Adaptive Mathematical Morphology for QRS Fiducial Points Detection in the ECG

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Abstract

Fixed structure Mathematical Morphology (MM) operators have been used to detect QRS complexes in the ECG. These schemes are limited by the arbitrary setting of threshold values. Our study aims at extracting QRS complex fiducial points using MM with an adaptive structuring element, on a beat-to-beat basis. The structuring element is updated based on the characteristics of the previously detected QRS complexes. The MIT-BIH arrhythmia and Physionet QT databases were respectively used for assessing the performance of R-waves and other fiducial points detection. Results show comparable or better performance than the state-of-the-art and an efficient extraction of Q- and S-waves as well as onset and offset points of the QRS complex.

1. Introduction

The electrocardiogram (ECG) is comprised of different electrical waveforms each representing either depolarization or repolarization of different muscles in the heart. Among these waveforms, the QRS complex is the most prominent representing the ventricular contraction. The shape of this complex as well as the time of its appearance provides significant information in cardiac disease diagnosis such as arrhythmia analysis [1]. Due to its peakiness and the fact that other wave forms can be small, or in some cases not even present in the ECG, the QRS complex plays a fundamental role in automatic detection of heartbeats.

Generally, approaches consider two phases in QRS complex detection. In most cases, the ECG is first preprocessed by either a low-pass filter or a band-pass filter to suppress perturbations. Subsequently in the detection phase, a feature signal is extracted from the filter output and compared with some heuristically chosen thresholds to determine whether a QRS complex is taking place at a certain point in the ECG. Among these approaches, Pan and Tompkins [2] proposed a derivative based approach to use the steep slope characteristic of the QRS complex in the detection phase. They used simple difference equations along side a band pass filter to point out QRS complexes. Li et al. [3] applied a wavelet transform approach to the ECG and found that R-peaks can be picked out from perturbations such as baseline drift and other waveforms in the ECG if relevant scales in the WT is studied. Trahanias [4] used mathematical morphology (MM) operators on the ECG both in the noise removal and detection phases, each phase using a different yet fixed structuring element, and compared the feature signal with a threshold to detect QRS complexes.

To the best of our knowledge, all QRS detection approaches use some thresholds to detect these complexes in the ECG. These thresholds comprise physiological constraints, e.g. the time difference between two beats cannot be smaller than 250 and larger than 1800 milliseconds, and arbitrary thresholds, e.g. comparing the feature signal to a specific value to detect heartbeats, to lower false detection rate. The former thresholds are valid and can be useful in detection but the latter are based on the data at hand, can be hard to adapt when dealing with several subjects or may need adjustment in different acquisition scenarios. For instance, arbitrary thresholds can drastically reduce the detection rate when wearable device is used, instead of standard clinical acquisition system. Huge baseline drift and other noises due to movement of electrodes can then be sometimes observed. Moreover, proposed methods mostly focus on detecting the R-waves and not the other fiducial points in the QRS complex such as QRS-onset, QRS-offset, Q-point and S-point. Arrhythmia analysis is possible through studying RR intervals [5, 6] or by using power-frequency analysis of the ECG [7] or a combination of both [6]. Nevertheless, once accurate locations of QRS fiducial points are available for a series of consecutive beats, a simple post processing enables us to detect and classify different types of arrhythmia well as beat types [6, 8].

In this paper, we propose a mathematical morphology approach with an adaptive structuring element not only to overcome the issue of arbitrary thresholds, but also to extract other fiducial points in the QRS complex together with the R-waves. The proposed method is robust against baseline drift and other perturbations with low computational costs and good performance.

2. Mathematical Morphology (MM)

Mathematical morphology is a methodology proposed to extract useful topological information based on the analysis of geometrical structures. MM was first introduced for binary images with strong set-theoric concepts and non-linear operators, designed to extract useful information in images regarding shape and size [9]. MM is based on two elementary operators named dilation and erosion. Combining dilation and erosion leads to additional operators such as opening, closing, top-hat and bottom-hat as listed in the following equations:

$$Dilation \oplus : \ f \oplus g(n) = \max_{(1 \leq i \leq n)} \{f(i) + g(x - i)\} \quad (1)$$

$$Erosion \ominus : \ f \ominus g(n) = \min_{(1 \leq i \leq n)} \{f(i) - g(x - i)\} \quad (2)$$

