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Bed-Leaving Detection Using Piezoelectric Unrestrained Sensors and Its Measurement System Regarding QOL

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Abstract This paper presents a sensor system that predicts behavior patterns that occur when a patient leaves a bed. We originally developed plate-shaped sensors using piezoelectric elements. Existing sensors such as clip sensors and mat sensors require that patients be restrained. The features of our sensors are that they require no power supply or patient restraint for privacy problems. Moreover, we developed machine-learning algorithms to predict behavior patterns without setting thresholds. We evaluated our system for ten subjects at an experimental environment constructed in reference to a clinical site. The mean recognition accuracy was 75.0% for seven behavior patterns. Especially, the recognition accuracies of lateral sitting and terminal sitting were 90.0% and 96.7%, respectively. We consider that these capabilities are useful for bed-leaving prediction in practical use.

Keywords Piezoelectric Elements, Bed-leaving Prediction, Self-Organizing Maps, and Counter Propagation Networks.

1 Introduction

According to the National Population Census 2010 in Japan, the aging rate of the country is 23.1% [1]. This rate implies that Japan has entered a super-aging society, which is defined as the rate of the number of people aged over 65 years old is greater than 20 percent of the total population. A report of National Institute of Population and Social Security Research estimated that a quarter of Japanese residents will be more than 65 years old in 2015 [2]. Along with the longevity of the society, labor shortages will become severe, especially at nursing-care facilities [3]. Few caretakers must care for numerous patients. For this situation, caretakers monitor patients inadequately, especially during sleep at night [4]. One approach to this problem is to use bed-leaving sensors that signal when patients leave from their beds. They can be used to prevent falling from their beds. The number of hospitals and nursing-care facilities using these sensors has increased [5, 6]. Table 1 presents existing sensors to be used actually. We compare features of these sensors related to cost, detection speed, accuracy, privacy, and restrictiveness.

Actually, clip sensors are the lowest-cost sensors that can be introduced easily. This is a simple sensor attached to a patient's clothing [7]. According to protection of human rights, the usage of clip sensors has been prevented recently because it requires constraint of the wearer. For the performance of clip sensors, malfunctions and anomaly detections occur frequently because of the binary response used to detect bed-leaving behaviors. Regarding the reliability and perspective of management, clip sensors are insufficient to prevent falling from a bed completely. Moreover, accidents caused by binding of the neck in a cable have been reported [7]. We regard clip sensors as inadequate for use at clinical sites, although it is easy to introduce them at low cost.

Recently, mat sensors are widely used as a low-cost and convenient sensors that can be installed easily [8]. Haruyama et al. developed an alarm system to detect patients leaving from their beds using mat sensors [9]. Medical and welfare suppliers released various mat sensors installed on a floor, a bed, or on rolling handrails. Mat sensors used on a floor are unnecessary for authentication for medical devices under the pharmaceutical law. Regarding the performance of detection, a problem of a delay remains because of the response after sitting at the end of the bed, although such sensors are easy to produce and to sell. Moreover, sensor responses are apparent when medical staff members such as a nurse or a medical doctor walk on the mat. To distinguish the responses of patients and medical personnel is a challenging problem for signal pattern recognition. Sensors rolled over handrails not only obstruct a view of a bed, but also present a risk of removal of a sensor when a patient finds it and feels negatively about being restrained. Furthermore, false detection occurs when patients leave their bed without gripping a handrail. Mat sensors installed on a bed can detect bed-leaving with higher reliability than other mat sensors. However, existing mat

Table 1. Comparison of characteristics of existing bed-leaving sensors.

Sensor type	Cost	Timing	Accuracy	Privacy	Restriction	References
Clip	Low	Fast	Low	High	Yes	[7]
Bed mat	Low	Fast	Low	Low	No	[8, 9]
Floor mat	Low	Slow	Low	Low	No	[8, 9]
Handrail	Low	Fast	Low	Low	No	
Camera	High	Fast	High	High	No	[11]
Infrared	High	Fast	High	High	No	[15]
Ultrasonic	High	Fast	High	High	No	[14]
Strain gauge	High	Fast	Low	Low	No	[16, 17]

sensors are actuated by a binary response similar to that for clip sensors. Early detection is not realized, especially in the initial stage of bed-leaving behavior.

Large-scale systems using numerous sensors of various types have been proposed for prediction at the initial stage to measure behavior patterns in detail. Shimizu et al. proposed a bed-leaving detection system using ultrasonic array sensors [14]. They evaluated their system at a hospital as a demonstration experiment. Hirasawa et al. proposed a method to expose infrared rays to the upper part of the bed as a system to prevent falling accidents [15]. Uezono et al. proposed a large-scale monitoring system for detecting bed-leaving behavior patterns using 96 strain gauges assigned for a reticular pattern [16]. These large-scale sensor systems can realize higher accuracy and more stable detection than low-cost sensors, such as clip sensors or mat sensors, can. However, these sensors are not put into practical use because of their cost. Moreover, high expenditures are necessary to replace a bed or for construction for installation whenever these systems are improved for practical use in a market.

