

A Breath Counting System Based on a Non-invasive Method

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Abstract

In this paper, we implemented a system to count breath rate with a non-invasive sensor. The proposed system consists of a pad covered with a piezoelectric sensor, a breath extraction device amplifying and filtering the source signals and sending those to a viewer, and the viewer with a function of sensor data visualization and a breath counting algorithm. A breath counting experiment on three subjects was performed by changing the number of moving averages and values of thresholds. When the window size for moving average was chosen as $N = 50\sim 60$ and the threshold value for each subject was customized, the proposed system showed less than 5% error rate.

Keywords: *breath, non-invasive method, piezoelectric sensor, bio-signal processing, u-healthcare*

1. Introduction

Asphyxia means the failure of pulmonary respiration caused by disrupted transportation between the alien and lungs. In most cases, the death due to suffocation occurs within 4-5 minutes and therefore, without being treated quickly and properly, suffocation leads to a sudden death. That is why it may well be classified as a very dangerous disease [1]. In particular, a major cause of 29.3% among infant deaths is the respiratory distress and congenital malformations of the heart [2]. Therefore, we need a simple respiratory diagnostic device that facilitates an instant treatment to cope with emergency situations such as suffocation.

Many researches are underway in a variety of ways to develop a method of measuring the breath signal. Invasive measurement method is to pierce the skin for measuring biological signals or to insert a probe or a sensor for measurements through a passage such as the esophagus or urethra. The use of an invasive type sensor enables accurate measurements. However, it is very inconvenient for people whose biological signals need to be monitored in their daily lives in the long term [3]. Therefore, this paper aims to develop a suffocation prevention device which utilizes non-invasive sensors to get the breathing information without causing any inconvenience for everyday life by the non-bound or non-intrusive method to which the subjects can be insensible.

The breath counting system implemented in this paper consists of the cover pad with an off-the-shelf piezoelectric sensor, a device to amplify, filter, and AD (analog-to-digital) convert the breathing signal, and a viewer program to visualize the sensor data and count breath rate.

This paper is organized as follows. In Section 2, the existing related works are introduced and discussed for comparison. Section 3 presents the overall structure of the breath counting system and describes the elements constituting the system. Section 4 explains about experimental method for breath counting, preprocessing and a devised algorithm. Section 5 shows experimental results of applying the algorithm to extract the breathing signal and count breath rate. Conclusion is made in Section 6.

2. Related Works

Y. Yamana *et al.*, [4] let ultrasonic waves emitted from an opening made under the bed mattress and used the reflected waves to extract the breathing signal for obtaining the information about the respiratory activity and physical movement of the user.

Xin Zhu *et al.*, [5] carried out a research to utilize a tube-type pressure sensor installed under the pillow to measure the bio-signal around the back part of the head and use the signal to collect the information about breathing and motion of the subject in the sleep state in a long period of time. The wavelet-based algorithm and statistical moment-based technique are used to extract medically meaningful information from the signal data collected at the pressure sensor. This network-connected system can not only monitor the sleeping state of the subject for a long period of time at a low cost, but also analyze the biological rhythm such as the menstrual cycle.

Ji-Young Cha *et al.*, [6] utilized a pillow equipped with a PPG (Photoplethysmogram) sensor to monitor the respiratory activity during sleep where the PPG sensor picks up the breathing signal based on the linear relationship between the blood volume varying with contraction and relaxation of the heart and the amount of light absorbed by hemoglobin in the blood. They tried to extract the breathing information from the magnitude and phase of the signal measured at the PPG sensor. However, the sensor mounted on the pillow, while easy to install, maintain, and repair, has a problem that continuous monitoring fails when the subject's head gets away from the pillow during sleep.

T. Reinvoio *et al.*, [7] performed an experiment of measuring the respiratory rates of 10 subjects in a supine position and in a sitting position where a belt with a high-resolution accelerometer is attached to their chest and an EMF (Electro-mechanical film) pressure sensor to their sternum, heart, xiphoid, and the pit of the stomach. The experimental results show that both MEMS and EMFi sensor methods are fine for the respiration measurement purpose and their average reliabilities are 90% and 90~100%, respectively.

