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Letter to the Editor

A novel approach in R peak detection using Hybrid Complex Wavelet (HCW)

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Abstract

In this letter, by design of Complex Morlet Wavelet and Complex Frequency B-Spline Wavelet and linearly combining them, a novel approach, Hybrid Complex Wavelet, has been proposed to identify and detect the components of ECG signal such as QRS complex and R peak. By train and test of implementing the proposed method on both clinically recorded signals from 40 patients and 30 signals of MIT BIH database, we reached better recognition accuracy in comparison to other well-known approaches.

Keywords: Complex wavelet; Hybrid; Detection; R peak; B-spline

1. Introduction

The characteristics of Q, R, S and T, as the ECG signal components, represent the clinical status of a cardiac disease patient, among which the R wave properties have more significant importance. Different Linear, Nonlinear and Morphological algorithms have been proposed to detect QRS complex [1,2]. The morphological algorithms, such as Neural Network, although are slow, but if they are trained well, they could search for and detect a specific characteristic of ECG such as QRS complex [3]. Rapid examples of morphological methods are Wavelet Transform (WT) and Complex Wavelet Transform which do not need to be trained [4–7]. In this letter, Complex Morlet Wavelet (CMW) and Complex Frequency B-Spline Wavelet (CFBSW) are designed and linearly combined together to acquire a more efficient transform named, Hybrid Complex Wavelet (HCW). This novel wavelet can overcome the deficit of CMW in not detecting all the available R peaks and can overcome the deficit of CFBSW in detecting some redundant R peaks in ECG signal with a satisfactory trade-off between accuracy and rapidity. We have used the cross validation method to train the algorithm and test its performance by some clinically recorded and also some signals from MIT BIH database. Comparing the results of our method with the results of CMW and CFBSW shows better performance in R peak detection.

2. Materials and method

2.1. Wavelet transforms

As a morphological method, Continuous Wavelet Transform (CWT) of the signal $x(t)$ is calculated as:

$$\mathrm{CWT}(a,b) = \frac{1}{\sqrt{a}}\int x(t)\psi^*\left(\frac{t-b}{a}\right).\mathrm{d}t \tag{1}$$

Where $\psi \in L^2$ and ψ^* is the complex conjugate of the mother wavelet, a is the dilation level parameter (scale) and b the translation in time.

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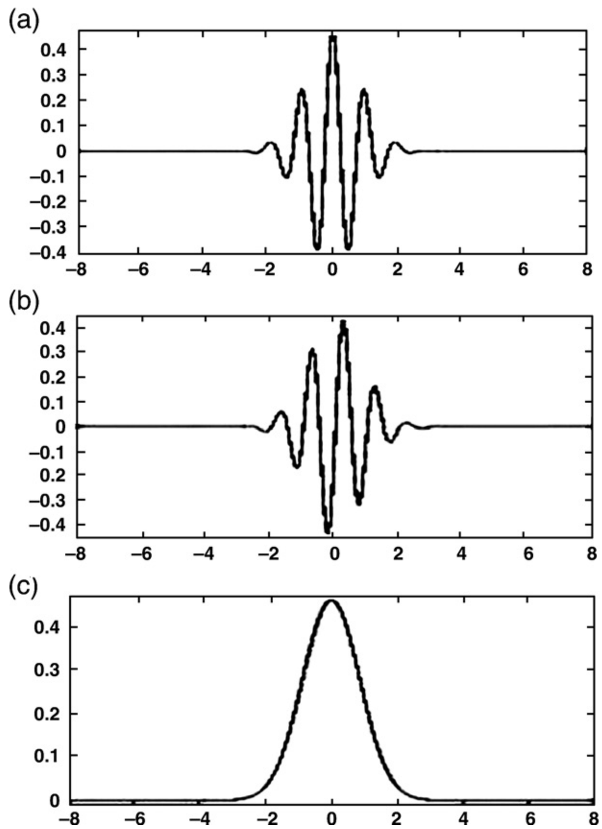

Fig. 1. (a) Real part, (b) Imaginary part, (c) Modulus of CMW.

The Complex Morlet Wavelet (CMW) function is defined as:

$$\psi(t) = \frac{1}{\sqrt{\pi f_b}} e^{2j\pi f_c x} e^{-\frac{x^2}{f_b}} \tag{2}$$

while Complex Frequency B-Spline Wavelet (CFBSW) function is:

$$\psi(t) = \sqrt{f_b}\left(\sin c\left(\frac{f_b t}{m}\right)\right)^m .e^{2i\pi f_c t} \tag{3}$$

Where m, f_b and f_c are integer order parameter, bandwidth parameter and wavelet center frequency respectively. In Figs. 1 and 2, the real, imaginary and modulus parts of CMW and CFBSW are depicted respectively.

