R Wave Detection using Coiflets Wavelets

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***Abstract*—Accurate detection of QRS complexes is important for ECG signal analysis. In this paper, a generic algorithm using Coiflet wavelets is introduced to improve the detection of QRS complexes in Arrhythmia ECG Signals that suffer from: 1) non-stationary effects, 2) low Signal-to-Noise Ratio, 3) negative QRS polarities, 4) low QRS amplitudes, and 5) ventricular ectopics. The algorithm achieves high detection rates by using a signal-to-noise ratio threshold instead of predetermined static thresholds. The performance of the algorithm was tested on 48 records of the MIT/BIH Arrhythmia Database. It was shown that this adaptive approach results in accurate detection of the QRS complex and that Coiflet1 achieves better detection rate than the other Coiflet wavelets.**

I. Introduction

The automatic detection of QRS complexes is critical for reliable Heart Rate Variability (HRV) analysis, which is recognized as an effective tool for diagnosing cardiac arrhythmias [1-3], understanding the autonomic regulation of the cardiovascular system during sleep and hypertension [4,5], detecting breathing disorders like Obstructive Sleep Apnea Syndrome [6,7], and monitoring other structural or functional cardiac disorders. The motivation behind this work is to find the most appropriate Coiflet wavelet for accurate QRS detection in Arrhythmia ECG Signals that suffer from: 1) non-stationary effects, 2) low Signal-to-Noise ratio, 3) negative QRS polarities, 4) low QRS amplitudes and 5) ventricular ectopics using the MIT-BIH Arrhythmia ECG database [8].

II. Methodology

The algorithm is described as follows:

A. Baseline wander and high frequencies removal

We used a third order Butterworth filter with a passband of 5-15 Hz to remove baseline wander and high frequencies

B. Apply Wavelet

The Coiflet wavelet system is an orthogonal multiresolution wavelet system. Therefore, the wavelet function can be defined at scale m and location n as

$$\psi_{m,n}(t) = \frac{1}{\sqrt{a_0^m}}\psi\left(\frac{t - nb_0a_0}{a_0^m}\right) \tag{1}$$

where, a_0 is a fixed dilation parameter, and b_0 is the location parameter. The discrete wavelet transform values $T_{m,n}$ of a continuous signal $x(t)$ can be expressed as inner product between the signal and the wavelet function $\psi_{m,n}$ as

$$T_{m,n} = \left\langle x, \psi_{m,n} \right\rangle \tag{2}$$

The signal detail corresponding to scale index m is defined for a finite length signal as

$$d_m(t) = \sum_{n=0}^{2^{M-m}-1} T_{m,n}\psi_{m,n}(t) \tag{3}$$

The choice of the wavelet function depends on the application. The Haar wavelet algorithm has the advantage of being simple to compute and easy to understand. The Coiflet algorithm is conceptually more complex and has a slightly higher computational overhead. But, the Coiflet algorithm picks up details which are missed by the Haar wavelet algorithm. Moreover, Coiflet is similar in shape to QRS complex. Details of levels 3-5 (d_3 - d_5) were kept and the remaining details were removed [9].

C. Square

This makes all data points of signal (output of step B) positive and emphasizes the higher frequencies.

D. Thresholding

We used moving averages (MA) to demarcate the onset and offset of the QRS complex. To calculate the optimal threshold value we use an approximate to signal-to-noise based on the wavelet coefficients, $\sigma^2_{d_1}/\sigma^2_{d_5}$, where $\sigma^2_{d_1}$ is the standard deviation of the DWT coefficient of the 1st decomposition level and $\sigma^2_{d_5}$ is the standard deviation of the DWT coefficient of the 5th decomposition level.

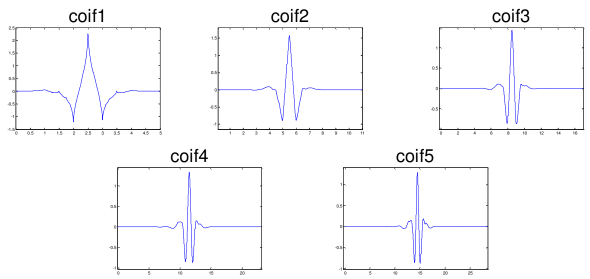

Fig. 1. Coiflets Wavelets

III. RESULTS

The QRS detection algorithms were evaluated using the following statistical parameters: FN is the number of false negatives, and FP is the number of false positives. The Incorrect Detection (Beats) is the sum of FN and FP. The Incorrect Detection rate is the percentage of Incorrect Detection (Beats).

