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COMPARISON OF CWT WITH DWT FOR DETECTING QRS COMPLEX ON WEARABLE ECG RECORDER

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Abstract:

Wearable ECG Recorder can detect not only Biosignal but also Motion artifact and other surrounding noises. This study used wavelet transform as a way of removing such noise and compared Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). Each transform is designed to optimize the QRS Complex. CWT was designed to detect the Maximum energy scale from QRS Complex. DWT was designed to decompose 8-Levels and to reconstruct detailed coefficient with the frequency of the QRS Complex. To test the performance of two methods, data were collected from MIT-BIH Arrhythmia Database and Wearable ECG Recorder(WER) at the speed of 3km/h, 6km/h, 9km/h, 12km/h. By analyzing the data from two methods, the effectiveness for detecting QRS Complex while eliminating the surrounding noises.

Keywords:

ECG; Continuous wavelet transform; Discrete wavelet transform; QRS Detection, wearable ECG Recorder (WER)

1. Introduction

Electrocardiograph(ECG) is a recording of heart'ssuccessive action potential propagation by electrodes attached to the skin [1]. The signals that are produced from ECG are labeled as P, Q, R, S, T and the size, interval, shape, and cycle are essential elements in interpreting the graph. Detecting QRS Complex is the most important and the first step of analyzing the graph [2].

Recent research focuses on wearable sensor for ECG since it can record the electrical impulses during outdoor activities without the nuisance of electrodes.

Wearable ECG Recorder (WER), which traces ECG through wearable sensor has many advantages, one of which enables Dynamic Monitoring during normal daily life.

Despite the advantage, the wearable sensor uses Textile Electrode and causes more motion artifact than when regular electrodes are used. This creates more noises and lowering the level of clarity in ECG[3].

Types of noises that come with the wearable sensor include motion artifact, impulsive noise from muscle contraction, and 60Hz power noise from power-line interference and baseline drift from breathing. Researchers have been done to reduce such noises and many filtering methods have been introduced[2].

Among them are mathematical morphology (for removing Impulsive noise), adaptive filtering (for removing operator and motion artifact), and band-pass filtering (for removing baseline drift)[2-5]. All of these methods were effective in reducing certain type of noise. However, with WER, many types of noises including motion artifacts can occur, and it requires different solution.

This study suggests Wavelet as a solution for removing noise and detecting QRS Complex during the use of WER. CWT and DWT were analyzed and compared in the area of detecting QRS Complex.

2. IMPLEMENTATION

Wavelet Transform is divided into two ways Continuous Wavelet Transform and Discrete Wavelet Transform. Continuous Wavelet Transform is defined as follows.

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

In this formula, $x(t)$ refers to the impulse, a is Scale Parameter, b is Shifting Parameter, $\psi(t)$ refers to wavelet function[6]. All variables and functions are determined in the realm of real number.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \qquad (2)$$

The most noticeable characteristic change in wavelet from this formula is that the scale factor a was used to increase or decrease wavelet $\psi(t)$ and the translation factor b was used to move the wavelet[7].

Multi-resolution Analysis that Mallet's suggested is the

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most well-known DWT algorithm it is composed of Filter bank with two sub-bands[8]. Original signal is analyzed into two functions Scaling Function and Wavelet Function, by both of which the signal are each analyzed into Approximation and Detail Approximation is again analyzed into High-scale, Low-frequency Component and the Details are analyzed into Low-scale, High-frequency.

The process of returning Detail Coefficient is done as below x(t) is broken down by the expansion and movement of prototype function ψ named Mother Wavelet. The signal from basis function projects the Detail Coefficient as below.

$$dx(a,b) = < x(t), \psi_{a,b}(t) > \tag{3}$$

$$\psi_{a,b}(t) = 2^{-a/2}\psi(2^{-a}t - a) \tag{4}$$

Approximation Coefficient can be gained by the projection of the signal from expansion and movement of Scaling function.

$$\varphi, a_x(a,b) = < x(t), \varphi_{a,b}(t) > \tag{5}$$

$$\psi_{a,b}(t) = 2^{-a/2}\psi(2^{-a}t - a) \tag{6}$$

2.1. Continuous Wavelet Method

CWT operates arithmetic on all scales[9]. On the high domain of the Scale, low frequency noises such as Motion Artifact show the strong Correlation. On the low domain of the Scale, high frequency noises such as Impulsive Noise shows the strong Correlation. We checked the QRS on the scale through scalorgram because our research interest was in the QRS Complex signs on ECG.

