Non-Invasive Monitoring of Respiratory Rate and Respiratory Status during Sleep Using a Passive Radio-Frequency Identification System

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SUMMARY In recent years, checking sleep quality has become essential from a healthcare perspective. In this paper, we propose a respiratory rate (RR) monitoring system that can be used in the bedroom without wearing any sensor devices directly. To develop the system, passive radio-frequency identification (RFID) tags are introduced and attached to a blanket, instead of attaching them to the human body. The received signal strength indicator (RSSI) and phase values of the passive RFID tags are continuously obtained using an RFID reader through antennas located at the bedside. The RSSI and phase values change depending on the respiration of the person wearing the blanket. Thus, we can estimate the RR using these values. After providing an overview of the proposed system, the RR estimation flow is explained in detail. The processing flow includes noise elimination and irregular breathing period estimation methods. The evaluation demonstrates that the proposed system can estimate the RR and respiratory status without considering the user’s body posture, body type, gender, or change in the RR.

key words: passive radio-frequency identification (RFID), received signal strength indicator (RSSI), respiratory rate (RR), sleep monitoring

1. Introduction

In recent years, owing to the advancement of Internet technologies and applied research, smart homes have gained prominence. In addition, monitoring people’s lives in smart homes has become essential from a healthcare perspective. Recording daily activities in the long term can enable visualization of changes in lifestyle and behavior. In addition, it can lead to the identification of diseases caused by unhealthy lifestyle habits. Furthermore, easier monitoring is expected to be useful not only for users interested in health, but also for health management in children, older adults, and users with disabilities. Several studies have demonstrated that monitoring the respiratory rate (RR) is an essential factor for effectively monitoring sleep quality. In general, changes in RR are one of the earliest major indicators of serious complications or diseases. However, they are often ignored because of the limitations of clinically established measurement techniques that require sensor mounting. In addition, concerns about breathing disorders during sleep are increasing. However, illnesses such as sleep apnea syndrome (SAS) are difficult to detect at an early stage, and patients often approach the hospital after their symptoms worsen. Furthermore, improving the quality of sleep improves the quality of life. Therefore, it is important to understand and improve the adverse effects of sleep deprivation and sleep disorders by sleep monitoring, which leads to a better quality of life. For long-term monitoring, it is essential to develop a simpler and less restrictive system.

There is a reported method to monitor RR using commercial cameras [1]. It allows the measurement of systolic blood pressure in addition to the RR and pulse. However, the use of a camera in ordinary households is challenging because the feeling of being monitored can lead to unignorable stress in users. Furthermore, it is difficult to store the raw data for an extended period because of the large amount of image data. Another way to monitor the RR is to use a microphone mounted on a smartphone [2]. However, it may not be suitable for elderly people or those requiring care because the battery of the smartphone needs to be managed, or it may be lost. A common vital-sign monitoring method is to use a wearable device. Monitoring of respiration is possible in real time using a pressure sensor built into an arbitrary position on clothing, and low power consumption is achieved by attaching a magnetometer sensor to the body [3]. However, it can also be difficult for elderly people and care recipients to use it for the same reasons associated with the use of smartphones. Some systems focusing on detecting RR during sleep have also been proposed [4]–[6]. The movements of the chest and abdomen can be monitored individually by adopting an air mattress with multiple air chambers, thereby enabling the monitoring of respiration [4]. Furthermore, a method of placing a pressure sensor under a pillow instead of a lower-body sheet has been proposed [5]. Similar to the abovementioned methods, it is possible to monitor the respiratory rhythm and pulse in real time from the precise movement of the head. Because sheet-type sensors are used for various purposes, their shapes and sizes vary. In [6], a narrowband electrocardiogram and respiratory variability were acquired by incorporating a capacitive sheet sensor into infant underwear. Similar to our system, several other systems use signals to detect vital information. Although these systems can detect the RR during sleep, they require dedicated sensors or equipment, and it is often difficult for the users to obtain them.

