Software Library for Real-Time Cardiac Beat Detection

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Abstract— This paper shows a software library with functionalities for real-time cardiac beats detection, which is defined by a facade pattern. An interface enlaces three detectors in a subsystem, all of them activated by a specific command. This design pattern assures the complexity of the software, warranting the portability and allowing changes in the subsystem components. The implemented detectors combine state-of-the-art algorithms of cardiac beats detection for improving performance. Assessments were made with the MIT-BIH Arrhythmia Database, totalizing 24 h of electrocardiogram (ECG). The results (up to 99.75% sensitivity and 99.85% positive predictivity for 0.41% detection fails) indicate better performances than the original algorithms.

Keywords- software library; facade design pattern; cardiac beat detection; real-time monitoring.

I. INTRODUCTION

Sudden cardiac death (SCD) is mainly caused by cardiopathies, where 80% of cases are ventricular fibrillation and 15 to 20% are bradiarrhythmias [1]. Estimations show that incidence of SCD in Brazilian population could be greater than that observed in USA (300.000 to 400.000 cases per year), due to similar lifestyles and the existence of endemic Chagas disease [2], which compromise the cardiovascular autonomic control and increases the risk for arrhythmic mechanisms that contribute to SCD. The diagnosis and preventive treatments of cardiac arrhythmias are efficient in reducing the SCD risks. Arrhythmias could be detected by the analysis of morphology and temporal evolution of the electrocardiogram (ECG) [3]. The normal ECG is composed by P, Q, R, S and T waves, having a quasi-periodic comportment. P wave represents the atrial activation, QRS complex, the ventricular activation, and T wave represents the ventricular repolarization. Fig. 1 shows one complete cycle of a normal ECG.

To upgrade the efficiency of clinical diagnostic, real-time monitoring systems are employed, helping the decision-making process for patients care. These systems are based on application, and depend on specialist knowledge and the implementation of decision rules that give enough computational intelligence to prevent situations and minimize errors.

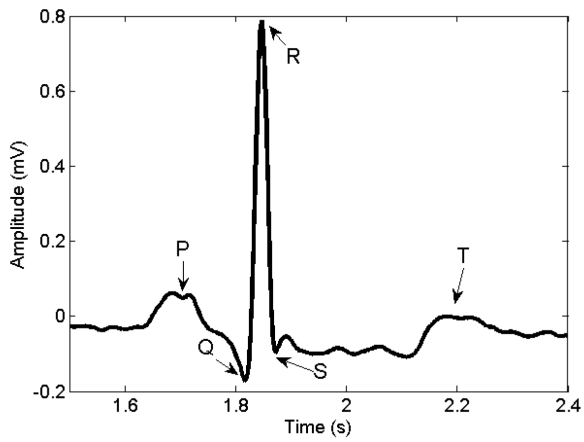

Figure 1. Normal ECG Signal – Record 100 MIT-BIH [12]

A cardiac arrhythmia monitor includes algorithms for cardiac beat detection and classification. Detecting beats is the main process in the monitoring, but it is not a trivial process: the ECG is affected by noise from different sources (muscle activity, mains interference, motion artifacts, baseline drifts) and other ECG components with similar morphologies to the QRS complex, and shows physiological variability, presenting alterations along the time for the same patient. Thus, it becomes important to project filters that improve the signal to noise ratio (SNR), evidencing the QRS complexes and allowing the detection of cardiac beats and the signalization of fiducial marks — the time of occurrence of the R-wave peaks. In the last decades many approaches to QRS detection have been proposed: artificial neural networks [4,5], digital filter banks [6,8], analysis of first and second derivate the ECG signal [6,7], and Wavelet transforms [9-11]. This paper proposes a model and presents a subsystem for automatic detection of cardiac beats. The subsystem structure has a code library, with three detectors enlaced in a single interface, which could be integrated in different platforms or systems.

