R-Peak Detection Using a Complex Fractional Wavelet

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Abstract

In a recent paper we have introduced and used a real fractional wavelet for the detection of the QRS complex in ECG signal. This fractional wavelet is the second derivative of the Cole-Cole distribution which is widely used in the modelling of dielectrics by a fractional power pole. This work presents a QRS detection scheme using a complex fractional wavelet function. The absolute value of this wavelet is the Cole-Cole distribution function. The method consists of using the real and the imaginary parts of the CWT along with the multiscale product to distinguish the R waves from the high P and T waves, the noise and the artefacts. The study of the proposed algorithm and the analysis of the results have been done using the first four-minutes of the 24 records of the MIT-BIH arrhythmia database. The R wave detection results have been compared to the annotation file accompanying each ECG signal. We have found that the proposed detection algorithm gives high accuracy.

1. Introduction

The detection of QRS complex in ECG signal is of vital importance in number of clinical instruments. It has many applications including R-R interval analysis, ST segment examination, ECG compression and arrhythmia classification. In the literature, there are many QRS detection algorithms available which use a variety of signal analysis methods (matched filters, time-frequency decomposition method, neural networks, genetic algorithms, etc.).

Kohler et al. [1] have performed an analysis of the most important and recent QRS complex detectors. The wavelet transform, which has been used in biomedical signal processing [2], also, has its role in ECG characterization and detection. This class of algorithms normally uses discrete wavelet transforms (DWT) and continuous wavelet transforms (CWT) to decompose, analyze and compress the ECG signals. In recent years, real and complex wavelet based QRS detection methods have been suggested by a variety of researchers [3-6].

This work presents a QRS detector with a new preprocessing scheme using the CWT with a complex fractional wavelet based on the Cole-Cole distribution [7]. The first four minutes of all the 24 records of the MIT/BIH arrhythmia database have been used to test and analyse the proposed algorithm. The obtained results have compared to those obtained by the technique proposed by Dinh et al. [8].

2. Complex fractional wavelet

The first thing needed for a wavelet transform is to choose a convenient mother wavelet [9]. A function $\Psi(t)$ is said to be a wavelet if it has a finite spectrum, that is:

$$\int_{-\infty}^{+\infty} \frac{|\Psi(\omega)|^2}{|\omega|} d\omega = C_\omega < +\infty \qquad (1)$$

where $\Psi(\omega)$ denotes the Fourier transform of $\Psi(t)$. This condition implies that $\Psi(t)$ can not have a dc component, it is oscillatory and its area is zero, that is:

$$\int_{-\infty}^{+\infty} \Psi(t)dt = 0 \qquad (2)$$

We denote by $\Psi_a(t)$ the dilation of $\Psi(t)$ by the positive scale a and it is defined as:

$$\Psi_a(t) = \frac{1}{\sqrt{a}} \Psi(t/a) \qquad (3)$$

The wavelet transform of a function $f(t)$ at scale a and position b is given by:

$$Wf(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t) \Psi^* \left(\frac{t-b}{a} \right) dt \qquad (4)$$

where Ψ^* denotes the complex conjugate of Ψ. When $\Psi(t)$ is a complex function, the result of the CWT is also a complex function. The wavelet function we have used is the complex fractional wavelet defined by:

$$\Psi(t) = G(t).e^{j2\pi f_c t} \qquad (5)$$

where f_c is the wavelet central frequency and $G(t)$ is the Cole-Cole distribution function given by [7]:

$$G(t) = \frac{1}{2\pi} \left[\frac{\sin(1-m)\pi}{\cosh\{m(t-t_0)\} - \cos(1-m)\pi} \right] \qquad (6)$$

The parameter m is such that 0<m<1. It is used to modify the wavelet's shape. We selected m = 0.8 for the admissibility condition. This parameter m is, also, the fractional order of the fractal system given in the following relation [7]:

$$H(s)=\frac{1}{1+(s\tau)^m}=\int_0^{+\infty}\frac{G(\tau)}{1+s\tau}d\tau \qquad (7)$$

Where s = jω is the complex frequency or the Laplace variable. The real, the imaginary and the modulus parts of the complex fractional wavelet function are depicted in figure (1). We select $f_c = 0.5$ for small oscillations.

