

A Novel Approach to Classify Significant ECG Data Based on Heart Instantaneous Frequency and ECG-derived Respiration using Conductive Textiles

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Abstract— Our study focuses on classifying as significant Electrocardiogram (ECG) data from home healthcare system. Generally, spectral analysis of RR Interval (RRI) time series is used to determine periodic component of Heart Rate Variability (HRV). It is well known, moreover, that Low Frequency (LF) component is associated with blood pressure regulation, and High Frequency (HF) component is referred to respiration as Respiration Sinus Arrhythmia (RSA) in the HRV power spectra. In many cases, however, LF and HF components may be entirely superimposed on each other and, therefore, the method by division of power spectra range can not be evaluated diagnostically. We propose another approach to interpret well better than before. The method which we suggest is that it finds high correlative data using frequency analysis comparison Heart Instantaneous Frequency (HIF) based on extracting the instantaneous fundamental frequency with EDR. The reason which we use HIF is that it is simpler and more powerful against noise than HRV. First of all, we show the EDR extraction process, and then prove that HIF signal is useful or not through comparison with HRV. Finally, we classify significant signal data through comparison High Frequency (HF) component obtained frequency analysis of HIF with that of EDR.

I. INTRODUCTION

IT has taken a growing interest in home healthcare as time goes by. This concern causes that boundary of healthcare expand out of hospital by Korea society as well as international. Bio-signal instrumentation methods, moreover, are changed from old method which has restriction like attachment electrode to unconsciousness and noninvasiveness method. The concept of home healthcare is not only spreading to world wide in a context, but also makes rapid progress about study of that at all around. It, besides, is not the concept that healthcare system move simply from hospital to home. It is the one that you can check your health

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condition whenever and wherever you want. It, however, is unreasonable that ordinary people diagnose their condition, also can be damaged by all wasted prescription. We consider this concern as an easily solvable problem by applying the concept of “Ubiquitous”. It connects anyone who use this service to server which administer the users, also can always check own condition. Electronic healthcare systems which have ubiquitous concept can enable medical professionals to remotely make real-time monitoring, early diagnosis, and treatment for potential risky disease, and provide the medical diagnose and consulting results to the patient via wired/wireless communication channels [1]. The most important features of these devices are unconscious and noninvasive instrumentation method. Devices for home healthcare should be reflected with these considerations as follows. The one is that acquisition of health condition information does not give pain or burden to patient. Another is that these devices must no restriction of living condition.

As a part of constructing ubiquitous healthcare system in our research, we have built testbed for simulating general outcome. This testbed is composed of 3 sections, bedroom, living-room, and lavatory. In this study, we focus bedroom section where electrocardiography (ECG) signal is acquired continuously from the bed using two conductive textile electrodes. The concept of no attachment electrode is suitable to nonconsciousness and noninvasiveness. Respiration signal, moreover, is attained by ECG without a thorax belt by signal processing. It is known that the heart rate fluctuates in response to changes in real respiration. This fluctuation is called Respiration Sinus Arrhythmia (RSA). We classify the RSA as a frequency modulation occurring in the cardiac signal, which makes the heart rate vary according to changes in respiration, that is, ECG-Derived Respiration (EDR) signal. Generally, individual frequency range of the High Frequency (HF) component of Heart Rate Variability (HRV) has been determined only by means of distinctive parameters of respiration such as respiratory rate, range and median value of respiratory rate, etc [2]. However, in many cases Low Frequency (LF) components and HF components may be superimposed on each other totally or particularly and can not be diagnostically estimated because respiratory rhythms are individually much remarkably differentiated.

Therefore, it is necessary to classify significant respiration signal which reflecting real that signal. In this study shows the classification using frequency analysis between Heart

Instantaneous Frequency (HIF) and EDR signal from ECG, whereas that using frequency analysis between HRV and EDR signal from ECG in [3]. It is the reason that HIF signal is simpler than HRV signal. It is necessary to get HRV signal that R-wave detection method which requires a hundreds of sampling frequency, but HIF method can be used to estimate the HRV from ECG signal sampled at a frequency about 5Hz [4].

