Review

Software QRS detection in ambulatory monitoring — a review

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Abstract—*The QRS detection algorithm is an essential part of any computer-based system for the analysis of ambulatory ECG recordings. This review asserts that most one-channel QRS detectors described in the literature can be considered as having the same basic structure. A discussion of some of the current detection schemes is presented with regard to this structure. Some additional features of QRS detectors are mentioned. The evaluation of performance and the problem of multichannel detection, which is now gaining importance, are also briefly treated.*

Keywords—*Ambulatory monitoring, QRS detection*

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1 Introduction

THE widespread interest in ambulatory monitoring of the electrocardiogram, especially during the last ten years, has prompted the development of software QRS detection. The demands on QRS detector performance in ambulatory monitoring are high. QRS complexes with a broad spectrum of morphologies should be detected in the presence of different physiological and technical 'disturbances'. Since a recording typically lasts 24 h it is crucial to design computationally feasible algorithms in order to arrive at a reasonable overall processing time of the analysis system. Fig. 1 demonstrates the signal-processing steps employed in computer-based analysis of ambulatory recordings. The term 'postprocessor' includes all further algorithmic or human processing of the QRS detector output. In most systems postprocessing is synonymous with R-R interval analysis and/or QRS waveform classification. A review of various postprocessors, as well as total systems for analysis, is given by THOMAS *et al.* (1979).

It is important to be aware that the various links in the signal-processing chain are highly interdependent. For example, a QRS detection algorithm which has been 'tuned' to a certain recording/replay system may have to be retuned if it is to be used with another system having e.g. different frequency characteristics. Furthermore, if the postprocessor is a sophisticated waveform classifier, the demands on the QRS detector are quite different from those when the postprocessor is simply an algorithm for R-R interval analysis. The waveform classifier can typically accept more false detections from the QRS detector than the R-R interval analyser.

Other areas in which software QRS detectors are employed include processing of resting and exercise ECGs and monitoring of intensive care patients. Since the cost of microprocessors is now so low, even simple devices such as heart-rate meters are often equipped with digital QRS detectors.

Conceptually, most QRS detectors described in the literature can be divided into two entities: the preprocessor and the decision rule (Fig. 2). These two entities are discussed in Sections 3 and 4, as well as some additional features of QRS detection schemes. Since most detectors use a one-channel ECG, the emphasis in these sections is on such detectors. The evaluation of performance and QRS detection in multichannel systems are briefly considered in Sections 5 and 6, respectively. Some QRS detectors incorporate morphological information acquired in the postprocessor to further improve detector performance (MEAD *et al.*, 1979). Since such feedback tends to be very system dependent, it will not be considered in this review. Another subject which is not

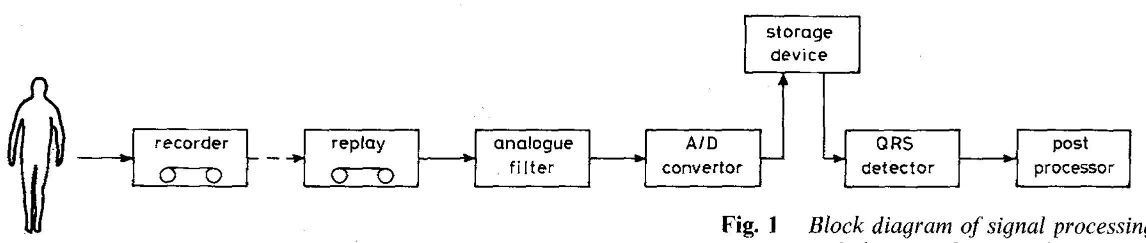

Fig. 1 *Block diagram of signal processing steps in the analysis of ambulatory ECG recordings*

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covered is syntactic QRS detection (HOROWITZ, 1975; BELFORTE *et al.*, 1979; BIRMAN, 1982).

Fig. 3*a* every third QRS complex is quite different in morphology from the others, although roughly equal in

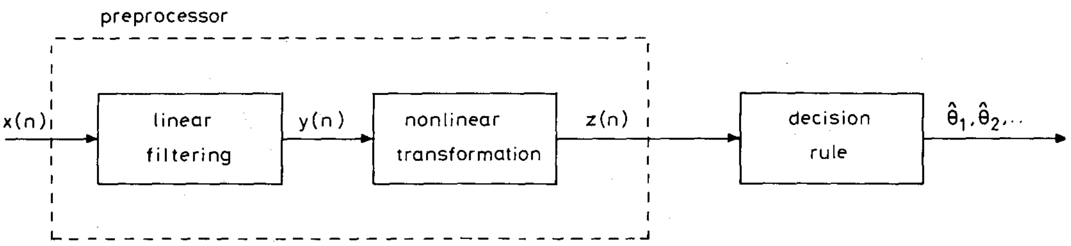

Fig. 2 *Block diagram of a QRS detector, composed of a preprocessor and a decision rule. The preprocessor is often subdivided into linear filtering and nonlinear transformation. The detector outputs,* $\hat{\theta}_1, \hat{\theta}_2, \ldots$, *denote estimates of the locations of QRS complexes in time*

2 Signal problems

Before we address the main issue of the present review a brief outline of some commonly encountered signal problems seems warranted. Signal problems are of physiological and technical origin. They can be classified into two main categories, namely morphology changes (including amplitude changes) and occurrence of disturbances. These categories can be further subclassified:

I Changes in QRS morphology
- (*a*) of physiological nature
- (*b*) due to technical problems

II Occurrence of disturbances
- (*a*) myopotentials ('noise')
- (*b*) transient artefacts (mainly due to electrode problems)
- (*c*) large P- or T-waves.

