Unconstrained Respiration States Classification by Detecting Respiratory Cycle Using Autocorrelation

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Abstract: Daily sleep monitoring is necessary to make potential patients with sleep apnea syndrome aware of their respiration state during sleep. Although it is desirable to have an unconstrained system for daily monitoring in a home environment, the amplitude of respiration measured by an unconstrained sensor varies depending on the participants’ properties and the recumbent positions. In this study, we propose an algorithm for classifying the respiration state by extracting the respiratory cycle in the signal measured by an unconstrained respiration measurement system as a feature. We confirmed that the respiratory cycle obtained using autocorrelation has different characteristics between the breathing/respiratory arrest periods. By analyzing the respiratory cycle in the biological signal, it was found that the method was resilient to amplitude changes due to differences in the participants’ properties and in the recumbent positions. As a result of cross-validation to evaluate the proposed algorithm, the evaluation indices are all high, and it is confirmed that the algorithm is resilient to variations in the participants’ properties and in the recumbent positions.

Keywords: Autocorrelation, Respiration, Sleep Apnea, Pressure Sensor, Normal Distribution

1. INTRODUCTION

Sleep apnea syndrome is a fairly common sleep disorder. Although 930 million adults are estimated to have sleep apnea worldwide [1], the diagnosis rate is low—approximately 15%. Hence, daily respiration monitoring in a home environment is essential to make potential patients aware of their symptoms and encourage them to take appropriate countermeasures at medical institutions. Conventional studies using wearable sensors [2] are not suitable for daily use because of their strong constraints. Under these circumstances, unconstrained methods that could measure respiration without attaching any sensors to the participant’s body have been proposed [3]. The simplest way to detect respiratory arrest during sleep by an unconstrained method is simply by detecting a threshold to the time-series waveform from the sensor. Doing this is trivial because the amplitude of the waveform during a respiratory arrest is smaller than that of a breathing period. However, one reason for the difficulty in detecting respiratory arrest using the threshold method is that the amplitude varies with the patients’ properties such as body weight, height, and recumbent position. This study proposes an unconstrained method to classify respiration states that are resilient to variations in the participants’ properties and recumbent positions.

2. PROPOSED METHOD

Figure 1 shows an overview of the signal processing for breathing/respiratory arrest classification from the detected cycles by calculating an autocorrelation for the signals measured by the unconstrained respiration measurement system.

![Proposed method](image)

**Figure 1: Proposed method**

2.1 Unconstrained Respiration Measurement System

The vibration due to respiration propagates to change the inner pressure of the air mattress placed under the bed mattress. The inner pressure is measured by a pressure sensor, and the continuous signal is passed through an A/D converter to the computer as a discrete signal.
Since the size of the lungs is closely related to their physical properties, such as weight and height, respiration amplitude is different from individual to individual. In addition, the contact area between the bed mattress and the chest varies depending on the person’s recumbent position, which changes the vibration’s propagation efficiency and affects the amplitude of the pressure sensor output. Thus, the measured signal greatly depends on the participants’ properties and the recumbent position.

2.2 Signal Processing Flow to Classify Respiration States
We focused on cycles in the biosignal to classify respiration states (i.e., breathing and respiratory arrest) that were resilient to variations in the participants’ properties and recumbent positions. In this study, the recorded discrete signal is divided into 10 s segments, and the cycle is detected by calculating the autocorrelation of each segment. Three cycles were determined by finding the time peak locations and determining the average differences between them: the long, intermediate, and short cycles. These three cycles correspond to the respiration, pulse, and harmonic components of the pulse, respectively. To classify respiration states, the long cycle, which is the respiratory cycle, was used among the three cycles detected by autocorrelation in this study.

In the respiratory arrest period, the respiratory cycle is not detected, or even if detected, it is assumed to have different characteristics from the breathing period. Therefore, we detected the long cycle by autocorrelation using the training data and approximating the two-dimensional normal distribution in the breathing/respiratory arrest period from the scatter plot created by the sum of the correlations and the frequency of the long cycle in advance.