Hatsukari et al. developed a bed-leaving detection system using strain gauges installed inside of actuators to obtain weight changes of a person on a bed [17]. They embedded sensors and a controller to Paramount beds as a new product of their company Paramount Bed Co. Ltd. The detection accuracies for longitudinal sitting and terminal sitting were, respectively, 87.0% and 98.1% [17]. For their system, three actuators are used in a bed. Each actuator has four biaxial strain gauges installed on diagonal lines. We regard this as the most popular bed-leaving sensor system in practical use currently. It has both high performance and reliability. However, an important limitation of this system is that it is used only for the lifting beds of that company's products with installed actuators. Moreover, it is necessary to install sensors into actuators at the manufacturing phase of beds. Therefore, users must buy it if they need to use this function of bed-leaving detection. These are not casually used sensors that can be installed later. In addition, strain gauges used for this system have uncertain response to thermal changes. For characteristic variation caused by thermal changes, they described that they accommodated it with software. Moreover, this system requires that the weight setting of a person to be selected from three divisions in advance.

Using a camera as a bed monitoring sensor can provide a low-cost system. Moreover, it can obtain much information for a subject. However, it is a challenging task to predict behavior patterns obtained from images, even when state-of-the-art computer vision technologies are used. For this method, medical staff members must observe images directly. It is impossible to monitor numerous subjects simultaneously with a few operators. Moreover, we must consider aspects of human rights and quality of life (QOL). Especially, it is impossible to recognize behavior patterns related to bed-leaving using only sensor responses, even when detailed analyses are conducted, because behavior patterns differ among people [11]. Moreover, monitoring using a camera imposes a mental load on patients because they feel as though they are under surveillance all day and all night.

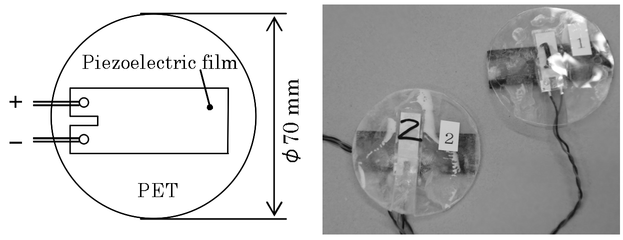
For solving these problems, this paper presents a non-restraining sensor system using piezoelectric films. We developed a machine-learning-based method that obviates the setting of thresholds in advance. Moreover, we developed an integrated system that can send data obtained from sensors to a monitoring computer using a close-range wireless module. We intend to reduce the amount of data used for predicting and minimizing incorrect recognition given a minimum number of sensors. An important benefit of our sensor system is not only that it has no electric power supply, but also that it is not vulnerable to temperature because it uses piezoelectric elements. We evaluated our sensor system in an environment that represents a clinical site. Results show that our method predicted seven behavior patterns related to bed-leaving, especially for longitudinal sitting and terminal sitting.

2 Bed-leaving prediction sensor systems

2.1 Pad sensors

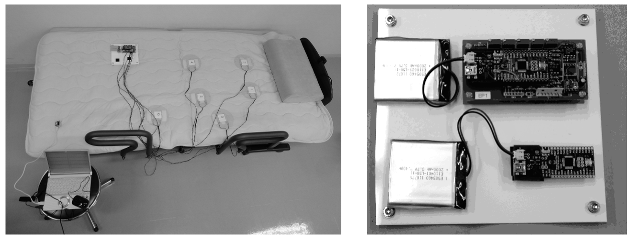
High-performance and functional sensors of various types were used for existing bedside monitoring systems for targeting expensive care or medical treatments [9, 14, 15, 16]. In contrast, we designed a system providing low cost and user-friendliness for practical use. Our originally developed plate-shaped sensors can be installed easily under a bedsheet.

As a prototype, we developed a sensor using piezoelectric films by Measurement Specialties Inc [12]. We fixed a piezoelectric film between two polyethylene terephtha-



(a) Upper view (b) developed sensors

Figure 1. Design and developed sensors



(a) Whole system (b) Sensor boards

Figure 3. Photographs of our sensor system.

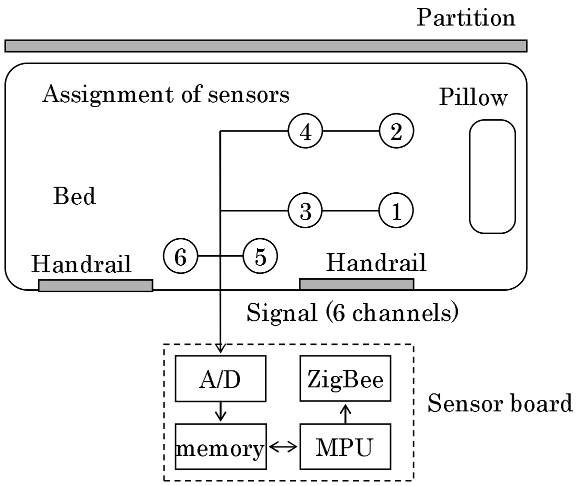


Figure 2. Block diagram of our proposed system and assignment of pat sensors on the bed. S1–S6 denote sensor positions.

late (PET) plates of laminated polyester. The polyester and PET plate sizes were, respectively, 125 μm and ϕ70 $\times$ 0.5 mm. Fig. 1 depicts the design structure and an overview photo of our prototype sensors [13].

Output voltage is generated from the bent piezoelectric films when a subject transfers body weight on the bed. This sensor can measure recursively because the reference potential is offset when the bending stops. Moreover, the strength of weight according to changes of the body is obtainable linearly because the bend of the piezoelectric film and output voltage has a relation of proportionality. Furthermore, piezoelectric films are less troublesome and provide no false operations because they have simple wiring without electric power supply for measurements. Additionally, we can provide a low-cost system requiring no maintenance related to replacement of a battery.