Scalorgram in Figure 1 shows that Maximum energy of QRS Complex is diagramed between scales a= 50 and a=60. This paper detected the QRS Complex only by adding the Coefficient between a=50 and a=60, based on the Maximum energy distribution on the standard ECG.

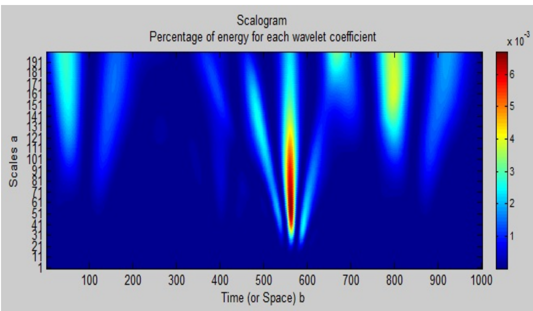

Figure 1. Scalorgram shows Wavelet on a Scale a=1~200 per beat that was traced by Coefficient Daubechies3 function

2.2. Discrete Wavelet Method

Decomposition is composed of two types of Filter. After the signal passes the Low Pass Filter (LPF), Approximation Coefficient is gained Detail Coefficients through High Pass Filter (HPF)[11].

We designed LPF and HPF by using Scaling Function and Wavelet Function of Daubechies3 function. Figure 2 shows the design that has 8-Levels Decomposition.

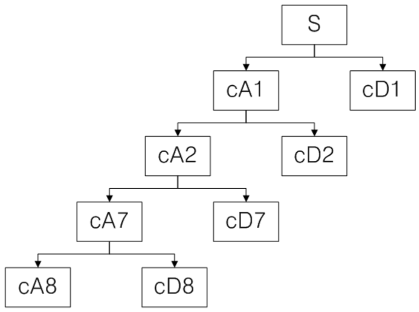

Figure 2. Diagram of ECG with 8 Level Decomposition

We selected and reconstructed cD8, cD7, cD6, cD5 which turned out to have the most of QRS Complex components through on 8-Levels Decomposition. In general, QRS Complex was concentrated on 5~15Hz Motion Artifacts were highly concentrated 1~5Hz Muscle Noise 5~40Hz with wide range of frequency[5]. On the other hand, Muscle Noise didn't show much energy. Based on the experiment, we selected and reconstructed cD8, cD7 and cD6, cD5 which has the highest QRS frequency.

$$\hat{S}(t) = cD8 + cD7 + cD6 + cD5 \tag{7}$$

cA8 was excluded in the reconstruction because of low frequency noise from motion artifacts or baseline drift

2.3. QRS Detection Algorithm

QRS detection follows the five steps as seen in Figure 3. The detection algorithm is similar to that of PAN-Tompkins algorithm. In the first step, CWT and DWT were used to eliminate the noise from ECG. In the second step, Motion Artifacts and Baseline Drifts were eliminated by Differential Operation[4]. In the third step, Negative Peak was altered to Positive Peak by Squaring[5]. In the fourth step, Smooth Filtering was done to ensure the high detection rate of QRS Complex through Thresholding in the final step, the Threshold was set to detect the QRS Complex points and to change according to the signal change.

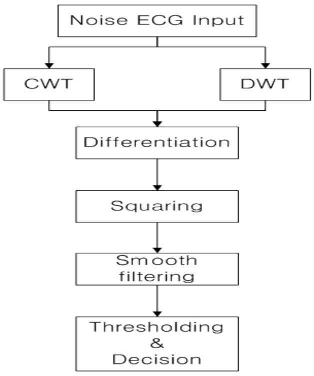

Figure 3. QRS Complex detection flowchart

The max value between intervals is multiplied by Threshold value and it is used for detecting QRS.

3. Experiments and Result

Database from MIT-BIH Arrhythmia and the data from Wearable ECG Recorder (WER) were used in analyzing the performance of detection of QRS Complex and removal of unnecessary noises.

