849	+0.119
+56.000			+81.000		
-36.000	+0.836	+0.123	-36.000	+0.848	+0.121
+57.000			+82.000		
-36.000	+0.837	+0.122	-35.000	+0.848	+0.121
+58.000			+83.000		
-37.000	+0.839	+0.121	-34.000	+0.848	+0.121
+59.000			+84.000		
-36.000	+0.839	+0.121	-34.000	+0.848	+0.121
+60.000			+85.000		
-37.000	+0.842	+0.120	-37.000	+0.849	+0.121
+61.000			+86.000		
-36.000	+0.842	+0.120	-37.000	+0.850	+0.121
+62.000			+87.000		
-36.000	+0.843	+0.120	-38.000	+0.851	+0.120
+63.000			+88.000		
-41.000	+0.849	+0.117	-37.000	+0.851	+0.121
+64.000					
-40.000	+0.850	+0.117			
+65.000					
-40.000	+0.852	+0.116			
+66.000					
-34.000	+0.845	+0.119			
+67.000					
-39.000	+0.848	+0.119			
+68.000					
-37.000	+0.847	+0.119			
+69.000					
-38.000	+0.849	+0.118			
+70.000					
-39.000	+0.852	+0.117			
+71.000					
-37.000	+0.850	+0.118			
+72.000					
-36.000	+0.850	+0.118			

OKAN Model Identification, sampling interval = .0512 sec.

BLOCK NO: 600		+25.000		+50.000	
-38.000		-32.000	+0.993	-29.000	+0.995
+1.000		+26.000		+51.000	
-39.000	+1.026	-33.000	+0.994	-30.000	+0.995
+2.000		+27.000		+52.000	
-39.000	+1.013	-33.000	+0.995	-31.000	+0.996
+3.000		+28.000		+53.000	
-38.000	+1.000	-33.000	+0.995	-30.000	+0.995
+4.000		+29.000		+54.000	
-37.000	+0.993	-32.000	+0.994	-29.000	+0.995
+5.000		+30.000		+55.000	
-36.000	+0.990	-32.000	+0.994	-28.000	+0.994
+6.000		+31.000		+56.000	
-37.000	+0.995	-33.000	+0.995	-27.000	+0.994
+7.000		+32.000		+57.000	
-37.000	+0.996	-32.000	+0.995	-27.000	+0.994
+8.000		+33.000		+58.000	
-37.000	+0.996	-32.000	+0.995	-29.000	+0.995
+9.000		+34.000		+59.000	
-39.000	+1.003	-33.000	+0.996	-31.000	+0.996
+10.000		+35.000		+60.000	
-39.000	+1.002	-34.000	+0.996	-33.000	+0.997
+11.000		+36.000		+61.000	
-39.000	+1.002	-34.000	+0.996	-32.000	+0.997
+12.000		+37.000		+62.000	
-38.000	+1.000	-33.000	+0.996	-32.000	+0.997
+13.000		+38.000		+63.000	
-38.000	+1.000	-32.000	+0.995	-31.000	+0.996
+14.000		+39.000		+64.000	
-38.000	+1.000	-31.000	+0.995	-31.000	+0.996
+15.000		+40.000		+65.000	
-37.000	+0.998	-31.000	+0.995	-31.000	+0.996
+16.000		+41.000		+66.000	
-36.000	+0.997	-30.000	+0.994	-32.000	+0.997
+17.000		+42.000		+67.000	
-34.000	+0.994	-30.000	+0.994	-34.000	+0.998
+18.000		+43.000		+68.000	
-35.000	+0.995	-31.000	+0.995	-35.000	+0.998
+19.000		+44.000		+69.000	
-34.000	+0.994	-31.000	+0.995	-35.000	+0.998
+20.000		+45.000		+70.000	
-35.000	+0.996	-31.000	+0.995	-34.000	+0.998
+21.000		+46.000		+71.000	
-34.000	+0.995	-31.000	+0.995	-33.000	+0.997
+22.000		+47.000		+72.000	
-33.000	+0.994	-32.000	+0.996	-32.000	+0.997
+23.000		+48.000		+73.000	
-32.000	+0.993	-31.000	+0.995	-30.000	+0.996
+24.000		+49.000		+74.000	
-32.000	+0.993	-30.000	+0.995	-31.000	+0.997

