J. Biomed. Eng. Res.
Vol. 24, No. 2, 107-112, 2003

Resonace theory에 기반을 둔 index function을 통한 새로운 QRS 검출 알고리즘

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(2002년 9월 16일 접수, 2003년 3월 11일 채택)

A New QRS Detection Algorithm Using Index Function Based on Resonance Theory

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(Received September 16, 2002. Accepted March 11, 2003)

요 약 : 본 연구는 공진이론에 기초한 인덱스 함수(index function)를 이용하여 간단하게 QRS를 검출하는 새로운 알고리즘에 관한 것이다. ECG는 몇 개의 사인파형의 조합으로 모델링 가능하며, 이때 ECG의 일차차분 값은 사인파형의 크기 및 주파수와 관계가 있다. 이 사실에 근거하여, R-L-C 회로의 허수부의 제곱값과 유사한 인덱스함수를 디자인하였으며, 인덱스 함수의 응답에 적응방법(adaptive method)를 첨가하여 QRS를 검출하였다. 이 알고리즘은 다른 QRS 검출 알고리즘에 비해 비슷하거나 높은 검출성능을 보였고, 복잡한 전처리 또는 후처리 과정이 필요치 않으므로 실시간 검출에 유용하게 사용될 수 있을 것이다.

Abstract : This paper describes a new simple QRS detection algorithm using index function based on resonance theory. The ECG signal can be modeled with several sinusoidal pulses and its first difference has some relations with the amplitude and frequency of sinusoidal pulse. Based on above fact, an index function, similar to the square of the imaginary part of a simple R-L-C circuit, was designed. A QRS complex is detected by applying the adaptive method to the response of index function. The algorithm showed a performance comparable to or higher than the other algorithms. Because it does not require any complicated preprocessing or postprocessing, it can be implemented in real time.

Key words : QRS detection algorithm, Index function, First order difference, Real time

INTRODUCTION

A good performance of an automatic ECG diagnostic system depends highly upon the accurate and reliable detection of the QRS complex. There are many methods employed for QRS complex detection to get a good and stable performance, despite the morphological variety and several types of noise that these complexes could have.

The methods for QRS detection can generally be divided into three categories : nonsyntactic, syntactic and hybrid. The methods based on syntactic are time-consuming, due to the need for grammar inference for each class of patterns. So, most of the applicable QRS detectors are nonsyntactic. But, the implementations of these techniques also have trouble with manipulating the noise, such as baseline drift, motion artifacts, power-line interference, etc. A nonsyntactic method is accomplished by mainly observing the amplitude of filtered signal, first (or se-

본 연구는 보건복지부 보건의료기술진흥사업의 지원에 의하여 이루어진 것임(02-PJ3-PG6-EV08-0001)

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cond) order derivative signal or both of them[1]. To improve the performance, Laguna et al. studied about an adaptive threshold which changes depending on a heart rate[2]. Recently, many hybrid algorithms using wavelet transform or neural network have been developed and shown significant improvement[3-6].

Recent algorithms are so complicated, time-consuming and expensive, however, that is why a simple but reliable algorithm is needed for the realization on a logical hardware or micro-processor. So, in this paper, we proposed a new algorithm which detects QRS complex by detecting a symmetric pulse corresponding to the QRS complex using resonance theory.

It can be simply implemented and detect QRS complex as specialists do, that is, it finds a QRS complex, within a signal segment of QRS frequency range, using the information of relative amplitude to neighboring peaks.

