Sensor signal processing

Lightweight and High Accurate RR Interval Compensation for Signals From Wearable ECG Sensors

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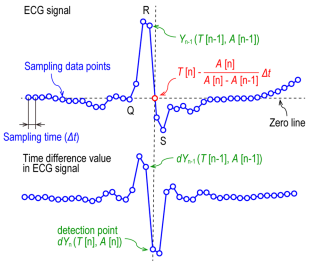
Abstract—This letter presents a new lightweight and high accurate RR intervals (RRIs) compensation technique suitable for wearable electrocardiogram (ECG) sensors. RRIs are among the important features of ECG signals and are thus widely used in medical and healthcare applications, and their estimation is commonly implemented in wearable ECG sensors. The data sampling rate is one of the factors influencing on the RRI accuracy from ECG signals acquired by wearable sensors. However, in wearable sensors, high sampling rates consume substantial electrical power, leading to a tradeoff between power consumption and RRI accuracy. A spline interpolation is one of the conventional compensation methods obtaining high-resolution RRI at low sampling rates. However, the method requires heavy computational processing for high-order interpolation. Therefore, a method that achieves highly accurate RRI interpolation with lightweight computational processing is desirable for low power consumption in wearable measurement. Here, we developed a novel lightweight and high-accurate RRI compensation method suitable for wearable ECG sensors. The method is specifically designed for algorithms commonly used for R wave detection in wearable ECG sensors. Validation results using simulated ECG signals confirm that the proposed method enables accurate RRI estimation for sampling rates ranging from 50 to 1000 samples, demonstrating superior performance compared with the conventional cubic spline interpolation. Furthermore, the proposed method was confirmed to meet the accuracy requirements for heart rate variability analysis, even at a low sampling rate of 66.7 samples. In addition, the effectiveness of the proposed method was experimentally confirmed during specific actions with various motion artifacts. These results demonstrate the effectiveness of the proposed method for RRI compensation in wearable ECG sensors. With the future introduction of wearable ECG devices, we expect our method to provide a needed balance between low power consumption and high resolution.



Index Terms—Sensor signal processing, electrocardiogram (ECG), interpolation, RR interval (RRI), sampling rate, wearable sensors.

I. INTRODUCTION

The RR interval (RRI) in an electrocardiogram (ECG) represents the time interval between successive R waves, indicating variation in the heart rate. It is recognized as one of the most important features in the ECG and has various healthcare and medical applications, including evaluation of heart rate variability [1], risk of sudden cardiac death [2], exercise physiology [3], [4], [5], sleep [6], and heart rate control [1], [7], [8], [9]. Furthermore, with recent technological advancements, it has become possible to acquire real-time ECG signals and detect RRIs using wearable sensors [10], [11], [12], [13], [14]. The data sampling rate is one of the factors influencing on the accuracy of RRI from ECG signals acquired by wearable sensors [1], [15], [16]. For instance, when used for heart rate variability analysis, ECG measurements must have a high sampling rate of over 500 samples [1], [17]. However, a significant portion of power consumption in wearable ECG devices is attributed to signal processing in the analog front-end and analog-to-digital converter for data acquisition. Therefore, high sampling rates increase the amount of signal processing occurring within the device and present challenges for the power efficiency of wearable devices [18]. A spline interpolation method has been reported as a means of obtaining high-resolution RRI at low sampling rates [19]. However, this method requires heavy computational processing for high-order interpolation. Therefore, a method that achieves highly accurate RRI interpolation with lightweight computational processing is desirable for low power consumption in wearable measurement. In addition, wearable ECG devices have limited computational resources, necessitating the use of fast and executable algorithms for R wave detection. One of the most commonly used R wave detection algorithms combines a method that enhances peaks derived from R waves using the time differential of the ECG and a method that detects peaks based on data points exceeding a threshold set around those peaks [20].

In this letter, we numerically and experimentally investigated a lightweight and high accurate RRI compensation method for the R wave detection algorithm utilizing the time differential of the ECG.

