Ventricular beat classifier using fractal number clustering

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Abstract—*A two-stage ventricular beat 'associative' classification procedure is described. The first stage separates typical beats from extrasystoles on the basis of area and polarity rules. At the second stage, the extrasystoles are classified in self-organised cluster formations of adjacent shape parameter values. This approach avoids the use of threshold values for discrimination between ectopic beats of different shapes, which could be critical in borderline cases. A pattern shape feature conventionally called a 'fractal number', in combination with a polarity attribute, was found to be a good criterion for waveform evaluation. An additional advantage of this pattern classification method is its good computational efficiency, which affords the opportunity to implement it in real-time systems.*

Keywords—*Classification, ECG, Extrasystole, Fractal number, QRS*

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1 Introduction

A FULLY automatic ventricular beat classifier could support an arrhythmia discriminator in Holter-type or bedside patient monitoring.

Most of the efficient classifiers evaluate pattern shapes through template matching with cross-correlation techniques (LANZA *et al.*, 1990; FORSTER and HANDWERKER, 1990; SALERNO *et al.*, 1987; LIN and CHANG, 1989; LIN *et al.*, 1988) or multiparameter statistical classification (PAPARELLA *et al.*, 1987; GELSEMA *et al.*, 1988; MERRI *et al.*, 1989). Other classification approaches are the distance quantification in some feature space (WOLBERG and MANGANSARIAN 1990; SÖRNMO *et al.*, 1981) and the application of expert knowledge and fuzzy labelling of events (BARRO *et al.*, 1990).

These algorithms are currently accepted and put into practice, but they label the examined events according to some relatively synthetic class borders with statistical or threshold criteria, thus *a priori* not being able to react flexibly enough in all cases. A satisfactory classification could also be attained by these methods, but at the cost of computational complexity and processing-time expansion. The attempts to reduce the error factor formally lead inevitably to classification limitations [e.g. single feature statistics (KOHN, 1989)].

The purpose of this paper is to present another classification approach which tries to follow the natural phenomena more closely. After beat identification and characteristic features extraction, the algorithm implemented performs the most important section: investigation of the grouping of events (beat patterns) into naturally self-organised clusters.

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2 Method

2.1 *Adaptive beat identification*

Accurate ventricular beat identification is a basic preliminary task, prior to any further processing. It is valid for almost any kind of automatic ECG analysis. The following beat classification procedure sets additional requirements for beat identification.

2.1.1 *Signal preprocessing.* To amplify the QRS characteristic features common in all leads and to suppress slower waves, as the first part of a two-stage preprocessing, a fast procedure to compute the pseudospatial velocity is applied, which combines the event information from L leads:

$$Y(i) = \sum_{j=1}^{L} [X_j(i+1) - X_j(i-1)]$$

where $X_j(i)$ is the amplitude of data sample i in lead j, and $Y(i)$ is the current pseudospatial velocity value.

To improve the beat detection prerequisites, the Menard derivative (FRIESEN *et al.*, 1990) is employed on the computed data Y:

$$Z(i) = -2Y(i-2) - Y(i-1) + Y(i+1) + 2Y(i+2)$$

where Z is the preprocessed data used for beat identification decisions only (Fig. 1).

2.1.2 *Iterative decision rule.* The decision rule should detect all beat events occurring, independently of their shape or peak amplitude, to respond to the further classification requirements. An adaptive iterative procedure is implemented on the Z data to extend the advantages of the preprocessing. Each identified beat modifies a weighted mean peak amplitude estimator and a weighted mean $R-R$ interval estimator, both defining the adaptive search features of this detection technique.

