A Real-time Sleep Monitoring System with a Smartphone

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***Abstract*— Recently, health care service is not only considered as a business, but also a wellness service offered by the public sector. In the past, the health care focuses on primary care, specialty care, and emergency treatment. In the present, the goal of the current health care is disease prevention and wellness. Today, home health care is one of the fastest-growing categories of health care services. Although home health care services respond to the needs of the cognitively impaired for help with ADL and IADL impairments, sleep-related problems in physiology have increased due to absence of physical diagnosis skills. In this paper, we propose a real-time sleep monitoring system that analyzes the sleep state using obtained signals from multiple sensors. The proposed system collects various signals including ECG, orientation, audio, acceleration signals in real time. From the signals, the system analyzes the sleep quality, the sleep apnea, and stroke. In the experiments, the proposed system shows the estimation results of heart rate, respiratory rate, obstructive sleep apnea, and stroke diagnosis.**

Keywords—Health care; Sleep monitoring; OSA; Sleep apnea; Smartphone, Acoustic sensor, Quality of sleep

I. INTRODUCTION

Ubiquitous healthcare (u-health) indicates health care and medical services that can be used “anytime and anywhere” with multiple devices and network technology. U-health care can be applied to medical service prevention of a disease and diagnosis. Recently, numerous researches based on u-health care technologies have performed to investigate in primary care, specialty care, and emergency treatment while asleep.

In this paper, we developed a sleep state monitoring system to prevent the obstructive sleep apnea (OSA) and stroke. OSA is one of an insomniac and is caused by obstruction of the upper airway. In the other hand, a stroke occurs when the blood supply to part of the brain is suddenly interrupted or when a blood vessel in the brain bursts, spilling blood into the spaces surrounding brain cells. Sleep problems are common after a stroke. More than half of all stroke survivors have some type of sleep problem. Poor sleep can slow your recovery and lead to depression, memory problems, and night-time falls. Sleep plays an important part in not only helping the brain to heal, but in physical healing as well. In order to sleep better and improve sleep quality, the proposed system not only collects ECG signals, orientation, audio, and acceleration data, but also estimates heart rate, audio, sleep pose, and the number of apneas while asleep.

Finally, the proposed system analyzes quality of sleep [1]. Furthermore, the system also carries out diagnosis of OSA and stroke.

II. METHODS

A. Acoustic and apnea analysis

The audio signal was collected from a built-in microphone sensor on a smartphone. The audio signal was recorded at 8 kHz using uncompressed one-channel 16-bit pulse-code modulation. In addition to sound signals, the amplitude of the envelope was also computed. First, the audio signals were low-pass filtered at a cutoff frequency. The amplitude of the envelope was calculated as the magnitude of its analytic signal which is computed by variance of a log [2] every second as follows:

$$Y_{\text{audio}}(\mathrm{n}) = \log(\mathrm{Var}\,[\mathrm{S(n)}] + 1), \tag{1}$$

where S(n) is the amplitude acquired audio signal.

The resulting signals were then digitized and stored into the smartphone for further processing offline. Breathing rate ranges from 0.03Hz to 0.83Hz frequency and an apnea is defined when there is no breath for 10 seconds [2][3]. In this paper, filtered audio signal is obtained by FFT. Figure 1 shows the experimental setup using a microphone and measured audio signals. As shown in Figure 1-(a), a microphone was attached around subject’s nose. Figure 1-(b) shows audio raw

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signals that measured by a microphone sensor for 30 seconds during sleep.

(a)

(b)

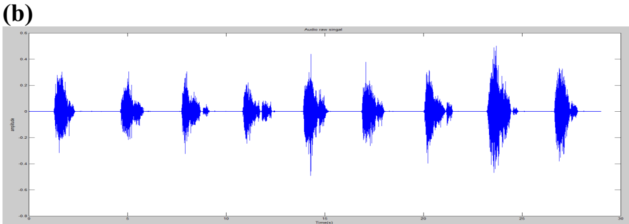


Figure 1. Example of recorded breath sound. (a) experimental setup; (b) raw audio signal

B. Actigraphy and body position

Actigraphy is a non-invasive method of monitoring human rest and activity cycles. Sleep actigraphs are generally watch-shaped and worn on the wrist of the non-dominant arm. They are useful for determining sleep patterns and circadian rhythms and may be worn for several weeks at a time. In this paper, actigraphy was developed using acceleration data obtained from a built-in 3-axis accelerometer on a smartphone. In order to measure the accurate moving data, the acceleration of gravity was removed from raw data.

