QRS Complex Detection Using Combination of Mexican-hat Wavelet and Complex Morlet Wavelet

Chao Zeng[1, 2]
[1]School of Geosciences and Info-physics, Central South University, Changsha, China
[2]College of Information Science and Technology, Shihezi University, Shihezi, China
Email: zengc_bme@csu.edu.cn

Hongli Lin[1, 3], Qiyun Jiang[*1] , and Min Xu[1]
[*1]School of Geosciences and Info-physics, Central South University, Changsha, China
[3]College of Information Science and Engineering, Hunan University, Changsha, China
Email: jiangqiyun @csu.edu.cn

***Abstract*—QRS complex detection is usually the most important step for automated electrocardiogram (ECG) analysis. In this paper, we present a new approach of QRS complex detection. The Mexican-hat wavelet and complex Morlet wavelet are used to transform the ECG signal, and according to the trait that the modulus maxima of the two wavelet coefficients above correspond with R peaks of ECG signal, a detector unit of R waves which is based on the jump of modulus maxima sequence in wavelet coefficient is proposed. Traditional wavelet based QRS complex detection methods employs only one kind of wavelet to perform the transformation of ECG, whereas the proposed method use two kind of wavelet at the same time, and then using the proposed detector unit in the linear combination of the two wavelet coefficients to detect R waves. In this processing, group search optimizer is introduced to get some best thresholds. Experiment results show that our QRS complex detection achieved a detection sensitive of 99.71% and positive prediction of 99.53% according to the MIT-BIH database. A combination of two wavelets is a simple and efficient way to improve the performance of wavelet based QRS complex detection methods.**

***Index Terms*—ECG, QRS complex, Mexican-hat wavelet, Complex Morlet wavelet, Group search optimizer**

I. INTRODUCTION

As the electrical recorded signal of the heart activity detected at the surface of the body, the electrocardiograph (ECG) provides much valuable information about the heart function state. The QRS complex, which reflects the electrical activity within the heart during the ventricular contraction, is the most striking waveform within the ECG. Since its occurrence as well as its shape proved much information about the current state of the heart, the detection of the QRS complex is the first step and a central theme toward analyzing the ECG signal [1] [2]. At the same time, QRS detection is also necessary to detection the heart rate and as reference for beat alignment [3] [4].

However, developing a robust and accurate algorithm for the detection of the QRS complexes in ECG signal is not easy. The ECG signal is often contaminated by various noises such as baseline shift, power line interference and motion artifact, and it also has a time-varying morphology subject to physiological variation. So the QRS complexes are not always the strongest component in an ECG signal [5] [6]. In the past 30 years, a number of methods have been proposed for the detection of the QRS complexes, including genetic algorithm [7], band pass filter [8], filter banks [9], linear adaptive filter [10], optimized filtering [11].

Recently, a number of wavelet-based techniques have been proposed to detect QRS complex. Those employed wavelets including Daubechies 6 wavelet [12], Mexican-hat wavelet [13], complex Morlet wavelet [14], complex frequency B-spline wavelet [14], and so on. Wavelets have shown their outperformance in the field of QRS detection, and a wavelet based detection method can generally be divided into two units: a wavelet coefficient calculation unit and a threshold based detector unit. In the wavelet coefficient calculation unit, traditional ways mostly employs just one kind of wavelet.

This contribution aims to discuss the accuracy of combination of two kinds of wavelet in the wavelet coefficient calculation unit, and in the threshold based unit, a novel method based on the jump of modulus maxima sequence has been proposed, with its best thresholds achieved by an efficient evolution algorithm: group search optimizer (GSO) [15][16]. The paper is organized as follows: firstly, the QRS detection problem is formulated, and the details of techniques for QRS detection and validation are presented in section 2. Result of experiments to test Mexican hat-wavelet, complex

* Corresponding author: Qiyun Jiang, Email: jiangqiyun@csu.edu.cn.
This work was partially supported by the National Natural Science Foundation of China under the grant project No. 81201151, the Science Foundation of Hunan Province, China under the grant project No. 12JJ6061, and the Research Plan on Science and Technology of Hunan Province, China under the grant project No. 2012SK3185

doi:10.4304/jcp.8.11.2951-2958

Morlet wavelet and a combination of the two are described in the next section. A discussion and conclusion is given in section 4.

