

PAPER

An Ultrasonic and Air Pressure Sensing System for Detection of Behavior before Getting out of Bed Aided by Fuzzy Theory

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SUMMARY This paper proposes a sensing system for a behavior detection system using an ultrasonic oscillosensor and an air pressure sensor. The ultrasonic oscillosensor has a cylindrical tank filled with water. It detects the vibration of the target object from the signal reflected from the water surface. This sensor can detect a biological vibration by setting to the bottom bed frame. The air pressure sensor consists of a polypropylene sheet and an air pressure sensor, and detects the pressure information by setting under the bed's mattress. An increase (decrease) in the load placed on the bed is detected by the increase (decrease) in the pressure of the air held in the tube attached to the sheet. We propose a behavior detection system using both sensors, complementally. The system recognizes three states (nobody in bed, keeping quiet in bed, moving in bed) using both sensors, and we detect the behavior before getting out of bed by recognizing these states. Fuzzy logic plays a primary role in the system. As the fundamental experiment, we applied the system to five healthy volunteers, the system successfully recognized three states, and detected the behavior before getting out of bed. As the clinical experiment, we applied the system to four elderly patients with dementia, the system exactly detected the behavior before getting out of the bed with enough time for medical care support.

key words: health monitoring, ultrasonic oscillosensor, air pressure sensor, behavior monitoring system, fuzzy inference

1. Introduction

The falling accident when the elderly stands by themselves from bed is a serious problem. For the elderly, the falling accident from bed causes serious problems such as bone fracture, head banging and others. The incident may cause a deadly accident. Therefore, it is necessary to detect it, exactly. In addition, once the accident occurred, it tends to be repeated. Thus, we must prevent the accident. In an aging society, the urgent solution are required. However it is not easy to prevent the falling accident from bed. Causes of the accident are inactive condition of body, muscular weakness of legs by aging, false recognition of height of bed, and forgetting physical disability of themselves caused by senile dementia. It is effective to prevent the accident by detecting

the behavior before getting out of bed. However the accident often occurs at night, then caregiver sometimes lacks at night. In addition, all night care means heavy burden, it is also a serious problem. To solve this problem, the use of an automated health monitoring system is a candidate. We can prevent the accident by developing the system that can detect the behavior before getting out of bed.

Almost monitoring systems like electrocardiograms constrain the patient [1], [2]. These methods are inadequate for the daily monitoring. An unconstrained system is absolutely necessary for daily monitoring. The method in Ref. [3] detects getting up and movements of patients by using an infrared sensor on bedside. However, it is not easy to apply to practical care, since it is easy to cover the sensor by obstacles such as a close or a blanket. Moreover patients often refuse to use the sensor because it looks like a video camera. Unconscious is also important for the patients. The method in Ref. [4] reported an unconscious and unconstrained system. This method detects the behavior that he/she already got out of bed by using an ultrasonic sensor. This system can detect the accidents, but it cannot prevent the accident. Another method in Ref. [3] detects the behavior before getting out of bed by using the bed mat sensor. However, this method has a problem of a location dependency.

In our study, we propose a fuzzy detection system of behavior before getting out of bed by using an ultrasonic oscillosensor [4]–[7], an air pressure sensor [8], [9]. The air pressure sensor consists of a sheet and a pressure sensor, and detects the biological information by setting under the bottom of a mattress. This sensor detects a pressure change by expanding and deflating of the tube contained in the sheet. This sensor has a location dependency. While, the ultrasonic oscillosensor has a cylindrical tank filled with water. This sensor detects a vibration of a target object by obtaining the echo signal reflected from the water surface. Thus, this sensor is compact, and it can detect the biological vibration with low frequency by setting to the under frame of a bed. Moreover, this sensor can detect the vibration in spite of the position of human. Additionally, this sensor unconstrainedly detects the vital signals. It is difficult for a conventional vibration sensor such as velocimeter and accelerometer to detect the low-frequency vibration of 10 Hz or less and the vibration for all three axes. Since this low-frequency vibration is primary in the range of the biological vibration generated by heartbeat and behavior,