J. Alametsä *et al.*, [8] proposed a measurement system in which the sensor output data is recorded into their own Mobile Physiological Measurement Station. They used the sensors attached to the chest (below the shoulder and above the waist), the arm (the wrist and upper part of the arm), and above and below the leg (the thigh and the ankle) to pick up the bio-signal while the subjects are normally breathing. The bio-signal can be picked up through an EMFi sensor sheet mounted to the seat on which the subject sits or the ECG (Electrocardiogram) electrodes attached to both sides of the chest.

Breath monitoring is considered as an important indicator for determining the physiological state of a human-being. In this context, the breathing information is extracted and used for diagnosis in a normal medical examination or treatment as well as an emergency situation. It is an example that the presence or absence of patient respiration, abnormal respiration rate (RR), and the breathing pattern are important data for the diagnosis of heart disease. It is another example that an abnormal increase of respiratory volume is an important data for the diagnosis of oxygen deficiency in human tissue [9].

3. The Proposed System

3.1. The Overall System

The proposed system, shown in Figure 1, is made of three components, the sensor pad, a breath extraction device, and a viewer program for sensor data analysis. The cloth-covered sensor pad contains an off-the-shelf piezoelectric sensor.

The breath extraction device amplifies, filters, and AD-converts the sensor output signal, and then transmits the digital data to the viewer via a UART (Universal Asynchronous

Receiver / Transmitter). The viewer can visualize and save the digital sensor data into a file, play it back, and capture the screen output. When a subject lies on the bed mattress, the piezoelectric sensor generates a voltage signal reflecting the pressure change caused by breathing and transmits it to the microcontroller mounted on the bio-signal processing board.



Figure 1. System Configuration

3.2. Piezoelectric Sensor

The sensor used in this paper is an EMFIT's L-3060SL sensor [10], which is a thin wide film type of piezoelectric sensor. It has a weight of 110g and a size of 600×300 mm so that it can be embedded in the pad, being suitable as a non-restraint sensor. A piezoelectric sensor, like a condenser consisting of two parallel plates (electrodes) separated by a dielectric, outputs a voltage proportional to the force applied to the sensor regardless of wherever it is pressed. Its capacitance varies as the width of the plates and the distance between the two plates change due to an external pressure or displacement [11]. That is, given pressing force to the piezoelectric sensor is corresponding to the magnitude of the output power voltage.

To get the reference signal helping in measuring a breath rate, an Interlink Electronics FSR-408's power (force) sensor [12] of size 15×622 mm is used where its resistance varies with the pressing force.

3.3. Breath Extraction Device

The pressure applied to the sensor depending on the breathing of the subject lying on the pad laid over the bed is to be measured, but it is very weak. In the implemented breath extraction device, the source signal from the piezoelectric sensor is about 40,000-fold amplified using a 2-stage OP-AMP (Texas Instruments LM358 [13]) and then filtered through a virtual BPF (band-pass filter). The BPF has been realized by a cascade connection of two Butterworth-type filters [14] where one is a HPF (high-pass filter) with cutoff frequency 0.72Hz and the other is a LPF (low-pass filter) with cutoff frequency 0.79 Hz so that its passband is 0.72~0.79Hz as shown in Figure 2.

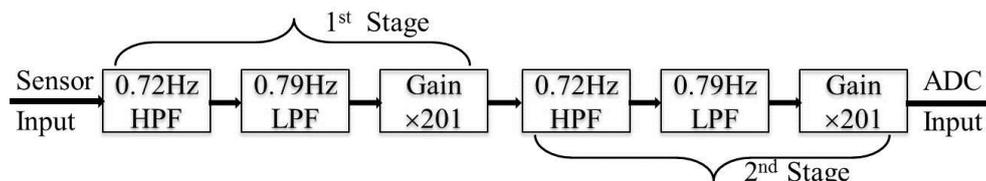


Figure 2. Amplifier and Filter Configuration

The BPF output is applied as an input to the 12-bit ADC in which it is sampled with sampling frequency 1 kHz, passes through a data smoothing filter, and then is converted

into 12-bit digital data with the period of 50Hz. The 12-bit ADC is converted to a positive number in the size of 4095 for the input voltage [15].

We have used TM4C1231E6PM [16] of ARM Cortex-M series, Keil MDK ARM Compiler 4.72 [17], and RL ARM 4.0 as microcontroller, compiler, and real-time operating system, respectively. Convenient maintenance and stability is well modularized program features.

3.4. Viewer for Data Analysis

The digital sensor data by the ADC is applied as an input to the computer by serial communication via the USB cable and analyzed by the viewer. The viewer can visualize and save the digital sensor data into a file, play it back, and capture the screen output and save it as an image in a JPEG file.