RR detection methods using Wi-Fi are also popular [7]–[13]. In [7] and [8], an estimation of the RR that

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is independent of body orientation or face orientation is presented. In [9], the RR of each participant was estimated using the channel state information phase difference data, despite the presence of multiple people in the target space. Several techniques have focused on obtaining RR during sleep [10]–[12]. In [10], a breath-monitoring system using off-the-shelf Wi-Fi devices was proposed. In [11], continuous and long-term heart rate estimation was conducted, in addition to the RR, whereas in [12], posture and changes in posture during sleep were detected. Another method uses the strong radio waves of Wi-Fi to enable simultaneous estimation of the RR of multiple people, regardless of obstacles such as walls [13]. However, when using Wi-Fi, it is not possible to know from which position in the room the information is obtained. Therefore, these Wi-Fi-based systems are not suitable for location-specific purposes.

Various RR detection methods that apply radio-frequency identification (RFID) technology have been proposed [14]–[19]. RFID systems were originally used for inventory management in factories; however, in recent years, attention has been focused on acquiring vital information wirelessly using this technology. In [14], wireless sensor networks were combined with existing RFID systems and vital-sign monitoring technologies to simultaneously monitor vital signs, such as the RR, while tracking the user’s location. [15] proposed a stable RR estimation and apnea detection by real-time calibration of an RFID system. In [16], RFID systems implemented monitoring of respiratory activity, the uterus during labor, and biofeedback, including periodic movements to prevent deep vein thrombosis. There are reported methods of estimating the heart rate and RR of infants utilizing the batteryless features of passive RFID [17] and collecting the information from the tags using the received signal strength indicator (RSSI) to monitor respiration for detecting movement [18]. In [19], stable RR estimation was achieved without being affected by body movement by attaching a passive RFID tag to clothing. Although the methods introduced in [17]–[19] perform expected tasks, they request the users to attach some RFID tags directly on their own body.

There are several advantages of using a passive RFID system. First, the tag itself has no battery, which makes it very lightweight and small. Therefore, the user can record the vital signs without feeling the stress of wearing the device. Furthermore, because the tags are inexpensive, it is easier to deal with problems such as dirt and damage compared with the aforementioned methods. In addition, because there is no battery, users do not need to worry about charging, which is also an essential factor for a wide range of users. Second, an ID is assigned to each tag. This makes it possible to acquire more detailed information, such as from which tag the information has been obtained and where the tag is located. Because of these advantages, the acquisition of vital signs using RFID systems will be advanced further in the future.

In this study, a passive RFID system was used to detect non-invasive long-term RR and respiratory status. This system enables monitoring of the quality of sleep over a long period and detecting sleep disorders at an early stage. In fact, we have reported related research results using a passive RFID system [20], [21]. However, the system presented in [20] detects body posture on a bed, and its purpose and data processing method are completely different from those reported in this study. In [21], only preliminary experimental results for RR estimation were reported. Although we used the same hardware equipment, the data processing method was enhanced to improve the estimation accuracy. Furthermore, we propose a new respiratory status estimation method.

The main contributions of this study are as follows:

- The proposed system monitors the RR and respiratory status during sleep without attaching any devices to the user’s body.
- Users can monitor their sleep quality without any restrictions on charging the device’s battery or any hindrance to sleep by attaching several passive RFID tags to the blanket.
- Raw data are recorded, and respiratory information is analyzed to identify changes in sleep lifestyle and to predict signs of diseases.
- Elderly people or patients do not feel that they are being watched, but rather feel safe by using the above-mentioned functions of the smart home with RFID.

The remainder of this paper is organized as follows. First, the details of our proposed system are introduced in Sect. 2. Next, the RR and respiratory status estimation methods are described in Sect. 3. The evaluation results and remarks are then reported in Sect. 4. Finally, conclusions and future work are presented in Sect. 5.