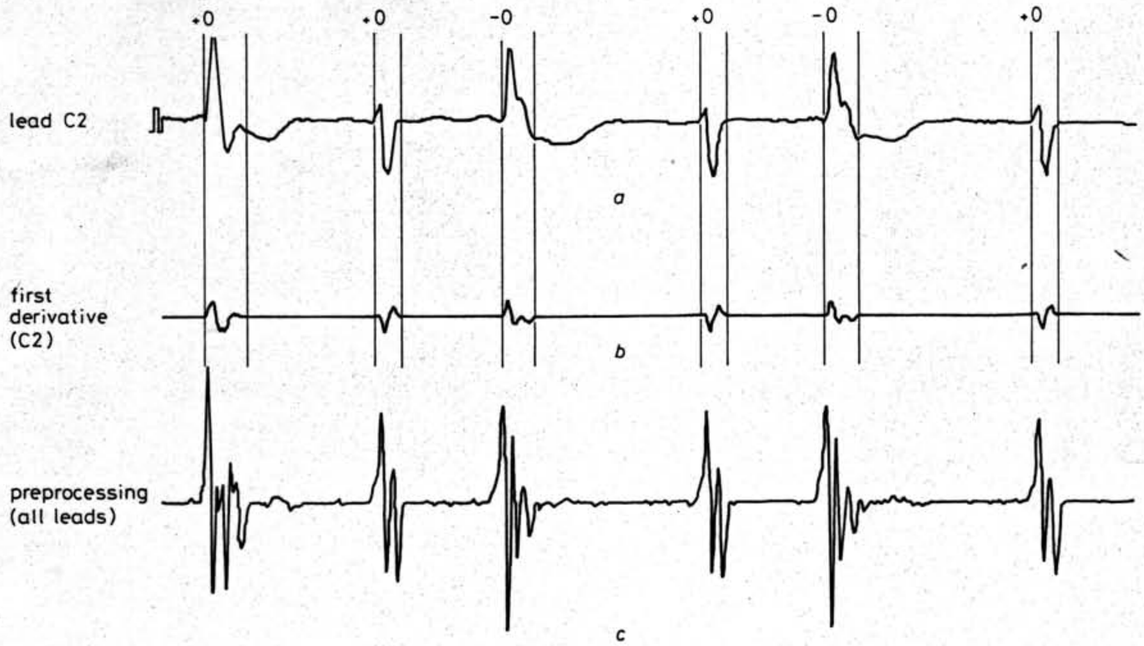


Fig. 1 *Data processing: (a) original ECG data; (b) first derivative of data for estimation of the ventricular beat onsets/offsets; (c) pseudospatial velocity with consecutive derivative preprocessing for beat identification*

The peak amplitude estimator (PAE) accounts for the past several ventricular beats and the very last detected peak amplitude value (PAV) on the detection threshold. The new weighted mean PAE is updated by a forgetting factor of 1/33, and the actual detection threshold (DT) value pursued on the preprocessed data is set initially at 33 per cent of the adapted PAE. This unusually low detection threshold is possible due to the specific preprocessing and is indispensable because a series of ectopic beats could set the current PAE too high. For each beat b, the following relationships are valid:

$$PAE(b) = \frac{32PAE(b-1) + PAV(b)}{33}$$

and

$$DT(b) = PAE(b)\,\frac{33}{100}$$

so that

$$DT(b) = \frac{32PAE(b-1) + PAV(b)}{100}$$

A forward search is performed using an adaptive search length, defined in a similar way by a variable, called the weighted mean $R-R$ interval estimator (RIE). Each new interbeat interval $R-R(b)$ updates this estimator by a forgetting factor of 1/8:

$$RIE(b) = \frac{7RIE(b-1) + R - R(b)}{8}$$

and the actual search length for the next beat is set at 200 per cent of the current RIE. As usual, a refractory blanking period is provided as well.

If, in a first pass, a normal or low-amplitude beat cannot be detected within the current search length, an iterative procedure performs new back searches, each with a 25 per cent decrease in the current detection threshold (PAE remains unchanged), until the next beat is identified. Finally, the successful detection of beat b after r recursions has established the following local threshold value:

$$LDT(b) = 2^{-2r}DT(b)$$

The Z peak position for each beat is found by searching for the maximum of Z data after the detection point. These locations are beat fiducial marks, labelling the identified ventricular beats.

Finally, the two adaptive weighted mean estimators can already be updated for the next beat search, taking into account the last Z peak amplitude and $R-R$ interval.

2.2 *Ventricular beat onset and offset*

Ventricular beat onsets and offsets are searched in the ECG data first derivative (simple slope)

$$dX_j(i) = X_j(i) - X_j(i-1)$$

for each lead j individually. A new beat location marker is placed on the first X data point, with actual slope dX exceeding a preset but variable slope threshold after the previously found fiducial mark. We proceed further using an iterative search to the left and right of the beat marker. The first scan in each direction proceeds within a maximum search length, until a region with slope lower than an initial value of the slope threshold is located, and its inner end is found (Fig. 1*b*). The maximum search length in both directions is set equal to the current $R-R$ interval estimator. If, in any direction, this procedure is unsuccessful, the slope threshold is incremented, and an iterative search is repeatedly undertaken, until the onset and offset points of the ventricular beat for the investigated lead j are found and labelled.

2.3 *Ventricular beat characterisation parameters*

Attempting to describe ventricular beat patterns, we tested the following input parameters: ventricular beat signed and absolute area, duration, R-amplitude, 'sign', fractal number of raw data and fractal number of the first derivative. Some of these parameters were further selected according to their efficiency in the corresponding classification stages.

2.3.1 *Beat 'sign'.* This feature is rather conditional, because different parameter values reflect different types of polarity variation only for the purpose of comparison. The parameter beat 'sign' is rather artificial, but it should be accepted as a useful tool for the following classification procedure. A linear interpolation between the ventricular beat onset and offset for the examined lead determines the relative beat baseline, and the maximum and minimum amplitude deviations from this beat baseline (*min* and *max*) are found. Their relationship specifies the value of the parameter beat 'sign' for lead j in a fast comparative procedure, regardless of shape, by means of a sign indicator function $s(b)$:

$s(b) = 1$ if $max/min \geqslant 3/2$ beat b is labelled positive

$s(b) = 0$ if $max/min \leqslant 2/3$ beat b is labelled negative

$s(b) = 2$ otherwise beat b is labelled biphasic

If, later in the process of classification, in some lead $s(b) = 2$ for most of the typical beats, $s(b)$ is redefined to increase the 'sign' parameter reliability for this lead, as follows:

$s(b) = 1$ if $max/min \geqslant 5/4$

$s(b) = 0$ if $max/min \leqslant 4/5$

$s(b) = 2$ otherwise

2.3.2 *Beat absolute area.* Each beat absolute area for a given lead is defined as the sum of absolute values of the amplitude deviations from their corresponding baseline points within the beat duration.