METHODS

1. Decomposition of ECG signal

Suppappola et al. modeled ECG with several symmetric pulses[7]. This implies that the ECG segment can be approximated by the sum of m symmetric pulses. Let an ECG segment x(n) which contains P, QRS, and T waves be represented by equation (1).

$$x(n) = \sum_k W_k(n) \quad k = P,\ QRS,\ T \tag{1}$$

where W_P, W_{QRS} and W_T mean P, QRS and T wave of same beat segment, respectively. Then, the estimated ECG, $\hat{x}(n)$ can be expressed as equation (2).

$$\begin{aligned}\hat{x}(n) &= \hat{W}_P(n) + \hat{W}_{QRS}(n) + \hat{W}_T(n) \\ &= \sum_{i=1}^{m_1} SP_{Pi}(n) + \sum_{j=1}^{m_2} SP_{QRSj}(n) + \sum_{k=1}^{m_3} SP_{Tk}(n)\end{aligned} \tag{2}$$

where SP_{Pi}, SP_{QRSj} and SP_{Tk} represent the symmetric pulses which constitute P, QRS and T wave, respectively and m is the total number of pulses shown as $m = m1 + m2 + m3$. Because the decomposed symmetrical pulses are approximated by sinusoidal pulses, the symmetrical pulse SP is characterized by equation (3).

$$\begin{aligned}SP(\tau, A, f) &= A\sin\{2\pi f(t-\tau)\} \quad , 0 \le 2\pi f(t-\tau) \le \pi \\ &= 0 \quad , otherwise\end{aligned} \tag{3}$$

where τ, A and f are the beginning position, amplitude and frequency of SP. Fig. 1 is the example of intuitive decomposition of ECG using five sinusoidal pulses which were generated by SP. And, The beat segment is sampled from MIT/BIH database. Finally, the reconstructed ECG $\hat{x}(n)$ can be approximated by the sum of sinusoidal symmetrical pulses. For this case, the NRMSE (normalized root mean squared error) between original ECG and reconstructed ECG was 0.15.

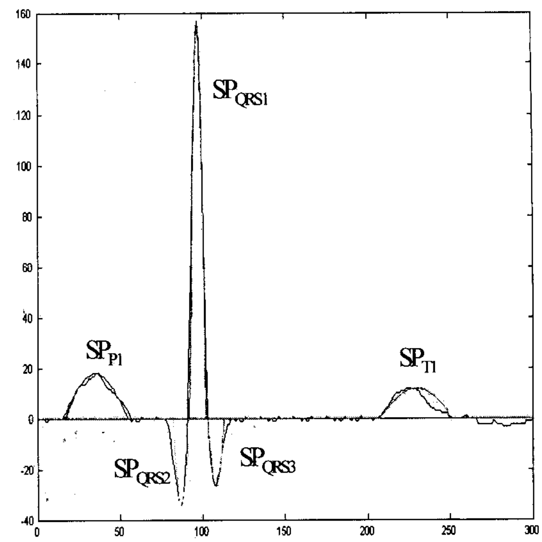


Fig. 1. Example of ECG decompostion using sinusoid pulses

2. Resonance and index function

Based on the above description, an ECG segment can be represented by one major sinusoidal pulse which has the dominant characteristic frequency of QRS complex and the other minor sinusoidal pulses. For its major sinusoidal pulse which has amplitude A and frequency f, the difference of two sequent sample points $\triangle x$ depends both on amplitude and frequency. And, it is known to be far from that of P or T wave and noise such as baseline wandering or power-line interference so that it is widely used to attenuate low frequency noise and to detect QRS complex. For this reason, $\triangle x$ is selected as a parameter of index function for QRS detection and the proposed index function is shown in equation (4).

$$I(\triangle x) = \left(\triangle x\, L - \frac{1}{\triangle x\, C}\right)^2 \tag{4}$$

