Proceedings of the 29th Annual International
Conference of the IEEE EMBS
Cité Internationale, Lyon, France
August 23-26, 2007.

Electrocardiogram QRS Detection Using Multiscale Filtering Based on Mathematical Morphology

Fei Zhang, *Student Member, IEEE* and Yong Lian, *Senior Member, IEEE*

Abstract— **A novel QRS detection algorithm based on multi-scale mathematical morphology (3M) and multi-frame differential modulus cumulation is proposed in this paper. The algorithm introduces the multi-stage filtering based on mathematical morphology from image processing field into ECG analysis to suppress the impulsive noise, and adopts multi-frame differential modulus cumulation to remove the baseline drift and enhance the signal. An average QRS detection rate of 99.67%, a sensitivity of 99.86% and a positive prediction of 99.80% have been achieved against the MIT/BIH Arrhythmia Database. Comparison with existing methods reveals that the proposed algorithm achieves better detection accuracy.**

I. Introduction

ECG is a valuable tool in the diagnosis of cardiac disease. ECG signal is often corrupted by impulsive noise due to muscle contraction or power line interference and baseline drift of signal due to the respiration or motion artifacts. Hence, accurate QRS detection is of great importance for the evaluation of current heart conditions in ECG wave analysis. QRS detection, as the basis of ECG analysis, has been an essential research topic for several decades. Papers [1], [2] have provided good overviews of conventional and newly-proposed QRS detection algorithms for heart monitoring.

Mathematical morphology originates from 2-D image processing [3], [4] and was induced into 1-D ECG signal processing [5]-[7]. Successful removal of impulsive noise and background normalization of ECG were reported employing the single-scale mathematical morphology methods [5]-[7]. In 2003, Yang et al [8] proposed a novel multiscale mathematical morphology (3M) filtering for image processing, and it demonstrated better performance than conventional single-scale mathematical morphology and median filters.

In this paper, we introduce the multiscale filtering concept based on mathematical morphology into the QRS complex detection of ECG waveform. The proposed method adopted the multiscale top-hat and bottom-hat operators, together with multiscale morphological opening and closing filtering, and multiframe differential modulus cumulation to suppress the different artifacts and enhance the signal. The standard MIT/BIH ECG database [9] is used to verify the superiority of proposed QRS detection method.

This paper is organized as follows. In Section II, we give a brief introduction of multi-scale mathematical morphology filtering, which serves as a basis for the proposed algorithm. In Section III, we present the new algorithm and discuss the detailed steps involved in the algorithm. The evaluation of the algorithm is done by using the MIT/BIH Arrhythmia Database and the results are shown in Section IV. Conclusion remarks are drawn in Section V.

II. Multiscale Mathematical Morphology Filtering

Mathematical morphology, based on set operations, provides a way to analyze signals using nonlinear signal processing operators that incorporate the geometry information of the signal. The shape information of the signal is extracted by using a structure element to operate on the signal. Such operators serve two purposes, i.e. extracting the useful signal and removing the artifacts. In fact, the ECG signal processed by the single-scale operators is similar with image processed by gray-scale morphology. Details are available in [3].

3M [8] is the extension of the single-scale morphology. Both of them have the same basic mathematical morphological operators: Dilation, Erosion, Opening and Closing. The top-hat and bottom-hat operators are composite operations of them. Multiscale morphological filtering performs morphological operations many times by using the structure elements of different shapes and sizes. The elementary operators of gray-scale mathematical morphology for signal $f(x)$ are reviewed here firstly:

Dilation: $$f \oplus g(x) = \max_{(i)}[(f(x-i)+g(i)], \quad (1)$$

Erosion: $$f \Theta g(x) = \min_{(i)}[(f(x+i)+g(i)], \quad (2)$$

Opening: $$f \circ g(x) = f \oplus g(\Theta g)(x), \quad (3)$$

Closing: $$f * g(x) = f \Theta g(\oplus g)(x), \quad (4)$$

Top-hat: $$THat(f(x)) = f(x) - f \circ g(x), \quad (5)$$

Bottom-hat: $$BHat(f(x)) = f(x) - f * g(x), \quad (6)$$

Manuscript received April 2, 2007. This work was supported by the research grant 052-118-0060 from Singapore Agency for Science Technology and Research (A*STAR) Thematic Strategic Research Programme: Embedded & Hybrid System II under the project of Wireless Body Area Network --ECG Sensor.

