[7] J. H. Battocletti, A. Sances, Jr., S. J. Larson, R. E. Halbach, S. M. Evans, R. L. Bowman, and V. Kudravcev, "A review of NMR techniques applied to biological systems," in *Biologic and Clinical Effects of Low-Frequency Magnetic and Electrical Fields*, ch. XXII, J. G. Llaurado *et al.*, eds. Springfield, Illinois: C. C. Thomas, 1974.
[8] P. Buchman, "NMR blood flowmeter," M.S. thesis, Univ. of Washington, 1959.
[9] J. R. Singer, "Biological flow and process tracing using nuclear and electron paramagnetic resonance," *IRE Trans. Med. Electron.*, vol. ME-7, pp. 23–28, Jan. 1960.
[10] A. I. Zhernovoi and G. D. Latyshev, *NMR in a Flowing Liquid*, p. 98, trans. by Consultants Bureau, Plenum Press, 1965.
[11] O. C. Morse, III, "NMR blood flow measurements," Ph.D. thesis, pp. 20–21, Univ. Calif. (Berkeley), 1970.
[12] A. G. Anderson and A. G. Redfield, "Nuclear spin-lattice relaxation in metals," *Phys. Rev.*, vol. 116, pp. 583–591, 1959.
[13] S. H. Koenig and W. E. Schillinger, "Nuclear magnetic relaxation dispersion in protein solutions—I. Apotransferrin," *J. Biol. Chem.*, vol. 244, pp. 3283–3289, 1969.
[14] A. S. Mildvan and M. Cohn, "Aspects of enzyme mechanisms studied by nuclear spin relaxation induced by paramagnetic probes," *Advances Enzym.*, vol. 33, pp. 1–70, 1970.
[15] B. Sheard and E. M. Bradbury, "NMR in the study of biopolymers and their interaction with ions and small molecules," *Progr. Biophys.*, vol. 20, pp. 187–246, 1970.
[16] J. A. Walter and A. B. Hope, "NMR and the state of water in cells," *Progr. Biophys.*, vol. 23, pp. 1–20, 1971.
[17] M. J. Tait and F. Franks, "Water in biological systems," *Nature*, vol. 230, pp. 91–94, 1971.
[18] O. Jardetzky and N. G. Wade-Jardetzky, "Application of NMR spectroscopy to the study of macromolecules," *Ann. Rev. Biochem.*, vol. 40, pp. 605–634, 1971.
[19] B. D. Sykes and M. D. Scott, "NMR studies of the dynamic aspects of molecular structure and interaction in biological systems," *Ann. Rev. Biophys. Bioeng.*, vol. I, pp. 27–50, 1972.
[20] A. Abragam, *The Principles of Nuclear Magnetism*, Chap. III. Oxford: Clarendon Press, 1961.
[21] D. E. Woessner, "Nuclear transfer effects in NMR pulse experiments," *J. Chem. Phys.*, vol. 35, pp. 41–48, 1961.
[22] D. E. Woessner and J. R. Zimmerman, "Nuclear transfer and anisotropic motional spin phenomena: Relaxation time temperature dependence studies of water adsorbed on silica gel IV," *J. Phys. Chem.*, vol. 67, pp. 1590–1600, 1963.
[23] B. Blicharsaka, Z. Florkowski, J. W. Hennel, G. Held, and F. Noack, "Investigation of protein hydration by proton spin relaxation time measurements," *Biochim. Biophys. Acta*, vol. 207, pp. 381–389, 1970.
[24] R. Kimmich, "Nuclear magnetic relaxation spectroscopy in solutions of bovine hemoglobin," *Z. Naturforschung*, vol. 26b, pp. 1168–1170, 1971.
[25] A. C. Guyton, *Medical Physiology*. Philadelphia: W. B. Saunders Co., 1971, p. 44.
[26] F. L. Viera, R. I. Sha'afi, and A. K. Solomon, "The state of water in human and dog red cell membranes," *J. Gen. Physiol. London*, vol. 55, pp. 451–466, 1970.
[27] T. Conlon and R. Outhred, "Water diffusion permeability of erythrocytes using an NMR technique," *Biochim. Biophys. Acta*, vol. 228, pp. 354–361, 1972.
[28] E. Odeblad, B. N. Bhar, and G. Lindstrom, "Proton magnetic resonance of human red blood cells in heavy-water exchange experiments," *Arch. Biochem. Biophys.*, vol. 63, pp. 221–225, 1956.
[29] E. C. Albritton, *Standard Values in Blood*. Philadelphia: Saunders, 1952.
[30] T. Lindstrom, unpublished data.