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this sensor can effectively detect these biological vibration. The ultrasonic oscillosensor does not have a location dependency. Therefore, the ultrasonic oscillosensor complements the location dependency of the air pressure sensor. Additionally, these sensors are easy handling for nurses, and unconsciously and unconstrainedly detect the biological information for patients. Thus, these two sensors are suitable as the daily health monitoring sensor. We estimate three human states (nobody in bed, keeping quiet in bed, moving in bed) using both sensors, and use fuzzy logic to recognize these states, and we detect the behavior before getting out of bed using these states. In the result of applying the system to five healthy volunteers, the system successfully recognized three states and detected behavior before getting out of bed. In the result of applying the system to four elderly patients with dementia, the system exactly detected the behavior before getting out of bed with enough time for medical care support.

2. Preliminaries

Our system is composed of an ultrasonic oscillosensor, an air pressure sensor, a control device (Japan Medical Instrument Co. Ltd., ANC-01) and a personal computer. Figure 1 shows the mounted places of the both sensors. Section 2.1 introduces the ultrasonic oscillosensor. Section 2.2 introduces the air pressure sensor.

2.1 Ultrasonic Oscillosensor [4]–[7]

The structure of an ultrasonic oscillosensor system is shown in Fig. 2. This sensor consists of a sensing device and a control device, which includes an ultrasonic pulser/receiver and an A/D converter. As shown in this figure, the ultrasonic pulser/receiver transmits and receives the ultrasonic wave via the ultrasonic probe. The received ultrasonic wave is provided to the personal computer through the A/D converter. A sensing device consists of a cylindrical tank of 26 mm (diameter) $\times$ 10 mm (height) filled with water and an ultrasonic probe (central frequency: 2 MHz) set to the bottom of tank. The ultrasonic wave is transmitted from the ultrasonic probe, and it reflects at the water surface. The ultrasonic probe receives the reflected wave. The ultrasonic wave reflects according to the difference of the acoustic

impedance and propagates underwater. Therefore, the ultrasonic wave reflects on the water surface. Moreover, the maximum amplitude value of the reflected wave varies by the condition of water surface. Thus, the vibration of a target object is detected by analyzing the temporal change of the maximum amplitude value of the reflected wave. The reflected waves are acquired at a interval of 20 msec., and each detected maximum amplitude value is quantized to 1024 levels (10 bits) by an A/D converter. We obtain this quantized data as time-series data of vibration of a target object by the personal computer. The ultrasonic oscillosensor does not have a location dependency. Therefore, the ultrasonic oscillosensor complements the location dependency of an air pressure sensor.

2.2 Air Pressure Sensor [8], [9]

The structure of an air pressure sensor system is shown in Fig. 3. This system consists of a sensing device and a control device (contained A/D converter). The sensing device consists of polypropylene sheet of 175 mm $\times$ 780 mm and the pressure sensor (Fuji Ceramics Co., FKS-111). As shown in Fig. 3, the sheet contains natural rubber tube of 5 mm (inside diameter) $\times$ 7 mm (outside diameter) $\times$ 3 m (length), and this tube is set in a horizontal type. The head of this tube is oppilated, the other is connected the pressure sensor. In the principle of this sensor, an air pressure change is generated by expanding and deflating of this tube contained in this sheet. The air pressure change is transmitted to the pressure sensor through the tube. The pressure sensor converts the air pressure change to an electronic signal, and outputs the signal based on 1.35 V as shown in Fig. 4. A pressurization change is outputted a plus electronic signal. A depressurization change is outputted a minus electronic signal. This signal is acquired at a interval of 20 msec., and quantized to 1024 levels (10 bits) by the A/D converter as shown in Fig. 4. The quantized data of pressure change is obtained by the personal computer. Figure 5 shows comparing the obtained signals of each sensor. In these figures, a human is lying and sometimes rolling over in bed. As shown in Fig. 5 (a), the pressure signal is not stable, because the air pressure sensor has a location dependency. On the other hand, in Fig. 5 (b), the ultrasonic signal is stable. Therefore, the ultrasonic sensor complements the location dependency

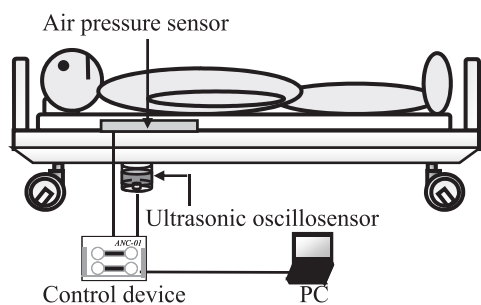


Fig. 1 Experimental bed and mount positions.

