Strain Detection based on Breath and Motion Features Obtained by a Force Sensor for Smart Toilet Systems

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Abstract

Aging people may be prone to accidents in bathrooms and toilets. The detection of strain motion for a smart toilet application has not been studied sufficiently. In this paper, we propose a method for strain detection from a force sensor placed on a toilet seat for a smart toilet healthcare application. The method first extracts breath and motion features that are assumed to be key components for the strain detection. The method then learns the discriminator model based on the random forest classifier using the aforementioned features. Finally, the method recognizes actions in the toilet room. There were five detection actions: seating, taking up toilet paper, wiping bottom, which are normal actions when sitting on a toilet seat, and strain actions (strong and weak). An experiment with 19 subjects was also conducted. Compared with a microwave sensor-based recognition, which is a conventional method (accuracy = 61.6%), our method was able to recognize the actions with high accuracy of 80.2% (significant test: T = 12.7, P < 0.01) in the experiment. Our strain detection method has the potential to be used as a smart toilet system to prevent blood pressure elevation and collapse caused by strain in the future.

1. Introduction

As the global population ages, several studies on health care monitoring have been conducted recently [1-7]. Using widely variable sensors from wearable-based [7] to noncontact-based [4], a lot of applications such as activity recognition [5], vital sensing [8], and identification were investigated. In particular, several studies focused on activities done daily, including those done in a bathroom. This is because accidents in a bathroom are often harmful for aging people as they may lead to heart attacks or hypertension [2, 4, 7].

Several researches have statistically analyzed accidents that occur in the bathroom based on a large number of patients with subarachnoid hemorrhage, cerebral infarctions, and cardiac arrests. The incidence of these diseases frequently occurred in lavatory and occurred more frequently here than in any other place in the house [9-13]. The number of incidences for elderly people was also higher than that for younger people [10, 11].

Among patients affected by cardiac arrest in the toilet space, only 10% were found soon after the heart attack; furthermore, only 1% lived longer than 12 months after the heart attack [9].

From the physiological aspect, defecation induces cardiovascular and blood pressure changes, and has relation with cardiac arrest occurrences [14]. When a person is under strain, a sudden rise in blood pressure occurs [15], which can lead to cardiopulmonary arrest or cerebral infarction for elderly people [16]. Regarding the healthcare of elderly people, it is known that the percentage of people suffering from chronic constipation increases with age [17]. In the case of constipation, excessive strain occurs during bowel movement. The longer the cardiac arrest, the lower the probability of recovery and survival [18]; however, the time taken to realize that someone has a cardiac arrest in the toilet tends to be greater since the toilet space is a private space [9].

Therefore, we propose a strain detection method for a smart toilet system. The paper is organized as follows. Section 2 describes works related to smart toilets and healthcare monitoring techniques. Section 3 describes the methods employed in the study. Section 4 provides the experimental settings of the study, while Section 5 provides the result and discusses them. Finally, Section 6 concludes the study.

2. Related works

Several studies have been conducted on public toilet maintenance systems for smart toilet applications. These systems monitor toilet occupation, activities of the user, and the water condition, for toilet maintenance using big data from sensors attached to the toilet [1, 2].

For more personal usage and health care monitoring, motion recognition using cameras or infrared sensors, as well as the monitoring of daily life based on the usage of home appliances have been studied [4, 19, 20]. As described in Section 1, monitoring at home, especially in the bathroom space, is becoming increasingly important, and privacy needs to be considered.

There are several researches on individual identifications and vital sign sensing for smart toilet, while placing emphasis on privacy [5, 21]. For monitoring the elderly people in the toilet room, several anomaly detection techniques have been investigated, such as the falling detection and unusual long-stay [8].

For noncontact based technologies that ensure privacy, microwave sensor-based sensing, such as anomaly detection [22] and motion recognition [23], have been proposed. The microwave sensor detects reflected waves from the human body and estimates the motion of the human. From the pattern of the reflected waves, the method detects the following actions: falling, unusual long-stay, taking off pants, and the winding of toilet paper.

Another type of sensor that ensures privacy is the pressure sensor, and studies have also been conducted on them [4, 5, 8]. From the obtained pressure signals, several states, such as being occupied, number of uses, length, human falling, and daily change of weight, etc. were detected.