Figure 3 illustrates a viewer showing the graph, which is the plot of the respiratory sensor data in real time for a subject lying on the bed. The graphic window is shown in Figure 3, where the x-axis represents time as seconds, minutes, and hours and y-axis represents the value of ADC converted to a positive number.



Figure 3. Viewer for Data Analysis

We have used the Java language in Eclipse 4.2 Kepler, JDK 7u15 environment to develop the viewer program where the major libraries and tools are listed in Table 1.

Table 1. Libraries and Tools

Libraries and Tools	Details
JFreeChart	plots the piezoelectric sensor data vs. time
RxTx Comm	presents functions for serial communication in Java environments
WindowsBuilder Pro	enables editing window control easily (like Visual Studio) for making window applications in Java Eclipse environment
JSmooth	converts JAR programs composed in Java into Window execution files
Matlab R2009b	reads the sensor data saved in a file and analyzes the respiratory data

4. Breathing Extraction Algorithm

4.1. Experimental methods and conditions

In the experiment for developing a breathing extraction algorithm, the respiratory signal has been collected when the subject is lying in a relaxed state on the pad with a piezoelectric sensor. Every time the subject starts breathing, the force sensor attached to the breathing extraction device is tapped so that the reference signal for respiration is obtained.

The experiment related with this paper has been performed for a 20-year-old man, a 50-year-old man, and a 50-year-old woman in a laboratory as shown in Table 2. It took a total of 4 hours for two days in order to collect the breathing sensor data for 5 minutes per subject.

Table 2. Information about Subjects

Subject	Age	Sex
A	20	Male
B	50	Male
C	50	Female

4.2. Preprocessing

The respiratory sensor output signal is often contaminated by a large noise of high frequency and has nonzero values even during the idle time with no subject. A moving average filter [18] is effective for the purpose of removing the high frequency noise. We obtain the average by adding the new values except the oldest of the moving average. In general, the moving average is used to highlight the long-term trends or cycles and smooth short-term variations in the time axis.

The moving average used in this paper can be expressed as

$$M_t = \frac{1}{N} (X_t + X_{t-1} + \dots + X_{t-N+1})$$

where as the sample size N increases, the original signal is less preserved while the high-frequency noise is more reduced.

To determine an adequate value of N such that the original signal can be preserved well enough while most high-frequency noises are removed, we repetitively applied the moving average filtering with $N = 20, 30, 40, 50, 60,$ and 70 where $N = 50$ or 60 yielded 100% recognition rate for the subject B. The same trials have been run for the other subjects.

4.3. Breath Counting Algorithm

The breathing counting algorithm after the pre-process consists of three phases as shown in Figure 4. The first phase is to set the threshold for the rising/falling of the breathing signal. The second phase is to estimate the average duration of one respiration period and the average respiratory interval between successive breaths for a certain period of time. The third phase is finally to count the number of breathing cycles. Before the algorithm is performed, find the average of the peak values $\{M_1, M_2, M_3, \dots\}$ of the sensor data obtained for a certain period of time, and calculate the averages of respiratory durations and inter-breath intervals.

The algorithm is depicted as a flowchart in Figures 4~6.

(Step 1) Compare the last value that a peak value M_i has been read by the algorithm.

(Step 2) Find the average \bar{M} of the peak values $\{M_1, M_2, M_3, \dots\}$ of the sensor data obtained for a certain period of time, and set properly at the threshold value TH for the rising and falling intervals. Let $D_{r,1}, D_{r,2}, D_{r,3}, \dots, D_{r,i}$ and $D_{i,1}, D_{i,2}, D_{i,3}, \dots, D_{i,i}$ be the respiratory durations and the inter-breath intervals respectively. Set $D_{r,i} = M_{2i} - M_{2i-1}$, $i=1, 2, \dots$ and $D_{i,i} = M_{2i+1} - M_{2i}$, $i=1, 2, \dots$, and compute the average \bar{D}_r of $D_{r,i}$, the average \bar{D}_i of $D_{i,i}$, and $\bar{D} = (\bar{D}_r + \bar{D}_i) / 2$ where \bar{D}_r and \bar{D}_i are the averages of respiratory durations $D_{r,i}$ and inter-breath intervals $D_{i,i}$. Let C, C_r , and C_i be the number of breathing cycles, the number of respiratory durations, and the number of inter-breath intervals respectively. Initialize all variables C, C_r , and C_i to zero.

