SMART DETECTION ALGORITHM FOR SNORING AND APNEA

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Abstract- To evaluate sleep quality, it is necessary to be able to accurately measure and analyze sleep disorders such as snoring or apnea. In recent years, sleep care applications and devices have been introduced, but accurate measurement techniques are required because these applications and devices do not take users' snoring intensity and characteristics into consideration. In this paper, we proposed a smart snoring measurement method and algorithm that correct the data measured in sensors by considering regular snoring characteristic and snoring sound strength that vary from person to person. Furthermore, the proposed algorithm was developed to detect more than 10 seconds of apnea so that the degree of sleep disorders can be evaluated. In addition, we have proved the cognitive performance of the proposed algorithm through experiments and suggested ways to improve the accuracy in the PSQI index, which indicates quality of sleep in the sleep medicine field.

Keywords- Internet of Things, Snoring, Apnea, Smart Algorithm, Sensor, PSQI

I. INTRODUCTION

Sleep disorders such as snoring or apnea may cause chronic fatigue and reduce agility, leading to the increased risk of cardiovascular and endocrine disorders. It is possible to diagnose the degree of sleep disorders through the polygraph, but this is inconvenient and costly because several sensor devices must be attached to the body for 12 hours.

As the number of smartphones users increases, sleep care applications with various functions have been developed. These applications can easily measure sleep information without help from others, they do not provide adaptive services tailored to user personality, because snoring sound strength and sleep patterns vary from person to person. In particular, the time to go to sleep and sleeping hours vary from day to day, they cannot be evaluated appropriately while providing sleep care services.

In this paper, the authors propose a smart adaptive snoring method that compensates for snoring sound strength, which varies from person to person. This measurement technique can acquire more accurate information on sleep disorders by continuously compensating using the initially set threshold value to set the snoring sound strength to fit the person to be measured.

The authors intended to implement an adaptive snoring algorithm and conduct experiments to compensate for actual sounds and recognize snoring and apnea, validating the proposed technique

Using this algorithm can improve the accuracy in the Pittsburgh Sleep Quality Index (PSQI), which is used to evaluate an individual's sleep disorders from the perspective of sleep medicine. PSQI is an index of sleep quality, which is composed of 19 questions and evaluates the sleep information over the last one month through examination by interview. Measurement and accumulation of sleep data automatically using the adaptive snoring algorithm proposed in this paper makes the calculation of the PSQI index more accurate than the conventional method which relies on memory. Thus, this method has the advantage of facilitating more accurate sleep care.

II. SMART DETECTION ALGORITHM

The algorithm in Fig. 1 begins from when the user goes to bed and falls asleep (state <- sleep).

A sound timer is used to periodically measure the sound generated during sleep to acquire e (envelope) signal data.

To determine if the e-value it falls into the snoring category, the sound is compared with t (threshold) value. Experimental results show that the snoring sounds have periodicity at intervals of about 1 to 2 seconds, so it confirms SoundOn () and isSoundOff () in Fig. 1. If the snoring sound (e) falls into a category, it is stored in the data (GatheringData ()). If unexpected noise is detected in the process of sound measurement, it is filtered (RemoveOutliner ()).

Apnea refers to a state where breathing has stopped for more than 10 seconds. If there is no sound for more than 10 seconds after snoring, this is considered sleep apnea (state <- apnea).

However, if there is no sound for more than 45 seconds, it is judged to be sleeping without snoring (state <- sleep) rather than apnea. Therefore, the algorithm has two timers to execute isSnoreCycleOn () and isSnoreCycleOff () to confirm the periodicity of the snoring sound.

```
Detection algorithm for snoring and apnea
state <- Sleep
Initialize(e<-envelope, t<-threshold, data)
InitTimer(Soundtimer)

For all timeout event of Soundtimer {
 switch (state)  {
   case Sleep :
        If  isSoundOn(e, t)
          if  isSoundOff(e, t)
              data <- GatheringData(e);
              if (data) state <- Snoring
         else
            data<-RemoveOutliner(e)
```

```
case Snoring :
        If (10 <= Timeout >= 45)   state<-Apnea
        if (Timeout < 45)  state <- Sleep
        else
           Settimer(10, 45)
           if  (isSnoreCycleOn(e, t))
              ResetTimer()
              if  (isSnoreCycleOff(e, t))
                Settimer(10, 45)
case Apnea :
        state <- Snoring;
 }
}
```