where L and C are the parameters related to the curve

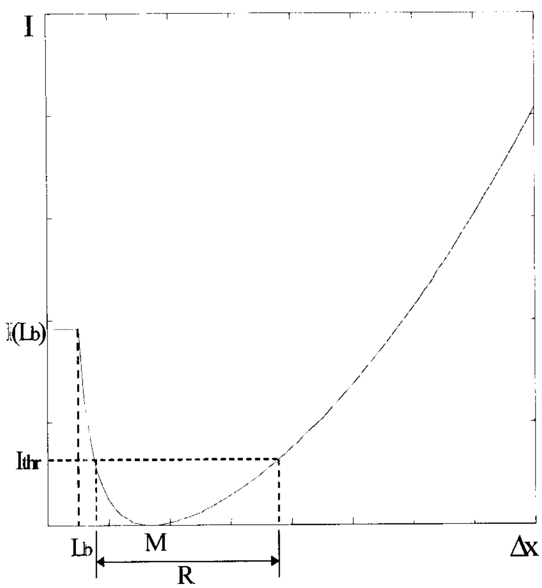


Fig. 2. The characteristic curve of index function
The resonant point at which the index function has the minimum value is marked as M
The low bound L_b and $I(L_b)$ which is assigned for all smaller Δx than the low bound L_b are shown. And, the detection threshold Ithr and the detection window R which the detection threshold determines, are also shown

shape of the index function. The index function, $I(\triangle x)$ is similar to the square of the imaginary part of a simple R-L-C series circuit except that frequency component ω is replaced by $\triangle x$. The value of L and C determine the characteristic of the index function and the index function has a minimum value when $\triangle x = 1/\sqrt{LC}$.

In Fig. 2, an example of characteristic curve of an index function is plotted and the resonant position M and the low bound, L_b are marked. If $\triangle x$ is smaller than L_b, the index function only gives a fixed value $I(L_b)$ so that the effect of small non-QRS components are suppressed.

3. QRS detection algorithm

In order to detect QRS complex, the ECG signal is preprocessed with a bandpass filter of 1-30 Hz bandwidth and the first order difference of bandpass filtered signal, $\triangle x(n)$ is computed. Then, we find the index function for QRS detection by selecting initial L and C.

After this, the index function in terms of each $\triangle x(n)$ is computed. When it comes to a QRS complex, the index function has more than two downward pulses. And, a

Table 1. The conditions of resonant position M to be moved adaptively

condition	deviation
$P_{QRS}(i) \leq 0.5 \times P_{QRS}(i-1)$	-5 %
$P_{QRS}(i) \geq 1.5 \times P_{QRS}(i-1)$	+5 %
$AP_{QRS}(i) \leq 0.7 \times AP_{QRS}(i-1)$	-5 %
$AP_{QRS}(i) \geq 1.3 \times AP_{QRS}(i-1)$	+5 %
$RR\ interval \geq 1.8 \times previous\ RR\ interval$	-10 %

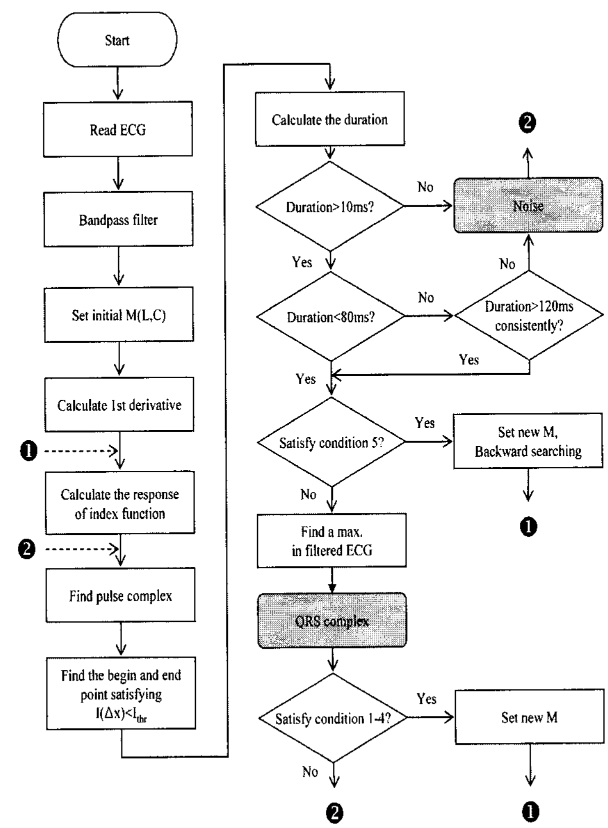


Fig. 3. The algorithm flowchart for QRS complex detection

signal is generated by clipping the part higher than detection threshold, I_{thr} from the index function. From this, a start point of the first downward pulse is defined as a beginning of a pulse complex and last point of the last pulse, within general QRS duration range from the start point, is defined as an end of a pulse complex. Then, within a pulse complex, the duration between the first point and last point of complex can be calculated. If the value of duration is more than an empirical value (10ms), a QRS complex is assumed to be detected and if it is more than normal limit of QRS duration (80ms), the pulse