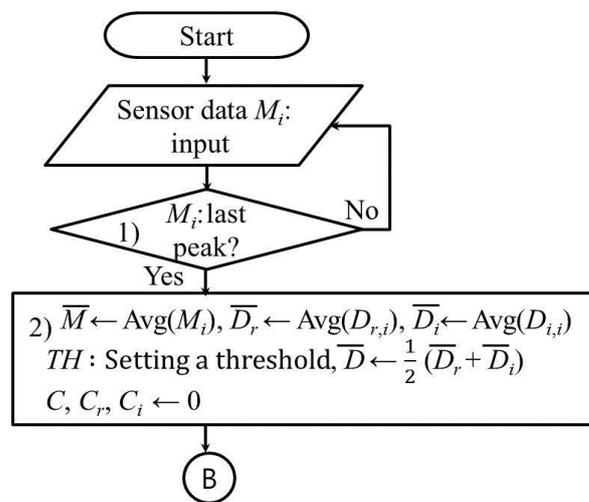


Figure 4. Flowchart of the Breathing Extraction Algorithm (phase1)

(Step 3) Input a respiratory duration $D_{r,i}$.

(Step 4) Compare whether a value $D_{r,i}$ is greater than $\bar{D}_r - 20$.

(Step 5) If a respiratory duration $D_{r,i}$ is greater than $\bar{D}_r - 20$, it is determined as a breathing cycle and thus C_r is increased by one. But if it is not, it is determined as a duplicated input signal and thus go to step 8 without any counting.

(Step 6) Compare whether a respiratory duration $\bar{D}_{r,i}$ is greater than $\bar{D}_r + 20$.

(Step 7) If $D_{r,i}$ is greater than $\bar{D}_r + 20$, it is determined as a wrong respiratory duration, despite of the presence of respiratory signals and thus C_r is increased by the rounded integer part of the quotient of the respiratory duration $D_{r,i}$ and \bar{D} .

(Step 8) Make sure the algorithm have read the last value of $D_{r,i}$.

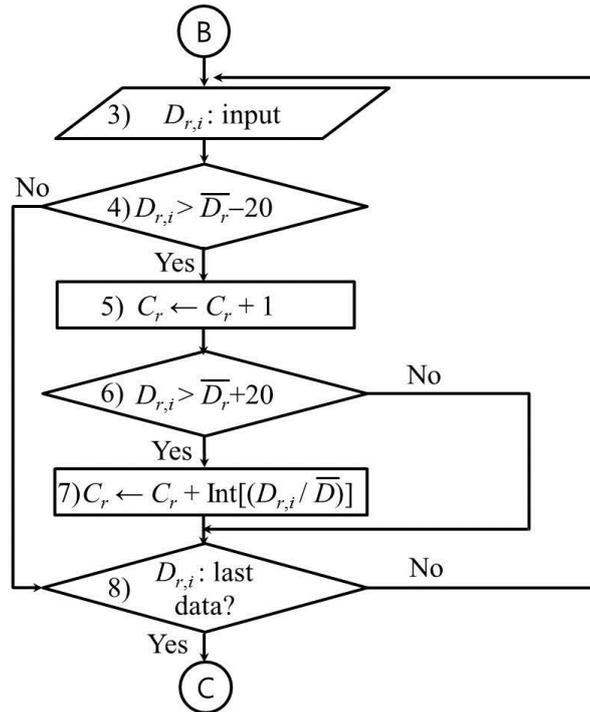


Figure 5. Flowchart of the breathing extraction algorithm (phase2)

(Step 9) If $D_{r, i}$ is the last value, run from step 3 to step 7(the add/delete algorithm) for $D_{i, i}$.

(Step 10) Make sure the last value of $D_{i, i}$ has been read. If it is not the one, go back to the step 9, and then repeat the steps.

(Step 11) If the values $D_{r, i}$ and $D_{i, i}$ has been finished all processes, fix the number C of breathing cycles as $C \approx \frac{C_r + C_i}{2}$ rounded to the nearest integer.