2.2 System Structure

Figure 2 portrays the entire structure of our sensor system that we originally developed for this study. Our system comprises six plate-shaped sensors installed on the bed and a microprocessor board that can obtain output voltage from each sensor for sending to a monitoring terminal computer. The output voltage is generated from these sensors when piezoelectric films are bent to receive body weight changes with movements of a subject caused by rolling or rising on a bed. The assignment of six sensors is S1 and S2 for the shoulder part, S3 and S4 for hip part, and S5 and S6 for the terminal part. We assigned these six sensors referring to the literature related to the development of a monitoring system for users of welfare care beds [5, 6].

The primary feature of our system is that it realizes monitoring using non-restraining sensors. We consider QOL for a patient to live life normally. Our system requires no supervision using infrared cameras or constraining sensors such as clip sensors. Moreover, we can create a low-cost system using piezoelectric films as sensors that can function with little trouble or missed operations, and with remarkable characteristics for pressure resistance. This board obtains output voltage from each sensor for wireless communication. Figure 3(b) depicts the exterior of our capturing board equipped with a microprocessor and a wireless module. For this study, we developed this board using Open Source Hardware ArduinoFIO. With consideration of power consumption, we used short-range wireless communication standard ZigBee communicated with a monitoring terminal computer. The input of this board is four channels. We used two boards for six sensors.

Measured signals are displayed to a monitoring computer in real time. Fig. 3(c) depicts our developed monitoring software. We embedded our method based of machine learning to this software for bed-leaving prediction.

3 Bed-leaving detecting method

3.1 Target behavior patterns

The target behavior patterns for bed-leaving prediction comprise three groups: sleeping, sitting, and leaving. For this study, we attempt to classify detailed behavior patterns from the responses of six sensors. The sleeping comprises three patterns: face-up sleeping, left sleeping, and right sleeping. The sitting comprises three patterns: longitudinal sitting, lateral sitting, and terminal sitting [19]. The total prediction target is to produce seven patterns including leaving. Fig. 4 depicts photographs in each pose for the target behavior patterns. The following are features and estimated sensor responses in each pattern.

(1) Face-up Sleeping A subject is sleeping on the bed normally to the upper side of the body. The sensor response is that S1–4 give outputs, whereas S5 and S6, which are installed near the terminal of the bed, give no output.

(2) Right Sleeping A subject is rolling over on the

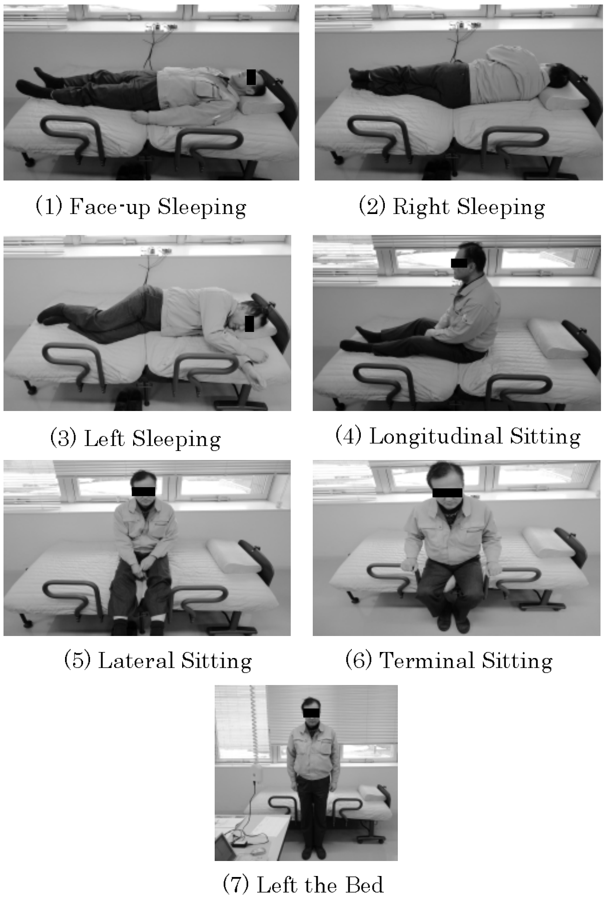


Figure 4. Photographs of target patterns for each body position on the bed.

bed to the right side. The sensor response is that S1 and S3, which are installed on the right side of the bed, give outputs.

(3) Left Sleeping A subject is rolling over on the bed to the left side. The sensor response is that S2 and S4, which are installed on the left side of the bed, give outputs. These three patterns occur as sleeping behaviors. The following are the target patterns of bed-leaving prediction.

(4) Longitudinal Sitting A subject is sitting longitudinally on the bed after rising. The sensor response is that S3 and S4, which are installed on the hip of a subject, give outputs.

(5) Lateral Sitting A subject is sitting laterally on the bed after turning the body from longitudinal sitting. The sensor response is that S3 and S4, which are installed the center of the bed, and S5 and S6, which are installed on the terminal of the bed, give outputs.

(6) Terminal sitting A subject is sitting in the terminal position on the bed trying to leave the bed. The sensor response is that S1, S2, S3, and S4 give no outputs, and that S5 and S6, which are installed near the exit part of the bed, give outputs. Rapid and correct detection are necessary because of the terminal situation for leaving the bed.

