Biomed Eng Lett (2011) 1:143-150
DOI 10.1007/s13534-011-0023-x

ORIGINAL ARTICLE

Optimization Methods for Improving the Performance of Heart Rate Detection by a Wearable ECG System During High-intensity Exercise

Uk-jin Yoon, Yeon-Sik Noh and Hyung-ro Yoon

Received: 21 January 2011 / Revised: 12 May 2011 / Accepted: 18 May 2011

Abstract
Purpose Wearable electrocardiogram (ECG) systems are exposed to more noises than the general ECG systems, because of the high impedance between electrodes and the skin and the need to acquire ECG data during exercise or in daily life. The purpose of this study was to enhance heart rate detection by optimizing electrode and signal processing in a wearable system during high-intensity exercise.
Methods To create an optimal electrode condition, we quantitatively measured the change in noise according to a change in pattern of textile electrodes by using 3 textile electrodes with the same material quality but different patterns. We also measured the degree of skin hydration by using an MPA5 (CK Electronics, Germany) to obtain the optimal condition between electrodes and skin. To accurately detect the QRS complex, use of an improved algorithm based on a wavelet, which has strong noise tolerance, was suggested.
Results We obtained root-mean-square (RMS) values that were expected to be similar to those measured with the Ag-AgCl electrode at the point of >120% of skin hydration. The QRS complex detection rate of the wavelet method that was suggested in this study was compared to that of an adaptive filter and mathematical morphology operator. We used the data collected during actual exercise performed at 15 km/h. The QRS complex detection rate of the proposed algorithm was 99.9%.
Conclusions Through optimization of the wearable system that was suggested in this study, collection of a more accurate heart rate value is expected. In addition, the influence of noise could be minimized in the wearable system.

Uk-jin Yoon, Yeon-Sik Noh and Hyung-ro Yoon (✉)
Department of Biomedical Engineering, Yonsei University
Tel : +82-33-760-2807 / Fax : +82-33-763-1953
E-mail : hryoon@yonsei.ac.kr

Keywords Wearable, Textile electrode, High-intensity exercise, Skin hydration, Wavelet, Adaptive filter, Mathematical morphology operator

INTRODUCTION

The need for systematic and safe exercise management through analyzing bio-signals during exercise has recently emerged. Thus, bio-signal measurement technology, which involves measurement of bio-parameters during exercise, is being rapidly introduced to the field of sports science [1]. The application of bio-signal measurement technology to the field of sports science offers the ability to prevent medical accidents and protect health status during exercise. In particular, electrocardiogram (ECG) signal measurement during exercise can prevent sudden cardiac arrest or death.

Design of an unconstrained system is required to introduce bio-signal measurement technology to the field of sports science. A wearable system can be used to measure the unconstrained bio-signals during exercise. In particular, the heartbeat measurement system of the wearable sensor has been much commercialized in the field of sports health care [2]. However, such commercialized products focus only on measuring exercise quantity by measuring the heartbeat, and do not have the ability to prevent heart-related accidents that occur suddenly during exercise. Accordingly, incorporation of the ability to collect a high-quality ECG to monitor cardiac function during exercise is very important.

Generally, the wearable sensor uses a conductive textile electrode to ensure measurement and non-restrictive wear. Textile electrodes are mostly dry electrodes. Thus, the impedance between the skin and electrodes tends to increase. Increases in impedance negatively affect signal quality. Moreover, the textile electrode has a lower tolerance to noise than the Ag-AgCl electrode, which is widely used to measure

ECG [2]. The textile electrode relies heavily on signal quality via its material quality and pattern [2] and the degree of skin hydration [5]. In addition, this sensor is directly attached to the body. Thus, the material used needs to be carefully selected [2].