2.3.3 *Beat fractal number of the first derivative.* Our experience with 'traditional' shape evaluation methods revealed the need of a new fast and efficient pattern sensitive descriptor. It is known that fractals can be a powerful tool for image processing. Fractals are structures that do not have a characteristic scale of measurement (MANDELBROT, 1983). This basic feature permits a more comprehensive description of many natural phenomena.

The generator set of the ventricular heartbeat electrical activity produces a rapidly conducting branching depolarisation wavefront, due to the specialised His-Purkinje network and slower excitation of the ventricular myocardium itself. This generator set could be assumed to be a fractal structure, as it is organised hierarchically in a specific way (GOLDBERGER, 1987). Thus, the measured electrical activity of this heart fractal structure should possess fractal properties (a variety of characteristic scales) as well. The arguments for calling this hypothetical ECG curve fractal are no less persuasive than in the case of the fractal coastline of England (MANDELBROT, 1983, p. 36).

The assumption of fractal properties of the body surface electrocardiogram turns out to be exaggerated to some extent, because the scaling properties are almost lost due to electrical signal integration processes in the tissue smoothing the curve. Additional scale loss is provoked by the low sampling rate used in normal ECG signal processing. In the investigated ventricular segments of the ECG curve the range of the measurement scale invariance becomes so small that it is impossible to really call these segments scale invariant (the inner and outer cutoffs of the measurement scales become too close). The fractal aspect degenerates to a great extent, due to the loss of fractal variability.

Nevertheless, we could use a modified version of the fractal similarity dimension D (MANDELBROT, 1983), under the conditional notion of pattern 'fractal number' D_n (KATZ, 1988; KOHN, 1989):

$$LEN_n = DIAM_n^{Dn}$$

so that

$$Dn = \frac{\log (LEN_n)}{\log (DIAM_n)}$$

where LEN_n is the total pattern length, i.e. the sum of all point-to-point distances, and $DIAM_n$ is the pattern 'diameter', i.e. the maximum distance between any two pattern points in the same scale.

By true fractal structures, the relationship is valid for any measurement scale. In our case, only one characteristic scale is used, defined by the sampling rate and resolution. Therefore the exponent Dn cannot be called a 'fractal dimension' in this case but it continues to reflect very successfully the shape of a waveform, if used correctly. In this simplified version, it is insensitive to polarity inversions.

The 'fractal number' should depict a kind of pattern quantification to be used for the shape comparisons. To obtain adequate boundary values ($Dn = 1$ for a straight line, and $Dn = 2$ for a plane-filling curve), the fractal number has to possess an isotropic quality. The pattern duration must be set equal to the pattern amplitude range. Therefore each ventricular beat duration is linearly interpolated to a constant number of pattern samples $dNORM$, and the beat amplitude range is normalised to the same number of $dNORM$ arbitrary amplitude units. In that way, the ventricular beat waveforms are transformed into comparable normalised patterns, and their pattern fractal numbers can be computed (Fig. 2). Thus, this pattern feature offers an isotropic sensitivity to any shape transmutations. This normalisation approach can be verified for the two extreme cases:

$$Dn = \frac{\log (dur_n\ range_n)}{\log (dur_n)} = 2 \quad \text{for the plane-filling pattern}$$

$$Dn = \frac{\log (dur_n\ 1)}{\log (dur_n)} = 1 \quad \text{for the straight line}$$

where dur_n is the pattern duration (in samples), and $range_n$ is the pattern amplitude range (in arbitrary amplitude units).

The computation of the ventricular beat pattern fractal number actually used (Dn') is performed on the more sensitive first derivative dX of the raw ECG data.