(7) Left the Bed A subject is leaving the bed. The sensor response is that no sensor gives any output. Herein, sensor responses disappear in the status of losing consciousness or a life crisis such as cardiopulmonary arrest. For such circumstances, monitoring devices such as electrocardiographs are used. Therefore, such circumstances are beyond our prediction targets.

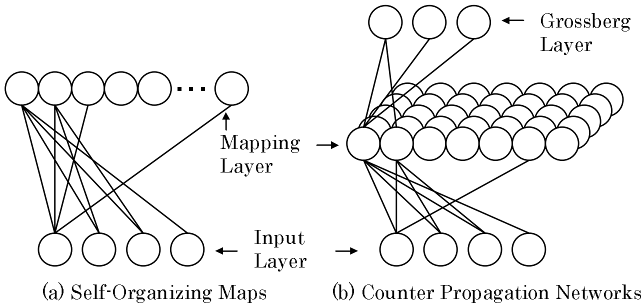


Figure 5. Network architecture of SOM and CPN.

Longitudinal sitting is just a behavior pattern by which a subject sits up. In numerous cases, subjects will return to sleeping. In lateral sitting, a subject will move to leave from their bed because they move to turn the body to the terminal. Therefore, our system must determine lateral sitting immediately to predict a subject leaving the bed. Moreover, rapid and correct detection is necessary because of the terminal situation for leaving the bed if a subject moves to longitudinal sitting. We consider that our system can protect patients from injury or accidents caused by falling from the bed because it can detect such phenomena before a subject leaves completely.

3.2 Preprocessing

Actually, original signals include much more noise, which decreases the recognition accuracy and increases calculation costs. As a method to remove noise signals, filters set by thresholds have been used widely for preprocessing. However, calibration or resetting is necessary according to a target because thresholds are set subjectively or empirically in most cases. Moreover, it is a difficult task to absorb characteristic variation of sensors used only for fixed thresholds. For targeting humans as a measurement objective, individual variations have strong effects.

To set a body weight of a subject in advance is commonly used as a solution against this problem [17]. The load changes are strongly related to body weight. We consider that it is insufficient for calibration used only for body weight because behavior patterns vary among sexual and age differences. In contrast, we are aiming at developing an approach for bed-leaving prediction without setting thresholds in advance. For this study, we use machine-learning algorithms dealing with individual differences among subjects. Nakamura et al. described the effectiveness for adaptation of individual differences using machine-learning methods [18]. Similarly, our method is necessary without setting thresholds through learning patterns in each subject from original signals obtained using sensors.

Various methods have been proposed for machine-learning algorithms. For this study, we use Self-Organizing Maps (SOMs) [20], which learn similarities of input data through the process of learning. Based on the concept of neighborhood and competitive learning, SOMs create clusters using self-mapping characteristics of unsupervised learning. Using the advanced calculation performance of computers, SOMs have facilitated various applications such as remote sensing, facial image processing, and character recognition. For actual applications, SOMs are validated as effective and superior performance through various existing studies [21].

Actually, k-means [22] is widely used for unsupervised-learning based clustering. Vesanto et al. validated that SOMs have superior performance to that of k-means through their experiments [23]. Moreover, Terashima et al. demonstrated that false recognition accuracy of SOMs decreased to the minimum compared with k-means used for clustering. Therefore, we used SOMs because of these benefits.

Fig. 5(a) depicts a network architecture of SOMs. The network comprises two layers: an input layer and a mapping layer. Units on the input layer are assigned as the number of features of input data. We set six units because six pad sensors were used for this system. The mapping layer consists of units in a low-dimensional space. In our method, we assigned mapping units for one dimension because we used it for vector quantization on clustering. Learning is conducted to burst a unit on the mapping layer when a set of input signals is given.

The learning algorithm of SOMs is the following. $w_{i,p}(t)$ are weights from an input layer unit i ($i = 1..., I$) to a mapping layer unit p ($p = 1..., P$) at time t. These weights are initialized randomly before learning. The Euclidean distance d_p between $x_i(t)$ and $w_{i,p}(t)$ is calculated as

$$d_p = \sqrt{\sum_{i=1}^{I}(x_i(t) - w_{i,p}(t))^2}. \tag{1}$$

The unit for which d_p is the smallest is sought as the winner unit c.

$$c = \mathrm{argmin}(d_p). \tag{2}$$

The neighborhood region $N_p(t)$ around c is defined as

$$N_p(t) = S\left(1 - \frac{t}{O}\right). \tag{3}$$

Therein, S ($0 < S \leq P$) is the initial size of $N_p(t)$; O is the maximum iteration for training. Subsequently, $w_{i,p}(t)$ of $N_p(t)$ are updated to close input feature patterns.

$$w_{i,p}(t+1) = w_{i,p}(t) + \alpha(t)(x_i(t) - w_{i,p}(t)). \tag{4}$$

Therein, $\alpha(t)$ is a learning coefficient that has decreasing value with the progress of learning as

$$\alpha(t) = \alpha(0)\left(1 - \frac{t}{O}\right), \tag{5}$$

where $\alpha(0)$ ($0 < \alpha(0) \leq 1.0$) is the initial value. In the initial stage, the learning speed is fast when the rate is high. In the final stage, the learning converges while the rate decreases.