CMW transform of an ECG signal may not detect all the available R peaks, while CFBSW transform may result to some redundantly detected R peaks, because of some small side lobes available in its modulus (Fig. 2c) that might be amplified and be wrongly detected as R peaks. Therefore, to enhance the performance of R peak detection, we proposed a novel approach, Hybrid Complex Wavelet (HCW), by designing two CMW and CFBSW mother wavelets and linearly combining them:

$$\mathrm{HCW}(x) = \alpha \cdot \mathrm{CMW}(x) = \beta \cdot \mathrm{CFBSW}(x) \tag{4}$$

This linear combination will be more efficient in detecting all the available R peaks in ECG and consequently, the number of redundant R peaks will be lessened.

2.2. Implementation

We have used cross validation method to train and test the algorithm. To acquire a signal with the most correlation to the QRS complex morphological characteristics, a pre-processing band pass frequency filter with cut-off frequencies of 15 and 30 Hz was used to attenuate other unwanted signals and artifacts from every signal. The time-frequency mother wavelet filters, CMW and CFBSW, are designed such that they have the most similarity to the morphological characteristics of QRS complex. While using them in the CWT of ECG signal with a fixed dilation level (scale), they will substitute the QRS complex in ECG signal and after taking the absolute value of CWT decomposition, a waveform similar to the absolute value of the these mother wavelets (Figs. 1c, 2c), could be observed in the place of a QRS complex. By taking the average from all the available R peaks in a certain interval and defining a threshold level for the rest of the signal from this average value, R peaks can be detected.

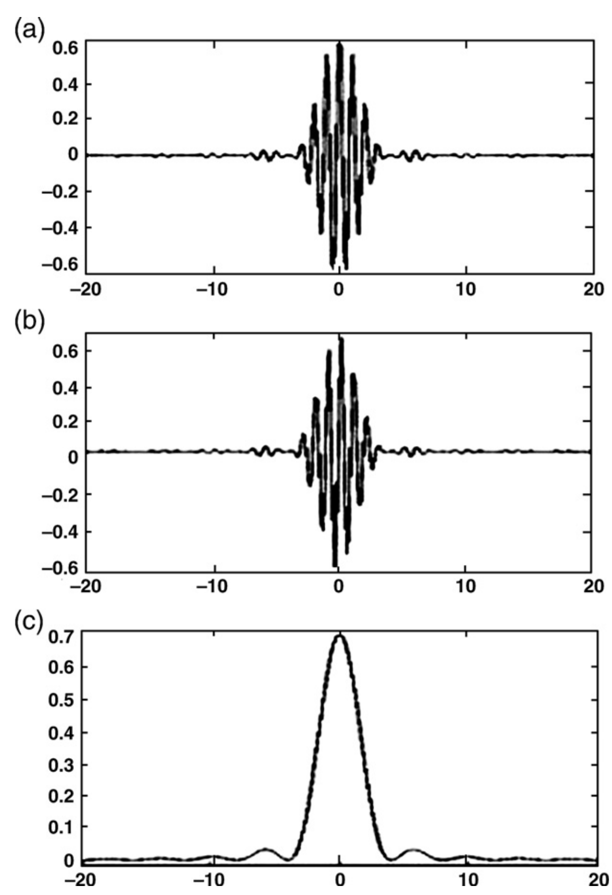

Fig. 2. (a) Real part, (b) Imaginary part, (c) Modulus of CFBSW.

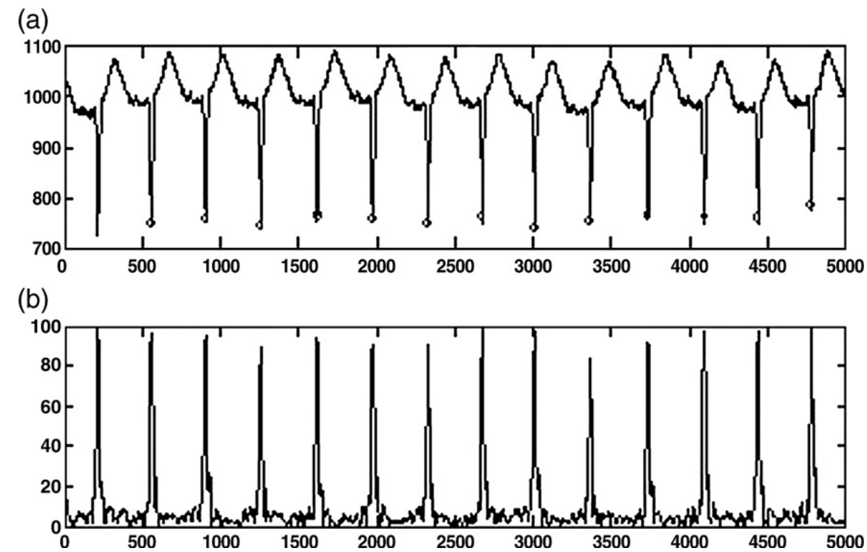

Fig. 3. (a). ECG of a 25 years old woman, (b) Corresponding HCW transform.