II. Materials and Methods

A. Problen Formulation

Our proposed QRS complex detection algorithm contains two units: wavelet coefficients calculation unit and threshold based detector unit (see Figure 1). After it has been passed through the wavelet coefficients calculation unit, which is to reduce noise and emphasize the QRS complex, the ECG signal is sent to the threshold based detector unit for the accurate detection of QRS. Mexican-hat wavelet, complex Morlet wavelet and a combination of the two are used and compared in the first unit. As to the second unit, a novel approach is proposed, and group search optimizer is introduced to determine the best threshold in this unit.

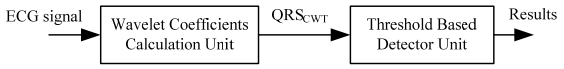


Figure 1. Scheme of proposed QRS complex detection method consist of two unit: wavelet coefficients calculation unit and threshold based detector unit.

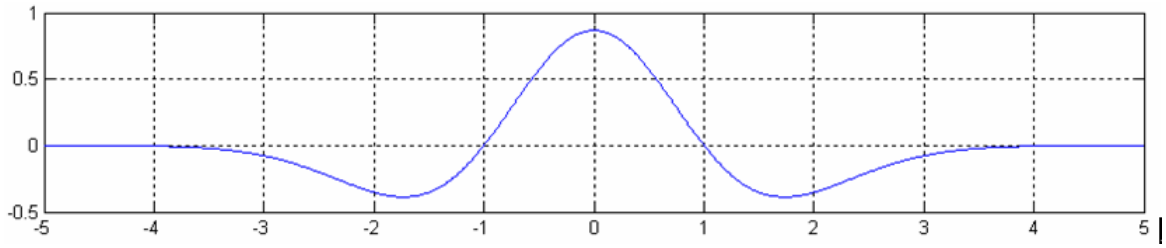


Figure 2. The mother wavelet function of Mexican-hat wavelet.