During the learning phase, the process above is repeated until O to pick up from training datasets for random sampling. After learning, training datasets are presented again to the network for searching burst units. These units interpret labels against training datasets and share the same labels as clusters. Herein, for our sensor system using piezoelectric elements, output voltages near the offset are given when no load is changed. The range around the voltages is mapped to numerous signals. We can estimate the appearance of a unit that corresponds to the maximum number of signals on the category map. Therefore, we can select invalid signals that are necessary for recognition to remove invalid signals corresponding to the unit.

3.3 Recognition method

After removing noise from original signals, we recognize behavior patterns using supervised learning-based methods. The purposes of supervised learning and unsupervised learning are to acquire information representation[25] and to create mapping relations[26]. Popularly used methods for supervised learning are Support Vector Machines (SVMs), which provide advanced performance with mapping to a high dimensional space using a kernel function, or Boosting, which is a method combining numerous weak learning machines. For this study, we use Counter Propagation Networks (CPNs) [27], a supervised learning algorithm to be expanded based on SOMs of unsupervised learning.

We use CPNs, not SVMs or Boosting, because of the following two features. 1) The learning algorithm is easy to implement for inserting a Grossberg layer to SOMs that we used for preprocessing. 2) Relations among signals are visualized though the process of creation of mapping structures. We describe formulas of the learning algorithms on CPNs in different parts of SOMs. Visualization of relations among signals is actualized on a category map [21]. We particularly present visualization of results obtained using figures at the evaluation experiment.

The CPNs proposed by Nilsen [27] contain the network structure to append a Grossberg layer, which is given teaching signals, as the third layer. Fig. 5(b) depicts the network architecture of CPNs. The input and mapping layers of CPNs are similar to SOMs. The Grossberg layer is assigned to the counter position of the input layer. For this study, we selected the two-dimensional mapping layer for visualization of similarity among features of input data.

The CPN learning algorithm is the following. The algorithm from presenting input data through updating weights after searching the winner unit c consists of the similar procedure of SOMs. However, weights and neighborhood regions are changed respectively to $w_{i,p,q}(t)(p = 1..., P, q = 1..., Q)$ and $N_{p,q}(t)$ because of the use of a two-dimensional mapping layer. The $v_{j,p,q}(t)$ are weights from a Grossberg layer unit j ($j = 1..., J$) to a mapping layer unit (p, q) ($p = 1..., P; q = 1..., Q$) at time t. $v_{i,p,q}(t)$ and its neighborhood units inside $N_{p,q}(t)$ are updated based on the following Grossberg learning algorithm.

$$v_{j,p,q}(t+1) = v_{j,p,q}(t) + \beta(t)(T_j(t) - v_{j,p,q}j(t)), \quad (6)$$

where T_j represents teaching signals. Similarly to $\alpha(t)$, $\beta(t)$ is a learning coefficient that decreases its value with the progress of learning as

$$\beta(t) = \beta(0)\left(1 - \frac{t}{O}\right), \quad (7)$$

where $\beta(0)$ $(0 < \beta(0) \leq 1.0)$ is the initial value. Finally, as the maximum value of $v_{j,p,q}(t)$ for the Grossberg layer unit j, label $L_j(t)$ is searched for the following.

$$L_j(t) = \underset{1 \leq j \leq J}{\operatorname{argmax}}(v_{j,p,q}(t)). \quad (8)$$

After labeling all units, a category map is created as a learning result. Subsequently, datasets for testing are given to the network. A mapping layer unit is bursted as the minimum of the Euclidean distance in the formula (1). Results of CPNs are presented for corresponding labels.

4 Experimental results

4.1 Datasets

We set up an experimental environment similar to a clinical site for evaluation of our developed sensor system. Fig. 3(a) depicts a bed used for this experiment. For this study, the number of subjects is ten persons: Subjects A–J. They repeated the behavior sequences of seven patterns for six times. Therefore, we obtained 42 pattern datasets. Each behavior is switched in 20 s intervals. We set the sampling rate for capturing signals to 50 Hz.

Table 2 portrays setting parameters used in SOMs and CPNs. We determined these values based on our former study [28] and the literature by Hosokawa et al. [29]. As an evaluation method, we use leave-one-out Cross Validation (CV) [30]. For this experiment, five datasets and the remaining one dataset were used, respectively, for training and testing. Therefore, we evaluated our method for six combinational patterns in each subject.

4.2 Measured signals

Fig. 6 depicts output values of time-series signals obtained from six sensors. The vertical and horizontal axes respectively depict the output voltage and transition time. The dashed lines depict boundaries of each behavior pattern. Output signal patterns are changed according to the transition of longitudinal sitting after sleeping, lateral sitting after turning the body to the exit, and terminal sitting, which is the situation immediately before leaving the bed.

The range of output voltage on S1 though S4 was expanded, especially in the status of face-up, right, and left sleeping. Salient output voltages were given from S5 and S6, although they include some noise. The output voltage on S3 becomes high for longitudinal sitting. We consider that the body weight is concentrated to the hip area according to the rising behavior. For terminal sitting, the output voltage was given from S5 and S6. No output voltage was given from S1, S2, and S3. Moreover, S4, which is located near S5, gave output voltage slightly. After leaving the bed, no output voltage was given from any sensor.