Moreover, the textile electrode used in the wearable system further deteriorates the signal due to the influence of several noises given measuring ECG signal, especially during high-intensity exercise. Accordingly, to acquire high-quality ECG signals, sensor optimization is essential. Diverse ECG parameters such as QT/QTc and ST segments need to be analyzed to prevent medical accidents and to monitor health status via bio-signal measurement during exercise. To analyze diverse ECG parameters this way, the QRS complex needs to be detected accurately. One QRS complex detection method before the 1990s used a mainstream algorithm of a FIR/IIR filter and a differentiator during pre-processing [10]. However, since the 1990s, new algorithms with better noise tolerance have been developed, such as the wavelet transform, adaptive filter, neural network, matched filter, and morphology operator [14]. However, these methods have limited suitability for bio-signal processing, are complex to operate, and are difficult to use with small low-powered equipment [6].

This study suggests the optimal textile electrode and skin hydration for measuring ECG signals using textile electrodes in order to acquire high-quality ECG using a wearable sensor and system. Moreover, we propose an optimization method for more effective heart rate detection during high-intensity exercise that uses the improved wavelet method applied to a real-time low-power system that is suitable for bio-signal processing.

METHODS

Data acquisition

In order to optimize signal acquired by the wearable system during high-intensity exercise, we had to consider 2 major factors. The optimal electrode had to measure the ideal skin hydration level to use the textile electrode, and had to evaluate noise in the ECG according to changes in the textile electrode's patterns. We used ECG data that were collected by the actual wearable system. The skin hydration evaluation was conducted by an MPA5 (CK Electronics, Germany) by using gradual increases in skin hydration. Measurements were taken when the electrodes touched the skin directly.

Second, ECG data during exercise were acquired by the wearable system when each participant was moving at 15 km/h on a treadmill to confirm the detection rate of the QRS complex. We used the MIT-BIH Noise Stress Test Data Base (NSTDB) to evaluate the noise tolerance of each signal-processing method. The NSTDB contains mixed electrode

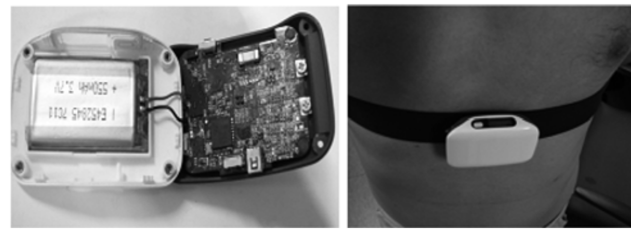

Fig. 1. Wearable ECG system and sensor placement.

motion artifact (EM) noise based on the data of 118 and 119 of the MIT-BIH Arrhythmia Database. This is what reconstituted the signal, so that performance can be evaluated according to a change in noise intensity by lowering the signal-to-noise ratios (SNRs) of the EM noise in these data [17].

The treadmill exercise was used to collect the data of 12 physically healthy men (age, 26.9 ± 3.2 years). Using the wearable system, the signal was acquired with a sampling frequency of 500 Hz for the ECG and of 10 Hz for the accelerometer.

Skin hydration measurement

The degree of skin hydration is an important element that affects the impedance between the textile electrode and skin. Accordingly, it is important to first survey the connection between skin hydration and the ECG signal. To quantitatively evaluate a change in ECG amplitude that is dependent on the degree of skin hydration, the root-mean-square (RMS) value was calculated using formula (1). We then compared the RMS of data acquired by using the Ag-AgCl electrode with that of data acquired using the textile electrode.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\|u(t_i)\|^2} \quad (1)$$

Textile electrode pattern change noise evaluation

The pattern or texture of the textile electrode can greatly influence the impedance between the skin and electrode. As such, several textile electrodes were evaluated to determine the effect of different patterns on ECG signal quality.

Fig. 2 shows the textile electrode (AJINELECTRON, Korea)

a b c

Fig. 2. Textile electrode pattern in the experiment.

made of a conductive silver fabric base material that has silver within the polyester.

Textile electrode patterns may be knitted, woven, embroidered, or non-weaved, and differences in the impedance and signal quality of these preparations have been reported. The weaving type is primarily used to acquire the bio-signals [2, 4].