Each main category contains problems of a physiological as well as a technical nature.

Morphology changes are demonstrated by Figs. 3*a*–*c*. In Fig. 3*a* every third QRS complex is quite different in morphology from the others, although roughly equal in amplitude. In Fig. 3*b* two morphologies occur; one is remarkably lower in amplitude than the other and biphasic. These two examples represent ventricular extrasystoles (VES) and are thus of physiological origin. Fig. 3*c* demonstrates a technically mediated, rather drastic variation in QRS amplitude.

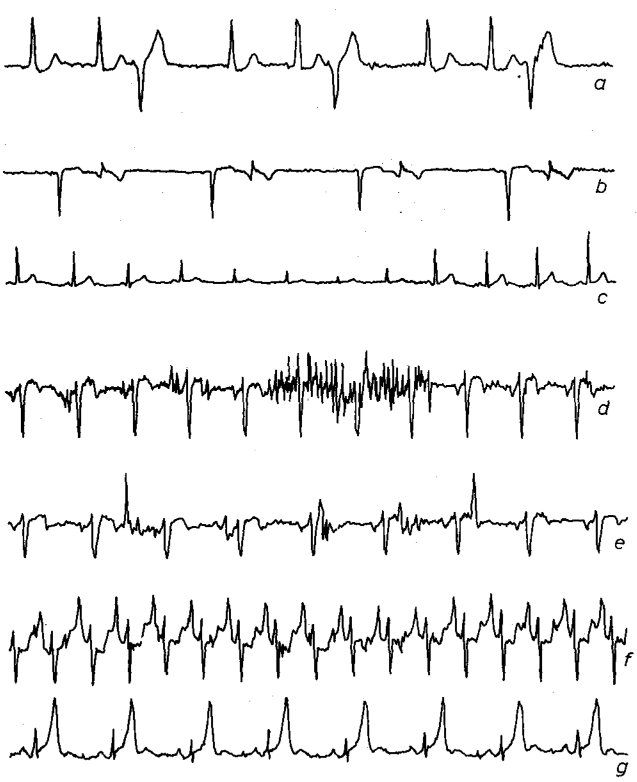

Fig. 3 *Various signal problems of physiological and technical origin. The examples are further discussed in the text*

Various common types of disturbances are indicated by Figs. 3*d*–*g*. Fig. 3*d* shows a short burst of noise, probably of muscular origin. It is noted that some of the wave shapes in the noise episode are 'QRS like', which makes them rather difficult to deal with. Fig. 3*e* shows an example of an even more tricky type of artefact, probably due to electrode problems. The shapes and amplitudes of the artefacts are fairly typical for QRS complexes and only the time relationships and the complete absence of 'T-wave' reveals to the trained eye that they are not QRS complexes. Finally, Figs. 3*f* and *g* show situations where P- and T-waves could be misinterpreted as QRS complexes by a QRS detector. In Fig. 3*f* tall, pointed and uniphasic P-waves precede the rather small and biphasic QRS complexes. In Fig. 3*g* the QRS complexes are very low in amplitude relative to the T-waves.

Naturally, care should be taken to minimise technical problems through careful electrode preparation etc. Such measures are more effective than trying to cope with poor signal quality in the detector. It is also important to avoid electrode positions that give disadvantageous P/QRS or QRS/T relationships. However, even if they are avoided at the outset, the relationships may change during the time of the recording, e.g. due to positional changes of the patient.

3 Digital preprocessing

The purpose of the preprocessor is to enhance the QRS complexes of the digitised ECG, while suppressing noise and artefacts. Preprocessing can be divided into linear filtering and nonlinear transformations. The nonlinear transformations consist of operations such as rectification or squaring of the filtered signal. Not all preprocessors employ nonlinear transformations; the filtered signal can be fed directly to the decision rule instead.

3.1 *Linear filtering*

The earliest attempts to produce a signal better conditioned for the decision rule employed the first difference of the ECG (CACERES, 1963; PRYOR *et al.*, 1969; HOLSINGER *et al.*, 1971). The same technique has since been used in several QRS detectors (BELFORTE *et al.*, 1979; BOLTON and COLEMAN, 1981). When analysing resting ECGs, the first difference may perhaps be an acceptable choice. The first difference, however, also accentuates high-frequency noise and is thus not appropriate in situations with moderate or low signal-to-noise ratio (SNR), e.g. in ambulatory monitoring.

Results from the detection of a known signal in Gaussian noise provide a basis for designing a suitable linear filter. It is well known that the optimum detector includes a matched filter, which for a white noise situation has an impulse response equal to the QRS complex but reversed in time. This implies the use of a bandpass filter, since the frequency content of a QRS is essentially in the interval 5–30 Hz. In contrast to signals encountered in communication theory, however, the QRS morphology often varies with time and the noise is not stationary. The design of a linear, time-invariant bandpass filter must therefore not impose any strict requirements on the transition regions of the frequency response of the filter, but instead try to reconcile the different conflicting demands made upon it. For example, the lower cutoff frequency should be chosen so as to minimise the influence of large-amplitude P- and T-waves while still accentuating ectopic beats. Furthermore, the upper cutoff frequency should be chosen so as to suppress motion artefacts but not narrow QRS complexes. Owing to the rather loose requirements on the frequency response, simple structured filters can be successfully used. This is of major importance in real-time monitoring and when analysing long-term ECG recordings, since the number of calculations associated with a certain filter is decisive for the total processing time.