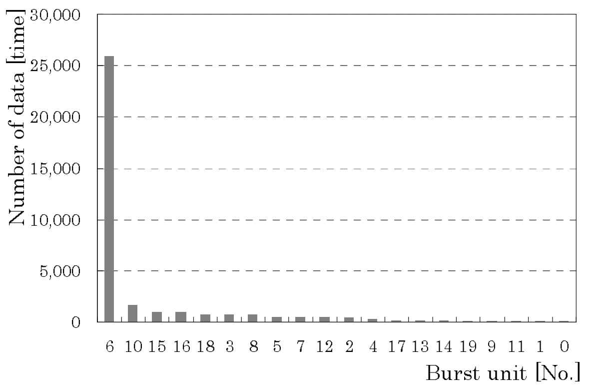


Figure 7. Histogram of classification results obtained using SOMs.

This is the dataset of Subject A at the first trial. Output patterns of signals and their intensity differ in each subject and each trial. Therefore, it is a challenging task to set thresholds for removal of noise or for recognition solely from original signals. In contrast, our machine-learning based method can execute the following process automatically.

4.3 Noise removal results

For improving recognition accuracy and to reduce processing costs together, we removed noise patterns using SOMs. Fig. 7 portrays a clustering result of training datasets using SOMs. The horizontal and vertical axes depict the position of a burst unit and the number of burst iterations, which correspond to the number of datasets in each unit. We sorted a unit's numbers according to the maximum of the bursting iterations from the left side. Most output voltages remained near the offset value shown in Fig. 6 because no output voltage is given from piezoelectric elements when no load change is given without bending. In Fig. 8, the sixth unit corresponds to this unit. For this case, 25,954 signals were mapped to the unit that corresponded to 74.2% for all data of 34,976 signals. Other signals of 15.8% were mapped to the remaining 19 units, similar to a long-tail shape. We confirmed that this tendency was obtained in other cases when we changed the number of units.

Fig. 8 portrays signal patterns after removing signals mapped into the sixth unit. Additionally, we present extended figures at the bottom side of each signal pattern between 0–40 s on S1. We can visually confirm results after removing slight noise around the offset value.

4.4 Recognition results

Fig. 9 depicts an example of category maps for Subjects A–C created as classifiers. The numbers on the category maps correspond to respective behaviors that were labeled though learning. Labels 1, 2, and 3, which correspond to sleeping, are distributed outside of the map in Subject A. An individual cluster is created at the center of the map with Label 6 of terminal sitting.

Table 2. Setting values of parameters on SOMs and CPNs.

Method	I [unit]	J [unit]	P [unit]	Q [unit]	S [unit]	$\alpha(0)$	$\beta(0)$	O [epoch]
SOM	6	–	20	–	16	0.5	–	1,000,000
CPN	6	7	20	20	16	0.5	0.8	100,000

