

Performance Evaluation of a System to Detect Awakening Behavior of Bedridden Patients with a Quilt Using a Depth Sensor

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Abstract: We evaluate a system that monitors bedridden patients covered by different types of quilts by utilizing a proximity depth sensor with an infrared projector (Kinect). This system is capable of detecting people as they wake up. We believe that this system could be useful for monitoring patients in hospitals or private homes who must occasionally be left unsupervised. The system, which utilizes an optimal linear discriminant function, is demonstrated with subjects covered by quilts of different thicknesses. The detection rate of a basic system using height and space data for four cases - lying on the back, lying on the side, sitting up, and no longer in bed—was 99.2 % when a thin quilt was used and 80.4 % when a thick quilt was used. The detection rate was also low (80.8 %) when two variables were used for the cases using either thin or thick quilts. The rate improved to 96.3 % using the data of the initial condition of the subject. Good performance was obtained regardless of the thickness of the quilt.

Keywords: Kinect, Depth sensor, Awakening behavior detection, Optimal linear discrimination.

1. Introduction

Many clinics and healthcare providers worldwide are urgently seeking accurate, low-cost, and easy-to-use technological solutions for predicting risks owing to a patient's frailty and falling, which are the most common causes of unintentional injury and death. The demand for methods of monitoring patients in hospitals and private homes is increasing. In hospitals, if a patient awakens, it is important that the responsible healthcare professionals are cautioned because the patient might fall out of bed and suffer severe injuries. Older people being cared for by family members at home can be similarly injured. Furthermore, the wandering of older people suffering

from dementia is a serious social problem. However, providing complete 24-h supervision is difficult.

We herein describe a system that monitors bedridden patients who are in a coma or sleeping due to anesthesia and detects awakening behaviors. Numerous types of monitoring systems for patients or older people are available or have been proposed [1-8]. These include passive camera-based image-processing systems, mat sensors, and ultrasonic sensors. However, the recognition rates of passive camera-based systems and ultrasonic systems are low, and mat sensors are subject to mechanical failure. Some investigations have been reported on the measurement of human activities or the monitoring of patients or older adults using a depth sensor [9-18].

However, such systems monitor active people who can move about within the room and detect the action of falling down on the floor or falling out of a bed. For monitoring comatose patients or patients who are sleeping due to anesthesia, detection of the patient waking up is important to prevent them from falling out of the bed. Such patients may be groggy, and this comes with a high risk. Therefore, immediate support of caregivers is required when the patients wake up.

Some systems detecting awakening behavior have been reported. H. Satoh et al. proposed a system using an RGB camera and neural network [19, 20]. Takeda proposed a system for medical use using a Kinect depth sensor and neural networks [21]. They placed the RGB camera or Kinect sensor besides the bed. They classified the behavior into two classes: (a) safety action (lying, being sitting up, or sitting) and (b) dangerous action (almost falling). However, it is sometimes too late if the caregivers are called when the dangerous action occurs. Ni et.al proposed a get-up event detection for hospital fall prevention using the Kinect RGB-D sensor and multi-kernel learning framework [22]. In their study, the sensor was located beside the bed. We have also reported a system that uses a depth sensor and optimal linear discriminant analysis (OLDA) with future amounts of the height, space, and volume above the bed to detect the awakening behavior of subject [23]. The depth sensor was mounted on the ceiling. They are classified in four cases: (a) lying on the back (b) lying on the side (c) sitting up, and (d) no longer in bed; the caregiver is called in the case of occurrence of b, c, and d. A high detection rate was obtained. However, patients are generally covered by many types of quilts, and the shape of the subject on the bed is blurry. The previous studies did not focus on the influence of the quilt.

Herein, we discuss the performance of that depth sensor for monitoring situations wherein the subjects are covered by quilts of different thicknesses. The discrimination was performed by considering the quilt thickness and the subject size.