Although these types of sensors detect motion well, all motions occur after the user falls, and these sensors do not necessarily predict or prevent them efficiently enough. Although these researches detect the anomaly after the event well, detecting the signs of the abnormal event or factors of the fall or faint are still challenging for healthcare monitoring systems in the toilet room.

For prevention from emergency caused diseases, daily vital sign detection systems embedded on the toilet seat were also proposed [3, 21]. The pressure on toilet seat measures the weight of the user, and their electrocardiogram is used as a daily heart rate monitor; the system achieves this while ensuring privacy.

However, only a few studies have been conducted on the detection of strain motion for a smart toilet application.

If a smart toilet system is able to detect whether a user while in toilet strains or not, or detects the intensity and frequency of the strain, sudden rises in blood pressure and collapse due to excessive strain can be prevented. The system can also notify a third person who supervises the user, such as a caregiver or a doctor, when the user generates excessive strain or undertakes unusual motion.

Therefore, this study aims to detect strain motion in the toilet room. During the strain period, large body movements occur less frequently; therefore, detecting strains using only motion features is quite challenging. However, when people strain, several small movements and tremors often appear on the body, and the breath decreases or ceases completely. Therefore, a key idea of this work is to estimate the strain by extracting the tiny movement of the body and their characteristics. However, in the toilet, other motions also occur, such as staying calm, winding of the toilet paper, and wiping [24]. Therefore, the system also needs to distinguish the strain from these multiple actions.

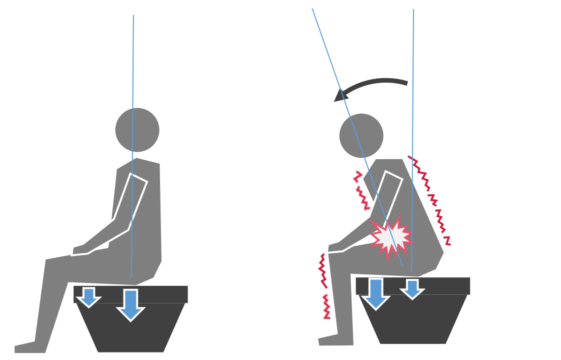


Figure 1: Gravity for the basic sitting posture and during strain motion.

In addition to recognizing the strain, it is necessary for the smart toilet system to detect motions without taking daily measurements. This work uses a pressure sensor attached on the toilet sheet. The pressure sensor extracts tiny movement and breath features.

3. Strain detection method

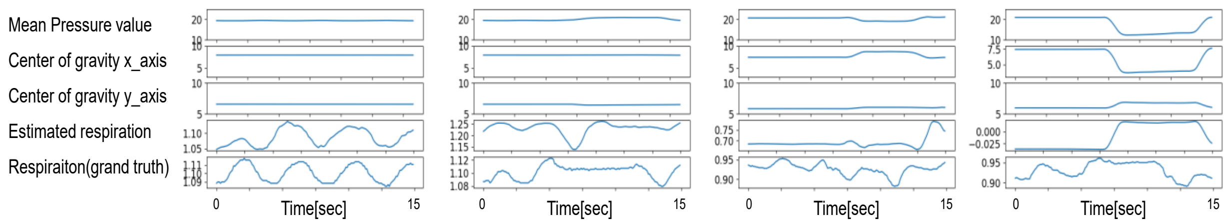
In this section, a procedure for extracting the motion and respiration signals of the subject from the pressure sheet sensor is described. Furthermore, an explanation on the way to create feature parameters from the signals and classify them using Random Forest is explained.

3.1. Strain motion

Figure 1 illustrates examples of strain motions and physical features. When a person is under strain, the upper body tends to tilt forward and the center of gravity shifts due to the force applied to the lower abdomen. Furthermore, as the body tilts forward, the weight is distributed to the grounded foot, and the weight on the buttocks decreases. However, there are cases where the subject pulls the legs toward the body, in which case the center of gravity shifts backward and the weight on the buttocks increases. In addition, during the strain motion, muscle tremors occur and the weight on the buttocks changes slightly.