Breathing/respiratory arrest classification is performed by comparing probabilities. The probabilities are calculated using the approximated normal distribution for the sum of the correlations and the frequency of the long cycle detected by calculating the autocorrelation of the test data. If the probability of respiratory arrest is larger than that of breathing, the period is assumed to be a respiratory arrest period. In contrast, if the probability of breathing is larger than that of respiratory arrest, the period is assumed to be a breathing period.

3. EXPERIMENT

3.1 Experimental System
In this study, a pressure sensor was used [3] to measure respiration signal. A tube was sandwiched between two sheets: one end was sealed, and a pressure sensor was placed at the other end.

By placing this air mattress under the bed mattress, signals including respiration, pulse, body movements, and noise of the participant lying on the bed could be measured. The air mattress was placed 65 cm from the head end of the frame, such that it was placed under the participant’s chest. A bed mattress with a thickness of 20 cm was placed on top, and a participant lay down on it, as shown in Figure 2.

3.2 Procedures and Participants
In this experiment, the participants were asked to sleep in four possible positions assumed during sleep: supine, right lateral, left lateral, and prone.

The experimental flow is shown in Figure 3.

First, the participant lay down on a bed mat and was given a 40 s resting period. Then, simultaneous with the start of data measurement, the voice file created in MATLAB was executed. This voice file instructed the participant to stop breathing and reproduce the respiratory arrest state. During the 180 s of data measurement, the participant was instructed to reproduce the respiratory arrest state for 20–40 s, 80–100 s, and 140–160 s. In this verification experiment, we considered eight participants with various heights and weights. The total number of data points obtained was 32. The sampling frequency for the A/D conversion was set to 100 Hz.
3.3 Evaluation Method

The proposed system is evaluated by two types of cross-validation: leave-one-participant-out cross-validation and leave-one-recumbent-position-out cross-validation. Furthermore, five indices were calculated as follows:

\[
\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (1)
\]

\[
\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (2)
\]

\[
\text{PPV} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (3)
\]

\[
\text{NPV} = \frac{\text{TN}}{\text{TN} + \text{FN}} \quad (4)
\]

\[
\text{F-value} = \frac{2 \times \text{TP}}{2 \times \text{TP} + \text{FN} + \text{FP}} \quad (5)
\]

where TP, TN, FP, and FN represent a “true positive” (apnea detected as apnea), a “true negative” (non-apnea detected as non-apnea), a “false positive” (non-apnea detected as apnea), and a “false negative” (apnea detected as non-apnea), respectively.

4. RESULTS

4.1 Typical Example of Respiration Signals

Two examples of the output signals from the pressure sensor, namely, 10 s in the breathing period and 10 s in the respiratory arrest period, are shown in Figure 4.

![Figure 4: Respiration signal measured by the proposed unconstrained respiration measurement system](image)

Figure 4(a) shows the output signal in the breathing period. It includes many types of biosignals, such as respiration, pulse, and harmonics. Figure 4(b) shows the signal output during the respiratory arrest period. It only includes pulses and excludes harmonics with respiration. By calculating the autocorrelation of this 10 s waveform, we find three cycles: a long cycle, an intermediate cycle, and a short cycle. The results of the autocorrelation are shown in Figure 5. Long cycle peaks detected by autocorrelation are shown as pink inverted triangles, intermediate cycle peaks as blue asterisks, and short cycle peaks as red circles.

![Figure 5: Comparison of differences after autocorrelation between breathing and respiratory arrest periods](image)

Figure 5 shows the results of the autocorrelation in the breathing period. Three cycles due to respiration, pulse, and harmonic have been detected. Figure 5(b) shows the result of autocorrelation in the respiratory arrest period. In these 10 s, the long cycle was detected, but it shows different characteristics than the breathing period.

Figure 6 shows the two-dimensional normal distribution approximated from the sum of the correlations and the long cycle frequency components using the training data with Figure 4 and 5 as test data. It shows a scatter plot with the frequency components on the horizontal axis and the sum of the correlations on the vertical axis, as well as the marginal distribution of the approximated normal distribution.

