

Method for an automatic analysis of the ECG

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ABSTRACT

A method is presented for an analysis of the ECG. Using cubic spline techniques we proceed first to a smoothing of the signal and then to the elimination of baseline drift. The properties of the calculated derivatives are used to establish criteria for the identification of the ECG waves and the measurement of their essential parameters. The complete procedure can be carried out by a computer, without human intervention. The results of this fully automatic procedure can be used directly as a means of classifying the ECG.

Keywords: ECG smoothing, baseline estimation, wave recognition

INTRODUCTION

One ever-present difficulty in any analysis of the electrocardiogram¹⁻⁸ is the noise created by power lines, muscles, recording amplifiers etc; to these must be added the baseline drift. All of them affect the parameters of the signal and make their measurement uncertain. A number of analogue and digital filtering methods have been used to minimize the effect of these unwanted signals.

We present a fully automatic method for an analysis of the ECG. The elimination of human intervention can make the procedure faster and in many cases more accurate. However, 'alarm keys' are provided in the programs, which do permit intervention in exceptional cases.

We remove the noise in the digitized ECG using a cubic spline technique as a low pass filter, based on the local statistics of the signal; a similar technique is used as an interpolator for removing the baseline drift. The derivatives calculated during these processes are used for the establishment of criteria for the identification of the P, Q, R, S, T waves as well as the measurement of their parameters. The first wave to be recognized is the R wave and the identification of the P, Q, S, T waves is based on this recognition.

The recorded signals were 12-lead ECGs taken from human subjects, each lead including five to eight ECG complexes. They were recorded on analogue tape and prefiltered at 1 kHz and were subsequently, digitized off-line at a 250 Hz sampling frequency by a 10 bit A/D converter and coded by 11 bits/sample.

Programs were written in FORTRAN 77; they are in three parts: preprocessing, signal analysis and identification of ECG waves.

PREPROCESSING

Smoothing

For smoothing of the ECG a cubic spline technique (CUSP) is used, it approximates the digitized signal

by a series of third order piecewise polynomials.⁹ The intersections of the polynomial components are called 'knots'. The knots are found by an algorithm which estimates the position of the knots by minimizing a local error based on the local statistics of the signal¹⁰. The flow diagram of the routine used is shown in *Figure 1a*.

In *Figure 2* an ECG signal is shown before smoothing (Y) and after smoothing (S). Also shown is the difference $e = Y - S$ which corresponds to the removed noise; it is almost band-limited white noise. We have selected the cubic spline technique because it is particularly suitable for smoothing signals which have regions of sharp variation and regions of low variation. This is due to the piecewise nature of the polynomial, which permits quick adaptation to the changes of the original signal¹⁰. The fact that the number of knots is not predefined is an advantage of the method, given that the estimation of knots by the local properties of the signal is much more accurate.

Elimination of baseline drift

For the elimination of the baseline drift we use some characteristics of the first derivative, calculated during smoothing. *Figure 3* shows the first derivative S' of the smoothed ECG S of *Figure 2*. It can be seen that the values of S' are large and change abruptly; they are low and change slowly during the inactive periods. This is true even when the baseline drift is large. We take advantage of this characteristic of S' to detect the baseline segments.

We detect the segments of the filtered signal lying between two knots, during which time the absolute value of S' is lower than a threshold: $S' < \epsilon$. If this condition holds for at least three sequential segments, their union is identified as a 'baseline segment' (SE).

