Awakening Detection System for Patients Covered by a Quilt Using a Depth Sensor and a Neural Network

Geer Cheng[1,a*], and Hideo Furuhashi[1,b]

[1]Dep. Electrical and Electronics Technologies, Aichi Institute of Technology, 1247, Yachigusa, Yakusa-cho, Toyota, Aichi, 4700392, JAPAN

[a]chenggeer2008@yahoo.co.jp, [b]furuhasi@aitech.ac.jp

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Abstract. An awakening detection system for bedridden patients covered by a quilt using a ceiling-mounted depth sensor is evaluated. The performance of the depth sensor for monitoring situations where subjects are covered by quilts of different thicknesses using a neural network is discussed. The state of the subject was differentiated into four cases: “lying on back in bed,” “lying on side in bed,” “sitting up in bed,” and “no longer in bed.” The network obtained from the dataset of a specific quilt cannot be used for discrimination in a general case with quilts of different thicknesses. The network obtained using datasets with quilts of different thicknesses shows a good performance. Further improvements in the performance can be obtained by including the values of the maximum height and thickness of the quilt in the datasets.

1. Introduction

Many clinics and healthcare providers worldwide are urgently seeking accurate, low-cost, and easy-to-use technological solutions to predict risks due to a patient’s frailty and their probability of falling, which are the most common causes of unintentional injuries and deaths. Therefore, the demand for methods to monitor patients in hospitals and private homes is increasing.

Here, we describe a system that monitors bedridden patients who are in a coma or sleeping due to anesthesia and detects awakening behaviors. Currently, multiple types of monitoring systems for patients or older persons are available or have been proposed [1-6]. However, such systems monitor active people who can move around a room and detect the action of falling down on the floor or falling out of bed. When monitoring patients in a coma or patients who are sleeping due to anesthesia, the detection of the awakening behavior is important to prevent patients from falling out of bed. Such patients are groggy just after waking up, and there is a risk of falling. Therefore, the immediate support of caregivers is required when these patients wake.

Several systems detecting awakening behavior have been reported. Satoh et al. proposed a system using an RGB camera and neural networks [7, 8]. Takeda proposed a system for medical use using the depth sensor Kinect and neural networks [9]. Ni et al. proposed get-up event detection for hospital fall prevention using an RGBD sensor (Kinect) and a multichannel learning framework [10]. We proposed a system that uses a depth sensor and optimal linear discriminant analysis with the projected values of the height, space, and volume above the bed to detect the awakening behavior of a subject covered by a specific quilt [11]. However, the influence of the quilts on such systems has not been discussed in detail.

Here, we discuss the performance of the awakening detection system using a depth sensor when monitoring situations where subjects are covered by quilts of different thicknesses using a neural network. Improvements in the performance when including the maximum height and the thickness of the quilt with the depth image in the datasets are also discussed.

2. Experimental

A depth sensor, Kinect (Microsoft Corp.), was mounted on the ceiling 240 cm above the floor. The height of the bed was 35 cm. The area of the bed was 215 cm × 290 cm. There was a subject (the patient) on the bed who was covered with a quilt. Data measured by the depth sensor were fed into a computer and converted into height data from the floor. The total area of the height data, 210 × 500 pixels, was divided into 7 × 8 areas (1 area has 30 × 50 pixels), and the height values were averaged in each area. The data series, 7 × 8 = 56, was used as the dataset for the neural network analysis.