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II. MATERIALS AND METHODS

A. Interpolation Method

We propose a simple compensation method suitable for R wave detection based on the time differential of the ECG. For the description of the method, we define the sampling data points of the ECG signal as Yi(T[i], A[i]) (i = 0, 1, 2, …), and the corresponding data points of the time differential values of the ECG signal as dYi(T[i], dA[i]), as shown in Fig. 1. In the signal representing the time differential values of the ECG signal, each point detected by the R-wave detection

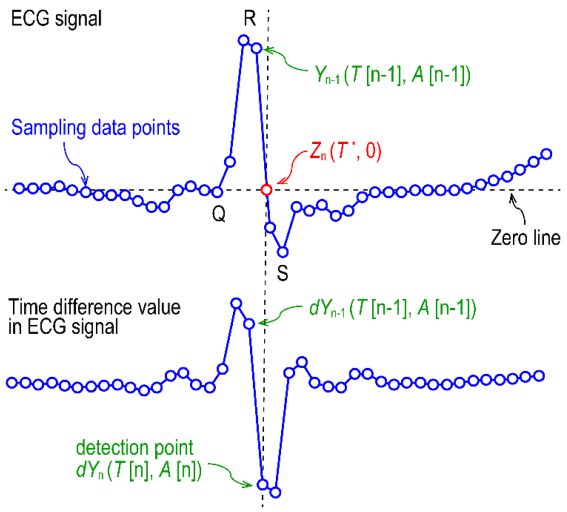

Fig. 1. Schematic illustration of the proposed RRI compensation method.

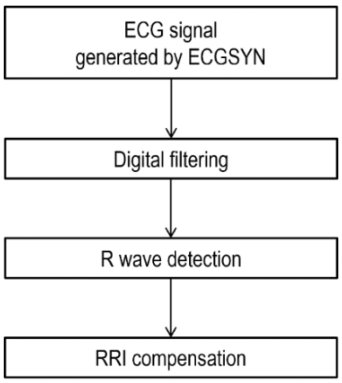

Fig. 2. Overview of the procedures for R wave detection and RRI correction.

algorithm using the time differential values of the ECG signal is denoted dYn(T[n], dA[n]), the data sample preceding dYn is denoted dYn−1(T[n − 1], dA[n − 1]), the data sample of the ECG signal corresponding to dYn is represented as Yn(T[n], A[n]), and the data sample preceding Yn is denoted Yn−1(T[n − 1], A[n − 1]). In the RRI compensation method, the zero-crossing Zn(T∗, 0) along the RS segment of the ECG signal is estimated from T[n], A[n − 1], A[n], and the sampling time interval Δt. The occurrence time T∗ of Zn is used as the reference time for the RRI calculation as

$$T^* = T[n] - \frac{A[n]}{A[n] - A[n-1]} \cdot \Delta t. \tag{1}$$

B. Demonstration of Compensation Method

We validated the proposed compensation method using ECGSYN [21], which is an ECG signal generation program freely available on PhysioNet [22], a large-scale database of physiological signals and open-source software related to physiological signals. Fig. 2 gives an overview of the procedures for R wave detection and RRI correction for the validation ECG signals. We used the R wave detection algorithm [23] based on the time differential of the ECG signal, which is the target of this letter, to detect peaks derived from R waves in ECG signals generated using ECGSYN. Based on the fact that QRS duration is almost constant in people without cardiorespiratory diseases, the algorithm selectively makes the QRS-induced peak sensitive to the specific time width determined by considering the nature of an ECG, and then performs R wave detection based on the ECG time difference values. The algorithm enables lightweight processing and high-accurate R-wave detection for ECG waveforms affected by noise caused by body motion than the conventional detection algorithm based on a threshold-based peak search. The generated validation ECG signals had predetermined sampling rates (1000, 500, 250, 125, 66.7, 50 samples) and predetermined RRI intervals (ranging from 30 to 240 bpm in intervals of 10 bpm). We applied our proposed compensation method to perform RRI correction. The settings and parameters for ECG signal generation using ECGSYN are given in Table 1. As a comparison, we also performed compensation using the conventional cubic spline interpolation method as an alternative to the proposed method. The RRI error was calculated as

Table 1. Settings of Each Parameter During ECG Signal Generation with ECGSYN

Parameter	Value
Approximate number of heart beats, N	1000
Amplitude of additive uniform noise, A	0 mV
Low frequency, f_1	0.1 Hz
High frequency, f_2	0.25 Hz
Low frequency standard deviation, c_1	0 Hz
High frequency standard deviation, c_2	0 Hz
LF/HF ratio, γ	0.5

$$E_{\mathrm{rri}} = \mathrm{RRI}_{\mathrm{est}} - \mathrm{RRI}_{\mathrm{in}} \tag{2}$$

where E_{rri} (ms) represents the RRI error, $\mathrm{RRI}_{\mathrm{in}}$ (ms) represents the input RRI value, and $\mathrm{RRI}_{\mathrm{est}}$ (ms) represents the estimated RRI value. The accuracy of the RRI is defined as the boundary value of the 95% confidence interval of the absolute value of the RRI error $|E_{\mathrm{rri}}|$.