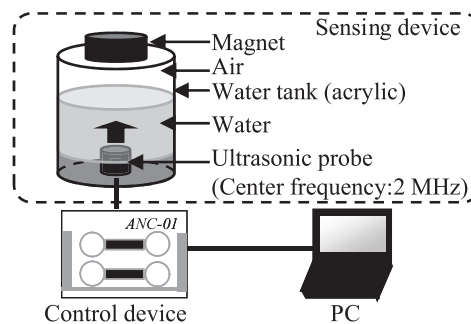


Fig. 2 Ultrasonic oscillosensor system.

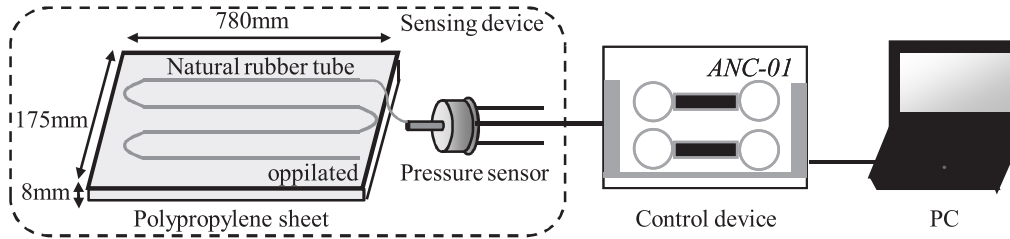


Fig. 3 Air pressure sensor system.

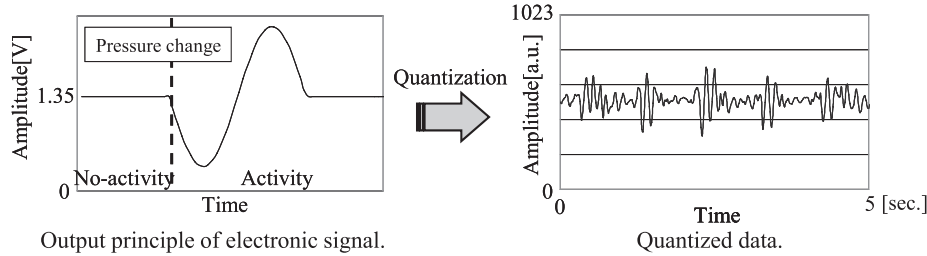
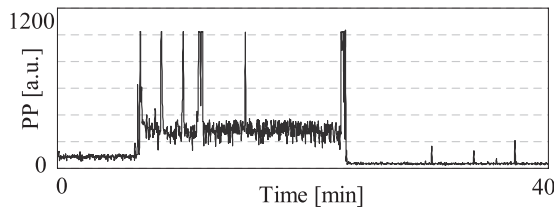
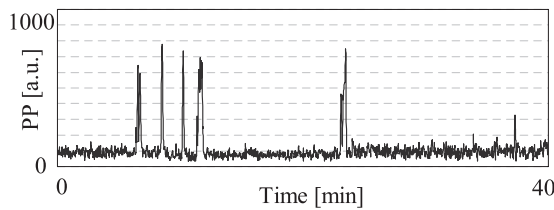


Fig. 4 Series of the quantized electronic signal.



(a) Air pressure signal.



(b) Ultrasonic signal.

Fig. 5 Comparing the obtained signals of each sensor.

of the air pressure sensor.

3. Behavior Detection Method

Figure 7 shows the procedure of the proposed method. Firstly, in order to quantify the differences of the obtained data on human states, we calculate PP, which is the difference value between the maximum and the minimum values at an interval of 2 sec. Next, we recognize the human states using these PP. Using the recognized states on both sensors, we detect a candidate behavior before getting out of bed. Using the detected candidate behavior and the PP of ultrasonic sensor, we detect a behavior before getting out of bed. Finally, we update the parameter used in the analysis.