Fig.1. Smart detection algorithm for snoring and apnea

III. EXPERIMENT AND RESULT

3.1. Experiment procedure

Fig. 2 shows a testbed for monitoring sleep state. It implemented a sleep monitoring module including a smart detection algorithm in RaspberryP3 (A). A humidity sensor (F), an illuminance sensor (I) for monitoring sleeping environment, an NFC reader (D) for recognizing and identifying the user, a human body sensor (H), and a sound sensor (G,E) to monitor sleep state are connected to (A) through the interface module (B).

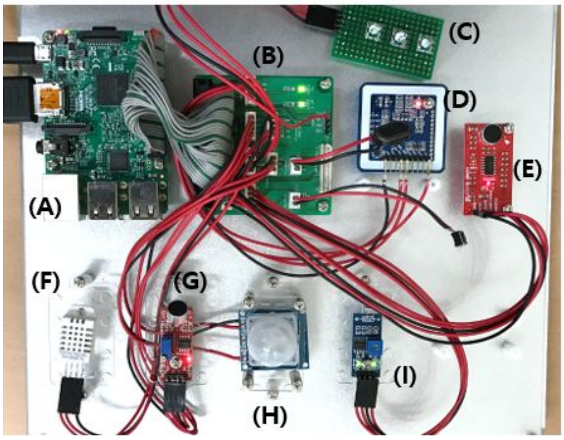

Fig.2. Testbed on raspberry pi platform

A Raspbian operating system was installed on the Raspberry Pi (A) hardware platform and the smart detection algorithm was programmatically implemented with JavaScript on the Node.js framework.

In this experimental environment, when the user goes to sleep, the user prepared for sleep with an NFC card tacking. From this moment, whether the users entered a sleep state was detected using the H, I, or E sensors. When the user was recognized as in a sleep state, E sensor and smart detection algorithm were used to measure snoring and apnea. E sensor used LMV324, and the measured data was compensated by considering the snoring intensity and the sleep pattern of the user.

Two experiments were carried out: one to acquire the compensation factor (a) to compensate the measurement data and the other to recognize snoring and apnea using the obtained compensation factor.

3.2. Experimental result

The LMV324 sensor (E in Fig. 2) outputs an analog volt value (envelope) according to the sound strength. The value is 50-90 when the sound is quiet,100-120 when sound is normal, and 130-250 when the sound is loud.

When the snoring sound is normal, the results shown in Fig. 3 were obtained. As in the third case, if the snoring sound was normal (upper part of Fig. 3), the sound was not measured properly in some cases (lower part of Fig. 3). The problem is that if the snoring sound is low, it cannot be measured properly. To resolve this problem, the measured data values envelope values were compensated as shown in Fig. 4.

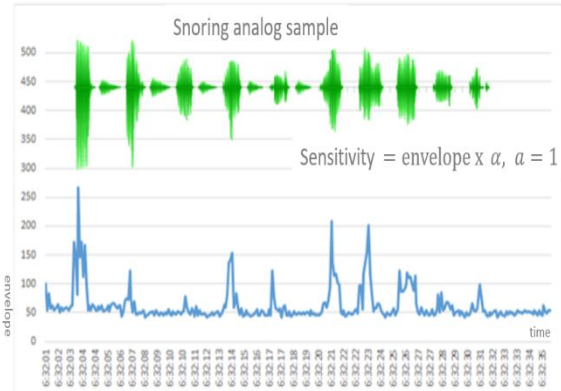

Fig.3. Signal for snoring sound and its detection signal from LMV324 sensor using α=1

As shown in Fig. 4, the third snoring sound was recognized as a snoring sound. By multiplying the original envelope value by 2, more accurate recognition could be achieved.

