A SIMPLE ALGORITHM FOR QRS PEAK LOCATION: USE ON LONG TERM ECG RECORDINGS FROM THE HMS-MIT-FFMS DATABASE

Marcelo R. Risk[1], Jamil F. Sobh[2], Riccardo Barbieri[2], J. Philip Saul[2]

[1] University Institute of Biomedical Sciences, Medical School, Favaloro Foundation. Solis 453 (1078) Buenos Aires. Argentina. [2] Dept. of Cardiology, Children's Hospital and Harvard Medical School, 300 Longwood Ave. Boston, MA. 02115 USA.

Abstract - A simple algorithm for QRS peak detection was developed using ECG recordings from the HMS-MIT-FFMS database. The algorithm uses two leads to calculate RR intervals and beat type for subsequent use in time- and frequency- domain analysis. The algorithm provides independence from lead orientation, excludes P and T wave detection, is resistant to noise, and yields automatic beat classification for inclusion in later analysis.

I. Introduction

Accurate detection of QRS peak locations and beat types is critical to studies of long and short term heart rate variability [HRV], in either the time or frequency domain [1]. This study was designed to develop a simple computationally efficient QRS detection algorithm which allowed for lead independence, noise rejection and beat classification. The algorithm is based on nonlinear transforms, derivatives, and RR interval history patterns QRS detection and beat rejection [2] [3].

II. Methods

Algorithm

The two ECG leads (l_1 and l_2) are squared and added to calculate the vector ($x(nT)$), implemented with the difference equation

$$x(nT) = \sqrt{l_1^2(nT) + l_2^2(nT)} \qquad (1)$$

where n is an arbitrary integer and T is the sampling period.

Then the vector is filtered using a simple FIR low pass filter, implemented with the difference equation

$$y(nT) = (x(nT-T) + x(nT-2T) + x(nT-3T) + x(nT-4T) + x(nT-5T) + x(nT-6T))/6 \qquad (2)$$

The output of the filter is differentiated using Eq (3) equation, as in the algorithm of Hamilton and Tompkins [2]:

$$y(nT) = (x(nT) - x(nT-T))/2 \qquad (3)$$

First, the squared derivative *d1* must cross a threshold value *th1*. Then, a fiducial point can be identified within the next 40 ms by having the derivative of *d1*, defined as *d2*, cross a second threshold *th2*. The location of the threshold crossing is stored as the fiducial point *fp*, and the value of the next minimum of *d2* is stored as a morphology index for each beat. Figure 1 shows the two leads and the derivative signals. The location of the *fp* is annotated and is used to calculate the RR intervals.

Both *th1* and *th2* are dynamically set, updating their values from the normal beats, using a predefined percentage of the peak *d1* and *d2*, set in the initial configuration.

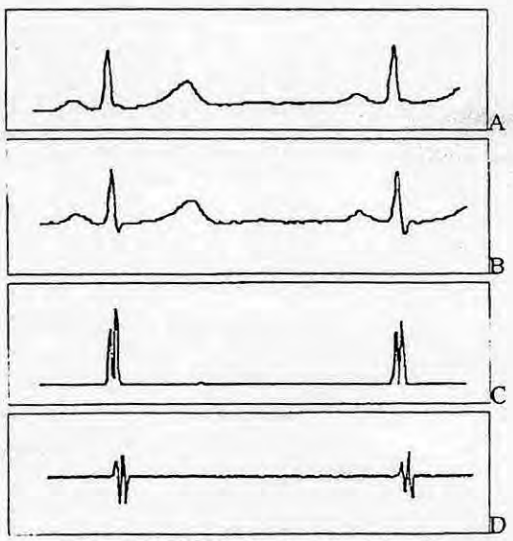

Fig. 1: A: *l1*, B: *l2*, C: *d1* and D: *d2*.

A detailed graphic of *d1* and *d2* around the QRS complex is showed in the Figure 2.