This study comparatively analyzed the weaving type and the mesh type, the latter of which is thinner than the former. Images (a) and (b) correspond to the weaving type, whereas image (c) shows the mesh type. The mesh type is less dense than the weaving type. The basic material of the conductive electrode is silver, which is absorbed by the polyester yarn.

To evaluate the performance of the textile electrode by pattern, we measured the noise index of the ECG in a stable state [15]. Noise index measurements were compared by measuring RMS power in the isoelectric line of the ECG signal. To measure noise, the isoelectric line is extracted between the endpoint of the T wave and the beginning point of the P wave. We created 1 signal by averaging the isoelectric lines extracted from several cycles, and then measuring the RMS values. Ultimately, the textile whose electrode pattern has the smallest RMS value in the isoelectric line can be said to have the strongest noise tolerance.

Signal processing methods to compare QRS complex detection

We compared 3 algorithms to identify the optimal signal-processing method to detect the QRS complex during exercise: adaptive filter (AF), multi-scale mathematical morphology operator (3M), and convolution wavelet (CNW) [9, 13]. The AF method used the NLMS algorithm to normalize the standard least mean squares (LMS) algorithm. The LMS algorithm adjusts the filter coefficients to minimize the cost function. The normalized LMS (NLMS) algorithm is a modified form of the standard LMS algorithm. This method has been effectively used to remove the motion artifact observed in many studies to date. A method of using signals in the X, Y, and Z axes of an accelerometer as the reference input is typical. The 3M filter, a method of non-linear signal transformation that modifies the geometric shape of a signal depending on position, is based on mathematical morphology, a method of analyzing an image that was first introduced by Matheron and Serra. The non-linear transform method has been suggested so far as the effective method of removing the electromyogram noise or the noise in the form of an impulse in ECG. In reality, the impulse noise could effectively be removed with little computational complexity. Fei Zhang recently enhanced the performance than that observed with the existing morphological filter method by using 3 pieces of mutually different structural elements [9]. The CNW method was suggested for this study since it can reduce the computational complexity for real-time signal processing and still be suitable for bio-signal processing.

Improved wavelet method for reducing computational complexity

The proposed wavelet algorithm is a method for optimally detecting the QRS complex. Wavelet function was newly generated through convolution in the wavelet and scaling functions. The newly generated wavelet function removed noise again through convolution with the ECG signal and amplified the energy of the QRS complex.

The wavelet function used the Daubechies2 function, which has orthogonality, and can be divided into scaling and wavelet functions. The scaling function plays the role of a low-pass filter, while the wavelet function plays the role of a high-pass filter.

First, an approximate value is obtained up to k = 1–3 in the scaling and wavelet functions by using a filter coefficient of Daubechie2. The positive integer k determines the number of iterations computed, and thus, refines the approximations. It is a newly generated function that is available for optimally detecting the QRS complex through convolution as k = 3 both in the scaling and wavelet functions out of approximate-value functions.

$$CNW(t) = \psi(t)_{k=3} * \phi(t)_{k=3} \quad (2)$$

The function generated by formula (2) was created with convolution in both the wavelet and scaling functions; therefore, we named it CNW. Ultimately, the energy of the QRS complex is indicated to be 5–15 Hz. The magnitude response of (f) in Fig. 3 is known to play a role in the band-pass filter, which amplifies the energy to 5–20 Hz.

Decision rule for QRS complex detection

The stage of the decision rule for detecting the actual QRS complex after signal processing was used algorithm, which used adaptive threshold after amplifying the energy in the QRS complex through the Envelop process following passage through the adaptive filter, the 3M algorithm, and CNW algorithm.