## OKAN Model Identification, sampling interval = .0512 sec.

+75.000		+100.000		+125.000	
-30.000	+0.996	-28.000	+0.996	-28.000	+0.997
+76.000		+101.000		+126.000	
-29.000	+0.996	-28.000	+0.996	-28.000	+0.997
+77.000		+102.000		+127.000	
-29.000	+0.996	-28.000	+0.997	-27.000	+0.997
+78.000		+103.000		+128.000	
-30.000	+0.996	-28.000	+0.997	-28.000	+0.997
+79.000		+104.000		+129.000	
-31.000	+0.997	-28.000	+0.997	-28.000	+0.997
+80.000		+105.000		+130.000	
-31.000	+0.997	-27.000	+0.996	-28.000	+0.997
+81.000		+106.000		+131.000	
-31.000	+0.997	-27.000	+0.996	-28.000	+0.997
+82.000		+107.000		+132.000	
-31.000	+0.997	-27.000	+0.996	-29.000	+0.997
+83.000		+108.000		+133.000	
-30.000	+0.997	-28.000	+0.997	-28.000	+0.997
+84.000		+109.000		+134.000	
-29.000	+0.996	-27.000	+0.996	-26.000	+0.997
+85.000		+110.000		+135.000	
-29.000	+0.996	-27.000	+0.996	-26.000	+0.997
+86.000		+111.000		+136.000	
-29.000	+0.996	-29.000	+0.997	-27.000	+0.997
+87.000		+112.000		+137.000	
-30.000	+0.997	-30.000	+0.997	-29.000	+0.997
+88.000		+113.000		+138.000	
-31.000	+0.997	-30.000	+0.997	-30.000	+0.998
+89.000		+114.000		+139.000	
-31.000	+0.997	-29.000	+0.997	-29.000	+0.997
+90.000		+115.000		+140.000	
-30.000	+0.997	-29.000	+0.997	-28.000	+0.997
+91.000		+116.000		+141.000	
-30.000	+0.997	-28.000	+0.997	-28.000	+0.997
+92.000		+117.000		+142.000	
-29.000	+0.997	-29.000	+0.997	-29.000	+0.997
+93.000		+118.000		+143.000	
-29.000	+0.997	-29.000	+0.997	-30.000	+0.998
+94.000		+119.000		+144.000	
-30.000	+0.997	-29.000	+0.997	-31.000	+0.998
+95.000		+120.000		+145.000	
-31.000	+0.997	-29.000	+0.997	-31.000	+0.998
+96.000		+121.000		+146.000	
-31.000	+0.997	-29.000	+0.997	-30.000	+0.998
+97.000		+122.000		+147.000	
-30.000	+0.997	-30.000	+0.997	-28.000	+0.997
+98.000		+123.000		+148.000	
-29.000	+0.997	-30.000	+0.997	-28.000	+0.997
+99.000		+124.000		+149.000	
-29.000	+0.997	-29.000	+0.997	-27.000	+0.997

## OKAN Model Identification, sampling interval = 1.536 sec.

BLOCK NO:600		+25.000		+50.000	-
-38.000		-8.000	+0.944	-1.000	+0.940
+1.000		+26.000		+51.000	
-32.000	+0.842	-7.000	+0.943	-1.000	+0.940
+2.000		+27.000		+52.000	
-33.000	+0.921	-7.000	+0.944	-1.000	+0.940
+3.000		+28.000		+53.000	
-30.000	+0.917	-7.000	+0.944	-1.000	+0.940
+4.000		+29.000		+54.000	
-29.000	+0.927	-4.000	+0.942	-1.000	+0.940
+5.000		+30.000		+55.000	
-27.000	+0.928	-4.000	+0.943	-1.000	+0.940
+6.000		+31.000		+56.000	
-27.000	+0.936	-1.000	+0.942	-1.000	+0.940
+7.000		+32.000		+57.000	
-25.000	+0.935	-3.000	+0.942	-1.000	+0.940
+8.000		+33.000		+58.000	
-27.000	+0.948	-5.000	+0.942	-1.000	+0.940
+9.000		+34.000		+59.000	
-24.000	+0.942	+0.000	+0.941	-1.000	+0.940
+10.000		+35.000		+60.000	
-24.000	+0.946	-1.000	+0.941	-1.000	+0.940
+11.000		+36.000		+61.000	
-24.000	+0.949	+0.000	+0.941	-1.000	+0.940
+12.000		+37.000		+62.000	
-22.000	+0.948	+1.000	+0.941	-1.000	+0.940
+13.000		+38.000		+63.000	
-20.000	+0.946	+1.000	+0.941	-1.000	+0.940
+14.000		+39.000		+64.000	
-18.000	+0.944	+0.000	+0.941	-1.000	+0.940
+15.000		+40.000		+65.000	
-19.000	+0.947	+1.000	+0.941	-1.000	+0.940
+16.000		+41.000		+66.000	
-19.000	+0.949	+2.000	+0.941	-1.000	+0.940
+17.000		+42.000		+67.000	
-19.000	+0.951	+2.000	+0.941	-1.000	+0.940
+18.000		+43.000		+68.000	
-16.000	+0.947	+4.000	+0.941	-1.000	+0.940
+19.000		+44.000		+69.000	
-17.000	+0.950	+3.000	+0.941	-1.000	+0.940
+20.000		+45.000		+70.000	
-13.000	+0.945	+3.000	+0.941	-1.000	+0.940
+21.000		+46.000		+71.000	
-12.000	+0.945	-1.000	+0.940	-1.000	+0.940
+22.000		+47.000		+72.000	
-11.000	+0.945	-1.000	+0.940	-1.000	+0.940
+23.000		+48.000		+73.000	
-12.000	+0.946	-1.000	+0.940	-1.000	+0.940
+24.000		+49.000		+74.000	
-9.000	+0.944	-1.000	+0.940	-1.000	+0.940