Pattern Recognition Applied to Monitoring Waveforms

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***Abstract*—This paper demonstrates that fetal heart rate (FHR) patterns can be classified by algorithmically determined linear discriminants. A nonparametric learning algorithm was applied to 17 samples of five-vectors. The coordinates of each sample vector were visual features derived from the FHR curve and the simultaneous uterine contraction pressure data in accord with medical training-literature. Data were obtained from strip-chart recordings from the Cedars–Sinai Medical Center, Los Angeles, where an FHR monitoring and on-line computer processing system based on an IBM System/7 is being installed. The algorithm converged to linear discriminants that correctly classified all the 17 training samples under four different combinations of initial weights, training sequence, and correction increment. Each of the four linear decision-rules so obtained was applied to 14 new sample vectors. Three classified 11 samples correctly and one classified 13 samples correctly. Medical anomalies (atypical data) were present in all three misclassified patterns. A perfect success record was found in classifying all seven medically ominous new sample vectors.**

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1.0 INTRODUCTION

THE principal role of fetal monitoring is to provide more accurate information on the fetal condition so the obstetrician can determine the best course of action during labor and delivery. Fetal monitoring refers to two techniques:

1) Observation of the fetal heart rate (FHR) and its changes throughout the course of labor with particular attention to the effect of uterine contractions (UC's);
2) Measurement of the acid–base changes which occur during the course of labor through the evaluation of fetal scalp blood samples [1].

This paper is concerned with showing that the first technique can be automated. That is, as a long-range bioengineering objective, our work involves development of computer programs for the interpretation of FHR changes in relation to UC's. Although we do not use on-line data, instrumentation for continuous FHR monitoring can be obtained and this paper shows that computer algorithms for processing such data can be developed from existing pattern recognition theory [2].

There are two principle objectives and three techniques which are employed in this paper. The objectives are:

1) The development of a working classification algorithm for detection of a nonnormal medical condition.
2) The demonstration that encoding laboratory records in accord with the medical training-literature yields data which satisfy the pattern recognition field "linear-separability" condition.

The following techniques are used:

1) Quantitative representation of text-described properties of two waveforms (records of time variations).
2) Repeated correction of a linear decision-rule until it stabilizes and correctly classifies an initial set of data.
3) Test of our classification rule on a new set of data.

All the techniques are algorithmic or are described by a flow chart showing how hand-derived data can be developed algorithmically. Several alternate starting values, data sequences, and increment rates were studied in the computations. Specific medical ambiguities were noted in the few anomalous cases.

The paper is organized into four other major sections. Section 2 describes the biomedical problem and draws upon the medical training-literature. Section 3 applies and summarizes the pattern recognition theory and explains how the numerical data ("patterns") were derived from Cedars–Sinai strip-chart recordings. Section 4 presents our computational results. This section explains in detail how the mathematical pattern recognition theory summarized in Section 3 was applied to the derived data set. In addition, computer experiments with the pattern recognition algorithms we used and test results from classifying new data are presented here. Section 5 presents conclusions regarding the suitability of these techniques for on-line FHR monitoring.

2.0 BIOMEDICAL CONSIDERATIONS

FHR patterns may be classified as either periodic or baseline. Periodic FHR changes are those which occur with contractions. Baseline changes are those which occur between periodic FHR changes or between contractions if no periodic FHR changes are present or when the patient is not in labor. Periodic FHR patterns are classified further as:

1) normal
2) early deceleration (ED)
3) late deceleration (LD)
4) variable deceleration (VD)
5) acceleration [3], [4].

A normal FHR pattern has the range 120 to 160 beats per minute (bpm), and there is no FHR-slowing associated with contractions. (See Fig. 1.)

The ED pattern is characterized by an onset of deceleration that begins early in the contracting phase of the uterus. The heart rate returns to normal before the end of the contraction. Usually, the FHR does not go lower than 100 bpm and the deceleration has a duration of less than 90 sec. The baseline FHR is in the normal range. Clinically, ED is associated with head compression. It is considered innocuous. (See Fig. 2.)

LD has an onset late in the contracting phase of the uterus. The heart rate recovers well after the contraction has ended. It usually ranges from 120 to 180 bpm but may drop as low as 60 bpm in severe cases. Like ED, LD usually has a less than 90 sec duration. The baseline FHR, however, is in the high normal range. The LD pattern is attributed to uteroplacental insufficiency. It is considered ominous. (See Fig. 3.)

VD has an onset that bears a variable time-relationship to the beginning of the associated UC. It usually falls below 100 bpm and frequently drops as low as 50 to 60 bpm. The deceleration has a duration that varies from a few seconds to minutes. The baseline FHR associated with it is in the normal or low normal range. It is thought to be caused by umbilical cord compression. VD is associated with about 90% of the patients where a clinical diagnosis of fetal distress is made [3]. (See Fig. 4.)

The two major types of FHR acceleration are:

a) a consistent uniform FHR acceleration which reflects the shape of the associated UC. This type of acceleration may merge to cause a rise in baseline FHR.

b) transitory, variable FHR acceleration which precedes and follows VD [4].