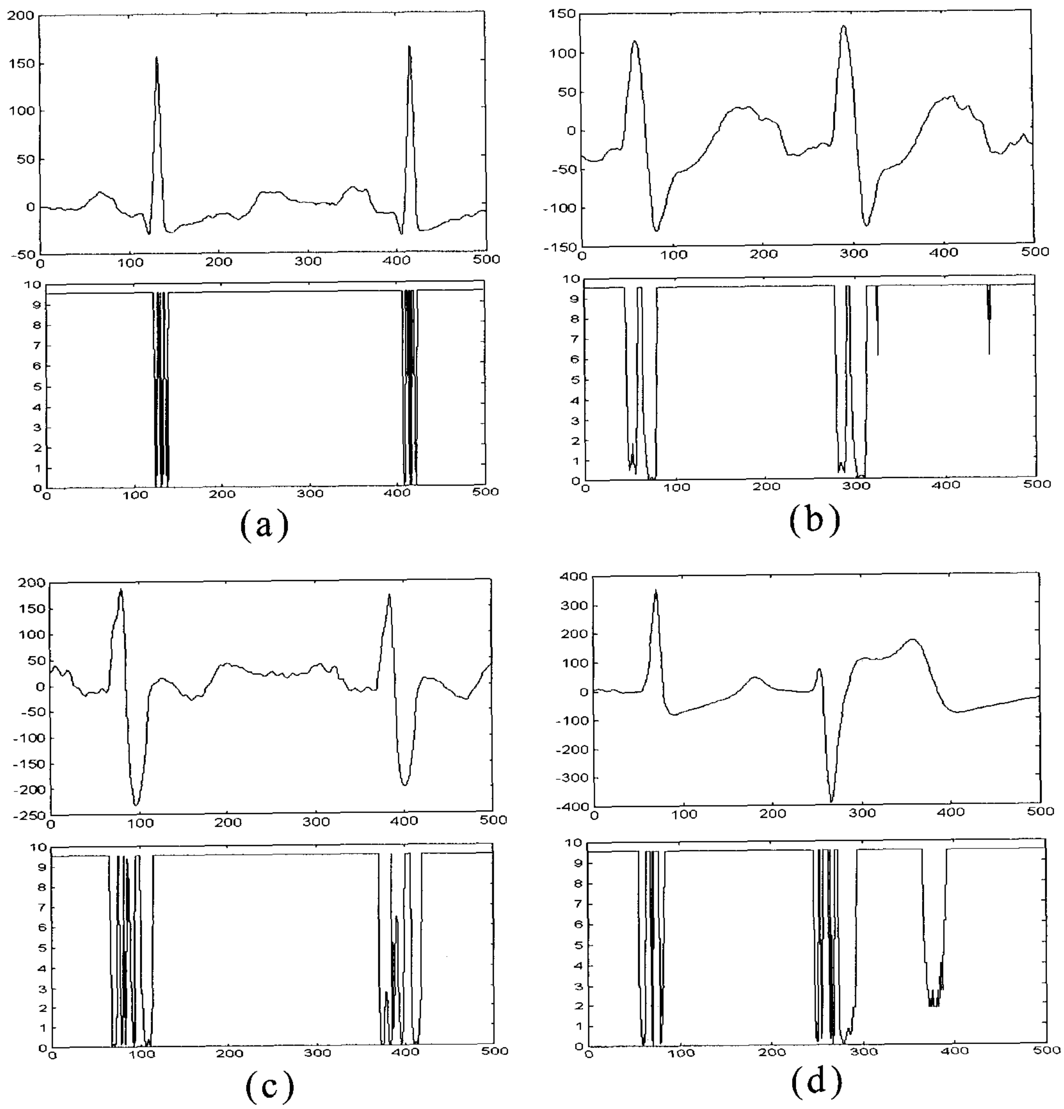
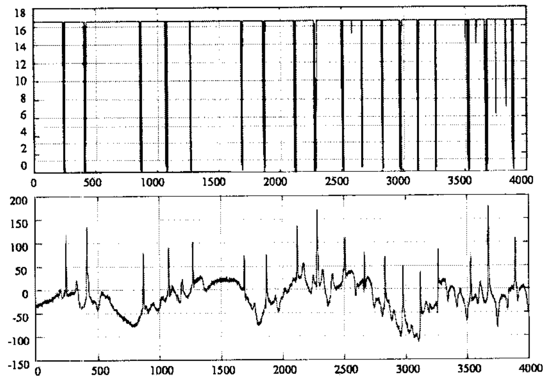