The state of the subject is differentiated into four cases: case 1 “lying on back in bed,” case 2 “lying on side in bed,” case 3 “sitting up in bed,” and case 4 “no longer in bed.” Here, “lying on back in bed” means that the subject is sleeping on the bed. “Lying on side in bed” means that the subject has awakened. In this case, the immediate risk of falling out of the bed is not very high. However, support by a caregiver is required to decrease risks involving falling out of the bed. “Sitting up in bed” has a large risk of the subject falling out of the bed. The case “no longer in bed” is very dangerous, and the caregiver should be notified as soon as possible. Figure 1 shows the alarm system considered in this study. The classification is performed using the depth data captured by the sensor. If the state of the subject is classified as “lying on side in bed,” a notification alarm is generated, and the system returns to the classification process. If the state of the subject is evaluated as “sitting up” or “no longer in bed,” a warning alarm is generated, and the system stops. Otherwise (“lying on back”), the system returns to the classification process.

Ten datasets each for six experiments with subjects (60 datasets) were collected. Datasets were then collected for all four cases for each of the six subjects (240 datasets). The subjects’ heights were 165–178 cm, and their weights were 52–83 kg. The subjects were covered with quilts with thicknesses of 5.5 or 38.5 mm. Weka (Machine Learning Group at the University of Waikato) was used for the data analysis using a multilayer neural network with back propagation for the classification.

Figure 2 shows a schematic diagram of the system. The datasets of the neural network analysis included not only the depth image but also the values of the maximum height and the thickness of the quilt.

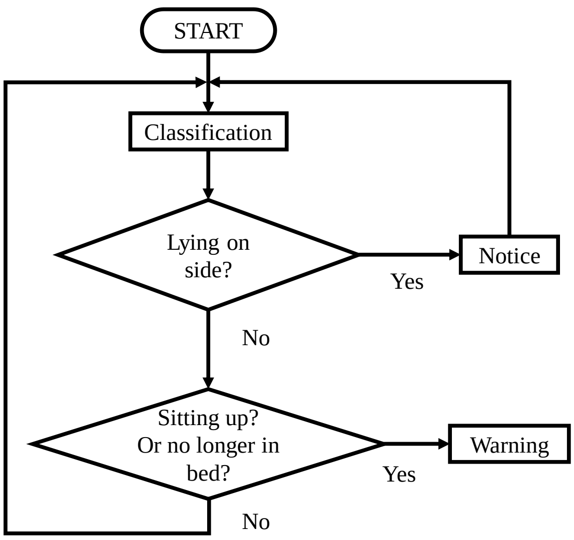


Fig. 1. Flowchart of the awakening detection system.

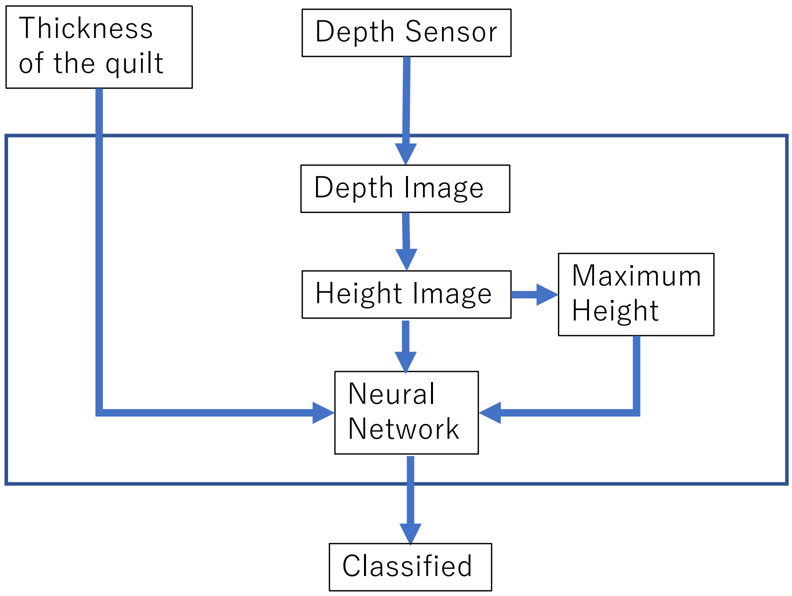
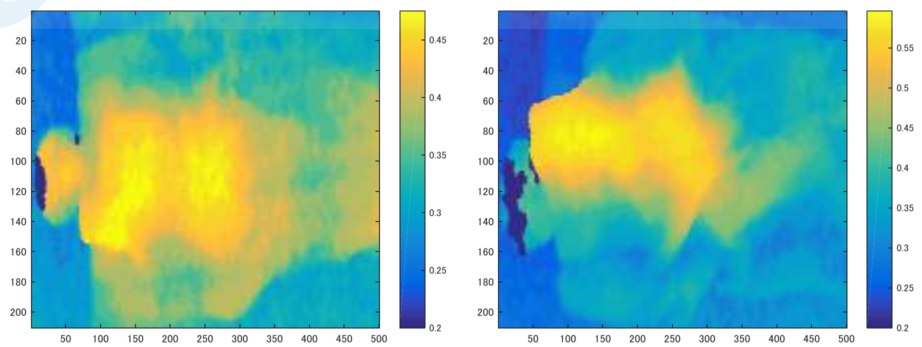


