Comparison of General Purpose ECG Analyzers in Patients with an Implanted CRT device

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Abstract

Many QRS boundaries detectors have been previously proposed and have showed good performance with conventional ECG databases. In this study, two of such algorithms, one based on empirical mode decomposition and one based on the curve-length transformation were tested against a database obtained from patients with an implanted CRT device. This is a case of interest since increased QRS duration is a crucial clinical criteria for CRT implantation and also because the alterations on QRS morphology and stimulation artefacts present in these cases may mislead general purpose algorithms. Results showed that both methods were incapable of accurately measure QRS duration, showing significant differences ($p<0,05$) respect to measures obtained from expert annotation. Average errors of 17±9 and -22±19ms in the estimation of the duration of the QRS complex were obtained with EMD and CLT methods respectively. These results highlight the necessity of validating general purpose algorithms before using them in more concrete scenarios.

1. Introduction

Cardiac Resynchronization Therapy (CRT) has become a therapeutic standard in patients with symptomatic heart failure, reduced left ventricular function and electric asynchrony [1]. One of the main clinical criteria to find candidates for a CRT device and asses their response is the duration of the QRS complex, although there is controversy about the predictive power of this parameter [2]. Given this, automatic algorithms for QRS delimitation can be a useful tool for performing large scale studies involving CRT.

Many of such methods have been previously proposed and have showed good performance with standard ECG databases such as QT or MIT-BHI arrhythmia database [3, 4]. However, when more specific or challenging scenarios are faced general purpose algorithms still need to be validated.

Studies involving patients implanted with a CRT device are a good example since variability exists among these patients regarding the different pathologies leading to the implantation, they usually present alterations on QRS morphology and also, when the device is operating, stimulation artifacts may appear along with greater alterations of QRS morphology. All of these situations may potentially mislead the algorithms and so justify the need for validation.

In this study two previously proposed algorithms were tested against a database obtained from patients with an implanted CRT device. The first method relayed on empirical mode decomposition [3] and the second one on the curve-length transformation [4] in order to detect QRS onset and offset. The aim of the study was to determine if these general purpose algorithms were still accurate in this particular situation.

2. Methods

2.1. Database

12-lead 10 seconds long ECG signals at a sample rate of 500Hz were recorded from 11 patients with an implanted CRT device. 2 records per patient were acquired during routine check-ups, one with the implant switched off and one with the implant switched on.

2.2. Signal processing

Each signal was band-pass filtered with a Butterworth IIR filter with 0.5 and 60 Hz as low and high cut-off

frequencies respectively. A notch filter with a center frequency of 50Hz was also applied in order to remove power-line interference. QRS complexes were then automatically detected and manually revised and corrected by a clinician.

Finally, windows with duration of 1.25 times the average RR interval and centered at the QRS detection marks were aligned and averaged in order to obtain 1-cycle length patterns for each lead. Cross-correlation maximization was used as the alignment criteria and QRS complexes showing a cross-correlation coefficient lower than 0.85 with the current pattern were rejected.

These patterns were manually annotated by a clinician to serve as reference using a custom-made user interface.

2.3. QRS delimitation using EMD

This method was first described in [3]. First, the pattern was decomposed using EMD (1)[3], where x(t) is the original signal, IMF_i is the i^{th} level intrinsic mode function and r_n is the residue at level n. Intrinsic mode functions from levels 1 to 3 were summed to obtain $f2c_3$ function (2). This levels contain the sharpest information of the signal and so the information relative to the QRS.

$$x(t) = \sum_{i=1}^{n} IMF_i(t) + r_n(t) \quad (1)$$

$$f2c_3(t) = \sum_{i=1}^{3} IMF_i(t) \quad (2)$$

QRS onset and offset were defined as the first zero crossing points of f2c3 beyond the left minimum (maximum) and the right minimum (maximum) of the positive (negative) R-wave [3], considering the R-wave as the most prominent wave within the complex.

An example of the f2c3 function along with the detection points indicated by red arrows are presented in figure 1-A.