The middle point of each SE (MSE) is calculated. We obtain the slowly varying component (SVC), which is a good approximation of the baseline drift, by using a cubic spline interpolator, the knots of which are the MSEs. Subtracting the slowly varying component from the smoothed signal, we remove the

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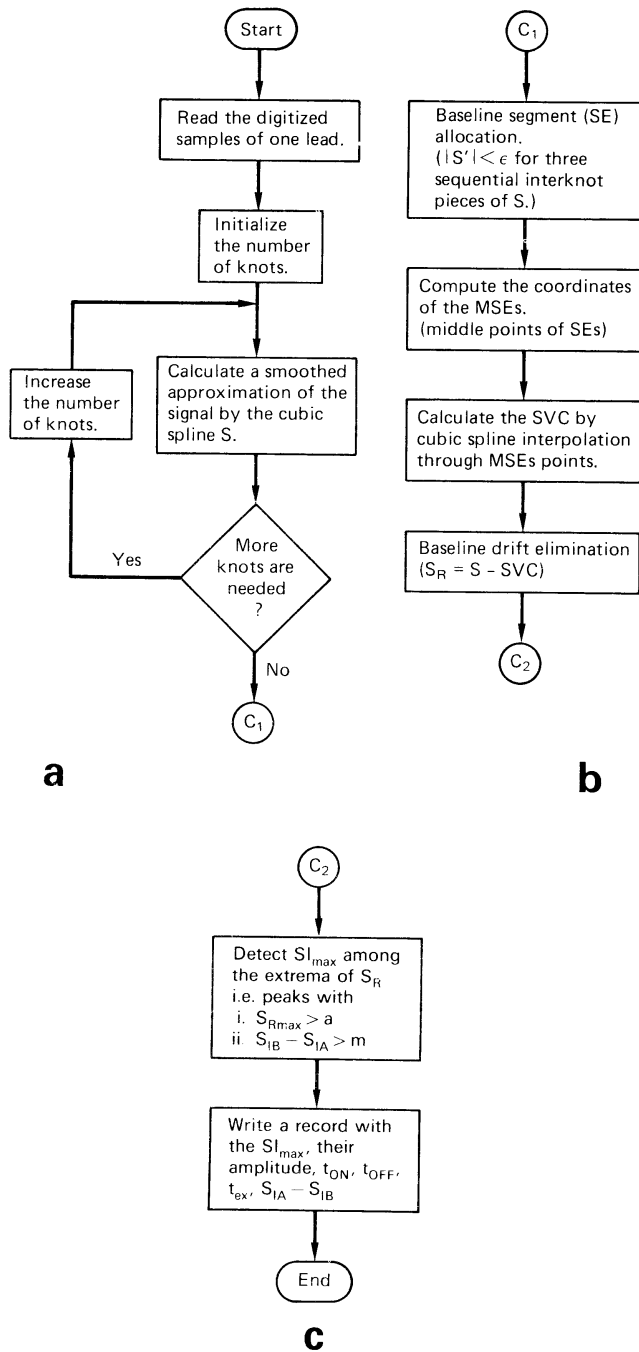


Figure 1 Flow diagrams for the algorithms. (a) Smoothing. (b) Removal of the baseline drift. (c) Detection of the significant maxima

baseline drift; the result is the reconstituted signal S_R .

This result, for the ECG of *Figure 2*, is shown in *Figure 4*: baseline drift is removed without deformation of the ECG waves.

The cubic spline technique has been used before by other authors for the removal of baseline drift^{11,12}. The advantage of our method is that it can be carried out by the computer without external intervention; the knots are not predefined but found by the program. Moreover, at this step, the waves of the ECG are not identified and cannot be used as knots in an automated method.

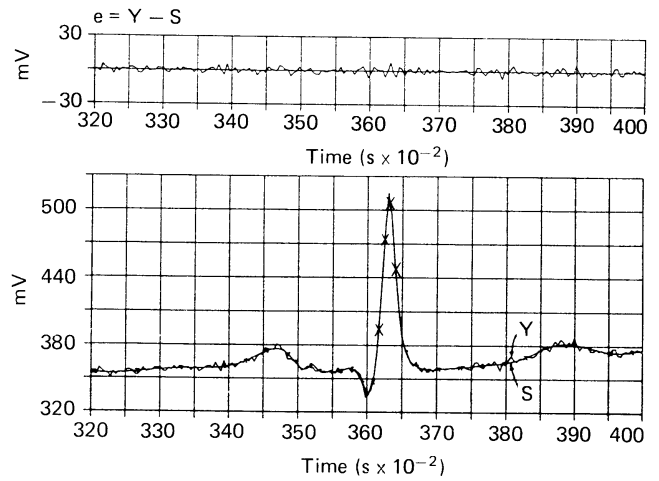


Figure 2 An example of an ECG signal before (Y) and after smoothing (S), and the difference $e = Y - S$. Y is the sample ECG data, X is the estimated knots for the spline S and S is the smoothed ECG signal