$$Open \circ : \ f \circ g(n) = (f \oplus g) \ominus g(n) \quad (3)$$

$$Close \bullet : \ f \bullet g(n) = (f \ominus g) \oplus g(n) \quad (4)$$

$$Top - Hat : \ THat(g(n)) = f(n) - f \circ g(n) \quad (5)$$

$$Bottom - Hat : \ BHat(f(n)) = f(n) - f \bullet g(n) \quad (6)$$

Where $g(n)$ represents the structuring element of length n, i indicating the ith element of the structuring element and f the signal to which the MM operator is applied. These operators are quick, simply defined and use a structuring element to extract useful information and suppress artifacts. Depending on the effect sought when using these operators, a specific structuring element must be used. Shape and length of the structuring element should be carefully chosen as they play an important role in the outcome of these operators [4, 9, 10]. For example, the average of an opening and closing of a signal with a flat structuring element can be used for noise suppression while the same average with a peaky structuring element tends to enhance peaks and valleys in the signal.

3. Proposed method

As mentioned in the introduction, before the detection of QRS complex in the ECG is carried out, the signal must be conditioned by removing different potential perturbations. Signal acquisition noise, high frequency muscle activity and low frequency baseline drift are among the most dominant perturbations. In order to condition the ECG for QRS detection, we use a low-pass filter with a cutoff frequency at 50 Hz mainly to remove the acquisition noise introduced by the electrocardiograph. Since frequency components of the QRS complex are typically in the range of about 10 Hz to 25 Hz, ECG waveforms are preserved. Then, a QRS complex-like structuring element is synthesized with a duration of 90 milliseconds, which represents an average normal QRS duration, Fig. 1-a. Using this synthesized structuring element, top-hat and bottom-hat operators are applied to a small time window of the ECG, a 2-seconds window based on the upper limit of RR-interval, giving rise to peaks and valleys. The average of the top-hat and bottom-hat operators results in a feature signal with non-zero values at peaks and valleys, mostly corresponding to QRS complexes, with peaks at R-waves and valleys before and after, Q- and S- points. QRS-onset and QRS-Offset are considered respectively as the start and end of non-zero activity in the feature signal. Purterbations might cause non-zero feature signal values at positions where QRS complexes do not occur. Therefore, the following physiological thresholds where used to prevent false QRS detection:

$$QRS_{Valid} = \begin{cases} R_{candidate} - R_{previous} >= 250\,ms \\ R_{candidate} - R_{previous} <= 1800\,ms \\ QRS_{Width} >= 17\,ms \end{cases} \quad (7)$$

Where $R_{candidate}$ represents the time index of the R-wave of the QRS candidate in the feature signal, $R_{previous}$ the time index of the R-wave of the previous QRS complex and QRS_{Width}, the duration of the QRS candidate. The RR-interval between the candidate QRS and the previous QRS cannot be smaller that 250 milliseconds (or larger that 1800 ms) since it is humanly impossible [1]. Furthermore, the threshold on the length of the QRS is set based on the minimum QRS duration observed in patients with extreme heart conditions [11].

Once a QRS complex is detected, its topological features such as shape, size and amplitude are used to update the structuring element to enhance QRS detection. More specifically, for each fiducial point, the location and the amplitude is extracted from the feature signal and is used to update the corresponding fiducial point in the structuring element, as shown in the following equations:

$$NewLoc = (1 - \alpha) \times Curr\_Loc + \alpha \times ExtractedLoc \quad (8)$$

$$NewAmp = (1 - \alpha) \times Curr\_Amp + \alpha \times ExtractedAmp \quad (9)$$

In these equations, α represents the learning coefficient and for each fiducial point, $Curr\_Loc$ and $ExtractedLoc$ are calculated as the distance with regards to the QRS onset, respectively extracted from the structuring element and the feature signal. Furthermore, for each fiducial point, $Curr\_amp$ and $ExtractedAmp$ represent its amplitude in the structuring element and the feature signal. Using New_Loc and $NewAmp$, the structuring element is updated and the same procedure is applied to the next ECG window. In other words, after the detection of each QRS complex the structuring element is adapted to enhance the detection.

