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Pattern Recognition in Urodynamics: An Application to Cystometry

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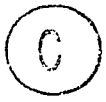

Pradeep N Modur

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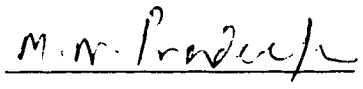

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The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies and Research for acceptance, a thesis entitled **Pattern Recognition in Urodynamics: An Application to Cystometry** submitted by **Pradeep N Modur** in partial fulfillment of the requirements for the degree of **Master of Science**.

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May 05, 1993

To my parents,

for their affection, encouragement and support.

Abstract

Urodynamics is a primary diagnostic study in the evaluation of lower urinary tract function. As an essential component of urodynamic studies, *cystometry* is performed to assess the storage and voiding functions of urinary bladder. A graphic record of pressure changes and flow rate, obtained during cystometry, is called *cystometrogram* (*CMG*). Cystometry is interpreted by observation of various *events*. Invariably, the recognition of these events is rendered difficult by *artifacts*, which arise as a result of frequent mechanical malfunction in the catheters and pressure lines. Since artifacts represent erroneous data, their elimination is of paramount importance for valid interpretation of cystometry. The research work described in this thesis represents an original contribution towards on-line recognition of events and artifacts by means of a pattern recognition program called *CART* (*C*ystometric *A*rtifact *R*ecognition *T*ool).

Cystometric data from patients were recorded on a video-urodynamic system and stored in a computer. Based on thorough analyses of existing CMGs, the commonly encountered patterns were grouped into 13 *pattern classes* — 5 of events and 8 of artifacts. A set of ten discriminatory *features*, characterizing these classes, was chosen empirically. Two methods of pattern classification were adopted: *counters* to classify the relatively simple patterns; a *trainable pattern classifier*, based on perceptron approach, to classify the complex ones. An algorithm, operating on-line in the time domain, was designed to perform the tasks of data acquisition, pattern demarcation, feature extraction,

classification, plotting and alert actuation. CART was implemented on an 80386-based PC.

The performance of the trainable classifier was evaluated on 43 patient files. These files were divided into two sets of 21 and 22 files. The evaluation was done in two stages: for the first stage, the first set was used for training and the second set was used for testing; for the second stage, the two sets were interchanged. The results from the two stages were combined to obtain the final results. Accordingly, the total number of patterns tested was 1833 (1082 from first stage and 751 from second stage). The final results were expressed in terms of four indices of performance: *sensitivity* 99%; *false positivity* 3%; *concurrence* 89%; *misclassification* 11%.

The results indicate that CART had high sensitivity and moderately low false positivity. Some of the misclassifications could be attributed to inadequate number of testing patterns and to deficiencies in training. Future efforts could focus on: refinements in pattern demarcation, feature selection and training; enhancements, in the form of automated report generation and decision-support; integration with existing software in urodynamic systems.

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I would like to thank Dr. Derek Griffiths for giving me the basic idea to start the project. He has been a great source of help with virtually every aspect of this projecct. I really appreciate the amount of freedom he gave me in pursuing my own ideas and implementing them during the course of this research work. His continued interest, appreciation and encouragement significantly influenced the achievement of the goals of this project.

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Table of Contents

List of Tables

List of Figures

List of Abbreviations

CART	Cystometric Artifact Recognition Tool
CMG	Cystometrogram
ECG	Electrocardiogram
EMG	Electromyogram
UDE	Urodynamic equipment
VCUG	Video-cystourethrography

List of Notations

r	Dimensionality of pattern space
n	Dimensionality of feature space
M	Number of pattern classes
ω_i	i^{th} pattern class
$\mathbf{X} = \begin{pmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_n \end{pmatrix}$	Feature vector
$\mathbf{X}' = (x_1, x_2, \ldots, x_n)$	Transposed feature vector
$\mathbf{P}' = (p_1, p_2, \ldots, p_r)$	Transposed pattern vector
$\mathbf{W} = \begin{pmatrix} w_1 \\ w_2 \\ \cdot \\ \cdot \\ \cdot \\ w_n \\ w_{n+1} \end{pmatrix}$	Weight vector

$\mathbf{W}' = (w_1, w_2, \ldots, w_n, w_{n+1})$	Transposed weight vector
$\mathbf{W}'\mathbf{X} = \sum_{i=1}^{n} w_i x_i$	Dot product of vectors **W** and **X**
$\mathbf{W}_i$	Weight vector of class ω_i
$d(\mathbf{X})$	Discriminant function
$d_i(X)$	Discriminant function of class ω_i
$d_i(X) = \mathbf{W}'_i\mathbf{X}$	Linear discriminant function
k	Iteration index
$\mathbf{X}(k)$	Feature vector at k^{th} iteration
$\mathbf{W}(k)$	Weight vector at k^{th} iteration
α	Correction increment

Chapter 1

INTRODUCTION

In recent years, our society has been confronted with the problem of "information explosion", resulting from rapid advancements in scientific research. We are made to cope with ever-increasing amounts of information in our day-to-day lives. Fortunately, the advent of computers seems to have ameliorated the problem. One of the central issues in information handling is automated pattern recognition and classification. In general, the situations in the real world cannot be evaluated in terms of isolated observations. Instead, they are described in terms of patterns, which are aggregates of closely related observations. The recognition of these patterns by human beings depends on the nature of the observations and the information-processing abilities of the brain. In other words, recognition of abstract relationships depends on our cognitive abilities, while recognition of concrete relationships depends on our perceptual abilities. In order to build "intelligent" machines that can interact with humans in an intuitive way, it is necessary to implement these cognition and perception capabilities in the computers. The research work described in this thesis is related to the application of pattern recognition techniques in solving a commonly encountered problem in the field of urodynamics. The following section provides an overview of the research work.

1.1 An Overview of the Research Work

Before proceeding further with the rest of the thesis, it is advantageous to provide an overall picture of the research work. Accordingly, this section is devoted to a discussion of the problem, a proposed solution and objectives of the research project.

1.1.1 The Problem

Urodynamics constitutes a basic diagnostic study in the evaluation of lower urinary tract abnormalities such as urinary incontinence, lower urinary tract obstruction, etc. Although urodynamics is a collective term for a wide range of tests, one of the most frequently quoted tests is *cystometry* [Blaivas 1988; Torrens 1987; Torrens 1984; Abrams et al. 1983; Blaivas et al. 1982]. The topics of urodynamics and cystometry will be discussed at length in Chapter 2, but they are touched upon briefly in the following lines to facilitate definition of the problem.

Essentially, cystometry, as referred to in this thesis, involves catheterizing a patient and observing the behaviour of urinary bladder. The observations are made in two phases, the filling phase, in which the bladder is filled with a fluid, and the voiding phase, in which the patient empties the bladder. Although various parameters are measured during the test, the two most commonly measured are pressure variations in the bladder, and voiding flow rate. The graphic record of pressure and flow rate with respect to time is referred to as *cystometrogram* (*CMG*). In state-of-the-art urodynamic systems, the data are processed by a computer and the resulting graphs are displayed on a monitor. This

test is generally performed by a trained nurse or technician, and interpreted by the clinician. The amount of time required for the actual performance of the test is quite variable, and is usually not less than 20 minutes.

The diagnostic interpretation of a CMG depends on the observation of several physiologic *events*, and their relationship to voiding and to changes in external sphincter tone. Unfortunately, on many occasions, the CMG traces are found to be obscured by undesirable *artifacts*. In such cases, the recorded data generally turn out to be invalid and potentially misleading, often necessitating repetition of the test on a different occasion. This problem of misinterpretation, caused by artifacts, has long been recognized [Abrams 1984; Griffiths 1984; Stephenson and Wein 1984].

1.1.2 A Proposed Solution

A solution to the problem outlined above can be approached in at least two different ways:

(1) recognizing artifacts at the time of interpretation of CMG (i.e., after the cystometric test has been completed), and exercising caution in drawing conclusions from such traces

(2) recognizing artifacts *during* cystometric testing itself, and taking appropriate measures to eliminate them in order to obtain a valid set of data

If cystometry is conducted by a person inexperienced in recognizing artifacts, the chances of recording erroneous data are high, and the clinician who interprets such a test is left

with only the first approach in solving the problem. On the other hand, if an experienced person performs the test, a recourse to the second approach would be possible. Even here, some artifacts can escape detection if the CMG traces on the monitor are not followed with undivided attention. In the light of the above discussion, the reasons for persistence of artifacts, during cystometry and in CMGs, can be summarized as being due to two factors: lack of knowledge about artifacts; failure to follow the traces diligently on the monitor.

Comparing the two approaches, it is readily apparent that the second is superior to the first. This is because, the first approach, although good in taking care of misinterpretations, does not necessarily preclude test repetition; the second approach, on the other hand, provides a solution to both factors. On further examination, it becomes clear that practical implementation of the second approach entails *on-line recognition* of artifacts. That is, artifacts have to be detected in real time during the performance of the test. This implies the use of a high-speed computer, and the development of a fast algorithm. Since artifacts appear as waveforms in the time domain, the task of their detection can be viewed as a *pattern recognition and classification problem.*

There have been many reports of computer applications in clinical urodynamic practice. These are reviewed in [Kramer and Jonas 1988; Woodside 1988; Regnier 1986]. Specifically, computers have been used in *data acquisition, storage and retrieval* [Shank et al. 1990; Eadie et al. 1986; Saini and Thiede 1986; Crawford and Walker 1985;

Abrams et al. 1984; Woodside and Morris 1982], *research and analysis* [Best et al. 1986; Griffiths and Van Mastrigt 1985; Jacobs et al. 1984; Kramer and Jonas 1984; Van Mastrigt 1984; Jonas et al. 1978], *database management* [O'Donnell 1990], and *decision-support* [Hatano et al. 1989; Riss and Koelbl 1988]. However, there are no reports of using computers in automated recognition of artifacts. This apparent lack of a suitable solution prompted the current research work, which can therefore be viewed as a first step towards automated recognition of artifacts.

The abundance of literature on pattern recognition techniques [Fukunaga 1990; Pao 1989; Tou and Gonzalez 1974; Duda and Hart 1973; Andrews 1972; Becker 1972], and their successful applications in many waveform-recognition tasks in the medical domain [Miller et al. 1992; Bessette and Nguyen 1989; Chang et al. 1989; Revow et al. 1986; Schemann et al. 1985; Ripley 1984; Fusfeld 1982; Van Bemmel and Willems 1977; Chik et al. 1975; McFarlane and Lawrie 1974; Serafini 1973; Wartak 1970] provided the rationale for adopting these techniques in solving the CMG artifact recognition problem.

1.1.3 Objectives of the Project

Influenced by the nature of the problem, the proposed solution, the availability of resources and the inevitability of constraints, the following objectives were defined:

- identify the events and artifacts that are commonly seen, and that need to be recognized
- define objective criteria to differentiate the various events and artifacts

- develop an algorithm to automate the process of recognition
- implement the algorithm as software for a real-time recognition task
- evaluate the software's performance for its potential usefulness in clinical urodynamic practice

It may be noted that, although the major thrust was directed at detection of artifacts, an attempt was made to detect the events as well in the hope of possible future applications.

1.2 Organization of the Thesis

This thesis is organized into six chapters and two appendices. This chapter, *Introduction*, has provided an overview of the research work. The second chapter, *Background*, provides introductory material on urodynamics and pattern recognition principles. The third chapter, *Pattern Recognition System for Cystometry*, describes CART, the computer program developed in this research work in terms of its architecture, design principles, implementation and evaluation. The fourth chapter, *Results*, presents the results of evaluation of performance of CART. The fifth chapter, *Discussion*, focusses on interpretation of the results. The sixth chapter, *Conclusions and Future Directions*, provides the conclusions and outlines some suggestions for future work. Appendix 1, *Illustration of Events and Artifacts*, provides graphical illustrations of the examples of various events and artifacts as seen on the screen during clinical use. Appendix 2, *Using CART*, describes the general functions and the modes of operation of CART as a guide to using it.

Chapter 2

BACKGROUND

This chapter provides introductory material on urodynamics and pattern recognition principles. The topics on cystometry and perceptron approach are discussed in some detail as they are relevant to the understanding of the research problem addressed in this thesis. As noted in the previous chapter, since there are no critical references on automated pattern recognition in cystometry, no attempt is made to review any literature on that subject.

2.1 Urodynamics

The human urinary system consists of the kidneys, ureters, urinary bladder and urethra. Two kidneys are connected to the urinary bladder by means of a pair of ureters. The urinary bladder opens to the exterior via the urethra. The urinary bladder and the urethra, together, constitute the *lower urinary tract*. The wall of urinary bladder (or, simply, bladder) consists of a smooth muscle, called *detrusor*, whose main function is to pump the urine into the urethra during micturition (or voiding). A short segment of the urethra is surrounded by striated muscles forming the *external sphincter*, which plays an important part in the maintenance of urinary continence.

The evaluation of patients with symptoms related to dysfunction of the lower urinary tract involves a variety of procedures [Diokno 1988; Shah 1984; Turner-Warwick and Whiteside 1982], one of them being *urodynamics*. The term, urodynamics, was introduced in 1954, as a parallel to cardiovascular dynamics [Perez and Webster 1992; Torrens 1984]. Now, urodynamics has a range of meanings, all related to the observation of the changing function of the urinary tract over a period of time, encompassing the morphological, physiological, biochemical and hydrodynamic aspects of urine transport and storage [Abrams et al. 1988].

2.1.1 Clinical Significance

The role of urodynamics in objective clinical assessment of lower urinary tract function has been firmly established in the past two decades [Perez and Webster 1992]. This has been due, largely, to an improved understanding of the physiology of lower urinary tract, and the availability of reliable measuring systems [Abrams et al. 1983]. From a clinical perspective, the purpose of urodynamic testing is to measure and record various physiologic variables while the patient is experiencing those symptoms that constitute his/her usual complaints. In this context, urodynamic studies may be considered to be provocative tests of vesicourethral function. Thus, it is the responsibility of the examiner to ensure that the patient's symptoms are, in fact, reproduced during the study [Blaivas 1988].

Urodynamics aims at assessment of the three basic aspects of the physiology of lower urinary tract: storage function of the bladder; voiding function of the bladder; urine transport functions of bladder and urethra. The assessment of the above functions is helpful in diagnostic decision-making, treatment planning and basic physiological research [Torrens 1984].

Based on a consideration of various factors, three main indications for performing urodynamic studies have been put forward [Torrens 1984]: persistent lower urinary tract symptoms that defy simpler modalities of investigation; before and after any operation or procedure designed to alter the function of the lower urinary tract; failure of response to initial treatment.

2.1.2 Sequence of Tests

A full urodynamic study involves performance of a number of tests. From a practical point of view, these tests can be grouped into five categories [Blaivas 1988]: *cystometry*; *uroflowmetry*; *electromyography*; *urethral pressure profilometry*; *fluoroscopic visualization of lower urinary tract*.

Technically, cystometry is defined as a study of the pressure/volume relationship of the bladder. For many years, cystometry was performed by filling the bladder with a fluid in increments of 50 ml, and drawing a graph by joining the points marked for the pressures recorded after each increment [Abrams et al. 1983]. Since the test basically

involved observing the behaviour of the bladder by filling it with a fluid, it was also known as "filling cystometry" [Abrams et al. 1983]. Cystometry is principally a test of detrusor muscle function; therefore, there is a requirement for supplemental testing to define the other aspect of detrusor function, namely, voiding [Hald and Bradley 1982]. The voiding function has been traditionally assessed by continuous simultaneous measurement of the pressure inside the bladder and the urine flow rate during micturition. This type of assessment, which measures the pressure/flow relationship, has been referred to as the "pressure-flow study of voiding" [Abrams et al. 1983]. Fortunately, with the advent of computer-based urodynamic systems, it has been possible to obtain continuous measurements of several variables including bladder pressure and flow rate. In modern state-of-the-art urodynamic systems, the different variables — pressures, flow rate, volumes and EMG — are represented graphically as a function o. time in a multi-channel polygraph. Usually, a fluoroscopic image of the bladder is also presented along with the graphic traces, and facilities are provided for recording the image and the traces on a video tape. This type of comprehensive urodynamic study has been referred to as *video-cystourethrography* (*VCUG*).

In our unit, urodynamic assessment of all the patients is done by VCUG. Details about the various tests may be found in [Blaivas 1988; Torrens 1987; Abrams 1984; Abrams et al. 1983]. Since this research project is concerned with cystometry, the latter is discussed in detail in the next section.

2.2 Cystometry and Cystometrogram

In our unit, cystometry is performed as part of VCUG. It is important to note that the description that follows relates to the manner in which cystometry is performed and interpreted in our unit. Accordingly, the material presented below may not be completely on par with similar descriptions found elsewhere.

2.2.1 Technique

For the sake of convenience, the technique of cystometry is considered under the following four headings: intravesical pressure measurement; abdominal pressure measurement; bladder filling; flow rate measurement [Abrams 1984]. A brief description of the technique is given in the following lines.

Intravesical pressure (denoted by *Pves*) refers to the pressure measured from within the bladder. The pressure is measured by means of a transurethral catheter, which is connected to the pressure transducer by means of a fluid-filled tube. The pressure transducer is mounted externally on a stand, and its height is adjusted to coincide with the level of the upper border of pubic symphysis; at this height, the transducer is set to read zero pressure.

During cystometry, it doesn't suffice if only the intravesical pressure is measured. This is because changes in intravesical pressure can be due to two factors: pressure generated by the bladder wall due to detrusor activity (denoted by *Pdet*) and changes in pressure

around the bladder, most frequently due to abdominal straining (denoted by *Pabd*). Thus, the intravesical pressure is actually given by: $Pves = Pdet + Pabd$. Since *Pdet* is the pressure that is of interest, it can be calculated if *Pabd* is known. *Pabd* is usually obtained as an approximation in terms of intrarectal pressure, which is measured by inserting a fluid-filled catheter in the rectum.

Bladder filling forms the initial part of cystometry. However, before starting to fill, the patient is asked to empty the bladder normally. Upon catheterization, the post-void residual urine, if any, is collected, and the amount measured. The bladder is then filled with a solution, at room temperature, containing a radiological contrast material. A medium rate of filling (i.e., 10-100 ml/min) is generally followed. A peristaltic pump is used to regulate the rate of filling, and also to prevent reflux of urine along the tube should the bladder pressure increase at any time. The test is initially carried out with the patient in the supine position; testing at sitting and standing postures may be done subsequently, if required. Periodically, during filling, the patient is asked to cough in order to check that the catheters and their connections are working properly, and also to provoke involuntary detrusor contractions. The bladder pressure and volume are noted at the instant when the patient feels the urge to void. The occurrence of involuntary detrusor contractions, if any, are noted. The *maximum cystometric capacity* is recorded as the volume at which the patient has a strong desire to void, or voids either voluntarily or involuntarily.

The voiding phase forms the latter part of cystometry. When the patient develops a strong urge to void, an accompanying detrusor contraction may or may not be seen. If the urge is accompanied by a detrusor contraction, the filling is stopped, and the patient is asked to try to suppress voiding as far as possible. If he/she is unable to do so, the detrusor contraction is considered to be *involuntary*. In such cases, bladder filling may be repeated to confirm the presence of involuntary contractions. On the other hand, if the strong urge to void is not accompanied by a detrusor contraction, the patient is asked to void in a normal manner. In these cases, voiding is initiated by a *voluntary* detrusor contraction. Some patients may become inhibited by the unnatural environment, and may be unable to generate a detrusor contraction. Some may initiate voiding with abdominal straining, and in them, the detrusor contraction and straining will be superimposed. In any case, when the patient voids, the urine is directed by means of a funnel into a flowmeter. The voided stream is made to fall on a weight transducer which calculates the flow rate by differentiating the weight of the voided urine with respect to time. In addition, *pressure at maximum flow*, which is the pressure recorded at the time of maximum flow rate, and *maximum voiding pressure*, which is the maximum value of the measured pressure, are noted.

As mentioned earlier, *Cystometrogram* (*CMG*) refers to the graphic representation of the measurements recorded during cystometry. Essentially, CMG consists of traces of several variables with respect to time. These traces are displayed in differrent channels on a monitor during cystometry, and can be printed on paper after the completion of the

test. A typical CMG printed at the end of a test is shown in Figure 2.1. Since the trace is obtained as part of VCUG, it contains EMG data as well. The different channels, and the corresponding variables are shown in Table 2.1.

2.2.2 Interpretation

In general, the interpretation of a urodynamic study depends on several factors: accurate history; knowledge of the physiology of the lower urinary tract; understanding of the working of the equipment; experience in radiological evaluation of the detrusor and sphincter functions; selection of appropriate tests for the individual patient; collection of valid data free of artifact; presence of an experienced clinician. Out of these factors, the first five may be adequately taken care of by proper training of the personnel involved in urodynamics. Although the ability to detect artifacts comes with experience, it is not always possible to *prevent* their occurrence. Lastly, the presence of an experienced clinician *during* the performance of urodynamic tests cannot always be assured. It may be noted that the last two statements reiterate the problem outlined in subsection 1.1.1.

Cystometry is interpreted in terms of its two phases: *filling phase*; *voiding phase*. These are described below.