2.4. QRS delimitation using CLT

In order to apply this method which was first proposed in [4] patterns were first low-pass filtered with a cut-off frequency of 15 Hz and then CLT was applied as described in (3), where L(t) is the result of the transformation, f_s is the sampling frequency and x(t) is the original signal. The parameter w defines the length of the window used to calculate the transformation and must be similar to QRS duration. Since most patients with a CRT device present wide QRS complexes we used a window with duration of 150ms.

$$L(t) = \sum_{k=t-w}^{t} \sqrt{\frac{1}{f_s^2} + (x(k) - x(k-1))^2} \quad (3)$$

Then the same decision rule as in [4] was applied. This is, the minimum (m) and maximum (M) of L(t) signal in a 250ms window around the QRS detection point were searched and their difference (D) was calculated. Two thresholds were defined as m+D/100 and M-D/20. Threshold crossing points of L(t) were taken as QRS onset and offset points beginning in the R-peak. Finally, as in [4], these points were adjusted by -20ms for QRS onset and +20ms for QRS offset. This method is illustrated in figure 1-B, where th1 and th2 are the thresholds.

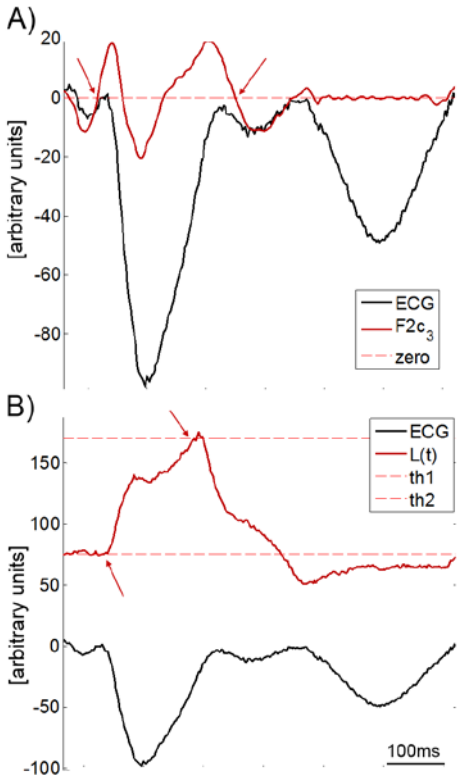

Figure 1: Example of QRS onset and offset detection using the EMD based method (A) and the CLT based one (B).

2.5. Result analysis

QRS onset (QRS_{on}) and QRS offset (QRS_{off}) marks were generated by both methods for each pattern, denoted as EMD and CLT respectively, and were compared with the manually annotated reference denoted as MAN.

QRS duration (QRS_{dur}) measurements derived from those marks were also compared using paired t-tests.

All analysis were performed separately for the registers with the CRT device switched on (STIM) and those with de device switched off (CONT) given their potential different characteristics.

3. Results

Both methods committed significant errors in the detection of QRS_{on} and QRS_{off} ranging from 6 to 14ms in average as seen in table 1. Anyhow, the EMD method performed slightly better showing lower average errors in all cases. Also, QRS_{on} was estimated more accurately in general than QRS_{off} by both methods. The main sources of error were related with QRS morphology alterations and with the presence of the stimuli. These cases are illustrated in figure 2. The presence of the stimuli and the presence of slow dynamics in the late QRS in conjunction with elevation of the QT segment made impossible to fix standard thresholds for the CLT method that worked well in all cases. Also, the presence of fractionated QRS complexes gave rise to unexpected zero crossing points in the $f2c_3$ function which confounded the EMD method.

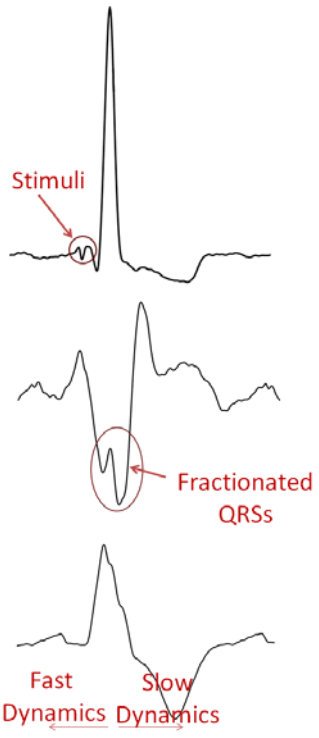

Figure 2: Examples of the main sources of error in QRSon and QRSoff detection.

Anyhow, it should be noted that each method showed a clear bias in the detection of QRS_{on} and QRS_{off} respectively. While EMD method tended to produce early detections of QRS_{on} and late detections of QRS_{off}, leading to an overestimation of QRS_{dur} (+17±9ms), CLT method, on the other hand, clearly showed the opposite behaviour, tending to underestimate QRS_{dur} (-22±19). This effect can be observed in figure 3.