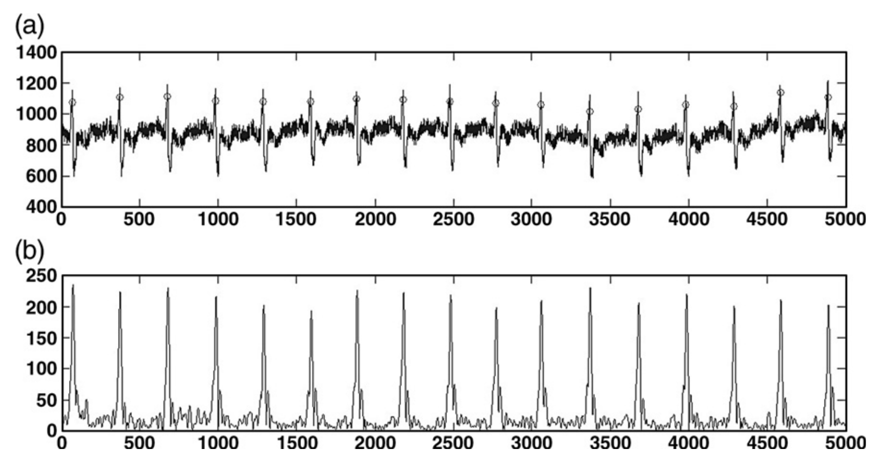

Fig. 4. (a). ECG of a 30 years old man, (b) Corresponding HCW transform.

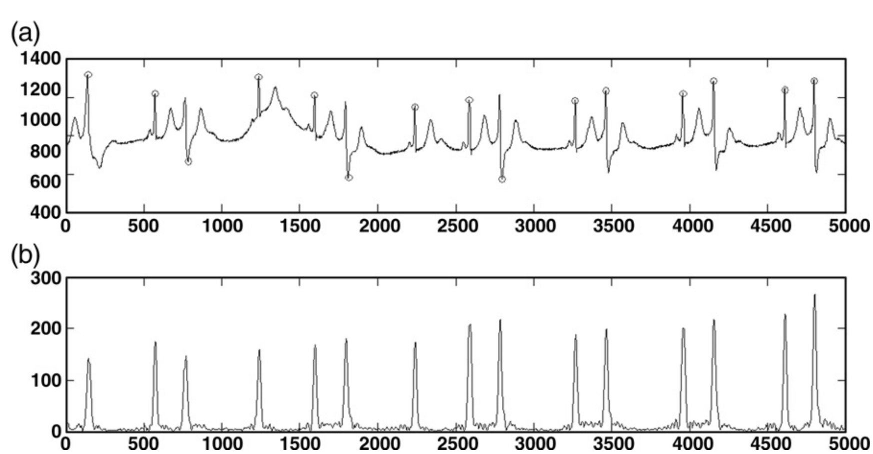

Fig. 5. (a). X-213 from MIT-BIH database (b).Corresponding HCW transform.

Table 1
Validity table of HCW in comparison with CMW and CFBSW

Variable	HCW%	CFBSW%	CNW%
True positive (TP)	99.7%	99.2%	98.8%
False negative	0.2%	0.7%	0.5%
False positive	0.1%	0.1%	0.7%
Accuracy	99.7%	99.2%	98.8%

To evaluate the parameters of these two mother wavelets in Eqs. (2) and (3), we first extracted an ideal QRS complex waveform from the x-100 signal of MIT BIH database. For every ECG train signal, by randomly changing parameters in certain intervals, we have acquired different functions among which the parameters of a mother wavelet with the maximum correlation to the ideal QRS complex waveform were chosen. Then the acquired parameters for different train signals are averaged. Therefore, the CMW with the parameters $f_b=1$, $f_c=1.5$ and scale=27 in Eq. (2) and CFBSW with the parameters $f_b=2$, $f_c=1.5$, $m=1$ and scale=27 in Eq. (3) were selected. The values of α, β are also changed randomly in intervals for every train signal and the best values which result to the best *HCW* with the highest amplitude of correlation to ideal QRS complex waveform are chosen. The values ($\alpha=0.35$, $\beta=0.65$) were obtained after averaging the acquired values of α and β for different train signals.

3. Results

We've implemented our method on 40 different recorded ECG signals from different patients with the overall number of 24000 R peaks and 12000 R peak from over 30 MIT-BIH signals as train and test dataset signals in a cross validation method. To reduce any anti symmetric changes in these R peaks, they were chosen with proper distribution. Figs. 3, 4 and 5 depict the implementation results of our method to two clinically ECG signals, recorded with three channel ECG recorder Ambisea AV-9300 and the X-213 signal from MIT BIH database, respectively.

The performance of HCW was compared with CMW and CFBSW methods and the results of this comparison are included in the *validity* table (Table 1). As it can be seen, R peaks have been detected by HCW more efficiently than CMW and CFBSW. The True Positive (TP) refers to the amount of available correctly detected R peaks in ECG signal, False Negative (FN) refers to percentage of unavailable R peaks which were detected wrongly and False Positive (FP) amounts to the percentage of available R peaks which are not detected by the algorithms. True Negative (TN) is zero in our case because of the format of our method. As it can be seen, R peaks have been detected by HCW more efficiently than CMW and CFBSW.

4. Conclusion

In this letter an efficient method, to R peak detection in ECG signal, HCW was proposed. The obtained results show a good trade-off between accuracy and rapidity.

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