## APPENDIX E

## OKN AND OKAN MODEL SIMULATION PROGRAM

The following pages contain an assembly program for the PDP-8/E computer. This program simulates OKN and OKAN response for a given set of model parameters and a step input. The program also computes the model error and the integral square error. These response curves can be plotted by using the PLOT subroutine in the program. Note that only the main program is included here, the system configuration definitions are the same as in the program in Appendix C.

## /OKN AND UKAN SIMULATION PROGRAM

	*0010		*10	
000010	0000	PTRDAT,	0	/POINTER TO DATA
000011	0000	PARPTR,	0	/POINTER TO DATA
000012	0000	PTREKR,	0	/ERROR POINTER
	*0070		*70	
000070	0006	R,	0006	/40 AS FP NUMBER
000071	2400		2400	
000072	0000		0000	
000073	0000	A,	0000	/0.985267 AS FP NUMBER
000074	3742		3742	
000075	0000		0000	
000076	7772	BETA,	7772	/0.0136873 AS FP NUMBER
000077	3434		3434	
000100	0000		0000	
000101	0000	ALPHA,	0000	/0.9979541 AS FP NUMBER
000102	3774		3774	
000103	0000		0000	
000104	0000	C,	0000	/0.575 AS FP NUMBER
000105	2232		2232	
000106	0000		0000	
000107	0002	QCKDRP,	0002	/QUICK DROP =3
000110	3000		3000	
000111	0000		0000	
000112	0000	TEMP1,	ZBLOCK 3	
000115	7620	CUUNT1,	7620	/-(657-477), BEFORE OKN STARTS
000116	6117	CUUNT2,	6117	/-(2540-657), OKN DURATION
000117	5261	CUUNT3,	5261	/-(5257-2540), OKAN DURATION
000120	0000	YMM1,	ZBLOCK 3	/Y(M-1)
000123	0000	ISE,	ZBLOCK 2	/INTEGRAL SQUARE ERROR

*0200		*200			
000200	6201	COF	00	/SET DATA FIELD =0	
000201	7300	CLA	CLL	/CLEAN UP	
000202	1377	TAD	(477	/TO THE BEGINNING OF SIMULATED DATA	
000203	3010	DCA	PTRDAT		
000204	6221	AA,	COF	20	/SET DATA FIELD =2
000205	3410	DCA	I	PTRDAT	/ZERO BEFORE UKN BEGINNING
000206	6201	COF	00	/DATA FIELD =0	
000207	2115	ISZ	COUNT1	/DONE?	
000210	5204	JMP	AA	/NO	
000211	4407	FENT		/ENTER FPP	
000212	5104	FGET	C	/Y(0)=CR	
000213	3070	FMPY	R		
000214	6120	FPUT	YMM1		
000215	0000	FEXT		/EXIT FPP	
000216	4264	JMS	DNORM	/FPP NUMBER TO 12 BIT NUMBER	
000217	6221	COF	20	/PREPARE FOR STORAGE	
000220	3410	DCA	I	PTRDAT	/STOKE IT
000221	6201	COF	00	/BACK TO FIELD 0	
000222	2116	ISZ	COUNT2	/COUNT UP	
000223	4407	BB,	FENT	/ENTER FPP	
000224	5120	FGET	YMM1	/A*Y(M-1)+BETA*R=Y(M)	
000225	3073	FMPY	A		
000226	6120	FPUT	YMM1		
000227	5076	FGET	BETA		
000230	3070	FMPY	R		
000231	1120	FADD	YMM1		
000232	6120	FPUT	YMM1		
000233	0000	FEXT		/LEAVE FPP	
000234	4264	JMS	DNORM	/CONVERT FP NUMBER TO 12 BIT NUMBER	
000235	6221	COF	20		
000236	3410	DCA	I	PTRDAT	/SAVE IN FIELD 2
000237	6201	COF	00	/FIELD 0	
000240	2116	ISZ	COUNT2	/OKN DONE?	
000241	5223	JMP	BB	/NO	
000242	4407	FENT		/ENTER FPP	
000243	5120	FGET	YMM1	/ADD QUICK DRUP	
000244	2107	FSUB	QCKDRP		
000245	6120	FPUT	YMM1		