Table 1. Error in ms commited by each method in the estimation of QRSon, QRSoff and QRSdur.

	EMD		CLT	
	CONT	STIM	CONT	STIM
QRSon	-6±4	-7±4	8±4	8±4
QRSoff	11±3	10±3	-13±4	-14±3
QRSdur	17±9	17±9	-20±19	-23±19

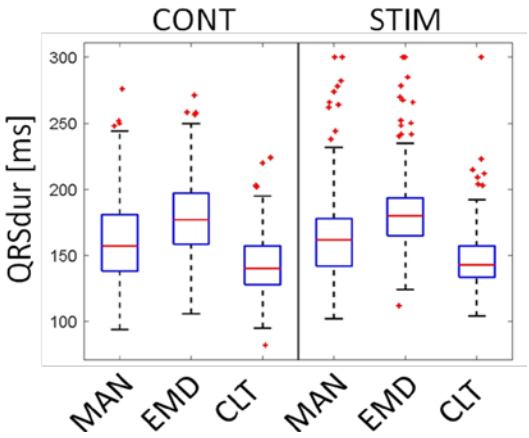

Figure 3: Boxplot showing reference QRSdur (MAN) and the measurements of this parameter obtained by each method (EMD and CLT).

These tendencies were stable through all leads as showedin figure 4. In this figure, it can be observed that the methods performed quite uniformly for all leads, especially EMD. Although some exceptions to this can be found as in the case of QRS_{on} detection in V5 with the CLT method, in which case the errors are especially low.

No differences were observed either regarding the presence or absence of stimulation. This is supported by results shown in table 1, which are very similar in the CONT and STIM cases, and data represented in figures 3 and 4, where differences between CONT and STIM situations did not show any specific trend despite that the presence of the stimuli had been identified as a source of error.

The analysis of QRS durations showed statistically significant differences between real and measured QRSdur ($p<0.05$) but not significant differences were observed between CONT and STIM situations.

4. Discussion and conclusions

The results obtained show how the algorithms under

test fail at measuring QRS duration with precision in the context of CRT. The variability in QRS morphology in combination with its alterations difficult the adjustment of the parameters of the CLT method and at the same time confounds EMD method which highly depends upon QRS morphology.

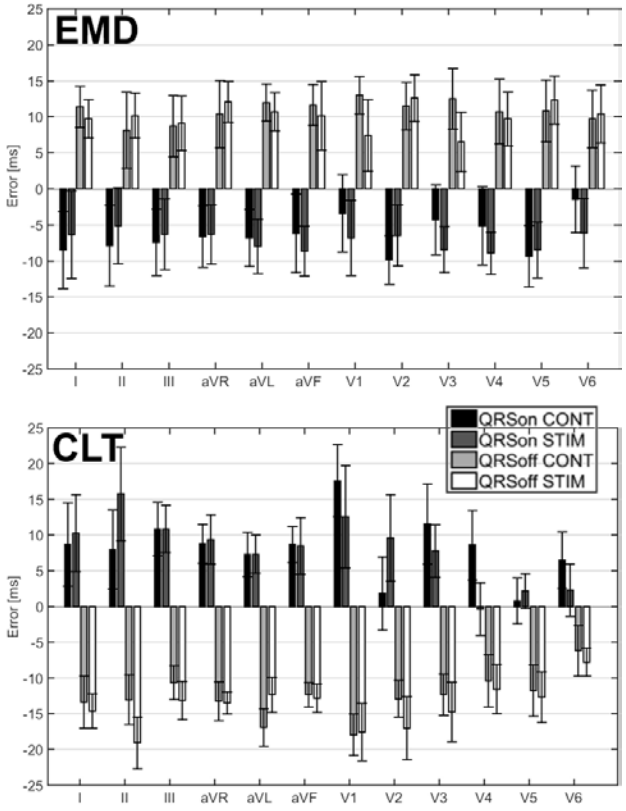

Figure 4: Errors committed by each method in the detection of QRSon and QRSoff in CONT and STIM situations.

The fact that errors in QRS_{off} detections are higher,in general than those in QRS_{on} may be due to the fact that most morphological alterations appear on the late QRS.

Also, although no significant differences were observed between CONT and STIM cases, we identified stimulation artifacts as a potential source of error and we believe that their effect may be noticeable with more accurate algorithms.

In conclusion, it has been proved that studies involving CRT devices represent a challenging scenario for automatic QRS delimitation algorithms being necessary nowadays the manual revision of the marks.

References

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