C. Experimental Test

The resistance of the proposed method to body motion artifacts was experimentally confirmed. First, ECG signals during specific movements were acquired by one subject using a wearable device (hitoe transmitter TX02, NTT Technocross Corporation). The sampling frequency of the ECG is 1 kHz. We measured four movements: resting, upper body twisting, walking 4 km/h, and stair climbing. For each acquired ECG data, we applied a 15th order FIR high-pass and low-pass filters with cutoff frequencies of 10 and 40 Hz to remove low-frequency body movement noise and then calculated RRI using three different methods. First, RRI was calculated for the filtered ECG signals by the algorithm used in the previous section [23]. Second, the RRI was calculated by the algorithm and corrected by the proposed method after sampling to 125 Hz for the filtered ECG. Third, the RRI correction in the second is replaced by the conventional method (cubic spline interpolation). Using the RRI calculated by the first method as

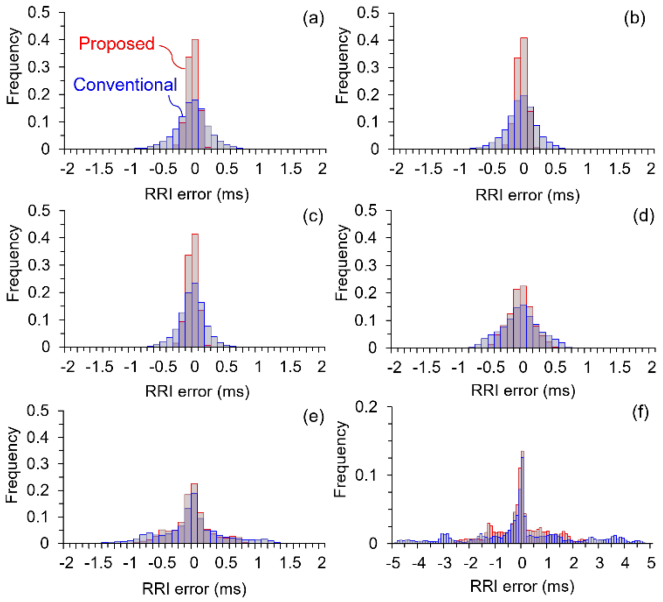

Fig. 3. Histograms of RRI errors when applying the conventional and the proposed methods to ECG signals with different sampling rates: (a) 1000 samples, (b) 500 samples, (c) 250 samples, (d) 125 samples, (e) 100 samples, and (f) 66.7 samples.

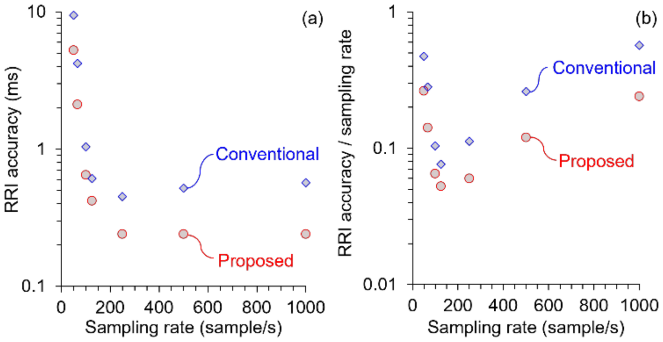

Fig. 4. Results of applying the conventional method (cubic spline interpolation) and the proposed method as the compensation method for ECG signals with different sampling rates: (a) RRI accuracy and (b) (RRI accuracy)/(sampling time) plotted against sampling rate.

a reference value, we calculated the RRI error calculated by the latter two methods.

III. RESULTS AND DISCUSSION

A. Demonstration of Compensation Method

Fig. 3 shows typical histograms of RRI errors obtained with the proposed and conventional methods applied to ECG data with various sampling rates. In addition, Fig. 4(a) shows the RRI accuracy for each method according to the sampling rate. From these results, it can be observed that the conventional method improves the RRI accuracy with increasing sampling rates up to 250 samples, but experiences a decrease in accuracy at 500 and 1000 samples. On the other hand, the proposed method demonstrates monotonic improvement in RRI accuracy with increasing sampling rate. Furthermore, comparing the two methods confirms that the proposed method achieves a higher RRI accuracy than the conventional method across all tested sampling rates.