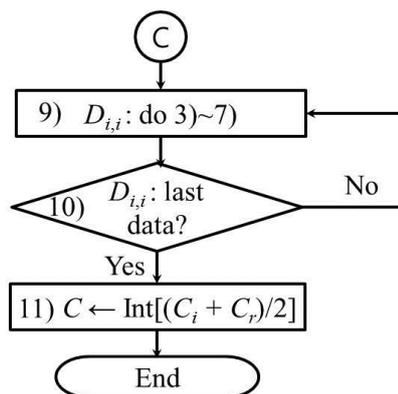


Figure 6. Flowchart of the Breathing Extraction Algorithm (phase3)

The parameters used for the estimation of the number of breathing cycles are listed in Table 3.

Table 3. Variables in a respiration extraction algorithm

Symbol	Meaning
M_i	Peak value of breath signal at time t
TH	Threshold of breath signal level
$D_{r,i}$	Respiratory duration
$D_{i,i}$	Inter-breath interval
C	Number of breathing cycles
C_r	Number of respiratory durations
C_i	Number of inter-breath intervals

5. Breath counting experiment and analysis

5.1. Application of the breathing counting algorithm

Figure 7 shows the respiratory signal of Subject A that has been collected for 30 seconds since 31 seconds after the experiment began where the number of samples for the moving average of breathing signal peak values is $N = 50$, the average peak value is 1717, the threshold value is $TH = 1100$, and the average respiratory duration and average inter-breath interval are $\overline{D_r} = 166 \approx 3.3[\text{sec}]$ and $\overline{D_i} = 133 \approx 2.7[\text{sec}]$, respectively. From the graph, the number of breathing cycles is estimated to be 5 since the interval between the last two peak times is so short (shorter than $\overline{D_r} - 20$) that it cannot be counted as a breathing cycle.

5.2. Result of a breathing counting experiment

For Subjects A, B, and C, the actual numbers of breathing cycles have been determined by comparing the estimated ones and the reference ones. The experiment has been performed with different values of thresholds (TH s) and the sample size N

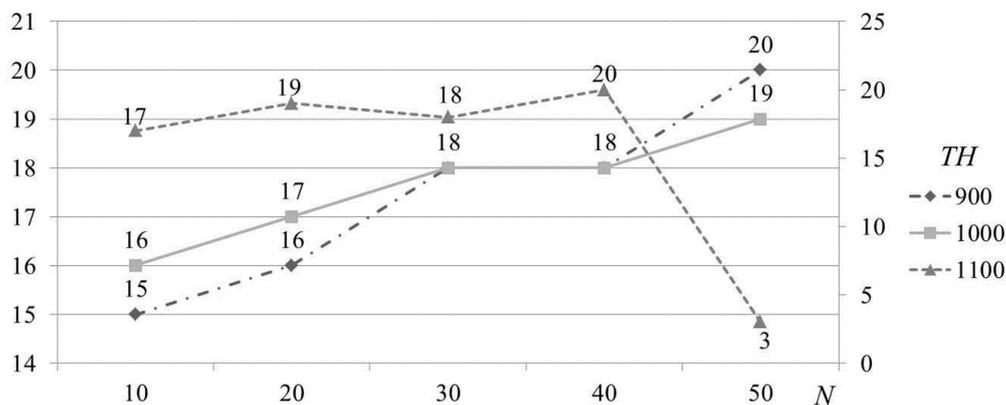


Figure 8. Estimated number of breathing cycles of the Subject A

for moving average (M.A.) and the results showed in Figures 8, 10~11 where the error rate is defined as

$$\text{Error rate} = \frac{\left| \begin{array}{l} \text{Actual number of breathing cycles} \\ - \text{estimated number of breathing cycles} \end{array} \right|}{\text{Actual number of breathing cycles}} \times 100 [\%]$$