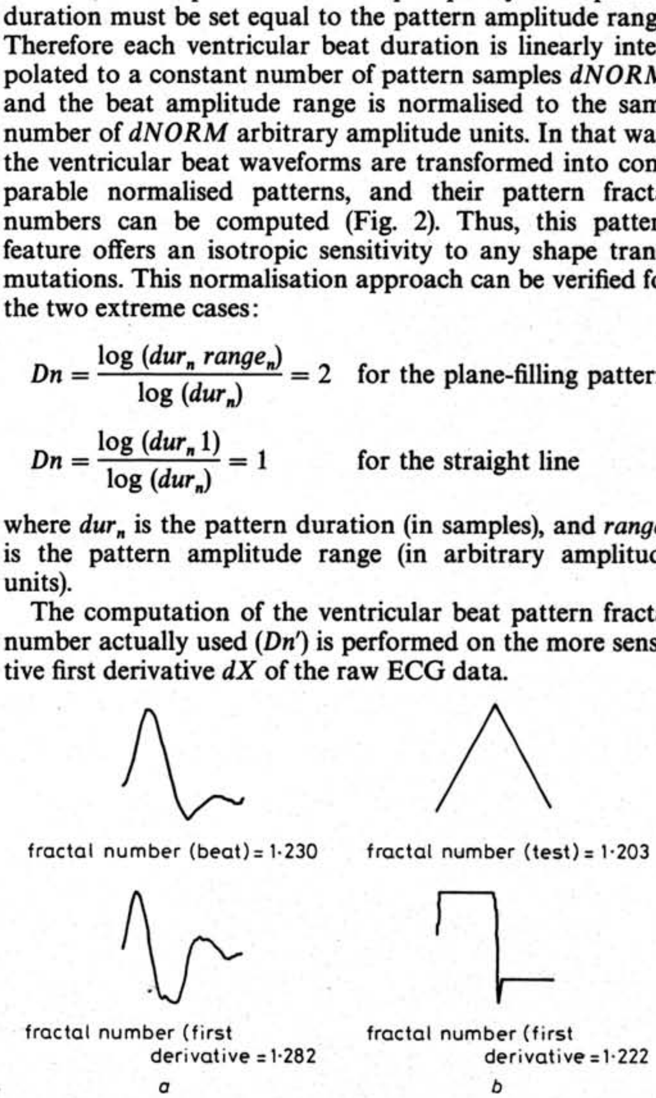


Fig. 2 *Pattern shape evaluation through a 'fractal number' feature: (a) normalised ectopic beat with first derivative and their fractal numbers; (b) normalised test triangle with first derivative and fractal numbers to compare with shape evaluation in (a). Note that pattern duration is set equal to pattern amplitude range before the fractal number is computed. The pattern evaluation feature 'fractal number of a normalised waveform'* $Dn = \log (LEN_n)/\log (DIAM_n)$ *offers an isotropic sensitivity to any shape transmutations. The computation of the ventricular beat fractal number is performed on the first derivative* dX *of the ECG data*

2.3.4 *'Representative' beats selection.* A reference is necessary in every attempt for quantification of natural phenomena. A 'ventricular beat area representative' and a 'fractal number representative' are selected, in each lead, to hold the most typical values of these parameters.

The idea 'most typical value' is implemented by a median selection among all computed parameter values for a learning period. I suggest a period of 160 s for good reliability, but a much shorter learning time interval down to several seconds could be applied too, although it would reduce the accuracy of classification.

2.4 *Associative beat pattern classifier*

2.4.1 *Extraction of extrasystoles.* The extraction of the ventricular beats differing from the typical beats is the first stage of the actual classification.

This procedure is an OR test function, when a ventricular beat b is tested. A beat b is considered not typical, and it is labelled an extrasystole, if in any lead either the 'sign' indicator value $s(b)$ differs from the 'sign' of the area representative of this lead taken as a reference, or if the absolute beat area deviates more than 30 per cent (but is not less than $\pm 2 \times 10^{-5}$ V s) of the area value of the area representative for this lead:

$$\left[area_j(b) < \frac{70}{100}\ area_j(area\ representative) \right]$$

$$\text{OR} \left[area_j(b) > \frac{130}{100}\ area_j(area\ representative) \right]$$

$$\text{OR}\ [s_j(b) <> s_j(area\ representative)]$$

for any lead $j = 1 \ldots L$.

2.4.2 *Ventricular beat pattern clustering.* The second stage of the classifier incorporates the idea that statistical and threshold group separation techniques are too artificial and unsatisfactory for actual partitioning of natural patterns, and the separation methods usually applied could become a problem in borderline cases.

Our alternative solution is to follow the inclination of natural phenomena to clustering and to recognise the clusters of similar beat patterns (Fig. 3*a*). Their characteristic property is that, in some shape-sensitive parameter space, equal or smoothly transmuting pattern parameter values can build up parameter associations. These clusters are equivalent to classes of patterns with adjacent shape parameter values. Hence, it remained to find out whether such a parameter related closely enough to the QRS pattern. The suitable candidate is defined above: the fractal number of the ventricular beat's first derivative $Dn'_j(b)$. As this parameter is vertically invariant, its clustering for each beat is restricted in advance only within a separate parameter space predestined from the valid beat 'signs' (Fig. 3*b*). Thus, the use of two pattern parameters, fractal number and 'sign', facilitates the ventricular beat classification at the second stage.

The practical implementation of this idea imposes the use of information from all leads, by a technique of parallel unification and iterative patterns incorporation by delineation of the self-organised clusters.