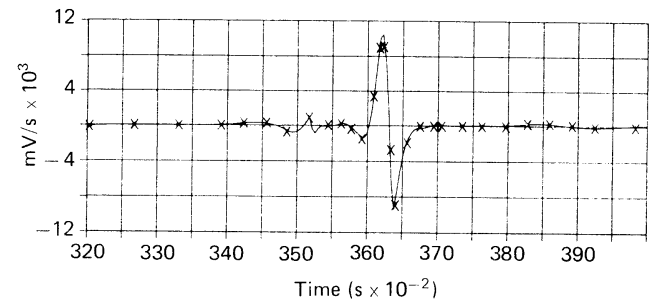


Figure 3 The derivative S' of the smoothed signal of *Figure 2*. The points give the position of the spline's knots

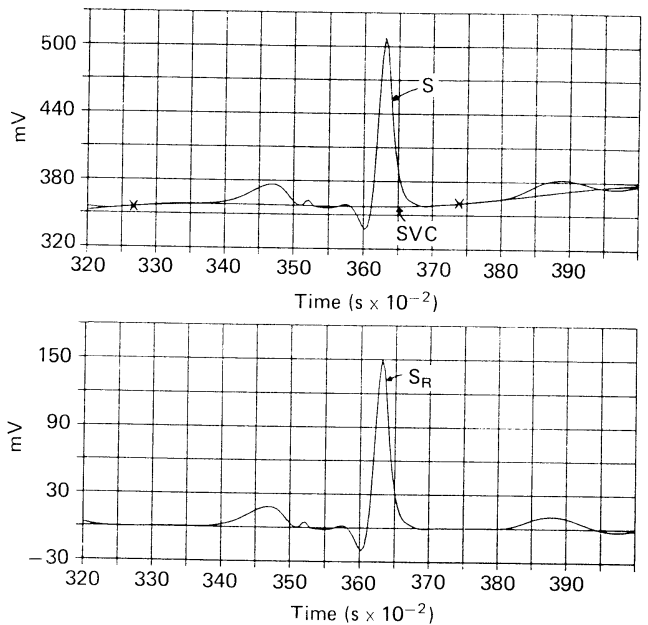


Figure 4 The estimation and removal of baseline drift. X are the automatically detected MSEs points on the S , used as the knots of an interpolating spline, which approximates the SVC. The $S_R = S - SVC$ is the reconstituted ECG signal. S is the smoothed ECG signal, X is the estimated points of the ECG baseline, SVC is the spline that approximates the baseline drift and $S_R = S - SVC$ is the reconstituted signal