The accelerometer data consists of three measurements at each time step, corresponding to the acceleration along each of the three axes x, y, and z. We combined these three measurements to form a single measure of the magnitude of the acceleration vector a as follows:

$$a = \sqrt{x^2 + y^2 + z^2} - g, \tag{2}$$

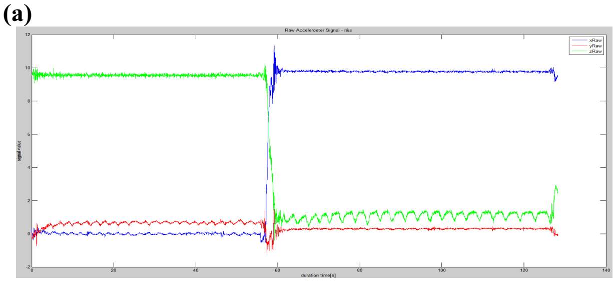
where $g = 9.8\mathrm{m}/s^2$ is the Earth's gravity.

Subtracting g causes the acceleration when the device is at rest or moving at a constant velocity to be 0. The acceleration vector a is applied to low-pass filter for noise removal, which is computes by logarithm of the variance [2] with the computed acceleration vector every second.

$$Y_a(\mathrm{n}) = \log\left(\mathrm{Var}\left[\mathrm{A(n)}\right] + 1\right). \tag{3}$$

Figure 2 shows 2-minute recording with a 3-axial accelerometer. Figure 2-(a) shows acceleration raw signal x, y and z on a smartphone during sleep that measured with sampling rate of 50Hz for 2 minutes. Figure-2 (b) shows magnitude that computed using filtered acceleration with cut-off frequency at 1.65Hz.

(a)



(b)

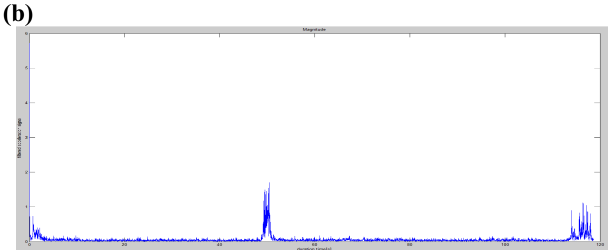


Figure 2. Example of recorded acceleration and magnitude. (a) 3-axis acceleration during sleep; (b) magnitude that is computed using acceleration data

The body position is computed using an accelerometer sensor and a geomagnetic sensor on a smartphone. The roll angle is computed using x, y and z measured from an accelerometer sensor. Table 1 shows the body position mapping with the pitch and roll angles.

Table 1 Body position mapping (pitch and roll)

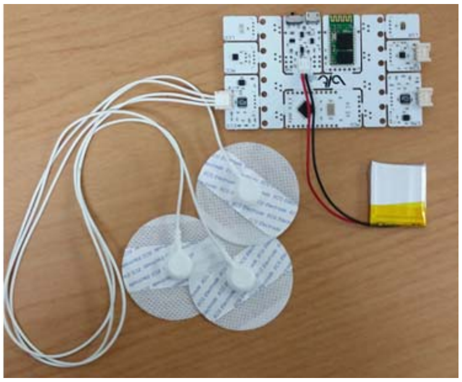
Position	Pitch (degree)	Roll (degree)
Supine	-45 ~ 45	-45 ~ 45
Prone	-45 ~ 45	-180 ~ -135 or 135 ~ 180
Right	-	-90 ~ -45
Left	-	45 ~ 90
Sitting	-135 ~ -45 or 45 ~ 135	-45 ~ 45

C. Heart rate estimation

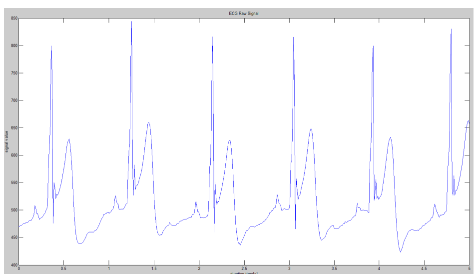
From the ECG, the heart rate is measured using the R wave to R wave interval (RR interval). ECG data were obtained from Bitalino [4] that is able to communicate with a smartphone via Bluetooth in real-time. The measured signals were filtered using a moving average filter. In addition, QRS slope is computed from filtered signals for finding the R-peak. The R-peak is found by the QRS slope value using the moving-window integration. Finally, it decides whether R peak is really generated. Physiologically, if QRS occurs, it does not detect R peak because peak does not occur again in less than 300ms. If peak occurs and new R peak occurs in less than 300ms, When it is a half times more than previous peak, it can decide as new R peak otherwise it. If R peak is greater than the detection threshold, it is considered QRS complex. Otherwise, it is considered to be noise [5].

Figure 3 shows an ECG device on Bitalno, measured ECG raw signals, and filtered ECG signals. Figure 3-(b) shows measured raw signal for 3 second by using Bitalino. ECG signals are measured by sampling rate of 300Hz. Figure 3-(c) shows filtered ECG signals with passed moving average filter that is smoother than Figure 3-(b).