The use of a digital bandpass filter in the preprocessor is described in many recent papers on detectors. The filter has a centre frequency between 10 and 25 Hz, a bandwidth of 5–10 Hz and is usually implemented with a finite impulse response (FIR) structure. (Readers who are unfamiliar with digital filtering, are referred to the introductory textbook by HAMMING, 1983.) A class of simple digital filters has been suggested by BÖRJESSON *et al.* (1982). Filters belonging to this class have been used by several authors. The impulse response of each filter is defined by two integer parameters K and L

$$h(k) = Z^{-1}\{(1-z^{-K})(1+z^{-1})^L\} \quad . \quad . \quad . \quad . \quad . \quad (1)$$

where $Z^{-1}\{\cdot\}$ is the inverse Z-transform. In the time domain, the first part $(1-z^{-K})$ forms a difference between the input signal and the delayed input (K samples), and the second part $(1+z^{-1})^L$ is a low-pass filter with decreased bandwidth for increased L. Each filter in this class has linear phase. Furthermore, the filters can be implemented solely with arithmetical operations (Fig. 4). The number of operations increases linearly with L. The above-mentioned first difference is given by $(K, L) = (1, 0)$. It has been found that, for the sampling rate $f_s = 100$ Hz, a good performance was obtained by using $(K, L) = (1, 2)$ (SÖRNMO *et al.*, 1982). These parameters yield a bandpass filter with $f_c = 20$ Hz and a rather large bandwidth (Fig. 5). Since there is a large spectral variability in QRS complexes a smaller bandwidth will increase the number of beats missed. By using a filter with lower centre frequency, e.g. $(K, L) = (4, 3)$, it was found that the number of false detections due to T-waves was considerably increased. For $f_s = 100$ Hz, the filter $(K, L) = (1, 1)$ has been employed by NYGÅRDS and HULTING (1979) and FANCOTT and WONG (1980). For a higher sampling rate, i.e. $f_s = 250$ Hz, the filter $(K, L) = (5, 4)$ appears to be an appropriate choice, also being a filter with $f_c = 20$ Hz (Fig. 6) (ENGELSE and ZEELENBERG, 1979). By using any of the above-mentioned combinations of sampling rate and filter parameters the 50 Hz mains frequency will be cancelled.

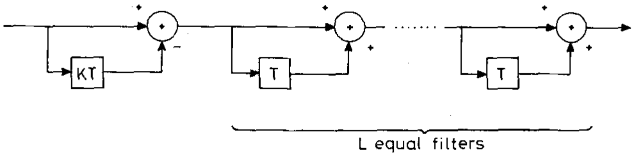

Fig. 4 *Realisation of the class of filters defined by eqn. 1. A box labelled with nT denotes an n-sample delay*

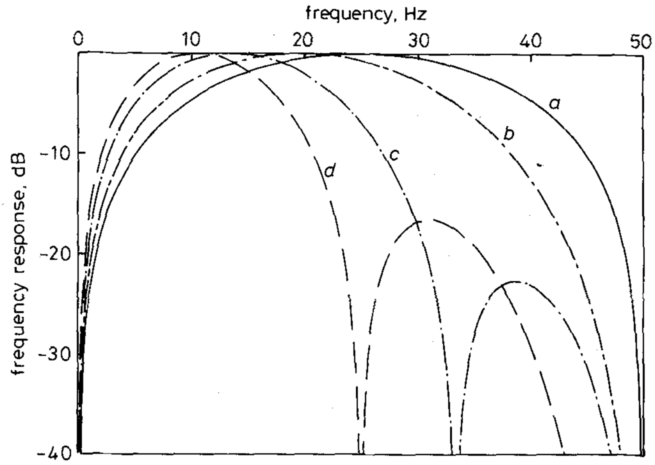

Fig. 5 *Frequency response for filters described by parameters K and L, using 100 Hz sampling frequency*
(a) $(K, L) = (1, 1)$, *(b)* $(K, L) = (1, 2)$, *(c)* $(K, L) = (3, 2)$, *(d)* $(K, L) = (4, 3)$

Another digital bandpass filter which is useful for preprocessing of the ECG signal has been presented by KUNT *et al.* (1982) and LIGTENBERG and KUNT (1983). The filter has been designed to achieve robustness and simplicity of structure. The filter consists of two cascaded filters, the first of which reduces the baseline wandering and cancels the mains frequency, while the second accentuates the QRS complexes. The first filter is obtained by combining four averaging filters. For the input ECG signal $x(n)$ the output $y(n)$ is then given by

$$y(n) = \frac{1}{K_1^2} \sum_{m=n-K_1+1}^{n} \sum_{k=m-K_1+1}^{m} x(k) - \frac{1}{L_1^2} \sum_{m=n-L_1+1}^{n} \sum_{k=m-L_1+1}^{m} x(k) \quad . \quad . \quad . \quad . \quad (2)$$