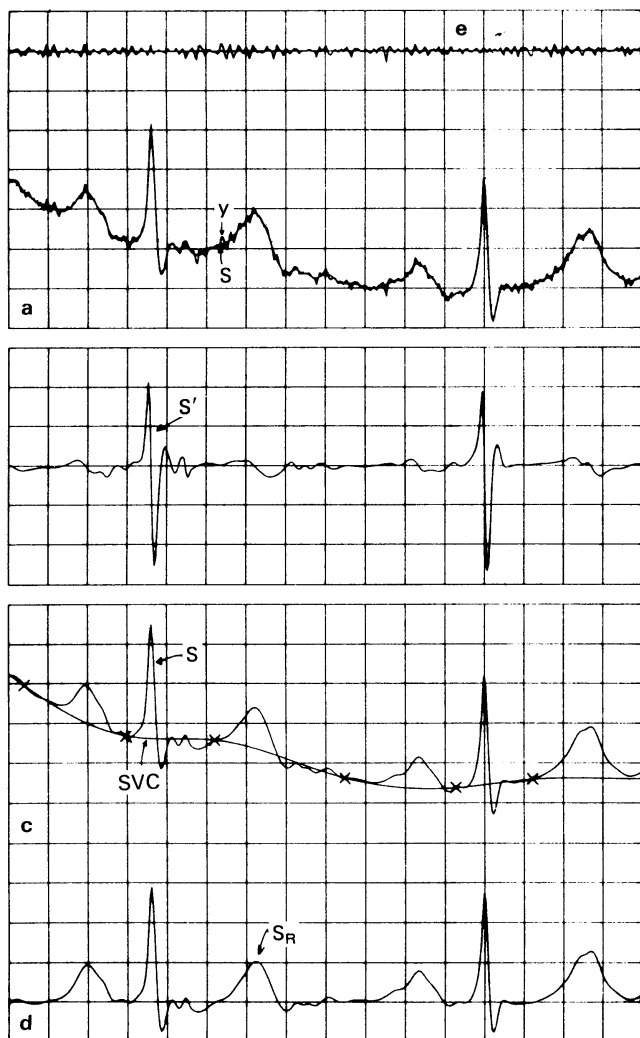


Figure 5 Example of ECG treated by our method: **a**, original (Y), smoothed (S) and noise removed from the signal (e); **b**, the first derivative (S') of the smoothed ECG; **c**, the identified MSEs points (X) and the baseline estimation (SVC); **d**, the smoothed and reconstituted ECG (S_R)

Figure 5 shows another ECG signal preprocessed by our method and Figure 1b shows the diagram of the corresponding routine.

SIGNAL ANALYSIS

After the removal of the noise and baseline drift we can proceed to the analysis of the reconstituted signal S_R .

This is done in two steps: first, detect significant local peaks which can be ECG waves and second measure their duration, amplitude and relative position in the complex (with relation to the peak of the R wave).

Detection of the significant maxima

We show a local maximum in Figure 6, and store its time of occurrence (t_{\max}) and its amplitude ($S_{R\max}$), together with its inflexion points I_B (before) and I_A (after) the maximum. The discussion which follows applies to both maxima and minima.

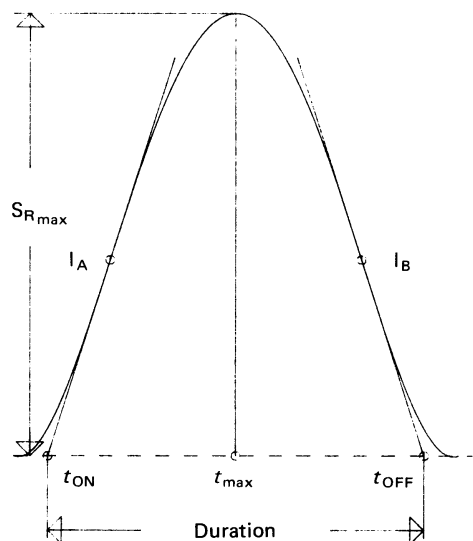


Figure 6 Representation of a local maximum. The coordinates (t_{\max} , $S_{R\max}$), the inflexion points I_B , I_A and the duration $t_{\text{OFF}} - t_{\text{ON}}$

A local maximum is considered to be significant (SI_{\max}) if the two following conditions are satisfied: (i) The absolute value of the maximum amplitude is greater than the threshold a : $|S_{R\max}| > a$. (ii) The absolute value of the difference of the first derivative S' of the two inflexion points I_B , I_A is greater than a threshold m : $|S'_{I_B} - S'_{I_A}| > m$.

Using the above criteria, we reject the minor local maxima of S_R , which cannot be ECG waves but occasional fluctuations; significant local maxima (SI_{\max}) may be the ECG waves. The values of the thresholds a and m were found by repeated tests on different ECGs. Figure 1c shows the flow diagram for this routine.