II. Material and Methods

A. Data Selection

The employed MIT-BIH Arrhythmia Database [13] is composed by 48 documented ECG records. Each record contains 30 min of ECG, taken from a standard 24-hour two channel Holter signal. For this study, only the first channel was used, corresponding to the modified thoracic bipolar lead II. The database has a wide variety of QRS shapes, artifacts (records 100 to 124) and rhythms (200 to 234), in order to represent the reality observed in the cardiac monitoring centers. The complete database was analyzed, except for record 207, where a data segment showing ventricular flutter was excluded. The database is available in MIT proprietary format, digitized at 360 samples per channel and 11-bit resolution. Annotations provided by two cardiologists were employed to validate the system, consisting of information on time of occurrence of each beat and its classification.

B. Cardiac Beat Detector

The software library for automatic cardiac beat detection is composed by three detectors, combining characteristics of three high-performance methods. Each detector differs from each other by the preprocessing and the decision rules used for cardiac beat identification. A cardiac beat detector is divided in a preprocessing stage and a taken decision stage where different rules are applied over the preprocessed signal. In the preprocessing stage, the ECG is filtered to eliminate power-line interference, baseline drift and motions artifacts, and to maximize the high frequencies related to the QRS complex. In the second stage, improved decision rules based in specialists knowledge are employed to optimize the performance in atypical signals, either presenting high levels of noise or high morphological variability by the occurrence of different arrhythmias. Various parameters were experimentally adjusted, like detection threshold (the most important), search-back threshold (that permits revalidation in a signal that has a significant time interval without detection), blanking (here events immediately following a QRS detection are ignored for a set time), and use of slope (to distinguish between T waves and early ectopic beats). In all detectors the threshold level is adaptive to the signal. The decision rules were optimized empirically to minimize the occurrence of false positive (FP) and false negative (FN) beats. Different predictors for R peak value were tested: a percentage of the last detected peak, as well as mean and median of latest peaks. The median predictor has the lower prediction error, and the detection threshold was defined as a percentage (B) of the estimated R peak value:

$$\text{Detection Threshold} = B \times \text{R peak estimate} \qquad (1)$$

The detector I has a preprocessing stage composed by cascaded filters, including a bandpass filter from 5 to 15 Hz, a derivative filter and a moving window integrator, as proposed by Pan and Tompkins [6]; the decision stage provides a combination of rules used by Pan and Tompkins [6], Hamilton and Tompkins [14] and Lima [15]: the width of the QRS complex is used as a delimiting parameter and the median of the last eight detected beats amplitude is used to define the detection threshold. The output of the moving window integrator is submitted to the decision stage. The signal is evaluated in windows of 150 ms, and when it crosses the detection threshold the delimitation process of a possible QRS complex is activated. This process will verify if the event happened in a correct interval considering the estimated RR interval and respected a refractory period of 200 ms. Events that occurred between 200 and 360 ms from the last accepted beat are submitted to other parameter analysis, for eliminating false detections due to abnormal T waves. Search back requires the analysis of the estimated RR interval: if no QRS complex was detected within 150% of the estimated RR interval, then the search back is applied with a lower threshold. If the decision stage accepts a peak, all parameters will be actualized and thus, the detection threshold is adapted to the signal characteristics in real-time.

The Detector II employs a derivative filter proposed by Engelse and Zeemberleng [16] and changed by Lima [15] with a cutoff frequency around 16 Hz, and the decision stage combines Engelse and Zeemberleng [16] and Hamilton and Tompkins rules [14]. The absolute value of the derivative filter output is analyzed in the decision stage, where will be accounted the number of intersections of the detection threshold in a period of 150 ms. This number represents the first criterion for discriminating between a possible QRS complex, which will be further evaluated, and a burst of noise, which is thus rejected. A possible QRS complex is validated according to rules that include the estimated RR intervals, the complex width, and the analysis of the first derivate of the signal.

In Detector III the preprocessing stage comprehends the cascaded filters proposed by Pan and Tompkins [6] and decision rules based on Hamilton and Tompkins [14] and on Difference Operation Method (DOM) algorithm [17]. This method presents the lowest mathematical complexity among the three ones, taking the first difference of filters output and then applying the decision rules in windows of 150 ms. The delimitation process allows localizing the Q, R and S waves.

C. Performance Assessment

The detection performance was defined in terms of sensibility, positive predictivity and failed detection. For each event detected it is performed a comparison with the annotations file. If a time delay between detection and a database annotation is lower than 150 ms, the event is considered a true-positive (TP), whereas a detection fail is accounted as a false-positive (FP) or false-negative (FN), depending on detection having occurred before or after the database annotation, respectively. The flowchart of the performance evaluation algorithm is shown in Fig. 2.