The interpretation of filling phase of cystometry involves consideration of four parameters —capacity, compliance, contractility and sensation [Blaivas 1988; Torrens 1987; Abrams et al. 1983]. The *maximum cystometric capacity* is defined as the volume at which the

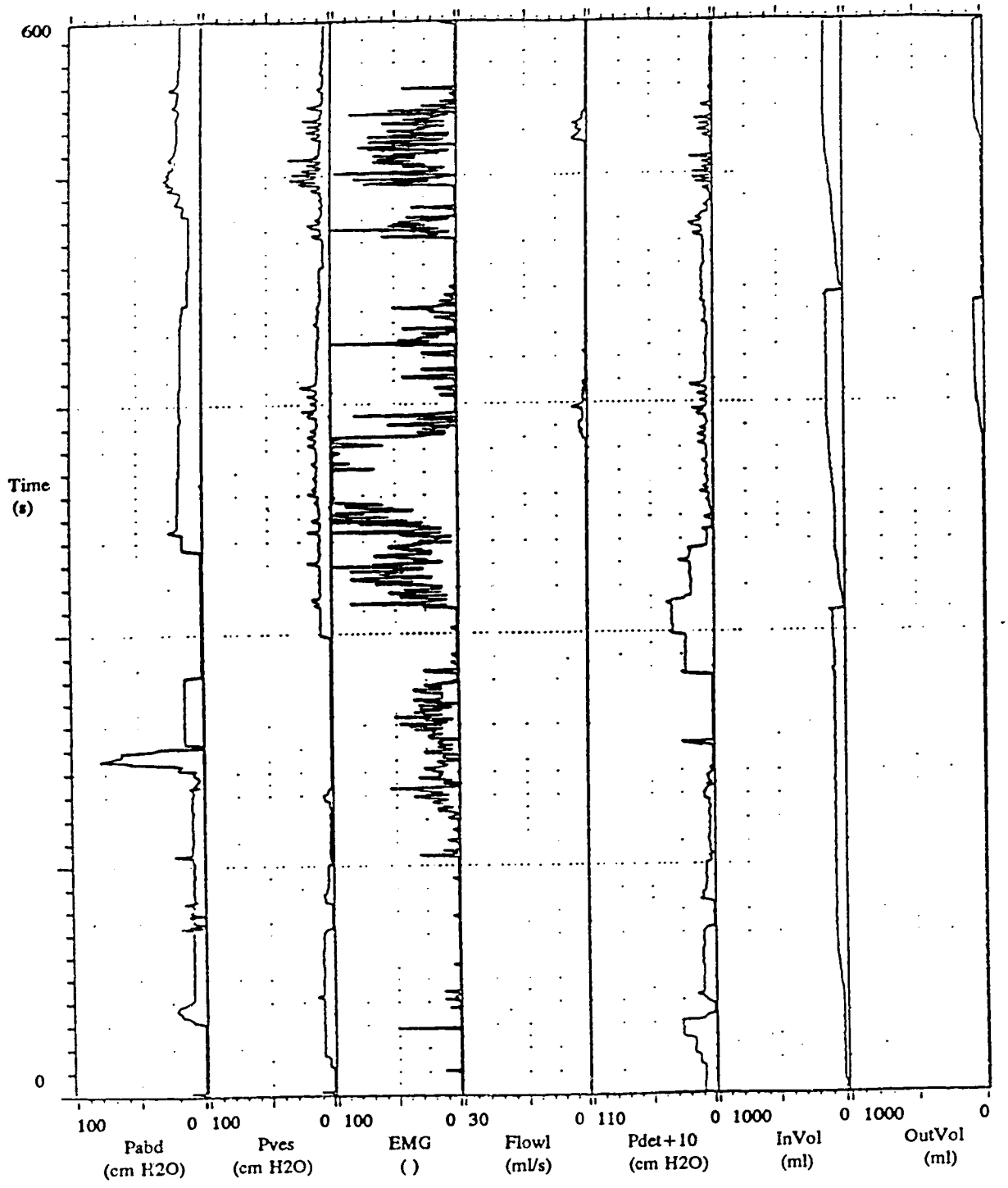

Figure 2.1 Cystometrogram

Channel	Variable measured	Unit
Pves	Intravesical pressure	cm H_2O
Pabd	Abdominal pressure	cm H_2O
Pdet	Detrusor pressure	cm H_2O
Flowl	Urine flow rate	ml/sec
InVol	Volume infused into bladder	ml
OutVol	Volume output from bladder	ml

Table 2.1 CMG channels

patient has a normal strong desire to void. The normal range for maximum cystometric capacity is 400-600 ml. *Compliance* is defined as the change in volume for a given change in pressure. It is given by $C = \Delta V/\Delta P$, where ΔV is the volume increment, and ΔP is the pressure increment. Most bladders are compliant even when filled fast; the pressure increase is less than 10 cm H_2O at 300 ml, and less than 15 cm H_2O at capacity. In normal subjects, the bladder should not contract during filling under any circumstances. An involuntary detrusor contraction that occurs spontaneously or on provocation, during the filling phase while the patient is attempting to inhibit micturition, is usually considered abnormal, and described as an *unstable contraction.* Description of the *sensory phenomena* during bladder filling, obtained from the patient, may not be particularly useful or accurate until the point is reached when the patient is uncomfortably full or wishes to void. The volume at which this sensation occurs is significant; a normal person can tolerate at least 300 ml.

The voiding phase of cystometry is usually interpreted by taking into account the maximum flow rate and the corresponding detrusor pressure. A *normal flow rate* is inherently that produced by a normal detrusor contraction emptying the bladder through a normal urethra. However, normal flow may also occur when a powerful detrusor contracts against an obstructed urethra. Also, especially in women, normal flow may occur in the apparent absence of a detrusor contraction. A *low flow rate*, especially when associated with a high or normal detrusor contraction, most commonly indicates bladder outflow obstruction in males, though not necessarily in females. On the other hand, a

low flow rate associated with a low detrusor voiding pressure indicates an abnormality of detrusor contractility. *Irregular* or *interrupted voiding* may be due to three conditions: abdominal straining; fluctuating detrusor contraction; dissociation between detrusor contraction and urethral sphincter mechanism. The relationship between pressure and flow rate has been formalized by defining various *urethral resistance factors*, as described in [Griffiths 1980].

2.2.3 Events

The pressure and flow data obtained during cystometry are represented graphically in a CMG. In the previous subsection, the interpretation of these data was considered from a clinical standpoint. In the following paragraphs, the basic observations that are required for making those interpretations are examined.

2.2.3.1 Definition

As described earlier, the interpretation of a CMG depends on observing certain phenomena and measuring several variables. In most cases, these observations and measurements are made at points that bear a specific time relationship to the occurrence of certain well-defined *events*. The following two examples serve to clarify this point.

(1) The occurrence of an unstable bladder contraction is anticipated following a cough; here, the unstable bladder contraction is an *observation*, and the cough is an *event*.

(2) The measurement of maximum voiding pressure is taken at the height of a bladder contraction associated with voiding; here, the maximum voiding pressure is a *measurement*, and the bladder contraction is an *event*.

These events can be further qualified by the following statements:

- they are "physiologic" in the sense that they are the result of voluntary or involuntary actions on the part of the patient
- they may be sought deliberately as part of the cystometric procedure
- they may not necessarily be "normal" in the usual sense of the word
- their origin cannot be attributed to improper technique or equipment malfunction

2.2.3.2 Types

Based on the above definition, the commonly encountered events in a CMG can be listed as follows: *cough*; *abdominal strain*; *bladder contraction*; *rectal contraction*; *minor baseline change*. It is worth mentioning here that the above events have been named and defined on the basis of pressure changes in the Pves, Pabd and Pdet channels. Even though the CMG, as obtained in our unit, consists of three other channels, namely, flow, inflow volume and outflow volume, the changes in these channels are not taken into account in defining these events. These events are explored in greater detail in subsection 3.2.1.

2.2.4 Artifacts

The technique of cystometry involves extensive use of electrical and mechanical components. In particular, the measurement of intravesical and abdominal pressures entails the use of three principal components: transducers; catheters; connecting tubes. The quality of data acquired during the procedure depends very largely on the proper functioning of these components. Furthermore, reliable interpretation of CMG depends, in turn, on the quality of acquired data.

2.2.4.1 Definition

Unfortunately, the malfunction of one or more of the components mentioned above is extremely common during cystometry. Transducers pose few problems, but catheters and connecting tubes "go out of order" relatively frequently during clinical tests. When this happens, erroneous pressure readings are recorded, making the resulting traces difficult to interpret. Such traces contain a variety of anomalies, referred to as *artifacts*, that manifest in three principal ways:

- as new entities distinct from events
- as distortions of events
- as partial or total failure of registration of events

2.2.4.2 Types

Some of the commonly encountered artifacts in CMG are described in [Griffiths 1984]. Based on the above description, and on further work that was undertaken as part of the

current research project, three main types of artifacts have been identified. These are as follows: *steps*; *under-registrations*; *flat traces*. These artifacts can occur in one or both of Pves and Pabd channels. Since the Pdet channel only reflects the changes in Pves and Pabd channels, it is sufficient to define artifacts in the latter two channels. Further details about the nature and characterization of these artifacts are provided in subsection 3.2.2.

2.2.4.3 Causes

The origin of these pressure artifacts can be attributed to a variety of causes [Abrams 1984], which are described in the following paragraphs.

Inappropriate catheter positioning

During cystometry, it is important to ensure that the tips of the catheters are well within the bladder and the rectum. If they are not, invalid data will be recorded. Generally, loosely secured catheters may get displaced when the patient coughs or strains forcefully.

Blockage of catheters and pressure lines

Catheters and pressure lines can get blocked when there are air bubbles inside, or when they are kinked or curled up. The tip of the bladder catheter can get entangled within the mucosal folds such that the hole becomes covered by mucosal tissue, and thereby blocked. The rectal catheter, on the other hand, can get clogged by fecal matter or it can get compressed under a buttock.

Fluid leaks from pressure lines

Catheters are connected to the pressure transducers by means of fluid-filled tubes with stop-cocks interposed. This arrangement can cause fluid leaks from the connection sites.

Improper zeroing of transducers

When external transducers are used, they should be set to read zero pressure at the level of the upper border of the pubic symphysis. This is generally done by adjusting the level of fixation of transducers on the stand so as to coincide with the upper border of the pubic symphysis, and making them read zero pressure at that level by means of a keyboard command. If the zeroes are not set properly, falsely high or low pressures are recorded.

Improper calibration of transducers

Transducers should be calibrated using a 100-cm water column connected to the pressure lines. The calibration is done by the manufacturer, and usually there is no need to recalibrate unless there is significant drift (see below).

Transducer drift

The clinician should be aware of the physical properties of each transducer. It is important to know whether any alteration occurs with changes in temperature, or whether there is any inherent instability of the transducer. If such changes are noted, the defective transducer/s may have to be recalibrated or replaced.

2.2.4.4 Precautions and Remedies

In order to avoid artifacts, certain precautions have to be taken before starting the test. Once the test is underway, if artifacts are encountered, appropriate remedial measures are called for, as summarized in the following paragraphs.

Proper zeroing of transducers

Before starting the cystometric procedure, it is important to adjust the position of transducers on the stand such that they register zero pressure at the level of the upper border of pubic symphysis. This position needs to be altered appropriately if the patient's posture changes appreciably during the test.

Checking for calibration

This is done by alternately opening and closing the stop-cock so that the maximum pressure registered corresponds to the maximum level set during calibration. Transducer drift, if any, should become apparent at this point.

Secure fixation of tubes

Catheters and connecting tubes should be fixed securely by means of adhesive tapes to ensure that they do not fall off during the test. Also, it is important to ensure that they are not unduly at risk of compression or kinking.

Removal of air bubbles

This is done before starting the test. Fluid is run down the pressure lines so that all the air bubbles are expelled, and a free flow is established.

Repositioning of catheters

If the observed pressures appear improper at any time during the procedure, it is a good idea to slide the catheter/s in or out a little. This manoeuvre might help in positioning the catheters properly inside the cavity rather than abutting against the wall (the catheter holes can get blocked by mucosal tissue if they are in close contact with the walls of the viscus).

Flushing of catheters

If Pabd channel fails to register the pressure properly, the rectal catheter may be flushed with fluid to overcome any blockage caused by fecal matter.

Thus, it is indeed possible to collect artifact-free data during cystometry if the above basic techniques are followed. The successful application of these techniques depends, of course, on one's awareness of the existence of artifacts, and the ability to recognize them during clinical testing.

2.3 Pattern Recognition and Classification

The majority of human decision-making processes depend on perception of the environment. The perceptual task, in essence, involves recognition of physical objects or events, and assigning them to one of several predefined categories. Although human beings perform their perceptual tasks with apparent ease, the duplication of such performance with a computer has been anything but simple. This section explores, in brief, the central issue in machine perception — the theory of pattern recognition and classification.

2.3.1 Some Definitions

In this section, some of the basic definitions pertaining to the study of pattern recognition are provided. These definitions are considered in the three principal spaces: pattern space; feature space; classification space [Andrews 1972].

The term *pattern space* refers to the domain which is defined by the data observed from the real world. Its dimensionality is denoted by r. The term *pattern* refers to the physical object or event in the real world that needs to be recognized. The process of assignment of the object or event to one of several predefined categories is known as *pattern recognition and classification*. Each pattern is described by an r-dimensional vector, $\mathbf{P} = (p_1, p_2, \ldots, p_i, \ldots, p_r)'$, called the *pattern vector*. The component p_i of the pattern vector might be any measurable quantity, such as amplitude at a discrete point in

time, brightness or color. Thus, the pattern vector is comprised of scalar values, descriptive of a set of r measurements that define the pattern space.

Each pattern in the pattern space can be described by a set of common properties or attributes called *features*. All the patterns possessing similar values for a set of common features can be grouped together into a single category called *pattern class*. Now, the term *feature space* can be defined as the domain that contains these features. Thus, feature space forms a domain that is intermediate between the data gathering space and the classification process; the r-dimensional pattern vector $\mathbf{P}$ is reduced to an n-dimensional *feature vector*, $\mathbf{X} = (x_1, x_2, \ldots, x_i, \ldots, x_n)'$, where n is much smaller than r. If the pattern space consists of amplitude measurements for example, the components x_i of the feature vector could be such features as maximum amplitude, minimum amplitude, etc. Clearly, the essential objective in defining feature space and the feature vector is to reduce the dimensionality of pattern space while maintaining the discriminatory power of the data.

Classification space refers to the domain that encloses the decisions arising out of the pattern classification process. In other words, it is an M-dimensional space, where M is the number of pattern classes (for example, in an alphabet-recognition task, the classification space is typically 26-dimensional). During the classification process, this space is partitioned into M different regions, and the identity of the pattern is determined by observing its location in the partitioned space. This process can be accomplished by

a device which is either purely hardware-based or software-directed. For the sake of convenience, such a device is referred to as a *pattern recognition system* in this thesis.

2.3.2 Basic Steps in Pattern Recognition

The process of pattern recognition involves three basic steps: sensing; feature extraction; classification [Tou and Gonzalez 1974]. These are described in the following paragraphs.

Sensing involves representation of data that are input to the pattern recognition system. These data are measured from the patterns that are to be recognized, and each measured quantity describes a characteristic of the pattern.

As the name implies, *feature extraction* is concerned with extraction of characteristic features from the input data. This process is often referred to as preprocessing. Here, the extracted features are represented in the form of a feature vector, $\mathbf{X} = (x_1, x_2)'$, where x_1 and x_2 could be, for example, height and weight of an individual.

Classification is concerned with determination of optimum decision procedures that are needed to classify the various observed patterns into different pattern classes. Suppose that there are M pattern classes, denoted by $\omega_1, \omega_2, \ldots, \omega_M$. Then the feature space can be considered as consisting of M different regions, each corresponding to one pattern class. Now, the classification problem consists of generating decision boundaries which separate the M pattern classes on the basis of the values of observed features. Let the decision

boundaries be defined by the functions, $d_1(\mathbf{X})$, $d_2(\mathbf{X})$,..., $d_M(\mathbf{X})$. These functions, called *discriminant functions*, are scalar single-valued functions of pattern **X**. Based on these discriminant functions, the pattern can be classified as follows: if $d_i(\mathbf{X}) > d_j(\mathbf{X})$ for $i, j = 1,2,\ldots,M$, and for all $j \neq i$, then the pattern **X** belongs to pattern class ω_i. The generation of discriminant functions depends on the knowledge available about the pattern to be recognized. When complete *a priori* knowledge about the patterns is available, the discriminant functions may be determined with precision. On the other hand, when only qualitative knowledge about the patterns is available, at best only a reasonable guess of the form of the discriminant function can be made; in this case, the decision boundaries may be incorrect, necessitating a sequence of adjustments to achieve satisfactory performance. In the more general situation where little, if any, *a priori* knowledge exists about the patterns, the pattern recognition system is best designed by using a training or learning procedure. Arbitrary discriminant functions are assumed initially, and through a sequence of iterative training steps, these discriminant functions are made to approach optimum forms.

2.3.3 Design Concepts for Pattern Recognition Systems

The design concepts for automated pattern recognition systems are motivated by the manner in which pattern classes are characterized and defined. There are two main ways of designing a pattern recognition system: membership-roster concept and common-property concept [Tou and Gonzalez 1974]. These are described in the following paragraphs.

When a pattern class is characterized by a roster of its members, pattern recognition may be done on the basis of *membership-roster concept.* All the patterns belonging to each pattern class are stored in the pattern recognition system. When an unknown pattern is shown to the system, it is compared with the stored patterns one by one. If it matches one of the stored patterns, it is classified likewise to that pattern class. Clearly, this approach is simple and economical in its demands on resources if the pattern roster is of modest size. However, it works satisfactorily only under the condition of nearly perfect pattern samples, and has no means for classifying a combination of observations not in the roster.

When a pattern class is characterized by common properties or features shared by all of its members, pattern recognition may be done on the basis of *common-property concept.* The features, characterizing the various classes, are stored in the pattern recognition system. When an unknown pattern is observed by the system, its features are extracted, coded, and compared with the stored features. The new pattern will be classified as belonging to the pattern class with which it shares its features. Here, the main design effort lies in determining the common properties from a finite set of sample patterns known to belong to the pattern classes to be recognized. This approach has two main advantages over the membership-roster concept: the storage requirement for the features of a pattern class is much less than that for all the patterns in the class; since the features of a pattern class are invariant, comparison of features allows variation in individual patterns. As mentioned earlier, it is often extremely difficult, if not impossible, to

determine the complete set of discriminatory features for a pattern class. Therefore, utilization of this concept necessitates careful selection of optimum features.

2.3.4 Implementation of Pattern Recognition Systems

The design concepts for pattern recognition systems, described above, may be implemented by three principal approaches: heuristic; statistical; deterministic. These are outlined briefly in the following paragraphs. Details of these methods can be found in [Fukunaga 1990; Pao 1989; Tou and Gonzalez 1974; Duda and Hart 1973; Andrews 1972].

2.3.4.1 Heuristic Approach

Heuristics are "rules of thumb", derived from human intuition and experience, but not guaranteed to be accurate all the time. The heuristic approach can be applied to membership-roster and common-property concepts. A pattern recognition system designed using this approach generally consists of a set of specifically tailored *ad hoc* procedures. This approach is essentially qualitative and subjective, its structure and performance depending largely on the experience and insight of the system designers.

2.3.4.2 Statistical Approach

Statistical approach to pattern recognition involves formulation and derivation of classification rules in a statistical framework. The statistical methods can be further subdivided into two types: parametric methods; nonparametric methods.

In ***parametric methods***, the conditional probability densities are assumed. The discriminant functions are generally derived on the basis of Bayes' decision theory, which is a fundamental statistical approach to the problem of pattern classification. Bayes' theory is based on the assumption that the decision problem is posed in probabilistic terms, and that all of the relevant probability values are known. The discriminant functions can be linear, quadratic or piecewise linear; generally, linear discriminant functions are chosen for the sake of simplicity. Although conditional probability densities can have various distributions, the normal density distribution is usually assumed because of its analytical tractability. In a two-class classification, the normal density distribution is completely specified by the *mean* and *variance* parameters, whereas, in a multi-class case, it is specified by the *mean vector* and *covariance matrix* parameters. The design of the classifier involves estimation of these parameters from a set of sample patterns.

In ***nonparametric methods***, no assumptions are made regarding the distribution of probability densities. This situation may become necessary when there is a severe limitation on the number of samples that can be obtained, making the assumption of underlying densities difficult. In such cases, density estimates are obtained nonparametrically from a small number of neighbouring samples. There are three main types of nonparametric methods that are of interest in pattern recognition. The first one consists of procedures for estimating the conditional density functions $p(\mathbf{X} \mid \omega_i)$ from the sample patterns; if these estimates are satisfactory, they can be substituted for the true densities in designing the optimal classifier. The second type involves procedures for

directly estimating the *a posteriori* probabilities $P(\omega_i \mid \mathbf{X})$; these procedures bypass probability estimation, going directly to discriminant functions. The third type involves procedures that transform feature space so as to allow employment of parametric methods in the transformed space.

2.3.4.3 Deterministic Approach

Deterministic approach focuses on the design of a trainable classifier. None of the deterministic methods requires knowledge of the forms of underlying probability distributions, and in this sense, all of them can be said to be nonparametric. A trainable classifier is designed by generating discriminant functions from the training patterns by means of iterative "learning" or "training" algorithms. This process involves specifying the form of the discriminant function and then determining its coefficients. Deterministic algorithms are capable of learning the solution coefficients whenever the patterns in the training set are linearly separable (i.e., the decision boundary is a hyperplane) by the specified discriminant functions. The algorithms are deterministic in the sense that they are developed without making any assumptions regarding the statistical properties of the pattern classes. In the next section, the *perceptron approach* is discussed in detail since it is employed in solving the CMG pattern recognition problem.

2.4 Perceptron Approach

The word *perceptron* was coined in the early 1960s [Rosenblatt 1962] to describe a reinforcement learning scheme. The original perceptron model consisted of a network

of multiplying and summing functions. It was envisaged to be a natural and powerful model of machine learning.

The basic model of a perceptron capable of classifying a pattern into one of two classes is shown in Figure 2.2. It consists of an array S of sensory units, which are randomly connected to a second array A of associative units. Each of these associative units produces an output only if enough of the sensory units that are connected to it are activated. The sensory units may be viewed as the means by which the machine receives stimuli from its external environment, that is, its measurement devices, and the associative units as the first stage or input to the machine. The total response of the machine is proportional to the weighted sum of the associative array responses; that is, if x_i denotes the response of the i^{th} associative unit, and w_i is the corresponding weight, then the total response is given by

$$R = \sum_{i=1}^{n+1} w_i x_i = \mathbf{W}'\mathbf{X} \tag{2.1}$$

where $\mathbf{W}$ and $\mathbf{X}$ are the weight and feature vectors respectively.

If $R > 0$, the pattern belongs to ω_1; if $R < 0$, it belongs to ω_2; if $R = 0$, the class membership is indeterminable. Thus, subsequent to the sensory array, the basic perceptron model can be visualized as an implementation of a linear decision function. The model shown in Figure 2.2 can be easily extended to the general multi-class case by increasing the number of units in the R array to M, where M is the number of classes.

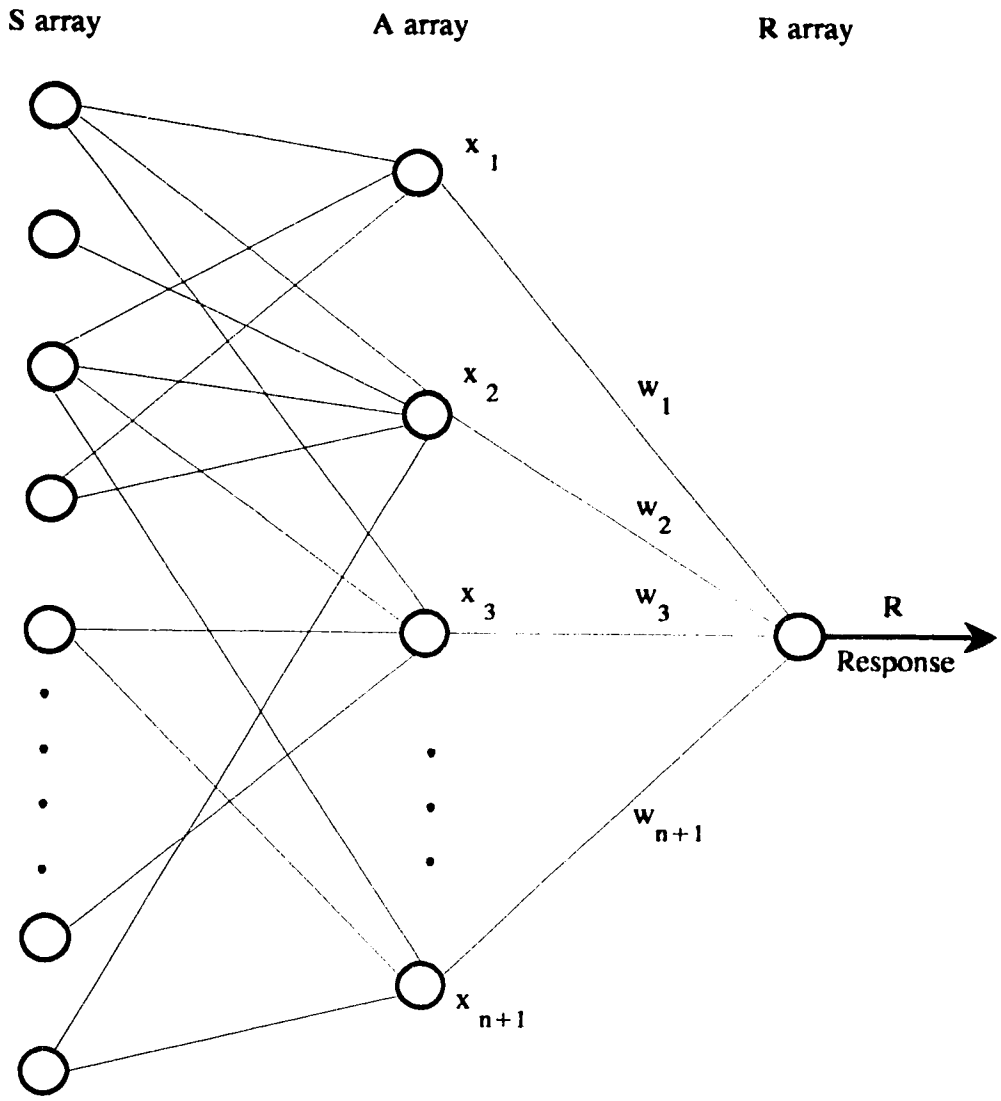

Figure 2.2 Perceptron model

In such a case, responses R_1, R_2,..., R_M are observed, and the pattern is assigned to class ω_i if $R_i > R_j$ for all $j \neq i$.