Detecting the SI_{\max} , we also know the amplitude and the times corresponding to each one. The duration is computed by estimating the onset and off-set time of each SI_{\max} . The onset and offset time are estimated in the following way: the tangents on the inflexion points I_A , I_B are extrapolated until they cross the reconstituted zero level at t_{on} , t_{off} , respectively (Figure 6). The difference, $t_{\text{off}} - t_{\text{on}}$ is the duration of the corresponding SI_{\max} .

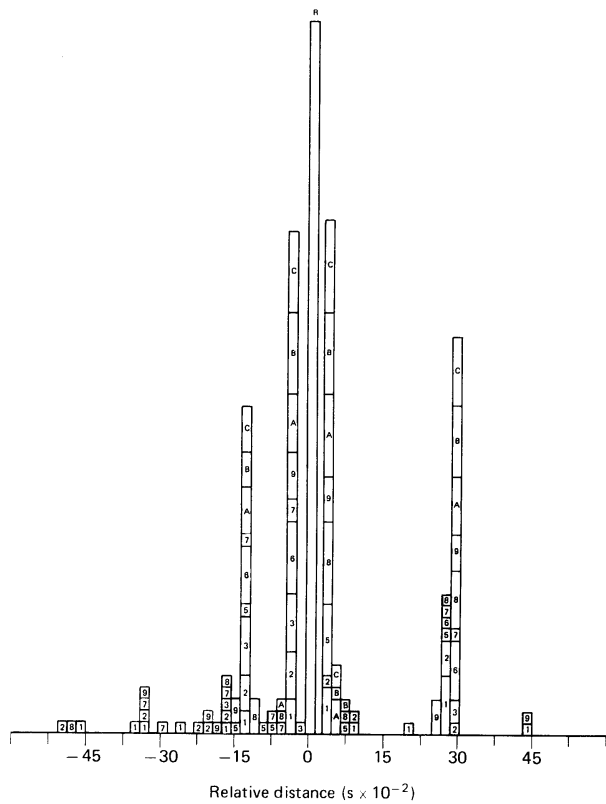
All the 12 leads of one subject are analysed by the above mentioned procedure. The result of this signal analysis is a population of SI_{\max} , fully defined by lead, time, amplitude, duration, and first derivative values of the two inflexion points.

THE IDENTIFICATION OF THE ECG WAVES

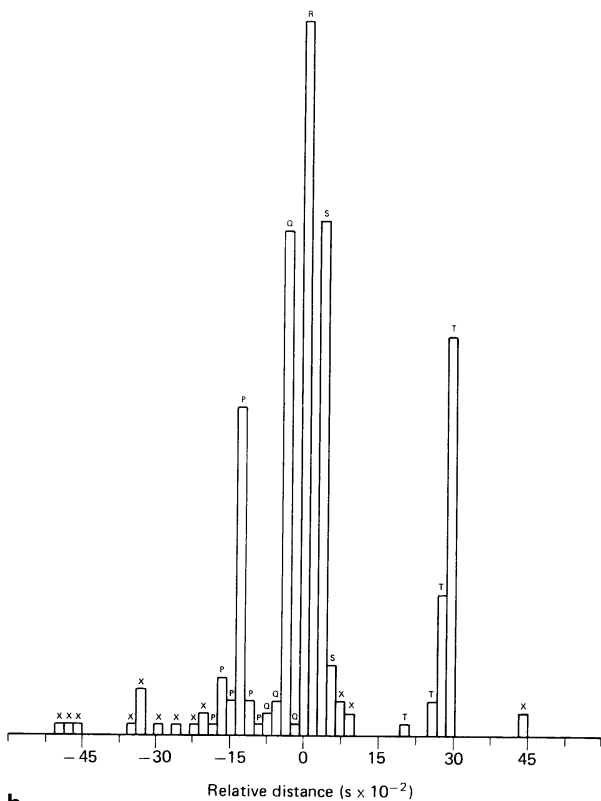
The SI_{\max} population is searched for the recognition of the P, Q, R, S, T waves. We first recognize the R waves and then we identify the others by constructing a histogram.

