Noise Tolerant QRS Detection using Template Matching with Short-Term Autocorrelation

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Abstract— **This paper describes a robust method for heart beat detection from noisy electrocardiogram (ECG) signals. Generally, the QRS-complex of heart beat is extracted from the ECG using a threshold. However, in a noisy condition such a mobile and wearable bio-signal monitoring system, noise increases the incidence of misdetection and false detection of QRS-complex. To prevent incorrect detection, we introduce a novel template matching algorithm. The template waveform can be generated autonomously using a short-term autocorrelation method, which leverages the similarity of QRS-complex waveforms. Simulation results show the proposed method achieves state-of-the-art noise tolerance of heart beat detection.**

I. Introduction

Mobile and wearable healthcare is expected to play an increasingly prominent role in health provision because of the advent of an aging society. Especially, biosignal measurements during daily life at home is important to prevent lifestyle diseases, which are expected to raise the number of patients and elderly people requiring nursing care.

Key factors affecting the usability of mobile and wearable systems are miniaturization and weight reduction. However, these constraints degrade the signal-to-noise ratio (SNR) of measured biosignal because the battery capacity and electrode size are strictly limited. The SNR is especially degraded if a subject is not at rest (e.g. during housework, exercise, and physical works). Consequently, a low-cost and noise tolerant biosignal measurement method is needed in this application.

This report specifically describes a noise-tolerant heart beat detection algorithm from noisy electrocardiogram (ECG). The monitoring heart activity from ECG is useful for heart disease detection, heart rate variation analysis, and exercise intensity estimation. Furthermore, the human activity in the daily life can be correctly estimated using the combination of the heart rate and an accelerometer.

In general, sophisticated analog front-end circuits are necessary to prevent SNR degradation of sensing systems. The analog front-end of the ECG monitoring system mainly comprises amplifiers, analog filters, and an analog-to-digital converter (ADC). However, it is difficult to use a high performance amplifier and analog filters with a high quality factor because these circuits have large circuit area and high power consumption. On the other hand, ultra-low-power ADCs, which have sub-μW power consumption and a limited sample rate, have been developed for biomedical applications. According to Moore's law, the power of digital components increases with the progress of process technology. Therefore, the digital signal processing is effective to reduce the performance requirements of analog components and total power consumption.

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II. Conventional Heart Beat Extraction

Recently, various algorithms have been proposed to improve the accuracy and reliability of heart rate extraction. Extracting R-waves using threshold determination is a widely used approach for IHR detection from ECG.

The Pan–Tompkins (PT) algorithm [1] uses band-pass filtering, differentiation, squaring, and moving window integration. Periodically, the threshold is adjusted automatically using QRS morphology and the heart rate. The SQRS [2] and WQRS [3] algorithms can respectively detect QRS based on ECG slope and length transform. The SQRS uses band pass filtering for noise reduction, which uses only the integer coefficient. The WQRS also uses a low-pass filter to remove baseline wander. The Discrete Wavelet Transform (DWT) [4–6] uses a wavelet transform with quadratic spline wavelet (QSW). The threshold is calculated using the root mean square value of the wavelet transform. The DWT requires a small amount of calculation and hardware cost because it can be implemented using only adders and shift operators. Therefore, this algorithm has been used in robust ECG monitoring LSI [6]. The QSW requires a small amount of calculation and hardware cost because it can be implemented using only adders and shift operators. The Quad Level Vector (QLV) algorithm [7] is generated using DWT and the adaptive threshold. Then, the threshold is determined by the maximum mean deviation (MD) of the previous heartbeats. The Continuous Wavelet Transform (CWT) algorithm [8–10] employs a Mexican hat wavelet in the frequency interval of 15–18 Hz. The R-peak can be extracted using the adaptive threshold, which is calculated using the modulus maxima of the CWT. The CWT is a most noise tolerant algorithm.