(a)



(b)



(c)

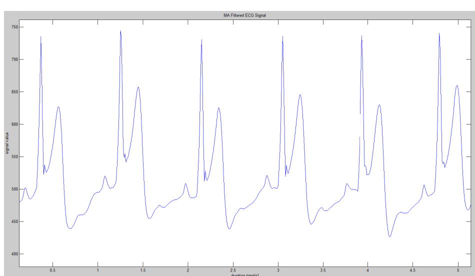


Figure 3. Example of recorded ECG signal on Bitalino. (a) ECG device on Bitalino; (b) ECG raw signal on Bitalino; (c) MA Filtered ECG signal

D. OSA diagnosis

OSA is diagnosed by acoustic, apnea analysis, and an actigraphy using multi scale entropy (MSE) [6][7] to analyze the filtered signals. Then, the proposed system classifies activities with a kernelized support vector machines (SVM)[8], then, estimates the diagnostic rate with OSA.

E. Stroke symptom

HRV (heart rate variability) is the physiological phenomenon of variation in the time interval between heartbeats. HRV changes measured from stroke patients are significantly lower than that from normal person. Based on ECG analysis, the stroke symptom is diagnosed by calculating the RMSSD [9] obtained from the HRV value. The RMSSD is calculated as follows:

$$RMSSD = \sqrt{\frac{\sum_{i=1}^{n-1}(N_i - N_{i+1})}{n-1}}, \qquad (4)$$

where *n* indicates the total number on the analyzed signal and *i*, the duration of the i-eth interval; N is the number of R-R intervals in the series of selected data. In general, the RMSSD of normal persons is approximately 18.9 to 44.3 milliseconds, whereas the RMSSD of patients with stroke symptoms is 7 to 39 milliseconds [10].

F. Quality of sleep

Sleeping pose is defined as unconscious motions during sleep such as rotational body movements. A change in sleeping pose is defined as a series of trunk motions from a static state to the static state from rotational motions during sleep [11]. The movement of limbs alone was not regarded as a change in sleeping pose. Hence the body positions are grouped into four categories: supine, prone, left, and right as follows:

$$S_{quality} = A * W, \qquad (5)$$

where *A* is the normalized magnitude value of the acceleration vector and W is weight factor, which is empirically determined: $\mathrm{W_{supine}} = 0$, $\mathrm{W_{prone}} = 1$, and $\mathrm{W_{left\ and\ right}} = 0.5$.

III. Experiments

Data were collected from 3 subjects who are between 24 and 28 years old. To acquire ECG, acceleration, and acoustic signals for OSA and to measure sleep quality, and apnea, each participant was asked to sleep for 7 hours with a smartphone and a built-in microphone was placed around a subject's nose as shown in Figure 4.

Figure 4. Experimental setup for sleep monitoring

Figure 5 shows screenshots of the developed smartphone application for sleep monitoring that shows ECG, Actigraphy, acoustic readings, and the number of sleep apnea.

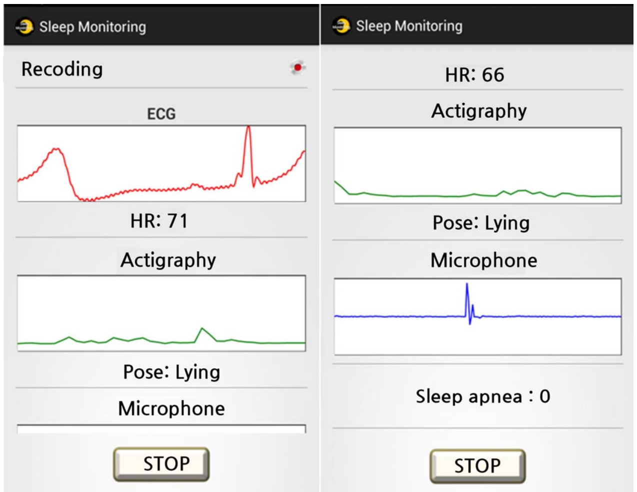


Figure 5. Smartphone application for sleep monitoring

For the evaluation, ECG MIT-BIH database [12] has been used for diagnosis of a stroke symptom. Table 2 shows the experiment results of sleep quality. The average sleep time was roughly 7 hours, Subject 1 experienced the best sleep quality over the three subjects because indicators of the Subject 1 represent better than the one of other subjects. The number of sleep apnea and total time of subject's dominant sleeping pose are more important than the total time of sleep. The sleep quality of Subject 3 was calculated is the lowest sleep quality because Subject 3 actually suffered from OSA. These results show that the proposed sleep quality monitoring system has very high efficiency and reliability.

Table 2 Experimental results

Subject	RMSSD	OSA	Body position	$S_{quality}$
1	23 ± 14	25 %	Supine	80.0
2	25 ± 14	45 %	Left	75.3
3	22 ± 13	50 %	Supine	70.0

IV. Conclusion

In this paper, we have developed a real-time sleep monitoring system that can collect vital signals from an ECG device and a smartphone. It is shown from the preliminary results that the OSA and Stroke can be prevented by the OSA diagnosis and quality of sleep. It is expected that future work by either our laboratory or others will result in additional other vital sign capabilities directly from ECG with a smartphone via Bluetooth and acoustic signals acquired from either a smartphone or tablet for sleep monitoring.

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