2. System Design

2.1 System Overview

Figure 1 shows an overview of the proposed system. Five passive RFID tags (Alien Technology ALN-9770, Higgs-4, 920-MHz band) [22] are attached to a blanket. Two RFID antennas (Yeon Technologies, YAP-101CP), connected to
an RFID reader (Impinj Inc., Speedway Revolution IPJ-REV-R420-JP2), are installed on a wall next to a bed. The RSSI and phase values of the tags on the blanket are read by the RFID reader via the RFID antennas. The data (i.e., the tag IDs, RSSI values, phase values, and timestamps) are stored in a PC connected to the RFID reader. The RSSI and phase values change according to the distance between the tag and the antennas. When the user moves on the bed, the tags on the blanket move as well. Thus, by determining the change in RSSI and phase values, the moving distance of the user can be estimated. Here, the number of RFID tags and antennas and their locations were tuned through preliminary experiments, described later, to minimize the system cost.

2.2 Deployment of Antennas and Tags

It is important to consider how to deploy the antennas and RFID tags in practice to monitor bedtime breathing in a continuous and stable manner.

2.2.1 Antenna Placement

In our system, two antennas are used to continually estimate the RR. As shown in Fig. 1, Antenna 1 is installed on the wall above the user, and Antenna 2 is installed on the left wall, where the user lies down, face up. Both antennas are approximately 50 cm away from the user. Therefore, if the tag information is received by one of the antennas, then the system can continue monitoring the RR.

2.2.2 Tag Arrangement

A preliminary experiment demonstrated that the RSSI and phase values were affected in different ways by the sleeping position and breathing of the user. Therefore, we decided to use five RFID tags to cover all conditions. Because the human upper body exhibits better breathing influence than the lower body, all tags are attached close to the upper body in a T-shape. Three tags are attached to certain positions on the blanket, forming a vertical line from the chest to the stomach. The other two tags are attached to specific places on the blanket, corresponding to the left and right shoulders (see Fig. 1).

3. Respiratory Rate and Status Estimation

In this section, methods for estimating RR and respiratory status are introduced. To conduct both estimations smoothly, data preprocessing, which consists of three steps, is applied first. An RR estimation is then conducted. Subsequently, using the outputs of the RR estimation, a respiratory status estimation is performed.

3.1 Data Preprocessing

To estimate the RR every second, we apply a 60-s time window to the RSSI and phase data collected from each RFID tag. Here, if a series of collected RSSI or phase data starts from $t = 0$ and ends at $t = T + 60$, that is, data $(0, T + 60]$, the RR estimation is applied using the initial data $(0, 60]$. Once the initial estimation is completed, the time window is shifted by 1 s. The second estimation is performed using data $(1, 61]$. The cycle of one-second window shifting and RR estimation is continuously repeated until data $(T, T + 60)$. Here, the time window starting from time $t$ is called the “$t$-time window” in this paper. An RR for every second was obtained after 60 s. Figure 2 shows the data preprocessing flow to obtain the data used in the RR and its status estimation, which consists of the following three steps.

3.1.1 Obtaining Input Data

The input data of the RSSI and phase values were collected from the five RFID tags via two antennas. In the time window, a total of 20 datasets are obtained simultaneously: $2 \times 5 \times 2 = 20$.

3.1.2 Fixing Outliers of Phase Data

Figure 3 (a) shows the typical raw phase data and waveform. The figure illustrates some outliers in the raw phase waveform. These phases consist of periodic and repeated data, and outliers also appear under this rule. Moreover, during the preliminary analysis, we observed that the outliers were shifted from 0 to $2\pi$. Therefore, the outliers are eliminated or fixed using the following process:

For the phase waveform, $\{p(i) \mid i = 1, \cdots, I\}$, where $I$ is the maximum number of sampled phase data points in the $t$-time window; if $|p(i) - p(i - 1)| \geq \frac{\pi}{2}$, then $p(i) \leftarrow p(i) - \pi$.

Figure 3 (b) shows an example of the fixed-phase waveform. Here, the outliers in the raw phase waveform are eliminated. This process is not required for RSSI waveforms,
As described above, an FFT is applied to the autocovariance result of each input waveform to acquire the frequency and its one-sided amplitude spectrum. Then, for each of the 20 waveforms, the frequency \( \{ f_j(t) \mid j = 1, \ldots, 20 \} \) was extracted. Here, \( f_j(t) \) is the frequency with the maximum power spectrum \( P(f_j(t)) \) for waveform \( j \) in the \( t \)-time window.