Fig. 2. Schematic diagram of the awakening detection system.

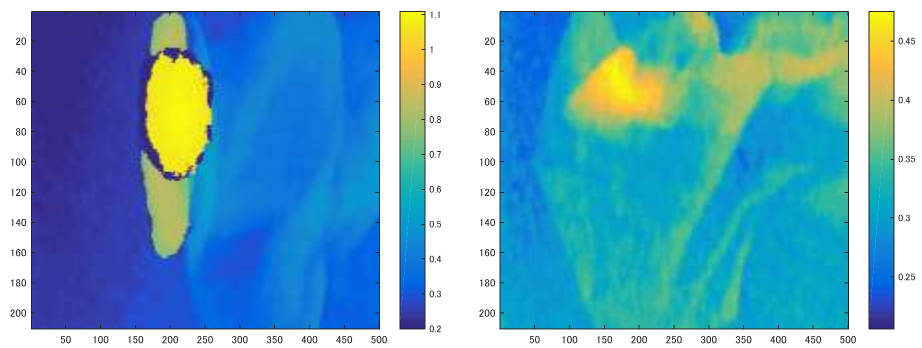
3. Results

3.1.Analysis of subjects covered by the thin quilt

Subjects covered by a thin quilt of 5.5 mm were analyzed using a neural network. Figure 3 shows examples of height images for the four cases. Figure 4 shows a low-resolution image of the data. Datasets having $7 \times 8 = 56$ series data were used for the analysis. The neural network learning employed 500 repetitions using back propagation and had one hidden layer with sigmoid nodes. The values of the maximum height and thickness of the quilt are not included in the datasets.