The original perceptron model was unable to perform certain trivial tasks [Minsky and Papert 1969]. The failure of perceptron in such tasks was attributed to its being *single-layered*, i.e., having only one layer of processing units (in Figure 2.2, R array is the actual processing layer; S and A arrays merely serve to distribute the input). It was concluded that the inadequacies of perceptron could not be overcome even by having multiple layers of processing units between the input and output layers [Minsky and Papert 1969]. Unfortunately, the capabilities of such *multi-layered* perceptrons could not be tested since algorithms for training them did not exist during the 1960s. Recently, perceptron research received fresh impetus with the introduction of a training algorithm for multi-layered perceptrons [Rumelhart et al. 1986]. In spite of some serious criticisms [Minsky and Papert 1988], multi-layered perceptrons have found several applications [Lippmann et al. 1991; Touretzky 1990; Touretzky 1989]; their applications in the biomedical field are reviewed in [Miller et al. 1992].

Although the recent trend in pattern recognition, as evident from the volume of literature published, is focussed on implementation of multi-layered perceptrons, the original single-layered perceptron still remains a simple and valuable tool for solving certain types of pattern recognition problems [Pao 1989]; a couple of recent applications of single-layered perceptron may be found in [Knerr et al. 1992; Chang et al. 1989].

Various algorithms for training single-layered perceptrons have been described from the perspectives of linear discriminant functions [Tou and Gonzalez 1974; Duda and Hart 1973] and neural networks [Aleksander and Morton 1990; Pao 1989; Wasserman 1989; Lippmann 1987]; the discussion that follows reflects the former perspective.

2.4.1 Perceptron Algorithm

The training algorithm for a single-layered perceptron consists of iterative determination of the weight vector **W**. This algorithm, for a two-class case, which is often called the *perceptron algorithm* [Tou and Gonzalez 1974], is stated as follows.

Suppose that the training set of samples consists of patterns belonging to two pattern classes, ω_1 and ω_2. Let $\mathbf{W}(1)$ represent the initial weight vector, which is arbitrarily chosen, and let α be the correction increment (discussed further below). Then, at the k^{th} training step:

if $\mathbf{X}(k) \in \omega_1$ and $\mathbf{W}'(k)\mathbf{X}(k) \leq 0$, then

$$\mathbf{W}(k+1) = \mathbf{W}(k) + \alpha \mathbf{X}(k) \tag{2.2}$$

if $\mathbf{X}(k) \in \omega_2$ and $\mathbf{W}'(k)\mathbf{X}(k) \geq 0$, then

$$\mathbf{W}(k+1) = \mathbf{W}(k) - \alpha \mathbf{X}(k) \tag{2.3}$$

otherwise

$$\mathbf{W}(k+1) = \mathbf{W}(k) \tag{2.4}$$

The training procedure is carried out in several cycles in which all the patterns contained in the training set are presented to the algorithm repeatedly. Each of these cycles is called an *iteration*. The algorithm makes a change in **W** if and only if the pattern being considered at the k^{th} training step is misclassified by the weight vector at that step.

The perceptron algorithm can be expressed in an equivalent form by multiplying the augmented patterns of one class by -1. Thus, arbitrarily multiplying the patterns of ω_2 by -1, the perceptron algorithm can be written as

$$\mathbf{W}(k+1) = \begin{cases} \mathbf{W}(k) & \text{if } \mathbf{W}'(k)\mathbf{X}(k) > 0 \\ \mathbf{W}(k) + \alpha\mathbf{X}(k) & \text{if } \mathbf{W}'(k)\mathbf{X}(k) \leq 0 \end{cases} \tag{2.5}$$

Convergence of the algorithm occurs when a weight vector classifies all the patterns correctly. It can be shown that the algorithm converges in a finite number of iterations if the classes under consideration are linearly separable [Tou and Gonzalez 1974; Duda and Hart 1973].

Several variations of the perceptron algorithm have been formulated, depending on how the value of the correction increment is selected [Tou and Gonzalez 1974; Duda and Hart 1973]. In *fixed-increment algorithm*, α is chosen as some arbitrary positive number, and kept constant. In *absolute-correction algorithm*, α is chosen at each iteration to be just large enough to guarantee that the pattern is correctly classified after a weight adjustment.

In *fractional-correction algorithm*, α is chosen at each iteration such that the weight vector moves closer to the solution vector by some preset positive fraction.

If there are M pattern classes, it can be assumed that there exist M discriminant functions with the property that, if $\mathbf{X} \in \omega_i$, then

$$d_i(\mathbf{X}) > d_j(\mathbf{X}) \quad \textit{for all } j \neq i \tag{2.6}$$

In such a case, the algorithm used to determine these M decision functions may be described as follows. Let there be M pattern classes, $\omega_1, \omega_2, \ldots, \omega_M$. Suppose that at the k^{th} training step, a pattern $\mathbf{X}(k)$ belonging to class ω_i is presented to the machine. The M discriminant functions, $d_j[\mathbf{X}(k)] = \mathbf{W}'_j(k)\mathbf{X}(k)$, $j = 1,2,\ldots,M$, are evaluated. Then, if

$$d_i[\mathbf{X}(k)] > d_j[\mathbf{X}(k)] \quad j = 1,2,...M; \quad j \neq i \tag{2.7}$$

the weight vectors are not adjusted, that is,

$$\mathbf{W}_j(k+1) = \mathbf{W}_j(k), \quad j = 1,2,...M \tag{2.8}$$

On the other hand, suppose that for some s

$$d_i[\mathbf{X}(k)] \leq d_s[\mathbf{X}(k)] \quad s = 1,2,...,M; \quad s \neq i \tag{2.9}$$

Under this condition, the following weight adjustments are made:

$$\begin{aligned} \mathbf{W}_i(k+1) &= \mathbf{W}_i(k) + \alpha\mathbf{X}(k) \\ \mathbf{W}_s(k+1) &= \mathbf{W}_s(k) - \alpha\mathbf{X}(k) \\ \mathbf{W}_j(k+1) &= \mathbf{W}_j(k), \quad j = 1,2,...,M; \quad j \neq i, \quad j \neq s \end{aligned} \tag{2.10}$$

where α is the correction increment. If the classes are linearly separable, it can be shown that the algorithm converges in a finite number of iterations for arbitrary initial weight vectors, $\mathbf{W}_i(1)$, $i = 1,2,\ldots,M$.

2.4.2 Nonseparable Behaviour

The fixed-increment algorithm, described above, provides a simple method for finding a separating weight vector when the samples are linearly separable. It is an error-correction algorithm because the weight vector is modified when and only when an error is encountered. The success of this algorithm on separable problems is largely due to its relentless search for an error-free solution [Duda and Hart 1973].

Of course, even if a separating vector is found for the training samples, it does not follow that the resulting classifier will perform well on independent test data to which it has not been exposed. This leads to the important question of determining the number of patterns required to achieve good generalization properties. The intuitive answer is to choose as many patterns as possible. However, in practice, the question of economics will usually place a constraint on the number of samples that can be gathered, and the computer time that will be available for the training phase. Very few analytical results exist that can be used as a guide in pattern selection. However, in the absence of any probabilistic information, it has been shown that the total number of training patterns chosen for a two-class problem must be at least equal to twice the dimensionality of the feature vector in order to yield meaningful generalization properties [Tou and Gonzalez 1974]. In practice,

it is customary to use several times that many training patterns to overdetermine the classifier, thereby ensuring that the performance on the test patterns approaches that on the training patterns. Unfortunately, the larger the training set the less likely its members are linearly separable [Duda and Hart 1973]. Thus, it is obvious that a suitable compromise between generalization and nonseparability has to be obtained.

Suppose that the designer aims at achieving good generalization by overcoming the economic constraints mentioned above. In such a case, the problem of nonseparability arises, so it is important to know how the error-correction procedure will behave when the samples are nonseparable. Since no weight vector can correctly classify every sample in a nonseparable set, it is clear that the corrections in an error-correction procedure can never cease. The fixed-increment algorithm produces an infinite sequence of weight vectors, any member of which may or may not yield a useful solution. The exact nonseparable behaviour of these algorithms has been studied thoroughly in only a few special cases. It has been shown, for example, that the length of the weight vectors produced by the fixed-increment algorithm is bounded [Duda and Hart 1973]. Empirical rules for terminating the correction procedure are often based on this tendency of the length of the weight vector to fluctuate near some limiting value. From a theoretical point of view, if the components of the samples are integer-valued, the fixed-increment procedure produces a finite-state process. If the correction is terminated at some arbitrary point, the weight vector may or may not be in a good state, making the resulting solution questionable.

In order to overcome the problem of nonseparability, several heuristic modifications of the error-correction procedures have been suggested, and studied empirically. The goal of these modifications is to obtain acceptable performance on nonseparable problems while preserving the ability to find a separating vector on separable problems. Some of the suggested heuristics are given below.

The *average weight vector* heuristic involves averaging the weight vectors produced by the error-correction procedure in the hope of reducing the risk of obtaining a "bad" solution by accidentally choosing an unfortunate termination time [Duda and Hart 1973]. The *variable increment* heuristic involves the use of a variable increment, α, with α approaching zero as the number of iterations, k, approaches infinity. The rate at which α approaches zero is quite important: if it is too slow, the results will still be sensitive to those samples that render the set nonseparable; if it is too fast, the weight vector may converge prematurely with suboptimal results. Two methods of choosing α have been suggested [Duda and Hart 1973]: one is to make α a function of recent performance, decreasing it as performance improves; the second is to set α such that $\alpha(k) = \alpha(k\text{-}1)/k$. Using the heuristic of *number of correct classifications* involves determination of the maximum number of training patterns that are correctly classified by a given weight vector [Tou and Gonzalez 1974]. Since the length of the weight vector fluctuates with each iteration, the one that correctly classifies the majority of the training samples can be retained as the final solution vector. One way to determine such a weight vector is to keep track of the percentage of the correct classifications during the training process.

Chapter 3

PATTERN RECOGNITION SYSTEM FOR CYSTOMETRY

In this chapter, the specific aspects of the research project are considered. The outcome of the project is *CART* (*C*ystometric *A*rtifact *R*ecognition *T*ool), a software-based pattern recognition system. CART employs a trainable classifier based on perceptron approach for recognition of patterns in cystometry. The architecture, design principles, implementation and evaluation of CART are discussed in detail in this chapter.

3.1 An Overview of CART

CART is a set of computer program modules, designed to recognize, on-line, the events and artifacts that occur during the clinical procedure of cystometry. In the description of CART

- the term "on-line" refers to real time processing of data during the course of clinical testing
- the term "event" refers to any physiologic change associated with cystometry, as described in subsections 2.2.3 and 3.2.1
- the term "artifact" refers to any non-physiologic change associated with cystometry that arises as a result of error in data acquisition, as described in subsections 2.2.4 and 3.2.2

It is worth noting here that, while cystometry involves obtaining several parameters besides pressures, CART analyzes only the pressure data to recognize the various events and artifacts.

3.1.1 Architecture

The architecture of CART is shown in Figure 3.1. The figure shows that CART consists of three modules. The input to CART is obtained from the urodynamic equipment (UDE), and the output is displayed on a monitor. While the UDE is itself microcomputer-based, CART as developed in this project runs on its own separate microcomputer. The functions of the various modules are described in the following paragraphs.

3.1.1.1 UDE-CART Interface Module

CART receives cystometric data from the UDE via a serial port after processing by the UDE software. The functions of the interface module include: storage of original data on the hard disk of the CART computer; extraction of the required pressure data from the entire data train; conversion of the extracted data into a suitable format for analysis. The formatted data are then fed into the pattern recognition module for further processing. The interfacing aspects are discussed in greater detail in subsection 3.3.2.

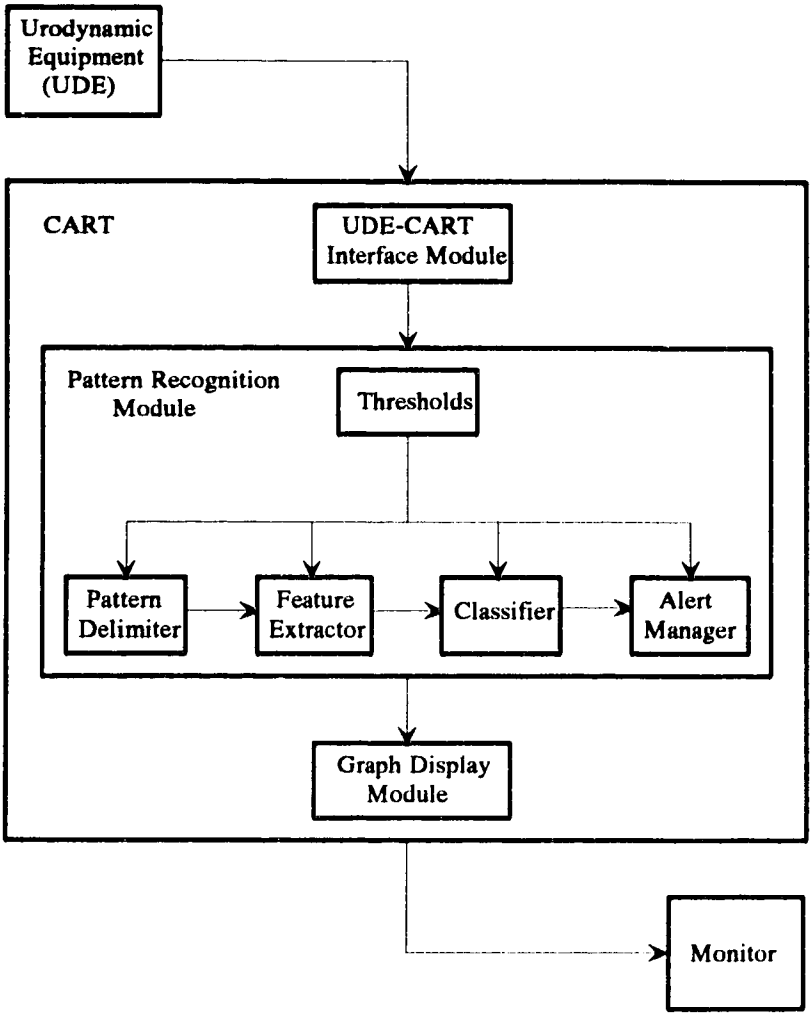

Figure 3.1 Architecture of CART

3.1.1.2 Pattern Recognition Module

This module is concerned with the task of recognition of the patterns in CMG. The task is accomplished by five coordinated submodules: thresholds; pattern delimiter; feature extractor; classifier; alert manager. These submodules are described below.

Thresholds submodule stores the various threshold values of CART. Thresholds are empirically obtained numerical values that serve to partition a set of values into two or more subsets. The thresholds govern almost all aspects of functioning of CART, including demarcation of waveforms, extraction of features, classification of patterns and actuation of alerts. These thresholds are constants relative to the functioning of CART, but depend, to a certain extent, on the hardware characteristics of the UDE.

Pattern delimiter submodule keeps a close track of the pressure parameters, and looks independently at each for the *onset* of any significant waveform suggestive of an event or artifact. If an onset is found, the subsequent data streams are continuously searched to determine the *end* of the waveform. The term *waveform* refers to a segment of the trace in a given channel between the onset and end, and is considered *significant* if it satisfies certain thresholds. The individual tracings in the three channels — Pves, Pabd and Pdet — together constitute a *pattern*. Thus, the basic function of this submodule is to break down the CMG traces into meaningful segments to facilitate further analysis. This initial step of pattern recognition is known as *pattern demarcation*, and is discussed more fully in subsection 3.2.9.

Feature extractor submodule performs the second step of pattern recognition, namely, *feature extraction*. This step involves scanning the demarcated waveforms in the three channels to obtain the values of the features. As mentioned earlier, the term feature refers to a characteristic that is used to describe a pattern. The feature values obtained in this step form the feature vector, which is input to the classifier submodule. The features that describe the CMG patterns are discussed in greater detail in subsection 3.2.6.

Classifier submodule performs the third step of pattern recognition, namely, *classification*. The feature vector, as derived from the previous step, is subjected to mathematical manipulation in order to determine the identity of the observed pattern. Details about the pattern classes and the classification schemes are discussed in subsections 3.2.5 and 3.2.7.

Alert manager submodule issues a message whenever artifacts are detected, so that the person conducting the clinical procedure can take appropriate remedial measures. The process of issuing alerts constitutes the final step of pattern recognition. Essentially, the function of this submodule involves deciding whether an alert should be issued, and if so, the type of alert. Management of alert actuation is discussed in detail in subsection 3.2.8.

From the foregoing discussion, it is clear that the pattern delimiter, feature extractor, classifier and alert manager submodules are activated in a sequential manner in accomplishing the task of pattern recognition. Furthermore, the entire process is governed and fine-tuned throughout, by the appropriate thresholds.

3.1.1.3 Graph Display Module

The output of CART consists of a graphic display of CMG, and a display of messages indicating the identity of detected events and artifacts. The graph display module is concerned with presenting this output to the user. Its main functions include: displaying the intravesical, abdominal and detrusor pressure traces in a scrolling fashion; displaying the identity of detected events and artifacts in the form of visual alerts; issuing auditory alerts if artifacts have been detected. The topics of graphic display and alert actuation are considered in greater detail in subsection 3.2.8.

3.2 Design Principles of CART

This section addresses the major issues involved in the design of CART. The first two subsections provide objective definitions of the commonly encountered events and artifacts in CMG, while the third subsection outlines an expert clinician's approach towards their characterization. From the fourth subsection onwards, the specific design aspects of CART are discussed. In the last subsection, CART's overall logic for recognition and classification of CMG patterns is presented.

3.2.1 Objective Definition of Events

As mentioned earlier, *events* denote physiologic alterations in pressure inside the bladder and the rectum that are observed during cystometry. They represent observations that are of interest to the clinician in the interpretation of CMG. In general, events are positive deflections of the baseline, characterized by an onset point, a rising phase, a peak or plateau, a falling phase and an end point. Events can be *bichannel* (registered in both Pves and Pabd) or *unichannel* (registered in either Pves or Pabd). The commonly encountered events are of five types: cough; abdominal strain; bladder contraction; rectal contraction; minor baseline change.

Examples of the commonly encountered events are illustrated in the form of screen print-outs in Figures A1.1 through A1.5 in Appendix 1. The individual events are described objectively in this section. In the following descriptions, the numerical ranges of amplitude and duration are arbitrary, and are provided only to facilitate easier visualization and differentiation of the individual events in a CMG. Furthermore, it is assumed that all these events start and terminate at the baseline reference point of 0 cm H_2O. It should be noted that the ranges are influenced by two factors: resolution of the urodynamic equipment; calibration of the transducers. The numerical values that are provided correspond roughly to those encountered by CART in the urodynamic equipment in our unit.

3.2.1.1 Cough

This is an event resulting from sudden changes in pressure associated with coughing. Although the event is termed cough for the sake of simplicity, similar changes may be observed with such other manoeuvres as sneezing, blowing nose, etc. Typically, a cough is a positive deflection, and appears "spiky" with a few steep upstrokes and downstrokes. It is a bichannel event, and is registered equally in Pves and Pabd channels, with minimal changes in Pdet. It has an amplitude of at least 10 cm H_2O, and a duration of 1-2 sec. This event is recorded deliberately, several times in each patient, because it helps in: assessing the patency of catheters; demonstrating stress incontinence; demonstrating detrusor instability by provoking an unstable bladder contraction.

3.2.1.2 Abdominal Strain

This occurs as a result of straining, i.e., voluntary contraction of the abdominal muscles. It is due to sudden or gradual changes in pressure, extending over a period of time. It is observed in association with changing posture, speaking, straining to void, etc. Strain is a positive deflection, and extends for a duration longer than a cough. It is a bichannel event, consisting of several upstrokes and downstrokes that are registered equally in Pves and Pabd channels, with minimal changes in Pdet. It has an amplitude of at least 10 cm H_2O, and a duration, greater than 2 sec. Although the clinician usually makes no deliberate attempts to record this event, the presence of abdominal straining during voiding, however, may provide some supportive evidence in favor of voiding dysfunction.

3.2.1.3 Bladder Contraction

This is an event resulting from contraction of the smooth muscle, detrusor, present in the bladder wall. The contraction may occur voluntarily (just before the beginning of void), or involuntarily (as in unstable detrusor contraction). It is a unichannel event that is recorded as a positive deflection in Pves (and hence in Pdet) channel. Typically, the bladder contraction consists of a slow rising phase, a peak, a plateau and a slow falling phase. It has a peak amplitude of at least 15 cm H_2O, and a duration of at least 3 sec in the Pdet channel. This classical description fits many bladder contractions seen in practice. However, it is not unusual to come across bladder contractions associated with some amount of abdominal straining. The timing and morphological characteristics of the bladder contraction provide important clues to the diagnosis of various types of incontinence and urethral obstruction.

3.2.1.4 Rectal Contraction

This is an event resulting from contraction of the rectal wall musculature. It is generally involuntary in nature, and is seen in occasional patients. Since it is a unichannel event that is recorded as a positive deflection in the Pabd channel, the corresponding part of the trace in Pdet shows a negative deflection. The rectal contraction consists of a slow rising phase, a peak and a slow falling phase, stretching for a period of at least 2 sec, with a peak amplitude of at least -5 cm H_2O in the Pdet channel. Although physiological in a strict sense, the rectal contractions do not play any significant role whatsoever, in the

interpretation of CMG. In fact, they might be misleading because of the occurrence of negative traces in Pdet.