3.2. Motion feature

In the toilet room, people generate several motions, even in the seated position. The movement generates change in the center of gravity on the seat, and weight shifts from the body to the feet. In addition, although the movement does not involve a large body movement, it is assumed that the abovementioned changes occur unconsciously and that tiny body tremors occur due to the force applied in the abdomen. To capture the change in the center of gravity due to body movement and the change of



(a) (b) (c) (d)

Figure 2: From left to right, signal of basic sitting posture, strain, winding paper and wiping, respectively. From top to bottom, each graph shows the mean value, center of gravity in the x axis and y axis, estimated respiration, and respiration of the grand truth. Horizontal axis of each signals shows time.

the weight on the seat, the average time variation of the center of gravity and the entire sensor is extracted.

3.3. Breath features

Fast independent component analysis (FastICA) was used to extract the respiratory features [25]. The extracted signals are assumed to compose of body movements, respiration, noise, muscle movements, and pulse waves. Therefore, the number of independent signals is set to five in this study.

The respiration signal was then selected from the separated five signals. The selection was based on the frequency spectrum. Breathing rate of an adult generally ranges between 12 to 18 times per minute (approximately from 0.2 to 0.3 Hz). However, the peak derived from the heartbeat appears to be approximately 1.0 Hz, and even when the signal is separated by the ICA, it is not completely separated, and the respiratory component might include the component derived from the heartbeat. Therefore, among the five signals separated by ICA, the signal with the maximum evaluation value according to the following equation is selected as the respiratory waveform [26].

$$E_r = R/C_1 \qquad (1)$$

R is a peak value in the 0.1– 0.7 Hz range and C_1 is a peak value in 0.9–1.1 Hz range.

3.4. Features of each motion

The example of signals obtained in this study are illustrated in Figure 2. Figures 2(a), (b), (c), and (d) present the following motions: stay calm, winding of the toilet paper, wiping, and strain, respectively. From top to bottom, the signals, mean of force value, center of gravity in x axis and y axis, estimated respiration, and grand truth of respiration are shown. In contrast to Figure 2(a), which shows staying, relatively huge motions such as winding paper and wiping generate huge change in the center of gravity and mean value since the upper body moves, as shown in Figures 2(c) and (d). Therefore, differences in value, variance, and interval of peaks are reasonable

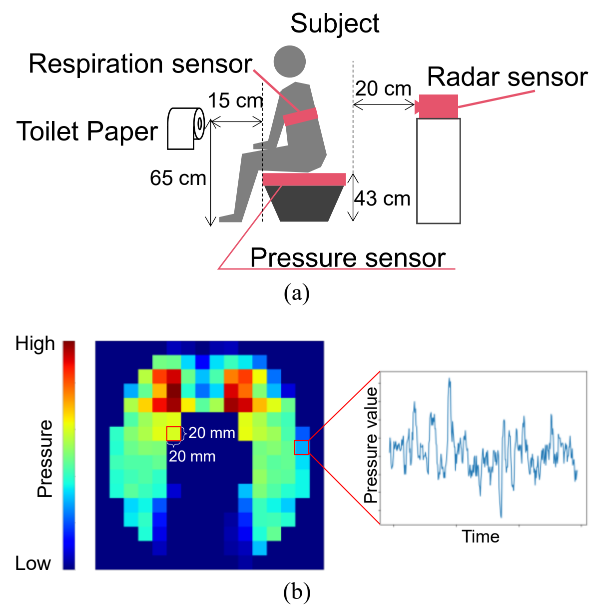


Figure 3: (a) experiment setup and (b) pressure sensor value (2-dimensional surface of one shot and 1 cell of time series data).

features that can be used. In contrast, staying (Figure 2(a)) and strain (Figure 2(b)) tend to show less motion and relatively clear breath signals. Furthermore, the strain motion causes less or pauses of breath. Therefore, the interval of the peak and the breath variance might also be effective as features.

In general, the use of several features in modeling classification can cause overfitting, and the use of less or in-effective features can cause the model to degrade. To select only effective features systematically, we use the Boruta method [27] for classification. Boruta creates fake features that do not contribute to discrimination and adds them to train the random forest. From the training results, the importance of the prepared features and the fake features are calculated. The number of times that the importance prepared features exceed the maximum importance of a false feature determines whether the prepared feature should be used. By using Boruta, in addition to removing noisy features, it is possible to select effective features for classification.

Table 1 shows the features selected by Boruta. In total, nine, eight, seven, and four features are selected from the mean weight, center of gravity in x-axis, center of gravity in y-axis, and respiration signal, respectively.

3.5. Motion recognition

To recognize the motions, the random forest technique was used. Eighty percent of the data from all subjects was used for training and the other 20 percent was used as test data, and evaluation was 50-time epochs.