The most difficult challenge in RR estimation using RFID systems is to reduce the effect of noise. To do so, \( f_j(t) \) that does not meet the following two conditions is eliminated as a candidate for RR estimation, and we obtain the candidate frequency set \( \{ f_j^c(t) \mid k = 1, \ldots, K; K \leq 20 \} \) with the corresponding power spectrum value set \( \{ P(f_j^c(t)) \mid k = 1, \ldots, K; K \leq 20 \} \) for the \( t \)-time window.

**[Condition 1]: Is sufficient data collected from the corresponding RFID tag?**

Depending on the user’s posture and body type as well as the location of the tag, the amount of data collected from an RFID tag often becomes clearly smaller than that of other tags. In addition, if the amount of data is small, the amount of noise will also be reduced. Thus, it is not expected to perform highly accurate RR estimation using such a small amount of dataset. On the other hand, even if a sufficient amount of data is collected, the data may contain considerable noise. In this case, the data should not be used for RR estimation. Thus, it is not appropriate to judge whether a collected dataset should be accepted using only the number of data points. Therefore, we introduce the following rule: Among the data from 20 sets of the waveforms, the spectral values that are at least three times larger than the median absolute deviation (MAD) of the corresponding data are treated as outliers and are not used for the RR estimation. MAD is a measure of statistical dispersion, and has more resilience for outliers compared to the standard division. Here, MAD is defined as follows:

\[
\text{MAD} = \text{median}(|x_i - \bar{X}|)
\]

where \( N \) is the number of data points obtained after FFT.

**[Condition 2]: Is the maximum value of the FFT power spectrum prominent?**

In a waveform with a marked amount of noise, the maximum value of the power is high, but the ratio of the protrusion is smaller than the other power values. Therefore, \( f_j(t) \) is used for the RR estimation only if it meets the condition that the power spectrum \( P(f_j(t)) \) is 1.25 higher than that of the frequency having the second highest power.

Note that the sampling rate of the data received at the RFID reader is not constant. According to our experiment, it changes from 10 Hz to 24 Hz. Thus, the results of the FFT applied to the autocovariance of the raw data also contain some errors. However, the FFT results contain frequency components at least less than 5 Hz (half of the lowest sampling rate, 10 Hz). The RR of a neonate during sleep is 60 times/min, that is, 1 Hz, which is known as the fastest RR
among all generations of human beings [23]. An alternative method for detecting which frequency component is related to RR is to use the data obtained by interpolating raw data using a constant sampling rate, for example, 20 Hz. However, the FFT results must include some frequency noise caused by data interpolation; thus, we introduced the above-mentioned method. Note that this is a preprocessing method to check whether the raw data collected at the RFID reader contain a frequency component related to RR, and the absolute value of the obtained highest power spectrum of the frequency component through this process is not directly related to the final RR estimation process.

3.2 Respiratory Rate Estimation

The frequencies that meet all the conditions in the data preprocessing are used as input for the RR estimation. Despite the effect of posture, RFID tags that are susceptible to respiration are biased by the user. Therefore, it is unlikely that the processing are used as input for the RR estimation. Despite the frequencies that meet all the conditions in the data preprocessing are used as input for the RR estimation. Despite the effect of posture, RFID tags that are susceptible to respiration are biased by the user. Therefore, it is unlikely that the processing are used as input for the RR estimation.

[Condition 3]: Is the estimated RR, the range [3, 30]?

To reduce the RR estimation error, we introduce this condition. It is rare to breathe fast during sleep, that is, breathing 30 times per minute or more. It is also not normal to breathe slowly, that is, less than 3 times per minute. In the case of adults, it is known that breathing of 24 or more times per minute indicates critical illness [24]. Thus, even if the range of RR estimation is restricted to [3, 30], it is sufficient to find abnormal breathing. The range of less than 3 times per minute is treated as the “non-breathing” range by following condition 3. Even so, SAS can also be detected under this condition.

This is our RR estimation process, and it is applied for every time window. The estimated RR set \( \{ \text{RR}_t | t = 0, \cdots, T \} \) can be obtained after the RR estimation.