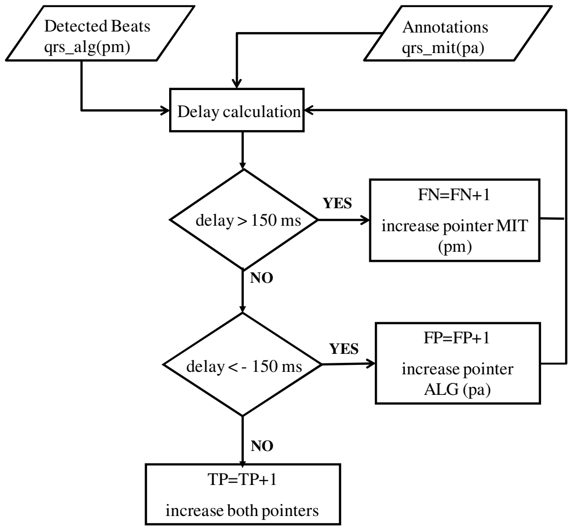

Figure 2. Algorithm for performance evaluation

III. RESULTS

A. Software Library Model

Fig. 3 presents the structural diagram of the cardiac beat detector, used in the software library based on facade design patterns.

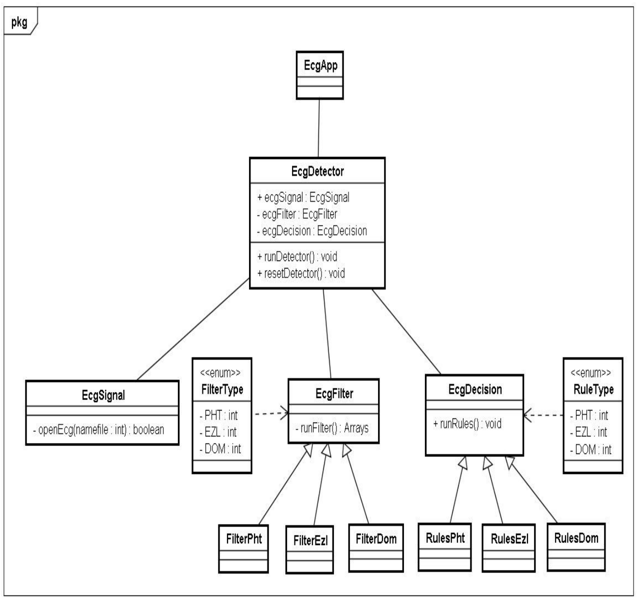

Figure 3. Structural diagram of software library

The *EcgApp* class is a client type that asks and waits responses from *EcgDetector*, without knowing details of its implementation and functionalities. *EcgDetector* is a class that knows which part of the subsystem is responsible for the attendance of a solicitation, and distributes works to the appropriated objects (instanced detectors), by classes of enum type *FilterType* and *RuleType*. *FilterPht, FilterEzl, FilterDom, RulesPht, RulesEzl* and *RulesDom* are specific classes of the subsystem that contains functionalities of the detection library, responsible to attending service solicitations from *EcgDetector*. This diagram does not show attributes and methods to improve the figure resolution.

B. Detectors Details

Fig. 4 presents the input and output of the band pass filter for a signal with a low SNR.

In Fig. 5, it is presented the output of each preprocessing stage of Detector I, for a signal that presents multiform ventricular arrhythmias.

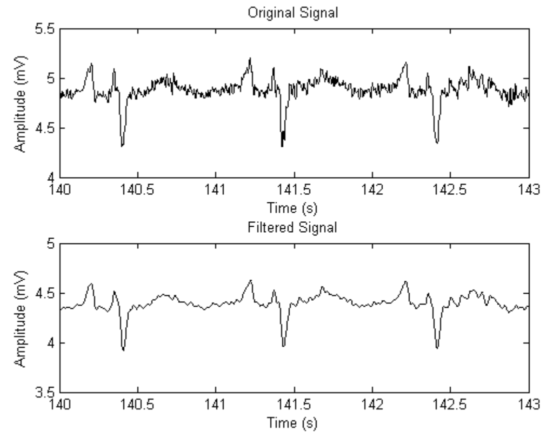

Figure 4. Bandpass filter of a noisy signal (record 108 of MIT-BIH [13])