When using clean ECG, there is no significant difference in the accuracy of these algorithms. However, as depicted in Fig. 1, both misdetection and false detection are increased in the wearable healthcare system by noise from various sources. Fig. 2(a) presents frequency characteristics of the PT, SQRS,

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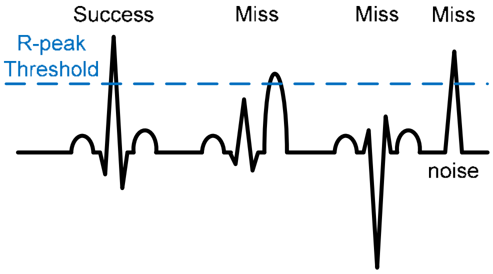

Figure 1. Noise problem with threshold based R-peak detection.

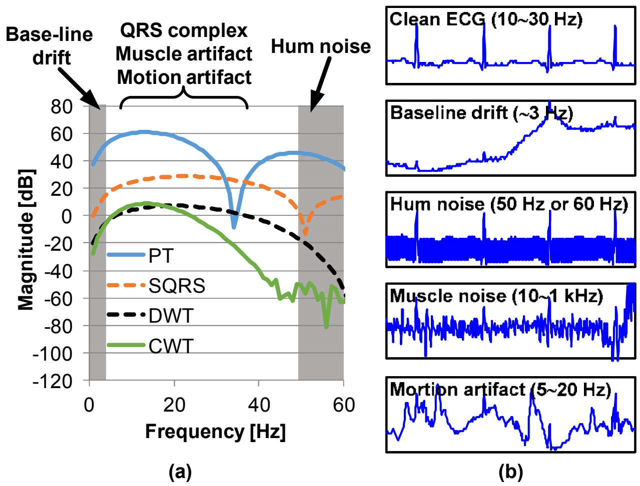

Figure 2. (a) Frequency characteristics of filters with 128Hz sampling rate, and (b) waveform example of ECG signals with various noises.

TABLE I. PREPROCESSING AND QRS DETECTION IN CONVENTIONAL METHODS.

	Preprocessing (filter technique)	QRS detection (threshold)
[1]	Bandpass filter, derivative, squaring, and moving window integrator	Signal peak and noise peak
[2]	Bandpass filter	Slope criterion
[3]	owpass filter and curve length transfor	QRS amplitude
[5]	DWT	Root Mean Square (RMS)
[7]	Discrete wavelet transform (DWT)	Mean deviation (MD)
[9]	Continuaous wavelet transform (CWT)	Modulus maxima

DWT, and CWT with 128 Hz sampling rate. Fig. 2(b) depicts the ECG and well-known noise waveforms. A base-line wander and a hum noise can be removed easily using digital filters. However, unfortunately, the frequency range of the muscle artifact and electrode motion artifact is similar to the desired ECG signals.

Therefore, we address the noise tolerance improvement in this work. Threshold based conventional algorithms can be classified by preprocessing method and QRS detection method as summarized in Table I. Our proposed method, which describes in Sect. III, can replace the threshold based method. On the other word, the proposed method can be combined with any other preprocessing filter techniques shown in Table I.

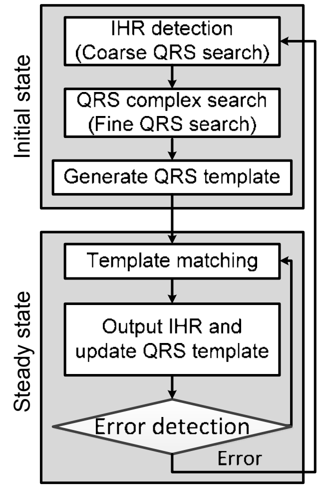

Figure 3. Flow chart of proposed method.

III. PROPOSED METHOD

To prevent erroneous detection, we introduce a novel template matching algorithm. The template waveform can be generated autonomously using short-term autocorrelation. Fig. 3 presents a flow chart of the proposed method.

A. *Autonomous Template Generation*

In our previous work, we proposed a two-step QRS complex detection algorithm using short-term autocorrelation [11]. This algorithm can extract the QRS complex from a noisy ECG because it uses similarity of the QRS waveform. For this work, we used this algorithm to generate a template autonomously.