Parallel unification consists in the formation of 'sign' series $S(b)$ and fractal number series $DN'(b)$, out of the parameter values from all L leads and for each beat b. Every different 'sign' series S, consisting of L beat 'sign' tokens, frames an L-dimensional parameter space. Every $DN'(b)$ measure belongs to the parameter space of its own $S(b)$ and could be considered a single point in it, which

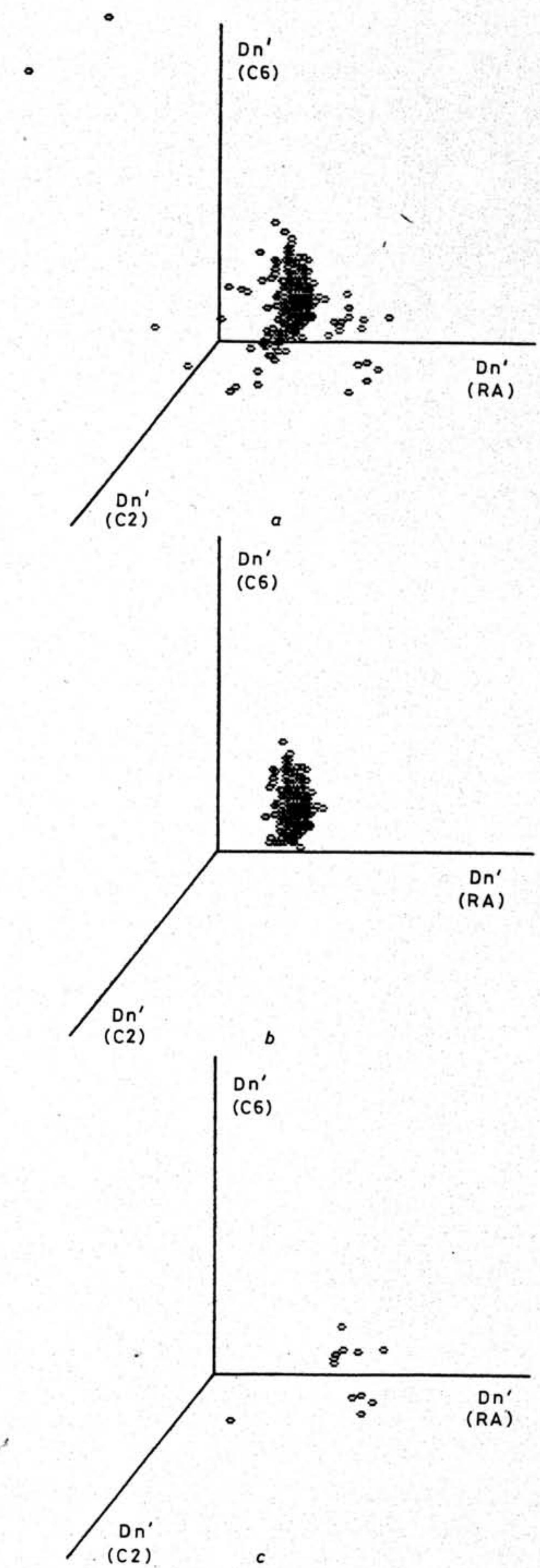


Fig. 3 *Ventricular beat class formation ($L = 3$): (a) pattern clustering in a three-dimensional parameter space of all beats within a period of 160 s; (b) clustering only of typical (normal) beats in a parameter space, with the 'sign' series S = '201'; (c) an example of a parameter space with the 'sign' series S = '111', where the tendency of self-clustering into separate pattern classes can be seen*

could join in a parameter association (cluster). There is only one problem: a fractal number contains much more information than a 'sign' indicator function and thus cannot be encoded in the same way as a single token in its measure $DN'(b)$. This difficulty can be solved by the use of quantification of the fractal number values, so that they are converted into fractal ranks. A fractal rank of 1 for beat b and lead j corresponds to a deviation of the quantification unit of $Dn'_j(b)$ from a median selected representative beat of a lead (Fig. 4). The range of each unit predetermines the degree of shape sensitivity and, in our implementation, is set to

$$\text{fractal rank } 1 = \frac{dNORM}{\frac{1}{10}\,[Dn'_j(\text{fractal-number representative})]}$$

The class delineation procedure attempts to discover all isolated cluster formations in every L-dimensional 'sign' parameter space individually (Fig. 3*c*). In a given parameter space, each dimension j is consecutively investigated, in the pursuit of uninterrupted chains of equal or adjoining fractal ranks. Such a chain delineates a one-dimensional projection of the investigated cluster regarding the QRS parameter values in the corresponding lead j. The examined one-dimensional chain is considered interrupted if there exists no adjoining fractal rank in this projection. In that way, the current investigated cluster boundary for the dimension j and further, for all L dimensions within this 'sign' parameter space, are found. Every incoming ventricular beat is incorporated (classified) by the following algorithm:

(*a*) estimation of the 'sign' series $S(b)$ of a beat, predestining the valid parameter space available or creating a new space
(*b*) estimation of the fractal rank series (measure) of a beat
(*c*) investigation of each fractal measure point location with the help of a cluster delineation procedure:

(i) if such a point location already exists in this parameter space (rank coincidence in all dimensions), then no change of class boundaries takes place, and the beat is labelled in the class
(ii) if the new point location is isolated (no adjoining point exists), then a new class is created, and the beat is labelled in it
(iii) if the point adjoins one existing cluster in this parameter space (it is located at an outer edge of a cluster), then the concerned class boundaries are expanded, absorbing the new point, and it is labelled respectively
(iv) if the incoming point location neighbours two existing clusters at the same time in this parameter space (it contacts the outer edges of two clusters simultaneously), then the two classes concerned are united, and new iterative delineation procedures are started to check for contacts, until all cluster formations in the parameter space are clarified. All beats (points) concerned are relabelled.