Three human states C_1 , C_2 and C_3 for each sensor are defined below. State C_1 on the ultrasonic sensor is a state that a human is not in the bed. State C_1 on the air pressure sensor is a state that a human does not touch the air pressure sensor. These States are equivalent to a state that a patient is dead. State C_2 on both sensors is a state that a human is keeping quiet in the bed. This state assumes a state that a patient is sleeping in the bed. State C_3 on both sensors is a state that a human is moving in the bed. This state assumes a state that a patient is rolling over in the bed, getting out of the bed and others. The obtained data on these states are shown in Fig. 6. The sampling interval of the sensors is 20 msec. We calculated the difference value between the maximum value and the minimum value at a interval of 2 sec. We denote this difference value as PP. Figure 8 shows the calculated PP in time series for these states of the sensors. As shown in this figure, we can see the difference of amplitude in these states. By converting the knowledge of this difference to fuzzy rules, we propose a detection system of the human behavior. The calculated PP on C_1 are shown in Figs. 8 (a) and (b). These PP were quite small. The calculated PP on C_2 are shown in Figs. 8 (c) and (d). These PP were larger than those of C_1 . The calculated PP on C_3 are shown in Figs. 8 (e) and (f). These PP were larger than those of C_2 . From these results of PP, we obtain Knowledge 1, Knowledge 2 and Knowledge 3 as follows.

- Knowledge 1: If the state of a patient is C_1 , then PP is quite small.
- Knowledge 2: If the state of a patient is C_2 , then PP is larger than that on C_1 .
- Knowledge 3: If the state of a patient is C_3 , then PP is larger than that on C_2 .

These knowledge are converted into the following fuzzy IF-THEN rules,

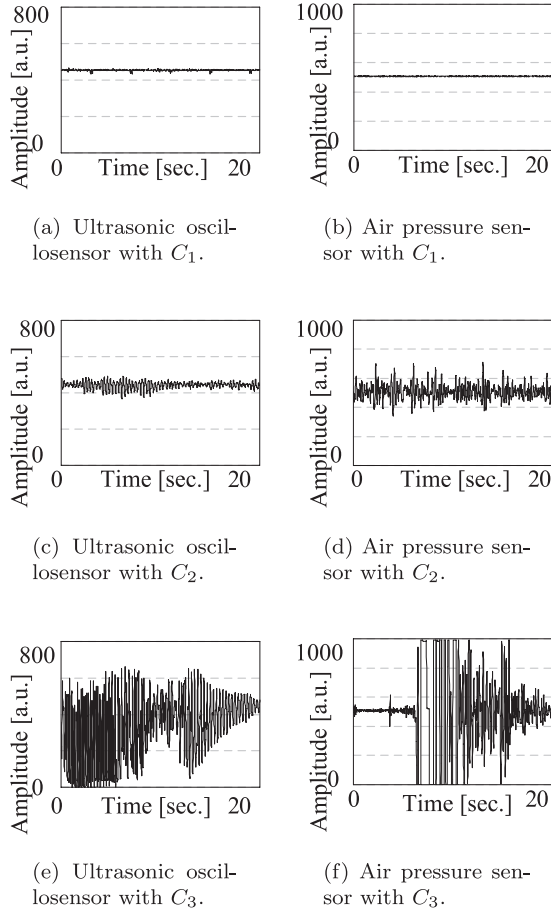


Fig. 6 Raw data.