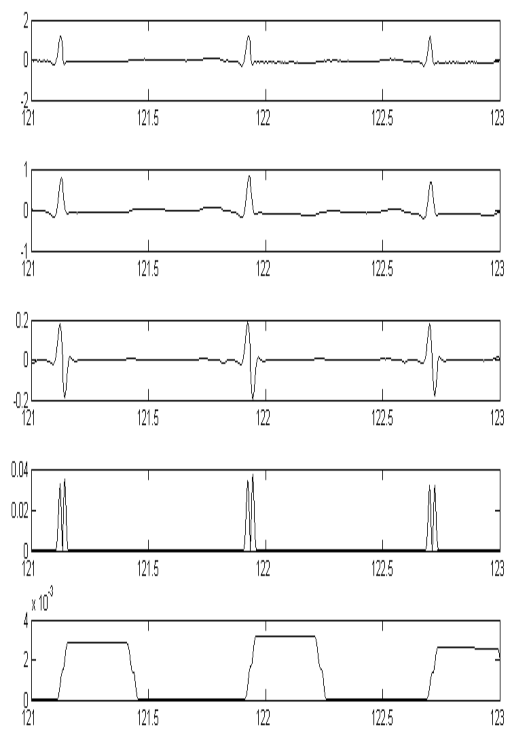

Figure 5. Output of each module of preprocessing stage of Detector I. From top to down: Original signal (record 100 of MIT-BIH [13]), output of bandpass filter, after derivative filter, quadrature of signal, and output signal of moving window integrator. The detection precess is applied in the resulting signal, and the localization of R wave corresponds to the midle of the rise slope.

C. Definition of Detection Parameters

The final parameters configuration was obtained according to the performance assessment, considering the rates of FP and FN. For Detector I the better results were obtained using an R peak predictor based on the median of the last eight beats detected, with B equal to 0.25 and rejecting some occurrences between 200 and 360 ms after the last detected beat. This rule eliminates FP caused by sharpen T waves that could be confused with R wave if only the detection threshold were considered. For detector II the RR interval was also estimated based on the last eight detected beats. In Detector III, it was only accepted beats detected within the interval between 0.4 and 1.2 s from the last detected beat.

D. Detectors Performance

Table I presents the performances obtained by the three detectors include in software library, when analyzing the complete MIT-BIH Arrhythmia Database [13].

TABLE I. INDIVIDUAL PERFORMANCE OF DETECTORS AND AVERAGE TIME

Detector	**Performance Indices**			***Average Time * (s)***
	Sensitivity (%)	***Positive Preditivity (%)***	***Detection Fails (%)***	
I	99.75	99.77	0.47	15.69
II	99.74	99.84	0.42	12.23
III	99.73	99.85	0.41	6.77

* PC with Intel Core Duo processor, 2.4 GHz, 4 GB RAM and Windows XP 64 bits.

IV. DISCUSION

The approach employed for implementing the library of cardiac beats detection indicated that the combination of state-of-the-art algorithms minimize the fail detection rate, when compared with the individual detector performances presented in [14, 15, 17]. The use of a unified interface by facade design pattern allowed transparency in library usage, leaving the user knowledge on the complexity of each detector, while minimizing the code compiling dependence. It also makes easy the portability and the inclusion of new functionalities; without modifying the main structure.

In the design of decision rules for QRS complex detection, the use of median estimates allowed the better adaptation of the algorithm to the ECG signal, and the occurrence of premature ventricular contractions in epochs with predominance of normal rhythm does not compromised the detection performance. In the validation of performance, some signals (104 and 108) presented increased FN rates due to lower R wave amplitudes. These cases required a compromise solution, by reducing the threshold down to a reasonable value. However, in a given case, the lower R-waves amplitudes appeared associated with anomalous P waves (record 106), and it could not be contemplated by this solution. All detectors presented satisfactory results in noisy signals (105 and 119), anomalous P waves (108 and 222) and multifocal ventricular arrhythmias (203).

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