3.2.1.5 Minor Baseline Change

On many occasions, pressure changes in the three channels are so small that they cannot be easily categorized into any one of the four events described above. This kind of a situation may arise, for instance, when

- normal respiratory movements are recorded
- a cough has very low amplitude
- an abdominal strain has very low amplitude and short duration
- a rectal contraction has low amplitude and short duration

These examples illustrate only a few situations out of several other similar ones. In all these cases, it is probably more sensible to categorize the observed event into a separate group, indicating the occurrence of a larger than normal excursion of the baseline. Such events (or, more appropriately, "the pressure changes") are termed *minor baseline changes* to signify that they are indeed noticeable changes but not quite convincing enough to be categorized into one of the other types. Theoretically, it may be possible sometimes to characterize these changes more definitively on the basis of the appearance of the trace before and after the occurrence of the pressure changes in question. However, in practice, such an effort is not considered worthwhile because the information provided by these minor baseline changes is generally limited and insignificant.

3.2.2 Objective Definition of Artifacts

As described earlier, *artifacts* are non-physiologic changes that result from malfunction of components in the urodynamic equipment. The commonly occurring mechanical artifacts in CMG can be divided into three main types: step; under-registration; flat trace. Examples of these artifacts are illustrated in the form of screen print-outs in Figures A1.6 through A1.12 in Appendix 1. In the following paragraphs, an attempt is made to provide objective definitions for the various types of artifacts. The comment made in the previous subsection, regarding the numerical ranges of amplitude and duration, applies to the following descriptions as well.

3.2.2.1 Step

A step refers to a jump in the pressure level. It can occur as a result of sudden blockage or relief of blockage in a catheter, or leakage of fluid from the pressure lines. It is recorded in Pves, Pabd or both channel/s as a positive or negative deflection. The changes in Pdet, of course, depend on the extent of registration in the other two channels. Typically, a step consists of a steep rise or fall that plateaus for a long period of time without returning to the baseline. The step artifacts result in baseline shifts that make the subsequent pressure measurements falsely high or low. Thus, whenever steps are observed, it is necessary to flush the catheter/s, or stop the leakage, before proceeding further with the investigation.

3.2.2.2 Under-registration

This refers to partial registration of a bichannel event in one of the channels. It results from partial blockage (for example, from air bubbles) or dislodgement of one of the catheters, or from improper calibration of one of the transducers. Since a bichannel event is supposed to be registered equally in both Pves and Pabd, any of the causes mentioned above results in under-registration of that event in the corresponding channel. Consequently, there is unequal registration in Pves and Pabd, with an abnormally large change in Pdet. Thus, the occurrence of under-registration artifacts calls for appropriate remedial measures such as flushing the catheter, repositioning the catheter or recalibrating the transducer.

3.2.2.3 Flat trace

This refers to total absence of registration in a channel. It is generally due to significant fluid leakage out of the pressure line/s, or to total blockage or dislodgement of the catheter/s. Transmission of pressure from a pressure-generating viscus to a transducer depends on the presence of a fluid column, a patent catheter, and proper placement of the catheter within the viscus. A total compromise in any one of the above factors leads to total failure of registration, so a flat line in the corresponding channel/s. Apart from those due to improper pressure transmission, flat lines may still be traced out under two hardware-related circumstances: (1) when the resolution of the analog-to-digital converter is too coarse to resolve the minute pressure changes; (2) the vertical resolution of the monitor is too poor to display minute pressure changes. The hardware design of our

urodynamic equipment is such that the smallest "jiggle" in the baseline corresponds to a pressure change of approximately 1 cm H_2O. Accordingly, for practical purposes, a flat trace is considered to be present whenever the pressure change remains less than 1 cm H_2O (i.e., "absolutely" flat without any "jiggles") for a sufficiently long duration of time. The presence of a flat trace calls for appropriate remedial measures along the lines described in the previous paragraph.

3.2.3 Recognition of Events and Artifacts: Clinician's Approach

Given the complexities, the process of automated pattern recognition of CMG might seem like an almost impossible task at first glance. However, like most other decision-making processes, this process too can be broken down into simple logical steps. In this section, the rationale behind the decision-making process, the problems encountered, and the criteria for recognition, are discussed.

3.2.3.1 Rationale

From the human perspective, the task of deciding about the identity of a time-varying pattern in CMG (i.e., an event or artifact) can be viewed as a two-step process: recognition of the presence of a pattern; classification of the recognized pattern.

The initial step of *recognition* implies that a pattern has to be positively identified before it can be further characterized. In most cases, the human recognition act depends more on the morphological appearance of the pattern than on anything else. Objectively, this

act of recognition consists of three basic steps: determination of onset of the pattern; determination of end of the pattern; observation of morphological characteristics of the pattern which is delimited by the onset and end points. In short, the process of recognition consists of defining the onset of a pattern, and following the pattern until it reaches the end point.

Once the presence of a pattern has been confirmed, the second step of *classification* can be undertaken, based on an analysis of its characteristic features. The process of classification can be further broken down into three sequential steps: formulation of a set of discriminatory features; extraction of feature values from the demarcated pattern; categorization of the pattern by means of a classification scheme. Thus, it may be seen that the intuitive task of characterizing a pattern can be accomplished by a series of steps occurring in a natural sequence.

3.2.3.2 Some Problems

The natural approach of human beings towards pattern recognition, as outlined above, sounds simple and straightforward. However, adoption of the approach for automated pattern recognition is always fraught with some problems. In relation to CMG specifically, these problems may be summarized as follows:

- the presence of channel multiplicity in CMG entails consideration of all the three channels simultaneously, making the recognition process rather tedious

- considering the amount of data generated per cystometric test, and the number of events and artifacts that may be present, it can be seen that the dimensions of pattern and classification spaces are indeed quite high
- the high dimensionality of pattern space necessitates formulation of a multi-dimensional feature vector to simplify the process of classification; this in turn brings up the problems associated with feature selection
- there is inherent extreme variability in the morphology of the recorded events and artifacts such that it is difficult to define truly objective criteria to characterize them

3.2.3.3 Criteria

Keeping the above problems in mind, and based on the human reasoning process, four major criteria — *amplitude*, *duration*, *slope* and *registration* — have been defined for recognition and classification of the patterns in CMG. Each of these criteria is discussed below. Although the descriptions are applicable to all CMGs in general, some pieces of information such as bit resolution, sampling rate, etc. relate specifically to the urodynamic equipment in our unit.

Amplitude denotes the height of a waveform with respect to a reference line (sometimes referred to as "baseline"), as shown in Figure 3.2. It is expressed in terms of cm H_2O, rounded off to the nearest integer. The value of amplitude varies within the 8-bit range. The interpretation of a waveform is often subjective, especially when there is some

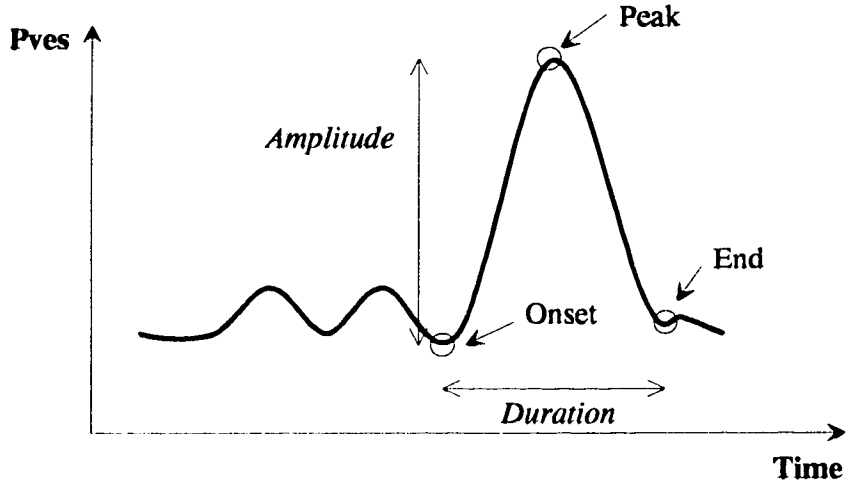

Figure 3.2 Amplitude and duration criteria

amount of uncertainty involved. In such cases, amplitude forms an important visual criterion in determining whether a waveform is significant (i.e., forming a part of an event or artifact), or is merely an insignificant undulation of the baseline.

Duration refers to the time interval between the onset and end points of a waveform (Figure 3.2). It is measured in terms of *data interval*, which is the interval between two consecutive data points. The sampling rate of the urodynamic equipment is 10 Hz, giving a resolution of 0.1 sec for data intervals. The importance of the duration criterion is somewhat similar to the amplitude criterion in determining the significance of a waveform.

Slope refers to rate of change of amplitude with respect to time. The change in amplitude between two consecutive data points is called *first difference* (see Figure 3.3), and is given by the formula

$$\Delta y_i = y_{i+1} - y_i$$

where y_{i+1} is the amplitude of the $(i+1)^{th}$ data point, and y_i is the amplitude of the i^{th} data point. Since the sampling rate is uniform, the first difference is equivalent to slope, and these two terms have been used interchangeably in this thesis. Although slope is an important criterion in visually distinguishing "fast and spiky" waveforms from "slow and smooth" waveforms, it is also useful in the objective assessment of a waveform in terms of defining its onset point, determining its directionality and identifying its different component frequencies.

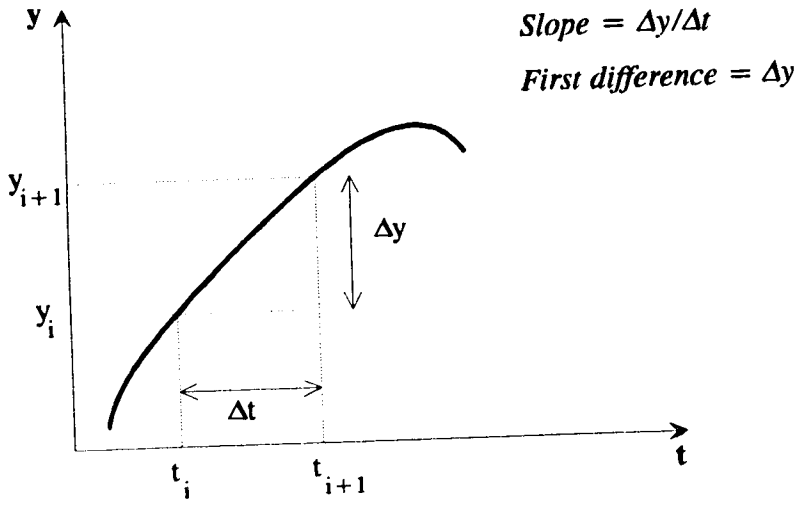

Figure 3.3 Slope and first difference

Registration refers to the extent of manifestation of a waveform in the different channels. From the discussion in subsections 3.2.1 and 3.2.2, it is clear that events and artifacts are channel-specific, i.e., they are registered in either Pves or Pabd channel (unichannel), or in both channels (bichannel). Apart from the mere presence of waveforms, the magnitudes of waveform amplitudes in the two channels are also important in determining registration. The changes in Pdet channel reflect the registration of waveforms in Pves and Pabd channels. Accordingly, Pdet may show minimal variation, or it may show a large waveform with net positivity or negativity, depending on the registration of waveforms in Pves and Pabd channels. In the former situation, waveforms are said to register *equally*, whereas in the latter case, they are said to register *unequally*, in the Pves and Pabd channels. In other words, the equality of registration can be inferred by looking at the magnitude and the direction of the waveform in the Pdet channel. In practice, the registration criterion is assessed by taking into account the amplitudes of the waveforms in Pves, Pabd and Pdet channels in conjunction. The concept of registration is illustrated in Figure 3.4.

So far, the discussion has focussed on the description of various events and artifacts that are commonly seen on a CMG, and their identification by certain empirically-derived criteria. The key issue in this discussion has been pattern recognition and classification from the human perspective. The following paragraphs examine how these general ideas are translated into the design of CART, in which the process of pattern recognition and classification is automated. Furthermore, an attempt is made to capture the meanings

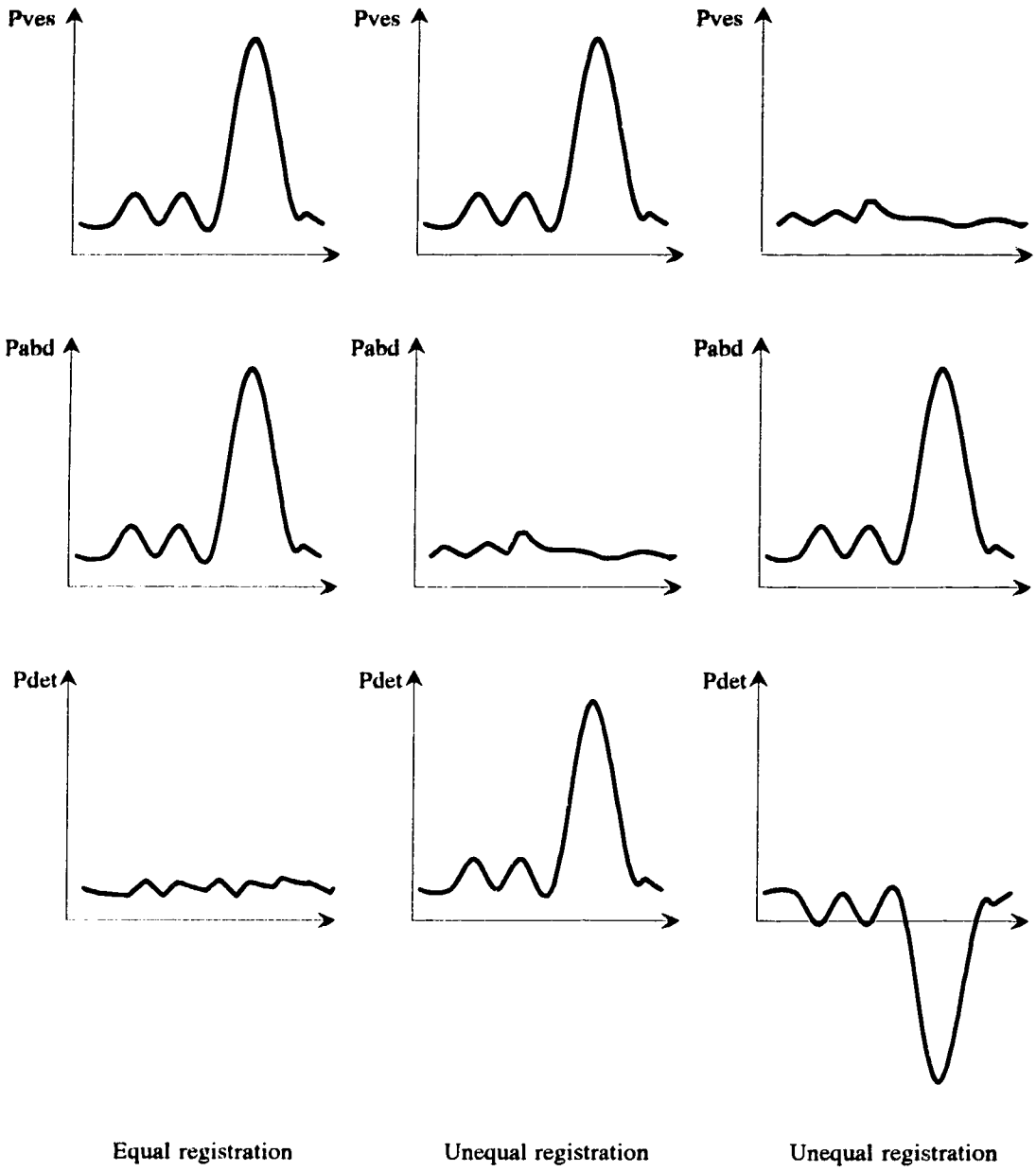

Figure 3.4 Concept of registration

of certain generalized and often loosely-coined terms, discussed above, into the more familiar and well-established jargon of pattern recognition.

3.2.4 Waveforms and Patterns

The distinction between a waveform and a pattern is crucial, so the definitions of the two terms are reiterated here. The term *waveform* refers to a distinctive segment of the CMG trace in a single channel between two points that are separated by a finite interval of time. The first point can be considered as the onset point, and the second point as the end point. Since CMG consists of three pressure channels, there can be three waveforms present at any given interval of time.

In the context of CART, the term *pattern* refers to the composite of the waveforms in the three channels. This definition might immediately bring up the question of whether a pattern has three separate onset points and three separate end points corresponding to different time instants. The answer to this question is no. A pattern has only *one* onset point and *one* end point: the onset point corresponds to the onset point of the *earliest-occurring waveform* suggestive of an event or artifact; and the end point corresponds to the end point of the above waveform. The method of determination of the onset and end points of a pattern is discussed further in subsection 3.2.9.

3.2.5 Pattern Classes

In the light of the definition of pattern class given in subsection 2.3.1, each type of event and artifact can be viewed as a *pattern class* without loss of generality. In order to achieve a higher degree of accuracy, the classes constituting the artifact group were resolved into seven classes instead of three, based on channel specificity of the observed patterns. Finally, a separate class characterizing the presence of flat traces in both Pves and Pabd was also defined. By combining all these classes together, a total of 13 pattern classes (5 of events plus 8 of artifacts) were formulated. Thus, the patterns encountered by CART can belong to one of these 13 classes. The various pattern classes in CART are shown in Table 3.1.

3.2.6 Features

As defined earlier, a feature is as an attribute or property that characterizes a pattern. Conversely, a pattern can be viewed as being characterized by a set of features. In order to accomplish the task of classification, it is important to find a set of discriminatory features that classifies the observed patterns into various classes. In practice, it is often difficult to derive, even with sound empirical judgement, an adequate number of features with sufficient discriminatory power for accurate classification. This fact is especially true when the number of pattern classes is large. Given the 13 pattern classes in CART, it is not surprising that the task of selecting the discriminatory features was indeed a challenging one. The rest of this section addresses the issue of feature selection in CART.

Class number	Character code*	Pattern class
1	C	Cough
2	S	Abdominal strain
3	B	Bladder contraction
4	R	Rectal contraction
5	M	Minor baseline change
6	1	Step in both Pves and Pabd
7	2	Step in Pves
8	3	Step in Pabd
9	4	Under-registration in Pves
10	5	Under-registration in Pabd
11	6	Flat trace in Pves
12	7	Flat trace in Pabd
13	8	Flat trace in both Pves and Pabd

Table 3.1 Pattern classes in CART

* Letters indicate events and numbers indicate artifacts

The task of selecting the suitable features for classification depends on the system designer's thorough knowledge of various patterns and pattern classes. In the design of CART, the feature selection task involved in-depth study of several CMGs, and detailed discussions with an expert clinician. Based on these, some broad conclusions were made regarding the nature of waveforms and patterns. Further refinement of these conclusions was done until a well-defined set of features with sufficient discriminatory power was obtained. Thus, the method of feature selection was *heuristic*, being based on an expert's intuition, "rules of thumb" and empiric judgement. This process involved experimentation with several features. As a result, considerable time was spent before the final feature set was determined.

Using the heuristic approach as described above, ten features were identified. These features were found to be satisfactory in distinguishing the various events and artifacts. The features defined in CART are shown in Table 3.2. The values of the features were obtained by some kind of arithmetic calculation, and were therefore real numbers. These numbers were rounded off to the nearest integer and the absolute values were taken to avoid the negative sign. The positive whole numbers, thus obtained, represented the *actual values* of the features. Since the range of these actual values was quite large, it was rather complicated and imprudent to use them as such in further analysis. In order to overcome this problem, the entire range of actual values was grouped into several continuous subranges or "bins". The number of such "bins" varied from feature to feature, ranging from two to seven. Thus, the entire range of the actual values of the

Number	Feature	Actual value range	Scaled value range
1	Pves height	- 20 to + 235 cm H2O	- 2 to + 3
2	Pabd height	- 20 to + 235 cm H2O	- 2 to + 3
3	Pdet height	- 127 to + 128 cm H2O	- 2 to + 3
4	Width	0 to ∞	0 to 3
5	Slope index	0 to ∞	0 to 3
6	Registration index	0 to ∞	0 to 2
7	Virtual end flag	0 to 3	0 to 3
8	Flat Pves flag	0 to 1	0 to 1
9	Flat Pabd flag	0 to 1	0 to 1
10	Height index	0 to ∞	-3 to + 3

Table 3.2 Features in CART

features was represented on a 7-point "bin" scale, ranging from -3 to +3. Furthermore, for each actual value of the feature, there was a corresponding value on the "bin" scale, known as the *scaled value*. To summarize, for the entire range of actual values, there could only be a maximum of seven scaled values, ranging from -3 to +3. The scaled values of all the features constituted a 10-dimensional feature vector, which was used in classifying the observed pattern. The various features are described below. Again, it should be noted that some of the information provided below is specific to the urodynamic equipment used in our unit.

3.2.6.1 Heights

The height feature is similar to the amplitude criterion discussed in subsection 3.2.3.3. The height in a given channel is, in fact, the *maximum* amplitude of the waveform between its onset and end points. The actual value of height can vary from -20 to +235 cm H_2O in Pves and Pabd channels, and from -127 to +128 cm H_2O in Pdet channel. This range is represented in terms of six possible scaled values. The waveform heights are useful, for example, in distinguishing a "minor baseline change" from cough or abdominal strain.

3.2.6.2 Width

This feature is similar to the duration criterion discussed in subsection 3.2.3.3. It is a quantitative measure of the duration of a pattern in terms of the *number of data intervals* it occupies. As mentioned earlier, a data interval refers to the interval between two

consecutive data points (i.e., 0.1 sec). The actual value of the width of a pattern is quite variable, ranging from under 1 sec to more than 90 sec. This range is represented in terms of four scaled values. Width is an important feature in distinguishing, for example, a cough from an abdominal strain.

3.2.6.3 Slope Index

As discussed in subsection 3.2.3.3, the slope criterion is useful in identifying the component frequencies in a waveform. In other words, the first differences, which represent slope, give a rough approximation of the component frequencies in a pattern. Because of uniform sampling, each waveform can be viewed as being composed of several deflections or *strokes*, each of which occupies one data interval. The individual strokes are labelled "fast" or "slow" on the basis of some slope thresholds. Extending the concept of component frequencies to patterns, it can be readily seen that there are two types of patterns: "fast" patterns (characterized by a predominance of "fast" strokes) and "slow" patterns (characterized by a predominance of "slow" strokes). Although this kind of differentiation sounds artificial at best, it is nevertheless useful in drawing a boundary between some of the patterns at least. The slope index plays a significant role in differentiating a "fast" pattern from a "slow" pattern.

The actual value of the slope index is obtained by multiplying the ratio of the number of "fast" strokes to the number of "slow" strokes with an arbitrary constant. It has four possible scaled values. This feature indicates whether a given pattern is "fast", "slow"

or a mixture of the two. It is useful, for example, in distinguishing a cough (a "fast" pattern) from a bladder contraction (a "slow" pattern).