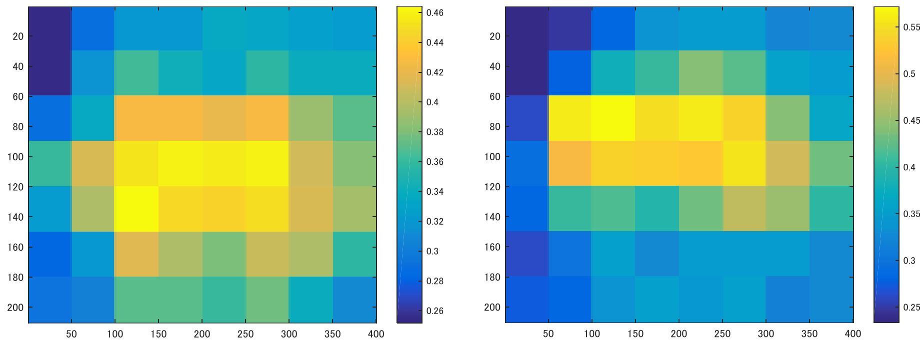


(a) Lying on back (b) Lying on side

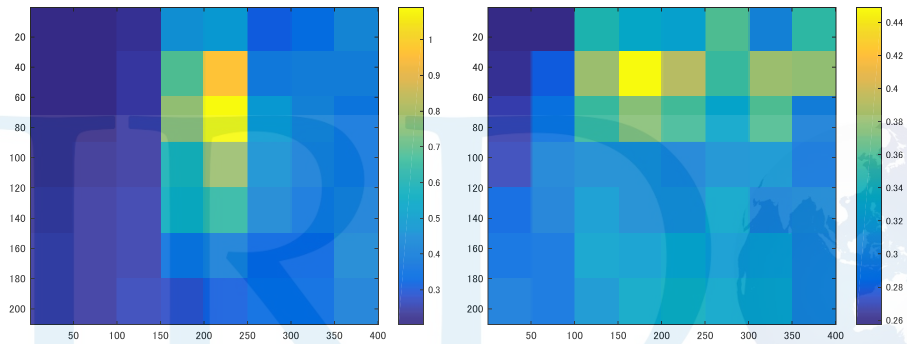


(c) Sitting up (d) No longer in bed

Fig. 3. Examples of height data for the four cases. The subject is covered by a thin quilt. One pixel is equal to 4.5 mm, and the color bars are in meters.



(a) Lying on back (b) Lying on side



(c) Sitting up (d) No longer in bed

Fig. 4. Examples of height data for the four cases at a low resolution of 7 × 8 pixels. The subject is covered by a thin quilt. The color bars are in meters.

A 10-fold cross validation was performed to evaluate the performance. The straight line in Figure 5 shows the percentage of states correctly classified depending on the number of sigmoid nodes. The percentages were 86.3%, 91.3%, 95.0%, 95.9%, 96.7%, and 97.5% for 0 (no hidden layer), 2, 5, 10, 30, and 56 nodes, respectively. Even though evaluations of the system using two hidden layers and 2000 learning repetitions were also made, improvements in the performance were not obtained. Table 1 shows the confusion matrix when the number of nodes is 56. The cases “lying on back” and “no longer in bed” are correctly classified. However, the case “sitting up” showed some errors in the classification.

Now, we consider the maximum height of each image. This is a good predictive value for the classification in the case of “sitting up.” The maximum height had values of 0.447–0.552, 0.547–0.614, 0.916–1.133, and 0.360–0.458 for cases 1, 2, 3, and 4, respectively. The values for case 3 do not overlap with those of the other cases. Therefore, the maximum height was included in each dataset. Each dataset then had 56 + 1 = 57 values. A 10-fold cross validation was performed to evaluate the performance. The broken line in Figure 5 shows the percentage of states correctly classified depending on the number of nodes. The percentages were 94.6%, 97.9%, 98.3%, 98.3%, 98.3%, 98.3%, 98.3%, and 98.3% for 0 (no hidden layer), 2, 3, 4, 5, 10, 30, and 56 nodes, respectively. A better performance was obtained than that in the analysis that did not include the maximum height values. Increases in the number of nodes to more than 3 did not improve the performance. Table 2 shows the confusion matrix when the number of nodes is 3.