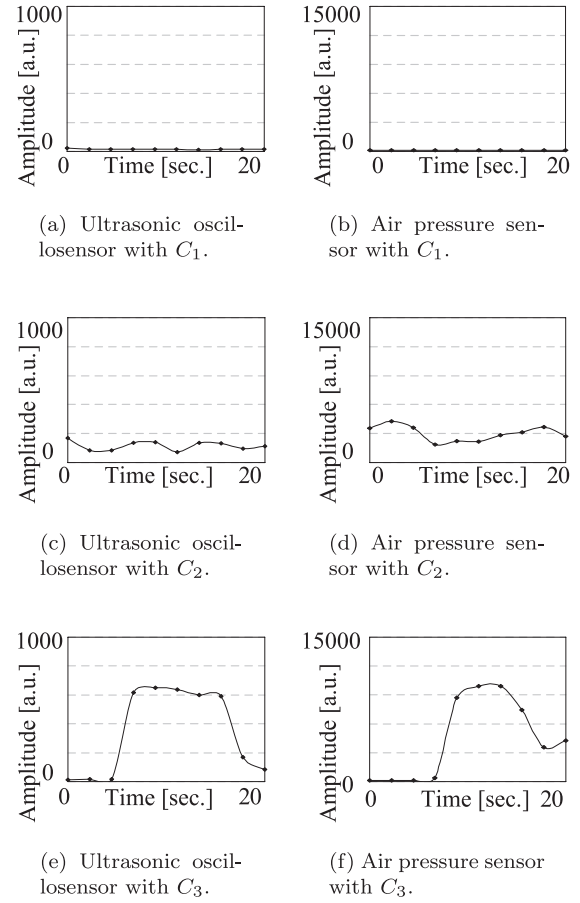


Fig. 8 Calculated PP.

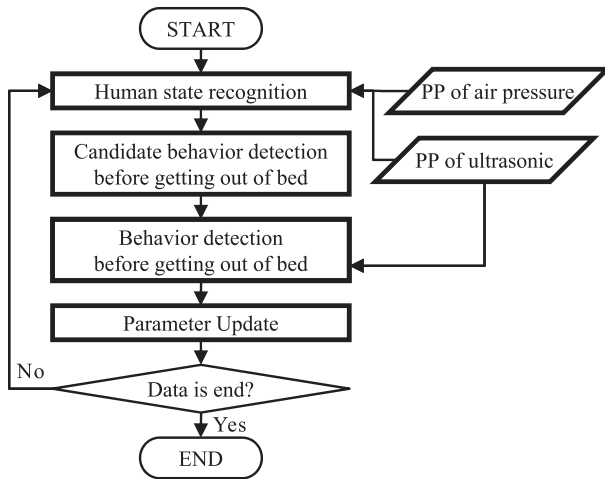


Fig. 7 Flow chart of proposed method.

- Rule 1: IF x_{pp} is Small, THEN $\mu_1(x)$ is high.
- Rule 2: IF x_{pp} is Middle, THEN $\mu_2(x)$ is high.
- Rule 3: IF x_{pp} is Big, THEN $\mu_3(x)$ is high.

The notations $\mu_1(x)$, $\mu_2(x)$ and $\mu_3(x)$ denote the degrees in C_1 , C_2 and C_3 for 2 sec., for input data x , respectively. x_{pp} denotes calculated PP from input data, x . “Small”, “Middle”

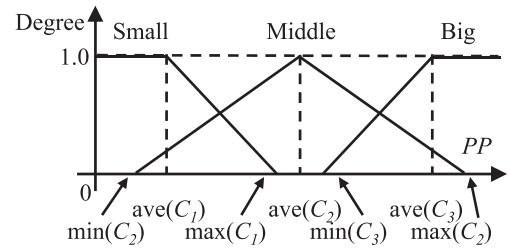


Fig. 9 Membership function for state recognition.

and “Big” membership functions of PP for C_1 , C_2 and C_3 are defined in Fig. 9. In this figure, $\text{ave}(C_1)$ and $\text{max}(C_1)$ denote the average value and the maximum value of PP in C_1 , respectively. The notations $\text{min}(C_2)$, $\text{ave}(C_2)$ and $\text{max}(C_2)$ denote the minimum value, the average value and the maximum value of PP in C_2 , respectively. The notation $\text{min}(C_3)$ and $\text{ave}(C_3)$ denote the minimum value and the average value of PP in C_3 , respectively. Fuzzy singleton function is defined by Eq. (1).

$$s_{xpp}(x) = \begin{cases} 1 & \text{if } x = x_{pp} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

The degrees of $\mu_1(x)$, $\mu_2(x)$ and $\mu_3(x)$ are calculated by the following Eqs. (2), (3) and (4).

