Sampling Rate Reduction for Wearable Heart Rate Variability Monitoring*

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Abstract— **This report describes a sampling rate reduction method for heart rate variability monitoring with a wearable device. This work was conducted to realize low-power measurement of biological signals necessary for heart rate variability (HRV) analysis. Continuous operation of the wearable device is an important factor for daily life monitoring. Therefore, the active time of the measuring circuit must be minimized. To reduce the required sampling rate, we propose a sampling error reduction method using interpolation and correlation of the heartbeat waveform. The proposed method is evaluated using measured electrocardiograms from five subjects. Evaluation results demonstrate that the sampling rate can be reduced to 32 Hz with 1 ms RMS error in heartbeat interval and 1.04% LF/HF degradation in HRV analysis.**

Keywords—Electrocardiography; heart rate variability (HRV) analysis; photoplethysmography; sampling rate

I. Introduction

Mobile and wearable healthcare devices are expected to play an increasingly prominent role in health provision because of the advent of aging societies in many nations. Daily life monitoring is important to prevent lifestyle diseases, such as cardiovascular diseases, which are expected to raise the number of patients and elderly people requiring nursing care.

This report describes an active rate reduction method for heartbeat monitoring. The heartbeat is a useful biosignal for heart disease detection, heart rate variability (HRV) analysis [1, 2], and exercise intensity estimation [3]. Especially, this research specifically examines HRV analysis. The heartbeat interval is not always constant: it is adjusted by the autonomic nervous and endocrine systems. It varies according to physical and mental stress, respiration, diet, posture, exercise, and other factors. Such periodic fluctuation of the heartbeat interval is designated as HRV. One can obtain autonomic nervous activity and indicators of biological signals acting on autonomic nerve activity by measuring fluctuation of the heartbeat interval. Therefore, autonomic nerve activity can be estimated by measuring fluctuation of the heartbeat interval.

Electrocardiography (ECG) or photoplethysmography (PPG) is generally used in wearable devices as a heartbeat measurement method. ECG measures the potential difference on the body surface attributable to the electrical activity of the heart. A PPG sensor irradiates green or red light to the body surface and measures the amount of light absorption by hemoglobin related to the volume change of blood vessels. The heartbeat interval is obtained by detecting the peak from the waveform of these biological signals. However, measuring these signals consumes large amounts of power. Particularly, PPG requires power consumption by one or more LEDs and phototransistors to measure the reflected waves. Furthermore, for ECG, the power consumed by the measuring circuit and the signal processing account for a large share of the power used by the entire system [4].

Therefore, this study assesses active rate reduction methodology to realize low-power heartbeat monitoring. Section 2 presents a sampling rate reduction method. Interpolation and autocorrelation methods are introduced to mitigate the accuracy degradation caused by sampling noise. To evaluate the proposed method, the ECG measured from a wearable sensor [5] is used.

By reducing the sampling rate and the active rate required for HRV analysis, the power consumption of the measuring circuit can also be reduced. Figure 1 presents the measurement circuit block of the ECG used in the wearable device.

II. Sampling Rate Reduction using Interpolation and Autocorrelation

A. Algorithm

A simple means of lowering the active rate of the measurement circuit is sampling rate reduction. The power of the digital circuit unit and the AD converter are reduced according to the active rate using clock gating or power gating. An SAR type AD converter is used in this work because it is energy efficient with low sampling rate compared with other AD converter architecture [6]. The power consumption of the SAR AD converter is closely proportional to the sampling rate. In addition, the requirements of the frequency band and the bias current are mitigated in the analog circuit of the sensor front end, which contributes to low-power circuit design.

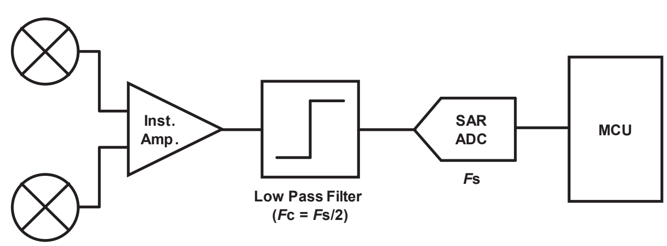

Fig. 1. Overview of ECG sensing block.

*This paper is based on results obtained from a project commissioned by the New Energy and Industrial Technology Development Organization (NEDO).