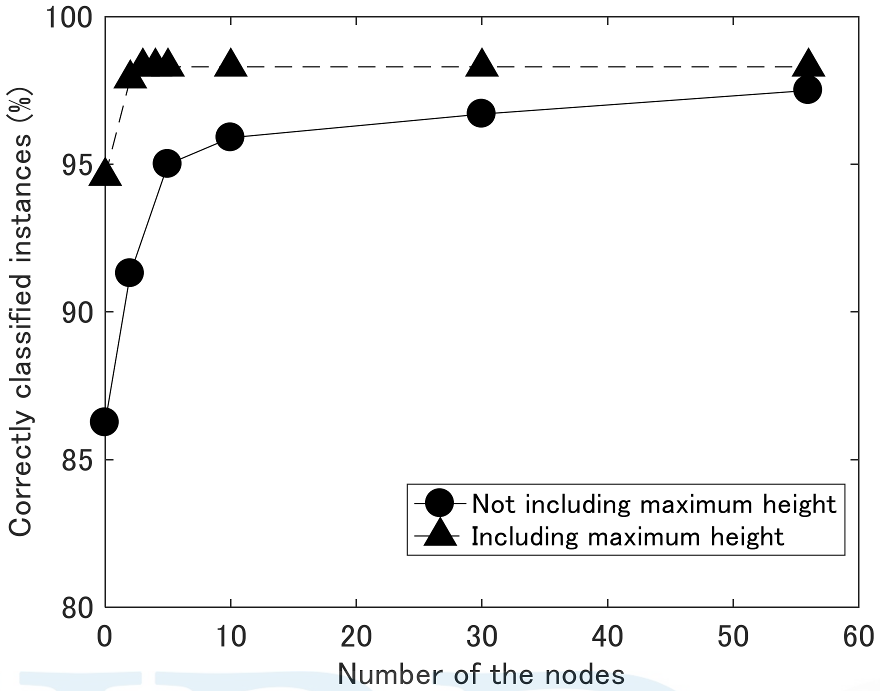


Fig. 5. The percentage of states correctly classified for a thin quilt depending on the number of sigmoid nodes.

Table 1. Confusion matrix for the datasets with a subject covered by a thin quilt.

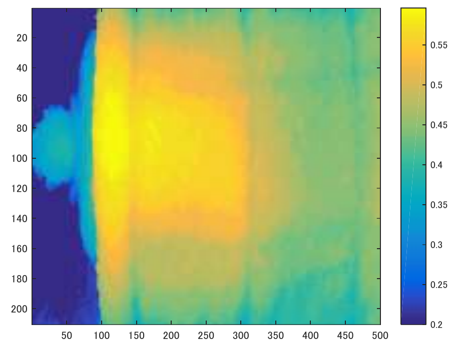
	Lying on back	Lying on side	Sitting up	No longer in bed
Lying on back	60	0	0	0
Lying on side	2	58	0	0
Sitting up	0	4	56	0
No longer in bed	0	0	0	60

Table 2. Confusion matrix for the datasets with a subject covered by a thin quilt including the maximum height value.

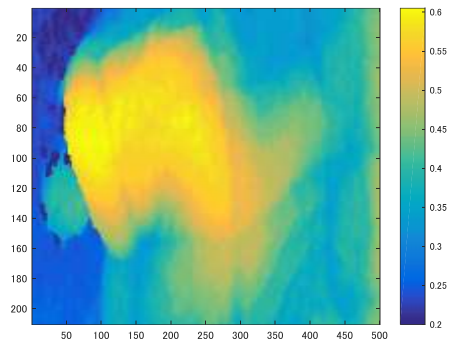
	Lying on back	Lying on side	Sitting up	No longer in bed
Lying on back	60	0	0	0
Lying on side	2	57	0	1
Sitting up	0	1	59	0
No longer in bed	0	0	0	60

3.2.Analysis of subjects covered by the thick quilt

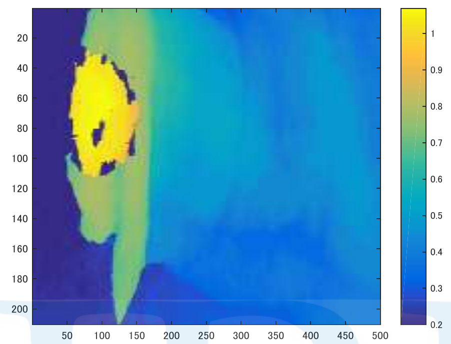
Subjects covered by a thick quilt of 38.5 mm were analyzed using a neural network. The values of the maximum height and thickness of the quilt are not included in the datasets. Figure 6 shows examples of the height images for the four cases. Figure 7 shows a low-resolution image of the data. The depth image spread is wider than that in the case of the thin quilt. Each thick quilt dataset had 56 series values and was analyzed using a neural network with one hidden layer.