000246	4407	CC,	FENT		/ENTER FPP
000247	5120		FGET	YMM1	/Y(M)=ALPHA*Y(M-1)
000250	3101		FMPY	ALPHA	
000251	6120		FPUT	YMM1	
000252	0000		FEXT		/LEAVE FPP
000253	4264		JMS	DNORM	/CONVERT FP NUMBER TO 12 BIT NUMBER
000254	6221		CDF	20	
000255	3410		DCA I	PTRDAT	/SAVE IN FIELD 2
000256	6201		CDF	00	/FIELD 0
000257	2117		ISZ	COUNT3	/DONE?
000260	5246		JMP	CC	/NO
					/SELECT CURVE TO BE PLOTTED
000261	4341		JMS	MISALN	/COMPUTE MODEL ERROR
000262	4765		JMS I	PEVAL	/COMPUTE ISE
000263	4303		JMS	PLOT	/PLOT SIMULATED DATA
000264	0000	DNORM,	.-.		/CONVERT FP NUMBER TO 12 BIT NUMBER ROUTINE
000265	7200		CLA		
000266	1044		TAD	44	/GET EXPONENT
000267	7500		SMA		/NEGATIVE?
000270	5273		JMP	.-3	/NO
000271	7200		CLA		/YES, INTEGER VALUE =0
000272	5302		JMP	GG	
000273	7040		CMA		
000274	1376		TAD	(14	/COMPUTE SHIFTS NEEDED TO MAKE IT INTEGER
000275	3301		DCA	SHFTCNT	
000276	7431		SWAB		/MODE B EAE
000277	1045		TAD	45	/GET MANTISSA
000300	7415		ASR		/SHIFT TO MAKE IT INTEGER
000301	0000	SHFTCNT,000			
000302	5664	GG,	JMP I	DNORM	/RETURN

000303	0000	PLOT,	.-.		/DATA PLOT ROUTINE
000304	6201	FF,	CDF	00	/DATA FIELD=0
000305	7300		CLA	CLL	/CLEAN UP
000306	1375		TAD	(3220	/POINTS TO BE DISPLAYED
000307	3115		DCA	COUNT1	
000310	1377		TAD	(477	/FIRST DATA POINT
000311	3010		DCA	PTRJAT	
000312	1010		TAD	PTRDAT	/FIRST PARAMETER POINT
000313	3011		DCA	PARPTR	
000314	3112		DCA	TEMP1	/DELAY FOR DISPLAY
000315	7621	EE,	CAM		/CLEAN UP
000316	6221		CDF	20	/DATA FIELD =2
000317	1410		TAD I	PTRDAT	/GET POINT TO BE PLOTTED
000320	6201		CDF	00	
000321	7413		SML;	4	/GAIN CONTROL
000322	0004				
000323	7000		NUP		
000324	6551		6551		/DISPLAY IT
000325	7621		CAM		
000326	6211		CDF	10	/FIELD 1
000327	1411		TAD I	PARPTR	/GET DISPLAY POINT
000330	6201		CDF	00	/FIELD 0
000331	7413		SML;	4	/GAIN CONTROL
000332	0004				
000333	6552		6552		/DISPLAY ON Y CHANNEL
000334	2112	DELY,	ISZ	TEMP1	/DELAY LOOP
000335	5334		JMP	DELY	
000336	2115		ISZ	COUNT1	/COUNT UP
000337	5315		JMP	EE	
000340	5304		JMP	FF	/REPLOT