Furthermore, another feature named Peak Activity (PA), measured as the sum of absolute values for every QRS complex is extracted from the feature signal. This feature helps setting the learning coefficient. α is set to 0.9 at the start of the algorithm. After detection of the second QRS

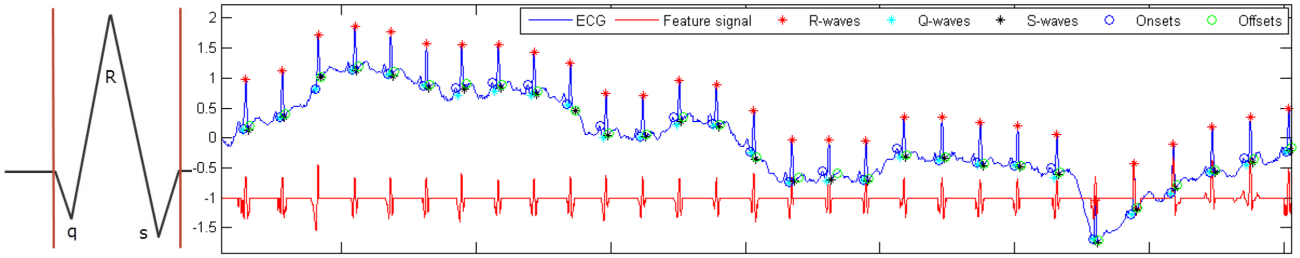

Figure 1. (a)Synthesized QRS structuring element. The vertical lines before the Q-wave and after the S-wave respectively represent the onset and offset of the structuring element. (b)AMM's result on a tape from MIT/BIH arrhythmia database alongside the extracted feature signal (in red).

complex, the PA of the newly detected QRS is compared to that of the previous detected QRS and alpha is updated using:

$$\alpha = \begin{cases} \alpha + 0.05 & NewPA < PreviousPA \times 0.9 \\ \alpha - 0.05 & NewPA > PreviousPA \times 1.1 \\ 0.3 & otherwise \end{cases} \qquad (10)$$

Results show not only that this adaptation improves heartbeat detection but also provides accurate locations for Q, S, onset and offset points. Fig. 1-b shows AMM detection performance on a part of tape number 121 of the MIT/BIH arrhythmia database.

4. Results and discussion

In order to evaluate the performance of the proposed method, MIT/BIH arrhythmia and QT databases were used for detection of QRS and other fiducial points. The first database consists of 48 half hour ECGs with 360 Hz sampling frequency and 11-bit resolution on a range of 10-mv. Among these records, some suffer from artifacts, baseline drift and abnormal shapes (such as record 108), which makes QRS detection a hard task. The second database, designed for waveform boundary evaluation, consists of 105 15-minutes two-channel ECGs with a variety of QRS morphologies. In this database, at least 30 beats in each record were manually annotated for a total of 3622 beats. For a precise evaluation, only manually annotated beats were considered for Q-point, S-point, onset, and offset detection evaluation. Tables 1 shows AMM's evaluation results for the MIT/BIH database.

Table 2 compares the performance of AMM with that of well-known QRS detection methods. As shown in this table, AMM provides comparable or better results while its beat-to-beat adaptation and low complexity makes it a suitable choice for body area networks, in which power consumption play a vital role.

AMM complexity consists of two elements namely, MM operation complexity and structuring element update. The total complexity can be expressed as $O(l \times n) + O(l \times r)$ where n represents the number of ECG samples, l the

Table 1. Performance of AMM on QRS complex detection on MIT/BIH arrhythmia database.