Accelerations have not been associated with fetal distress.

Slight irregularities are an integral part of the normal FHR: The FHR curve is not a smooth one (see Fig. 1).

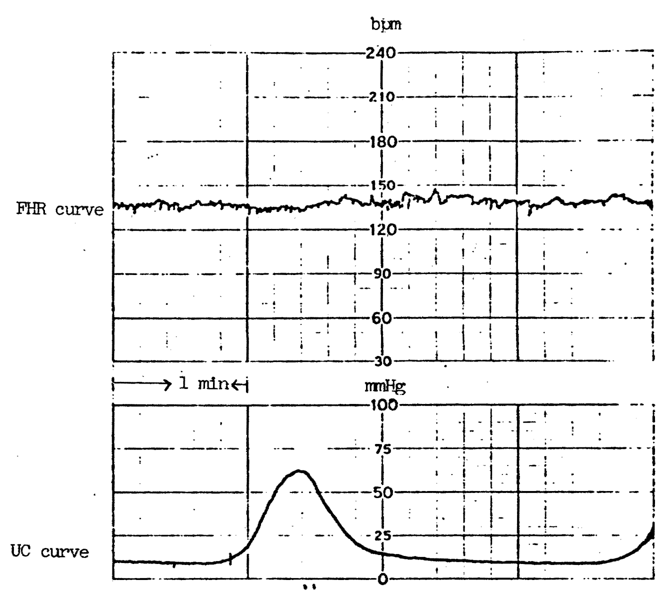

Fig. 1. Fetal heart rate and uterine contraction data (from Cedars–Sinai Medical Center strip-chart recordings).

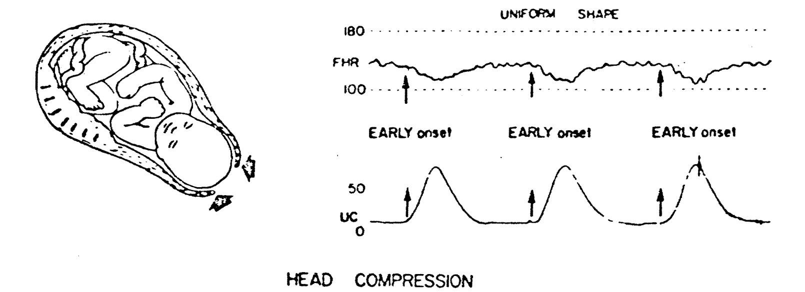

Fig. 2. Early FHR decrease. (*Note*: From [4]).

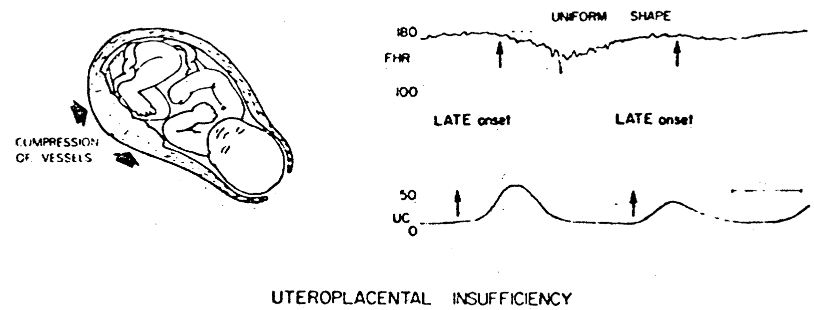

Fig. 3. Late FHR decrease. (*Note*: From [4]).

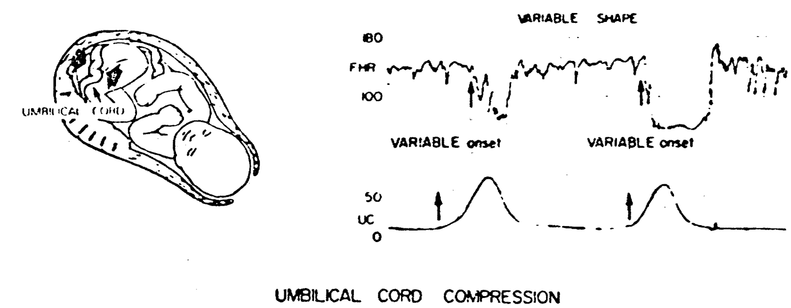

Fig. 4. Variability in FHR. (*Note*: From [4]).

The transitory fluctuations reflect the momentary balance of the systems which provide nervous control of the heart. Cardiac rate is controlled by a cardio-inhibitor and a cardio-accelerator center which are located in the medulla. Control is exerted through different autonomic nervous pathways; parasympathetic via the vagus nerve and sympathetic via the cervical ganglia and cardiac nerves. The end result of the interaction of the two systems is minor irregularities in beat-to-beat heart rate which reflect the reactivity of each system at that moment. Factors which affect the central or peripheral portions of the system therefore alter the degree of variability of the heart rate. For example, the beat-to-beat FHR pattern of an immature fetus, where the autonomic nervous system is less developed, is less irregular than that of a term infant [5].