First, we show the EDR algorithm. Second, check the cross-correlation between HRV and HIF, and then estimate to find out a significant respiration data by analyzing of frequency between EDR and high correlation HIF with HRV.

II. METHODOLOGY

Our system based on a ubiquitous concept transmits 1-channel ECG signal which acquired from two electrodes in bed to host server through Bluetooth node. All signal processing in this paper work with LabVIEW™ 8.2 version of National Instruments.

A. Hardware

In this study, as ECG amplifier using only two electrodes, it could not make a RL-drive. Therefore, It is necessary to make ECG amplifier with high common mode rejection ratio because it is used that each electrode which made up conductive textile (pillow electrode size: 103cm × 50cm, leg electrode size: 149cm × 41cm) is bigger than normal standard electrode. First, we assume that two electrodes and RL electrode are connected as impedance combination model. That output passes resister-capacitor connection of RL-drive, and then it enter two electrodes again. It makes low value of common mode input voltage. Incomplete common mode input voltage is sampled by multiple of this signal, removed by moving average filter in microcontroller (MSP430F149, Texas Instruments). Bluetooth model we used is Korwin Corporation's product using BTM2711CO of Samsung Electronics Corporation. Transmission part of Bluetooth is connected with RS232, transmit ECG data to host computer by 300Hz sampling frequency. Second, RF module model is Nano-24 of Octacomm Corporation. Because they have unique identification value each user respectively, a system identify user when user come near RF module. Then host computer compare data and store each user respectively by data included ID information.

B. EDR Extraction Method

The general procedures of EDR extraction methods are cubic spline interpolation and anti-aliasing low-pass filter for real-time measurement, respectively. Since the EDR extraction method using cubic spline interpolation is widely known, only the proposed method will be described herein. In this extraction method, R wave intervals are used without calculating the precise amplitude of R wave or the area of QRS section. Initially, baselines are removed by high pass filter, and then RR interval in determined and upsampling of

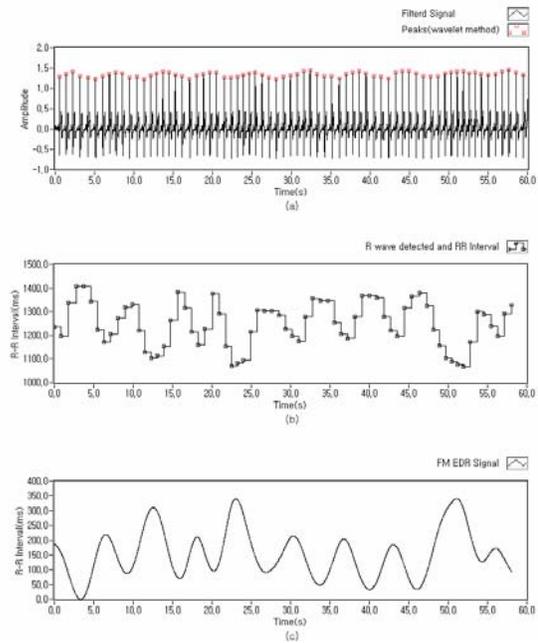


Fig. 1. EDR extraction process. (a) R wave detection process. (b) RR interval (cardiac event series). (c) Cubic spline interpolation method.

multirate signal processing is conducted [5]. Finally, the derived respiration is extracted by removing and regularizing DC and low frequencies. As a result, we get the single-lead EDR. Generally, single lead EDR is expected to be worse in performance than others using two leads [6], [7].

Nevertheless, lead dependency, which results in different ECG modulation tendencies depending on personal respiration characteristic, heart position, and rotation, is also expected and Lead I and III do not meet at right angles, thus the EDR extracted from single lead might show clearer results depending on a person [8]. As for the ECG-derived respiration extraction method with single lead, it can be obtained by using the amplitude of R waves and the area within QRS section or using RSA; in this study used the latter one.