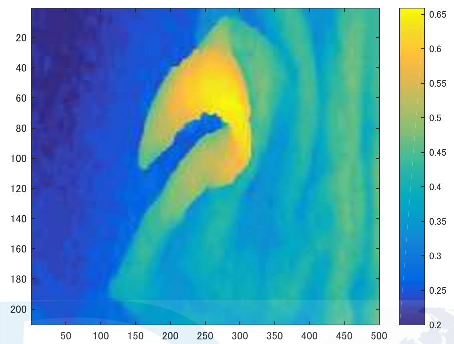
(a) Lying on back



(b) Lying on side

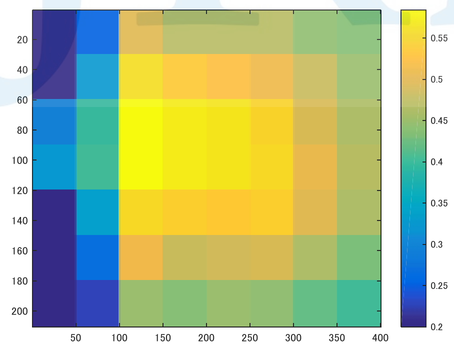


(c) Sitting up

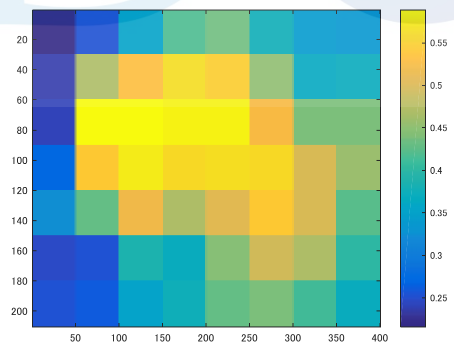


(d) No longer in bed

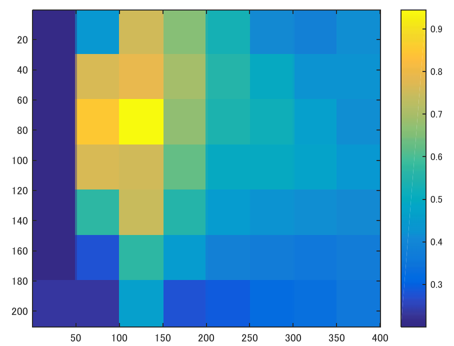
Fig. 6. Examples of height data for the four cases. The subject is covered by a thick quilt. One pixel is equal to 4.5 mm, and the color bars are in meters.



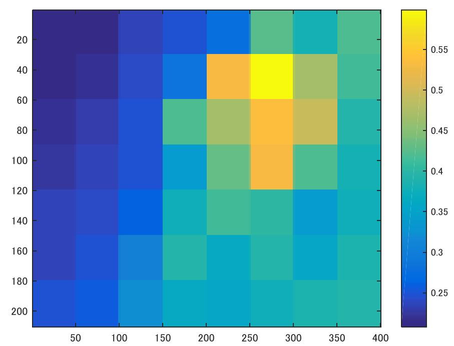
(a) Lying on back



(b) Lying on side



(c) Sitting up



(d) No longer in bed

Fig. 7. Examples of height data for the four cases at a low resolution of 7 × 8 pixels. The subject is covered by a thick quilt. The color bars are in meters.

A 10-fold cross validation was performed to evaluate the performance. The percentages of instances that were correctly classified were 93.8%, 95%, 97.1%, 97.1%, 97.5%, and 96.7% for 0 (no hidden layer), 2, 5, 10, 30, and 56 nodes, respectively. This is a similar performance to that of the case with a thin quilt. Even though evaluations using two hidden layers and 2000 learning repetitions were performed, a performance improvement was not obtained. Table 3 shows the confusion matrix when the number of nodes is 30. The cases "lying on back" and "no longer in bed" are correctly classified. However, again, the case "sitting up" showed some classification errors.