First, as portrayed in Fig. 4, an RR interval at time t_0 ($RR[0]$) is obtained as a window shift length (T_{shift}) that maximizes the correlation coefficient between the template window and the search window (CC_{ST}). Then, the window length L_{w} is set as 1.5 s. The value of T_{shift} is set as 0.25 s to 1.5 s because the heart rate of a healthy subject is 40 bpm to 240 bpm.

When the search window is fixed at $T_{\text{shift}} = RR[0]$, both the template window and the search window contain the QRS complex at the same distance from the right edge of the window. Therefore, as presented in Fig. 5, the time of a recent QRS complex ($T_{\text{QRS}}[1]$) at t_0 is identifiable using the autocorrelation of small windows in the template and search window. Then, the small window length (L'_{w}) should be set much smaller than that of L_{w}, and larger than the QRS complex length. For this study, L'_{w} was set to 0.1 s.

Finally, the first template can be generated using small windows at $T_{\text{QRS}}[1]$ and $T_{\text{QRS}}[0]$ ($=T_{\text{QRS}}[1] - RR[0]$) as depicted in Fig. 6.

B. *Template Matching and Error Detection*

Next, template matching is conducted to extract QRS complexes using the generated template as depicted in Fig. 6. Then, the search range of the QRS complex ($T_{\text{QRS}}[n]$) is defined as $T_{\text{QRS}}[n-1]$ to $T_{\text{QRS}}[n-1] + 1.5 \times RR[n-2]$. The window shift length T'_{shift} with maximum correlation

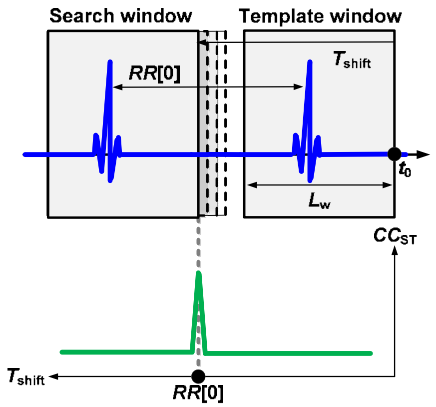

Figure 4. IHR detection using short-term autocorrelation.

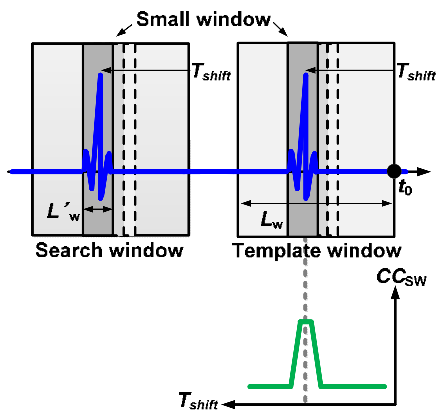

Figure 5. QRS complex search using small-window autocorrelation.