C. Heart Rate Variability

Investigation of HRV has been the subject of considerable interest in the status of the autonomic nervous system (ANS). The extraction of HRV and its power spectrum which shows the beat-to-beat modulation of the heart rate depend on accurate R peaks detection from variability of the QRS complexes. However, for obtaining HRV, we require high sampling of the ECG signal to the order of hundreds of samples per second. It involves large memory requirement and much calculation time in signal processing. On the other hand, although we get the HRV through high sampling, spectrum analysis of HRV is limited only to 0.4Hz. If the processing of R peaks detection does not working in any section of data, R peak missing, it replies transient response. Subsequently, in this study, we use HRV for comparison with HIF signal because of wasted memory and time issues.

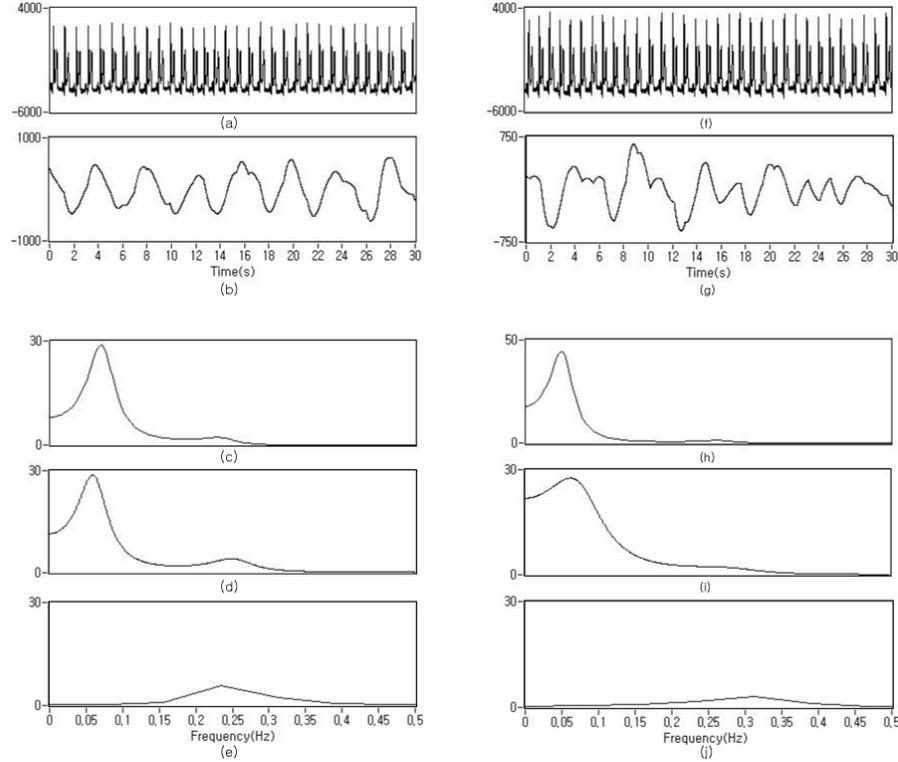


Fig. 2. Classification of significant data in every 5 minutes. Every power spectrum is processed by AR modeling. (a) ECG raw signal which have high correlation. (b) EDR raw signal which have high correlation. (c) Power spectrum of HRV which have high correlation. (d) Power spectrum of HIF which have high correlation. (e) Power spectrum of EDR which have high correlation. (f) ECG raw signal which have low correlation. (g) EDR raw signal which have low correlation. (h) Power spectrum of HRV which have low correlation. (i) Power spectrum of HIF which have low correlation. (j) Power spectrum of EDR which have low correlation.

D. HIF Extraction Method

HIF is basically extracted from the spectrum response of the ECG. It has to be filtered in an effective method, because ECG signal has multiple harmonics. That is having only the fundamental frequency of ECG signal. As this fundamental frequency varies with time, we consider filter characteristics according to time variation [9]. ECG signal which is acquitted at bed is originally sampled at 300Hz. First, ECG signal is down sampled to 5Hz. Next stage, the signal $S(t)$ which is filtered by band pass is estimated by Short Time Fourier Transform (STFT) in (1):

$$P(t, f) = \frac{1}{2\pi} \left| \int e^{-j2\pi f\tau} S(\tau) h(\tau - t) d\tau \right|^2 \quad (1)$$

where $h(\tau - t)$ is a window function which slides along $S(t)$. It is obtained that dominating frequency at each time point. This matches up the maximum of $P(t, f)$ in a given frequency range. We termed this value the $\delta(t)$, and it is given by (2).

$$\delta(t) = \arg \max_f [P(t, f)]_{\delta(t-\alpha)}^{\delta(t)+\alpha} \quad (2)$$

We define α as the frequency value that limits the search range, and $\delta(t-)$ as the value at previous time $t - [1]$. We give 0.5Hz to α , and it is same with filtering by 0.5-1.5Hz band pass.