Fig. 4. The index function to normal, LBBB, RBBB and PVC beats (MIT/BIH database)
(a) Normal (T100) (b) LBBB (T109) (c) RBBB (T118) (d) PVC (T114)

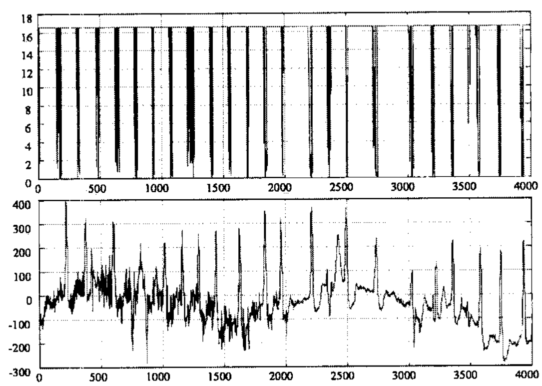
complex are assumed as a noise. In the meantime, if there exists a consistence of more than 120ms duration, it is regarded as a wide QRS complex. And, in filtered ECG, an R peak is definded as the position of maximum value while downward pulses are occurred. The detection threshold I_{thr} and the detection window R whose width and position depend on I_{thr} are shown in Fig. 2.

For providing the detection algorithm with adaptivity to the variation of amplitude of QRS peaks, a resonant point M needs to be moved based on Table 1, where $P_{QRS(i)}$ is the peak of i th QRS and $AP_{QRS}(i)$ is the i th average peak of the previous eight beats. In general, for applying an adaptive threshold method, when one of first four conditions in Table 1 occurs, a threshold is lowered or made higher by 20%. And, when fifth condition occurs, it is lowered by 50%. Then, a backward searching is followed. Similarly, when any condition is satisfied, M is adaptively changed.

The percentages in deviation column mean that the resonant point needs to be moved by the amount of the product of current resonant point and deviation percentage for each condition. Especially, in the case of the fifth condition, backward detection is additionally performed. The algorithm flowchart for QRS dectection is shown in Fig. 3.



(a)



(b)

Fig. 5. Examples of the index function for tracing T222(a) and T203(b) of MIT/BIH databases. Lower traces are ECG signals with baseline wander and high frequency noise. Upper traces are the responses of the index function

RESULTS AND DISCUSSION

The index function has some merits in QRS complex detection because its curve has different slopes in the left and right sides of the resonant point(Fig. 2). First, concerning the steep slope on the left side, although some Δx values of non QRS complex are close to the left of the detection window, the index function are higher than that of Δx within a detection window so that QRS complex and non QRS complex can be distinguished definitely. That is, even if two Δx values each corresponding to P (or T) wave and QRS complex have only a little difference, the response of these would be relatively more different. Secondly, for the dull slope on the right side in the event that the range of Δx values that corresponds to QRS complex is changed by a sudden increase in the QRS complex amplitude, the response of the enlarged QRS complex would be so similar to the response of the previous one that this QRS complex could also be detected by the same detection window and threshold. For QRS detection in MIT/BIH database which has 11-bit resolution over a 10 mV range, the index function was experimentally designed to initially have the minimum when $\Delta x = 17$ and both L and C were set at 0.0588 for it. For MIT/BIH database, this is an approximate median value of the first derivative at the beginnig of various R waves.