F. Zhang and Y. Lian are with the Department of Electrical and Computer Engineering, National University of Singapore, 119260, Singapore (e-mail: elezf@nus.edu.sg and eleliany@nus.edu.sg; phone: 65-6516-2993; fax: 65-6779-1103)

where $g(x)$ is the predefined structure element. When it comes to the 3M filtering, $g_J(x)$ equals to $g_1(x) \otimes g_2(x) \otimes g_3(x) ... \otimes g_j(x)$ as J scales. But the J-scale top-hat and bottom hat operators are expressed as

Top-hat: $THat(f(x))_J = f \circ g_{J-1}(x) - f \circ g_J(x)$, (7)

Bottom-hat: $BHat(f(x))_J = f * g_{J-1}(x) - f * g_J(x)$. (8)

III. The Proposed Methods

QRS complexes are composed of a group of consecutive positive and negative peak points. The block diagram of proposed scheme for QRS detections using 3M is given as a block diagram in Fig.1.

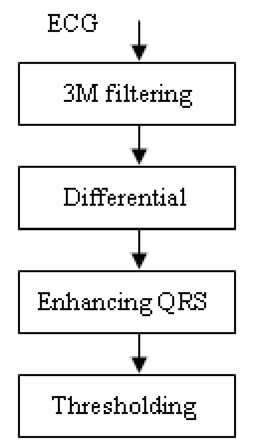

Fig. 1. Block diagram of the proposed algorithm for QRS detection

A. Multiscale Mathematical Morphology Filtering

As described in [8], the multiscale opening and closing filtering outperforms the multiscale dilation and erosion filtering due to its space independence. The multiscale opening and closing filterings are defined as

$$F(f(x)) = \alpha f \circ g_J(x) + (1-\alpha) f * g_J(x). \quad (9)$$

where α is the weight factor of opening filtering and J is the largest filtering scale. The final filtered result depends much on the weight factor of opening filtering. It is set to 0.5 usually.

Actually, Opening and closing filtering provides a simple and mathematically formal method for peak or valley extraction [5]. Subtracting the opening of a signal from ECG by a set $g(x)$ produces an output consisting of the signal peaks. This is so-called top-hat operator. Similarly, the valleys (negative peaks) can be extracted by the bottom-hat operator. The coefficients of top-hat and bottom-hat operators are modified to be a geometrical series with the common ration of 1/2 to reduce the influence of noise. So the combined peak and valley extractors form a peak-valley extractor, which is expressed as follows in 3M.

$$Hat(f(x)) = \frac{1}{2}\sum_{j=1}^{J} K_j^T That(f(x))_j - \frac{1}{2}\sum_{j=1}^{J} K_j^B Bhat(f(x))_j, \quad (10)$$

where $K_j^T = K_j^B = K_j = (\frac{1}{2})^{J+1-j}$ and j=1, 2… J.

The final multiscale mathematical morphology filtering can be defined as:

$$\begin{aligned} y(x) &= F(f(x)) + Hat(f(x)) \\ &= \frac{1}{2} f \circ g_J(x) + \frac{1}{2} f * g_J(x) + \\ &\quad \frac{1}{2}\sum_{j=1}^{J} K_j^T That(f(x))_j - \frac{1}{2}\sum_{j=1}^{J} K_j^B Bhat(f(x))_j. \end{aligned} \quad (11)$$

J is set to be 3.

B. Differential Operation

After the multiscale mathematical morphology filtering, the output ECG sequence $y(x)$ is differentiated in order to remove motion artifacts and base line drifts.

The first-order differential ($v(x)$=d/dt($y(x)$)) in discrete time domain can be demonstrated by

$$v(x) = \frac{1}{\vartriangle t}(y(x) - y(x-1)), \quad (12)$$

where x is the total number of samples and $\vartriangle t$ is the sampling frequency.

C. Enhancing ECG by Modulus and Combination

The absolute value of the differential output result is combined by multiple-frame cumulation, which is much alike with the more or less known energy transformation [10], [11]. The process can be written as,

$$\begin{aligned} m(x) &= |v(x) - v(x-1)|, \\ n(x) &= \sum_{x=-q/2}^{q/2} m(x). \end{aligned} \quad (13)$$

The value of q should correspond to the possible maximum duration of normal QRS complex.