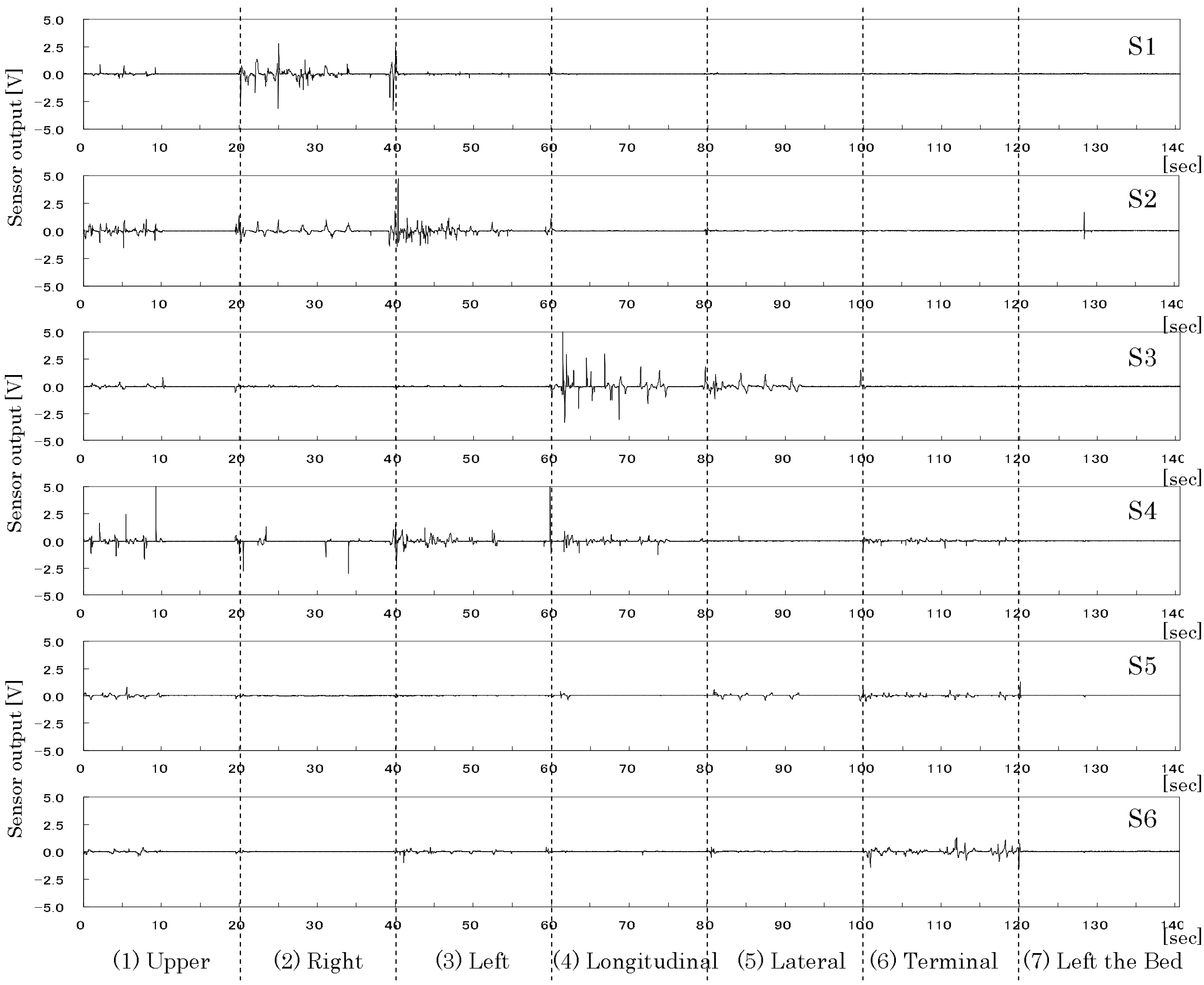


Figure 6. Time-series changes of sensor output in each behavior pattern (Subject A, First trial).

Label 4 of longitudinal sitting and Label 5 of lateral sitting are distributed to the left and bottom of the map surrounded by Label 6. For Subject B, Labels 4–6 are distributed to the left side of the map. The distribution of Label 4 is visible to expand not only the right-upper part, but also the whole of the map. The distribution of Labels 1–3 is divided roughly into two clusters of Labels 4 and 6. In Subject C, each label shows several distributions. From the category map, we can observe that the distribution of signals in each sensor differs in each subject with their positional changes.

Subsequently, we evaluated our method to recognize bed-leaving behaviors from matched labels that correspond to burst labels after presenting test datasets to the category maps. Table 3 portrays a result of recognition accuracy. We evaluated six combinations for CV. Herein, we calculated the recognition accuracy as a ratio of the number of ground truths and the number of labels in each behavior pattern that reached the maximum of responses during 20 s.

The mean recognition accuracy for ten subjects is 75.0%. The recognition accuracies of Subjects B and H are, respectively, 91.7% and 55.0% as the highest and the lowest. For respective behaviors, the recognition accuracy of leaving is 91.7%. The recognition accuracy of lateral sitting remained at 55.0%, although the recognition accuracies of longitudinal sitting and terminal sitting, which are the most important positions for bed-leaving detection, reached 90.0% and 96.7%, respectively. For lateral sitting, the recognition accuracy of Subjects C, D, and G is 100%. However, it dropped to 0% for Subjects B and F. We regard lateral sitting as a status that can accommodate diversity among individuals. For sleeping, the recognition accuracy of face-up sleeping is higher than that of right or left sleeping. We regard the body weight as gathered to the two sensors of the left or right sides in sleeping, whereas the load from the upper body is distributed on S1–S4 at the face-up sleeping.

Herein, the recognition accuracy is 88.3% in the case of three patterns: sleeping, sitting, and leaving. We

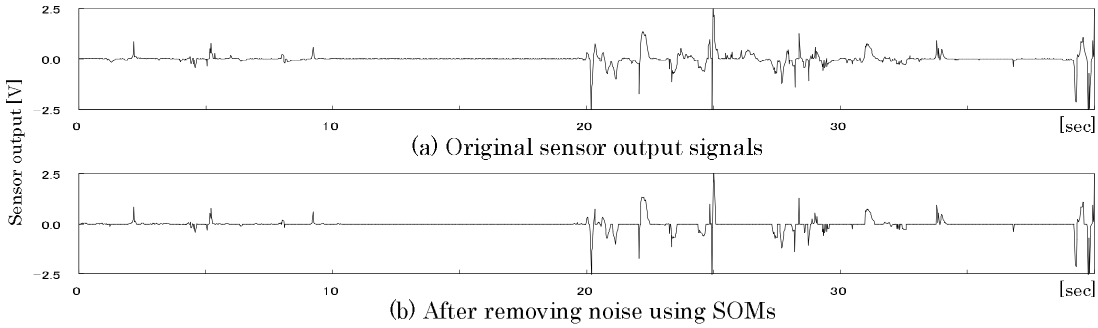
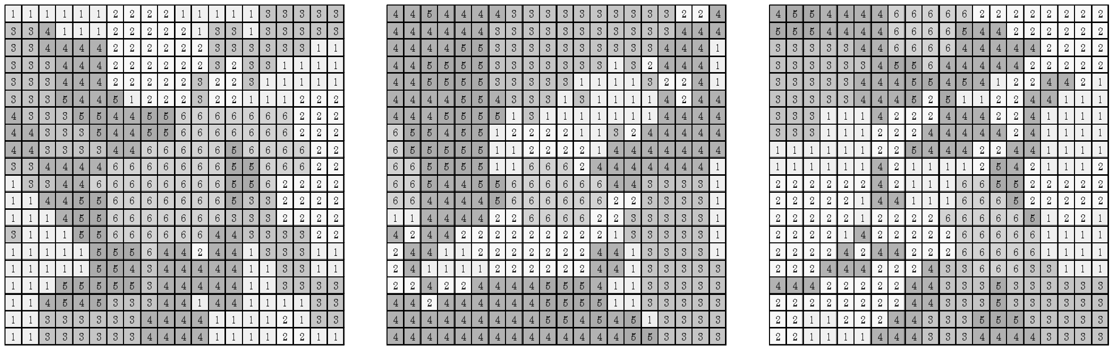


Figure 8. Output voltage from S1 before and after removing noisy signals contained in the sixth unit.