3. QRS complex detection method

The first step in the ECG preprocessing is a band pass filter to reduce the influence of muscle noise, 60 Hz interference, baseline wander, and T-wave interference. The desirable pass band to maximize the QRS energy is approximately 5-15 Hz. Generally, this band pass filter is made up of a cascaded low-pass and high-pass filters. In this work these two filters are obtained from [10] and they are given as follows:

- Low pass filter:

$$H(z)=\frac{(1-z^{-6})^2}{(1-z^{-1})^2} \qquad (8)$$

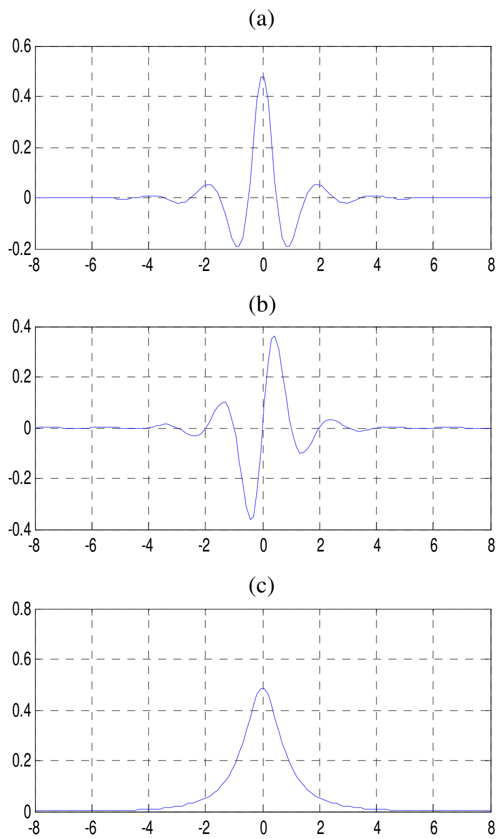

Fig. 1. (a) Real part, (b) Imaginary part, (c) Modulus of the complex fractional wavelet for m = 0.8.

- High pass filter:

$$H(z)=\frac{-0.03125+z^{-16}-z^{-17}+0.03125z^{-32}}{1-z^{-1}} \qquad (9)$$

The complex fractional wavelet prototype is designed such that the shapes of its real and imaginary parts look like the morphology of the real and imaginary parts, respectively, of the complex CWT of the regular QRS of the ECG signal.

In our approach, we have performed a point to point product of the real parts of the complex CWT of the ECG signal at the scales 2^3 and 2^4 to obtain the Sequence to be Threshold Compared (STC) [11]. These two scales are chosen while making a complex CWT of an ideal QRS extracted from the 100.dat signal of MIT-BIH database, and they correspond to a maximum correlation to the ideal QRS complex waveform [6].

The product of the imaginary part has been also performed for the zero-crossing confirmation for the detection process. Figure (2) shows the different steps mentioned above for a short time of the record 101.

Since the QRS complex amplitude can vary considerably within a short interval of time, this requires the use of an adaptive detection threshold computed using a 10-point iterative estimation. In the STC signal, a peak that crosses the threshold is marked as an R wave if it corresponds to a zero crossing in the product of the two imaginary parts signal.

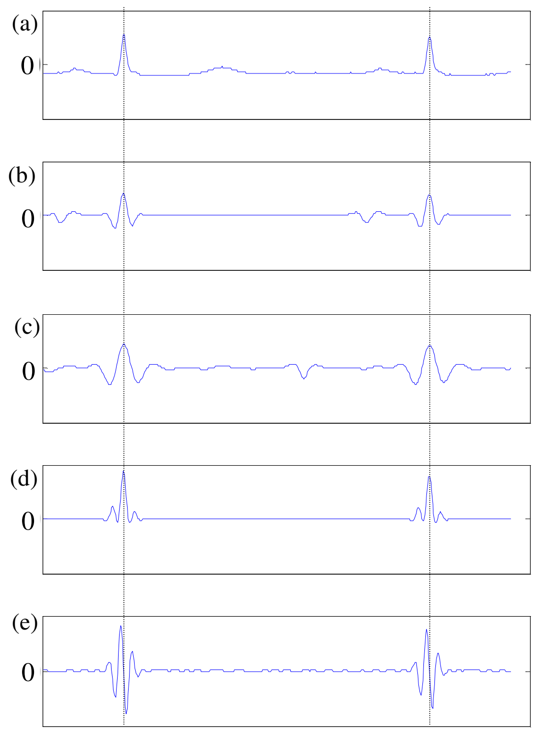

Fig. 2. (a) ECG signal (101.dat), (b) Real part of CWT of ECG for scale 2^3, (c) Real part of CWT of ECG for scale 2^4, (d) The product of the two signal in (b) and (c), (e) The product of the two imaginary parts of CWT of ECG for scales 2^3 and 2^4 confirming the zero crossing.

In most cases, the algorithm correctly detects the R peaks. However, some tactics outlined in [12] are still used to improve the detection:

1. A peak occurring within the refractory period (200 ms) is disregarded.
2. If no QRS complex was detected within 150% of the RR interval estimated by a 10-point iterative estimator, then search back is performed by dividing the threshold by two.