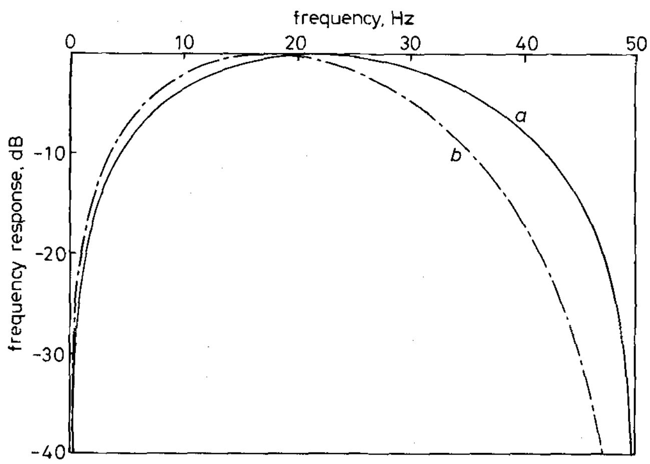

Fig. 6 *Frequency response for filters using 250 Hz sampling frequency*
(a) $(K, L) = (5, 4)$, *(b)* $(K_1, L_1) = (5{,}200)$ *followed by* $(K, L) = (1, 3)$

where K_1 and L_1 are two integer parameters defining the length of each averaging filter. The number of arithmetic operations associated with eqn. 2 can be reduced by taking advantage of the fact that each averaging filter can be implemented recursively. The second filter falls within the class defined by eqn. 1 with filter parameters $(K, L) = (1, 3)$. The overall frequency response for the two filters with a sampling rate of 250 Hz and with $(K_1, L_1) = (5{,}200)$, is shown in Fig. 6.

Other 'matched' filters for QRS detection have been described by McCLELLAND and ARNOLD (1976) and DILLMAN *et al.* (1978).

Several different choices of bandpass filters for analogue QRS detectors have been described (WINTER and TRENHOLM, 1969; DELL'OSSO, 1973; THAKOR *et al.*, 1980). The filters have centre frequencies in the interval 12–17 Hz and bandwidths ranging from 6 to 30 Hz.

3.2 *Nonlinear transformations*

Several heuristic approaches to nonlinear transformations of the filtered ECG can be found in the literature, e.g. MURTHY and RANGARAJ (1979) and OKADA (1979). A common objective for such approaches is to obtain a single positive peak for each QRS, which thus allows the use of a peak detector or a one-sided threshold. As is the case with linear filtering, it is also constructed so that it can obtain a signal in which the QRS complexes are enhanced from the background of P-waves, T-waves, noise and artefacts.

The QRS detection problem is to a certain degree analogous to the problem of separating voiced from unvoiced segments in speech signals. The latter problem has been treated by RABINER and SCHAFER (1978), using short-time analysis. This technique performs a memoryless nonlinear transformation on the input signal, followed by linear filtering. In relation to QRS detection the following transformation has been studied:

$$z(n) = \sum_{k=n-N+1}^{n} y^2(k)h_e(n-k) \quad . \quad . \quad . \quad . \quad . \quad (3)$$

which could be interpreted as an expression of the short-time energy. The signal $y(n)$ may either be the original ECG signal or a filtered version of it, see above. The squared signal is then fed to a filter with a finite impulse response $h_e(k)$. This filter provides the necessary smoothing of the signal so that only large-amplitude events of sufficient duration, i.e. the QRS complexes, are preserved in $z(n)$.

LIGTENBERG and KUNT (1983) calculated the signal $z(n)$ in eqn. 3 after linear filtering with a simple averaging filter:

$$h_{e,1}(k) = \begin{cases} 1 & k = 0, \ldots, N-1 \\ 0 & \text{otherwise} \end{cases} \quad . \quad . \quad . \quad . \quad (4)$$

A smoother behaviour of $z(n)$ could be obtained for this filter by increasing N. Although this reduces the influence of spike artefacts of short duration it also increases the risk of dropping small VES. Another type of filter was proposed by MURTHY and RANGARAJ (1979), who instead filtered the squared first difference of the ECG with a filter defined by

$$h_{e,2}(k) = \begin{cases} N-k & k = 0, \ldots, N-1 \\ 0 & \text{otherwise} \end{cases} \quad . \quad . \quad . \quad . \quad . \quad (5)$$

The successful application of eqn. 3 is largely dependent on the properties of the preceding linear filter. By using the first difference of the ECGs the resulting detector becomes extremely sensitive to high-frequency noise. To reduce this problem Murthy and Rangaraj modified their filter $h_{e,2}(k)$ by also using an averaging filter with $h_{e,3}(k) = h_{e,1}(k) * h_{e,2}(k)$ in eqn. 3.

Even though the ECG signal is not usually considered to be strictly band limited, the envelope representation is still advantageous for obtaining a positive-valued signal (NYGÅRDS and SÖRNMO, 1983). The envelope is defined by

$$z(n) = (y^2(n) + \hat{y}^2(n))^{1/2} \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (6)$$

where $\hat{y}(n)$ is the discrete Hilbert transform of $y(n)$. An approximation of the ideal Hilbert transform is required before calculation of the envelope. If, furthermore, threshold detection is employed, the ripple in the envelope must be smoothed out. A computationally attractive approximation of eqn. 6 is given by

$$z(n) \approx |y(n)| + |\hat{y}(n)| \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (7)$$

which, after smoothing, yields a signal similar to the one obtained by eqn. 6. BREKELMANS and DE VAAL (1981) described a QRS detector, in a multichannel setting, which preprocesses the bandpass filtered signal in essentially the same manner as eqn. 7.