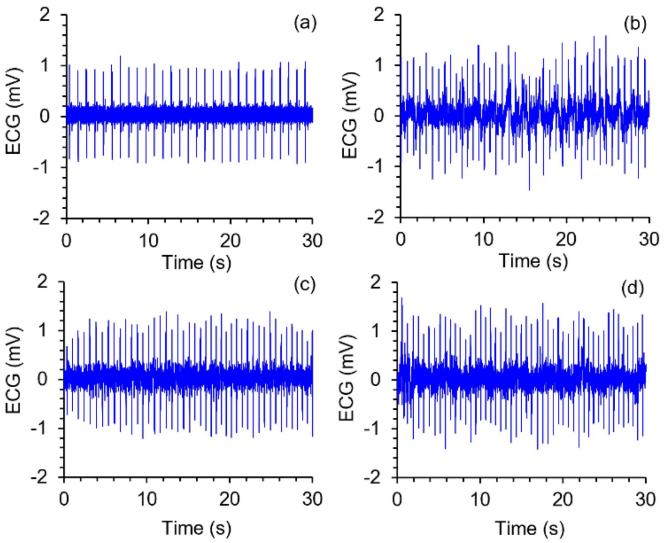

Fig. 5. 1 kHz-ECG signals during each action after the digital filtering. (a) Resting. (b) Upper body twisting. (c) Walking. (d) Stair climbing.

Table 2. RRI Error in Each Action, Each Compensation Method

Actions	RRI error without compensation mean±SD (ms)	RRI error with compensation by the conventional method mean±SD (ms)	RRI error with compensation by the proposed method mean±SD (ms)
Resting	7.80 ± 12.13	0.21 ± 1.04	0.17 ± 0.74
Upper body twisting	6.76 ± 15.83	0.20 ± 2.67	0.21 ± 1.67
Walking	8.01 ± 13.59	0.21 ± 1.72	0.20 ± 1.11
Stair climbing	8.38 ± 7.77	0.20 ± 1.28	0.20 ± 0.90

Considering that heart rate variability analysis requires a sampling rate of 250 samples or higher, it was confirmed that the proposed method can ensure the required RRI accuracy even at a sampling rate of 66.7 samples. In addition, to compare the effectiveness of each correction method for each sampling rate, the relationship between the RRI accuracy normalized by the sampling time and the sampling rate is shown in Fig. 4(b). Regarding the ratio of RRI accuracy to sampling time, for the conventional method, the values were 0.57, 0.26, 0.11, 0.076, 0.10, 0.28, and 0.47 for sampling rates of 1000, 500, 250, 125, 100, 66.7, and 50 samples, respectively. On the other hand, for the proposed method, the values were 0.24, 0.12, 0.06, 0.053, 0.065, 0.14, and 0.26 for the same respective sampling rates. The above results confirm that both the proposed method and the conventional method have an optimal sampling rate of 125 samples, at which the correction method is most effective.

B. Experimental Test

Fig. 5 shows the ECGs acquired during each action, and Table 2 shows the RRI errors for each action and each compensation method.

It is confirmed that the RRI error in the proposed method is smaller than that in the case of no compensation or in the conventional method for either action. Comparing the RRI errors in each action of the proposed method, the RRI errors increase in the order of resting, stair climbing, walking, and upper body twisting. This is because each motion artifacts affects the fluctuation of the RS wave in the ECG, and in the order described above, the effect is large. These errors can be reduced by improving the filtering method in the future.

C. Limitation of the Project

The RRI detection algorithm used in this letter [14], while lightweight and capable of highly accurate RRI detection, is an algorithm specialized for healthy subjects without cardiac disease, so the results are limited to healthy subjects. In order to apply the proposed compensation method to the detection of cardiac disease, it is necessary to validate it in combination with an R-wave detection algorithm that can detect cardiac disease in the future. In addition, since the human test was positioned as a basic study of the compensation method, it was limited to verification of basic daily activities. In order to apply the method into practical use, it is necessary to verify the method with a wider range of complex motions in the future. Furthermore, since the results of this verification were obtained by analyzing data acquired by commercial devices, it is necessary to implement the algorithm in hardware and verify its contribution to power consumption in the future.

IV. CONCLUSION

In this letter, we proposed a lightweight and high accurate compensation method for RRI estimation in wearable ECG sensors. The method utilizes the time differential values of the ECG signal and achieves both power efficiency and high accuracy in RRI calculation. Our numerical and experimental results demonstrate that the proposed method outperforms the conventional cubic spline interpolation method in terms of RRI accuracy, especially at higher sampling rates. Furthermore, the proposed method maintains the required accuracy even at a low sampling rate of 66.7 samples, which is essential for heart rate variability analysis. These findings demonstrate the potential of the proposed method for improving the performance of wearable ECG devices in various clinical and research applications. Future studies can explore the implementation of the proposed method in real-time monitoring systems and evaluate its performance in medical and clinical settings.

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