Tape No.	No. of Beats	FP	FN	Failed Detection %	Sensitivity
100	2273	0	0	0	1
101	1865	1	0	0.0536	1
102	2187	0	0	0	1
103	2084	0	0	0	1
104	2229	7	1	0.3589	0.9991
105	2572	22	15	1.4386	0.9884
106	2027	0	4	0.1973	0.9961
107	2137	0	1	0.0468	0.9991
108	1763	3	17	1.1344	0.9809
109	2532	0	1	0.0395	0.9992
111	2124	2	1	0.1412	0.9991
112	2539	0	0	0	1
113	1795	0	0	0	1
114	1879	4	2	0.3193	0.9979
115	1953	0	0	0	1
116	2412	0	20	1	0.9836
117	1535	0	0	0	1
118	2278	2	0	0.0878	1
119	1987	0	0	0	1
121	1863	0	2	0.1074	0.9979
122	2476	0	0	0	1
123	1518	0	0	0	1
124	1619	0	0	0	1
200	2601	4	1	0.1922	0.9992
201	1963	0	12	1	0.9878
202	2136	0	2	0.0936	0.9981
203	2980	18	12	1.0067	0.992
205	2656	1	2	0.113	0.9985
207	1860	3	3	0.3226	0.9968
208	2955	2	9	0.3723	0.9939
209	3005	4	0	0.1331	1
210	2650	3	4	0.2642	0.997
212	2748	0	0	0	1
213	3251	0	3	0.0923	0.9982
214	2262	0	0	0	1
215	3363	0	0	0	1
217	2208	6	4	0.4529	0.9964
219	2154	0	0	0	1
220	2048	0	0	0	1
221	2427	0	6	0.2472	0.9951
222	2483	4	4	0.3222	0.9968
223	2605	2	0	0.0768	1
228	2053	11	8	0.9255	0.9922
230	2256	0	0	0	1
231	1571	0	2	0.1273	0.9975
232	1780	4	0	0.2247	1
233	3079	5	1	0.1949	0.9994
234	2753	0	0	0	1
TOTAL	109494	108	137	0.2238	0.9975

Table 2. Comparison of performance with previously proposed methods on MIT/BIH arrhythmia database.

Fiducial point	No. of Beats	FP	FN	Failed detection %	Ref. No.
AMM	109494	108	137	0.224	—
Pan-Tompkins	109809	507	277	0.710	[2]
Wavelet	104184	65	112	0.170	[3]
3-MM	109510	204	213	0.3801	[10]

Table 3. Evaluation of the proposed method on the manually annotated beats for QRS fiducial points, QT database.

Fiducial point	Sensitivity	Detection Rate	Error Tolerance (ms)
R-wave	0.9987	0.9990	0
QRS-Onset	0.9684	0.9791	10
Q-point	0.9903	0.9902	4
S-point	0.9966	0.9966	4
QRS-Offset	0.9820	0.9818	10

length of the structuring element and r the number of detected heartbeats. Since $l \ll n$ and $k \ll n$ the second term can be omitted and AMM order of complexity can be written as $O(n)$.

The structuring element as the heart of AMM is carefully adapted after detection of each beat. This adaptation changes the location of fiducial points and their amplitudes resulting in a more precise detection. The more the structuring element resembles the QRS complex in the ECG, the more accurate the feature signal. Employing a general structuring element to detect all QRS complexes can result in unwanted activity in the feature signal, forcing a threshold which best separates actual QRS complexes from false positives. Moreover, the length and scale of the structuring element has drastic effects on the feature signal. Broadening the structuring element will give rise to peaks and valleys, which affects the localization of fiducial points. On the other hand, scaling up the amplitude of the signal weakens high frequency activities but also shrinks the peaks and valleys in the feature signal. Narrowing the structuring element or scaling down its amplitude has relatively opposite effects. Therefore, a compromise should be made in order to have a feature signal best representing the QRS complexes in the ECG. Our studies show that the best length and amplitude for the structuring element are actually the length and amplitude of the QRS complex. However, the amplitude should become larger as more noise sources are present. Therefore, we studied the effect of learning coefficient in order to best apply these changes with regards to the activities in the ECG and the previously detected QRS complexes. At the beginning, the learning coefficient is set to 0.9 due to the fact that the structuring element is synthesized and drastic changes in the structuring element might be needed. As more QRS complexes are detected, the topology of the structuring element becomes closer to the QRS topology of the subject and results in better detection of the QRS complexes as well as of the other fiducial points. Table 3 shows performance of AMM on the manually annotated sections of ECG in the QT database.

5. Conclusion and Future Work

In this paper we present a mathematical morphology approach with an adaptive structuring element to detect QRS fiducial points. Unlike most QRS complex detectors, in which a set of arbitrary and physiological thresholds are common, only physiological thresholds are used in AMM. The adaptive structuring element is updated after detection of each heartbeat to resemble patient QRS complex topology for better and more accurate heartbeat detection. Beat-to-beat QRS detection and low computational cost of AMM makes it a suitable choice for body area networks.

Furthermore, detected fiducial points together with the extracted RR-intervals can be used in future studies of beat classification and arrhythmia detection.

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