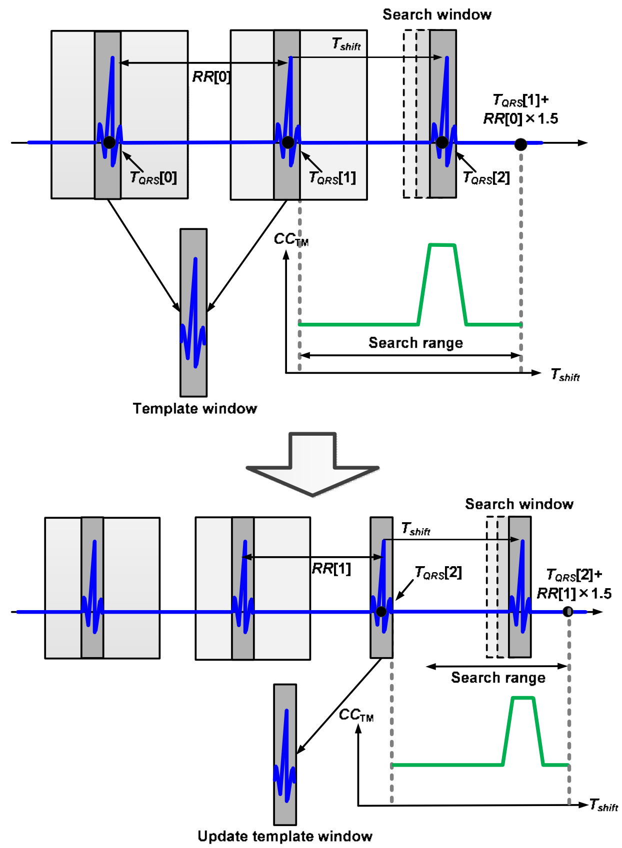

Figure 6. Template matching.

coefficient $CC_{TM}[n]$ between the template and ECG signals in the search range shows the nest QRS complex. Whenever the QRS complex is extracted, the QRS template is updated.

The proposed algorithm can be awake and can recover the error if misdetection or false detection occurs because of arrhythmia or intense noise. The coefficient of autocorrelation will decrease rapidly when such an error occurs. When the maximum value of correlation coefficient $CC_{TM}[n]$ is less than half of the previous maximum value of $CC_{TM}[n-1]$, then $T_{QRS}[n]$ is treated as an error. When an error has occurred in template matching, the template generation is executed again as depicted in Fig. 3.

IV. Performance Evaluation

To verify the effects of the proposed method, we performed simulation experiments using the public ECG database (MIT-BIH arrhythmia database [12]) and the noise database (MIT-BIH noise stress test database [13]).

The proposed template matching (TM) method can be combined with any other preprocessing filter technique shown in Table I. In this simulation, the DWT [5] and the CWT [9] are implemented as a filter. Conventional threshold-based DWT and CWT are also implemented for comparison with the proposed TM. These methods are modeled in Matlab.

Table II presents a performance comparison of QRS complex detection with 48 waveforms from MIT-BIH database without noise. Here, the definition of the sensitivity (*Se*) is $Se = TP / (TP + FN)$. The definition of the positive predictability ($+P$) is $+P = TP / (TP + FP)$ [7]. The error rate (*ER*) is defined as $ER = (FP + FN) / (TP + FN)$. Then, *TP*, *FN*, and *FP* respectively denote the number of correct QRS detection, the number of failures to detect the true QRS complex, and the number of false detections. The proposed TM with CWT filter achieves 95.8% sensitivity and 98.3% positive predictivity, on average.

Figs. 7, 8, and 9 present the relation between intensity noise and accuracy of QRS detection. The muscle artifact and the motion artifact are used in this simulation because these noises are difficult to remove. Furthermore, the ECG in daily life monitoring is often contaminated by these noises.

The signal-to-noise ratio (SNR) is defined as shown below.

$$SNR = 10\log\frac{S}{N\times a^2}$$

In that equation, *S*, *N*, and *a* are defined respectively as the signal power, frequency-weighted noise power, and scale factor [13].

As portrayed in Fig. 7, the conventional method has higher sensitivity in the noisy condition. However, the proposed methods have higher positive predictivity and a lower error rate (see Figs. 8 and 9). These results demonstrate that conventional methods lead to more cases of misdetection in noisy conditions.

V. CONCLUSION

As described herein, we proposed a template matching algorithm using short-term autocorrelation for heart beat detection in noisy environments. The proposed method, which is combined with a CWT filter, achieves 95.8% sensitivity and 98.3% positive predictivity, on average, for 48 ECG records. In the noise stress test, the proposed method produces a state-of-the-art error rate both with the muscle artifact and the motion artifact.

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TABLE II. PERFORMANCE COMPARISON OF QRS DETECTION.