3.0 MATHEMATICAL PATTERN RECOGNITION

This section applies the theoretical tools of mathematical pattern recognition to pairs of fetal heart rate and uterine contraction time-series data (strip-chart recordings obtained from Cedars–Sinai Medical Center). The objectives of this section are:

1. To develop a useful encoding of the data (i.e., one which facilitates computer processing for a representative biomedical classification problem).
2. To describe how the proposed encoding can be obtained by computer processing of digitized data (i.e., sampled FHR and UC data which could be obtained in an on-line system).
3. To derive a test set by hand methods from strip-chart data. This set is to be (arbitrarily) divided into two parts: training and evaluation data.
4. To describe the application of the pattern recognition theory to the test data for a representative biomedical classification task (here, the monitoring decision "ominous/questionable[1] or innocuous?")

The last objective includes the following subsidiary goals:

1. To bring a wider appreciation of the simplicity and utility of the pattern recognition algorithms. (These are generically described as nonparametric learning methods; they provide a means for deriving a decision rule from several instances of multivariate data without requiring any statistical assumptions.[2])
2. To demonstrate sufficient classification accuracy on the evaluation data for the given task to warrant further investigation leading to an on-line system.

[1] Ominous and questionable data were grouped together as a single alternative.

[2] However, some noteworthy similarities to traditional discriminant analysis method occur in theory and practice.

The following subsections are entitled with the corresponding mathematical pattern recognition terminology. "Features" are the useful data encoding and represent the visual properties perceived by an observer (physician) in the actual record. "Feature extraction" concerns organization of numerical data (typically that obtained from an analog to digital converter) to obtain the more useful feature values. "Pattern vectors" are sets of the different features obtained from a single instance (or individual). "Pattern classification" describes the general process of incorporating the individual pattern vectors into a decision rule (sometimes called "learning," "training," or "algorithmic adaptation"). This subsection reviews the theoretical methods which were applied to derive the detailed computational results presented in Section 4.

3.1 *Features*

In the preceding section, the different FHR–UC patterns were briefly described. From the characterizations of FHR–UC patterns [3], [4] the following seem to be natural choices of features that describe the FHR type:

1) $f_1 = t_h - t_c$, the time that elapses between the start of the UC and the beginning of the deceleration (see Fig. 5).

2) f_2 = the FHR at time t_h. This gives an indication of the baseline FHR (see Fig. 6).

3) f_3 = the minimum FHR (see Fig. 6).

4) $f_4 = t_2 - t_1$, which indicates how long the FHR remains less than or equal to 100 bpm (see Fig. 7).

5) $f_5 = t_e - t_h$, the duration of the deceleration (see Fig. 7).

A significant problem in FHR pattern recognition is the selection of an appropriate set of features. The problem is to obtain features which characterize the different patterns so that they can be classified correctly solely from feature-measurements. At the same time, the cost of extracting these features from each sample should be reasonable.

The simultaneous use of features is essential. A monitoring system wherein an alarm is signaled only when the FHR falls below (or above) certain levels, say 100 bpm and 180 bpm, respectively, is insufficient. For example, LD which is an ominous pattern that usually ranges from 120 to 180 bpm cannot be detected. The level to which the FHR falls (or rises) is only one of the features used in classifying FHR patterns. Features like f_1 to f_5 must be taken into consideration for more accurate FHR pattern classification.

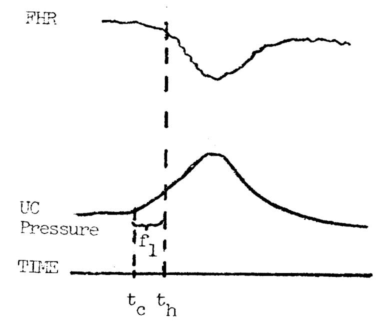

Fig. 5. Onset feature f_1.

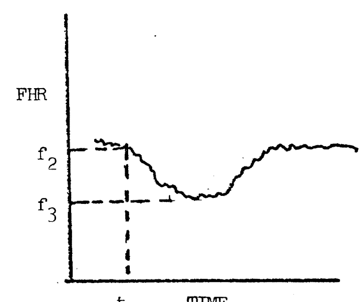

Fig. 6. Features f_2 and f_3 (from FHR curve).