Then, by the adaptive rule as mentioned in Table 1, L and C were equally varied and it caused the resonant point M to be moved as much as shown in the deviation column.

To verify the usefulness of the index function in QRS detection, the index function of Fig. 2 was applied to the different arrhythmia patterns in MIT/BIH database, and four examples of their results are plotted in Fig. 4.

The upper panel of Fig. 4(a) is the original ECG of T100 which is annotated as normal beat, and the lower panel is the index function. Figs. 4(b)-(d) are the original

Table 2. The performance of the QRS detection algorithm (FP : False Positive, FN : False Negative)

Record	Total (beats)	Detected (beats)	FP	FN	Detection Rate
T100	2273	2273	·	·	100.000 %
T105	2572	2620	51	3	97.900 %
T109	2532	2527	·	5	99.802 %
T112	2539	2541	2	·	99.920 %
T114	1879	1879	·	·	100.000 %
T123	1518	1518	·	·	100.000 %
T124	1619	1620	1	·	99.938 %
T200	2601	2608	7	·	99.731 %
T203	2980	2999	72	53	95.805 %
T205	2656	2649	·	7	99.736 %
T208	2955	2953	7	9	99.459 %
T209	3004	3024	20	·	99.334 %
T210	2650	2659	13	4	99.358 %
T214	2261	2266	5	·	99.779 %
T222	2483	2486	4	1	99.799 %
T223	2605	2607	4	2	99.770 %
T228	2053	2098	52	7	97.126 %
T233	3079	3084	6	1	99.773 %
Total	44259	44411	244	92	99.241 %

ECGs annotated as LBBB, RBBB, PVC and their responses. Note that low frequency noise did not affect the response, and their responses also show different shapes and widths for four different patterns. Since each response shows a shape of downward pulse-complex at the QRS complex, QRS complex can be recognized whenever the amplitude of downward pulse complex is lower than the detection threshold I_{thr}.

Fig. 5 shows examples of ECG signal(T222 and T203) and their corresponding responses. As shown in Fig. 5(a), it shows an excellent QRS detection for ECG signals which are infected with baseline wandering and noises of small magnitude and high frequency. On the contrary, we can see the false detection when an ECG signal is mixed with a noise of large magnitude and high frequency such as that in Fig. 5(b).

The eighteen records were chosen from MIT/BIH arrhythmia database, and this algorithm was applied to these. In Table 2, the results of QRS detection are listed. False positive beats were chiefly brought out under the condition that the T wave of R-on-T type PVC covers a wide range. Also, the ECG signal infected with the large amplitude and high frequency noise produced false positive beats. On the other hand, false negative beats are detected when $\triangle x(n)$ is extremely smaller than the estimated typical value of M. An ECG signal with a noise of small magnitude and high frequency can be ignored, because this algorithm depends on the gradient of ECG signal. And, if a high frequency signal has a large magnitude, but is not distributed as wide as a normal QRS width, it will be regarded as noise. The results showed a comparable or higher performance, compared with other algorithms[1],[8].

Generally, a nonsyntactic algorithm should incorporate complicated filtering techniques essentially and a syntactic or hybrid algorithm, such as wavelet transform, fuzzy logic inference, neural network or mixed method, is time-consuming and expensive. However, this algorithm just includes first order bandpass filtering, calculation of first derivative, computation of the index function for the input of first derivativ and check of the response with detection rule and adaptive modification of M, not any complicated preprocessing or postprocessing. So, it can be implemented in real time and available for the hardware or micro-processor realization.

Acknowledgement

This study was supported by a grant of the Korea Health 21 R & D Project, Ministry of Health & Welfare, Republic of Korea(02-PJ3-PG6-EV08-0001)

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