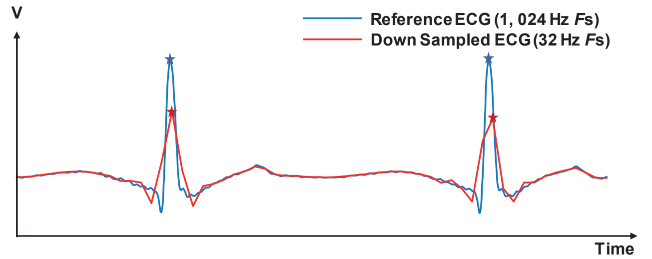

Fig. 2. Example of measured reference and downsampled ECG waveform.

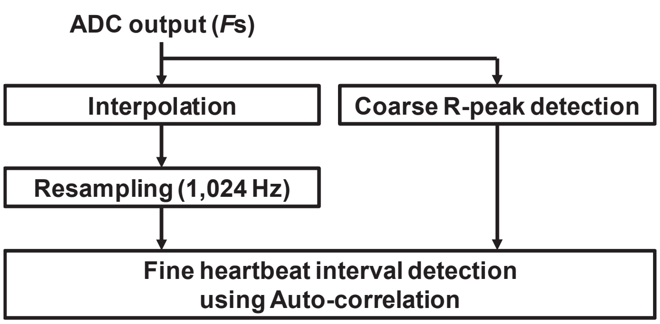

Fig. 3. Flow chart for coarse-fine heartbeat interval detection.

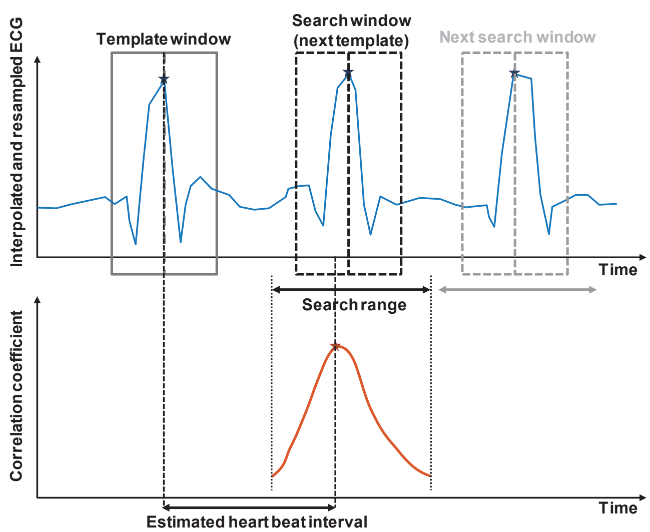

Fig. 4. Example of fine heartbeat interval detection.

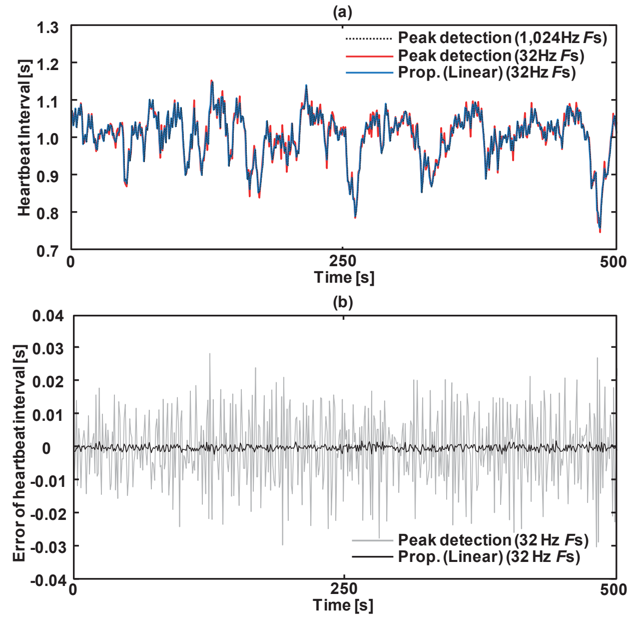

Fig. 5. Measured example of (a) extracted heartbeat interval and (b) relative error compared with peak detection with 1,024 Hz F_S.

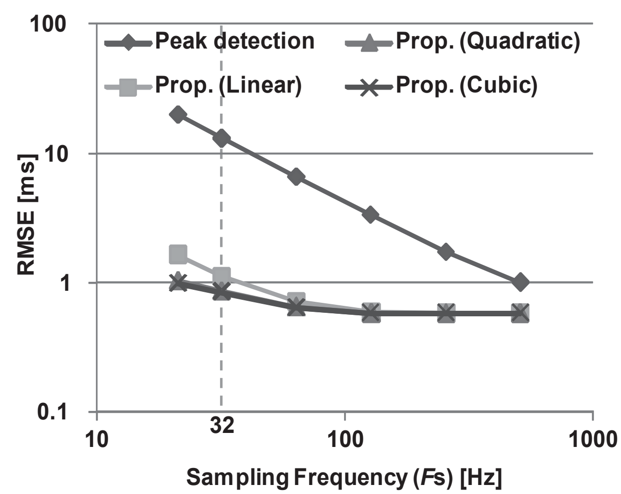

Fig. 6. RMS error comparison of extracted heartbeat interval from downsampled ECG.