4. Experimental

4.1. Experimental setup

Figure 3(a) illustrates the experimental setup. Assuming a smart toilet, a commercially available force sensor was embedded on the seat surface, that is, a prototype of a western -style toilet bowl with a height of 43 cm. Figure 3(b) is an example of the sitting state data by a color heat map. The heavier weight is red; the lighter is blue. The number of cells on the seat is 144, and the size per cell is 24 mm x 24 mm. Since there is no area in the center of the toilet seat, the center of the image is also shown in blue, which means there is no change of weight in the area. In contrast, the area of the back and foot are shown as red. The dynamic range is about 0.1–4 kgf / cm2.

To obtain the grand truth of the breath signal, a respiratory sensor (BANDO, Chemical Industries, LTD., Japan) was attached around the chest of the subjects. A conventional microwave sensor [28] was set behind the subject as a comparison method.

4.2. Protocol of experiment

The experiment was conducted on 19 subjects (ages: 25–59 years; gender: 17 males, 2 female). They were instructed to act five motions; staying, winding paper, wiping, strain strongly, and strain moderately [22]. Each action was performed in order. Approximately a 30 s pause was imposed in each action. Subjects performed the strain motion during bowel movement. Subjects were also instructed to perform the strain in two ways: strong and weak. The strong strain was instructed as normal strength, and the weak one was the half of the normal strength. After the strain motion, subjects were ordered to stay normal and perform the winding paper and wiping actions sequentially. The subjects were also instructed to do these motions naturally. The experiment was conducted with the approval of the in-house Ethical Review Committee and with the informed consent of the subjects.

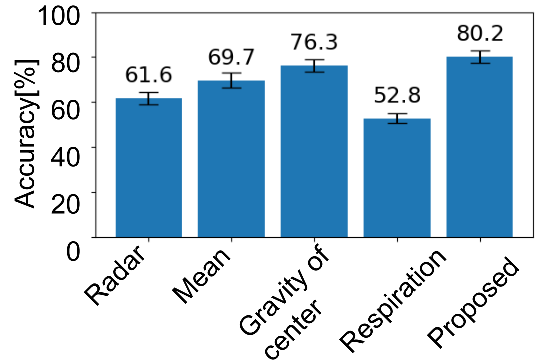


Figure 4: Accuracy of five classes (normal posture, strong strain, weak strain, winding paper and wiping bottom) by the proposed method.

Table 1: Features selected by the Boruta method

Signal	Selected features
Mean	Average of peak interval, variance of peak interval, variance of peak value, variance of signal value, difference between the maximum and minimum values, number of peaks, variance of peak detection confidence, maximum power spectrum value and frequency of maximum power spectrum value
Center of gravity x-axis	Average of peak interval, variance of peak interval, variance of peak value, variance of signal value, difference between the maximum and minimum values, addition value of small vibrations, variance of peak detection confidence and maximum power spectrum value
Center of gravity y-axis	Average of peak interval, variance of peak interval, variance of signal value, difference between the maximum and minimum values, addition value of small vibrations, variance of peak detection confidence and maximum power spectrum value
Respiration	Average of peak interval, variance of peak value and Maximum difference between peak values

5. Result and discussion

5.1. Result of motion recognition

The data set was cut every 10 s. Total data set accumulated to 708 for staying data, 600 for wipe operation, 590 for strong and weak strains, 574 for winding operation, and 630 for wiping operation. Classification of these five motions was performed. The average accuracy of 50 trials is shown in Figure 4. The vertical axis shows the accuracy, and each model were aligned in the horizontal axis by features. From left to right, the microwave signal (described as Radar), the average signal of the entire cell of the pressure sensitive sheet sensor, the center of gravity signal, the estimated respiratory waveform, and the proposed method that combined the mean, the center of gravity, and the respiratory feature, were described in horizontal axis. Error bars indicate standard deviation.

The accuracy of the proposed method was 80.2%, showing improvement on that of a conventional method (microwave sensor) whose accuracy was 61.6% with a significant difference (significant test: $T = 12.7$, $P < 0.01$).

The accuracy of each feature by the pressure sensor, which was breath, mean, and gravity center, was 52.8%, 69.7%, and 76.3%, respectively. The microwave sensor was superior to the pressure sensor when only using the respiration feature, indicating its advantage in detecting breathing features. However, the strain motion generated tiny motion and a change in gravity. Thus, the pressure sensor, which detected combinations of these features, detected the motions better in this study.