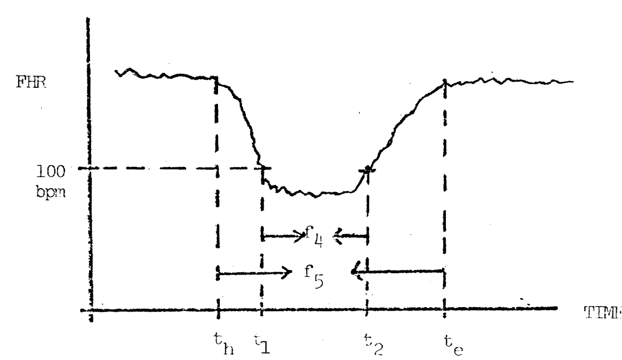

Fig. 7. Features f_4 and f_5 (from FHR curve).

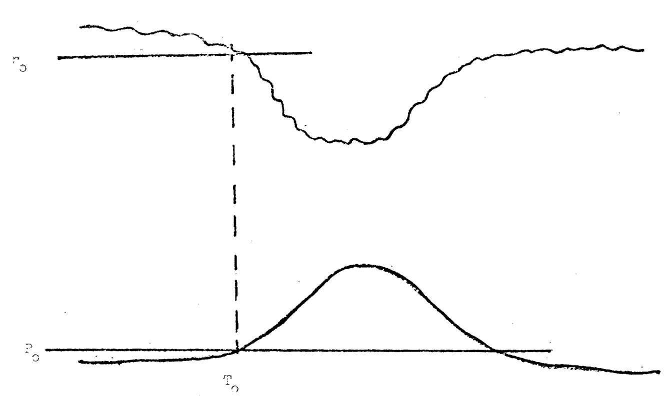

Fig. 8. Obtaining features from the crossing-level method.

3.2 *Feature Extraction*

The following discussion describes a method for automatic extraction of the features f_1 to f_5. Suppose that the FHR data have been digitized. To find the point where the contraction starts, the crossing-level method [6] can be used. Approximate the beginning of the UC by T_o (see Fig. 8), the time at which the intrauterine pressure exceeds the manually chosen level P_o, and sample the FHR, r_o (bpm), at T_0.

Without any loss of generality, suppose that the digitized sample points come at the rate of 1/sec. Then r_i will denote the FHR i seconds after r_o and $\{r_i \mid i = 0,1,2,\cdots\}$ will be the sequence of FHR sample points.

In a personal communication with S. Y. Yeh, M.D., it was pointed out that the FHR curve is not as well-behaved and predictable as the UC curve. Hence the method of manually choosing an FHR crossing level to find the point where the FHR starts decelerating does not work

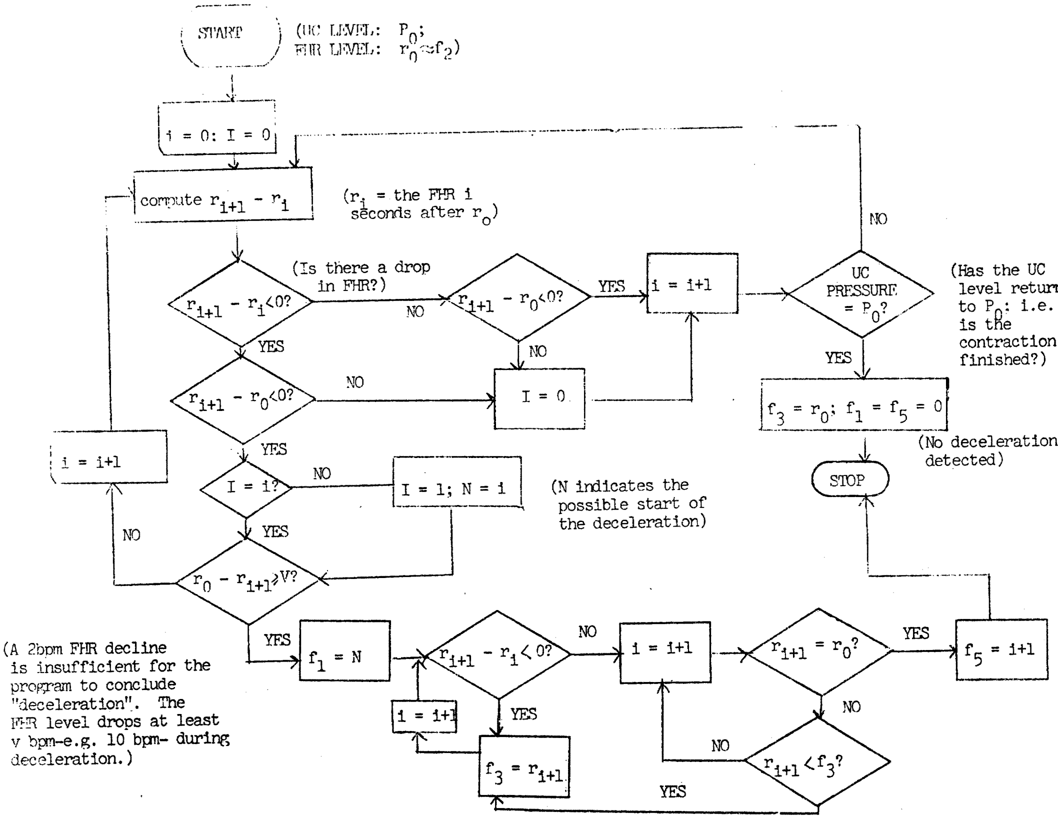

Fig. 9. Flowchart for obtaining several features.

as well as setting up P_o does in finding T_0 to approximate the beginning of the UC.