Although the above mentioned nonlinear schemes may be practically suitable, the theoretical basis for these schemes is not evident. A more formal approach for arriving at a nonlinear scheme is to formulate a stochastic, parametric model for the ECG (BÖRJESSON *et al.*, 1982). The specific structure of the nonlinear operations, as well as that of the decision rule, is obtained by applying optimal estimation techniques. Briefly, the ECG is modelled as an unknown number, q, of pulse-shaped waveforms $s(k, T_i)$, which have been corrupted by stationary Gaussian noise

$$r(k) = \begin{cases} \sum_{i=1}^{q} B_i s(k-\theta_i, T_i) + n(k) & 1 \leqslant q \leqslant n \\ n(k) & q = 0 \end{cases} \quad . \quad . \quad (8)$$

Each waveform occurs at a random time θ_i in the observation interval, and has a random amplitude B_i and width T_i. A crude, but useful, way to model the width is to assume that $s(k, T_i)$ is composed of two equal waveforms $v(k)$.

$$s(k, T_i) = v(k) - v(k+T_i) \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (9)$$

The purpose of the estimator is to find those values of $q, \theta_1, \ldots, \theta_q, B_1, \ldots, B_q, T_1, \ldots, T_q$ which for a given criterion give the best fit for the model to the observed ECG. Since *a priori* knowledge is assumed to exist for the parameters, it is natural to apply the maximum *a posteriori* criterion (VAN TREES, 1968). The resulting structure of the estimator depends, of course, upon the specific form of the *a priori* probabilities.

If one assumes a 'least informative' situation (i.e. with uniform distributions), the estimation procedure carries out a nonlinear transformation of the linearly filtered ECG, which, after some simplifications, is given by

$$z(n) = \max_{\tau_1 \leqslant T \leqslant \tau_2} |y(n) - y(n-T)| \quad . \quad . \quad . \quad . \quad . \quad (10)$$

where τ_1 and τ_2 are positive integers. The signal $z(n)$ in eqn. 10 is thus the rectified, maximum amplitude difference between two samples.

Owing to the large computational requirements associated with eqn. 10 (the maximisation is performed at each point in time n) an approximate scheme can be used in which $y(n)$ and $y(n-T)$ are chosen among the peaks and valleys in the filtered signal (SÖRNMO *et al.*, 1982). A preprocessing scheme in which $y(n)$ and $y(n-T)$ are chosen among successive peaks and valleys has been investigated by AZEVEDO and LONGINI (1980) for enhancement of foetal ECG recordings. The use of successive peaks and valleys in a bandpass filtered signal can, however, in certain situations, i.e. for split QRS complexes, produce a signal $z(n)$ in which the complexes are suppressed rather than enhanced (SÖRNMO *et al.*, 1982). A further simplification of eqn. 10 is obtained by using the absolute value of the difference between two samples separated by a fixed distance $\tau_1 = \tau_2 = \tau$ (JACKSON *et al.*, 1983).

By using a preprocessor consisting of a bandpass filter followed by a transformation defined either by eqn. 3 or eqn. 10, baseline shifts will be represented by positive peaks in $z(n)$. MEAD *et al.* (1979) included a 'vector sum' in their QRS detector for finding such shifts. This technique sums together the slope coefficients within a QRS complex; a QRS complex yields a sum close to zero but a baseline shift does not.

Fig. 7 demonstrates the output of some of the nonlinear transformations discussed in this section. In each case the input signal I is filtered by a filter defined by $(K, L) = (1, 2)$ in eqn. 1. The sampling frequency is 100 Hz. The short-time energy signal II is obtained by using the filter in eqn. 4 with $N = 6$ in eqn. 3. The envelope signal III was obtained by eqn. 6 and a smoothing filter with a triangular impulse response of length 5. An approximate Hilbert transform was obtained by using a filter of length 15 (NYGÅRDS and SÖRNMO, 1983). The rectified maximum amplitude difference IV was calculated with the parameters τ_1 and τ_2 chosen as 2 and 6, respectively. In the approximation of eqn. 10 by means of a peak-and-valley strategy V the same values of τ_1 and τ_2 were used.

It is noted in Fig. 7*a* that the short-time energy II produces a signal in which the noise background is better suppressed than in the other three preprocessors. In contrast small-amplitude QRS complexes tend to be too much suppressed (Fig. 7*b*). In Fig. 7*c* it is seen that in the short-time energy signal most T-waves are even larger than the QRS complexes. Note that some T-waves are not represented at all in the peak-and-valley signal V due to the width criterion.