$$\mu_1(x) = \min \{ \text{Small}, s_{xpp}(x) \} \quad (2)$$

$$\mu_2(x) = \min \{ \text{Middle}, s_{xpp}(x) \} \quad (3)$$

$$\mu_3(x) = \min \{ \text{Big}, s_{xpp}(x) \} \quad (4)$$

The input data x is determined as C_i with the maximum fuzzy degree among $\mu_1(x)$, $\mu_2(x)$ and $\mu_3(x)$. If it is not satisfied in rules, that is, $\mu_1(x) = 0$, $\mu_2(x) = 0$ and $\mu_3(x) = 0$, then we determine the target state as the state previously determined state (2 sec. before). Finally, the parameters in the determined state are updated. The process repeats at an interval of 2 sec. for the continuous input data.

By using the recognized states, a candidate behavior before getting out of bed is defined that the state on the air pressure sensor changes from C_3 (or C_2) to C_1 under the state on the ultrasonic oscillosensor is C_3 . However, the candidate may includes behavior that patient only detached from the air pressure sensor. Therefore, it is necessary to avoid it from this candidate. Here, the amplitude of calculated PP of ultrasonic sensor on C_3 is large in proportion to amount of movement of a patient in the bed. In addition, the amount of movement of the behavior getting out of bed is large. Thus, Knowledge 4 is derived.

- Knowledge 4: If the detected candidate is the behavior before getting out of bed, then PP of ultrasonic sensor is large.

The knowledge is converted into the following fuzzy IF-THEN rule.

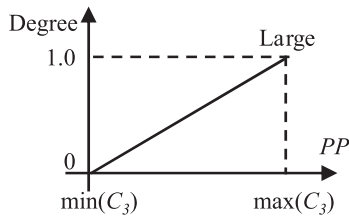


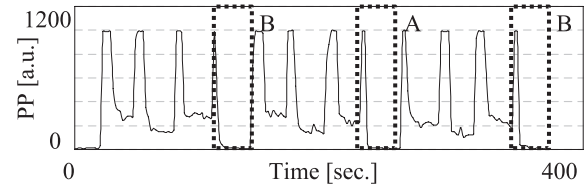
Fig. 10 Membership function for behavior detection.

Table 1 Time schedule of human behavior.

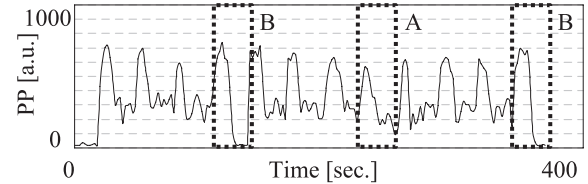
Time [sec.]			Behavior
0-20	120-140		Being not in bed.
20-30	140-150		Getting in bed.
30-50	150-170	270-290	Keeping quiet in bed. (facing up position)
50-60	170-180	290-300	Rolling over in bed.
60-80	180-200	300-320	Keeping quiet in bed. (lateral position)
80-90	200-210	320-330	Rolling over in bed.
90-110	210-230	330-350	Keeping quiet in bed. (facing up position)
110-120		350-360	Getting out of bed.
	230-240		Waking up.
	240-260		Keeping quiet in bed. (sitting position)
	260-270		Lying down.
		360-400	Being not in bed

- Rule 4: IF x_{pp} is Large, THEN $\mu_b(x)$ is high.

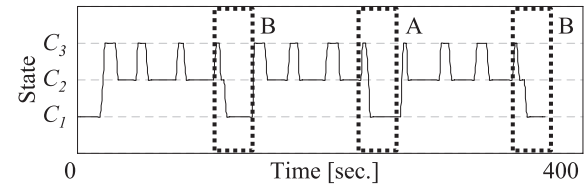
The notation $\mu_b(x)$ denotes the degree of the behavior getting out of bed for the input data x . “Large” membership functions of PP for the behavior getting out of bed are defined in Fig. 10. In Fig. 10, the notation $\min(C_3)$ and $\max(C_3)$ denote the minimum value and the maximum value of PP in C_3 , respectively. The degree of $\mu_b(x)$ is calculated



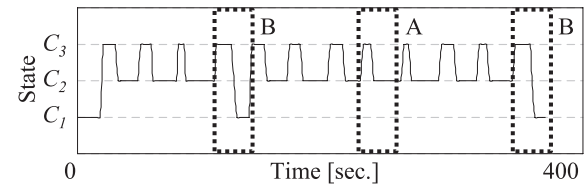
(a) Calculated PP of air pressure sensor.