The crossing-level method can be used to determine f_4 [6] the total amount of time that the FHR is less than or equal to 100 bpm. The following flowchart (Fig. 9) summarizes a suggested procedure for extracting the features f_1, f_2, f_3, and f_5.

3.3 *Pattern Vectors*

Consideration of FHR strip-chart recordings from the Cedars–Sinai Medical Center and [7] and [8] led to measurement of the features f_1 to f_5 for each of 17 FHR patterns associated with a UC and expression of the data as 5-component vectors of the form $(f_1, f_2, f_3, f_4, f_5)$. The 17 classified pattern vectors are as follows:

I. Acceleration
   (0, 140, 140, 0, 0)
II. Normal
   (0, 135, 135, 0, 0)
   (0, 130, 125, 0, 12)
III. Early Deceleration
   (0, 139, 126, 0, 72)
   (0, 150, 140, 0, 72)
   (6, 138, 127, 0, 60)
   (0, 140, 120, 0, 72)
IV. Late Deceleration
   A. Mild
      (58, 148, 130, 0, 78)
      (36, 140, 118, 0, 84)
   B. Severe and Severe with Variable Deceleration
      (40, 135, 85, 34, 96)
      (48, 180, 145, 0, 84)
V. Variable Deceleration
   A. Mild
      (24, 139, 80, 10, 24)
      (12, 140, 80, 16, 90)
   B. Severe
      (12, 120, 60, 20, 36)
      (18, 160, 70, 40, 72)
      (18, 135, 55, 48, 66)
      (0, 150, 60, 42, 72).

The 17 patterns were grouped into two classes. Class 1 consisted of the ominous and the questionable (and, therefore, requiring closer observation) patterns, namely, LD and VD. Mild VD is considered questionable while mild and severe LD and severe VD are considered ominous. Class 2 consisted of the innocuous patterns, namely normal, acceleration, and ED.

3.4 *Pattern Classification*

This section summarizes standard pattern recognition techniques and materials from [2] and [9]. In particular, a one-at-a-time algorithm [2] for generating a linear discriminant[3] is presented.

Let there be two classes C_1 and C_2 such that S_1 and S_2 are sets of classified samples[4] from C_1 and C_2, respectively, i.e.,

$$S_1 = \{x_1^{(1)}, x_2^{(1)}, \cdots, x_k^{(1)}\} \subset C_1$$

[3] In spite of the use of a statistical term, no assumptions regarding the statistics of pattern vectors or features are made. (It is conventional in pattern recognition theory to use the statistical term "discriminant" in this way.)

[4] Sometimes called the "learning set" or "training data" in the pattern recognition literature.

and

$$S = \{x_1^{(2)}, x_2^{(2)}, \cdots, x_m^{(2)}\} \subset C_2$$

where each $x_i^{(j)}$ is a pattern vector whose components are features of the sample it represents. If there are n features, i.e., if each $x_i^{(j)}$ has n components, then, ideally, what is wanted is a hyperplane separating S_1 and S_2 such that for any element $x_i^{(1)} \in S_1$,

$$w \cdot x_i^{(1)} + w_{n+1} > 0$$

and for any element $x_i^{(2)} \in S_2$,

$$w \cdot x_i^{(2)} + w_{n+1} < 0,$$

where $w = (w_1, w_2, \cdots, w_n)$.

It is now possible to formulate the decision rule that for any pattern vector y of unknown classification

$$w \cdot y + w_{n+1} > 0 \Rightarrow y \in C_1$$

and

$$w \cdot y + w_{n+1} < 0 \Rightarrow y \in C_2.$$

If $w \cdot y + w_{n+1} = 0$, the decision will usually depend upon the particular application. Usually, it is more dangerous to misclassify an element of one class than the other. For example, in the medical monitoring problem, misclassifying an innocuous pattern as belonging to class 1 and sounding an alarm is preferable to letting an ominous pattern belonging to class 1 pass unnoticed. Hence, if $w \cdot y + w_{n+1} = 0$, for some FHR pattern vector y, it is preferable to conclude that $y \in$ class 1.