We actually derive the mean value from STFT spectrogram. When we compare HIF signal of maximum value with that of mean value from STFT spectrogram, it is confirmed that the signal of mean value is more similar to HRV signal than maximum value.

III. TEST & METHOD

We acquire ECG signal from healthy 10 subjects. All of measurement environment accomplish during sleeping time, whole data is auto automatically divided in 1 hour interval, and then 1 hour data divided is divided in 5 minutes interval again. It prepares to start data analysis.

First, we must prove that the correlation between HIF and HRV has the value above 0.5 in (3).

$$hrv(t) * hif(t) = \int_{-\infty}^{\infty} hrv(\tau) hif(t - \tau) d\tau \quad (3)$$

We compare HIF with HRV each 1 hour data and result are shown at table 1. Each hour of values is cross

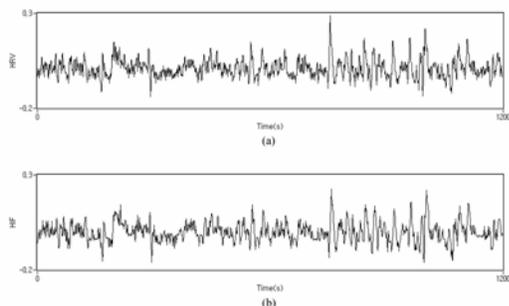


Fig. 3. The transformed time series of HIF and HRV. (a) HRV signal. (b) HIF signal.

correlation values about continuous 4 hours except first 1 hour and after 5 hour data. When comparison stage is finished, classification stage for significant EDR signal is processed using the compatible HIF data of former step.

We disregarded LF component but interested in only HF component because power spectrum of respiration signal by RSA have range from 0.15Hz to 0.4Hz [10]. If spectrum cross correlation is lower than 0.5, it is removed automatically. Figure 2 is shown that raw ECG signal, EDR signal, and power spectrum of HRV, HIF, and EDR. The spectrum below time domain signal is for classification of momentous respiration signal through cross correlation method.

The classification of set of significant data is confirmed as useful data because cross correlation results are mostly bigger than 0.6. Through this study, we show possibility of significant data acquisition using HIF during sleeping as well as active time.

TABLE I
RESULT OF CORRELATION BETWEEN HIF AND EDR SIGNALS

Subject	Cross correlation between HIF and EDR			
	1 st hour	2 nd hour	3 rd hour	4 th hour
1	0.51	0.48	0.69	0.65
2	0.54	0.58	0.46	0.58
3	0.69	0.61	0.59	0.53
4	0.68	0.63	0.67	0.61
5	0.55	0.57	0.56	0.53
6	0.54	0.46	0.67	0.64
7	0.44	0.64	0.67	0.66
8	0.57	0.62	0.61	0.45
9	0.61	0.68	0.59	0.56
10	0.59	0.50	0.69	0.64

IV. CONCLUSION

Generally, it exist an unwanted signal, transient response, etc, in bio-signal measurement. Data from home healthcare system based on ubiquitous, specially, is easily contaminated by noise because environment is not limited in contrast to the agency like a hospital.

In this paper, first of all, we show the probability that HIF

can instead of HRV as tool of finding to significant data range. Although EDR extraction procedures need the R peak detection process, HIF process is simpler than HRV because HIF does not need interpolation process, so that it can reduce analysis time on signal processing. Therefore, we can get the result faster than using HRV analysis.

In addition, we classified the ECG signal needed for the further diagnosis or research through comparison between HF components of HIF instead of HRV and a single lead EDR signal which the methods of extraction are already known.

In conclusion, this study can give help which delivers accurate diagnosis and treatment to patient by classification of significant bio-signal data in a short time.

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