3.3 Respiratory Status Estimation

In this study, respiratory status estimation is defined as a process to determine “breathing” or “non-breathing” periods in each time window. Figure 5 shows an example of the estimated RR, waveform and the raw data waveform used to obtain RR, for the t-time window. Note that only one cycle length of RR, is needed to perform the respiratory status estimation, but the RR, waveform is illustrated in Fig. 5 using a sine waveform to explain the concept.

To determine the “breathing” or “non-breathing” periods, we utilize the frequency with which the waveform crosses a threshold. Here, the threshold is the averaged value of the raw data waveform in the t-time window. In addition, a breathing array (BA) is provided to store the estimated breathing status at each second. The BA is a one-dimensional array BA = \( \{ b_1, \cdots, b_{T} \} \) where \( b_i = \{ 0 \text{ or } 1 \} \), and its length is \( T \) \( |\text{BA}| = T \), if we have \( T + 60 \) second-length data points. Furthermore, for each element of the BA, a value of 0 indicates “breathing,” while a value of 1 indicates “non-breathing” at the corresponding time. Thus, the actual respiratory status estimation algorithm enables the determination of a 0 or 1 in the BA as follows:

[Respiratory Status Estimation Algorithm]

(step 1): \( t = 0 \); all elements of the BA are initialized with “-1.” This means that the respiratory status was not estimated at the corresponding time.

(step 2): If \( \text{RR}_t \) obtained in Sect. 3.2, is -1 (i.e., \( \text{RR}_t \) is not estimated), (go to (step 5)).

(step 3): The time when the threshold and the waveform are crossed is investigated, and the time is labeled \( \{ CP_i | i = 1, \cdots, I \} \) as a cross-point time, where \( I \) is the maximum number of times that the threshold and the waveform are crossed in the t-time window. Here, each cross-point time is rounded to the nearest second.

(step 4): for (\( i = 1; i < I; i = i + 1 \) )

\[
\text{if} \ ((CP_{i+1} - CP_i) > 1/f_{\text{max}}) \text{ for } (j = CP_{i+1}; j \leq CP_{i+1}; j = j + 1) b_j = 1; \text{ else for } (j = CP_i + 1; j \leq CP_{i+1}; j = j + 1) \text{ if } (b_j = 1) b_j = 0; \]

(step 5): \( t = t + 1; \) if (\( t \leq T \) (go to (step 2)); else, [Exit];

Note that the waveform often has a trend or bias. In this case, it is removed before the threshold, that is, the average of the waveform data, is calculated. Here, the trend or bias...
is actually obtained as a regression line calculated using the raw data, and it is eliminated from the data. As a result, respiratory status estimation can be performed without the influence of a waveform with a small amplitude or a trend over the entire waveform. Because the trend/bias is removed, the threshold is highly likely to be at the center between the upper and lower limits of the amplitude. If breathing is performed correctly, the respiratory waveform and threshold intersect periodically. Theoretically, the threshold and the respiratory waveform cross three times during one cycle. Thus, in the algorithm (step 4), if the intersection interval between adjacent intersections is longer than one cycle of estimated RR (i.e., $1/f_{\text{max}}^t$), the interval is recoded as a “non-breathing” period by writing ‘1’ to the corresponding element of the BA. Otherwise, the time interval is recorded as a “breathing” period by writing ‘0’ to the corresponding element of the BA. Here, we do not overwrite ‘0’ if the BA element is already ‘1’. This means that if the corresponding status at the time was estimated as “non-breathing” once at other time windows, it must be maintained to issue a warning to the user. In Fig. 5, the intersection interval $(CP_1, CP_2)$ is estimated as a non-breathing period because the time interval is longer than one cycle time of estimated RR (i.e., $60 \times f_{\text{max}}^t$), while interval $(CP_1, CP_2)$ is estimated as a breathing period. This is because the intersection interval $(CP_1, CP_2)$ is less than one cycle time of RR.

This is our respiratory status estimation. The estimated results were saved in the BA. Here, if some of the elements in the BA are “−1,” it indicates that the status estimation is not performed at the corresponding time, and the breathing status is unknown.