Consider now the sets of augmented samples, $(n + 1)$-vectors:

$$S_1^A = \{(x_i^{(1)}, 1) \mid x_i^{(1)} \in S_1\}$$

and

$$S_2^A = \{(x_i^{(2)}, 1) \mid x_i^{(2)} \in S_2\}.$$

Let $W = (w, w_{n+1})$ and $Y = (y, 1)$. Using this augmented notation yields the following decision rule which is equivalent to the one stated earlier:

$$W \cdot Y > 0 \Rightarrow y \in C_1$$

and

$$W \cdot Y < 0 \Rightarrow y \in C_2.$$

It is easy to see that if $x_i^{(2)}$ is one of the classified samples from C_2, then $W \cdot (x_i^{(2)}, 1) < 0$, and hence $W \cdot (-(x_i^{(2)}, 1)) > 0$. It will be convenient to define the set $S = S_1^A \cup (-S_2^A)$, where $-S_2^A$ consists of the negative of the elements of S_2^A.

Consider the following one-at-a-time algorithm [2], also referred to as the fixed-increment error-correction procedure [9]:

$$W^{(i+1)} = \begin{cases} W^{(i)} & \text{if} \quad W^{(i)} \cdot Y^{(i)} \geq 0 \\ W^{(i)} + cY^{(i)} & \text{if} \quad W^{(i)} \cdot Y^{(i)} < 0 \end{cases}$$

where c is a positive constant, $Y^{(i)} \in S$, and as i increases $Y^{(i)}$ cycles through the elements of S. (For S as the "training set," let an infinite sequence of elements of S which has any one element infinitely often, be called a *training sequence*, and denote it by $\mathcal{S}$).

That this algorithm yields the desired weight vector W after a finite number of steps is justified by the following theorem [9]:

Let the training subsets S_1 and S_2 be linearly separable. Let S_w be the weight vector sequence generated by a training sequence obtained using S. If the fixed-increment error correction procedure beginning with some initial weight vector $W^{(0)}$ is used, then for some finite index k, $W^{(k)} = W^{(k+1)} = W^{(k+2)} = \cdots$.

This theorem, together with a corresponding one for the N-class problem, are proven in [9].

The heuristic justification is that if $W^{(i)} \cdot Y^{(i)} < 0$ and we set $W^{(i+1)} = W^{(i)} + cY^{(i)}$, then $W^{(i+1)} \cdot Y^{(i)} = W^{(i)} \cdot Y^{(i)} + cY^{(i)} \cdot Y^{(i)}$. Therefore, $W^{(i+1)} \cdot Y^{(i)} \geq W^{(i)} \cdot Y^{(i)}$ and the sample $Y^{(i)} \in S$ is more likely to be on the positive side of the hyperplane $W^{(i+1)} \cdot X = 0$ than of $W^{(i)} \cdot X = 0$, and the goal is a hyperplane $W \cdot X = 0$ with all elements of S on its positive side.

4. RESULTS

Three training sequences $\mathcal{S}_1$, $\mathcal{S}_2$ and $\mathcal{S}_3$, were generated from the set of 17 FHR pattern vectors. These are shown in Table 1.

Starting with $W^{(0)} = (1, .5, -1, 0, 0)$ using the sequence $\mathcal{S}_1$, and the correction increment $c = .1$, we found that the weight vector $W = (88.8, 4.7, -43, 6, 28.2, -.1)$ separated the two classes of patterns perfectly, after 45 steps. That is, 45 weight vectors were generated by the algorithm as it cycled through $\mathcal{S}_1$ until determining a hyperplane which separated classes 1 and 2.

Table II shows four values of W obtained by using different training sequences and different values of $W^{(0)}$ and c. The number of steps in finding each weight vector W is also indicated. Fewer steps were needed for each of the other three combinations of $\mathcal{S}_j$, $W^{(0)}$, and c (8, 6, and 6 compared to 45).

The weight vectors W_1, W_2, W_3 and W_4 (see Table II for numerical values) were used to classify 14 new samples, of which 9 belonged to class 1 (7 ominous and 2 questionable) and 5 belonged to class 2 (innocuous). Table III shows the results.

All four weight vectors W_1, W_2, W_3, W_4, misclassified

TABLE I
TRAINING SEQUENCES
$\mathcal{S}_j = \{Y^{(i)}; k = 1,2,\cdots, i = k \bmod 17\}, j = 1,2,3$

Order for $\mathcal{S}_1$	Pattern Vectors $Y^{(i)}$	Order for $\mathcal{S}_2$	Order for $\mathcal{S}_3$
1	(0, −140, −140, 0, 0, −1)	1	11
2	(0, −135, −135, 0, 0, −1)	3	12
3	(0, −130, −125, 0, −12, −1)	5	13
4	(0, −139, −126, 0, −72, −1)	7	14
5	(0, −150, −140, 0, −72, −1)	9	15
6	(−6, −138, −127, 0, −60, −1)	11	16
7	(0, −140, −120, 0, −72, −1)	13	17
8	(58, 148, 130, 0, 78, 1)	2	1
9	(36, 140, 118, 0, 84, 1)	4	2
10	(40, 135, 85, 34, 96, 1)	6	3
11	(48, 180, 145, 0, 84, 1)	8	4
12	(24, 139, 80, 10, 24, 1)	10	5
13	(12, 140, 80, 16, 90, 1)	12	6
14	(12, 120, 60, 20, 36, 1)	14	7
15	(18, 160, 70, 40, 72, 1)	15	8
16	(18, 135, 55, 48, 66, 1)	16	9
17	(0, 150, 60, 42, 72, 1)	17	10