However, lowering the sampling rate means that the sampling error becomes larger. As described later in Section 3, the sampling error also affects the HRV analysis results. Figure 2 shows heartbeat waveforms with 1,024-Hz and 32-Hz ECG sampling rates. Generally, when the heartbeat is extracted from ECG, the R wave peak is detected. As shown in Fig. 2, this method directly affects the sampling error.

For this study, a heartbeat interval extraction method using interpolation and waveform correlation is introduced to reduce the sampling error influence. As presented in Fig. 2, the waveforms for each heartbeat are very similar in the short term. Therefore, using the similarity of the whole heartbeat waveform including P, Q, R, S, and T waves, one can detect the heartbeat interval with higher precision than when using the conventional R peak detection method. In addition, because P and T waves have lower frequency components than R waves, they are less susceptible to sampling error caused by the sampling rate reduction.

Fig. 3 portrays a flowchart of the proposed signal processing. First, ECG is output from the AD converter with a low sampling rate (F_S). Next, ECG is interpolated and resampled at 1,024 Hz. In this case, it is assumed that the frequency components of F_S / 2 or more are filtered before AD conversion. Then, the R wave peak is coarsely detected. It is noteworthy that the sampling error has not been corrected yet at this process. Finally, the sampling error is corrected as portrayed in Fig. 4. A template window of 600-ms width is defined around the detected R peak. A search window with the same width is defined around the next R peak. The time at which the correlation is the highest is obtained by shifting the search window in the range of ±1 / F_S around the coarsely detected R peak. As a result, searching around the coarsely detected R peak shorten the search range and the calculation amount can be reduced. A period between that time and the previously detected R peak is estimated as the heartbeat interval.

B. Performance Evaluation

Fig. 5 depicts evaluation results of sampling error correction. A measured ECG with a healthy subject, a 23 -year-old man, is used. Linear interpolation is used as the interpolation algorithm. Figure 5(a) portrays a comparison of heartbeat intervals extracted from reference ECG with 1,024-Hz F_S, and downsampled ECG with 32-Hz F_S. As presented in Fig. 5(b), the proposed method can mitigate the sampling error of down-sampled ECG compared with conventional peak detection.

Fig. 6 portrays the relation between the sampling rate and root-mean-square error (RMSE) of the heartbeat interval. As the interpolation algorithm of the proposed method, three methods are compared: linear interpolation, quadratic spline, and cubic spline. Measured ECG with five healthy 22- to 24-year-old men are used. The duration of each ECG is 20,000 s. Using the conventional peak detection method, the RMSE increases because of the sampling error. However, the RMSE of the proposed method is 1 ms or less, even at 32-Hz F_S. Also, adequate precision is achieved even if linear interpolation is used. Linear interpolation with few calculations is beneficial to minimize the power consumption overhead. According to prior studies [7, 8], the sampling rate of 250 to 500 Hz or higher is required for HRV analysis. Because the sampling error is 2 ms with 500-Hz sampling rate, we choose 32-Hz sampling rate with linear interpolation, which has 2-ms or less RMSE as shown in Fig. 6.

III. Sampling Rate Effects in HRV Analysis

A. HRV Analysis

In HRV analysis, the heartbeat interval change is analyzed in the time domain or the frequency domain [1]. For this study, we specifically undertake analysis of frequency components of HRV in the frequency domain.

For frequency analysis of HRV, spline interpolation is performed on the series of heartbeat intervals, with resampling at 1 Hz. Then, a low-frequency component (LF) and a high-frequency component (HF) are used as indicators of HRV. The respective frequency ranges of LF and HF are 0.05 Hz to 0.15 Hz and 0.15 Hz to 0.40 Hz. The sum of the power spectra in those frequency ranges is calculated.