4. Results evaluation and discussion

The algorithm was implemented on a PC with a Pentium IV microprocessor of clock speed of 2.8 GHz. The study reports on the analysis of the first four-minutes signal of the 24 records. The R waves detected were compared to the annotation file accompanying each signal to determine the error. The performance of the R wave detector is measured in terms of the number of R wave missed (FN: false negative) and the number of R waves falsely reported (FP: false positive). The error, or failed detection rate, is defined by:

$$\text{Error} = (FP+FN) / \text{total number of beats} \qquad (10)$$

The evaluation results of the proposed R wave detector using the MIT/BIH arrhythmia database are given in table (1). This table contains also the detection results given in [8] for comparison. It provides a comparison of the use of the different wavelets, and it shows high efficiency.

5. Conclusion

We have proposed a complex fractional wavelet transform-based algorithm for R-wave detection. The effectiveness of the algorithm has been validated using the MIT/BIH arrhythmia database and compared to those obtained in [8].

Besides, we have used the multiscale point-wise product approach which permits to accentuate R-wave peaks and attenuate noise. The product tends to reduce input noise correlation while producing a very local response to R peaks. Further, the zero crossing test allows us to eliminate the false positive (false detection) caused by abrupt fluctuations of the baseline. Therefore, that will enable us to better develop the detection procedure for a complete use of the MIT/BIH database.

6. References

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Table 1: Results of evaluation of the R wave detector using MIT/BIH arrhythmia database (The first fourth columns are issues from the reference [8]).

		Cubic B-spline				Quadratic spline				Db3				Haar				Complex fractional wavelet			
Rec. N°	Total QRS	FP	FN	Err.	**Err. (%)**	FP	FN	Err.	**Err. (%)**	FP	FN	Err.	**Err. (%)**	FP	FN	Err.	**Err. (%)**	FP	FN	Err.	**Err. (%)**
100	297	0	0	0	**0.00**	0	1	1	**0.34**	0	1	1	**0.34**	0	0	0	**0.00**	0	0	0	**0.00**
101	279	2	0	2	**0.72**	2	1	3	**1.08**	2	3	5	**1.79**	2	1	3	**1.08**	2	0	2	**0.72**
102	294	0	0	0	**0.00**	0	0	0	**0.00**	0	2	2	**0.68**	0	0	0	**0.00**	1	1	2	**0.68**
103	282	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**
104	297	10	1	11	**3.7**	18	1	19	**6.4**	17	4	21	**7.07**	29	1	30	**10.1**	19	11	30	**10.10**
105	334	0	0	0	**0.00**	0	0	0	**0.00**	0	1	1	**0.3**	0	0	0	**0.00**	0	0	0	**0.00**
106	269	0	2	2	**0.74**	0	18	18	**6.69**	0	8	8	**2.97**	0	17	17	**6.32**	0	0	0	**0.00**
107	283	0	0	0	**0.00**	0	1	1	**0.35**	0	1	1	**0.35**	0	0	0	**0.00**	1	1	2	**0.71**
118	290	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**
119	261	0	1	1	**0.38**	0	8	8	**3.07**	0	4	4	**1.53**	0	9	9	**3.45**	2	2	4	**1.53**
200	339	2	8	10	**2.95**	4	4	8	**2.36**	3	1	4	**1.18**	7	1	8	**2.36**	0	0	0	**0.00**
201	356	0	1	1	**0.28**	0	2	2	**0.56**	0	0	0	**0.00**	0	3	3	**0.84**	0	0	0	**0.00**
202	212	0	0	0	**0.00**	0	0	0	**0.00**	0	1	1	**0.47**	0	0	0	**0.00**	0	0	0	**0.00**
203	403	2	12	14	**3.48**	3	8	11	**2.74**	2	7	9	**2.24**	5	6	11	**2.74**	9	4	13	**3.23**
205	359	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**
208	414	0	2	2	**0.48**	0	10	10	**24.15**	0	67	67	**16.18**	0	10	10	**26.09**	0	12	12	**2.90**
209	379	0	2	2	**0.53**	0	0	0	**0.00**	0	1	1	**0.26**	0	0	0	**0.00**	0	0	0	**0.00**
210	358	0	8	8	**2.24**	4	6	10	**2.8**	0	7	7	**1.96**	4	6	10	**2.8**	13	2	15	**4.19**
212	369	0	0	0	**0.00**	0	1	1	**0.27**	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**
213	441	0	1	1	**0.23**	0	7	7	**1.59**	0	7	7	**1.59**	0	7	7	**1.59**	1	1	2	**0.45**
214	308	1	2	3	**0.97**	2	3	5	**1.62**	2	2	4	**1.29**	2	4	6	**1.94**	7	3	10	**3.25**
215	455	1	4	5	**1.1**	1	4	5	**1.1**	1	2	3	**0.66**	1	4	4	**0.88**	5	0	5	**1.10**
217	290	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**	0	0	0	**0.00**
219	441	0	1	1	**0.23**	0	2	2	**0.45**	0	2	2	**0.45**	0	3	3	**0.68**	0	0	0	**0.00**
Average Error Rate (%)					**0.75**				**2.32**				**1.72**				**2.54**				**1.20**