The values of the maximum height were 0.480–0.603, 0.584–0.690, 0.814–1.110, and 0.452–0.462 for cases 1, 2, 3, and 4, respectively. These values are larger than those in the case of a thin quilt for cases 1, 2, and 4. For case 3, the maximum height values do not become large. A 10-fold cross validation was performed to evaluate the performance for datasets including the maximum height value. The percentages of instances correctly classified were 95.0%, 97.5%, 98.0%, 98.3%, 98.3%, 98.3%, 98.0%, 98.8%, and 98.3% for 0 (no hidden layer), 2, 3, 4, 5, 10, 20, 30, and 56 nodes, respectively. A better performance was obtained than that in the analysis that did not include the maximum height values. Increases in the number of nodes to more than 3 did not improve the performance. Table 4 shows the confusion matrix when the number of nodes is 3.

Table 3. Confusion matrix for datasets with a subject covered by a thick quilt.

	Lying on back	Lying on side	Sitting up	No longer in bed
Lying on back	60	0	0	0
Lying on side	1	59	0	0
Sitting up	1	4	55	0
No longer in bed	0	0	0	60

Table 4. Confusion matrix for datasets with a subject covered by a thick quilt including the maximum height value.

	Lying on back	Lying on side	Sitting up	No longer in bed
Lying on back	60	0	0	0
Lying on side	1	59	0	0
Sitting up	0	2	58	0
No longer in bed	0	0	0	60

3.3.Analysis of the combined dataset with thin and thick quilts

The influence of the quilt thickness was investigated. Table 5 shows the confusion matrix when the network obtained by the thin quilt datasets was evaluated using the thick quilt datasets. Table 6 shows the confusion matrix when the network obtained by the thick quilt datasets was evaluated using the thin quilt datasets. The values of the maximum height are included in the datasets. The evaluations used one hidden layer with 30 nodes. The percentages of instances that were correctly classified were 64.2% and 69.2%, respectively. These performances are not good. Therefore, a network obtained with a specific quilt cannot be used for the classification of a subject covered by a different quilt.

Table 5. Confusion matrix for datasets with a subject covered by a thick quilt classified using the network obtained using the thin quilt datasets.

	Lying on back	Lying on side	Sitting up	No longer in bed
Lying on back	58	2	0	0
Lying on side	31	29	0	0
Sitting up	1	1	57	1
No longer in bed	45	5	0	10

Table 6. Confusion matrix for datasets with a subject covered by a thin quilt classified using the network obtained using the thick quilt datasets.

	Lying on back	Lying on side	Sitting up	No longer in bed
Lying on back	39	0	0	21
Lying on side	39	10	0	11
Sitting up	0	1	58	1
No longer in bed	1	0	0	59

The combined datasets for thin and thick quilts together were used to analyze the dataset using the neural network. The total number of datasets was 480. A 10-fold cross validation was performed to evaluate the performance. The straight line in Figure 8 shows the percentage of instances that were correctly classified depending on the number of nodes. The percentages are 87.1%, 89.8%, 97.3%, 99.2%, 99.4%, and 99.4% for 0 (no hidden layer), 2, 5, 10, 30, and 56 nodes, respectively. Therefore, a good performance was obtained.

The result using the datasets including the values of the maximum heights is also shown in Figure 8 by the broken line. A better performance is obtained with small numbers of nodes. The percentages are 91.3%, 95.6%, 98.8%, 99.2%, 99%, 99.4%, 99.2%, and 99.4% for 0 (no hidden layer), 2, 3, 4, 5, 10, 30, and 56 nodes, respectively. The values of the maximum height values were 0.447–0.603, 0.547–0.690, 0.814–1.133, and 0.360–0.462 for cases 1, 2, 3, and 4, respectively. The values for case 3 do not overlap with those of the other cases. The values in cases 1, 2, and 4 overlap each other.