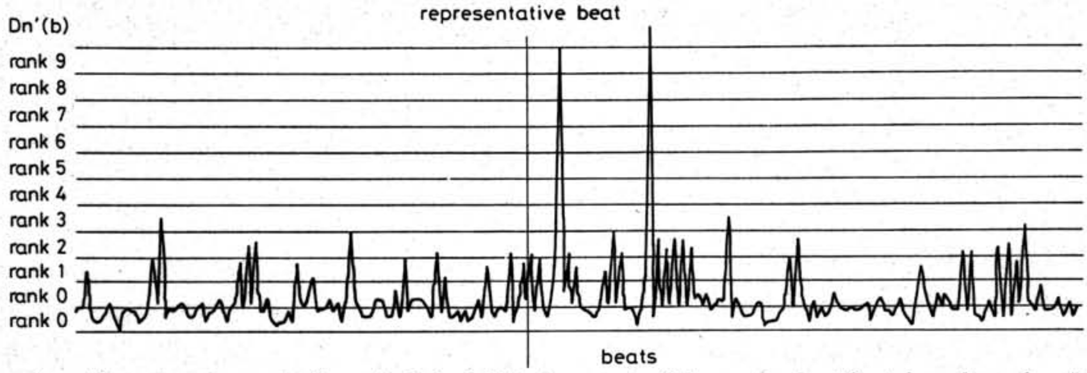


Fig. 4 *Construction of fractal number ranks for a single lead. This is a graph of the varying beat fractal number values Dn' for the entire period. The extent of deviation from a 'leader' beat value Dn'_j(leader), in a particular lead j, determines the fractal rank label of each beat for this lead. The fractal rank is a quantified measure of a ventricular beat shape dissimilarity of a beat compared with the 'representative' beat*

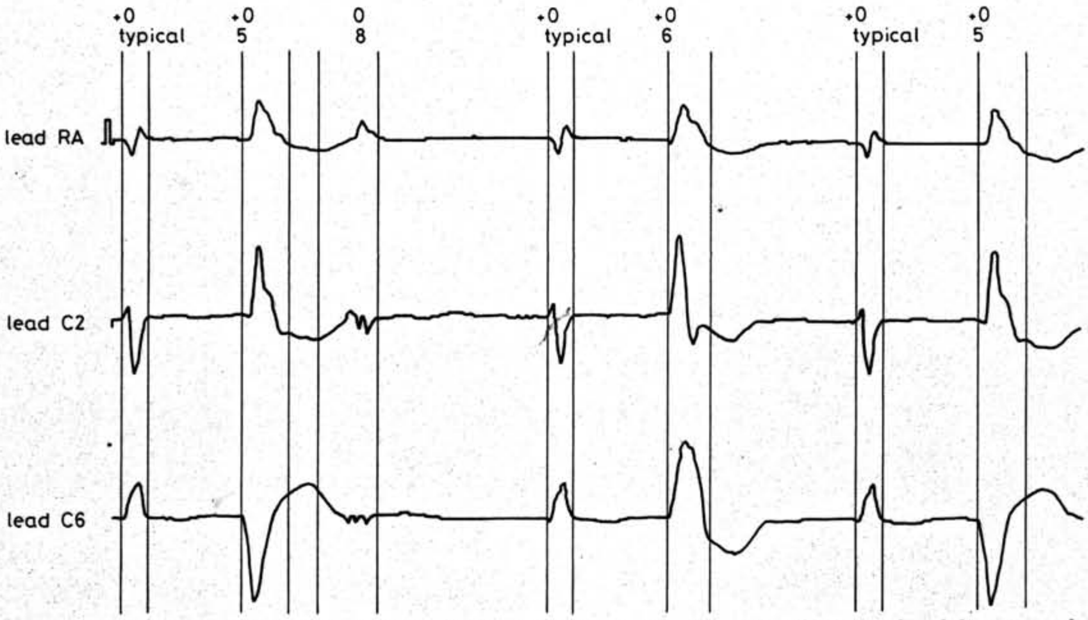
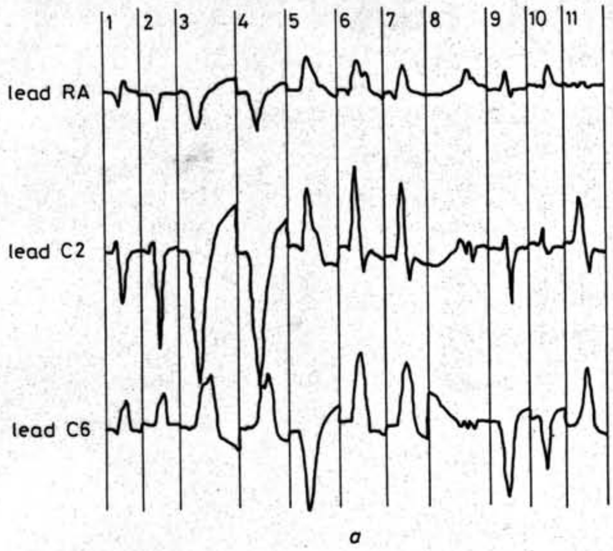
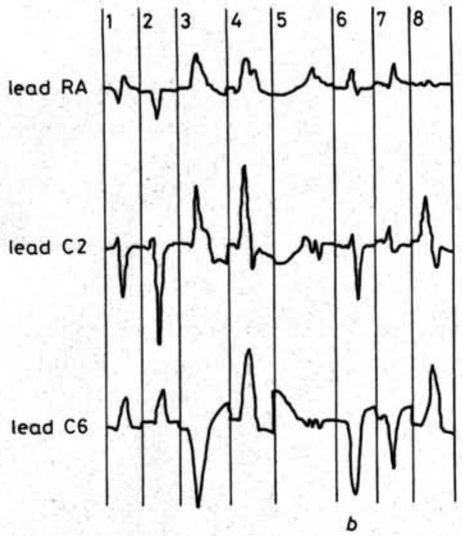