TABLE I
QRS DETECTION PERFORMANCE USING COIF1 ON MIT-BIH DATABASE

Record	No of beats	FP (Beats)	FN (Beats)	Incorrect Detection (Beats)	Incorrect Detection rate
100	**2273**	1	0	1	0.04%
101	**1865**	1	2	3	0.16%
102	**2187**	0	0	0	0.00%
103	**2084**	0	0	0	0.00%
104	**2229**	0	0	0	0.00%
105	**2572**	15	21	36	1.40%
106	**2027**	0	2	2	0.10%
107	**2136**	0	2	2	0.09%
108	**1763**	2	62	64	3.63%
109	**2532**	0	0	0	0.00%
111	**2124**	1	12	13	0.61%
112	**2539**	0	0	0	0.00%
113	**1795**	1	682	683	38.05%
114	**1879**	13	55	68	3.62%
115	**1953**	1	0	1	0.05%
116	**2412**	20	0	20	0.83%
117	**1535**	0	5	5	0.33%
118	**2278**	0	0	0	0.00%
119	**1987**	0	0	0	0.00%
121	**1863**	1	0	1	0.05%
122	**2476**	0	0	0	0.00%
123	**1518**	0	0	0	0.00%
124	**1619**	0	2	2	0.12%
200	**2601**	1	2	3	0.12%
201	**1963**	1	66	67	3.41%
202	**2136**	1	3	4	0.19%
203	**2980**	79	19	98	3.29%
205	**2656**	9	0	9	0.34%
207	**1860**	2	5	7	0.38%
208	**2955**	13	3	16	0.54%
209	**3005**	0	1	1	0.03%
210	**2650**	5	2	7	0.26%
212	**2748**	0	0	0	0.00%
213	**3251**	1	0	1	0.03%
214	**2262**	1	3	4	0.18%
215	**3363**	13	0	13	0.39%
217	**2208**	2	6	8	0.36%
219	**2154**	0	0	0	0.00%
220	**2048**	1	0	1	0.05%
221	**2427**	0	4	4	0.16%
222	**2483**	27	12	39	1.57%
223	**2605**	0	0	0	0.00%
228	**2053**	1	14	15	0.73%
230	**2256**	0	0	0	0.00%
231	**1565**	0	331	331	21.15%
232	**1780**	0	17	17	0.96%
233	**3079**	1	0	1	0.03%
234	**2753**	0	0	0	0.00%
	109487	214	1333	1547	1.73%

TABLE II
PERFORMANCE OF QRS DETECTION ALGORITHMS APPLIED ON All Coiflets Wavelets

	Wavelet	FP (Beats)	FN (Beats)	Incorrect Detection (Beats)	Incorrect Detection (%)
Coiflets	Coif1	214	1333	1547	1.73%
	Coif2	187	3150	3337	3.86%
	Coif3	173	3137	3310	3.85%
	Coif4	175	3091	3266	3.81%
	Coif5	167	3070	3237	3.79%

The method was tested on 48 records of the MIT/BIH Arrhythmia Database. Table I shows the results for Coiflet1. On average the algorithm detected only 1.73 percent of the beats incorrectly. Records which have a relatively large proportion of very poor quality signals, like 113 and 231 contain a large number of false negatives (FN). As shown in Fig.1, Coiflet1 is the widest wavelet and it scored the best results. Average results for the other Coiflet wavelets are given in Table2.

IV. CONCLUSION

An algorithm using an adaptive threshold based on an approximation of signal-to-noise ratio was developed to detect QRS complexes in Arrhythmia ECG Signals that suffer from: 1) non-stationary effects, 2) low Signal-to-Noise ratio, 3) negative QRS polarities, 4) low QRS amplitudes, and 5) ventricular ectopics. We investigated which of the Coiflet wavelets achieves the best detection rates. It was shown that the adaptive approach results in accurate detection of the QRS complex and that Coiflet1 achieves better detection rate than the other Coiflet wavelets.

REFERENCES

[1] Thong, T., J. McNames, M. Aboy, B. Goldstein, "Prediction of paroxysmal atrial fibrillation by analysis of atrial premature complexes", *IEEE Trans. On Biomed. Eng*., 51(4), pp. 561-569, 2004.

[2] Bashour, C.A., M. Visinescu , B. Gopakumaran,O. Wazni, F. Carangio, J.P. Yared, N. Starr," Characterization of premature atrial contraction activity prior to the onset of postoperative atrial fibrillation in cardiac surgery patients", *CHEST*, 126(4), pp. 831S, 2004.

[3] Tsipouras, M.G., D.I. Fotiadis, D. Sideris, "Arrhythmia classification using the RR interval duration signal", *Comp. In Card*., 29, pp. 485 - 488, 2002.

[4] U. J. Scholz et al., "Vegetative background of sleep: Spectral analysis of the heart rate variability," *Physiol. Behavior*, vol. 62, no. 5, pp. 1037–1043, 1997.

[5] J. Trinder et al., "Autonomic activity during human sleep as a function of time and sleep stage," *J. Sleep Re.s*, vol. 10, no. 4, pp. 253–264, 2001.

[6] L. Zapanta et al., "Heart rate chaos in obstructive sleep apnea in children," *IEEE Trans. Eng. Med. Biol.*, pp. 3889–3892, 2004.

[7] R. B. Shouldice et al., "Detection of obstructive sleep apnea in pediatric subjects using surface lead electrocardiogram features," *Sleep*, vol. 27, pp. 784–792, 2004

[8] MIT-BIH Arrhythmia Database, www.physionet.org.

[9] Paul S Addison, The illustrated wavelet transform handbook, IOP Pub., 2002.