D. Threshold and Judgment

Threshold is used as the decision function in connection with the proposed transformation for QRS detection [11]. By experiment, it is found the required threshold is a function of the maximum of the transformed ECG waveform. The feasible expression of the threshold is given by:

$$T = \begin{cases} 0.1Max & Max < 3 \\ 0.27Max & 3 \le Max \le 5 \\ 0.15Max & Max > 5 \end{cases} \quad . \tag{14}$$

where *Max* is the maximum value of the transformed ECG waveform which is within the range of mV.

The usual values of the transformed waveform are between 3 and 5. Values above 5 mean that spikes exist. Values below 3 mean that the QRS complexes are very small, and therefore low values of the threshold must be considered.

IV. RESULTS AND DISCUSSIONS

The MIT/BIH Arrhythmia database provided by MIT and Boston's Beth Israel Hospital is used for evaluation of the proposed QRS detection algorithm. It contains 48 half-hour recordings of 360 Hz and 11-bit resolution over a 10-mV range. Here, Table 1 shows the summary of obtained results of QRS detection only by using five first recordings of the MIT/BIH database. Figs. 2 and 3 show two detection examples performed over Tapes 100 and 105 from MIT/BIH database. It is obvious that the proposed algorithm correctly detects the QRS of ECG, even under the presence of noise and baseline drift.

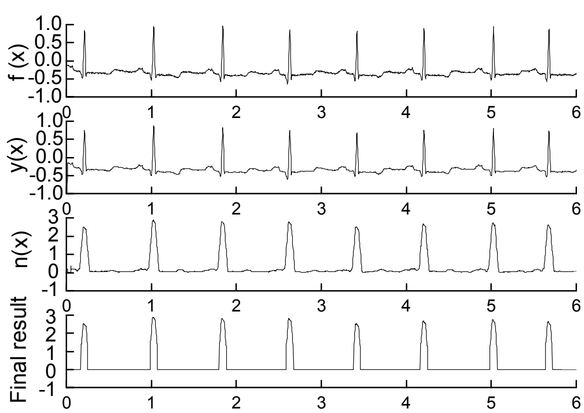

Fig. 2 Detection of QRS using the Tape 100 of MIT/BIH database

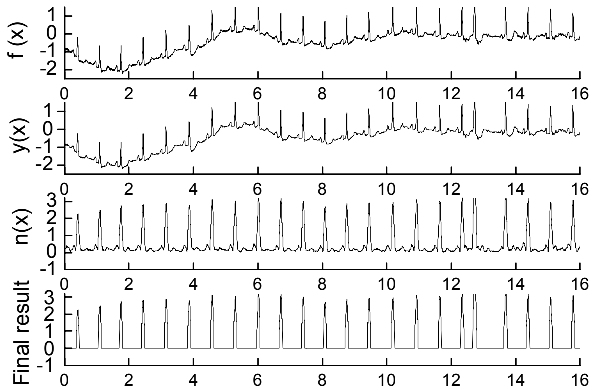

Fig. 3 Detection of QRS using the Tape 105 of MIT/BIH database

TABLE I
PERFORMANCE FOR PROPOSED ALGORITHM

Tape	Total	FN	FP	Se(%)	+P(%)	*DER*
100	2273	0	0	100	100	0
101	1865	0	1	100	99.95	0.0005
102	2187	0	0	100	100	0
103	2084	0	0	100	100	0
105	2572	19	7	99.26	99.73	0.0101

TABLE II.
PERFORMANCE COMPARISON WITH OTHER ALGORITHMS

Method	FP	FN	DER(%)	Ref
Genetic algorithm	86	5	3.54	[12]
Band pass filter(BPF)	67	22	3.46	[13]
Filter banks	53	16	3.22	[14]
Topological mapping	41	4	1.75	[15]
Wavelet transform	15	12	1.09	[16]
Proposed method	19	7	1.01	----

To evaluate the performance of detection algorithm, several performance indexes are introduced including false negative (FN) which means failing to detect a true beat (actual QRS), and false positive (FP) which represents a false beat detection. By using FN and FP, the Sensitivity (Se), positive prediction (+P) and detection error (DER) can be calculated using the following equations, respectively.

$$Se(\%) = \frac{TP}{TP + FN}, \tag{15}$$

$$+P(\%) = \frac{TP}{TP + FP}, \tag{16}$$

$$DER(\%) = \frac{FP + FN}{TotalQRS}, \quad (17)$$

where true positive (TP) is the total number of ORS correctly detected by the algorithm.