TABLE II
VALUES OF WEIGHT VECTOR W CORRESPONDING TO DIFFERENT VALUES OF c, INITIAL WEIGHT VECTORS, AND TRAINING SEQUENCES

W	c	$W^{(0)}$	Training Sequence	Number of Steps
W_1 = (88.8, 4.7, −43, 6, 28.2, −.1)	.1	(1, .5, −1, 1, 0, 0)	S_1 or S_3	45
W_2 = (12.4, 4.7, −10.5, 3.6, 6.6, 0)	.1	(1, .5, −1, 1, 0, 0)	S_2	8
W_3 = (11.2, 4.5, −9.1, 4.4, 5.8, 0)	.1	(0, 1, −1, 0, 1, 0)	S_2	6
W_4 = (56, 18.5, −41.5, 22, 25, 0)	.5	(0, 1, −1, 0, 1, 0)	S_2	6

TABLE III
CLASSIFICATION ERRORS OF W_1, W_2, W_3, W_4, ON 14 NEW SAMPLE PATTERN VECTORS

Weight Vector	Number of Misclassified Samples from Class 1	Number of Misclassified Samples from Class 2
W_1	1	0
W_2	1	2
W_3	1	2
W_4	1	2

the same pattern vector out of 9 from class 1. The misclassified pattern vector (14, 138, 100, 1, 20) represented an FHR pattern of mild variable deceleration ("questionable").

W_2, W_3, and W_4 also misclassified the same two new samples from class 2, both of which were early deceleration patterns represented by the vectors (6, 132, 95, 30, 66) and (6, 116, 85, 43, 78).

The sample (14, 138, 100, 1, 20) had a minimum of 100 bpm and stayed there for about a second only. On the other hand, the pattern vectors (6, 132, 95, 30, 66) and (6, 116, 85, 43, 78) both dropped below the 100 level for several seconds. (6, 116, 85, 43, 78) represented a pattern with a baseline FHR that is slightly out of the normal range. Thus, each of the three misclassified samples was actually atypical of the class to which it belonged. None of the 7 ominous patterns was misclassified by any of the weight vectors W_1, W_2, W_3, W_4.

5. CONCLUSIONS

The results indicate the potential applicability of algorithmically adapted pattern analysis (nonparametric learning of linear discriminants) in on-line FHR monitoring. This paper has demonstrated that FHR patterns can be classified by combining features derived from uterine contraction and heart rate data, and that such features can be derived from monitoring signals by currently available technology (hardware exists, software is proposed here). Although actual computations involved the IBM 360/91, the program could be implemented on a small computer. Hence, the techniques presented could be applied in general clinical situations for relatively modest expense, considering the amount of technical sophistication involved, i.e., the simultaneous use of many parameters to make a clinical decision. The medical anomalies found in the relatively few misclassified patterns and the perfect record of success in classifying medically ominous test cases support the applicability of these techniques to on-line monitoring.

REFERENCES

[1] L. S. James, Aspects of Fetal Monitoring, *Obstetrical Anesthesia*, Pfizer Laboratories Division, Pfizer, Inc., 1973.
[2] W. S. Meisel, *Computer-Oriented Approaches to Pattern Recognition*, Academic, 1972.
[3] E. H. Hon, *An Introduction to Fetal Heart Rate Monitoring*, Harty Press, Inc., 1969.
[4] E. H. Hon and R. H. Paul, *A Primer of Fetal Heart Rate Patterns*, Harty Press, Inc., 1970.
[5] S. Y. Yeh, A. Forsythe, and E. H. Hon, Quantification of Fetal Heart Beat-to-Beat Interval Differences, *Obstetrics-Gynecology*, vol. 41, no. 3, Mar. 1973.
[6] S. Y. Yeh, L. Betyar, and E. H. Hon, Computer Diagnosis of Fetal Heart Rate Patterns, *American Journal of Obstetrics and Gynecology*, vol. 114, no. 7, Dec. 1972.
[7] R. H. Paul and R. K. Freeman, Selected Records of Intrapartum Fetal Monitoring with Self Instruction, USC Postgraduate Division, 1971.
[8] R. H. Paul, Fetal Intensive Care, Intrapartum Monitoring Case Examples, LAC/USC Medical Center, 1971.
[9] N. J. Nilsson, *Learning Machines*, McGraw-Hill, 1965.