![Figure 6: Two-dimensional normal distribution with correlation and frequency components](image)

The sum of the correlations and the long cycle frequency components obtained from the breathing period in Figure 5 are 0.006 and 0.218 Hz, respectively, and they are located in the blue square in the scatter plot in Figure 6. In
the respiratory arrest period of Figure 5, the sum of the correlations and the frequency components are 0.011 and 0.518 Hz, respectively, and they are located in the red square. In the breathing period, the probability of the breathing period and the probability of the respiratory arrest period, calculated from the normal distribution of the training data, were 0.005 and 0.001, respectively. Because the probability of breathing was larger than that of respiratory arrest, it was classified as a breathing period. In the respiratory arrest period, the probabilities are 0.001 and 0.011, and the probability of respiratory arrest was higher. For this reason, it was classified as a respiratory arrest period. Thus, the maximum probability estimation correctly classified the breathing/respiratory arrest period.

Figure 7(a) shows the probabilities for 180 s of data. Figure 7(b) shows the results of the classification based on the probabilities. The blue and red areas indicate the breathing period and the respiratory arrest period by voice instructions, respectively.

![Figure 7](image_url)

**Figure 7:** Results of the classification breathing/respiratory arrest periods at each discrete time step based on the probabilities

The probability of the respiratory arrest indicated by the red line is higher in the respiratory arrest period, indicating that the correct discrimination is being made.

4.2 Aggregation of Breathing/Respiratory Arrest Classification Result

Table 1 shows the results of the cross-validation.

| Cross validation | Sen. | Spec. | PPV   | NPV   | F-value |
|------------------|------|-------|-------|-------|---------|
| Participant      | 0.92 | 0.82  | 0.76  | 0.95  | 0.82    |
| Recumbent position | 0.91 | 0.83  | 0.73  | 0.95  | 0.81    |

According to the results of the cross-validation of the participant, the average F-value is 0.82. According to the results of the cross-validation of the recumbent position, the average F-value is 0.81. The evaluation indices were high, and we confirmed that the proposed method was not susceptible to variations in the participants’ properties and in the recumbent positions.

5. DISCUSSION AND CONCLUSIONS

We have presented the classification breathing/respiratory arrest periods from the detected respiratory cycle by calculating autocorrelations for the signals measured by the unconstrained respiration measurement system. According to the results of two types of cross-validation to evaluate the degree to which the proposed system is resilient to variations in the participants’ properties and in the recumbent positions, the indices are sufficiently high. Unconstrained apnea detection without the influence of the participants’ properties and the recumbent positions is possible using the proposed method.

One limitation of the presented method is the occurrence of multiple apneas in the divided data. In this study, the data were divided into 10 s segments to classify the respiratory state. However, there may be cases in which apnea occurs multiple times. In such cases, there is a problem in that the number of apnea occurrences cannot be correctly evaluated.

Of the three cycles detected from the biosignals, only the respiratory cycle was used for analysis. In future work, we will improve this method for better performance by utilizing the cycle information corresponding to the pulse and harmonics.

REFERENCES

[1] A.V. Benjafield, N.T. Ayas, P.R. Eastwood, R. Heinzer, M.S.M. Ip, M.J. Morrell, C.M. Nunez, S.R. Patel, T. Penzel, J.L. Pépin, P.E. Peppard, S. Sinha, S. Tufik, K. Valentine and A. Malhotra, “Estimation of the global prevalence and burden of obstructive sleep apnoea: A literature-based analysis,” The Lancet Respiratory medicine, Vol.7, No.8, pp.687-698, 2019.

[2] G. Surrel, A. Aminifar, F. Rincón, S. Murali and D. Atienza, “Online obstructive sleep apnea detection on medical wearable sensors,” IEEE Transactions on Biomedical Circuits and Systems, Vol.12, No.4, pp.762-773, 2018.

[3] Y. Kurihara and K. Watanabe, “Sleep-stage decision algorithm by using heartbeat and body-movement signals,” IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, Vol.42, No.6, pp.1450-1459, 2012.