Next, the values of the thickness were included in the datasets. Therefore, each dataset included 58 data. The result using the datasets is shown in Figure 8 by the dotted line. The percentages are 91.5%, 96.3%, 98.8%, 99%, 99%, 99.4%, 99.4%, 99.4%, 99.6%, and 99.6% for 0 (no hidden layer), 2, 3, 4, 5, 10, 20, 25, 30, and 56 nodes, respectively. The performance was slightly improved. Table 7 shows the confusion matrix for the datasets including the values of the maximum height and the quilt thickness when the number of nodes is 30.

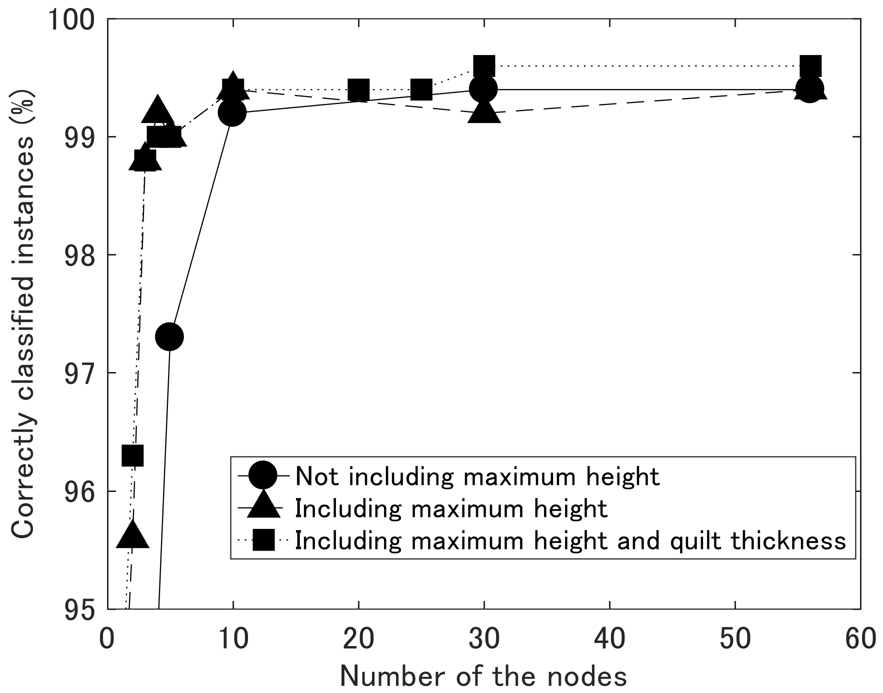


Fig. 8. The percentage of correctly classified instances for datasets including both thin and thick quilts depending on the number of nodes.

Table 7. Confusion matrix for datasets with a subject covered by different quilts classified using the network obtained using the datasets of the thin and thick quilts.

	Lying on back	Lying on side	Sitting up	No longer in bed
Lying on back	120	0	0	0
Lying on side	1	119	0	0
Sitting up	0	1	119	0
No longer in bed	0	0	0	120

4. Summary

An evaluation of an awakening detection system for bedridden patients covered by a quilt with a ceiling-mounted depth sensor was performed. A neural network was used to analyze the data. The state of the subject was differentiated into four cases: “lying on back in bed,” “lying on side in bed,” “sitting up in bed,” and “no longer in bed.” The influence of the quilt on the discrimination was discussed using quilts of different thicknesses. It was shown that the network obtained by a dataset of a specific quilt could not be used for a case with a quilt of a different thickness. However, the network obtained using datasets of quilts with different thicknesses showed a good performance. Further improvements in the performance were obtained by including the values of the maximum height and the thickness of the quilt in the datasets.

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