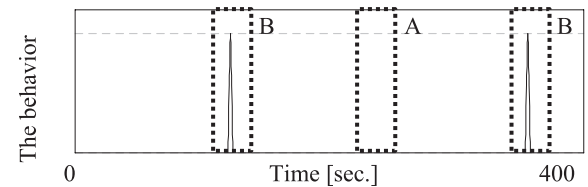
(b) Calculated PP of ultrasonic oscillosensor.



(c) Recognized states on air pressure sensor.

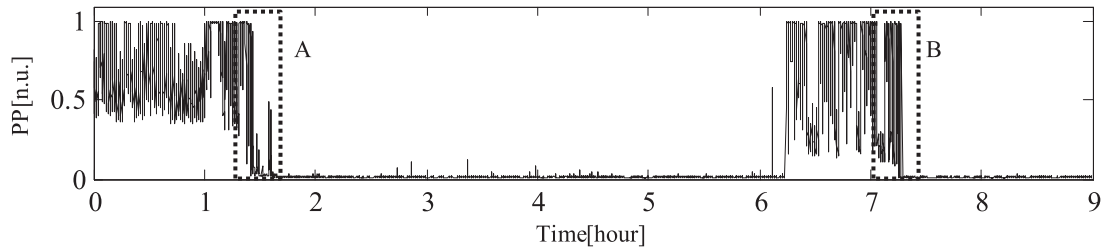


(d) Recognized states on ultrasonic oscillosensor.

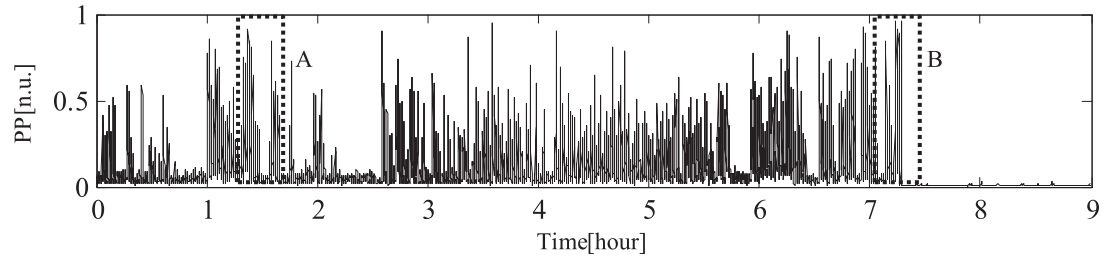


(e) Detected behavior before getting out of bed.

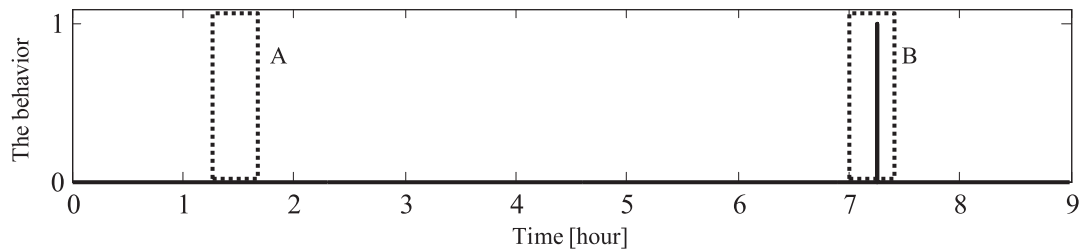
Fig. 11 Result of fundamental experiment (Subject A).



(a) Calculated PP of air pressure sensor.



(b) Calculated PP of ultrasonic oscillosensor.



(c) Detected behavior before getting out of bed.

Fig. 12 Result of clinical experiment (Subject D, Day 1).**Table 2** Result of fundamental experiment.

Subject	Experimental number	Waking up (A)	Before getting out of bed (B)	Success to A	Success to B	Success ratio (%)
A	1	1	2	1	2	100
B	1	1	2	1	2	100
C	1	1	2	1	2	100
D	1	1	2	1	2	100
E	1	1	2	1	2	100

Table 3 Result of clinical experiment.