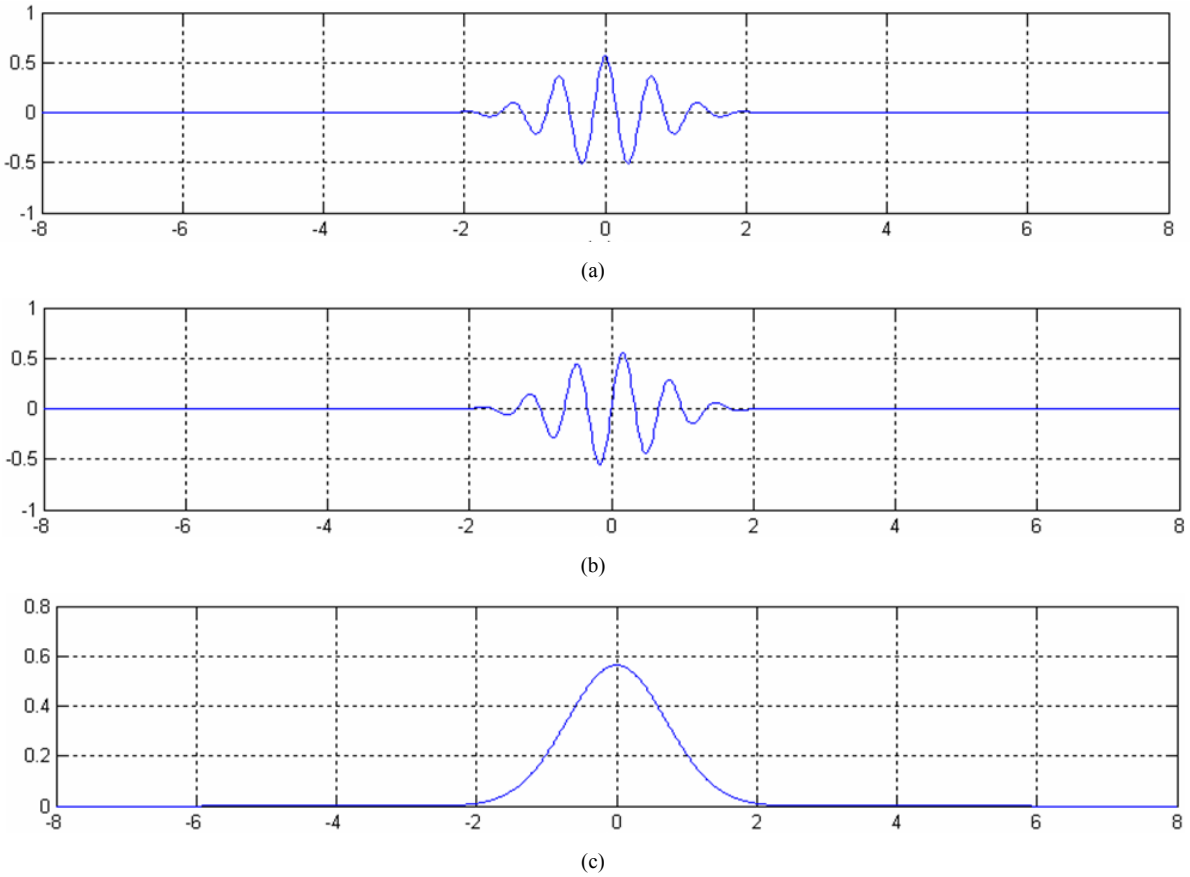


Figure 3. The mother wavelet function of complex Morlet wavelet: (a) Real part, (b) Imaginary part, and (c) Modulus.

B. Wavelet Coefficients Calculation Unit

The continuous wavelet transform (CWT) is a time-frequency analysis method, and it allows localization in time of high frequency signal feature. The CWT of a signal $x(t)$ is defined by:

$$CWT(a,b)=\frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty}x(t)\psi^{*}(\frac{t-b}{a})dt \qquad (1)$$

where $\psi^{*}(t)$ is the complex conjugate of the mother wavelet function $\psi(t)$, a is the dilation parameter of the wavelet, and b is the location parameter of the wavelet.

The Mexican-hat wavelet is the second derivative of a Gaussian function given by:

$$\psi(t)=(1-t^{2})e^{-\frac{t^{2}}{2}} \qquad (2)$$

As shown in Figure 2.

The complex Morlet wavelet is defined as:

$$\psi(t)=\frac{1}{\sqrt{\pi f_{b}}}e^{2j\pi f_{c}t}e^{-\frac{t^{2}}{f_{b}}} \qquad (3)$$

where f_b and f_c are bandwidth parameter and wave center frequency respectively. In Figure 3, the real, imaginary and modulus parts of complex Morlet wavelet are depicted respectively.

The conversion from wavelet scale to wavelet frequency given by:

$$f=\frac{f_{c}}{a\cdot\Delta t} \qquad (4)$$

where a is the wavelet scale, f_c is a center frequency of the wavelet, and Δt is the sampling period. In the case of the Mexican-hat wavelet, the center frequency is 0.25Hz, as shown in Figure 4a. As to the complex Morlet wavelet, the parameters $f_b=1$ and $f_c=1.5$ are selected, and the center frequency is 0.15Hz (see Figure 4b).

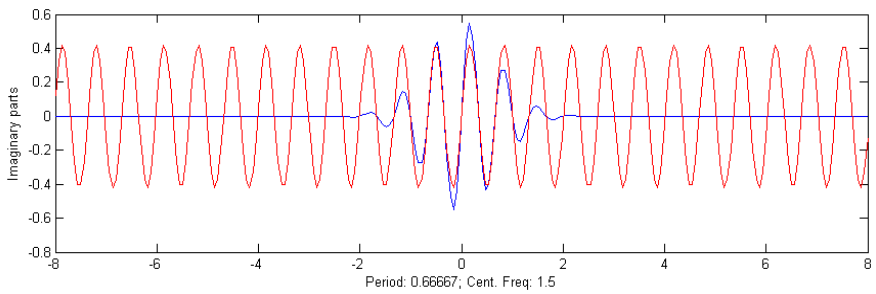
Both Mexican-hat wavelet and complex Morlet wavelet may not detect all the R peaks, and to improve the performance of the wavelet transform is introduced with the form as follow:

$$QRS_{CWT}=\psi_{1}(t)+k\psi_{2}(t) \qquad (5)$$

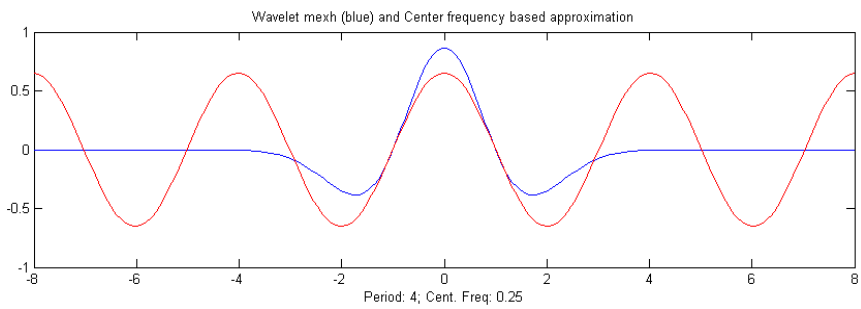
Where $\psi_1(t)$ and $\psi_2(t)$ are Mexican-hat and complex Morlet wavelet coefficients of ECG signals. Figure 5 shows a segment of ECG signal, its Mexican-hat wavelet coefficients, its Morlet wavelet coefficients and a combination of the two wavelet coefficients respectively:

C. Threshold Based QRS Detector Unit

In this paper, scale 6 for Mexican-hat wavelet [17] and scale 27 for complex Morlet wavelet [14] are applied. After the ECG signal is transformed by Mexican-hat wavelet or complex Morlet wavelet, R peaks is correspond with the modulus maxima in the wavelet coefficients, and a new QRS detector algorithm which is based on the jump of modulus maxima sequence in wavelet coefficient is proposed. The algorithm is described as follows:



(a)



(b)

Figure 4. Center frequency of: (a) Mexican-hat wavelet, and (b) complex Morlet wavelet.

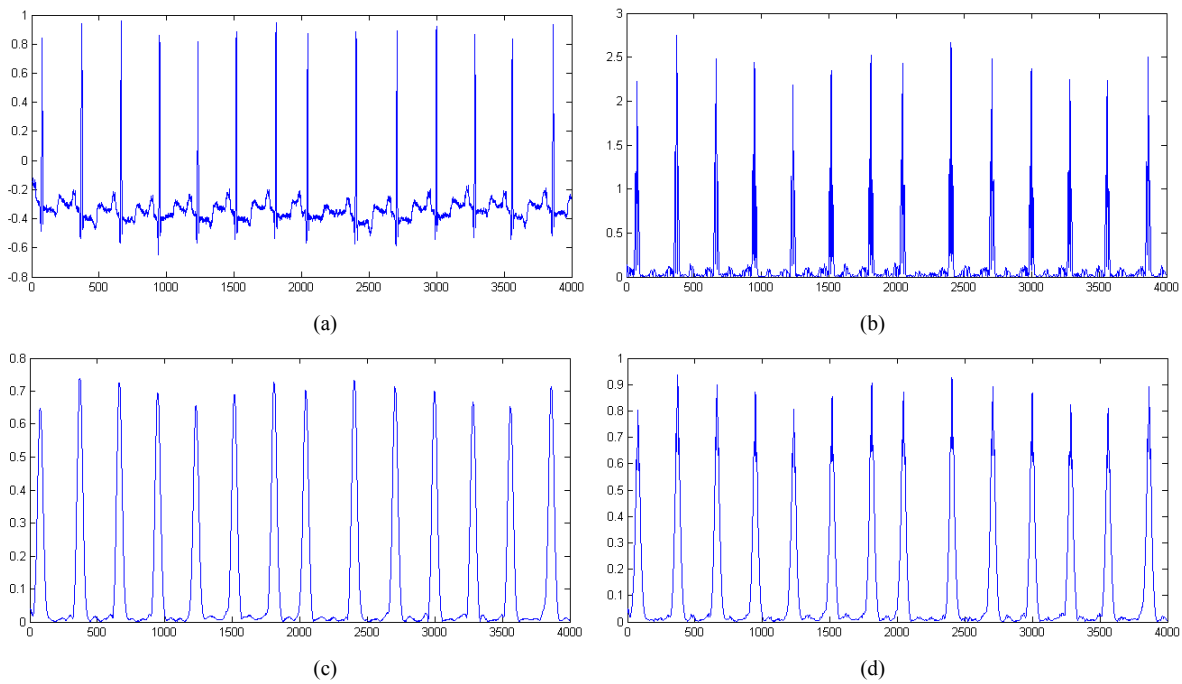


Figure 5. Wavelet transform of ECG signal: (a) A segment of ECG signal, (b) Its Mexican-hat wavelet coefficients, (c) Its complex Morlet wavelet coefficients, and (d) A combination of the two wavelet coefficients.