000341	0000	MISALN,	.-.		/ERROR SUBROUTINE
000342	7300		CLA	CLL	
000343	6201		CDF	00	/DATA FIELD 0
000344	1377		TAD	(477	/SET AUTO INDEX POINTERS
000345	3010		DCA	PTRDAT	/FIELD1
000346	1010		TAD	PTRDAT	
000347	3011		DCA	PARPTR	/FIELD 2, SIMULATED OUTPUT
000350	1010		TAD	PTRDAT	
000351	3012		DCA	PTRERR	/FIELD 2, ERROR
000352	1375		TAD	(3220	/POINTS TOTAL
000353	3115		DCA	COUNT1	
000354	6211	DD,	CDF	10	/SET DATA FIELD 1
000355	1411		TAD I	PARPTR	/E(M)=Y(M)-Z(M)
000356	6221		CDF	20	/SET DATA FIELD 2
000357	1410		TAD I	PTRDAT	
000360	3412		DCA I	PTRERR	
000361	2115		ISZ	COUNT1	/DDNE?
000362	5354		JMP	DD	/NO
000363	6201		CDF	00	/DATA FIELD 0
000364	5741		JMP I	MISALN	/RETURN
000365	0400	PEVAL,	EVAL		/POINTER TO EVAV ROUTINE
	*0375				
000375	3220				
000376	0014				
000377	0477				
	*0400		PAGE		

/PARAMETER ESTIMATION EVALUATION ROUTINE

```

000400 0000 EVAL,
000401 7300 CLA CLL
000402 6201 CDF 00
000403 1377 TAD (477
000404 3012 DCA PTRERR
000405 1012 TAD PTRERR
000406 3010 DCA PTRDAT
000407 1012 TAD PTRERR
000410 3011 DCA PARPTR
000411 1376 TAD (3230
000412 3115 DCA COUNT1
000413 1375 TAD (7767
000414 3116 DCA COUNT2
000415 7431 SAA8
000416 7421 MUL
000417 7445 DST; ISE
000420 0123
000421 7300 INTEGL, CLA CLL
000422 6221 CDF 20
000423 1412 TAD I PTRERR
000424 6201 CDF 00
000425 7510 SPA
000426 7041 CIA
000427 3112 DCA TEMP1
000430 1112 TAD TEMP1
000431 7421 MUL
000432 7405 MUY; TEMP1
000433 0112
000434 7443 DAD; ISE
000435 0123
000436 7445 DST; ISE
000437 0123
000440 2116 ISZ COUNT2
000441 5221 JMP INTEG1
    
```

```

/CLEAN UP
/FIELD 0
/INITIALIZE POINTERS
    
```

```

/INITIALIZE COUNTERS
/COUNT1=-3220+NO.OF POINTS IN INTEG. WINDOW
/COUNT2=- NO. OF POINTS IN INTEG. WINDOW
/MODE P EAE
/INITIAL ISE=0
    
```

```

/CLEAN UP
/DATA FIELD 2
/GENERATE ISE
    
```

```

/ADD UN NEW SQUARED DATA
    
```

```

/AND SAVE
/MINDOW DONE?
/NO
    
```

```

000442 6221 INTEG2, CDF 20 /DATA FIELD 2
000443 1410 TAD I PTRDAT /GET POINT BEFORE WINDOW
000444 6201 CDF 00 /DATA FIELD 0
000445 7510 SPA /GET ABSOLUTE VALUE
000446 7041 CIA
000447 3112 DCA TEMPI
000450 7501 MOA
000451 6221 CDF 20 /GET LAST ISE
000452 3411 DCA I PARPTR /SAVE IT
000453 6201 CDF 00 /GET LAST POINT
000454 1112 TAD TEMPI /IN HQ REGISTER
000455 7421 MJL /SQUAKE IT
000456 7405 MUY; TEMPI
000457 0112
000460 7575 DCM /SUBTRACT FROM LAST ISE
000461 7443 DAD; ISE
000462 0123
000463 7445 DST; ISE
000464 0123
000465 6221 CDF 20 /GET NEXT POINT
000466 1412 TAD I PTRERR
000467 6201 CDF 00
000470 7510 SPA
000471 7041 CIA
000472 3112 DCA TEMPI /SAVE IN TEMPI
000473 1112 TAD TEMPI /SQUARE IT
000474 7421 MUL
000475 7405 MUY; TEMPI
000476 0112
000477 7443 DAD; ISE /ADD ON LAST VALUE OF ISE EXPRESSION
000500 0123 DST; ISE /SAVE IT
000501 7445
000502 0123
000503 2115 ISZ COUNT1 /DONE?
000504 5242 JMP INTEG2 /NO
000505 5600 JMP I EVAL /RETURN
000575 7767 *0575
000576 3230
000577 0477

```

/OKM AND UKAN MODEL SIMULATION PROGRAM  
ASSEMBLY STATISTICS

P?S PAL V08M

TUE 28-JUL-81 PAGE 11

NO ERRORS DETECTED

NO LINKS GENERATED

6K MEMORY UTILIZED

1 FILE CREATED

155 SYMBOLS

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