The adaptive threshold method detected the signal peak for the first 6s to determine its maximum value. The maximum value detected is then set for the first variable threshold. After that point, the adaptive variable threshold is applied using formula (3). Thus, the QRS complex is detected. This method was developed for quickly detecting real-time QRS complex values.

$$TH_{n+1} = \frac{3}{4}TH_n + \frac{1}{4}\left(\frac{3}{4}P_i\right) \quad (3)$$

Fig. 4 shows the results of application of the Envelop process to the decision rule and the skin moisture of the electrocardiogram also was obtained when there was 80-

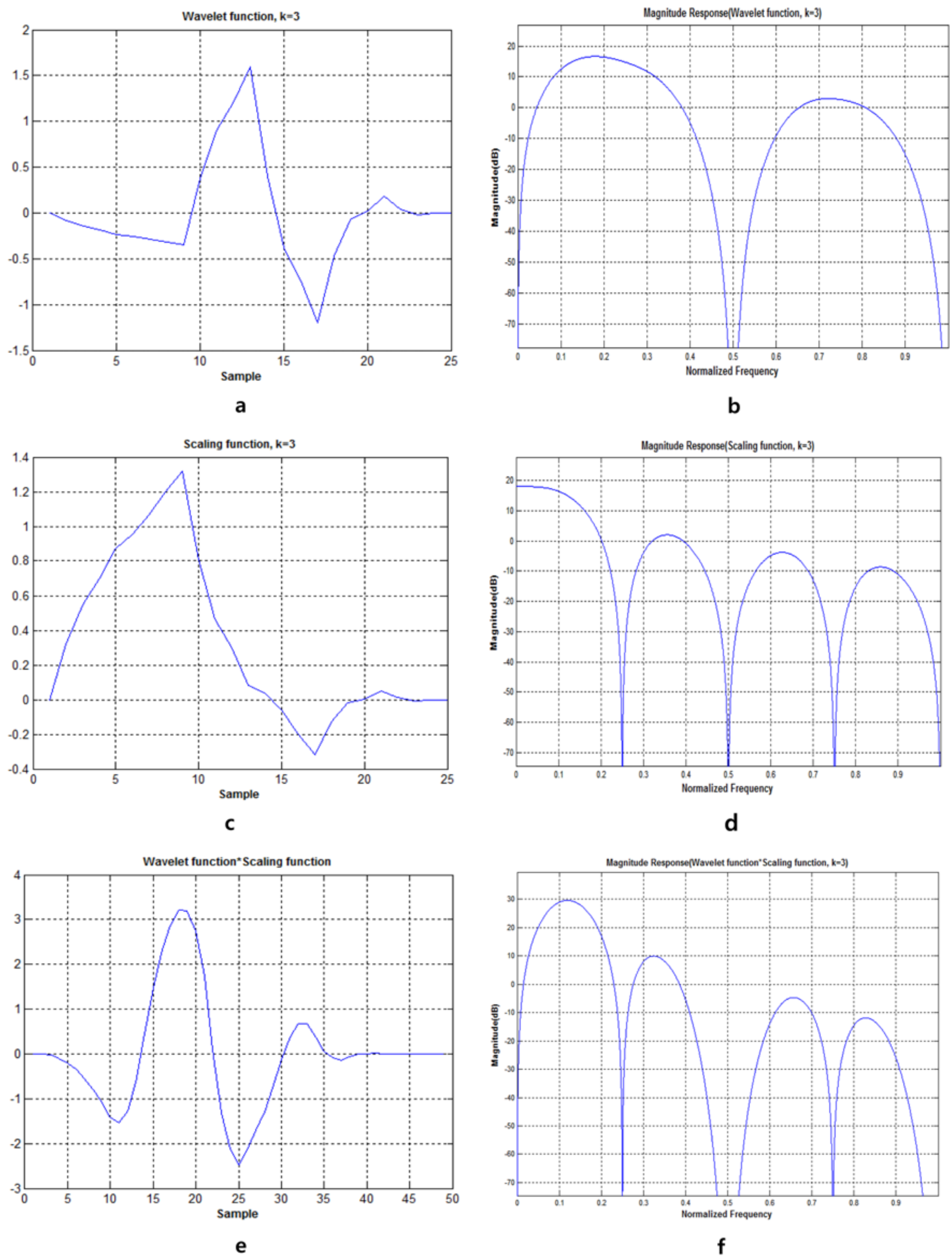

Fig. 3. Wavelet, scaling, and CNW functions of the magnitude response.