Step 1: A segment of 10 seconds wavelet coefficient is selected for processing every time. Each segment is divided into 50 sub-segments (see Figure 6). The algorithm search and preserve the modulus maxima in every sub-segments. The preserve modulus maxima are sorted to form a modulus maxima sequence (see Figure 7) to achieve the magnitude of the jump point in the sequence. In Figure 7, the 38th point is such a jump point. Then a threshold th_amp is got by:

$$th\_amp = c\_th \times mag\_jump \tag{6}$$

where mag_jump is the magnitude of the jump point in the segment, and c_th is a parameter.

Once the threshold th_amp is got, the algorithm searches modulus maxima in the segment of wavelet coefficient, if a modulus maximum is greater the threshold, its position is considered as a candidate position of an R peak.

Step 2: If the interval of two neighbored R peak candidates is less than 200ms, the R peak candidate with lower amplitude is removed, and the other is remained.

Step 3: If the interval of the current R peak candidate and its previous R peak candidate $rr\_interval$ satisfied:

$$rr\_interval \geq avg(rr) \times 1.66 \tag{7}$$

where $avg(rr)$ is the average interval of the eight previous R candidates, *Step 1* is reused with a lower threshold to search R peak candidate in a new interval. The boundary of the new interval is calculated by:

$$r\_low = r\_last + avg(rr) \times 0.92 \tag{8}$$

$$r\_high = r\_last + avg(rr) \times 1.16 \tag{9}$$

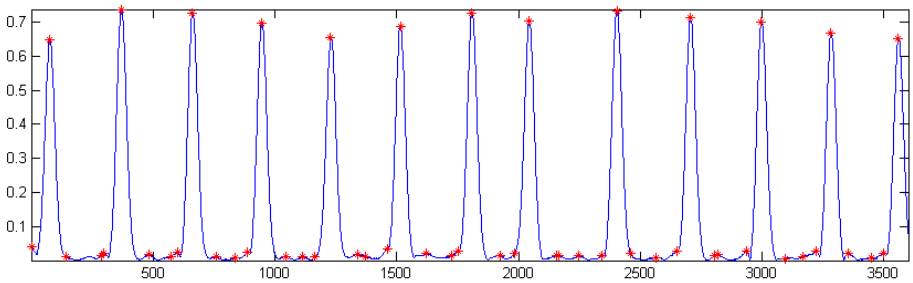


Figure 6. Modulus maxima in wavelet coefficient

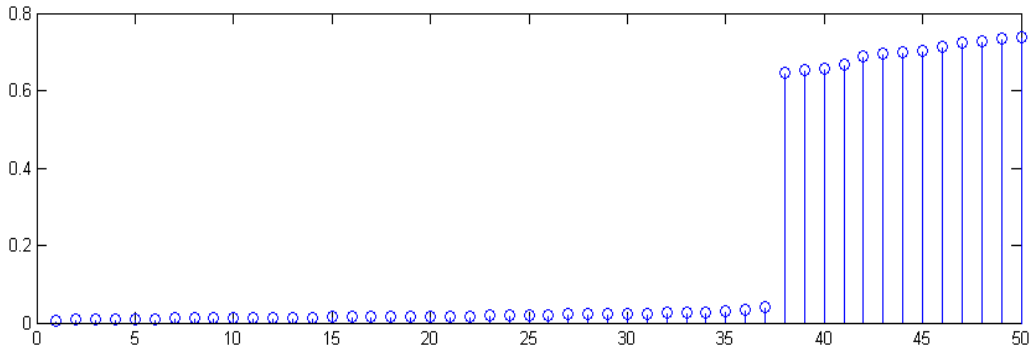


Figure 7. Modulus maxima sequence in wavelet coefficient.

where r_low is the lower bound of the new interval, r_high is the upper bound of the new interval, and r_last is the location of the previous R peak candidate.