LF of HRV is affected mainly by sympathetic nerve activity and partly by parasympathetic nerve activity. By contrast, the HF of HRV is affected mainly by the

(a)

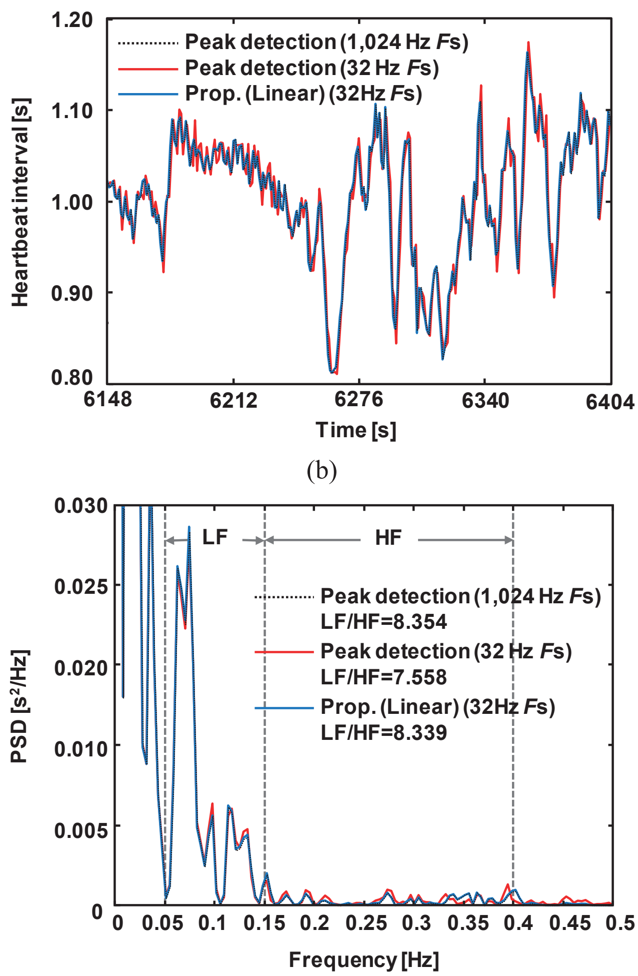

Fig. 7. Examples of measured (a) heartbeat interval extracted from 1,024-Hz F_S and (b) HRV analysis result with high LF/HF.

(a)

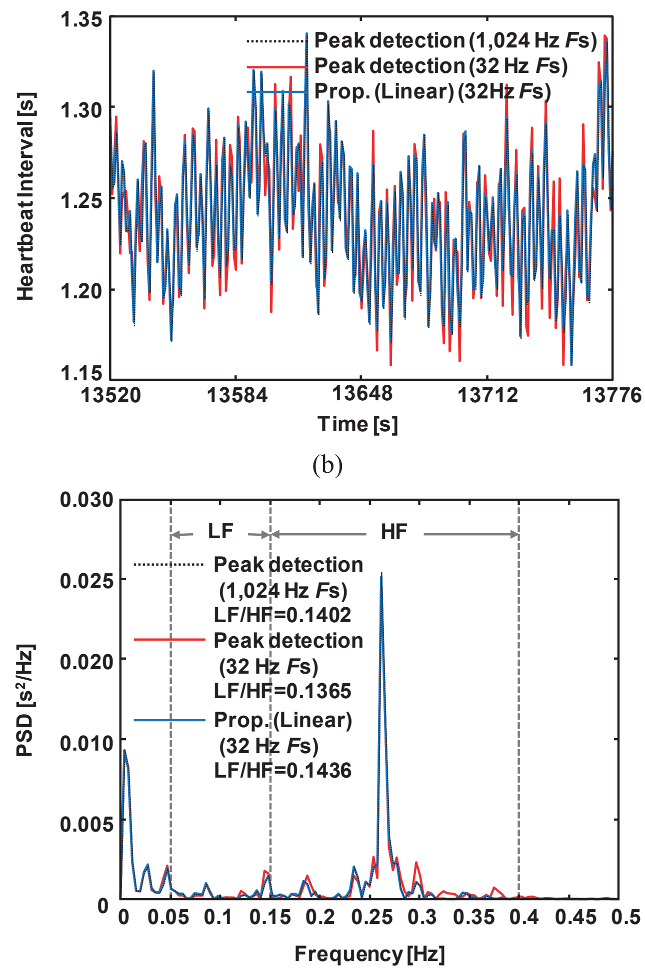

Fig. 8. Examples of measured (a) heartbeat interval extracted from 1,024-Hz F_S and (b) HRV analysis result with low LF/HF.

parasympathetic nerve. Therefore, the balance of autonomic nerves can be estimated from the magnitude and balance of LF and HF. As described herein, LF/HF, which is the ratio of LF and HF is adopted as an index. When LF is larger than HF, the sympathetic nerve is tensed. Conversely, when the HF is larger than the LF, the parasympathetic nerve is tensed.

Figs. 7 and 8 respectively depict examples of heartbeat intervals and its power spectral density (PSD) obtained by fast Fourier transform (FFT). The ECG with 1,024-Hz F_S and 32-Hz F_S are used, which are extracted parts of the data presented in Fig. 5. The FFT window length is set to 256 s.