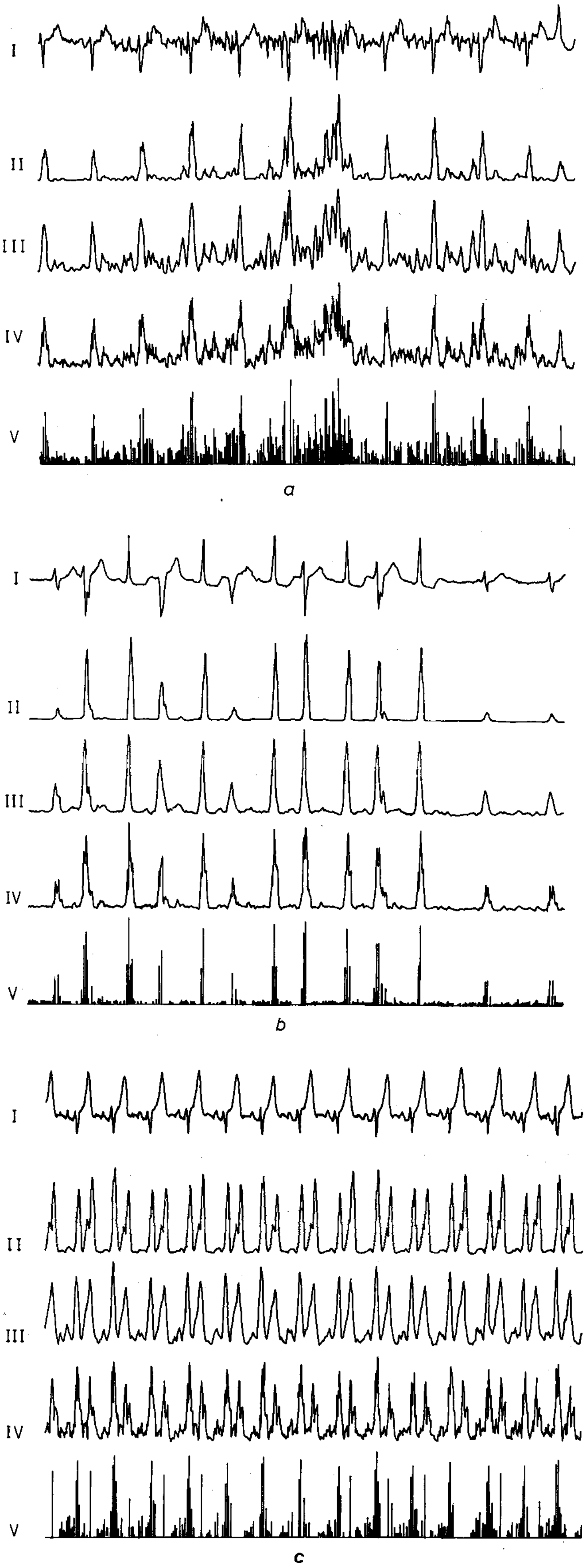

Fig. 7 *Three examples of QRS detector input and the output of four different preprocessors*
I is the input ECG signal
II is the short-time energy signal
III is the smoothed envelope signal
IV is the rectified, maximum amplitude difference between two samples
V is the signal obtained by a peak-and-valley strategy
For further clarification see text

4 Decision rule

A decision rule is applied to the output of the preprocessor to determine whether or not a QRS complex has occurred. The rule, which often involves an amplitude threshold, may be fixed or incorporate some kind of adaptivity. Although there are recent proponents for using a fixed threshold (BOLTON and COLEMAN, 1981), adaptive thresholds are now by far the most commonly applied. This is due to the fact that, in ambulatory ECG recordings, the QRS amplitude and morphology can change drastically during a short time interval; for an example, see Fig. 3. The detection of low-amplitude QRS complexes with a fixed threshold inevitably implies accepting several false detections. Besides comparison of the amplitude in the preprocessed signal to a threshold, the width of the waveform is often part of the basis for decision.

An inherent property of most detectors is their restrictive use of information available from the pattern of preceding RR-intervals. Even though a regular rhythm has prevailed for a long time, the next QRS to be detected is treated as if it could occur almost anywhere in the observation interval. The signal is usually processed in a 'causal' fashion, which means that QRS complexes are detected in temporal order, although the whole recording is available to the detector (i.e. from a computer disk). Several detectors described in the literature make use of a time-dependent threshold to reject large T-waves but still allow small VES to be detected. The threshold can be represented by

$$\eta(k) = \begin{cases} \alpha_1 & k = \theta+1, \ldots, \theta+D_1 \\ f(k) & k = \theta+D_1+1, \ldots, \theta+D_2 \\ \alpha_2 & k = \theta+D_2, \ldots \end{cases} \quad . \quad (11)$$

where the function $f(k)$ is such that

$$\alpha_1 \geqslant f(\theta+D_1+1) > \ldots > f(\theta+D_2) = \alpha_2 \quad . \quad (12)$$

and θ denotes the time instant for the most recently detected QRS complex (Fig. 8). The most common choice of eqn. 11 involves the 'eye-closing' period in which no detection can take place before $\theta+D_2$, i.e. with $\alpha_1 = \infty$, $D_1 = D_2-1$, and α_2 is adaptively updated, e.g. by making it equal to a fraction of the amplitudes of the most recently detected QRS