Fig. 5 *Example of a classified rhythm electrocardiogram of a 60-year-old woman. The class affiliation of each beat is marked*



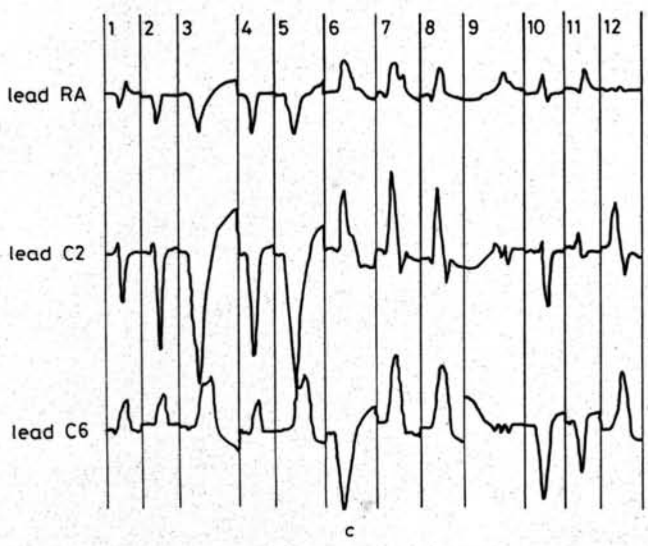
Class number	'Sign' series	Cluster boundaries
typical = 1	201	0...122
2	1	400...421
3	1	110...120
4	1	13...123
5	110	0...443
6	111	420...632
7	111	133...133
8	120	199...199
9	200	103...103
10	220	33... 33
11	221	120...120

Total number of beats = 246
Number of ectopic beats = 51
Number of ventricular beat classes = 11
Delineation units (maximum sensitivity = 1) = 2
Fractal rank range (percentage of the leader) = 5



Class number	'Sign' series	Cluster boundaries
typical = 1	201	0...122
2	1	0...423
3	110	0...443
4	111	120...633
5	120	199...199
6	200	103...103
7	220	33... 33
8	221	120...120

Total number of beats = 246
Number of ectopic beats = 51
Number of ventricular beat classes = 8
Delineation units (maximum sensitivity = 1) = 3
Fractal rank range (percentage of the leader) = 5



Class number	'Sign' series	Cluster boundaries
typical = 1	201	0...122
2	1	400...400
3	1	110...120
4	1	421...421
5	1	13...123
6	110	0...443
7	111	420...632
8	111	133...133
9	120	199...199
10	200	103...103
11	220	33... 33
12	221	120...120

Total number of beats = 246
Number of ectopic beats = 51
Number of ventricular beat classes = 12
Delineation units (maximum sensitivity = 1) = 1
Fractal rank range (percentage of the leader) = 5

Fig. 6 *Classification of ventricular beat patterns: (a) with delineation sensitivity of two fractal ranks when sensing for the cluster boundaries; (b) with a lower sensitivity of three ranks; (c) finest beat separation of one rank for the currently chosen rank range of 5 per cent from the leader's fractal number value*

3 Material and implementation

We used a rhythm ECG database of 100 recordings, each with a duration of 160 s. The ECG files contained 12-bit data from leads RA, C2 and C6 (so $L = 3$), recorded toward the left-leg electrode. The sampling rate was 200 Hz. All programs were implemented in the computer language Forth and run on an IBM-compatible PC/XT/AT with a Hercules monitor.

The processing time of our classification procedures (entirely in high language, three leads, 160 s learning period, 8 MHz XT) amounted to 0·7 s per beat. The complexity of the algorithm presented is not very high, so that it permits a real-time implementation, either by a shorter learning period, reduction of number of investigated leads, or by use of a faster processor, Assembly language optimisation.

A direct performance comparison of the technique introduced with others conventionally applied is quite difficult, due to the use of a wide variation of databases and instrumentation by different authors. Therefore we consider a major task of this paper to be the submission of a general classification approach, which follows the tendency of natural phenomena to self-clustering. A model implementation is presented in detail to stimulate further progress.