Finally, an average QRS detection rate of 99.67%, a sensitivity of 99.86% and a positive prediction of 99.80% are obtained against the 20 recordings of MIT/BIH database. The performance for detection of Tapes 100 to 105 is shown in Table I. The Tape 105 is the most difficult one for analysis due to large induced noises and is widely used by researchers to test the QRS detection algorithm. Table II compares the existing algorithms with the proposed one by using Tape 105 as a base.

It is obvious that the reliability of the proposed detector compares very favorably with published results of other QRS detection algorithms.

V. CONCLUSIONS

The QRS detection is very important to ECG diagnostic analysis. This paper aims to present a novel algorithm for QRS detection based on multiscale mathematical morphology and multiframe differential modulus cumulation. The algorithm is evaluated with MIT/BIH standard ECG database to achieve a QRS detection rate of 99.67%, a sensitivity of 99.86% and a positive prediction of 99.80%. In comparisons with other methods, the proposed algorithm demonstrates a better detection rate. The parameters such as J and q in the algorithm are tunable for different sampling frequency and different SNR to maximize the detection accuracy.

REFERENCES

[1] G.M. Friesen, T. C. Jannett, M.A. Jadallah, S.L. Yates, S.R.Quint, and H.T. Nagle, "A comparison of the noise sensitivity of nine QRS detection algorithms," *IEEE Trans. Biomed. Eng.*, vol. 37, pp. 85-98, Jan.1990.

[2] B-U Kohler, C Hennig, and R Orglmeister, "The principles of software QRS detection," *IEEE Eng. in Medicine and Biology Magazine*, vol. 21, pp. 42-57, Jan. 2002.

[3] A. Gasterators, I. Andreadis., and Ph. Tsalides, "Fuzzy soft mathematical morphology," *IEEE Proc. Vis. Imag. Signal processing*, vol. 145, pp. 41-49, Feb. 1998.

[4] F. Zhang, C. Li., and L. Shi, "Detecting and tracking dim moving point target in IR image sequences," *Infrared Phys. and Technol.* , vol. 46, Apr. 2005

[5] P. E. Trahanias, "An approach to QRS complex detection using mathematical morphology," *IEEE Trans. Biomed. Eng.*, vol. 40, pp. 201-205, Feb.1993

[6] C-H. N. Chu and E. J. Delp, "Impulsive noise suppression and background normalization of electrocardiogram signals using morphological operators," *IEEE Trans. Biomed. Eng.*, vol. 36, pp. 262-273, Feb.1989

[7] W. Hu, W. Yu, and A. Luo, "Impulsive noise suppression using morphological operators," in *Proc. of the IEEE Conf. Aerospace and Electron.*, vol. 1, pp.336-339, Feb.1995

[8] Z. Yang, Z. Pu, and Z Qi, "Novel edge preserving multiscale filtering method based on mathematical morphology," in *Proc of the second international conf. on machine learning and cybernetics*, pp.2970-2975, 2003

[9] Available:http://www.physionet.org/physiobank/database/mitdb/

[10] N.V. Thakor, J. G. Webster, and W. J. Tompkins, "Optimal QRS detector," *Med. Bio. Eng. Comput*, vol.21, pp.343-350, May. 1983.

[11] F. Gritzali, "Towards a generalized scheme for QRS detection in ECG waveforms," *Signal Processing*, vol. 15, pp.183-192, Sep. 1988.

[12] R. Poli, S. Cagnoni, and G. Valli, " Genetic Design of optimum linear and nolinear QRS Detectors," *IEEE Trans. Biomed. Eng.*, vol. 42, pp. 1137-1141, Nov.1995

[13] J. Pan, and W.J. Tompkins, " A real time QRS detection algorithm," *IEEE Trans. Biomed. Eng.*, vol. 32, pp. 230-236, Mar.1985

[14] V. X. Afonso, W.J. Tompkins, T. Q. Nguyen, and S. Luo, "ECG beat detection using filter banks," *IEEE Trans. Biomed. Eng.*, vol. 46, pp. 192-201, Feb.1999

[15] J. Lee, K. Jeong, J. Yoon, and M. Lee, "A simple real-time microprocessor QRS detection algorithm," in *Proc. of the 18th Annual Int. Conf. of the IEE Eng. and Med. And Biomed Society*, pp. 1396-1398,1996

[16] C. Li, C. Zheng, and C. Tai, "Detection of ECG characteristic points using wavelet transforms," *IEEE Trans. Biomed. Eng.*, vol. 42, pp. 21-28, Jan.1995