5.2. Comparison of methods for strain detection

Figures 5(a) and (b) show the confusion matrix of the five motions with the proposed method and microwave sensor, respectively. Rows and columns denote the true and estimated labels in each sensor, respectively. As shown in Figure 5(a), every motion was estimated with high accuracy.

In the microwave sensor, which is a conventional method, the accuracy of staying, rolling paper, and wiping, were 76.3%, 60.2%, 82.8%, respectively. In the proposed method, all motions except for strain were approximately 90%, which were higher than those of the conventional method. Focusing on the strain motion, in the conventional method, strong and weak strains were 45.2% and 37.2%, respectively. In the proposed method, they were 61.5% and 58.6%, respectively. Owing to the variety of strength caused by individual differences, distinguishing between weak and strong was more difficult than the other motions. However, without distinguish from weak and strong, the accuracy of the strain recognition was also approximately 92.0%, which was also higher than that of the convectional method.

In this study, the proposed method extracted the respiratory component and added it as a feature for classification since the body movement tended to be small and in contrast. However, the breath feature change was huge, such as stop, slowness, or disturbance when the subject were under strain. Among conventional methods, the microwave sensor is a prevalent method that captures the respiratory component well [29]. Considering the respiratory component, the force sensor seemed to be inevitably inferior to the microwave since the force sensor was attached on toilet sheet. Therefore, the microwave sensor was also assumed to suit for strain detection. However, the results of Figure 4(a) in the matrix show that the accuracy of the classification of strain by the force sensor (= 92.0%) was superior to that of the microwave sensor (= 71.3%).

When the subject strains, they generate motion features as well as respiratory features, and the force sensor could capture a combination of these features better than the microwave sensor. While the microwave sensor can obtain signals that are flat in left and right directions, the force sensor can acquire detailed movements of the body in the front, back, left, and right in the form of center of gravity signals, which may have contributed the accuracy.

Table 2: Cell position used to extract the center-of-gravity signal

Cell Position		Accuracy of 5class[%]	Accuracy of strain[%]
2×2cells block mean	The average value is calculated within a block of 2×2 cells. 8×8 blocks are used to extract the center of gravity signal.	80.1	92.4
6 cells	Extract the center of gravity signal using 3 cells on each side (near buttocks, middle and near knees).	76.1	91.0
4 cells	Extract the center of gravity signal using 2 cells on each side (near buttocks and near knees).	75.4	88.1
3 cells (only left side)	Extract the center of gravity signal using 3 cells on the left(near buttocks, middle and near knees).	73.5	85.4

Owing to the ideal conditions of the experiment, we could classify the motions with relatively high accuracy. Thus, with these results we are still not able to conclude that this method and force sensor are superior to previous methods in actual usage. For example, motions in a real toilet might vary and is different from that were simulated by subjects as an experiment.

Furthermore, even though we collected data from a wide range of ages (25–59 years), further analysis with more subjects is required for individual differences since the strength of strain might be different depending on ages. Physical conditions such as constipation also affect the motion. Further improvement and robustness with actual motion data with variable subjects are required for daily use.

In this study, the random forest technique was used because this technique relatively recognizes the motions well even with a small amount of data. However, further investigation and comparison with other methods such as DNN-based modeling is also required with a large amount of the variable subjects.

5.3. Resolution and setting place of force sensor

For commercial usage, resolution and number of sensors are important issues. To confirm the effects of the resolution and the number and place of the sensors, we varied the number and position of the force sensor cells. Table 2 shows the number of cells and positions and