(b) Subject A (b) Subject B (b) Subject C

Figure 9. Category maps of Subject A–C. The grids correspond to the units on the mapping layer of CPNs. Levels 1–7 denote the positions of face-up sleeping, right sleeping, left sleeping, longitudinal sitting, lateral sitting, terminal sitting, and leaving.

consider that this is a meaningful result for practical use because it is sufficient to recognize three patterns at a clinical site, although we set the recognition target to seven patterns for this study.

4.5 Discussion

We analyze false recognition using the confusion matrix shown in Table 4. For this matrix, the number of correct datasets is shown on the diagonal cells that we underlined. As the basis for the horizontal side, the number of false recognition datasets and their labels can be specified to refer to labels on the vertical side.

The recognition accuracy of lateral sitting is the second lowest. The number of correct recognition is 33 datasets. For this behavior, 12 and 13 datasets are falsely recognized respectively as lateral sitting and terminal sitting. The behavior patterns of a subject from longitudinal sitting to lateral sitting have a large gap because subjects turn their body about 90 deg on the bed. For both sitting positions, the load to be provided pad sensors is concentrated to the hip at the center of the bed. We consider that the false recognition in both behavior patterns results from this feature. In contrast, no dataset of longitudinal sitting was falsely recognized as lateral sitting. For lateral sitting, the load of the legs is gathered to the terminal as an exit of the bed. We consider that false recognition results from unclear boundaries between lateral sitting and terminal sitting. However, we consider that fatal errors of bed-leaving prediction can be avoided because no dataset of lateral sitting was falsely recognized as sleeping or bed leaving.

As shown in the second line of Table 4, 10 and 28 datasets of face-up sleeping were falsely recognized as longitudinal sleeping and right or left sleeping, respectively. For sleeping on the right, six datasets are falsely recognized as longitudinal sitting. We consider that this results from the load to be gathered S3 only depending on a subject, although the load on right sleeping is gathered to S1 and S3 normally.

Comparison with the bed-leaving sensor system that used strain gauges in actuators proposed by Hatsukari et al. [17] revealed that the recognition accuracies of their method were 87.7% for longitudinal sitting and 98.1% for terminal sitting. The recognition accuracies of longitudinal sitting and terminal sitting of our method are, respectively, 2.3% higher and 1.4% lower than their method, although the experimental environment and the number of subjects differ in the results. Their method remains for three target patterns of longitudinal sitting, terminal sitting, and leaving. Moreover, their method requires setting the body weight of a subject in advance. We consider that our method is superior to their method as a functional aspect without setting it in advance.

5 Conclusion

This paper presents a non-restraining sensor system to predict bed-leaving behaviors. We developed a prototype of plate-shaped sensors using piezoelectric films and a monitoring system consisting of microprocessor boards with wireless modules to capture data from sensors. Moreover, we developed a machine-learning based method to predict seven behavior patterns related to leaving the bed from sensor signals. We evaluated our

Table 3. Recognition accuracies of respective subjects and positions [%].

Subject	Face-up	Right	Left	Longitudinal	Lateral	Terminal	Left the Bed	Average
A	100	83.3	66.7	83.3	16.7	100	100	78.6
B	83.3	100	100	100	0	100	100	83.3
C	0	33.3	100	100	100	83.3	100	73.8
D	0	83.3	66.7	100	100	100	100	78.6
E	0	100	66.7	100	66.7	83.3	100	73.8
F	33.3	100	100	83.3	0	100	83.3	71.4
G	50.0	83.3	50.0	50.0	100	100	66.7	71.4
H	0	66.7	0	83.3	33.3	100	83.3	52.4
I	83.3	66.7	100	100	66.7	100	100	88.1
J	0	100.0	100	100	66.7	100	83.3	78.6
Average	35.0	81.7	75.0	90.0	55.0	96.7	91.7	75.0

Table 4. Confusion matrix of respective behaviors. Underlined figures show the quantities of correct data.

Position	Face-up	Right	Left	Longitudinal	Lateral	Terminal	Left the Bed
Face-up	**21**	22	6	10	0	0	1
Right	1	**49**	0	6	3	0	1
Left	2	1	**45**	7	0	2	3
Longitudinal	1	4	1	**54**	0	0	0
Lateral	0	1	1	12	**33**	13	0
Terminal	0	0	1	1	0	**58**	0
Left the Bed	0	2	2	0	0	1	**55**

system for three subjects at an experimental environment constructed in reference to a clinical site. The mean recognition accuracy was 75.0% for seven behavior patterns. Especially, the recognition accuracies of lateral sitting and terminal sitting were 90.0% and 96.7%, respectively. We consider that this result is useful for bed-leaving prediction in practical use.

We will achieve steady detection to expand the application range of our method and thereby increase the number of subjects. Moreover, we would like to apply our system to care facilities or single senior's homes for security and safety observation that simultaneously maintains QOL and privacy.

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