90%. The skin did not contain enough moisture, which resulted in a lot of background noise. And we applied the three kinds of signal processing methods to obtained ECG signal. As you can see in Fig. 4, eventually, the CNW function best amplified the energy of the QRS complex.

RESULTS & DISCUSSION

Optimization of wearable conductive textile electrode

Experiment was confirmed significance through 10 subjects. Generally, the degree of skin hydration before the use of a

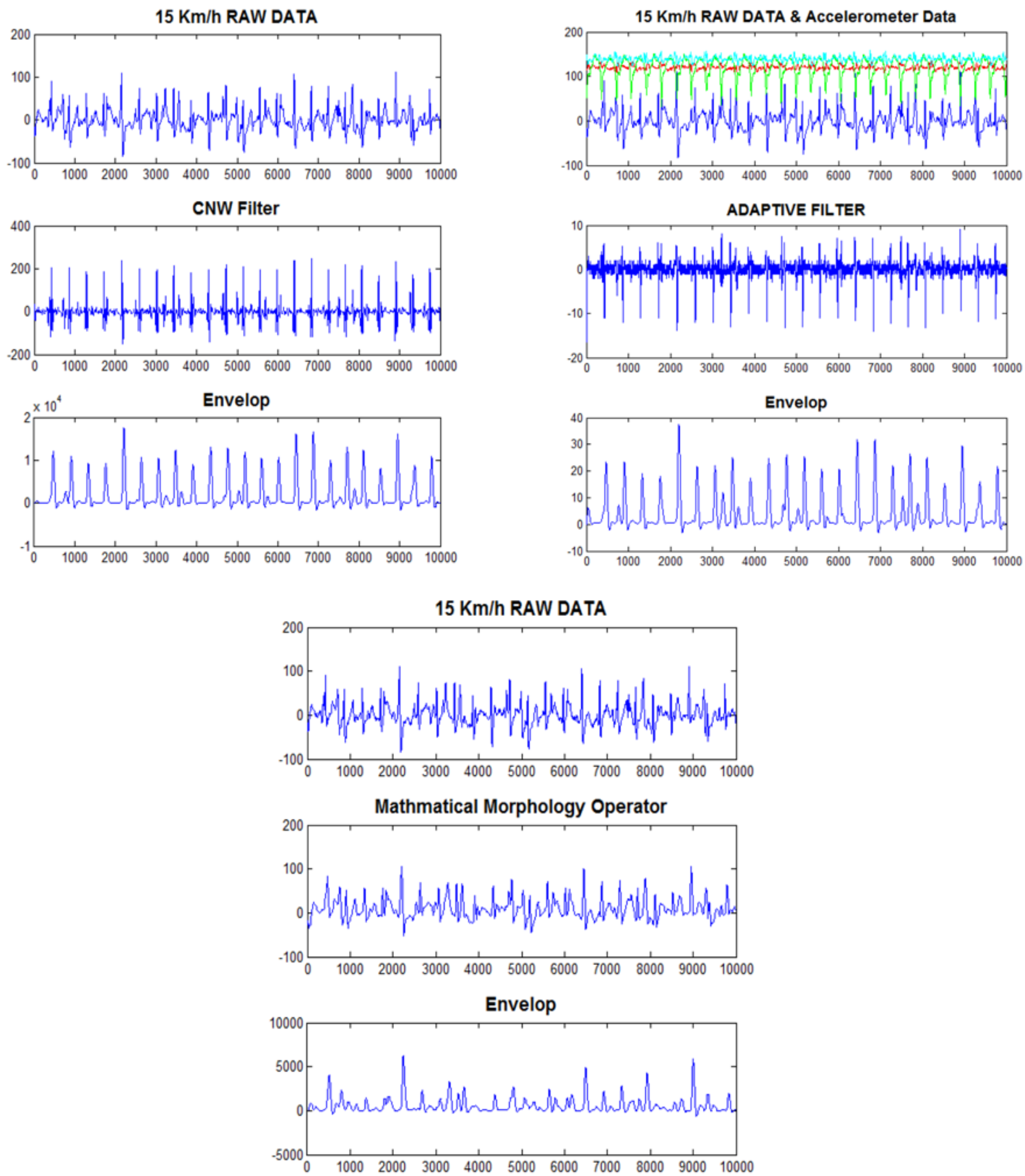

Fig. 4. Envelop process.

skin care product is 30–45%. At this degree of skin hydration, an ECG signal could not be acquired at all. However, an ECG signal whose amplitude is very low could be acquired at the point of 80% hydration. At 120% skin hydration, data with similar performance to those of the standard electrode (Ag-AgCl electrode) could be acquired. The degree of hydration in the MPA5 moisture measurement system is 200%.

As shown in Fig. 5, the amplitude of the ECG waveform is known to differ according to the degree of hydration. This finding implies that skin hydration may function as important element in signal quality, and that skin hydration needs to be >120% to ensure acquisition of a signal that is equivalent to that of a standard electrode in the wearable system.

