# Robust Derivative-Based Method to Determine Filtered QRS Limits in High Resolution Electrocardiography

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## Abstract

*The accuracy of high resolution electrocardiogram (HRECG) as a risk stratification tool relies on QRS offset detection, which is subject to variation due to signal residual noise level (RNL). This study proposed a technique for improving the accuracy of QRS offset detection, based on successive signal derivation (DER) and compared to the standard method recommended by the American College of Cardiology (ACC). The control group was composed by 18 healthy volunteers with no cardiac disease and SMVT Group by 18 subjects with sustained monomorphic ventricular tachycardia. Mean QRS duration was compared by paired Student t-test between groups. Sensitivity, specificity and predictive values (PV) were compared by $\chi^2$ test. For ACC and DER methods, the QRS offset was determined at a range of different RNLs simulated in the HRECG signal (from 0.2 to 0.8 μV), and the occurrence of linear correlation was tested ($\alpha < 0.05$). Mean QRS duration calculated by DER showed no differences when compared to blind visual detection by a specialist. Positive PV was higher in DER than ACC ($p < 0.05$). Linear correlation between QRS offset and RNL was found in ACC method for both groups. The DER method showed higher accuracy and lower sensitivity to RNL than standard ACC for QRS offset detection.*

## 1. Introduction

The high resolution electrocardiography (HRECG) is a non-invasive diagnostic tool employed to stratify individuals at risk for developing life threatening ventricular arrhythmias secondary to reentry mechanism, and accurate results have important clinical implications [1]. The terminal region of the QRS complex and the beginning of the ST segment are analyzed to identify the presence of ventricular late potentials (VLP), which are signals originated from abnormal ventricular activation over the damaged myocardium [2].

Currently, the standard assessment of the HRECG is based on time domain analysis [2, 3], and the success of the diagnostic evaluation depends on the correct signal alignment and identification of both onset and offset points of the QRS complex [4]. On the other hand, the morphology and the location of VLPs, as well as the parameters employed in signal acquisition and processing, even when standardized [3], influence the precision and the accuracy of QRS complex end points (QRS offset) estimation. A residual variability in QRS duration in successively performed exams is, thus, observed in the same patient [5]. Notwithstanding, the QRS duration is the most important index for the risk stratification of ventricular arrhythmia [6, 7].

By averaging successive beats, it is possible to reduce the interference or noise whereas relevant signal waveforms are preserved, allowing the identification of VLPs [8]. It is noteworthy that detection algorithms of fiducial points in current practice are based on a threshold level detector, which is calculated from the signal averaged residual noise level (RNL) [3].

Several studies have been carried out to investigate the capability of HRECG to detect individuals at high risk of developing ventricular tachycardia and the effect of the RNL on the variability of measured diagnostic indexes [5, 9, 10, 11]. Thus, this study assessed a novel technique for QRS complex limits detection, based on successive signal derivation (DER), and tested its performance on detecting QRS offset over a range of signal RNL.

## 2. Materials and methods

### 2.1. Study population

The ECG signals were extracted from an existing high resolution ECG database [12]. The study protocol was approved by the National Institute of Cardiology Ethics Committee (protocol: 0190/12.02.2008), and informed consent was obtained from each volunteer. Two different groups were adjusted by age, gender and anthropometric indexes: a Control Group consisted of 18 healthy volunteers' signals, age 52.1 ± 10.2 years (mean ± standard deviation), without documented heart disease;

and the SMVT Group (age 58.7 ± 12.9 years), comprising 18 subjects with past history of syncope of cardiac origin and documented sustained monomorphic ventricular tachycardia, either spontaneous or induced in electrophysiology study. Subjects in both groups were in sinus rhythm, and none presented complete bundle branch block.

## 2.2. Signal acquisition and processing

The HRECG signals were acquired using modified bipolar Frank *XYZ* orthogonal leads. Digital data were processed with custom-made pattern recognition software [8]. Each lead was analyzed to exclude ectopic and excessive noisy beats (a beat rejection automatically eliminated the following beat). Using the *X*-lead as a reference, the system identified each beat, after a template generated and updated until the $10^{th}$ consecutive normal accepted beat. To be considered compatible with the template, a given beat had to present a minimum correlation coefficient to 0.99. Each accepted beat was appropriately synchronized, according to an algorithm modified from Jane *et al*. (1991) [13], and averaged after weighting with the inverse of the spectral power between 40-250 Hz and carried out until a RNL below 0.2 µV.

Each lead was, then, bidirectionally filtered (Butterworth $4^{th}$ order / 40-250 Hz band-pass) and gathered in the vector magnitude ($Vm = \sqrt{X^2 + Y^2 + Z^2}$), in which were identified the QRS offsets [2, 3].

In each signal was added a range of different simulated RNLs (0.2, 0.3, 0.4, 0.5, 0.6, 0.7 and 0.8 µV) that were within the standardized limits for clinical HRECG use [3]. The RNL was implemented with a normally distributed random number generation function. The verification of generated RNL was carried out by variance calculation in a 100 points window width located over the baseline. For each level, noises were statistically compared by the $\chi 2$ test ($\alpha = 0.05$).