4. Performance Evaluation

In this section, the evaluation results for the RR estimation and respiratory status estimation proposed in the previous section are reported. Each estimation method was evaluated separately; however, the environment used was the same as the system outline described in Sect. 3. To simultaneously assess the effect of posture on estimation, subjects assumed four possible postures during sleep: face up, face down, looking left, and looking right. In one experiment, measurements were recorded for 240 s. Because the window size was set to 60 s, the RR and respiratory status estimations for each experiment were applied to the first 180-s period.

4.1 Evaluation A: Evaluation of Respiratory Rate Estimation

Evaluation of the RR estimation was conducted. Subjects performed natural breathing during the experiment, conscious of sleep. To confirm the accuracy of the proposed system, we measured the true value of respiration. A respiratory motion transducer was mounted on the chest or abdomen of the subjects, and a skin thermistor was placed in a position where the tip could be exhaled from the nose, using Biopac Student Lab (BSL), BIOPAC Systems, Inc. [25].

Typical waveforms obtained by BSL and our system are plotted in Fig. 6. The vertical dotted lines are drawn in the figure for reference. The time between any pair of the dotted lines is 2.5 s. The upper two waveforms are the data acquired by the respiratory motion transducer and the thermistor of BSL. Both waveforms represent the periodic breathing of the subject. Here, the phase of the waveform for the respiratory motion transducer mounted on the chest is almost 180° different from that of the waveform for the thermistor attached near the nose. This is because the movement of the subject’s lung is opposite to that of exhalation. The lower waveform represents the change in the RSSI values obtained from an RFID tag used in the proposed system. It also represents normal periodic breathing. In addition, its phase is almost the same as that of the waveform for the respiratory motion transducer because both measure the movement of the subject’s lung caused by his/her breathing.

Five subjects were prepared to evaluate the effects of the user’s body type and gender. Table 1 summarizes the height, body type, and gender of each subject. Body type was determined by calculating the body mass index (BMI) [26]. Body types within 15 ≤ BMI < 16 are considered “severely underweight,” within 16 ≤ BMI < 18.5 are “underweight,” within 18.5 ≤ BMI < 25 are “normal,” and within 25 ≤ BMI are “overweight.”

4.1.1 Posture Effect Evaluation

The estimation results for each posture were evaluated. The
true RR (TRR) and estimated RR (ERR) were divided into six groups over 180 s: 30 s each, from 1 s to 30 s, 31 s to 60 s, and so on. The experiment was conducted for 180 s per measurement; however, the estimation was performed every second from 60 s to 180 s because the window size was 60 s. Therefore, the evaluation was performed on four groups from 61 s to 180 s. The system was compared using the average values of TRR and ERR and the differences between TRR and ERR for each group. Table 2 shows the TRR, ERR, and absolute values of the differences between TRR and ERR for each posture and all postures for each group. The value of each posture used the average of the estimated values of the five subjects. There was no meaningful change in the RR over time in any position. Therefore, the average difference between the TRR and ERR was within approximately 2.0 breaths/min in all groups. In contrast, in the “looking left” posture for all groups, the difference was more than 2.0 breaths/min. Moreover, this value increased to 4.0 breaths/min in the group from 151 s to 180 s. In all groups, the group with the largest estimation difference was 1.85 breaths/min, and the group with the smallest difference was 0.79 breaths/min.

The following evaluation was performed to confirm whether this effect was due to the “looking left” posture.

### 4.1.2 User Difference Effect Evaluation

The state of breathing varies depending on the subject’s body type and gender, the posture of each subject during sleep, and the habit of breathing. We compared the results for each subject to confirm their effects. As in the evaluation shown in Sect. 4.1.1 (posture effect evaluation), TRR and ERR were divided into six groups every 30 s and evaluated for four groups using the average of each and the absolute value of their difference. Table 3 shows the results. The TRR in Table 3 indicates that the speed changes over time during breathing for 180 s, whereas the state of the change differs depending on the subject. The results for subjects #1 and #3 demonstrate that the difference in TRR was less than 0.5 breaths/min. Conversely, for subjects #4 and #5, the difference was reduced to less than 1.0 breaths/min in the group from 91 to 120 s. However, the difference in the subsequent groups obviously increased, as the subjects breathed very fast momentarily, causing an increase in TRR for those groups. Peak-to-peak techniques were used to determine the TRR. Therefore, it was possible to read a detailed change in the RR. In the proposed system, the RR was estimated by frequency analysis of the waveform within the 60-s time window. As a result, the local change could not be estimated, and the difference from the average TRR increased. According to the results of subject #2, in all the groups, the differences from the TRR were approximately 3 to 4 breaths/min, which was not sufficiently accurate for RR monitoring. Overall, the difference between the TRR and ERR for each group was approximately 2 breaths/min, as in the case of posture evaluation.