Table 1 compares the RMS value of the ECG according to degree of skin hydration collected using the textile electrode to that acquired using the standard electrode. The RMS values in Table 1 were calculated using the entire ECG waveform.

The experiment conducted to identify the optimal textile electrode pattern was carried out on mutually different patterns (Fig. 1). The textile electrode is absorptive, allowing

Table 1. RMS changes according to the percentage of skin moisture.

Subjects	ECG RMS									
	Ag-AgCl electrode	Skin moisture (%)								
		40 ± 5	50 ± 5	60 ± 5	70 ± 5	80 ± 5	90 ± 5	100 ± 5	110 ± 5	120 ± 5
Subject 1	1.8	0	0	0	0	0.2	0.4	1.1	1.34	1.32
Subject 2	2.4	0	0	0	0	0.3	0.8	1.8	2.34	2.32
Subject 3	1.9	0	0	0	0	0.6	0.5	1.0	1.21	1.64
Subject 4	1.8	0	0	0	0	0	0.4	1.05	1.5	1.52
Subject 5	2.4	0	0	0	0	0.2	0.5	1.7	2.24	2.32
Subject 6	1.6	0	0	0	0	0	0.4	1.3	1.35	1.41
Subject 7	2.5	0	0	0	0	0.4	0.7	1.9	2.31	2.42
Subject 8	1.9	0	0	0	0	0	0.5	1.1	1.22	1.65
Subject 9	1.9	0	0	0	0	0.4	0.4	1.08	1.4	1.52
Subject 10	2.8	0	0	0	0	0.2	0.6	1.9	2.2	2.39

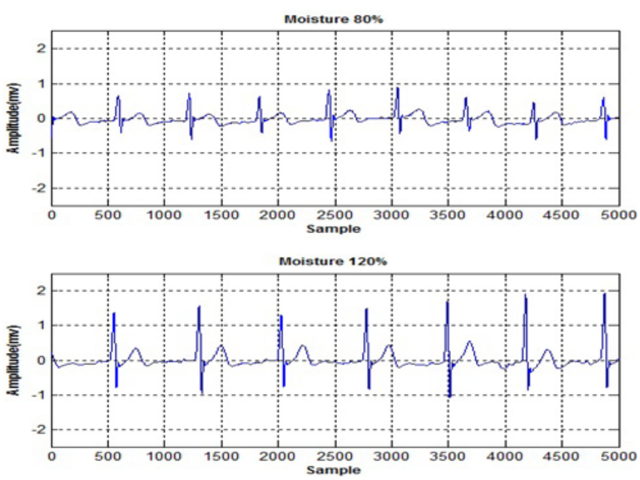

Fig. 5. Changes in skin hydration due to ECG waveform changes

Table 2. RMS change according to textile electrode pattern changes in an isoelectric line.