Then, the ventricular activation boundaries (QRS duration) in the *Vm* was carried out by three methods: i) recommendation by ACC (ACC method), ii) proposed, based on successive derivatives of *Vm* (DER method), iii) visual method (VIS) performed manually by an independent specialist, blind to study groups.

## 2.3. Standard HRECG analysis (ACC)

In the ACC method, the baseline noise was estimated as the lowest standard deviation (SD) obtained from a 40 ms window, swept throughout the *Vm* window at 1 ms steps. The QRS limits are determined automatically, and defined as the midpoint of a 5 ms segment (displaced from the extremes to the center of the *Vm* window) in which the mean amplitude exceed the baseline noise plus three times its SD [3].

After filtered QRS complex boundaries were determined by both algorithms, standards parameters were calculated in order to assess VLP: DUR- duration of the QRS complex in *Vm*, LAS40- the duration of the signal below 40 µV at the terminal region of the *Vm*, and RMS40- the root-mean-squared amplitude of the latest 40 ms of the *Vm*. The diagnostic exams were considered positive when two or more parameters have abnormal values: DUR > 114 ms, LAS40 > 8 ms and RMS40 < 20 µV. When RMS40 < 4 µV the exam was positive regardless of the other values [14].

## 2.4. Derivative-based method (DER)

The DER method employed as baseline noise estimate the lowest RMS value (*RMSnoise*) calculated in a 40 ms window, swept throughout the *Vm* window at 1 ms steps. For automatic determination of the *Vm* QRS boundaries, first, the RMS value of a 5 ms segment centered at its midpoint was calculated, and this value was divided by *RMSnoise*, defining the *RMSrelative* ratio. The QRS complex boundaries were, thus, calculated as follows:

i) QRS onset - the first of three consecutive points in which *RMSrelative* exceeds the threshold arbitrarily set at 10.

ii) QRS offset - backwards search was carried out from the *ST* segment to the ventricular activation, with the threshold set at 20, to identify a point within QRS complex near its terminal region. For precise QRS offset identification, the *Vm* was derived ($Vm_{(i')} = Vm_{(i)} - Vm_{(i-1)}$) and absolute values were taken. Then, the lowest SD segments of 40 ms was calculated, over the derivative *Vm* (*Vm'*). The new threshold was defined as three times that SD. To determine the new QRS offset, in the *Vm'*, the algorithm seek the direction from the QRS to the *ST* region, for the highest value of 3 ms segment which exceeds the new threshold. This process was repeated in successive derivatives orders until *RMSrelative* exceeds the threshold arbitrarily set at 20 (Figure 1).

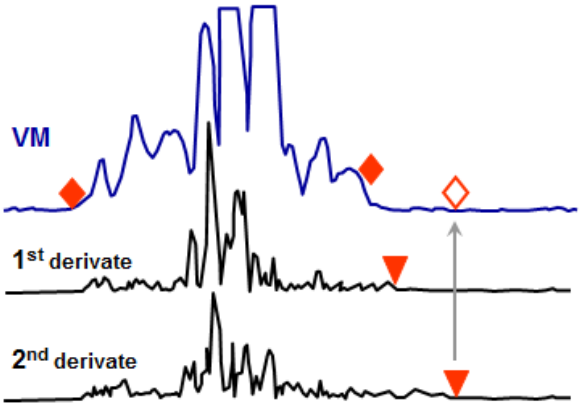


Figure 1. ♦ QRS complex limits identification before the

signal derivation; ▼ QRS-offset identification after each derivation; ◇ Definitive QRS-offset identification.

## 2.5. Statistical analysis

For ACC and DER methods, the mean *Vm* QRS duration was compared to VIS by paired Student t-test. Sensitivity, specificity and predictive values (PV) were calculated and compared by $\chi^2$ test. QRS offset was assessed as a function of different RNLs, and linear correlation coefficient calculated. All tests considered the significance level $\alpha < 0.05$.

## 3. Results

The mode of the number of times of each *Vm* signal had to be derived to allow QRS offset identification was twice (67%) and, for 94% of the signals it was not necessary more than three successive derivations.

The DER method satisfactorily detected QRS complex boundaries. In both groups, the mean QRS duration was significantly shorter for the DER when compared to ACC method (Table 1).

Table 1. QRS complex duration values (Mean ± SD).

| Method | Control | SMVT |
|---|---|---|
| **ACC** | 105.7 ± 17.9 | 136.5 ± 21.0 |
| **DER** | 96.3 ± 12.5* | 121.9 ± 15.9* |
| **VIS** | 94.7 ± 10.7# | 119.8 ± 15.7# |

* $p < 0.05$ ACC vs. DER; # $p < 0.05$ ACC vs. VIS.

The paired Student t-test showed significant differences between ACC and VIS in both groups (Control: $p = 0.004$; SMVT: $p = 0.044$). Between DER and VIS, the differences were not significant, (Control: $p = 0.483$; SMVT: $p = 0.393$).

The positive PV and negative PV of ACC and DER methods were organized in Table 2. Only positive PV showed significant differences between ACC and DER methods ($p = 0.02$).