Based on the abovementioned evaluation, the proposed system was affected by the user’s breathing method; however, it was found that it can be estimated regardless of body type, gender, or posture.

### 4.2 Evaluation B: Evaluation of Respiratory Status Estimation

The respiratory status, i.e., “breathing” or “non-breathing” periods, was estimated. The number of subjects was five in a group of subjects, which was different from the evaluation of the RR estimation. According to the results reported in Sect. 4.1, the proposed system is not affected by posture.
Therefore, only the “face-up” postures were examined in this evaluation. The subject breathed during the experiment according to a metronome set at an RR of 6.0 breaths/min (i.e., 0.1 Hz). During this time, the subjects were instructed to stop breathing at random times for 10 s or more. The results are shown in Figs. 7 and 8. For each subject, the upper waveform represents the change in the measured RSSI or phase data, while the lower waveform shows the estimation result of the respiratory status.

Figure 7 shows the cases in which our system could estimate the periods in which the subjects stopped their breathing. However, the estimated non-breathing periods lack accuracy. For example, in the case of subject #4, the detected periods are shorter than the actual periods, that is, 10 s or more. Figure 8 shows the case in which subject #5 actually stopped breathing in some time periods; however, our system could not estimate the periods.

In this evaluation, we instructed the subjects to breathe constantly by following the metronome and to stop breathing at random times for 10 s or more, and did not log the start and stop timing of the subject’s breathing exactly. However, as shown in Figs. 7 and 8, the accuracy of the respiratory status estimation obviously depends on how clearly the input waveform data contain respiratory information. In other words, it is possible to estimate the respiratory status using our proposed system if at least one of the 20 waveforms obtained at the RFID reader is affected by breathing.

Through Evaluations A and B shown in Sects. 4.1 and 4.2, we demonstrated that the proposed system can stably perform an estimation with sufficient accuracy for long-term respiration monitoring during sleep. It was also possible to detect dangerous respiratory conditions, such as respiratory arrest, at the same time.

There are uncountable sleeping conditions for people, and we cannot check all of them. Thus, in this study, we conducted Evaluations A and B by requesting the subjects to breathe so as to follow the instructions. That is, all subjects breathed normally in Evaluation A, while they breathed 6.0 times/s constantly and stopped breathing for 10 s or more at random times in Evaluation B. More continuous evaluations by changing breathing conditions are needed. This is a topic for one of our future studies.

In addition, all evaluations were performed under a situation where the user is always covered with a blanket. We could then estimate “breathing”/“non-breathing” periods for all data obtained in the evaluations. However, people often take off the blanket unconsciously during sleep. In this case, it is difficult to measure the RR correctly using the current system. One of the solutions to overcome this limitation is to attach additional RFID tags to the bed sheet, in addition to the blanket. We have used additional passive RFID tags attached to bed clothes to estimate sleeping postures [20]. This could provide a hint for solving this problem.

5. Conclusion

We proposed a system that estimates the RR and respiratory status by placing antennas close to the user and by attaching passive RFID tags on a blanket, instead of attaching devices directly to the user. The respiratory information while sleeping on a bed was estimated using the RSSI and phase values obtained from the RFID tags. The evaluation results indicated that the proposed system could consistently provide RR and respiratory status estimations that are not influenced by body posture, body type, and change in the RR. In future work, the proposed RR and respiratory status estimation methods should be extended to handle unintentional body movements during sleep, and more variations of examination are needed to confirm the completeness of the proposed methods.

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