	Isoelectric Line RMS		
	Electrode (a)	Electrode (b)	Electrode (c)
Subject 1	0.0990	0.0763	0.0609
Subject 2	0.1310	0.1330	0.0982
Subject 3	0.0832	0.0824	0.0811
Subject 4	0.0421	0.0652	0.0517
Subject 5	0.1872	0.1422	0.1314
Subject 6	0.0983	0.0977	0.0974
Subject 7	0.0873	0.0682	0.0419
Subject 8	0.0773	0.0823	0.0672
Subject 9	0.0991	0.1340	0.0835
Subject10	0.1210	0.0923	0.0734
Mean RMS	**0.10255**	**0.09736**	**0.07867**

the silver to be taken into the polyester cloth. Data were acquired in the stable state. The experiment was carried out after verifying sufficient skin moisture.

As shown in Table 2, the textile electrodes (a) and (b) had similar values; in contrast, the average RMS value of electrode (c) was somewhat closer to 0. An RMS close to 0 has minimal noise influence in the isoelectric line. This finding also implies that electrode (c) has higher noise tolerance.

Algorithm optimization for QRS complex detection

Performance evaluation of each QRS complex detection algorithm was made on the basis of 2 kinds of statistical methods: sensitivity and positive predictive values.

$$Se(\%)=\frac{TP}{TP+FN} \tag{4}$$

$$+P(\%)=\frac{TP}{TP+FP} \tag{5}$$

In formulas (4) and (5), false negative (FN) indicates failure to detect an existent QRS complex, while false positive (FP) indicates the detection of a non-existent QRS complex. Total point (TP) indicates the total number of QRS complexes detected by the algorithm.

The suggested algorithm is suitable for the bio-signal processing in the wearable-based system during exercise that can detect the correct QRS complex and has a strong noise tolerance. In general, most wearable-based systems are difficult to apply in the environment since they require low-power system drives and real-time processing. Thus, this study simplified computational complexity and maintained the existing signal-processing effect by using both the wavelet and convolution methods.

We show the result of quantitative analysis of signal processing methods in Table 3 and Table 4. Examining the results shown in Table 3, data were acquired using an optimized textile electrode and ideal skin hydration which is more than 120%. Thus, the AF, 3M, and CNW algorithms showed good performance in the aspect of QRS complex

Table 3. Comparison of adaptive filter and wavelet detection rate of the 3M method.

		Total	FN	FP	Se (%)	+P (%)
1	AF	2757	4	2	99.8	99.9
	3M	2757	7	5	99.7	99.8
	CNW	2757	1	0	99.9	100
2	AF	2682	3	4	99.8	99.8
	3M	2682	9	2	99.6	99.9
	CNW	2682	3	1	99.8	99.9
3	AF	2640	2	3	99.9	99.8
	3M	2640	5	5	99.8	99.8
	CNW	2640	0	2	100	99.9
4	AF	2824	12	7	99.5	99.7
	3M	2824	13	9	99.5	99.6
	CNW	2824	6	1	99.7	99.9
5	AF	2706	8	9	99.7	99.6
	3M	2706	11	7	99.5	99.7
	CNW	2706	5	3	99.8	99.8
6	AF	2853	2	1	99.9	99.9
	3M	2853	7	5	99.7	99.8
	CNW	2853	3	0	99.8	100
7	AF	2904	4	5	99.8	99.8
	3M	2904	8	9	99.7	99.6
	CNW	2904	3	3	99.8	99.8
8	AF	2651	0	2	100	99.9
	3M	2651	5	4	99.7	99.7
	CNW	2651	0	2	100	99.9
9	AF	2793	6	3	99.6	99.8
	3M	2793	13	6	99.4	99.6
	CNW	2793	3	1	99.8	99.9
10	AF	2676	5	2	99.7	99.9
	3M	2676	9	3	99.5	99.8
	CNW	2676	0	1	100	99.9
11	AF	2927	4	1	99.8	99.9
	3M	2927	8	7	99.6	99.6
	CNW	2927	2	2	99.9	99.9
12	AF	2402	5	2	99.7	99.9
	3M	2402	10	7	99.5	99.6
	CNW	2402	1	0	99.9	100

*Total number of QRS complexes detected. AF: adaptive filter; 3M: multi-scale mathematical morphology operator; CNW: convolution wavelet.