MIT-BIH Arrhythmia Database has 360Hz Sampling Rate and 11bit Resolution Wearable ECG has 500Hz Sampling Rate and 12bit Resolution. From a single read on the chest, the data was collected.

To create a normal routine environment, the speed on the treadmill was adjusted to 3km, 6km, 9km, 12km while the research participants were wearing Wearable ECG Recorder. As a result, the noise such as Motion Artifacts and Baseline Drift increased as the speed went up.

The result on Wearable ECG at the speed of 9km/h as in the Figure 4. shows that DWT and CWT were all effective in eliminating the noise, but the discrepancy between the original impulse and CWT was greater than that of DWT. As for detecting QRS Complex, CWT's detection rate was higher as seen Table1, Table2. The effectiveness of detection algorithm was measured by the following formula.

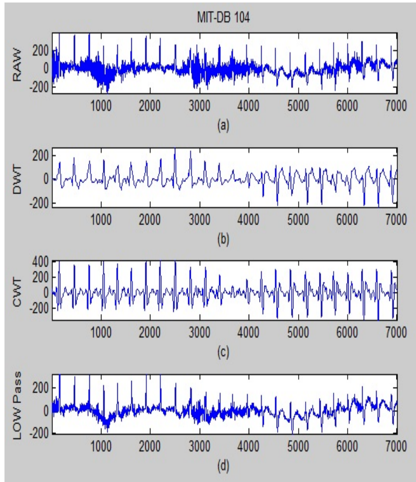

Figure 4. (a) MIT-DB 104,
(b) Data after DWT
(c) Data after CWT
(d) Low-pass filter with fc=25Hz

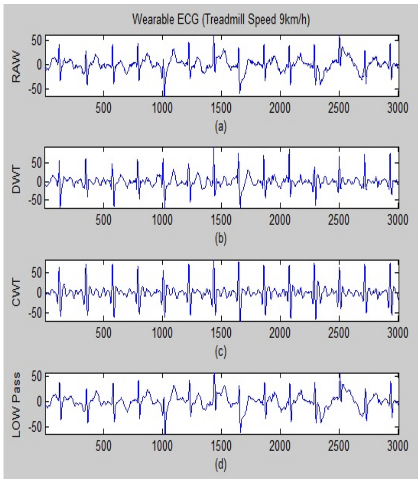

Figure 5. (a) Speed of 9km/h on the treadmill
(b) Data after DWT
(c) Data after CWT
(d) Low-pass filter with fc=25Hz

$$S_e(\%) = \frac{TP}{TP + FN} \quad \text{sensitivity} \tag{8}$$

$$+P(\%) = \frac{TP}{TP + FP} \quad \text{positive predictivity} \tag{9}$$

False Negative (FN) means that QRS Beat couldn't be detected. False Positive means QRS Complex that was falsely detected. The sensitivity was gained through FN and TP. TP is the total number of QRS Complex that were detected by algorithm.

TABLE1. COMPARISON OF DETECTION RATE BY USING MIT-BIH DATABASE

Tape No		Total	FN	FP	Se (%)	+P (%)
104	DWT	2229	1	4	99.99	99.82
	CWT	2229	0	2	100	99.91
116	DWT	2412	28	2	98.85	99.92
	CWT	2412	16	1	99.34	99.96
203	DWT	2980	22	5	99.27	99.83
	CWT	2980	15	3	99.50	99.90
213	DWT	3251	6	1	99.82	99.97
	CWT	3251	3	1	99.91	99.97
221	DWT	3427	7	3	99.80	99.91
	CWT	3427	4	3	99.88	99.91

TABLE2. COMPARISON OF DETECTION RATE BY USING TREADMILL SPEED

Treadmill Speed		Total	FN	Se(%)
3Km	DWT	710	0	100
	CWT	710	0	100
6Km	DWT	728	0	100
	CWT	728	0	100
9Km	DWT	742	2	99.73
	CWT	742	0	100
12Km	DWT	764	8	98.96
	CWT	764	2	99.74

4. Conclusion

We looked into ways to optimize the wavelet to detect QRS Complex on the Wearable ECG Recorder (WER). We compared the detection rate of CWT and DWT. The results showed that CWT detected better on WER. WER is usually used in the embedded context, so more study needs to be one on real-time process in order to apply proper CWT for QRS Complex detection

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