In addition, if the envelope value was multiplied by 3, the results shown in Fig. 5 were obtained. In this case, however, the sound was difficult to recognize as snoring. In other words, the data is distorted due to the correction. In conclusion, through experiments, we found that that multiplying by 2 gave proper results.

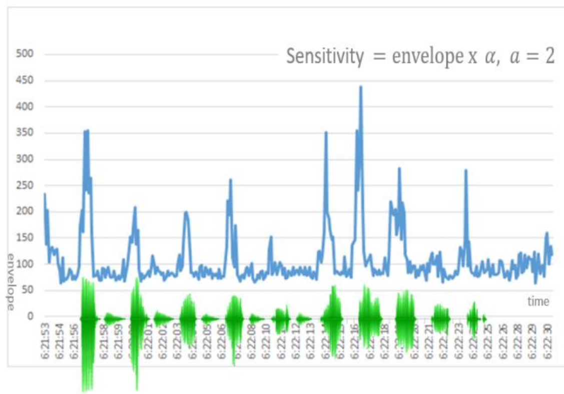

Fig.4. Signal for snoring sound and its detection signal from LMV324 sensor using α=2

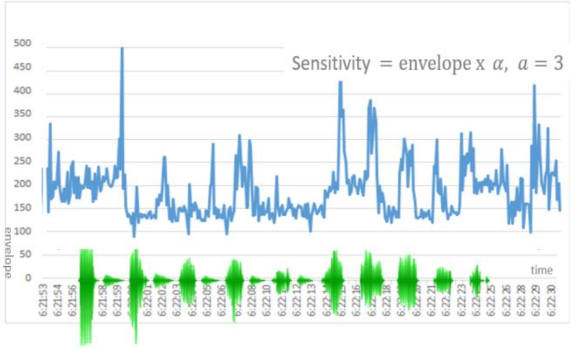

Fig.5. Signal for snoring sound and its detection signal from LMV324 sensor using α=3

In the following cognitive experiment, two-fold data compensation was used to see how accurately the snoring and apnea were recognized as shown in Fig. 6. One apnea cycle lasting from 10 to less than 40 seconds (a), consecutive snoring cycles, and the next snoring cycle (b) were checked where they were detected appropriately. The results showed that snoring cycle and apnea were detected accurately.

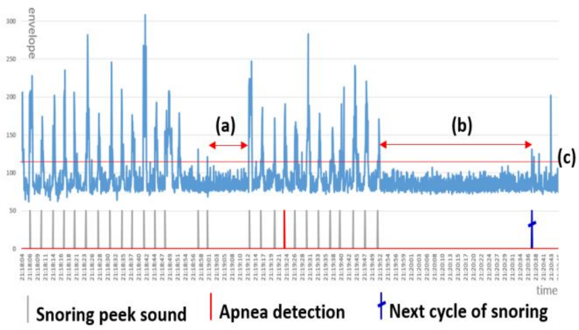

Fig.6. Experimental results for the detection of snoring and apnea

However, to solve the problem of incorrect recognition of noise as snoring in the experimental process, recognition was only possible when the next snoring cycle (+) was confirmed, causing slight differences in the timing.

CONCLUSIONS

Various sleep care applications have been developed, but proper sleep information must be measured to evaluate more accurate sleep quality. In this paper, the authors proposed an adaptive algorithm that simultaneously measures data from various sensors in the Raspberry Platform and evaluates sleep state and sleeping information using this data in a complex manner.

After compensating for the measured data from the sound sensor, the authors could verify the effectiveness of the proposed algorithm by detecting snoring and apnea. However, there was a difference in the timing in the process of detecting the next sound and determining whether the snoring cycle was a continuous snoring cycle or the end of a snoring cycle. Further studies on the compensation of the difference in timing are required.

In addition, further studies to optimize the threshold values are required because terminals and applications that measure the sleep information can serve to enable tailored services when they are shared between family members.

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