D. Group Search Optimizer

In our proposed QRS complex detection algorithm using combination of Mexican-hat wavelet and complex Morlet wavelet, there are two parameters, and must to be determined for the best performance of our algorithm. This problem can be formulated as a constrained optimization problem defined as follows:

$$\text{Minimize} \quad f(c\_th, k) = FN + FP$$

$$\text{Subject to:} \quad 0 \le k \le 100$$

$$0 \le c\_th \le 1$$

Where FN denotes the false negative detection and corresponds to the fail of detection a QRS complex where there is one, while FP denotes false positive detections and corresponds to false detection, by the algorithm, of QRS complex where there is none.

To solve this problem, GSO is introduced. GSO was inspired by animal behavior, especially animal searching behavior. The framework of GSO is mainly based on the producer-scrounger model. This optimization algorithm primarily used for continuous optimization problems. A set of 23 benchmark functions were employed to evaluate the performance of the GSO algorithm. Compared with PSO and GA, GSO returned the best performance on fifteen tests. The outperformance of GSO has been reported in mechanical design optimization problems [18], distributed generations location and capacity optimization problems [19], GSO is conceptually simple and easy to implement, and it can handle a variety of optimization problems..

E. Validation

We use the MIT-BIH arrhythmia database to validate our QRS detection algorithm. The performance of the algorithm is based on comparing the beat annotations related to the QRS complexes, of the MIT-BIH arrhythmia database, manually identified by cardiologists and those identified by our algorithm.

To quantitatively evaluate the performance of detection algorithm, indexes [20] such as sensitivity (Se), positive predictive value (+P) and detection error rate (DER), are used:

$$Se(\%) = TP / (TP + FN) \tag{10}$$

$$+P(\%) = TP / (TP + FP) \tag{11}$$

$$R(\%) = (FP + FN) / TotalQRS \tag{12}$$

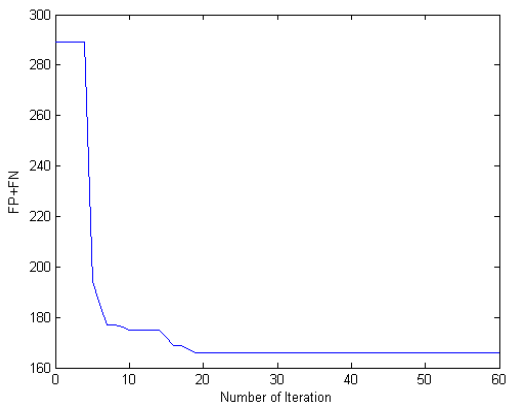


Figure 8. The convergence of the sum of FP and FN with the number of iterations of GSO

where TP denotes the number of the true positive detections of the QRS complexe

III. RESULTS

Our results correspond to Mexican-hat wavelet and complex Morlet wavelet using in the wavelet coefficients calculation unit are presented in table 1.

TABLE I.
RESULTS OF THE QRS DETECTION USING MEXICAN-HAT WAVELET AND COMPLEX MORLET WAVELET

Subjects	Beats	Mexican-hat wavelet			Complex Morlet wavelet		
		Se	+P	DER	Se	+P	DER
100	2273	100	100	0	100	100	0
101	1865	100	99.68	0.32	99.95	99.79	0.27
102	2187	100	99.95	0.05	100	99.73	0.27
103	2084	100	100	0	99.90	100	0.10
104	2229	99.82	94.56	5.92	99.60	98.80	1.62
105	2572	99.92	96.65	3.54	99.73	97.55	2.57
106	2027	95.17	99.84	4.98	99.16	99.90	0.94
107	2137	99.95	99.72	0.33	99.72	98.98	1.31
118	2288	99.56	98.27	2.19	99.56	99.96	0.48
119	1987	100	100	0	100	99.95	0.50
Total	21649	99.47	98.75	1.79	99.79	99.44	0.80

When a combination of Mexican-hat wavelet and complex Morlet wavelet are used in the wavelet coefficients calculation unit, two parameters, k and c_th are to be determined for the best performance of the QRS detection algorithm, and thus GSO is employed to undertake this task. The convergence of the sum of FP and FN with the number of iterations of GSO is shown in Figure 8, and with the number of iterations growing, the best value of k and c_th are achieved (see Figure 9).