Subject	Waking up (A)	Before getting out of bed (B)	Success to A	Success to B	Success ratio [%]	Time limit for caring [sec.]
A	0	1	0	1	100	80
B	0	2	0	2	100	68
C	0	2	0	2	100	87
D	2	4	2	4	100	68.5

by Eq. (5),

$$\mu_b(x) = \min \{ \text{Large}, s_{xpp}(x) \} \quad (5)$$

We calculate $\mu_b(x)$ during x from the timing of detecting the candidate behavior to the 4 sec. before timing of it. If the average of $\mu_b(x)$ exceeds a threshold, input data x is determined as a behavior before getting out of bed. We determined the threshold as 0.4, experimentally. All processes repeat for the detected candidate behavior.

4. Experimental Result

4.1 Fundamental Experiment

As the fundamental experiment, we applied the system to five healthy volunteers (age: 21.6 ± 0.5). Using the experimental system shown in Fig. 1, each subject acts according to Table 1. Each experiment includes 2 times of “behavior before getting out of bed” (B) in Table 2 and 1 time of “waking up” (A) in Table 2. Here, “waking up” is not a behavior before getting out of bed, and it was the most similar signals

to the behavior before getting out of bed. Therefore, we can consider that if this detection system can avoid “waking up”, this system can exactly detect “behavior before getting out of bed”. We applied the detection system to the all. As an example, the result of subject A is shown in Fig. 11. In these figure, dotted lines show the human behavior, which 2 times of “behavior before getting out of bed” and 1 time of “waking up”. Figures 11 (a) and 11 (b) show the calculated PP using both sensors. Figures 11 (c) and 11 (d) show the recognized state on both sensors. Finally, Fig. 11 (e) shows the detected behavior before getting out of bed. As shown in these figures, the system successfully recognized the human states and detected the behavior before getting out of bed. Table 2 shows all results. As shown in these results, the system successfully recognized three states, and detected the behavior before getting out of bed.

4.2 Clinical Experiment

As the clinical experiment, we applied the system to four elderly patients with dementia (age: 90.3 ± 4.2). Using the experimental system as shown in Fig. 1, we obtained data of 9 hours (22:00–7:00) for 4 days for each. The obtained data are normalized from 0 to 1. As an example, the result of subject D on day 1 is shown in Fig. 12. This figure shows the result in time series. This experiment includes 1 time of “behavior before getting out of bed” (B) and 1 time of “waking up” (A). As shown in this figure, the system did not detect “waking up” (A), and detected the “behavior before getting out of bed” (B). Table 3 shows all results. As shown in this table, the system exactly detected the behavior before getting out of the bed (B). In addition, average time between detected the behavior before getting out of bed (B) and the getting out of bed was 75.9 sec., 75.9 sec. is enough time to move the caregiver to the patient room.

5. Conclusion

This paper has proposed an ultrasonic and air pressure sensing system for detection of behavior before getting out of bed. The problem of the conventional system is a location dependency. In our system, the ultrasonic oscillosensor complemented a location dependency of the air pressure sensor. The system recognized three states (nobody in bed, keeping quiet in bed, moving in bed) by using the obtained from the ultrasonic oscillosensor and the air pressure sensor. Using the estimated state and the obtained data from the ultrasonic oscillosensor, the system detected the behavior before getting out of bed. The system was developed aided by fuzzy logic. In it, the scheme successfully worked to recognize the state and detect the behavior before getting out of bed. In the result of applying the system to five healthy volunteers for 400 sec., the system successfully recognized the states and detected the behavior before getting out of bed for all subjects. In the result of applying the system to four elderly patients with dementia for 9 hours and 4 days, the system exactly detected the behavior before getting out

of bed with enough time for medical care support. Consequently, the proposed system can contribute to prevent the falling accident when the elderly stands from bed. In the future work, we will evaluate the robustness of the system.

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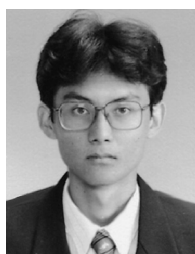


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