B. Sampling Error Effects

Figs. 7(b) and 8(b) respectively portray HRV analysis results obtained using the peak detection method and the proposed heartbeat extraction method, which are described in Section 2. As shown in Figs. 7(b) and 8(b), LF/HF fluctuates depending on the measured time, even for a single subject. Because HRV analysis uses heartbeat interval fluctuation, the heartbeat interval error affects the analysis result directly.

Not much difference is found between the results of the peak detection with 1,024-Hz F_S ECG and the proposed method with 32-Hz F_S ECG. However, the result of the peak detection with 32-Hz F_S ECG with high LF/HF (see Fig. 7(b)) is degraded by sampling error. This result agrees with the trend described in an earlier report [9]. The influence of the sampling rate on the error increases as the LF becomes higher, i.e., the LF/HF becomes higher. The proposed method mitigates shortcoming.

Finally, degradation of LF/HF is evaluated using 20,000 s duration long-term ECG data including previously used data shown in Fig. 5. Results show that the proposed method improves the root mean squared percentage error (RMSPE) of LF/HF from 28.3% to 1.04%. The root mean squared error (RMSE) also improves from 0.717 to 0.0291.

IV. Discussion

The sampling rate effect on the heartbeat interval extraction and HRV analysis was discussed in earlier works [9–11]. One report of the relevant literature [11] describes the use of interpolation and the Pan–Tompkins algorithm [12] to extract accurate heartbeat intervals from 50-Hz downsampled ECG. Then, the RMS error of 50-Hz F_S is 0.33 ms when compared with 5-kHz reference data. Although the absolute value of RMS error in this work (1 ms) is larger than the prior work, this larger error is attributable to the sampling rate of reference data, which is five times slower than in the earlier work [11]. The proposed method is superior in terms of the ratio of RMS error to the reference sampling rate. It is expected that the RMS error can be improved further if F_S of reference data are the same.

The proposed method can also be used for PPG sensors. Because the power consumption of the LED and the photodiode is large in the PPG sensor (see Fig. 9), they are operated concisely to conserve power [13]. Therefore, in PPG, the effect of lower power consumption by sampling rate reduction is greater than that of ECG.

Fig. 10 shows the result of sampling rate reduction in PPG.

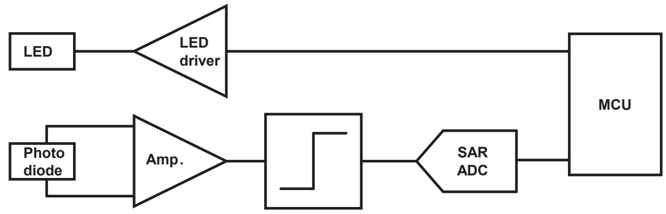

Fig. 9. Block diagram of PPG monitor.

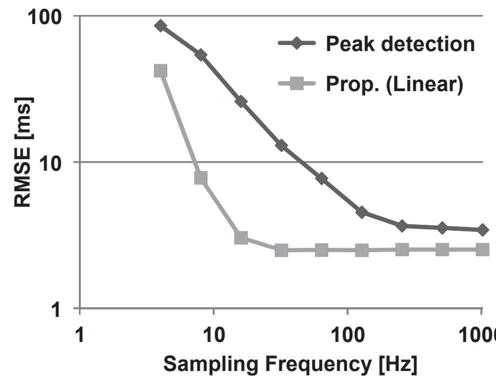

Fig. 10. RMS error comparison of heartbeat interval extracted from downsampled PPG. ECG with 1,024 Hz F_S is used as reference data. 60 s duration PPG and ECG data, measured simultaneously, are used in this evaluation.

For this evaluation, a 60 s duration of measured data with a 23-year-old subject is used. Then, 1,024 Hz F_S ECG, which is recorded simultaneously with PPG, is used as reference data. This result demonstrates that the proposed method is applicable to PPG and that it is more effective than ECG. Because PPG has a lower frequency component of peak waveform than ECG has, it is more suitable for use with the proposed method.

V. Conclusion

As described herein, we proposed a sampling rate reduction method for heart rate variability analysis with a wearable healthcare application. This study was conducted to reduce power consumption by reducing the active rate of the sensor front-end circuit. The evaluation results obtained using measured ECG show that the proposed fine-coarse heartbeat interval extraction method can reduce the sampling rate of ECG to 32 Hz F_S with 1 ms RMS error in heartbeat interval and 1.04% LF/HF degradation in HRV analysis.

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