3.2.6.4 Registration Index

This feature is based on the concept of registration discussed in subsection 3.2.3.3. If the waveforms constituting a "fast" bichannel pattern are registered *equally* in Pves and Pabd channels, then, by definition, the Pdet channel should not manifest any "fast" waveform. Conversely, if the waveforms constituting such a pattern are registered *unequally* in Pves and Pabd channels, then the Pdet channel does manifest a "fast" waveform. Thus, by considering the component frequencies of waveforms in Pves and Pabd in relation to those in Pdet, it is possible to infer about registration. That is, it is possible to determine the number of "fast" equal strokes ("fast" strokes with equal registration) and "fast" unequal strokes ("fast" strokes with unequal registration). In practice, this type of inference about waveform registration has been found to be more useful with respect to "fast" patterns than "slow" patterns.

The actual value of the registration index is obtained by multiplying the ratio of "fast" equal strokes to "fast" unequal strokes with an arbitrary constant. The registration index has three possible scaled values. This feature is useful, for example, in differentiating an under-registration artifact from a cough.

3.2.6.5 Virtual End Flag

This feature is based on the notion that patterns can have a *virtual* end point as opposed to a *real* end point (determination of end points will be discussed in greater detail in subsection 3.2.9). Depending on the onset point/s, the end point/s can be marked in Pves, Pabd or both channel/s. If the end point of a pattern happens to be virtual, the virtual end flag is set. In setting the flag, the slope, amplitude and duration criteria are taken into account. This feature has four scaled values, since the flag can take one of four values depending on whether the virtual end was noted in Pves, Pabd, both or none of the channel/s. If the flag is set in one or both channel/s, it provides a strong evidence for step artifacts, since, by definition, step artifacts are supposed to have a virtual end.

3.2.6.6 Flat Trace Flags

The two features — Flat Pves Flag and Flat Pabd Flag — are derived from a record of the first differences characterizing a pattern. A first difference of zero indicates a flat segment. By counting the number of zero first differences, and comparing it with the number of non-zero first differences, it is possible to determine the occurrence of flat traces. Each of these features can take one of two possible scaled values, indicating the presence or absence of a flat trace in the respective channel. These features are helpful in distinguishing a flat trace from under-registration whenever a bichannel pattern fails to register properly in one of the channels.

3.2.6.7 Height Index

This is mainly a supportive feature, helpful in substantiating the information provided by the three heights and the registration index. The actual value of this feature is obtained by multiplying the ratio of Pves height to Pabd height with an arbitrary constant. The actual value of this feature ranges from 0 to infinity, but there are only seven possible scaled values. In general, a large value of the height index indicates a bladder contraction or under-registration in Pabd, while a small value indicates a rectal contraction or under-registration in Pves.

3.2.7 Classification

Following extraction of features, the pattern is classified on the basis of a decision rule. The decision rule is derived from a discriminant function, which in turn is determined from a suitable classification scheme. In this section, the methods of pattern classification in CART are discussed.

As mentioned in subsection 3.2.5, the patterns encountered by CART can belong to one of the 13 pattern classes. Furthermore, from the discussions in subsections 3.2.1, 3.2.2 and 3.2.3, it is clear that patterns belonging to some of these classes may be identified easily without recourse to sophisticated pattern recognition techniques. Unfortunately, only a few patterns lend themselves to a simpler classification technique, necessitating the adoption of a more flexible technique. In CART, there are two approaches for classification: *classification by counters* and *classification by feature extraction*. These

two approaches will be described below. Before proceeding further, it is important to make one brief comment. It may be recalled that 13 pattern classes were shown in Table 3.1. Out of these 13 pattern classes, patterns belonging to the last class, "Flat trace in Pves and Pabd" are always classified by counters, while patterns belonging to the first ten classes (Cough through "Under-registration in Pabd" in Table 3.1) are always classified by the feature extraction method. However, patterns belonging to the 11^{th} and 12^{th} classes (i.e., "Flat trace in Pves" and "Flat trace in Pabd") can be classified by either method. Accordingly, it should be understood that whenever a reference is made to classification by counters, it implies that the last 3 pattern classes (i.e., the 3 flat trace artifacts) are considered; and a reference to classification by feature extraction implies a consideration of the first 12 pattern classes (i.e., all pattern classes listed in Table 3.1 with the exception of "Flat trace in Pves and Pabd").

3.2.7.1 By Counters

This is a simple intuitive approach towards pattern recognition and classification. This method involves setting up a *counter* to count the number of times a feature, characteristic of a given pattern class, is observed. Then the decision rule can be defined as

$$\mathbf{X} \in \omega_i \quad \text{if} \quad C_i(\mathbf{X}) \geq \theta_i$$

where $\mathbf{X}$ is a pattern (or equivalently, a 1-dimensional feature vector since only one feature is being considered), ω_i is the i^{th} pattern class, $C_i(\mathbf{X})$ is the value of the counter for the i^{th} pattern class, and θ_i is the threshold for the i^{th} counter.

This procedure is implemented by incrementing the counter for each successive occurrence of the single feature characterizing a particular pattern. When the counter reaches its threshold value, the pattern designated by it is inferred, and the counter is reset to zero. Furthermore, if the feature being observed changes its value so as to denote a different pattern, then also the counter is reset to zero. As mentioned earlier, this method of classification by counters is particularly useful in the recognition and classification of flat trace artifacts. In recognizing these patterns, counters are set up to monitor the first differences with a value equal to zero. The occurrence of flat trace is determined based on which counter exceeds the threshold value.

3.2.7.2 By Feature Extraction

This method of classification, as opposed to classification by counters, is fairly sophisticated in terms of its basic theory and the form of decision rule. The implementation of this method involves two main steps: *determination of weight vectors during training* and *determination of class membership during recall.* These two steps are discussed below.

From the discussion in section 2.4, it is evident that determination of the weight vectors is of utmost importance in implementing a trainable pattern classifier based on perceptron algorithm. The weight vectors are determined during training by making an attempt to classify all known patterns in the training set. In CART, the training pattern set consists of several feature vectors, each being a combination of ten features. The process of

training is carried out based on the fixed-increment algorithm as described in section 2.4. The final weight vectors are then stored in a file for use during subsequent recalls (described below).

During recall, CART is required to classify the unknown new patterns by using the stored weight vectors. Whenever the CART program is executed, the stored weight vectors will be read into memory right at the beginning, and will be used for all classification tasks in that session. The program then attempts to detect the presence of a pattern, i.e., it demarcates the pattern by determining its onset and end points. If a pattern has been detected, CART scans that pattern to extract the various features, and combines the extracted features to form the feature vector. The feature vector is then multiplied by each of the weight vectors to form the discriminant functions. Finally, the observed pattern is assigned to the class specified by the discriminant function having the maximum value. It is easily seen that the actual mathematical calculations involved in classification during recall is restricted to a small number of additions and multiplications that are hardly constrained by time in the modern hardware. This fact is important since the process of recall has to be carried out on-line in CART.

3.2.8 Alert Actuation

The main purpose of CART is on-line detection of events and artifacts in CMG. Once detection is done, the examiner has to be alerted so that appropriate measures could be taken. If artifacts have been detected, such measures include flushing the catheter,

repositioning the catheter, etc., as discussed in subsection 2.2.4.4. On the other hand, if events have been detected, no specific measures are necessary, except to notify the clinician that such events have indeed occurred, and that the clinical procedure is progressing as expected. In order to accomplish this task of notifying the clinician, specific alerts have to be issued whenever significant patterns indicative of events or artifacts are detected. The actuation and management of alerts forms the subject of this section.

The types of alerts in CART are based on the two most commonly used modalities of perception — vision and hearing. Accordingly, *visual alerts* and *auditory alerts* are incorporated in CART. The actuation and significance of these alerts will be described below. But before proceeding further with a discussion of alerts, it is helpful to understand what exactly constitutes the output of CART. This topic is discussed more fully in Appendix 2, but the following brief summary should suffice at this point. When CART is executed, the output consists of a graphic display of pressure traces in the three channels — Pves, Pabd and Pdet. These traces are displayed in 3 separate windows called *trace windows*. The traces appear at the right edges, scroll across, and disappear at the left edges of the trace windows. As a consequence of this scrolling, a given point on a trace stays on the monitor screen for a fixed time interval depending on the trace window width. The trace window widths are chosen such that the above time interval ranges from 20 to 30 sec.

3.2.8.1 Visual Alerts

The *visual alert* essentially consists of messages displayed on the monitor whenever an event or artifact is detected. There are two types of these messages. The first message consists of a letter or number, displayed in the *character window*, which is a small rectangular window located on top of the trace windows, and has the same width as the trace windows. The letters and numbers are unique, with the former encoding the events, and the latter, the artifacts. The main advantage of this message is that, the characters are displayed right at the time of detection of events and artifacts, and are scrolled in synchronization with the traces, so that the time relation, between the message and the corresponding event or artifact, is always maintained. The second message consists of the descriptive name of the detected event or artifact, and is displayed in the *description window* located adjacent to the trace windows. This message appears at the time of detection and disappears along with the disappearance of the character in the character window. Thus, the two messages constituting visual alert form a simple yet powerful way of alerting the examiner. However, visual alerts have the disadvantage that the clinician is required to check for messages periodically, which may not always be possible. The various windows, and the visual alert messages in CART are shown in the screen layout of Figure A2.1 in Appendix 2.

3.2.8.2 Auditory Alerts

Auditory alerts have been incorporated to overcome the disadvantage of visual alerts. The auditory alerts are actuated in the form of beeps from the computer's speaker. These

beeps are issued only when artifacts are detected, in order to keep unnecessary arousal in the investigation room to a minimum. Furthermore, the option of completely turning off the auditory alerts is also provided.

3.2.9 Overall Logic for Pattern Recognition and Classification

So far, the discussion in this chapter has focussed on the individual steps involved in the process of pattern recognition and classification by CART. This section provides the overall logic of CART based on the various concepts developed in the preceding subsections.

The flow chart of the process is shown in Figure 3.5. For the sake of simplicity in description, the process has been broken down into 9 major steps. However, it is important to point out that, in some cases, the distinction between the steps is not as clear as brought out in the following account.

(1) ***Initialization***

This step involves initialization of variables, initialization of screen for graphic output and reading of the weight vectors from the disk file into memory.

(2) ***Data input***

This step involves reading the pressure, flow, infused volume, outflow volume and EMG data, from the various channels, as output from the urodynamic equipment. These data

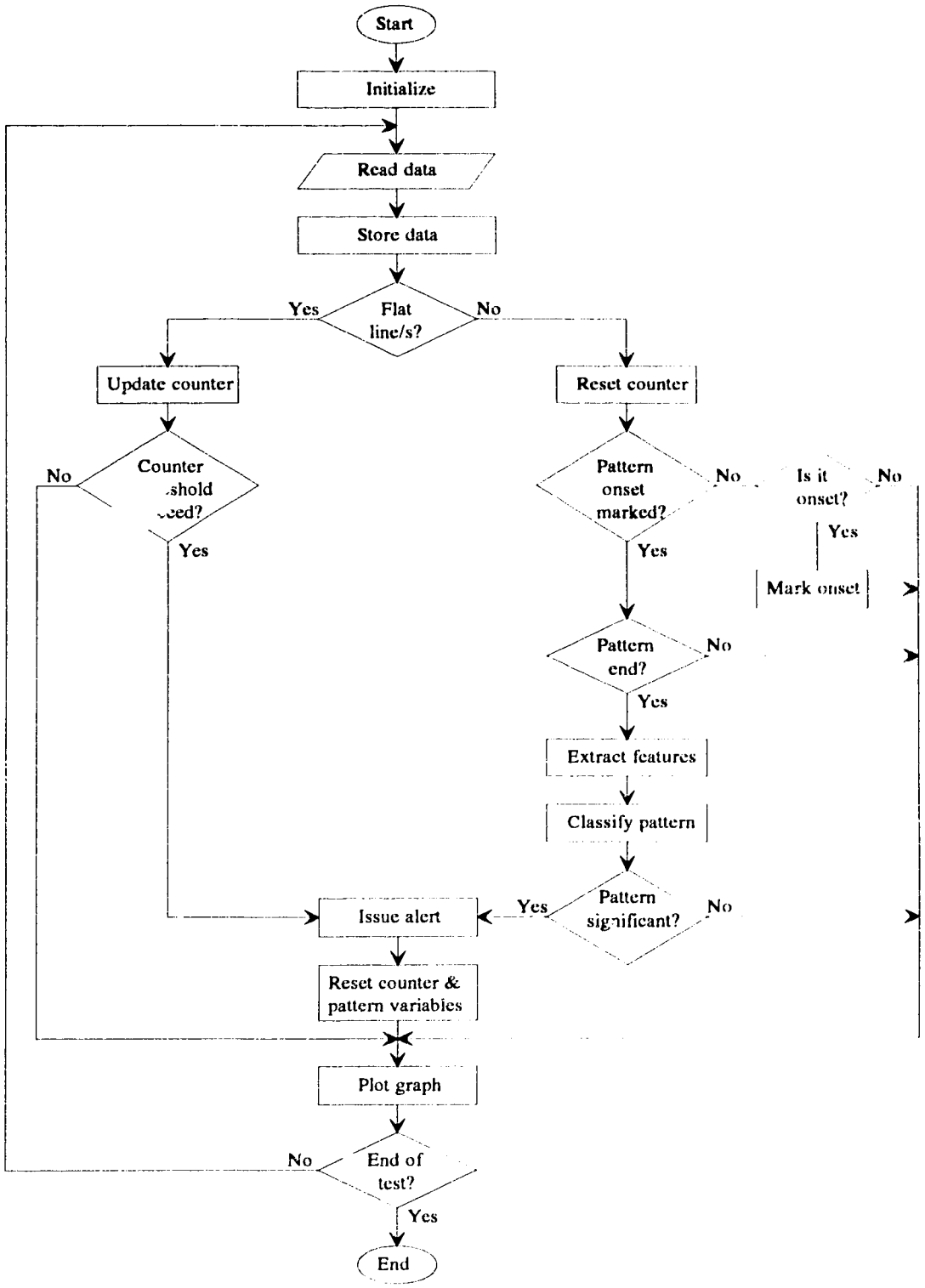

Figure 3.5 Flow chart of pattern classification

are input to CART via a serial port. Since only the pressure data are required for analysis, they are isolated from the original data string, and converted into a format suitable for further processing. These functions are handled by a routine that is bound to differ depending on the hardware and software characteristics of the urodynamic equipment used.

(3) ***Data storage***

In this step, the original data, as output from the urodynamic equipment, are stored on the hard disk to facilitate analysis at a later time. The data are stored in a file bearing the patient's name.

(4) ***Determination of onset***

In order to detect the presence of a pattern, its onset and end points have to be marked. The onset and end points of a pattern are determined from the onset and end points of its constituent waveforms. In the context of a waveform, the term *onset* refers to the very beginning of the waveform, which is distinct from the preceding part of the trace. Onset is said to occur if the first difference between any two consecutive data points exceeds a threshold. The first of the above two points is referred to as the *onset point*. The onset points are marked in Pves, Pabd or both channel/s. Basically, there are two ways of marking the waveform onset points:

(1) If the onset occurs in both Pves and Pabd channels *simultaneously*, the onset points are marked in both channels. In this case, it is important to note that

the two onset points correspond to a single instant in time since they are simultaneous.

(2) If the onset occurs in either Pves or Pabd channel exclusively, the onset point is marked in the channel showing onset. After an onset point has already been marked in one of the channels, if the second channel shows an onset before the end of the first waveform (see below for the discussion on determining the end of a waveform), then the onset in the second channel is ignored.

The single instant in time that corresponds to the marking of the waveform onset point/s is taken as the *onset of the pattern*. Once the waveform onset points have been determined, the amplitudes at these points, the *onset amplitudes*, are calculated and stored for subsequent analysis.

(5) ***Determination of end***

After marking the onset of a pattern, the program continuously searches the subsequent data points to determine whether or not the termination of the pattern has occurred. In the context of waveforms, depending on the channel/s showing the onset/s, the *end* is determined as follows:

(1) If the onset had been marked in either Pves or Pabd channel, the waveform is said to end when the amplitude in that channel at any given instant crosses the onset amplitude.

(2) If the onsets had been marked in both Pves and Pabd channels, then both the waveforms are said to end when the amplitude in either of the two channels at any given instant crosses the onset amplitude in that channel.

The instant in time at which the waveform ends is known as the *end point*, and the amplitude at this end point is known as the *end amplitude*. Like pattern onset, the single instant in time that corresponds to the waveform end point is taken as the *end of the pattern*.

If the pattern terminates in one of the two ways described above, it is said to have a *real end*. However, in some situations, the pattern continues to be active for a prolonged period of time without reaching a real end. When the pattern "levels off" in this manner, and the duration of the pattern from the onset point exceeds a threshold, the pattern is said to terminate with a *virtual end*. Depending on the channel/s in which the onset was marked, the virtual end may be seen in Pves, Pabd or both channel/s. The occurrence of virtual end forms the basis for determining the virtual end flag, a feature that was discussed in subsection 3.2.6.5. Obviously, this step of determining the end of a pattern will be skipped if the onset was not marked at all.

(6) ***Extraction of features***

This step is executed only after the onset of a pattern, and its corresponding end, have been identified. The pattern between the onset and end points is scanned to determine the

scaled values of the ten features. The ten feature values together constitute the feature vector that is passed on to the next step.

(7) ***Classification***

This step is executed only after a pattern has been detected, and its feature vector has been determined. Here, the discriminant functions for all the classes are calculated, and the maximum value is selected. Depending on the decision function with the maximum value, the class membership of the detected pattern is decided.

(8) ***Actuation of alerts***

In this step, a flag is set to issue appropriate alerts to the examiner. The classified pattern is considered to be *significant* if its maximum amplitude and duration exceed the corresponding thresholds. The basic idea behind this is that, when a pattern is significant, it gives a visual impression of "seeing something" rather than a mere fluctuation of the baseline. Since it is desirable to have as few distractions as possible during the course of the clinical procedure, the flags to issue alerts are set only when the detected patterns turn out to be significant.

(9) ***Graphic display***

This step involves display of the pressure traces, and the visual alert messages, if any, on a graphic screen. Furthermore, if the auditory alerts are enabled, they are actuated as well. This step is executed with every data point regardless of the occurrence of onset

of a pattern. In other words, it forms the final common path for the output of CART. The details of screen layout were described in section 3.2.8 and will be considered again in Appendix 2.

3.3 Implementation of CART

The implementation of CART involves 3 main steps: developing the computer program; establishing the interface with the urodynamic equipment; training the system under supervision. The first two steps are discussed in this section; the training aspects of the system are considered along with evaluation in the next section.

3.3.1 Hardware and Software

CART is implemented as a program on an IBM-compatible PC with a 20 MHz 80386 microprocessor having a memory of 2 MB. A hard disk with sufficient space is required for storing data files. A VGA color monitor with a resolution of 640x480 is used for graphic display. These requirements are recommended for a reasonable on-line performance.

CART is a standalone program, the size of the executable code being about 200 KB. It runs under DOS (of Microsoft Corporation). The entire program was written in Turbo Pascal version 6.0 (of Borland International). Pascal was chosen for various reasons such as familiarity with the compiler, structured nature of the language, and powerful debugging facilities. In addition, Turbo Pascal provides a built-in graphic environment,

the Borland Graphic Interface, which is adequate for performing most of the graphics-related functions in CART.

3.3.2 Interface

CART is intended as an application program for enhancing the quality of data collection and interpretation in clinical urodynamic practice. Ideally, CART should form an integral part of the existing software in the urodynamic equipment that performs the tasks of recording, viewing and printing the CMG traces. Since this is not the case at the present time, CART has to be interfaced with the urodynamic equipment. This interface between CART and the urodynamic equipment uses a standard serial port and a custom software.

The urodynamic equipment that is currently used in our unit consists of a device called *UDS-120*, manufactured by Laborie Medical Technologies. UDS-120 uses a 80486-based CPU and a built-in software for data acquisition and processing. Essentially, it samples the analog signals from the various channels at the rate of 10 Hz per channel, digitizes them and displays them graphically on a monitor. Besides data acquisition and display, it also performs such other functions as storage of data, retrieval of data, calculation of certain parameters and printing of results. In addition, the software has the special ability to output the original data on one of its RS-232 ports.

The data output from UDS-120's serial port form the input to CART. The data transfer is achieved by means of a cable between the serial ports of Laborie computer and

CART's computer. The acquisition of these data, and their subsequent processing for pattern recognition, are carried out by the UDE-CART interface module, as described in Chapter 4.

3.4 Evaluation of CART

CART uses a trainable pattern classifier to classify the majority of patterns that it encounters. Accordingly, the ultimate performance of the system depends, to a large extent, on the adequacy of its training. The process of training the system with known patterns is referred to as the *training phase*. Once the system has been trained with an adequate number of patterns, the subsequent stage involves assessment of the performance of the system by presenting it with unknown patterns. This stage is referred to as the *testing phase*. The alternating processes of training and testing may be undertaken several times until the system attains an acceptable level of performance. In this context, the training and testing phases are considered together as the two important aspects constituting the *evaluation* of system performance, although, in a stricter sense, the training phase is actually a part of system implementation. With the understanding that the term evaluation denotes a combination of training phase followed by testing phase, the method of evaluation is described in the following paragraph.

3.4.1 Method

The evaluation of CART is based on the patterns contained in patient data files. These data were obtained from 43 patients who were investigated at the Urodynamics Unit of

the Edmonton General Hospital over a period of 5 months (July to November 1992). Out of these 43 patients, 7 were males and 36 were females, and a majority of these patients had some type of urinary incontinence. These 43 files were divided into 2 sets, *set #1* consisting of 21 files, and *set #2* consisting of 22 files. There were about 2000 patterns in all the 43 files put together.

The actual process of evaluation was carried out in 2 stages. In *stage I evaluation*, set #1 was used as the *training set* (i.e., the patterns in this set were used for training CART), and set #2 was used as the *testing set* (i.e., the patterns in this set were used only for testing the performance of CART). In stage II evaluation, the sets were interchanged such that set #2 served as the training set and set #1 served as the testing set. The results obtained from the two stages were then combined to express the final results of evaluation of CART. This method of evaluation was adopted to offset the problem of inadequacy in the number of testing patterns that would have resulted had either set #1 or set #2 been used alone. In the following paragraphs, some of the issues pertaining to the training and testing phases are explored.

3.4.1.1 Training Phase

For stage I evaluation, 134 patterns were selected for training from set #1, which contained about 800 patterns from 21 data files. Similarly, for stage II evaluation, 158 patterns were selected for training from set #2, which contained about 1200 patterns from 22 data files. Both sets contained patterns belonging to the first 12 pattern classes (other

than the pattern class "Flat trace in Pves and Pabd") in Table 3.1. The training patterns were selected empirically by off-line play-back of the previously recorded CMGs. After selecting the training patterns for each stage of evaluation, the actual training procedure was carried out by using the perceptron algorithm as described in subsection 3.2.7.

3.4.1.2 Testing Phase

For stage I evaluation, 1082 patterns were selected for testing from set #2 of 22 data files, while for stage II evaluation, 751 patterns were selected for testing from set #1 of 21 data files. Thus, on the whole, CART was tested on 1833 (1082+751) patterns. It should be noted that the patterns in the testing sets were not equally distributed among the 12 pattern classes because of the great variation in the frequency of occurrence of these patterns.