Table 4. The mean value of Table 3.

Algorithm	Total			
	FN	FP	Se (%)	+P (%)
AF	55	42	99.6	99.7
3M	87	62	99.4	99.6
CNW	23	14	99.9	99.9

detection. However, CNW algorithm, which we suggested in this study, performs even better.

The performance speed of algorithm in STM32F103RE with a series of ARM Cortex M3 was compared on the basis of Table 5. The Arm Cortex M3 processor is the latest generation of ARM processor for embedded systems. In terms of performance speed, the algorithm suggested in this study is slower than the 3M method but could be faster than the AF method.

Table 5. STM32F103RE MCU algorithm processing speed.

	Algorithm processing speed
CNW	12.1 ms
3M	5.13 ms
AF	21.13 ms

AF: adaptive filter; 3M: multi-scale mathematical morphology operator; CNW: convolution wavelet

Table 6. Comparison of detection rate by SNR changes in NSTDB.

SNR (dB)		Total	FN	FP	Se (%)	+P (%)
118e24 (24 dB)	3M	350	0	1	100	99.9
	CNW	350	0	0	100	100
118e18 (18 dB)	3M	350	8	3	98.1	99.1
	CNW	350	0	0	100	100
118e12 (12 dB)	3M	350	20	8	94.8	98.1
	CNW	350	6	2	98.3	99.4
118e6 (6 dB)	3M	350	52	23	87.7	92.8
	CNW	350	19	5	94.8	98.5

SNR: signal-to-noise ratio; dB: decibels; 3M: multi-scale mathematical morphology operator; CNW: convolution wavelet; FN: false negative; FN: false positive.

To examine noise tolerance in more detail, we used 118e24, 118e18, 118e12, and 118e6 of NSTDB. The experiment using the NSTDB data was performed using only the 3M and CNW algorithms.

As seen in Table 6, the SNR of the noise at 6 dB rapidly dropped the detection rate. During high-intensity exercise, motion artifact intensity and external interference noise may occur highly. Thus, the more an algorithm can accurately acquire a QRS complex, the more effectively it can monitor an individual's health status and prevent accidents that can happen during exercise.

The 3M method has lesser computational complexity than the algorithm suggested in this study, but it has very low noise tolerance except to the noises that occur in impulse form; therefore, its use is not suitable for bio-signal processing. Thus, use of the improved wavelet method that was proposed in this study was confirmed to be the most efficient method.

CONCLUSIONS

This study measured the optimal skin hydration for acquiring ECG using a wearable ECG system. It also proposed the use of a signal processing method for detecting optimal QRS complexes in the high-intensity exercise environment with significant noise. It is difficult to use small equipment to obtain real-time data using the wavelet method, neural network, and adaptive filter methods that are conventionally used to detect the QRS complex. As a result, we suggested use of the CNW method, which is less complex and performs better than the existing QRS complex detection method.

Acquisition of a cleaner ECG signal during exercise can make it easier to analyze ECG parameters like ST or QT/QTc segments. Accurate QRS complex detection becomes the standard point for detecting ECG-specific points (e.g., T-offset, P-onset); thus, exact detection is important.

In conclusion, this study proposed a method to more easily acquire and analyze ECG data during exercise; this will help prevent accidents during exercise.

ACKNOWLEDGMENT

This study was supported by a grant of the Industrial Technology Development Program, Ministry of Knowledge Economy (MKE) of Korea. (Project No.70004268).

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