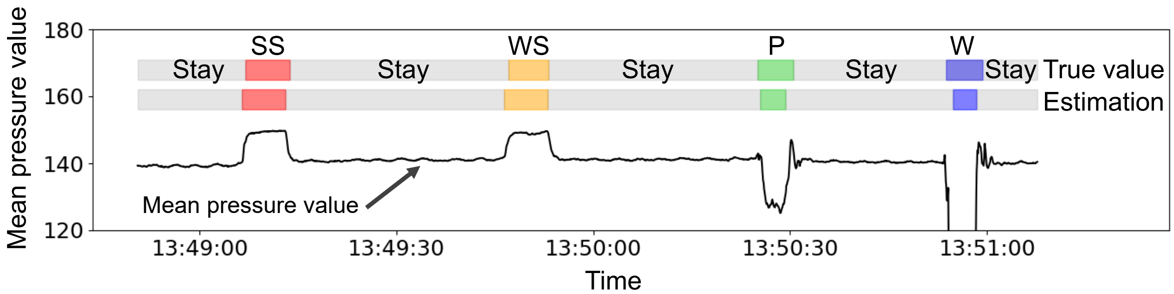


Figure 5: Motion classification (top: true value, bottom: estimated value) and mean pressure value in time series data. SS means strong strain, WS is weak strain, P is winding paper and W is wiping bottom.

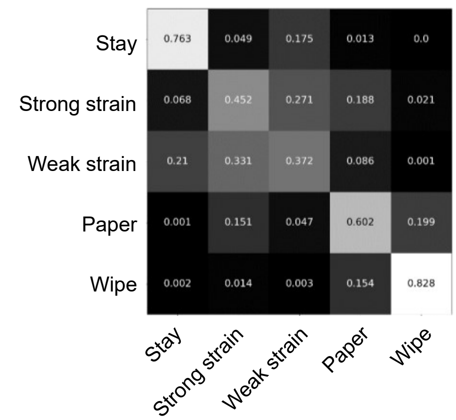
accuracy of all actions and only stain when using the cells. When the resolution was reduced to one block of 2 x 2 cells, the accuracy did not decrease much (= 80.2%). However, when the number of cells was reduced, the accuracy of the motions decreased by 4–7 %, and it was confirmed that the accuracy tended to decrease as number of cells decreased.

The result indicates that measuring the entire surface of the seat pressure seems effective in detecting the detailed toilet motions by capturing the trend of the center of gravity.

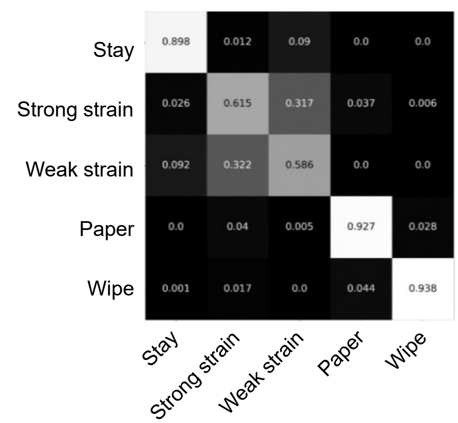
Even if in case of strain motion detection, we also confirmed decrease in 6 cells, 4 cells and 3 cells. In particular, 3 cells sensor means using only the left side sensor. Different from the winding paper action, the strain seemed to have less movement from the left to right side of the body. However, a decrease in accuracy was observed. This indicates that although there is no visible change in the center of gravity between the left and right side of the body when the subject is under strain, there is a characteristic change in the center of gravity, which is effective in measuring the entire surface.

5.4. Times and duration of strain state

In addition to the estimated motion label, the start and end points of the estimated motions were shown according their actual motions in Figure 6. Considering the usual usage, normal motion sequences, which were stay, several strains, winding paper, and wiping were performed. From top to bottom, instructed motion (as true value), estimated motion, and mean pressure signals are illustrated in Figure 6. Furthermore, errors of the start/end points in each motion, and every motion and its duration were estimated well, as shown in Figure 6. The error of each motion were at most 0.5 s. Furthermore, the method was able to detect the duration and times of the strain. For healthcare application, the duration and times of the strains are informative for daily healthcare monitoring [10, 14]. Therefore, the result indicates the potential of this method for future applications as a smart toilet.



(a)



(b)

Figure 6: The confusion matrix of five classes by (a) using the radar signal and (b) proposed method.

6. Conclusion

In this study, we proposed a strain detection method using a pressure distribution sensor for a smart toilet. By combining breathing and body movement features from the time-series data of pressure distribution, motions in the toilet room, such as sitting, wiping, paper winding, and wiping were estimated well with an accuracy of 80.2%. In addition, it was confirmed that the accurate time for breathing could be estimated after the behavior classification, including the strength of breathing, was performed from the continuous time series data.

Future works can model the estimated strength and weakness of breathing and the relationship between the time and the degree of risk caused by it, which can provide information that can be effectively used by the user.

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