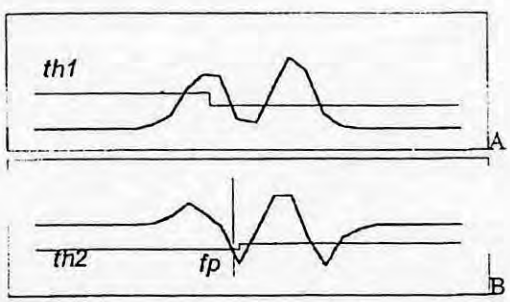

Fig. 2: Detailed graphic showing A: *d1* and *th1*, and B: *d2* and *th2*, where *fp* is the fiducial point.

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Beat classification is performed by comparing the current RR intervals with RR intervals averages of five previous normal to normal intervals (NN). A prematurity percentage (%P) for comparing is set in the initial configuration. When the current RR interval is greater than the %P of the previous average the beat is taken as normal (NN), and the classification is annotated for the current peak location: but when the RR is less than the RR interval average, the current value of *d2* peak and five previous *d2* peak average are investigated. A threshold *th3* is set in the configuration file as a predefined percentage of the $d2peak_{ave}$. If the current *d2peak* is less than *th3*, the beat is labeled a ventricular premature beat (VPB). If *d2peak* is greater than *th3* and less than $1.25xd2peak_{ave}$, the beat is labeled an atrial premature beat (ABP). Finally, if *d2peak* is greater than $1.25xd2peak_{ave}$ the beat is labeled NOISE.

Implementation

The algorithm was implemented in C++. Two channels of 24 hour ECG recordings were sampled at 256 Hz with 8-bit resolution (1-byte/sample). The record is analyzed in 30 seconds blocks, with allowances for edge effects. The program has interactive beat location and type editing functions which can override the automatic algorithms.

RR interval time series are computed using a modification of the algorithm described by Berger [4], in which only NN beats are used. A supplementary nonlinear filter is used on the time series to eliminate the effects of missed beats, and improperly classified beats [1].

III. Results

The algorithm was evaluated using records from the HMS-MIT-FFMS database. The RR time series shown in Figure 3 was derived from a noisy record with multiple apparent single lead detachments. The program yielded 102,325 NN intervals, and 156 was VBP's and 606 was labeled NOISE. The non-linear filter and manual review of all non NN beats revealed 123 incorrect classifications, yielding a very low of 0.12%.

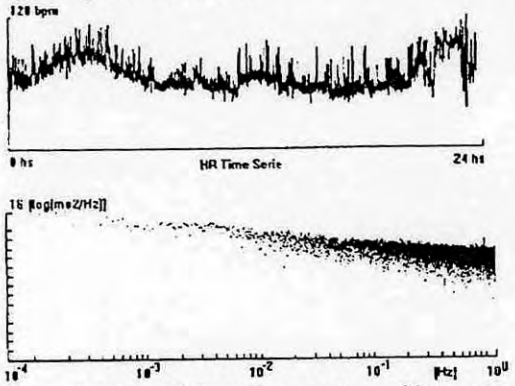

Figure 3: Show 24 hour time series and its spectra.

The RR time series is then used to perform multiple time and frequency domain (Figure 3) analyses on both the 24 hour series and sequential 5 minute segments, as described previously [5].

IV. Discussion

The use of time and frequency domain measures as the strongest single predictors of mortality after infarction [5,6] is dependent primarily on QRS fiducial point recognition and detection of "abnormal" RR intervals, rather than morphology recognition. These goals combined with the need to analyze an extremely large data set may be met by a relatively simple detection QRS algorithm which can run efficiently on a standard personal computer. This manuscript describes such an algorithm which accomplishes these goals by combining a vector computation, a simple linear filter, and a set of thresholds based on derivatives and squaring functions. Besides effiency, the algorithm is independent of lead polarity, almost independent of signal amplitude, and very resistant to noise artifact and single lead loss. Further testing is required to determine its utility in analyzing the broad range of 24 hour ECG recordings collected in clinical research studies.

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