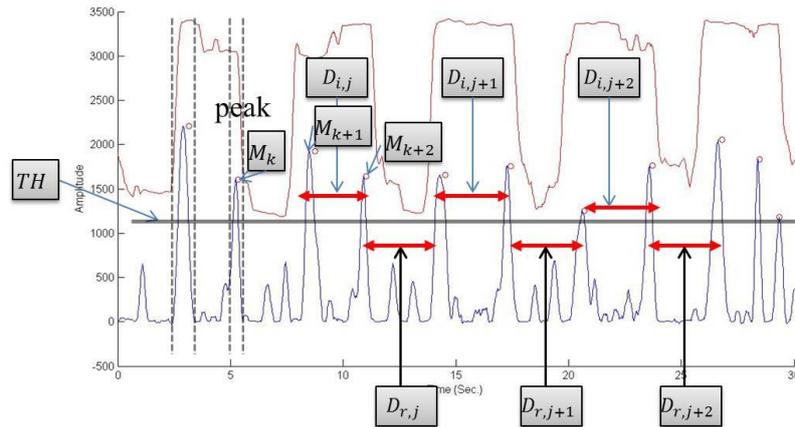


Figure 7. Respiratory signal of Subject A

The experimental data about Subject A in Figure 8 shows that the error rate turns out to be within 5% (the best) for the TH value of 900~1000 and the sample size $N = 50$ for M.A. where the actual number of breathing cycles for 2 minutes is 20, and the respiration period and inter-breath interval are $166 \approx 3.3[\text{sec}]$ and $131 \approx 2.6[\text{sec}]$, respectively.

In Figure 9 with the TH value of 1100 and the sample size $N = 50$ for M.A., only two peak values (greater than 1100) are detected and that is why the additive algorithm of the number of breathing cycles is run only in that interval between the two peaks. Consequently, the total number of breathing cycles is increased by 4 to become 6 so that the estimated number of breathing cycles is $6 \times (1/2) = 3$. Although the additive algorithm has been applied well in the above case, it may be difficult to estimate the number of breathing cycles exactly when the first and last peaks are not properly detected during the period of 1~120[sec](2 minutes). Also, when the sample size N for M.A. is as large as 60 and the TH value is as large as 1000~1100, the peaks become difficult to detect due to the large smoothing effect and the large TH value.

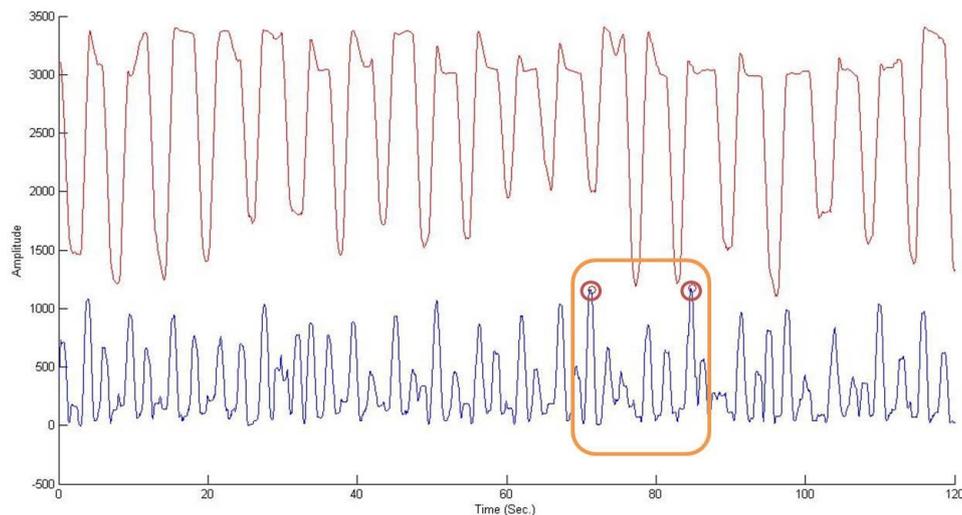


Figure 9. Respiratory signal of Subject A where $N = 50$, $TH = 1100$

The experimental data about Subject B in Figure 10 shows that the error rate turns out to be 0% for the following three cases:

- (i) $TH = 1000 \sim 1100$ and $N = 50$
- (ii) $TH = 900 \sim 1000$ and $N = 60$
- (iii) $TH = 1100$ and $N = 70$

where the actual number of breathing cycles for 2 minutes is 24, and the respiration period and inter-breath interval are $130 \approx 2.6[\text{sec}]$ and $95 \approx 1.9[\text{sec}]$, respectively.