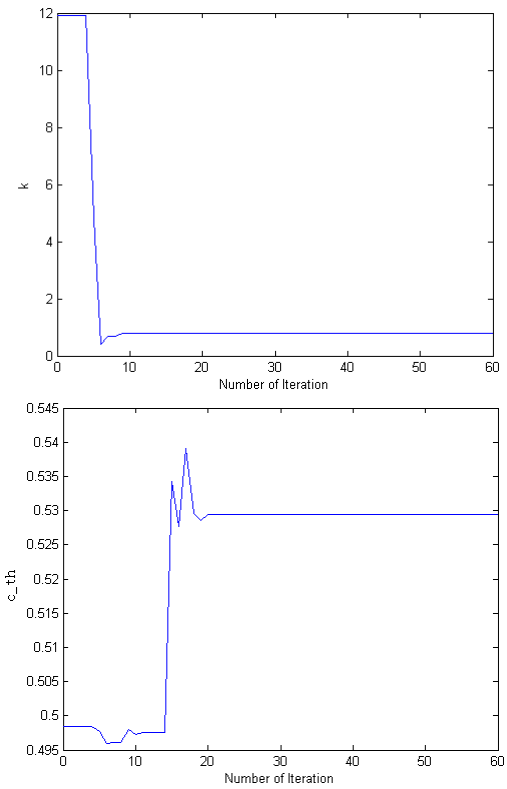


Figure 9. The convergence of k and c_th with the number of iterations of GSO

From Figure 9, we can see when =0.8 and =0.53, our QRS complex detection algorithm could get the best performance. Then, the results of the QRS complex detection are presented in table 2.

TABLE II.
RESULTS OF THE QRS DETECTION USING COMBINATION OF MEXICAN-HAT WAVELET AND COMPLEX MORLET WAVELET

Subjects	Beats	Se	+P	DER
100	2273	100	100	0
101	1865	100	99.73	0.27
102	2187	100	99.95	0.05
103	2084	100	100	0
104	2229	99.73	98.49	1.79
105	2572	99.88	97.90	2.26
106	2027	98.08	99.95	1.97
107	2137	99.81	99.72	0.47
118	2288	99.56	100	0.44
119	1987	99.95	99.95	0.10
Total	21649	99.71	99.53	0.77

IV. DISCUSSION AND CONCLUSION

In recent years, a variety of QRS complex detection algorithms based on wavelet have been proposed, and this contribution shows that a combination of two wavelet transform may be a simple and effect way for the improvement of such algorithms. Apart from Mexican-hat wavelet and complex Morlet wavelet, other wavelet transform are to be used and combined in this area. Besides, though in the threshold based detector unit, our proposed jump of modulus maxima sequence method has shown its ability to detect QRS complex correctly, it will also be tested and compared in other wavelet based QRS complexes algorithms.

ACKNOWLEDGMENT

This work was partially supported by the National Natural Science Foundation of China under grant project No. 81201151, the Science Foundation of Hunan Province, China under grant project No. 12JJ6061, and the Research Plan on Science and Technology of Hunan Province, China under the grant project No. 2012SK3185.