	DWT with TM			CWT with TM		
Record #	Se(%)	PP(%)	error(%)	Se(%)	PP(%)	error(%)
100	99.9	100.0	0.1	99.9	100.0	0.1
101	99.6	99.8	0.5	99.6	99.8	0.6
102	94.5	94.8	10.8	99.1	99.3	1.6
103	99.8	100.0	0.2	99.8	100.0	0.2
104	97.0	98.9	4.1	95.9	98.3	5.8
105	98.3	97.9	3.8	97.4	96.1	6.6
106	82.1	99.2	18.6	82.2	99.8	18.0
107	98.5	99.9	1.6	98.6	100.0	1.4
108	92.2	91.8	16.0	90.7	90.5	18.8
109	99.3	100.0	0.7	99.5	100.0	0.5
111	99.7	99.9	0.4	99.8	100.0	0.3
112	99.9	100.0	0.1	99.9	100.0	0.1
113	99.6	100.0	0.4	99.7	100.0	0.3
114	98.9	99.6	1.5	99.1	99.8	1.1
115	99.9	100.0	0.1	99.9	100.0	0.1
116	99.2	98.2	2.7	99.2	99.1	1.7
117	99.9	100.0	0.1	99.9	100.0	0.1
118	99.8	100.0	0.3	99.9	100.0	0.1
119	85.0	99.4	15.6	91.3	98.9	9.7
121	99.2	98.9	1.9	99.7	100.0	0.3
122	99.8	100.0	0.2	99.8	100.0	0.2
123	99.3	99.5	1.2	99.7	100.0	0.3
124	99.2	100.0	0.8	99.1	100.0	0.9
231	86.0	75.9	41.2	89.9	77.3	36.5
232	93.8	74.1	39.0	92.3	75.5	37.7
Worst (#100~234)	86.0	75.9	41.2	89.9	75.5	37.7
Best (#100~234)	99.9	100.0	0.1	99.9	100.0	0.1
Average (#100~234)	95.6	97.9	6.7	95.8	98.3	6.1

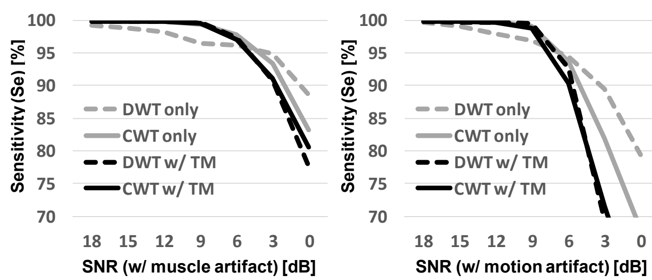

Figure 7. Noise stress test simulation results of sensitiviti (Se).

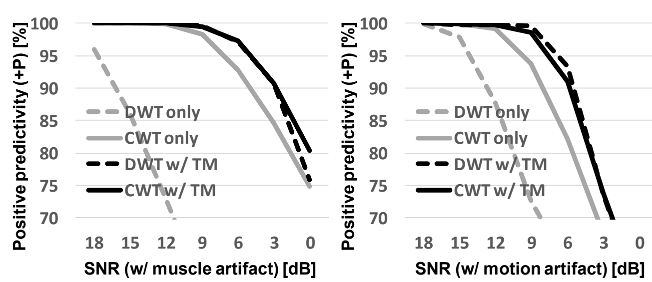

Figure 8. Noise stress test simulation results of positive predictivity (+P).

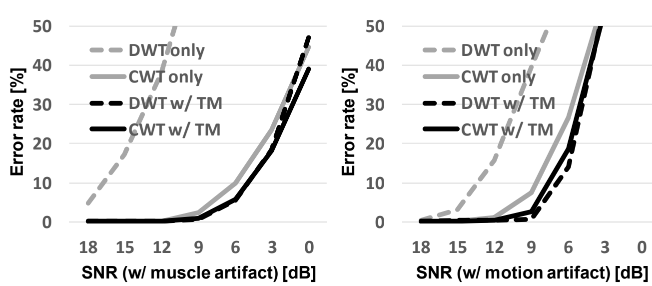

Figure 9. Noise stress test simulation results of error rate.