Before proceeding with the testing process, certain *criteria* were set regarding the nature of patterns selected for use in testing. All patterns that conformed to these criteria were selected. These criteria are listed below.

- the patterns belonging to the class "Flat trace in Pves and Pabd" were excluded from the testing set because all of them were classified entirely on the basis of counters
- the patterns belonging to the classes "Flat trace in Pves" and "Flat trace in Pabd" that were found to be classified entirely on the basis of counters, were also excluded

- the patterns that unequivocally resulted from calibration of the transducers, which is normally done prior to starting the bladder infusion, were excluded
- the patterns that appeared ambiguous, or otherwise confused the clinician to a considerable extent, were excluded

This pattern selection scheme explains the reduction in the number of patterns that could be used ultimately for testing as compared with the actual number of patterns in the testing sets.

Based on the above criteria, the testing process was performed. It was undertaken at several sittings by an expert clinician at the EGH/Urodynamics Unit. The method of testing consisted of the following four steps.

(1) ***Identification of false negatives***

In this step, the patterns missed by CART but considered significant by the clinician were labelled as false negatives. They were identified with respect to the approximate time of the end points, assigned appropriate classifications, and stored.

(2) ***Identification of true positives***

Here, if CART's classification of a pattern matched the clinician's impression, then the pattern was identified as a true positive, and stored as such.

(3) ***Identification of false positives***

This step is similar to step 2. If a pattern was detected by CART, but the clinician found it to be superfluous, then the pattern was considered to be a false positive, and stored with its classification.

(4) ***Identification of misclassified patterns***

This step is similar to step 2. If there was no agreement between CART and the clinician with respect to the classification of a pattern, then the pattern was labelled as a misclassification. In this case, the wrong classification of the pattern as well as its correct classification, were stored.

It may be noted that no specific attempt was made to identify the *true negatives*, since it was felt that the actual number of true negatives was not required in the derivation of indices of performance (described below).

3.4.2 Indices of Performance

On the basis of the identity of patterns, established during the testing phase, several indices, reflecting the performance of CART, were derived. These *indices of performance* are useful in three ways: expressing the performance of CART objectively; guiding the selection of optimum thresholds; establishing the standards for future development. At present, four indices of performance have been defined: sensitivity; false positivity; concurrence; misclassification. These are described in the following paragraphs.

(1) ***Sensitivity***

This index is a measure of the ability of CART to detect the occurrence of a pattern. It is defined as the ratio of the number of patterns detected by CART to the number of patterns it is supposed to have detected. It is expressed as a percentage, and is given by the following formula:

$$Sensitivity = \frac{Total\ number\ of\ patterns\ according\ to\ CART}{Total\ number\ of\ patterns\ according\ to\ clinician} \times 100$$

(2) ***False positivity***

This index is a measure of superfluous detection of patterns by CART. It is defined as the ratio of the number of false positives to the total number of patterns detected by CART. It is expressed as a percentage, and is given by the following formula:

$$False\ positivity = \frac{Number\ of\ false\ positives}{Total\ number\ of\ patterns\ detected\ by\ CART} \times 100$$

(3) ***Concurrence***

This index is a measure of the degree of agreement between CART's classification and the clinician's impression regarding the identity of patterns belonging to a given pattern class. Since 12 pattern classes are considered for evaluation (the pattern class, "Flat trace in Pves and Pabd", being excluded), there are 12 distinct measures of concurrence. Concurrence is defined as the ratio of the number of patterns classified as belonging to a given class by both CART and the clinician to the number of patterns classified as

belonging to that class by the clinician alone (after excluding the number of false negatives). It is expressed as a percentage, and for a given pattern class ω, it can be obtained from the following formula:

$$\textit{Concurrence } (\omega) = \frac{\textit{Number of patterns classified as } \omega \textit{ by both CART \& clinician}}{\textit{(Total number of patterns classified as } \omega \textit{ by clinician)} - \textit{(Number of false negatives belonging to } \omega\textit{)}} \times 100$$

(4) *Misclassification*

This index is a measure of CART's inability to correctly classify the detected patterns. In other words, it reflects the degree of nonconcurrence between CART and the clinician. If there are two pattern classes, ω_i and ω_j where ($i, j = 1,2,\ldots,12$ and $i \neq j$), a pattern belonging to class ω_i is said to be *misclassifed* as belonging to ω_j, if CART classifies the pattern as ω_j, but the clinician classifies it as ω_i. This situation is notationally expressed as ($\omega_i \rightarrow \omega_j$) misclassification. In principle, since there are 12 classes, a pattern belonging to a given class can be misclassified in 11 different ways. A ($\omega_i \rightarrow \omega_j$) misclassification can be obtained by the following formula:

$$\textit{Misclassification } (\omega_i \rightarrow \omega_j) = \frac{\textit{Number of patterns classified as } \omega_j \textit{ by CART, but as } \omega_i \textit{ by clinician}}{\textit{(Total number of patterns classified as } \omega_i \textit{ by clinician)} - \textit{(Number of false negatives belonging to } \omega_i\textit{)}} \times 100$$

The results of performance of CART, derived from the above indices, are presented in the next chapter.

RESULTS

In this chapter, the results of evaluation of CART's performance are presented. It may be recalled from the discussion in subsection 3.4.1.2 that the essence of testing phase involved identification of false negative, true positive, false positive and misclassified patterns. Once these patterns had been identified, they were saved on the disk as a *.RES* file bearing the name of the patient. Each pattern was stored as a record with two fields: the end position (in terms of data points) and the classification. Furthermore, the false negatives, the false positives and the misclassified patterns were assigned appropriate flags to facilitate easy identification. The results of testing were obtained and stored in the above manner for each individual patient. The individual *.RES* files were then merged into a single composite file.

The information in the composite file was processed in order to obtain a *concurrence-nonconcurrence matrix*, which reflects the extent of agreement and disagreement between CART and the clinician. The concurrence-nonconcurrence matrices obtained for stage I, stage II and the final stage (stages I and II put together) of testing are shown in Figures 4.1, 4.2 and 4.3 respectively.

C = Cough
S = Abdominal strain
M = Minor baseline change
R = Rectal contraction
B = Bladder contraction

1 = Step in Pves & Pabd
2 = Step in Pves
3 = Step in Pabd
4 = Under-registration in Pves
5 = Under-registration in Pabd
6 = Flat Pves
7 = Flat Pabd

* = No pattern detected

		Clinician													
		C	S	M	R	B	1	2	3	4	5	6	7	*	
CART	C	155	0	6	0	0	0	0	0	0	0	0	0	0	161
	S	0	148	0	4	1	0	0	0	4	1	0	0	2	160
	M	0	0	368	7	1	0	0	0	2	5	0	0	0	383
	R	0	0	0	25	0	0	0	0	2	0	0	0	5	32
	B	0	2	2	0	35	1	6	0	0	4	0	0	14	64
	1	0	0	0	0	2	27	1	1	0	0	0	0	3	34
	2	0	1	0	0	0	0	14	0	0	2	0	0	2	19
	3	0	0	0	0	1	0	0	8	0	0	0	0	2	11
	4	0	1	2	1	0	1	0	2	53	1	0	0	8	69
	5	0	1	1	0	0	0	2	0	1	82	0	0	0	87
	6	0	0	0	0	0	0	0	0	0	0	29	0	0	29
	7	0	0	1	0	0	0	0	0	0	0	0	16	1	18
	*	1	2	1	1	5	2	1	1	0	1	0	0	0	15
		156	155	381	38	45	31	24	12	62	96	29	16	37	1082

Figure 4.1 Concurrence-nonconcurrence matrix (Stage I)

C = Cough
S = Abdominal strain
M = Minor baseline change
R = Rectal contraction
B = Bladder contraction

1 = Step in Pves & Pabd
2 = Step in Pves
3 = Step in Pabd
4 = Under-registration in Pves
5 = Under-registration in Pabd
6 = Flat Pves
7 = Flat Pabd

* = No pattern detected

		Clinician													
		C	S	M	R	B	1	2	3	4	5	6	7	*	
CART	C	94	0	0	0	0	0	0	0	0	0	0	0	0	94
	S	0	99	0	2	0	4	0	0	0	0	0	0	4	109
	M	0	0	198	8	3	0	1	0	0	3	0	0	1	214
	R	0	0	1	40	0	0	0	0	1	0	1	0	5	48
	B	0	0	0	0	35	3	2	0	0	1	0	0	2	43
	1	0	0	0	0	1	32	0	1	0	0	0	0	5	39
	2	0	0	0	0	0	0	6	0	0	0	0	0	1	7
	3	0	0	0	0	0	2	0	17	0	0	0	0	1	20
	4	2	3	0	0	0	0	0	0	19	1	0	0	1	26
	5	1	2	2	0	0	1	0	0	0	93	0	0	4	103
	6	0	0	1	0	0	0	0	0	0	0	27	0	0	28
	7	0	0	0	0	0	0	0	0	0	0	0	11	0	11
	*	0	1	0	2	1	1	1	1	0	1	1	0	0	9
		97	105	202	52	40	43	10	19	20	99	29	11	24	751

Figure 4.2 Concurrence-nonconcurrence matrix (Stage II)

C = Cough
S = Abdominal strain
M = Minor baseline change
R = Rectal contraction
B = Bladder contraction

1 = Step in Pves & Pabd
2 = Step in Pves
3 = Step in Pabd
4 = Under-registration in Pves
5 = Under-registration in Pabd
6 = Flat Pves
7 = Flat Pabd

* = No pattern detected

		Clinician													
		C	S	M	R	B	1	2	3	4	5	6	7	*	
CART	C	249	0	6	0	0	0	0	0	0	0	0	0	0	255
	S	0	247	0	6	1	4	0	0	4	1	0	0	6	269
	M	0	0	566	15	4	0	1	0	2	8	0	0	1	597
	R	0	0	1	65	0	0	0	0	3	0	1	0	10	80
	B	0	2	2	0	70	4	8	0	0	5	0	0	16	107
	1	0	0	0	0	3	59	1	2	0	0	0	0	8	73
	2	0	1	0	0	0	0	20	0	0	2	0	0	3	26
	3	0	0	0	0	1	2	0	25	0	0	0	0	3	31
	4	2	4	2	1	0	1	0	2	72	2	0	0	9	95
	5	1	3	3	0	0	1	2	0	1	175	0	0	4	190
	6	0	0	1	0	0	0	0	0	0	0	56	0	0	57
	7	0	0	1	0	0	0	0	0	0	0	0	27	1	29
	*	1	3	1	3	6	3	2	2	0	2	1	0	0	24
		253	260	583	90	85	74	34	31	82	195	58	27	61	1833

Figure 4.3 Concurrence-nonconcurrence matrix (Final)

		Clinician			
		Events	Artifacts	Nothing	
CART	Events	1197	78	33	1308
	Artifacts	39	434	28	501
	Nothing	14	10	0	24
		1250	522	61	1833

Figure 4.4 3x3 Concurrence-nonconcurrence matrix (Final)

		Clinician		
		Events & Artifacts	Nothing	
CART	Events & Artifacts	1748	61	1809
	Nothing	24	0	24
		1772	61	1833

Figure 4.5 2x2 Concurrence-nonconcurrence matrix (Final)

In these figures, the rectangular region bounded by the double lines represents the concurrence-nonconcurrence matrix. In the matrix, the first twelve columns and rows indicate clinician's and CART's classification respectively; the 13th column and row indicate false positives and false negatives respectively. The column of numbers outside the matrix represents the row totals, while the row of numbers outside the matrix represents the column totals. The first 12 elements along the principal diagonal of the matrix indicate the number of instances of correct classification or *concurrence* between CART and the clinician with regard to the 12 pattern classes, while the 13th element, which represents the number of true negatives, is always zero, since no attempt was made to record them. The off-diagonal elements, on the other hand, represent the number of instances of misclassification or *nonconcurrence* between CART and the clinician. The information in Figure 4.3 is simplified, and expressed in the form of a 3x3 table in Figure 4.4, and as a 2x2 table in Figure 4.5.

The concurrence-nonconcurrence matrices were analyzed to obtain the results of CART's performance, which were then expressed in terms of the four indices — sensitivity, false positivity, concurrence and misclassification. The results were obtained individually for stage I and stage II evaluations, and were then combined to obtain the final results. These results are shown in Tables 4.1, 4.2 and 4.3.

Index	%
Sensitivity	
Events	99
Artifacts	98
Overall	99
False positivity	
Events	3
Artifacts	6
Overall	3
Concurrence	
Cough	100
Abdominal strain	97
Minor baseline change	97
Rectal contraction	68
Bladder contraction	88
Step in Pves & Pabd	93
Step in Pves	61
Step in Pabd	73
Under-registration in Pves	85
Under-registration in Pabd	86
Flat trace in Pves	100
Flat trace in Pabd	100
Events	90
Artifacts	85
Overall	87

Index	%
*Misclassification**	
R→S	11
B→M	19
B→1	5
2→B	26
2→5	9
3→1	9
3→4	18
4→S	6
5→M	5
Overall	13

Table 4.1 Results (Stage I)

*The characters represent the following: S=Abdominal strain; M=Minor baseline change; R=Rectal contraction; B=Bladder contraction; 1=Step in Pves and Pabd; 2=Step in Pves; 3=Step in Pabd; 4=Under-registration in Pves; 5=Under-registration in Pabd

Index	%
Sensitivity	
Events	99
Artifacts	98
Overall	99
False positivity	
Events	2
Artifacts	5
Overall	3
Concurrence	
Cough	97
Abdominal strain	95
Minor baseline change	98
Rectal contraction	80
Bladder contraction	90
Step in Pves & Pabd	76
Step in Pves	67
Step in Pabd	94
Under-registration in Pves	95
Under-registration in Pabd	95
Flat trace in Pves	96
Flat trace in Pabd	100
Events	92
Artifacts	89
Overall	90

Index	%
*Misclassification**	
R→M	16
B→M	8
1→S	10
1→B	7
1→3	5
2→M	11
2→B	22
3→1	6
4→R	5
Overall	10

Table 4.2 Results (Stage II)

*The characters represent the following: S=Abdominal strain; M=Minor baseline change; R=Rectal contraction; B=Bladder contraction; 1=Step in Pves and Pabd; 2=Step in Pves; 3=Step in Pabd; 4=Under-registration in Pves

Index	%
Sensitivity	
Events	99
Artifacts	98
Overall	99
False positivity	
Events	3
Artifacts	6
Overall	3
Concurrence	
Cough	99
Abdominal strain	96
Minor baseline change	97
Rectal contraction	75
Bladder contraction	89
Step in Pves & Pabd	83
Step in Pves	63
Step in Pabd	86
Under-registration in Pves	88
Under-registration in Pabd	91
Flat trace in Pves	98
Flat trace in Pabd	100
Events	91
Artifacts	87
Overall	89

Index	%
*Misclassification**	
R→S	7
R→M	17
B→M	5
1→S	6
1→B	6
2→B	25
2→5	6
3→1	7
3→4	7
4→S	5
Overall	11

Table 4.3 Results (Final)

*The characters represent the following: S=Abdominal strain; M=Minor baseline change; R=Rectal contraction; B=Bladder contraction; 1=Step in Pves and Pabd; 2=Step in Pves; 3=Step in Pabd; 4=Under-registration in Pves; 5=Under-registration in Pabd

The calculation of some of the indices of performance are illustrated by the following examples.

From Figure 4.5,

$$\textit{Sensitivity (Overall)} = \frac{1748}{1772} \times 100 \approx 99\%$$

and

$$\textit{False positivity (Overall)} = \frac{61}{1809} \times 100 \approx 3\%$$

From Figure 4.3,

$$\textit{Concurrence (Cough)} = \frac{249}{253 - 1} \times 100 \approx 99\%$$

and

$$\textit{Misclassification } (R \rightarrow M) = \frac{15}{90 - 3} \times 100 \approx 17\%$$

The interpretation of the above results of performance of CART are discussed in the next chapter.

Chapter 5

DISCUSSION

In this chapter, the results of evaluation of CART's performance are discussed. The following interpretations are based on the final results presented in Table 4.3.

CART had an overall sensitivity of 99%. The lowest rate of sensitivity of 93% was found with respect to the class of bladder contractions. CART failed to recognize 6 out of 85 bladder contractions. These bladder contractions were missed mainly because the amplitudes in Pves and Pdet channels failed to reach the threshold levels. A sensitivity index of 94% was observed with step artifacts in the Pves and Pabd channels. This lower index could be due to the fact that the number of testing patterns observed in each of the these two classes was small compared with that observed in the other classes.

CART had an overall false positivity of 3%. The major contributors to false positivity were bladder contractions (15%) and rectal contractions (12.5%). Many times, the bladder contractions and rectal contractions had such low amplitudes that it was hard to distinguish them from normal baseline wander. Furthermore, in such cases, it was not possible to classify the patterns as "minor baseline changes" because they usually had longer durations, violating the definition of a "minor baseline change". Such bladder contractions and rectal contractions were missed altogether, resulting in a diminished

sensitivity. A possible solution to deal with this problem included lowering of amplitude thresholds. Unfortunately, such threshold-lowering efforts resulted in more false positives. Like other pattern recognition systems, CART was not immune to the effects of this inherent inverse relationship between sensitivity and false positivity.

CART had an overall concurrence rate of 91% with respect to events. It showed high concurrence rates for coughs (99%), abdominal strains (96%) and "minor baseline changes" (97%). In the light of concurrence for these events, the concurrence rates for rectal contractions (75%) and bladder contractions (89%) may be viewed as low. These low rates of concurrence were mainly due to the rectal contractions and bladder contractions being misclassified as "minor baseline changes" because of their extremely low amplitudes (see the discussion on misclassifications below).

The overall concurrence rate for artifacts was 87%, with step artifacts showing the lowest rates of concurrence. This rather modest result may be explained by the following reasons without sounding overly defensive. Firstly, as mentioned earlier, the number of step artifacts (especially, "Step in Pves" and "Step in Pabd") in the testing set of patterns was low. This might have been a significant factor in distorting the concurrence. Therefore, it is natural to expect that the concurrence rates for the step artifacts, and hence the overall concurrence rate for artifacts, might have been higher had the testing set consisted of more of such patterns. Secondly, it is important to note that a quarter of the "Step in Pves" artifacts were misclassified as bladder contractions. This disturbing

result is not entirely surprising, and is in fact, readily explainable; it is brought out more fully in the following discussion on misclassifications.

Actually, the concurrence and misclassification rates should be discussed together as a single entity since they assess the same aspect of the performance of CART — the ability to accurately classify the observed patterns. But the two topics are split up and discussed separately mainly for the sake of convenience. Some of the misclassification rates depicted in Table 4.3 that are predictable and explainable are discussed below. It doesn't mean that the ones that are not discussed are unimportant; it only implies that they are either insignificant, or that there are no solid grounds to draw valid conclusions.

The ($R \rightarrow S$) and ($R \rightarrow M$) misclassifications were 7% and 17% respectively. In many cases of rectal contractions misclassified as abdominal straining, there was unmistakable evidence of the rectal contractions being superimposed on straining. In these cases, the rectal contractions were clearly visible in the Pdet channel since the straining component had subtracted out. Unfortunately, CART was not trained to recognize such "mixed" patterns. The majority of the rectal contractions that were misclassified as "minor baseline change" had very low amplitudes, making their distinction rather hazy. In these cases, no attempt was made to rectify the problem by lowering the amplitude thresholds, mainly to avoid increasing the number of false positives.

The 5% of ($B \rightarrow M$) misclassifications were again mainly due to the bladder contractions failing to reach sufficiently high amplitudes. This is similar to ($R \rightarrow M$) misclassification, and, for the reason cited earlier, no attempt was made to rectify this problem.

The ($1 \rightarrow S$) misclassification accounted for 6%. On many occasions, a "Step in Pves and Pabd" artifact and an abdominal strain appear quite similar, the only differentiating feature being that the former has a virtual end, and the latter has a real end. Since the definition of a virtual end is somewhat arbitrary, it is not surprising that some "Step in Pves and Pabd" artifacts tend to get misclassified as abdominal strains.

The ($2 \rightarrow B$) misclassification of 25%, which is by far the highest misclassification rate, certainly deserves special attention. This type of misclassification is predictable because of the striking similarity in the definition of the two pattern classes. In general, the "Step in Pves" patterns are composed of "fast" upstrokes and downstrokes, while the bladder contractions are almost exclusively composed of "slow" upstrokes and downstrokes. Under these general conditions, the distinction is fairly easy, and poses no serious problems. On the other hand, when the "Step in Pves" patterns are predominantly composed of "slow" upstrokes and downstrokes, their distinction from bladder contractions becomes highly superficial; this is more so because the step patterns have a virtual end (which is also consistent with the definition of a bladder contraction). Such "Step in Pves" patterns are frequently encountered during cystometry when the 3-way tap is opened to start the infusion after it had been closed for a while. Here, the pressure

trace in Pves, which had fallen off to a lower value due to closure of the tap and consequent draining away of the fluid, merely "steps up" to its original level. Therefore, these situations do not imply the presence of an artifact (the causes of which were outlined elsewhere), but only serve to indicate the normal response to resumption of filling. Nevertheless, it was indeed very difficult to distinguish objectively such "Step in Pves" patterns from bladder contractions. Accordingly, CART did not reliably learn to classify correctly the "Step in Pves" patterns with a predominance of "slow" upstrokes and downstrokes. In addition, this problem was further compounded by the insufficiency of the number of testing patterns belonging to the "Step in Pves" class. Consequently, the ($2 \rightarrow B$) misclassification rate soared to 25%. In spite of this lengthy and seemingly overdefensive justification, it is still felt that CART ought to recognize the step artifacts correctly, and not just "throw in" bladder contractions at inappropriate times.

To the author's best knowledge, there are no published reports of automated CMG pattern recognition systems such as CART. As a result, there is no "gold standard" against which the performance of CART can be compared. Nevertheless, based on empirical judgement, certain objective criteria were set, and the performance of the system evaluated. From the results of evaluation, it is clear that CART was not perfect in its function. The imperfections were probably inevitable under certain circumstances, as discussed in the previous paragraphs. In the following paragraphs, some general comments on these imperfections, and their practical implications, are noted.

With any machine-based pattern recognition system, it is unreasonable to expect a 100% accuracy in its performance. This statement, by itself, provides some degree of consolation when one takes a look at some of the frustrating results of performance. The preceding remarks can be made about CART too.

The sensitivity and false positivity indices of performance are fairly general in that they are used in the evaluation of almost all pattern recognition systems. On the other hand, the concurrence and misclassification indices are particularly useful in systems such as CART that deal with multiple pattern classes. When there are four indices, the question of which index/indices need/s to be optimized, in order to obtain a true representation of the performance of the system, becomes debatable. In a two-class problem such as recognition of ventricular premature beats as opposed to normal beats in an electrocardiogram, optimization of sensitivity over false positivity may be justified in the light of the life-threatening nature of ventricular premature beats. In CART, however, neither the events nor the artifacts are life-threatening to the patient; the main purpose of the system is to assist the examiner in obtaining valid error-free data. Consequently, it may not matter much if some events and artifacts are missed. Based on this argument, it is probably reasonable to give highest priority to misclassification (and hence to concurrence). However, it is also important to keep in mind the amount of annoyance that might be caused by frequent false positives, and its probable influence on the user acceptability of the system. A consideration of these various factors influenced the selection of thresholds during the testing stages. Accordingly, it is important to view the

results as reflecting an attempt to restore some degree of balance among the various indices.