4 Results

100 rhythm ECG recordings with 2387 beats were tested (an example is given on Fig. 5). The classification clustering itself showed 100 per cent sensitivity. The positive and negative predictivities were functions of the required shape separation sensitivity (Fig. 6), and their judgment was found to be to a great extent subjective.

All observed classification errors were due to the threshold approach of the ventricular beat onset and offset estimation procedure. In some cases, QRS onsets and offsets were significantly shifted by similar, but borderline, ventricular beat shapes within a recording, which caused further different waveform labelling for these shapes. The sensitivity of the onset/offset procedure in regard to the negative consequences on the following classification was found to be 96·2 per cent.

The beat identification sensitivity, which is not intended to be discussed in this paper, could not reflect on the classification quality: the missed beats simply did not participate in the labelling.

5 Discussion and conclusions

The structure of the two-stage classification algorithm presented is a result of many multiparameter tests which showed that:

(*a*) A threshold approach to pattern shape comparisons is unsatisfactory. The waveforms of different ventricular beats transmute smoothly, and that seems to be a typical feature of natural phenomena. A suitable alternative is the cluster delineation method.

(*b*) An optimal classification strategy for the important problem of combining various information sources has to be worked out. For example, the often applied technique of weighted source parameter summing (e.g. Wolberg and Mangasarian, 1990) leads in some cases to blending of event description borders and finally to classification ambiguity.

We apply another general classification approach by a parallel combination of the event descriptors. Keeping the description parameters separate by quantifying and uniting them in parallel (to generate new event labels) is a successful way to reduce the input information stream without losing details.

(*c*) Among all tested ventricular beat parameters (duration, *R*-amplitude, 'signed area', 'fractal number', 'fractal number' of the first derivative, 'sign' and 'absolute area'), the last three were found to be sufficient and most sensitive, if used correctly.

(*d*) To evaluate and quantify the parameter values, the concept of deviation from median selected parameter 'representatives' was applied. Beat parameter series were built (fractal number deviation measures and 'signs'), thus integrating parameter values from all leads. Each 'sign' series determines a parameter space, where the fractal measure becomes a pattern presenting the respective ventricular beat shape.

(*e*) The shape measures correspond to smoothly transmuting beat forms, self-organised in clusters with adjacent fractal measure values. Each separate cluster within a 'sign' parameter space can be considered a ventricular beat class.

The sensitivity of the class separation is adjustable and it depends only on the number of fractal measure units by which the pattern cluster boundaries are sensed (delineated) in the process of classification and on the fractal rank range chosen.

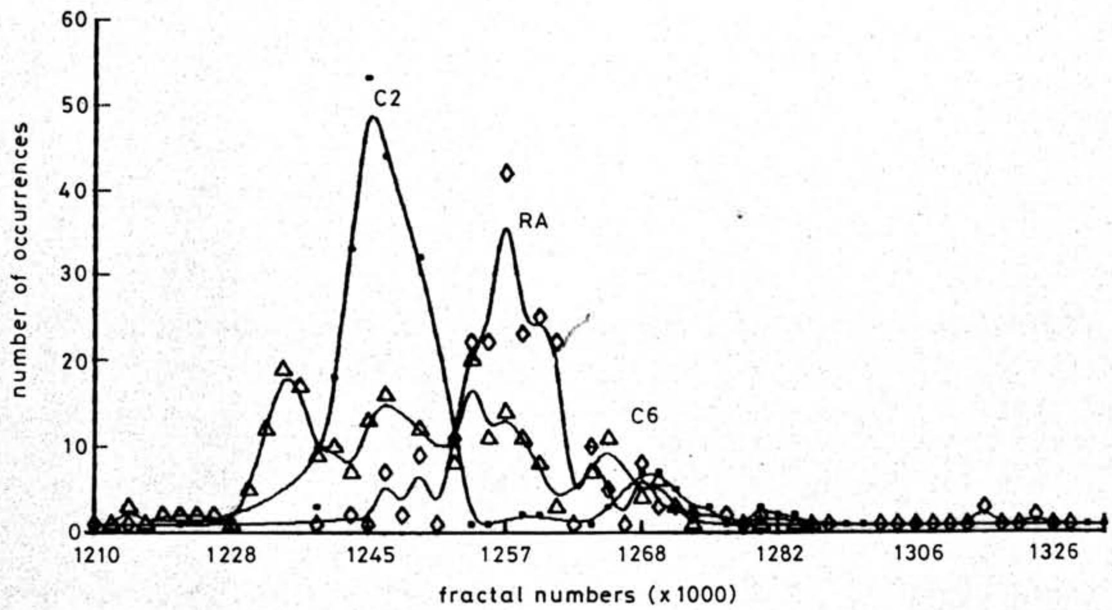


Fig. 7 *Example of QRS pattern (fractal number) distributions for 246 beats and three leads*

We must note that ventricular beat fractal number distributions could also be used as an additional morphologic information source of eventual diagnostic value (Fig. 7).

The ventricular beat classification of long-term ECG data, also considering the recorded beat-to-beat intervals, may be useful in diagnosing and guiding the therapy of some arrhythmias. Although the classification method proposed here is, of course, subject to further developments, the associative principles could be expanded to quantification attempts for other natural phenomena.

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