REFERENCES

[1] Bert-Uwe Köhler, Carsten Hennig, Reinhold Órglmeister, "The Principles of Software QRS Detection", IEEE Engineering in Medicine and Biology, vol.21, no.1, pp.42-57, 2002.
[2] Fei Zhang, Yong Lian, "QRS detection based on multiscale mathematical morphology for wearable ECG devices in body area networks", IEEE Transactions on Biomedical Circuits and Systems, vol.3, no.4, pp.220-2228, 2009.
[3] G. Zheng, T. Yu "Study of Hybrid Strategy for Ambulatory ECG Waveform Clustering", Journal of Software, vol.6, no.7, pp.1257-1264, 2011.
[4] Juan Pablo Martínez, Rute Almeida, Salvador Olmos, Ana Paula Rocha, Pablo Laguna, "A wavelet-based ECG delineator: evaluation on standard databases", IEEE Transactions on Biomedical Engineering, vol.51, no.4, pp.570-581, 2004.
[5] A. Ghaffari, H. Golbayani, M. Ghasemi, "A new mathematical based QRS detector using continuous wavelet transform", compputers and electrical engineering, vol.34, no.2, pp.81-91, 2008.
[6] Shubha Kadambe, Robbin Murray, G. Faye Boudreaux-Bartels, "Wavelet transform-based QRS complex detector", IEEE transaction on biomedical engineering, vol.46, no.7, pp.838-848, 1999.
[7] R. Poli, S. Cagnoni, G. Valli, "Genetic design of optimum linear and nonlinear QRS Detectors", IEEE transaction on biomedical engineering, vol.42, no.11, pp.1137-1141, 1995.
[8] Jiapu Pan, Willis J. Tompkins, "A real-time QRS detection algorithm", IEEE transaction on biomedical engineering, vol.32, no.3, pp.230-236, 1985.
[9] V.X. Afonso, W.J. Tompkins, T.Q. Nguyen, S. Luo, "ECG beat detection using filter banks", IEEE transaction on biomedical engineering, vol.46, no.2, pp.192-202, 1999.
[10] Q. Xue, Y.H. Hu, W.J. Tompkins, "Neural-network-based adaptive filtering for QRS detection", IEEE transaction on biomedical engineering, vol.39, no.4, pp.315-329, 1992.
[11] A. Ruha, S. Sallinen, S. Nissila, "A real-time microprocessor QRS detector system with a 1-ms tiing acauracy for the measurement of ambulatory HRV", IEEE transaction on biomedical engineering, vol.44, no.3, pp.159-167, 1997.
[12] Saurabh Pala, Madhuchhanda Mitrab, "Detection of ECG characteristic points using Multiresolution Wavelet Analysis based Selective Coefficient Method", Measurement, vol.43, no.2, pp.255-261, 2010.
[13] I. Romero Legarreta, P. S. Addison, M. J. Reed, N. Grubb, G. R. Clegg, C. E. Robertson, J. N. Watson, "Continuous Wavelet Transform Modulus Maxima Analysis of the Electrocardiogram: Beat Characterisation and Beat-to-Beat Measurement", International Journal of Wavelets, Multiresolution and Information Processing, vol.3, no.1,pp.19-42, 2005.
[14] P. Jafari Moghadam Fard, M.H. Moradi, M.R. Tajvidi, "A novel approach in R peak detection using Hybrid Complex Wavelet (HCW)", International Journal of Cardiology, vol.124, no.2, pp.250-253, 2008
[15] S. He, Q. H. Wu, J. R. Saunders, "Group Search Optimizer: An Optimization Algorithm Inspired by Animal Searching Behavior", IEEE Transactions on Evolutionary Computation, vol.13, no.5 pp.973-990, 2009.

[16] J. Fang, Z. Zhong, W. Li, L. Chen "A Modified GSO Based on Limited Storage Quasi-Newton Method", Journal of Computers, vol.6, no.8, pp.1613-1620, 2011.
[17] I Romero Legarreta, P.S Addison, N.Grubb, G.R. Clegg, C.E. Robertson, K.A.A. Fox, J.N. Watson, "R-wave detection using continuous wavelet modulus maxima", Computers in Cardiology, vol.30, pp. 565-568, 2003.
[18] Hai Shen, Yunlong Zhu, Ben Niu, Q.H. Wu, "An improved group search optimizer for mechanical design optimization problems", Progress in Natural Science, vol.19, no.1 pp.91-97, 2009
[19] Qi Kang, Tian Lan, Yong Yan, Lei Wang, Qidi Wu, "Group search optimizer based optimal location and capacity of distributed generations", Neurocomputin, vol.78, no.1, pp.55-63, 2012
[20] Fei Zhang, Yong Lian, "QRS Detection Based on Morphological Filter and Energy Envelope for Applications in Body Sensor Networks", Journal of Signal Processing Systems, vol.64, no.2, pp. 187-194, 2011.

Chao Zeng was born in Yiyang, China in August, 1982. He received his B.S. from Xiangtan University in 2005. He is now a Ph.D. candidate in Central South University, Changsha, China. He is also a lecture in Shihezi University, Shihezi, China since 2010. His major field of study covers biomedical image and biomedical signal processing techniques.

Hongli Lin was born in Henan, China in July, 1973. She received her Ph.D degree from Central South University in 2011. She is now an associate professor in Hunan University. Her major field of study covers biomedical image and software engineering.