R wave recognition

The R wave has some peculiarities. It is the largest and sharpest positive wave and has the shortest



a



b

Figure 7 The first histogram of the R waves, **a**, and the SI_{max} . The R waves are placed on a relative time distance equal to zero. The SI_{max} are placed in positions according to their relative time distances from the R waves of the cycle. The symbols 1, 2, ... B, C correspond to the lead in which the SI_{max} was found. The peaks are clearly seen, **b**. The same histogram as in **a**, but the waves are marked as identified. There are some rejected ones, marked by X

rise time. For its recognition we use the following three criteria, which must be valid simultaneously:

- (i) The amplitude $S_{R_{max}}$ is positive and maximum.
- (ii) The difference of the first derivative on the two inflexion points I_B, I_A is very large (sharpest wave).
- (iii) The first derivative on the inflexion point I_B must be positive and have a very large value: $S'_{I_B} > M$, (smallest rise time).

We do not need to estimate a precise threshold value for the sharpness of the R wave. We have noticed that a very large gap exists between the sharpness of the R wave and the sharpness of the other SI_{max} around it.

Using the above criteria we recognize the R waves present in all the ECG leads of one subject. The essential parameters of the R waves are the parameters of the corresponding SI_{max} . For every lead the R-R times are calculated as well as the middle points of the R-R intervals.

Identification of the P, Q, S, T waves

We identify the P, Q, S, T waves based on the R wave recognition.

The R-R intervals are already calculated, as well as their middle points. The time distance between two sequential middle points is defined as a 'period' of 'ECG cycle'. In every cycle is included one SI_{max} recognized as an R wave, and several other SI_{max} . We calculate the relative times of occurrence of the SI_{max} of the cycle with relation to the time of occurrence of the R wave of the same cycle. Then we construct a histogram of the frequency of appearance of the R waves and the SI_{max} as a function of their relative distance. For the construction of the histogram we use the cycles of all 12 leads from one patient. This means that we construct one histogram for one patient including all the R waves and the SI_{max} found in that recordings. The peaks of this histogram correspond to the relative position of the waves, in their natural sequence in the ECG (P, Q, R, S, T). The SI_{max} contributing to the peaks are correspondingly identified as P, Q, S, T waves (the R waves were already known). After their identification their essential parameters can be retrieved.

The time of every peak of the histogram represents the mean value of the relative time for the corresponding wave. The error of this determination is small, given that all the SI_{max} have been used.

In *Figure 7a*, the primarily constructed histogram is shown. The peaks can be immediately identified as P, Q, S, T (*Figure 7b*). There is some dispersion around the peaks. Most of the SI_{max} falling outside one peak can be positively identified through a comparison of their t_{on}, t_{off} times with the corresponding parameters of the SI_{max} falling on the peak. An example of that is the identification of the T wave in *Figure 7b*. Of course, there are some SI_{max} which cannot with certainty be identified as waves after this comparison; these are rejected (X in *Figure 7b*).

SUMMARY AND DISCUSSION

Two cubic spline techniques have been used to remove the noise and the baseline drift. The result is an analytical expression S_R of a smoothed version of the original ECG. Based on this expression and its first and second derivatives we have detected the significant maxima and have measured their amplitude, time of occurrence, and duration. Establishing criteria for the R wave, we have recognized these waves among the SI_{\max} and have identified the P, Q, S, T waves among the SI_{\max} based on their relative time from the R wave of the same cycle. The thresholds ε , a , m , M used by the method were found by repeated tests on a large number of 12 lead ECGs. Their values are estimated as $\varepsilon = 100$, $a = 5$, $m = 200$, $M = 1000$.

We have checked our method on a number of 12 lead ECGs taken for epidemiological studies and have chosen 16 representative ones (pathological or otherwise). The results of the method were fed to the Minnesota Classification Code. The classification of these 16 cases was in very good agreement with that obtained independently in the clinic.

If the histogram of the SI_{\max} has large dispersion and the peaks cannot be clearly recognized, an 'alarm key' is provided.

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