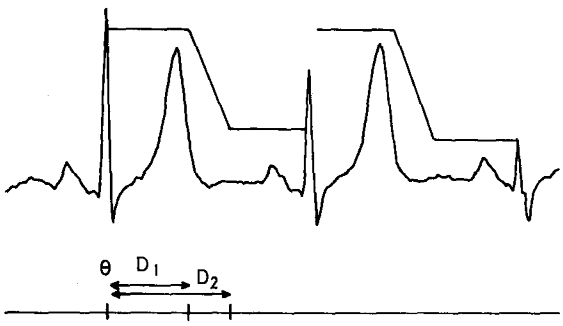

Fig. 8 *Amplitude threshold $\eta(k)$*

complexes. The eye-closing period is usually chosen in the interval 120–200 ms. The obvious risk of missing early VES necessitates choosing not too high values for D_1. A very short interval, and, of course, the exclusion of eye-closing will, however, increase the number of false detections not only due to T-waves, but also due to wide VES. There is thus a tradeoff in the choice of the eye-closing period which, as pointed out in the introduction, depends on whether or not waveform classification is performed. SHAH *et al.* (1977) have suggested a compromise between the conflicting demands described above. They use a finite α_1 in eqn. 11, but still with $D_1 = D_2 - 1$. Another choice of eqn. 11 is suggested by DILLMAN *et al.* (1978), where $\alpha_1 = \infty$ and $f(k)$ is a linearly decreasing function in the interval $[\theta+D_1+1, \theta+D_2]$. Whereas the eye-closing period D_1 is preset, D_2 is related to the length of the average RR-interval, i.e. when D_2 is smaller the function $f(k)$ decreases faster. When a tentative QRS complex has been detected, additional thresholds are applied to ensure that the detected waveform is not a P-wave.

Another type of decision rule can be found in a paper by ENGELSE and ZEELENBERG (1979). They have implemented an algorithm in which the rectified, linearly filtered signal is compared with an adaptive threshold. A QRS complex is detected if a known pattern of threshold crossings occurs within a certain time interval. The threshold is updated as an exponentially weighted average of the maximum filtered QRS amplitude of previously detected complexes. The use of this technique easily prevents false detections due to baseline shifts.

A detector which, to a certain degree, incorporates both past and future signal properties is described by BÖRJESSON *et al.* (1982). An observation interval is delimited within which QRS complexes are detected in their order of magnitude in the preprocessed signal, not in temporal order. Owing to this 'non-causal' property, eye-closing periods of equal length are applied both before and after each detected beat. The detection threshold is adapted with respect to the properties of the complexes, which delimit the interval. This approach allows the detector to find the QRS complexes even when a sudden decrease in amplitude occurs.

This section is concluded by mentioning some additional techniques which have been employed in QRS detectors.

(*a*) Since the spectral content of the muscle noise considerably overlaps that of the QRS, such noise will cause the performance to deteriorate. To cope with this situation, a noise detector or noise measurements will be of great value. Various strategies can be adopted for using the noise measurements. One way is to exclude disturbed parts of the recording from analysis; another is to indicate that detections are less reliable than usual (ARNOLD *et al.*, 1975; ENGELSE and ZEELENBERG, 1979; FANCOTT *et al.*, 1981; PAHLM *et al.*, 1981). A third approach is to use the noise measurements in the updating of thresholds. This is exemplified by LIGTENBERG and KUNT (1983), who utilise information on both average signal and noise level in the decision rule. A minimum-distance classifier is applied for comparison of the tentative QRS with the two averages to decide whether or not a QRS complex has occurred.

(*b*) The QRS detection process results in a sequence of RR-intervals. The properties of this sequence can be used to control a 'look-back' mode in the algorithm (PAHLM *et al.*, 1978; MEAD *et al.*, 1979; DEVLIN *et al.*, 1982). The occurrence of an RR-interval of approximately twice the length of the typical interval may, in cases of a stable basic rhythm, be due to an occurrence such as the missing of a low-amplitude ectopic beat. The processing of that interval with a lower amplitude threshold, or even with another linear filter in the preprocessor, may result in detection in the look-back mode.

(*c*) It is important to define a stable fiducial point of the detected QRS complex in many applications. Commonly used definitions such as the peak of R-wave or the maximum negative slope are unfortunately not suitable for one-channel ECGs (RIPLEY and MURRAY, 1980). These definitions will suffer from discontinuities for certain QRS shapes, and they are sensitive to noise. Techniques which probably offer a more stable definition are described by DILLMAN *et al.* (1978), GRADMAN *et al.* (1980) and NYGÅRDS and SÖRNMO (1983).

5 Evaluation of detector performance

In the preceding sections various approaches to QRS detection have been outlined. Before a detector can be implemented in a clinical setting the designer must

(*a*) determine suitable parameter values

(*b*) evaluate the performance for the set of parameter values chosen.

The choice of parameter values has, for the most part, been an integral part of the algorithmic development rather than the result of a separate optimisation. In doing so, the designer runs the risk of choosing values which are well adjusted to the learning material but not to subsequent materials. There are usually a large number of parameter values that must be fixed within each detector structure. A separate optimisation of all parameters in connection with some performance measure implies such a time-consuming amount of computations that it is prohibitive at our present stage of computer/technological development. An obvious way to cope with this problem is to optimise only those parameters which have the most profound effect on performance. Other values are fixed by *ad hoc* decisions; certain values may also be determined on physiological grounds. Although a single set of parameter values is ultimately to be used in practice, it is of great interest to investigate the performance as a function of a certain parameter. Remarkably little has, however, been published about the influence of different parameters on performance.