Table 2. Truth tables for both ACC and DER methods.

| ACC method | | | | |
|---|---|---|---|---|
| **Result** | **Control** | **SMVT** | **Total** | **PV (%)** |
| **Negative** | **13** | 9 | 22 | **59.1** |
| **Positive** | 5 | **9** | 14 | **64.3** |
| **DER method** | | | | |
| **Result** | **Control** | **SMVT** | **Total** | **PV (%)** |
| **Negative** | **17** | 12 | 29 | **58.6** |
| **Positive** | 1 | **6** | 7 | **85.7*** |

* $p < 0.05$ ACC vs. DER; PV = predictive value.

Considering the specificity and sensitivity (Table 3), only specificity showed significant difference between ACC and DER methods ($p = 0.0003$).

According to ACC and DER methods, respectively, linear correlation coefficients in Control Group were: -0.98 ($p < 0.05$) and -0.32 ($p$ = NS) (Figure 2-a), and in SMVT Group were: -0.75 ($p < 0.05$) and -0.67 ($p$ = NS) (Figure 2-b).

Table 3. Specificity and sensitivity for each method.

| | ACC (%) | DER (%) |
|---|---|---|
| **Specificity** | 72.2 | 94.4* |
| **Sensitivity** | 50.0 | 33.3 |

* $p < 0.05$ ACC vs. DER.

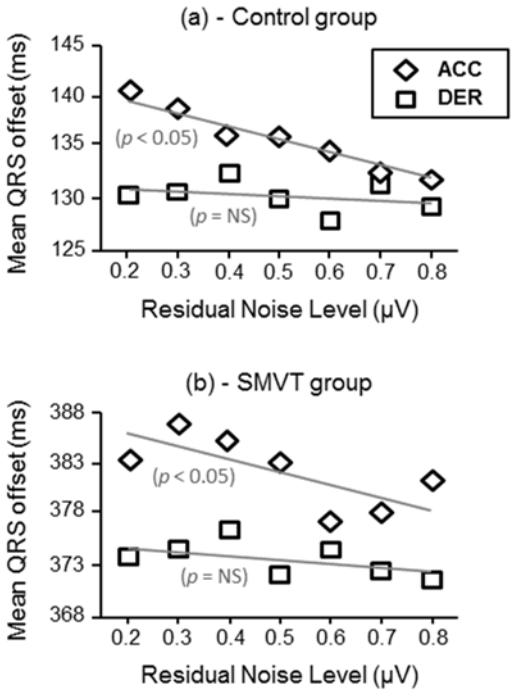


Figure 2. Mean QRS offset values as function of residual noise level for (a) Control and (b) SMVT Group.

## 4. Discussion

The novel method for determining the ventricular activation duration in the *Vm* showed to be effective. This method would potentially reduce the biases caused by statistical processes in QRS delimitation and, consequently, positively affect the diagnostic accuracy of HRECG exam. To the best of authors' knowledge, no previous applications of current method was tested on HRECG signals.

The exact definition of the ventricular activation duration is germane for the analysis of HRECG parameters. For the sake of an appropriate accuracy, ACC method usually requires visual inspection, in addition, to confirm QRS limits detected by automated algorithm,

which may become a shortcoming in the hands of non-experienced personal.

The classical algorithms employed in the ventricular activation delineation in the filtered signal relies on baseline noise measurements [5], which may lead to errors arising from statistical process. Since the noise cannot be totally removed, statistical algorithms identify the QRS complex boundary in a region where the amplitude signal exceeds an arbitrarily pre-stablished baseline noise value. The use of the derivative signal to determine the QRS complex limits aims to attenuate the RNL influence, becoming QRS delimitation less dependent on statistical processing, therefore based on deterministic properties.

The method rationale considers the following hypotheses: i) The signal is continuously differentiable throughout its length; ii) Its terminal region is always asymptotic to baseline and always has a maximum (or minimum) point before reaching the baseline; iii) the signal always has an inflection point immediately after the maximum (or minimum) point close to its terminal region. Thus, for each derivate, signal has the amplitude reduced (and displaced to the right) and noise level increased (1.41 times) until both signal amplitude and RMS noise becomes similar in amplitudes, thereby determining the QRS offset.

In Control group, the number of correct diagnostics increased from 13 (ACC) to 17 (DER). In contrast, the SMVT group had a reduction from 9 (ACC) to 6 (DER). The positive PV increased due to decrease in the QRS complex duration, which affected the estimation of other parameters, favoring control cases. Ideally, by adopting a method that reduces the mean QRS complex duration, it would be appropriate to redefine the criteria of normality, which will only be possible in a large cohort study.

In correlation analysis between mean QRS offset and RNL, only DER showed non-significant coefficients in both Groups (Figure 2), thus, confirming that DER method is less sensitive to RNL as compared to ACC.

## 5. Conclusion

DER method tracks QRS limits, increasing both specificity and positive predictive value when compared to standard ACC method. It was precise and effective in identifying ventricular activation boundaries in HRECG signals, and showed higher accuracy and less sensitivity to residual noise than ACC for QRS offset detection.

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