This point relates to the implication of certain types of misclassifications as exemplified by the following situation. Consider a situation in which there are 4 under-registration artifacts occurring successively as a "group" without any appreciable stretch of baseline separating them. Suppose that one of the under-registrations is misclassified as cough. In this situation, cough will certainly count as a misclassification for testing purposes. However, from a practical standpoint, the misclassification is not very significant because the basic problem of under-registration has already been signalled. Such misclassifications that occur within a "group" of patterns could be considered less important than the misclassifications associated with isolated patterns. Nevertheless, such misclassifications were included in the calculation of the indices.

Finally, CART represents an initial attempt at solving an apparently hitherto untouched problem. Accordingly, the emphasis was entirely on conceptualization of an approach than on improvement of an existing system. So, the current performance should be construed as a benchmark for evaluation of future versions of CART or of other similar systems.

CONCLUSIONS AND FUTURE DIRECTIONS

On the basis of the results and discussion presented in the preceding two chapters, the following conclusions about CART, and its performance, can be made.

(1) It has high sensitivity and moderately low false positivity for recognition of patterns

(2) CART is quite reliable in recognizing coughs, abdominal strains and "Minor baseline changes"

(3) It has a tendency to miss low-amplitude bladder contractions

(4) It has a tendency to misclassify low-amplitude rectal contraction as "Minor baseline change"

(5) It has a tendency to misclassify "Step in Pves" with predominant "slow" strokes as bladder contraction

(6) Irrespective of the numerical values of the indices of performance, CART has been found to be useful clinically, at least in our unit. At the present time, it has not been possible to demonstrate its usefulness in other centers owing to time constraints. However, judging from the amount of positive interest that CART has generated among the urodynamics professionals, it appears that CART has a bigger role to play in clinical urodyanamic practice.

The current status of CART is certainly not the end point of its evolution. CART represents an architecture that is not only currently viable but also has great potential for further growth and development. Future efforts could focus on five broad areas of development: *refinement*; *enhancement*; *integration*; *innovation*; *commercialization*. These are described below.

Refinement

This involves improvement of the existing program in order to achieve a better performance. The improvement could be directed at

- *Pattern demarcation algorithm*

  This involves a better definition of the onset and end points in order to obtain clearly demarcated patterns before proceeding with the classification process.

- *Selection of features*

  This involves an attempt at selecting features that are more discriminatory in separating the individual patterns.

- *Selection of thresholds*

  With more extensive testing and analysis, it is possible to identify the key thresholds that play a major role in the classification process. This effort could guide in the selection of proper values for such thresholds.

- *System training*

  By a careful review of the patterns, a list of patterns truly representative of the various classes could be obtained. Training the system with such

representative patterns might result in a reduction of the misclassification rates.

- *Graph display algorithm*

  In the current version, the relatively slow execution of the graph display algorithm results in loss of some data. Although this not a serious problem at the present time, the data loss could certainly be reduced by a better algorithm.

Enhancement

This involves addition of new capabilities to the program, or using the program in new but related applications. At least two novel ideas are worth pursuing:

- *Automated report generation and printing*

  This involves enhancing the existing automation of the system such that the detected artifacts are eliminated, and only the error-free data are retained in the patient files. With a clear delineation of the events, it is possible to automate the calculation of some of the routinely reported parameters. Furthermore, the final print-out of the study could be made compact and more meaningful by including only the events of significance, and leaving out the artifacts.

- *Decision-support in urodynamics*

  The removal of artifacts coupled with proper identification of events could help in automating the process of interpretation of CMGs. This could be achieved by building appropriate knowledge bases and inference techniques.

Integration

This involves incorporation of the pattern recognition algorithm of CART into the software of the urodynamic equipment. Conceivably, such an arrangement would eliminate the interfacing and graphic display functions of CART. This could solve the problem of data loss experienced with the present system, and possibly result in a better performance.

Innovation

This involves application of different approaches in solving the artifact problem. Based on the concepts regarding the nature of events and artifacts that originated from this research, different types of pattern demarcation algorithms and classification schemes could be tried to achieve the same goals. Such innovations could result in production of robust and reliable urodynamic systems in the future.

Commercialization

The desirable end point of an application-oriented computer program such as CART should be immediate implementation on a wide scale. With this, constructive ideas could be obtained quickly to enable a healthy growth of the software to take place. The key to such an effort lies in commercialization of the product. At present, efforts are underway to promote CART through the commercial route.

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Appendix 1

ILLUSTRATION OF EVENTS AND ARTIFACTS

Figures A1.1 through A1.12 in this appendix show the various events and artifacts that are defined in CART. The diagrams represent enlarged print-outs of the tracings of the examples of actual events and artifacts as seen on the monitor during cystometry. In each figure, the three channels — Pves, Pabd and Pdet — are shown. The *x*-axis in each channel represents time in seconds, and the *y*-axis represents amplitude in cm H_2O. The highlighted part of the trace in each channel represents the corresponding event or artifact as seen in that channel. The complete screen layout is shown in Figure A2.1 of Appendix 2.