Efforts have been most often directed towards evaluating the clinical system as a whole, rather than at performing a separate evaluation of the QRS detector block (OLIVER *et al.*, 1977). Although such an evaluation does not provide any direct information about the performance of the QRS detector, a large number of missed VES, for example, might indicate a failure in the detector. Since the performance of the QRS detector is a limiting factor for the overall system performance (RIPLEY and MURRAY, 1980), a separate evaluation of the QRS detector is of major importance. A number of results from evaluations of QRS detectors are found in the literature (MEAD *et al.*, 1979; OKADA, 1979; BOLTON and COLEMAN, 1981; SÖRNMO *et al.*, 1982; MOODY and MARK, 1982; THAKOR *et al.*, 1983). Different workers have collected their own databases because of the lack of a unified one. A comparison of published results has no validity, since, for example, signal quality or the number of aberrant beats may vary widely between test sets. Information concerning the tolerance between estimated occurrence time of the QRS complex and the manually annotated occurrence time is, moreover, not often reported. It is therefore hoped that the MIT/BIH database (SCHLUTER *et al.*, 1980) as well as that of the American Heart Association (HERMES *et al.*, 1980) will to some extent meet the needs of detector evaluation.

The performance is usually measured in terms of false detection rate and true detection rate for a given set of parameter values. To study the behaviour of the detector for different parameter values, the true detection rate can be displayed against the false detection rate in a so-called receiver operating characteristic (ROC). A system designer may choose the 'operating point' in the ROC curve to comply with the demands of the postprocessor. An example of such a diagram is shown in Fig. 9, where the ROC curves for three different detectors are compared. The performances of two QRS detectors were investigated in terms of ROCs (SÖRNMO *et al.*, 1982) by varying the parameters which determine amplitude and width criteria, and the filter parameters (K, L) in eqn. 1. The ROC for an analogue detector was, furthermore, studied for different types of amplitude thresholds by adding different levels of band-limited noise to a noise-free ECG (THAKOR *et al.*, 1983). The generation of such signals enables the designer to easily investigate the robustness of the detector with regard to various kinds of noise and artefacts. This is of particular interest in ambulatory monitoring, in which noisy signals are often found.

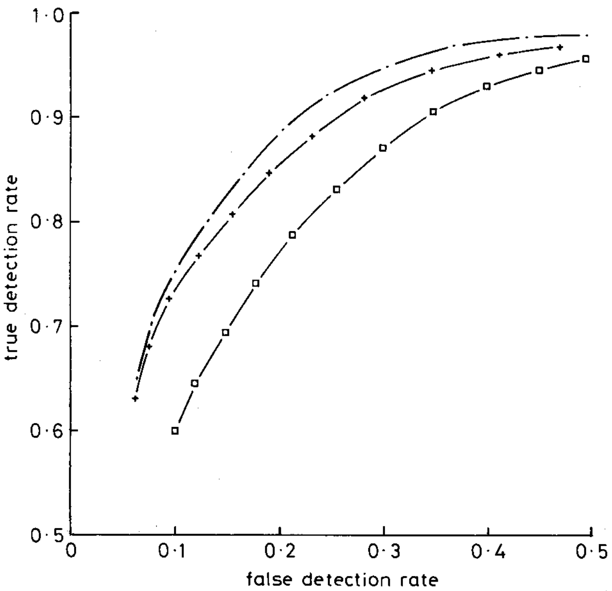

Fig. 9 *ROC curves obtained for three different QRS detectors. Each point is calculated for a certain value of an amplitude threshold. The material used consisted entirely of heavily disturbed ECGs*

6 Multichannel ECG recordings

The present review has provided an overview of approaches to QRS detection in one-channel ECG recordings. Although some multichannel systems for the analysis of ambulatory ECG recordings have been in use for several years (CLARK *et al.*, 1977; ROSENBERG and TARTAKOVSKY, 1979), their use has only recently tended to become widespread.

The reason for using multichannel detection and analysis in spite of the increased volume of data that has to be processed is the substantial improvement in performance that can be expected. Noise and artefacts often tend to occur intermittently during the recording period. Such episodes usually appear independently in different channels, so an improved immunity to disturbances can be obtained (ZYWIETZ *et al.*, 1981). Detection of ventricular extrasystoles will, moreover, be more reliable, since low-amplitude extrasystoles in one channel are usually larger in another channel.

Few detection strategies for multichannel ambulatory ECG analysis systems have been described. BRAGG-REMSCHEL and HARRISON (1980) report a hardware QRS detector in a two-channel system which employs majority logic for its decisions. The logic operates on tentative decisions obtained from two one-lead detectors operating in parallel and from a third detector operating on a signal derived by rectifying and summing the two original channels.

QRS detection algorithms in systems for resting and exercise ECGs generally employ a simple decision function obtained by combining several leads (e.g. WOLF *et al.*, 1972; SIMOONS *et al.*, 1975; WERNER *et al.*, 1976; BREKELMANS and DE VAAL, 1981; FALK *et al.*, 1982; MOSER *et al.*, 1982). In these schemes each channel contributes equally to the resulting decision function even if one of the channels is heavily disturbed. To our knowledge there is no description of a preprocessor which combines several leads in ambulatory monitoring in the literature. The design of such a preprocessor should most likely include a combiner which weights each channel according to its noise content.

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