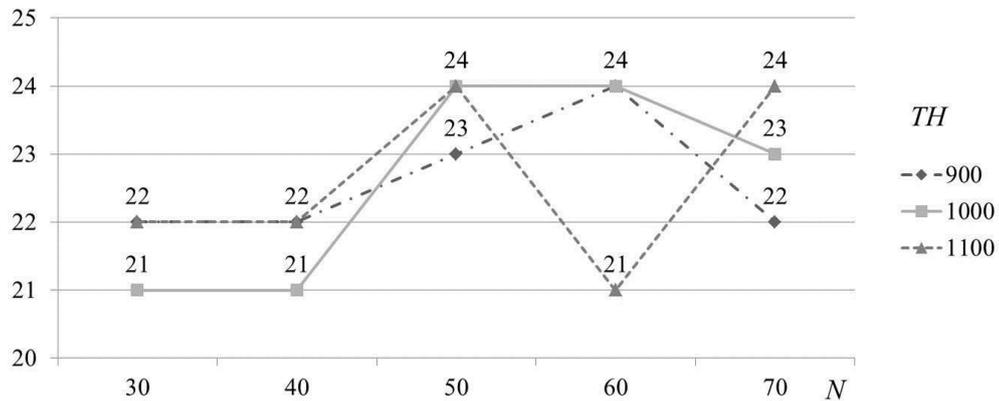


Figure 10. Estimated number of breathing cycles of the Subject B

In this case, the respiratory signal is so noisy that a large N , yielding a large smoothing effect, could result in a small error rate. Also, as the TH value becomes smaller, a larger value of N results in a smaller error rate.

The experimental data about Subject C in Figure 11 shows that the error rate turns out to be zero for $TH = 1300$ and $N = 50$, or for $TH = 1000$ and $N = 60$ where the actual number of breathing cycles for 2 minutes is 16, and the respiration period and inter-breath interval are $245 \approx 4.9[\text{sec}]$ and $108 \approx 2.2[\text{sec}]$, respectively. In this case, the respiratory signal is so noisy that the peaks could not be easy to detect with a small N and consequently, the respiration period and inter-breath interval become irregular, making the subtractive algorithm apply frequently. That is why such a relatively large value of N as $50 \sim 60$ has resulted in a smaller error rate.

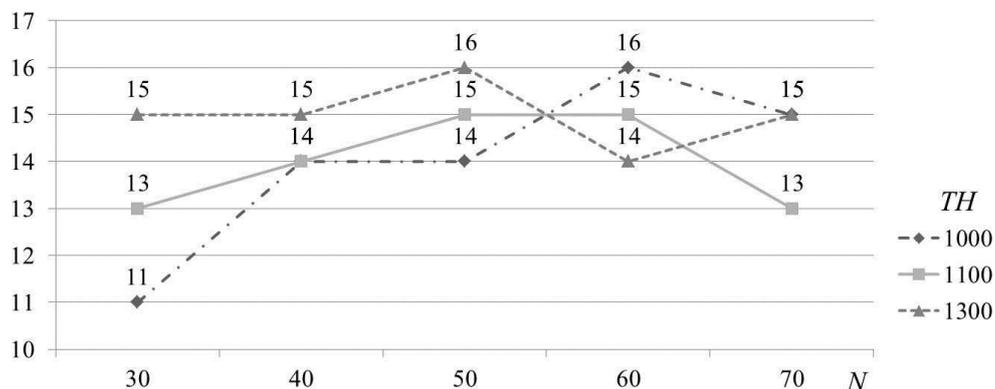


Figure 11. Estimated number of breathing cycles of the Subject C

In this case, the difference between the respiration period and inter-breath interval is so large that just removing the noise could yield a lower error rate.

Overall, as for the sample size for M.A., $N = 50$ yielded a good error rate for Subject A and similarly, $N = 50\sim 60$ yielded a good error rate for Subjects B and C. On the other hand, the range of TH values yielding a good error rate turned out to be different from subject to subject, which may be attributed to the unique physical feature of each subject. These results imply that it is good to choose the window size for M.A. as $N = 50\sim 60$ and customize the TH value for each subject. In the future, it needs to perform the experiments to collect the respiratory signals of the subjects while they are asleep.

6. Conclusion

In this paper, we implemented the system to extract breath signals and count the number of breathing cycles in which a non-invasive sensor is used to reduce inconvenience in a daily life. The proposed breath counting system consists of the cover pad with an off-the-shelf piezoelectric sensor, a breath extraction device with a microcontroller to amplify, filter, and AD convert the breathing signal, and the viewer to visualize, analyze, and store the sensor data. The system has been used to extract the breathing signals of three subjects with different values of thresholds (TH s) and the window size N for moving average (M.A.). According to the experimental results, it yielded a satisfactory error rate of 5% when $N = 50\sim 60$ and $TH = 900\sim 1300$.

The breath counting system is expected to make big contribution to protecting young infants and seniors living alone from some sudden death during sleep due to suffocation. Future research on a system that can count not only the breathing signal but also the pulsation signal is needed.

Acknowledgements

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