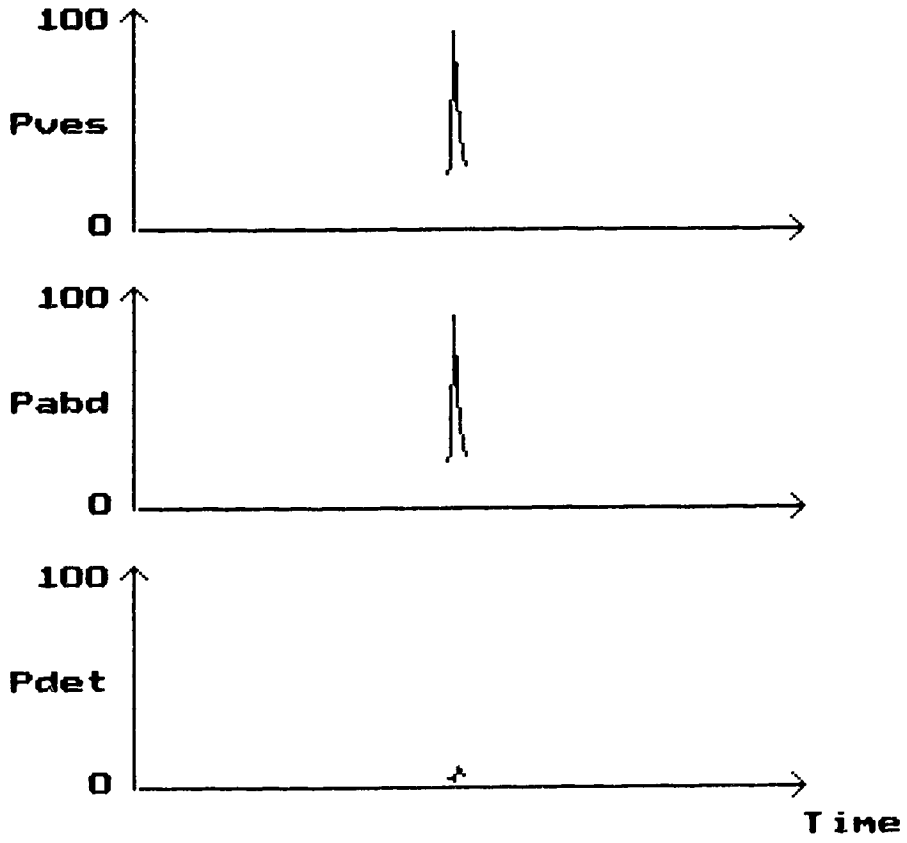

Figure A1.1 Cough

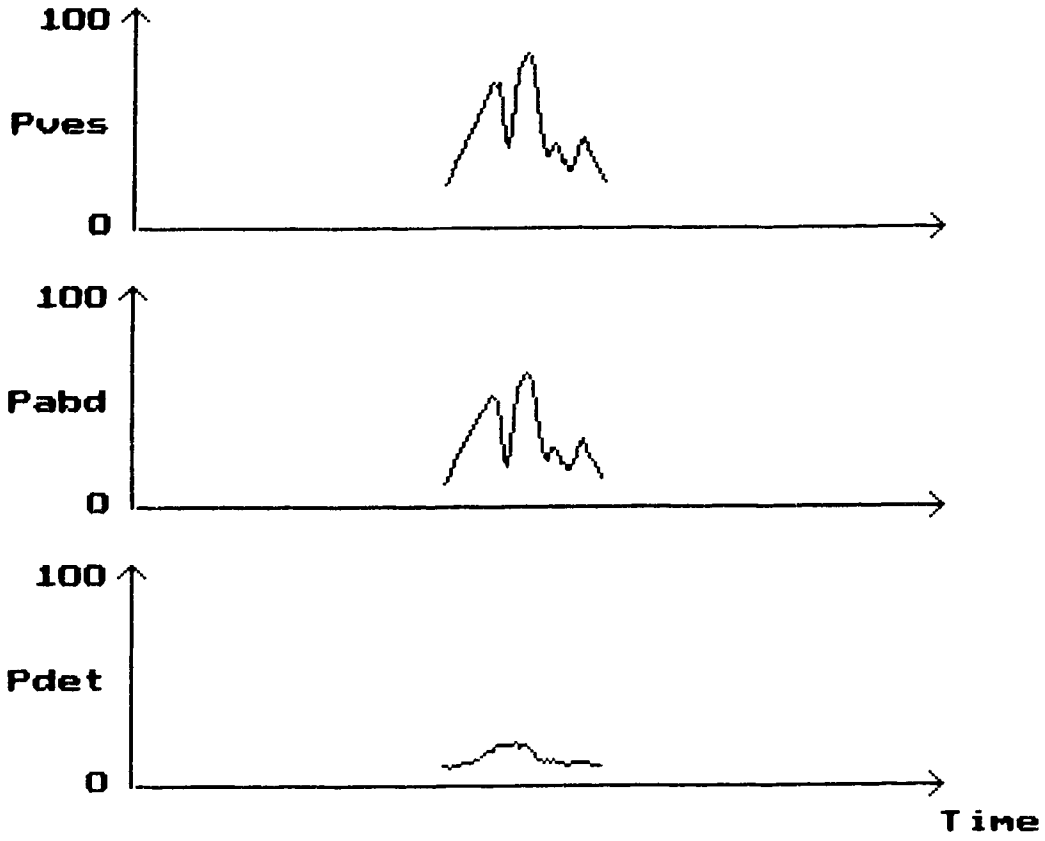

Figure A1.2 Abdominal strain

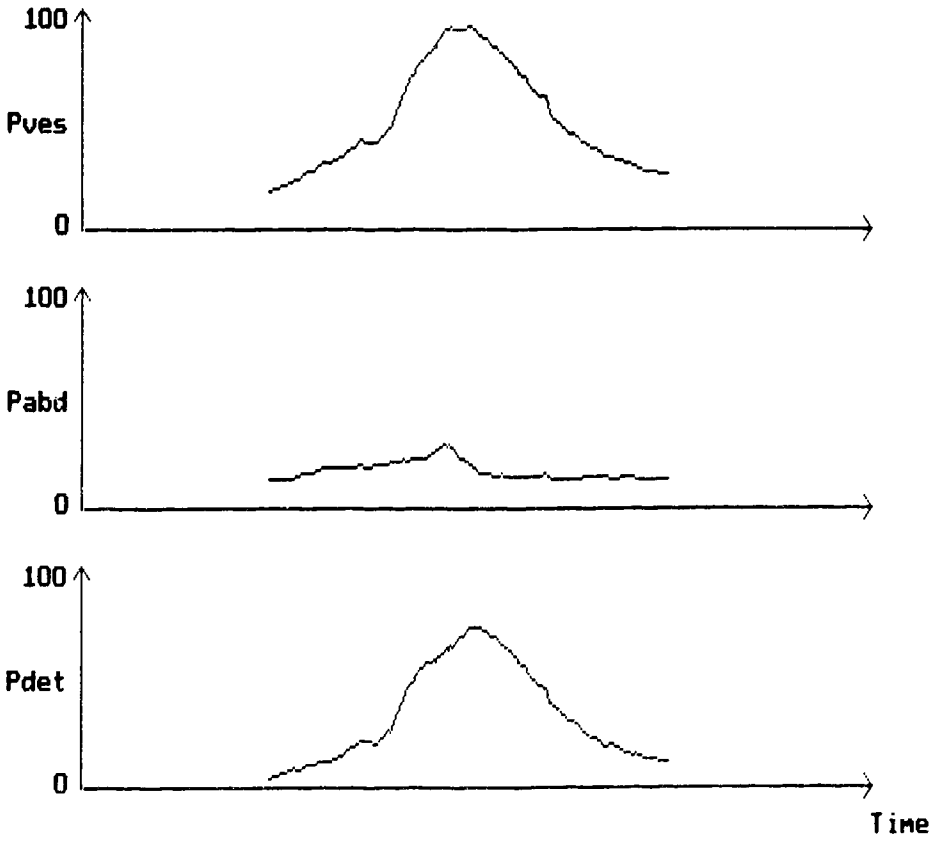

Figure A1.3 Bladder contraction

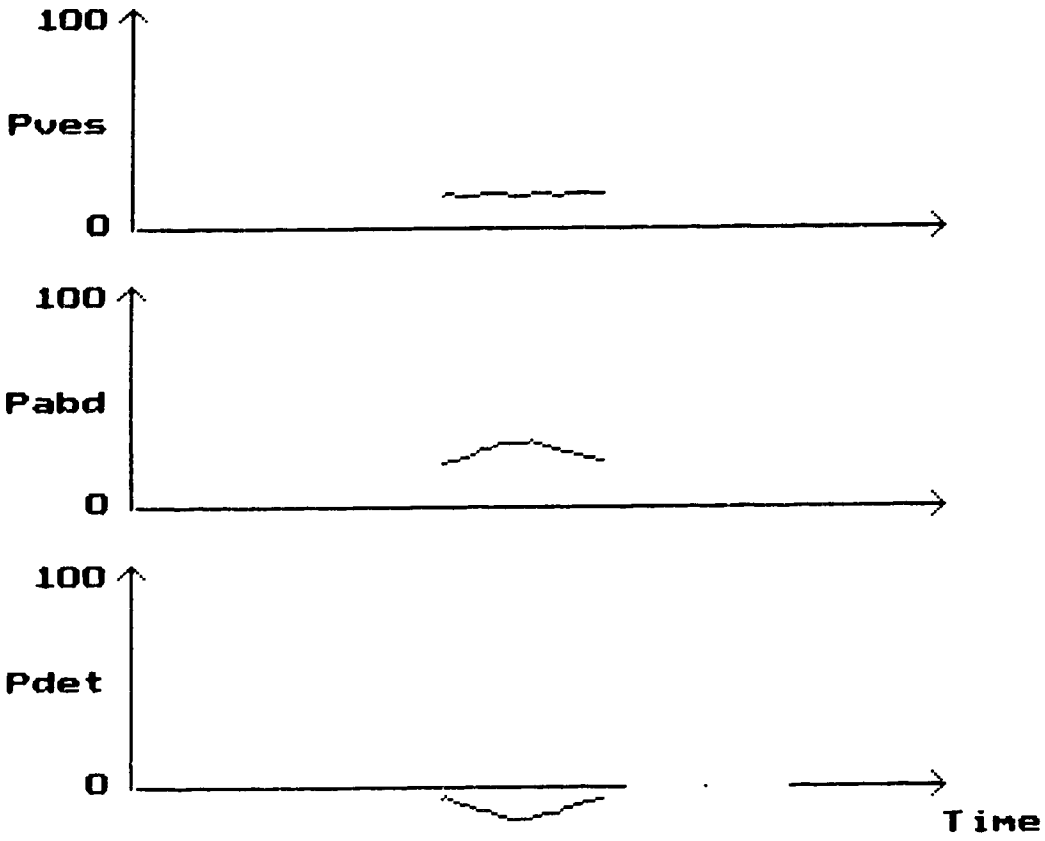

Figure A1.4 Rectal contraction

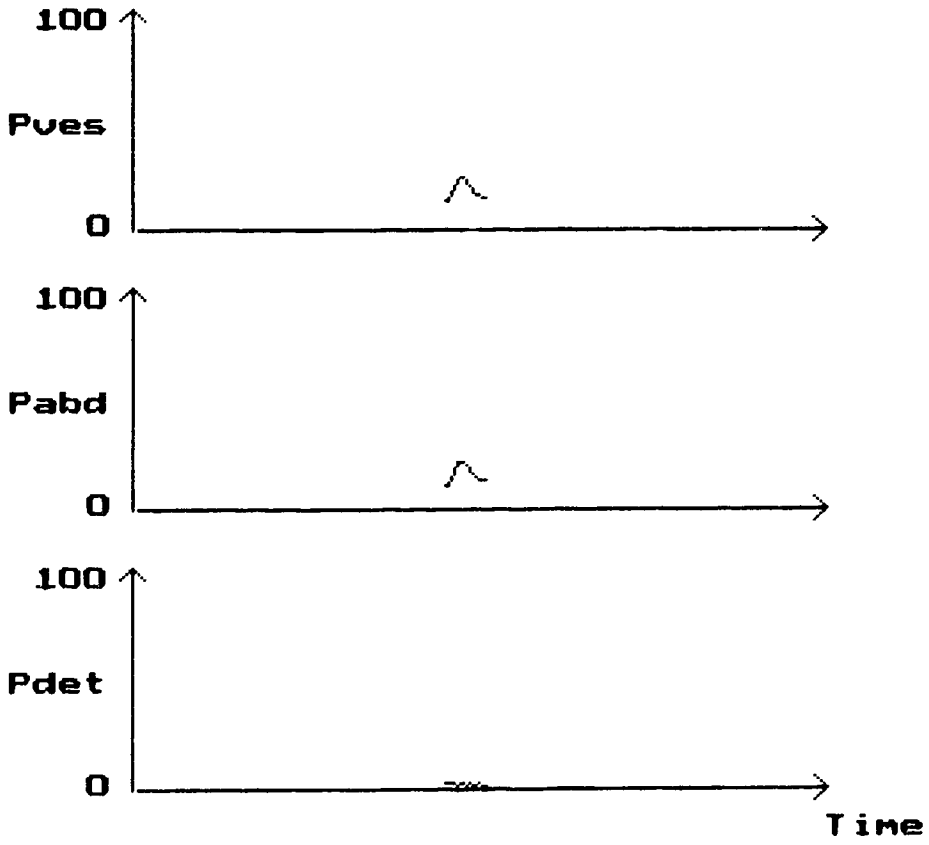

Figure A1.5 Minor baseline change

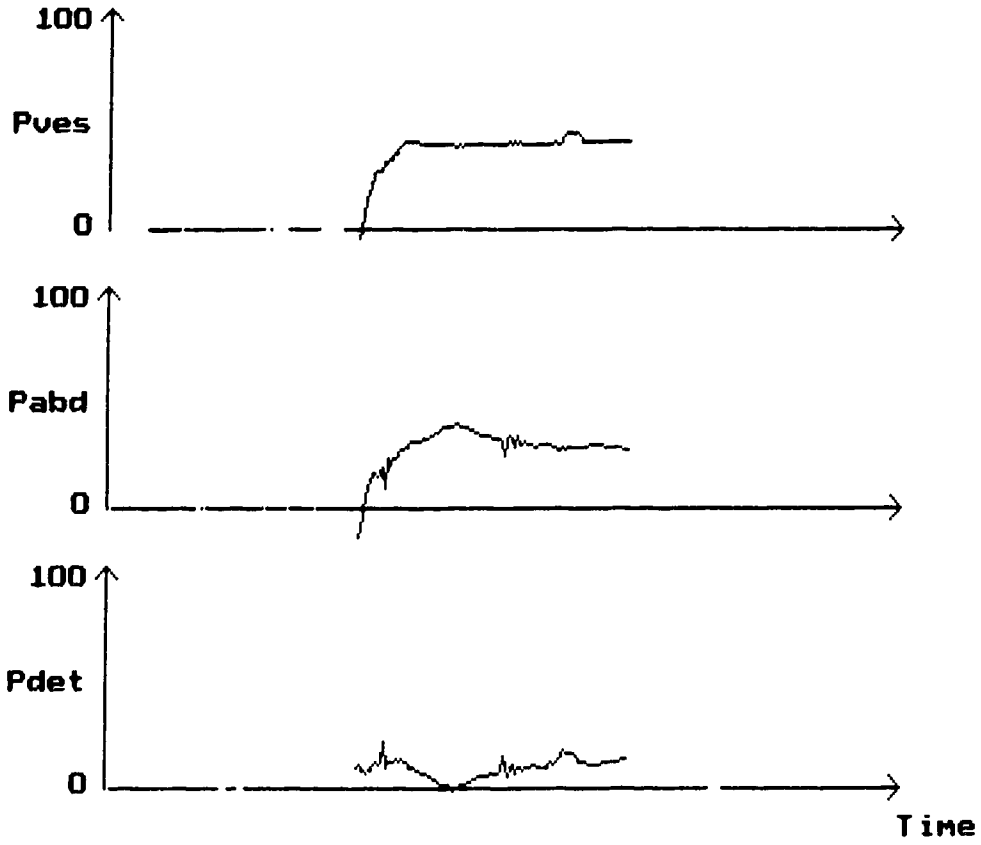

Figure A1.6 Step in Pves and Pabd

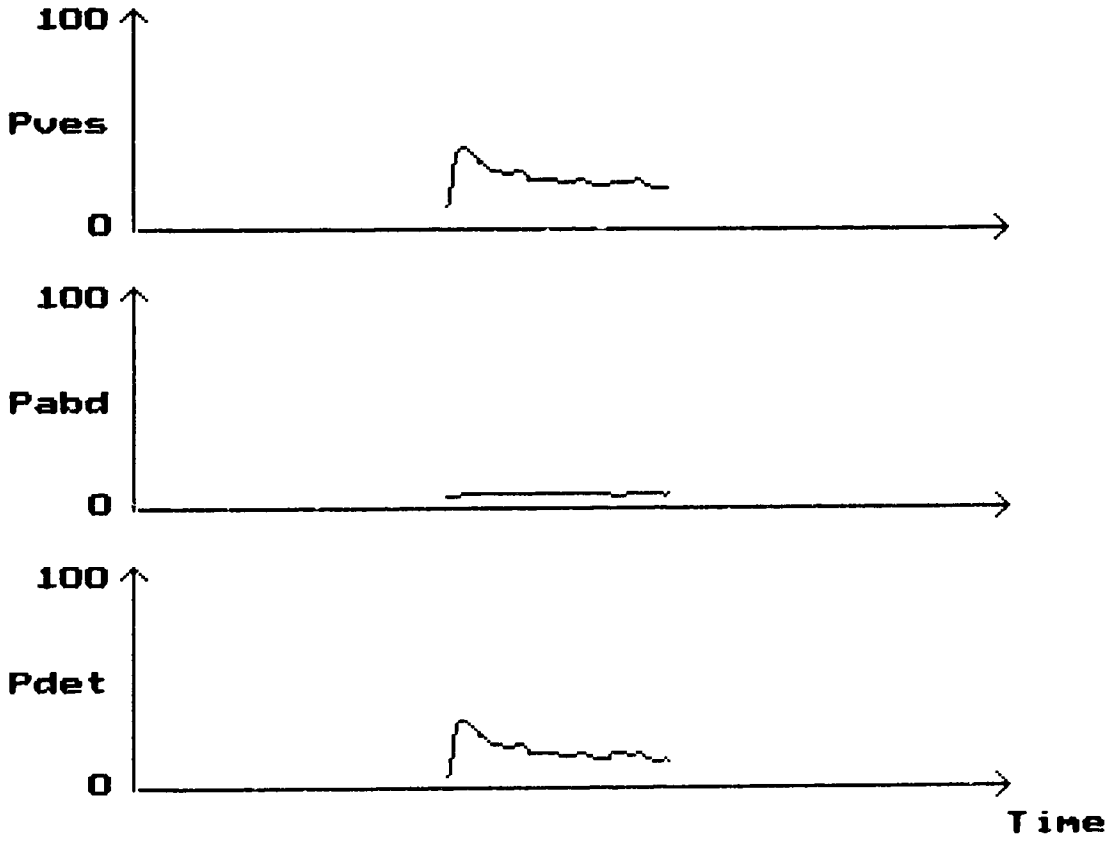

Figure A1.7 Step in Pves

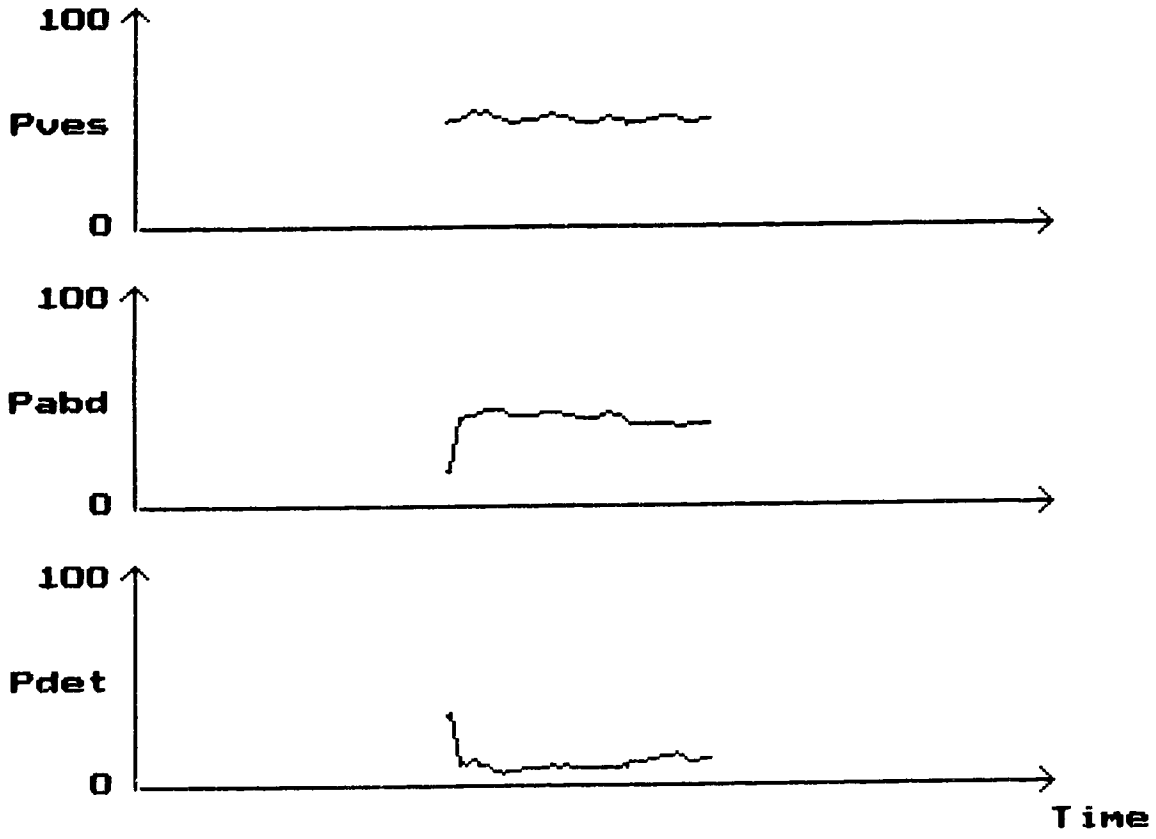

Figure A1.8 Step in Pabd

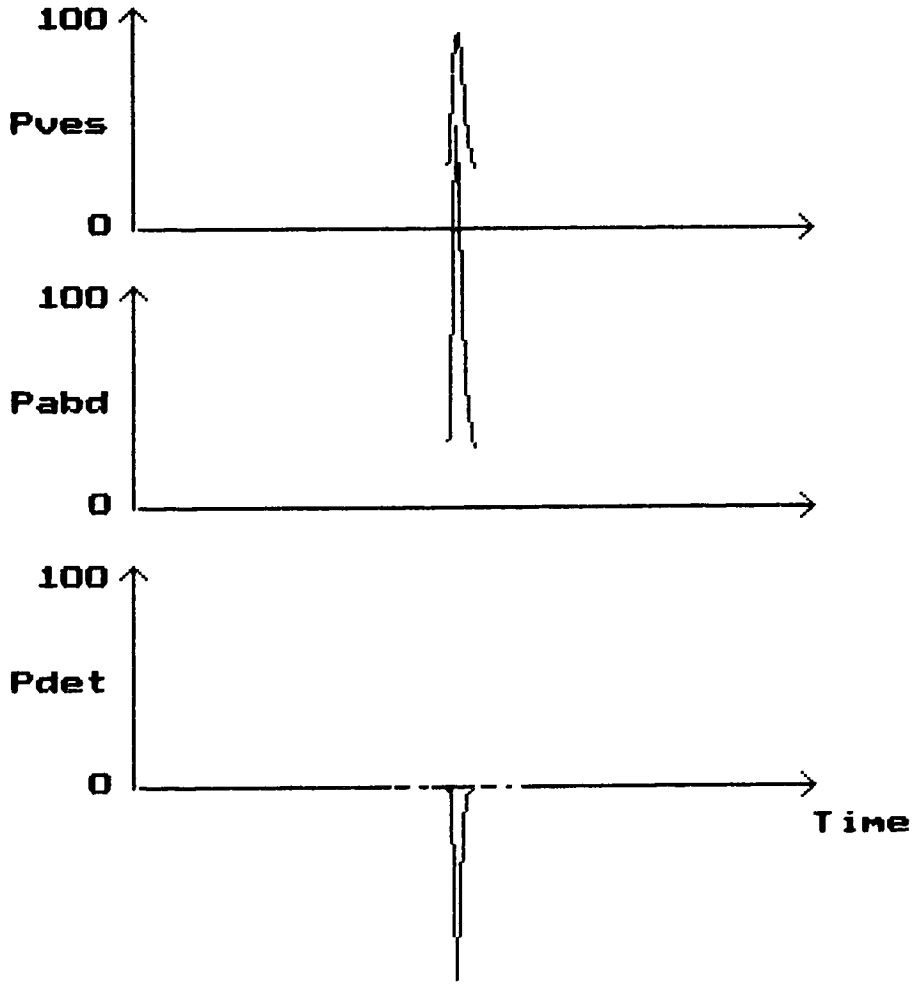

Figure A1.9 Under-registration in Pves

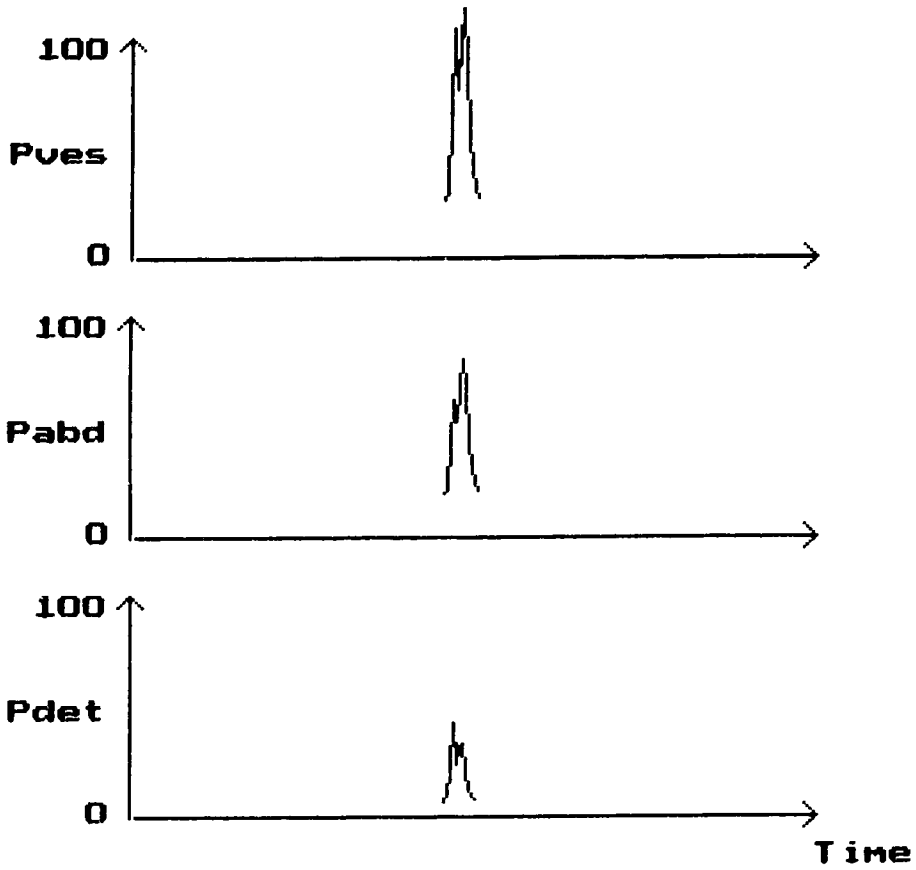

Figure A1.10 Under-registration in Pabd

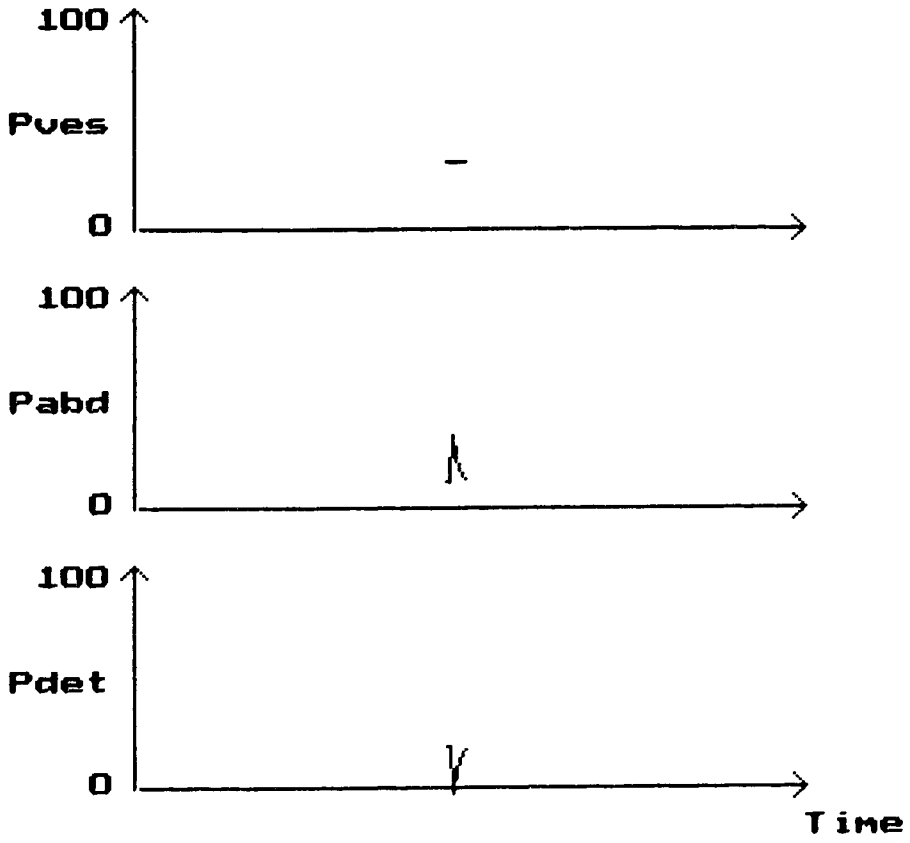

Figure A1.11 Flat trace in Pves

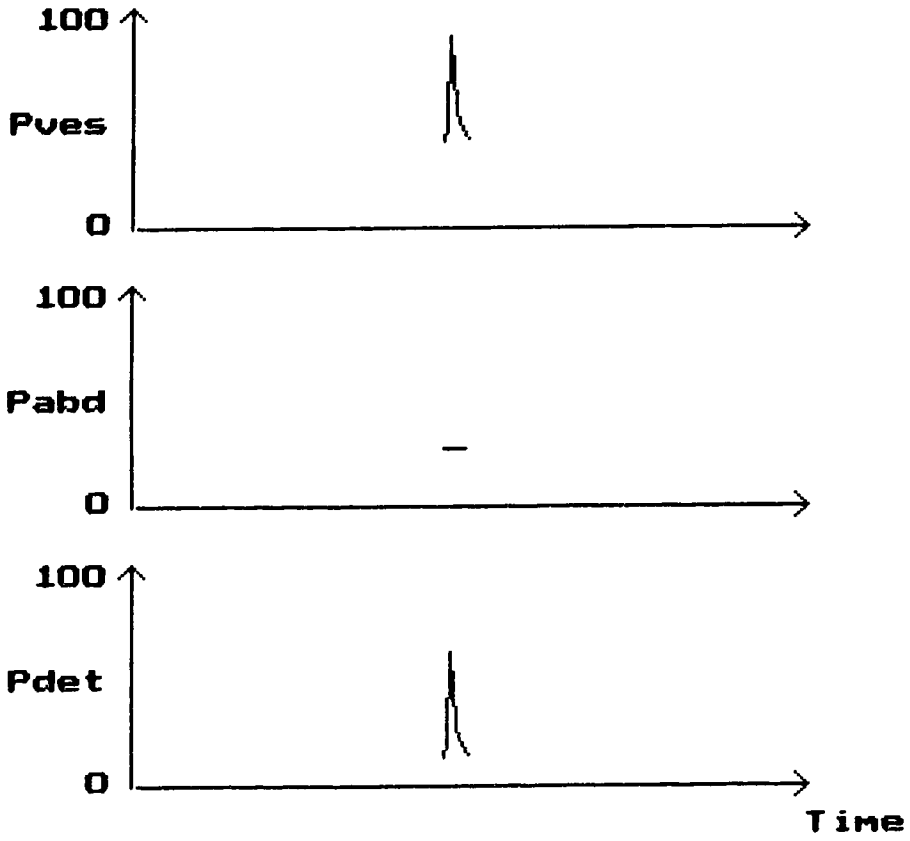

Figure A1.12 Flat trace in Pabd

Appendix 2

USING CART

The primary objective of CART is on-line detection of events and artifacts in CMG. This is achieved by displaying the CMG traces, and pointing out the events and artifacts as and when they occur. Apart from the on-line function, several other related functions are incorporated in CART. In this appendix, the various modes of operation of CART, and their associated functions, are described along with a diagrammatic illustration of the screen layout. Since a separate "user's guide" is not included in this thesis, the following description is intended to serve as a guide for using CART.

The main functions of CART can be listed as follows:

- display of pressure traces
- display of visual alerts
- actuation of auditory alerts
- provision of on-line help
- facility for simulation of events and artifacts
- facility for displaying pressure traces from disk files

CART operates in 3 modes: *on-line mode*; *simulation mode*; *disk mode*. The following general features of CART are common to all modes of operation.

- the screen is laid out in the form of windows
- a menu bar is provided at the top of the screen for accessing the various functions in the pull-down menus
- a status line is included at the bottom of the screen for displaying short help messages
- "hot keys" are provided for quick and easy access to the menu items
- there is provision for switching from one mode to another without exiting the program

A screen layout of CART operating in on-line mode is shown in Figure A2.1. In the figure, the following windows are shown:

- ***Title window***

  It is at the top, displaying the message *CART*.

- ***Menu bar***

  It shows the menu items - A (System), *File*, *Options*, *Help*, *Simulate* and *Graph*; the Graph item is active

- ***Character window***

  It displays the character *C*, indicating the presence of the event, cough.

- ***Description window***

  It displays the message *C Cough*, indicating the presence of the event, cough.

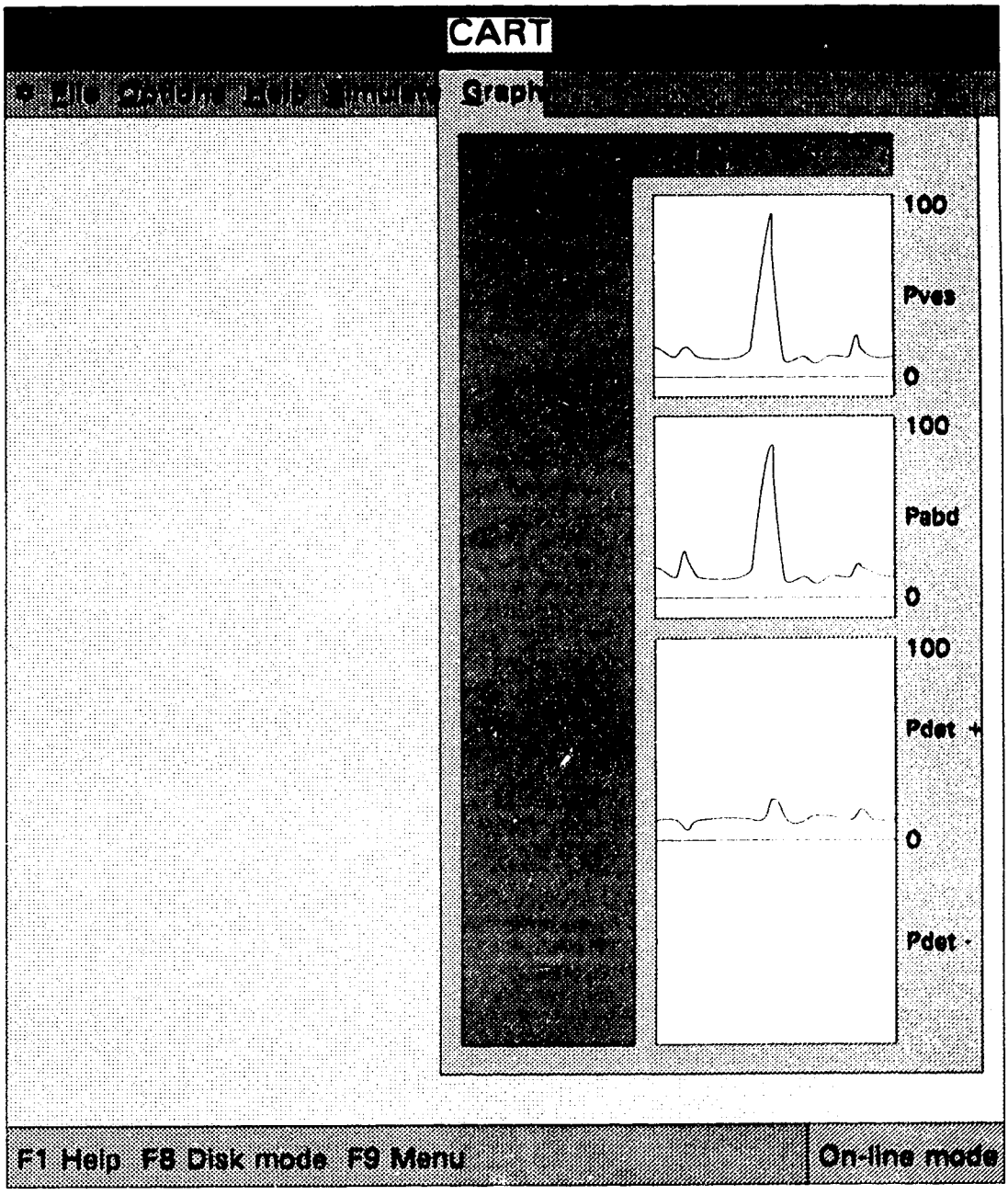

Figure A2.1 Screen layout in CART

- ***Trace windows***

  These are the 3 windows that display the pressure traces in the 3 channels: *Pves*, *Pabd* and *Pdet*.

- ***Status line***

  It displays the "hot keys", namely, *F1 Help*, *F8 Disk mode* and *F9 Menu*, and the current mode of operation, the *on-line mode*.

The modes of operation of CART are described in the following paragraphs.

On-line Mode

In the on-line mode of operation, CART is used along with UDS-120 during the actual cystometric procedure. Before selecting this mode, it is important to ensure that the connection between UDS-120 and CART is established, and that UDS-120 is running and transmitting the data. On selecting this mode, the user is prompted for the name of the patient. Once the patient's name has been entered, the program begins to plot the pressure traces from Pves, Pabd and Pdet channels. These traces are displayed in the trace windows as described earlier. The heights of these trace windows are large enough to represent the *Pves* and *Pabd* pressures in the range of -20 to +235 cm H_2O, and the *Pdet* pressure, in the range of -127 to +128 cm H_2O. The traces are made to scroll from right to left in order to conform to the natural human tendency of reading the traces from left to right. As a consequence, the traces appear initially at the right edges, move across, and disappear at the left edges of the trace windows. Although the window width

is not adjustable, it is ensured that the traces remain visible for a sufficient length of time before their disappearance at the left edge.

Whenever events or artifacts are detected, visual alert messages are displayed in the character and description windows. Furthermore, auditory alerts in the form of beeps, are actuated when artifacts are detected.

The other important function in CART is provision of on-line help. In addition to the basic help messages displayed on the status line, more elaborate help texts are incorporated in the program. These help texts are accessible in a context-sensitive manner, and are displayed in the special *help windows*. Help is available on a wide range of topics, such as modes of operation, description of events and artifacts, etc.

Simulation Mode

In the simulation mode, the generation of intravesical and abdominal pressures is simulated by squeezing saline bags connected to the transducers. The methods for simulating the various events and artifacts are defined, and they can be accessed whenever required. However, it should be noted that the results obtained with simulation might be considerably different from those obtained from a patient in an actual clinical setting, due to the highly artificial nature of simulation. Hence simulation does not carry much significance; it is useful for demonstration purposes, particularly since it is real-time.

Disk Mode

The disk mode of operation consists of reading the actual patient data stored in disk files, and displaying them in the same manner as the on-line mode. Essentially, this involves a play-back of the previously recorded data. Thus, it is important to note that the disk mode is off-line unlike the other two modes; it is mainly useful for demonstrating the program's capabilities and for reviewing a case.