2. Experimental Setup

Fig. 1 shows the experimental setup. We mounted a depth sensor, Kinect (Microsoft Corp), on the ceiling at a height of 240 cm above the floor. The bed height was 30 cm. A subject covered with a quilt lay on the bed. Two quilts of thicknesses 5.5 and 38.5 mm were used for the experiments. The data measured by the depth sensor were fed into a computer and analyzed.

Fig. 2 shows the measurement process used for data analysis. Initially, depth data were acquired in the area of the bed without a subject or a quilt on the bed. The area of the bed was 215 cm × 290 cm. Next, depth data were acquired in the same area with a subject and a quilt on the bed and was subtracted from the depth data of empty bed. Therefore, the subtracted data were based on the height from the bed. Next, the volume, maximum height, and area with height above a threshold value were calculated. Data were acquired

for four cases a subject: (1) lying on the back, (2) lying on the side, (3) sitting up, and (4) no longer in bed. Finally, we calculated the volume, maximum height, and space above a threshold value and then analyzed the data using optimal linear discriminant analysis (OLDA).

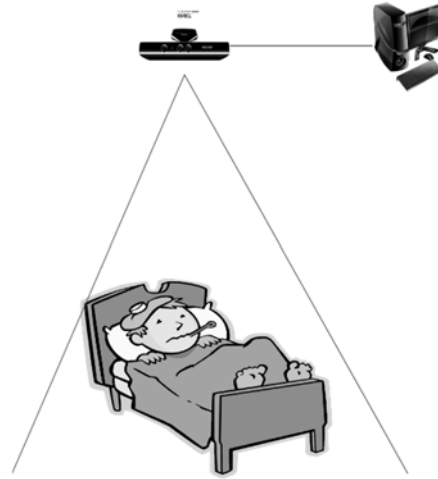


Fig. 1. Experimental setup showing the monitoring sensor on the ceiling and a subject on the bed covered with a quilt.

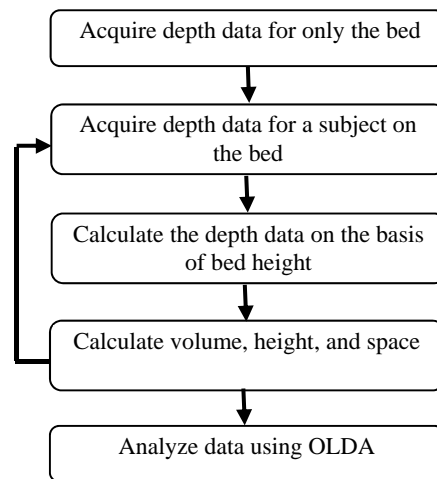


Fig. 2. Measurement flowchart for data analysis.

The bed area volume V , maximum height H_{max} , and the space S_{area} for which the height from the bed is higher than a threshold value h_{thres} are calculated by the following equations. x and y represent position coordinates of a pixel in the depth image.

$$h_0 = f_0(x, y) \quad (1)$$

$$h = f(x, y) \quad (2)$$

$$V = \int_S (h - h_0) dS \quad (3)$$

$$H_{max} = \text{Max}_s(h - h_0) \quad (4)$$

$$S_{area} = \int_{(h-h_0) > h_{thres}} dS, \quad (5)$$

where h_0 and h are the heights of the bed without and with a subject, respectively. f_0 and f represent the functions giving h_0 and h , respectively, for position (x, y) .

Ten sets of data for experiments with six subjects (60 sets of data) were collected, and then such data sets were collected for all four cases for each of the six subjects (24 experiments and 240 sets of data) with a thin or thick quilt. The subjects' heights were 165–178 cm and their weights were 52–83 kg.

3. Data Analysis

3.1. Thin Quilt

Fig. 3 shows examples of the height data for the four cases with a thin quilt covering the subject. Table 1 shows the calculated volumes, maximum heights, and spaces. The volume characteristics are similar in the four cases. However, the space and maximum height characteristics show differences. The space values were smaller for the case wherein the subject was no longer in bed than for other cases. The maximum height values were larger for the case wherein the subject was sitting up than for other cases.

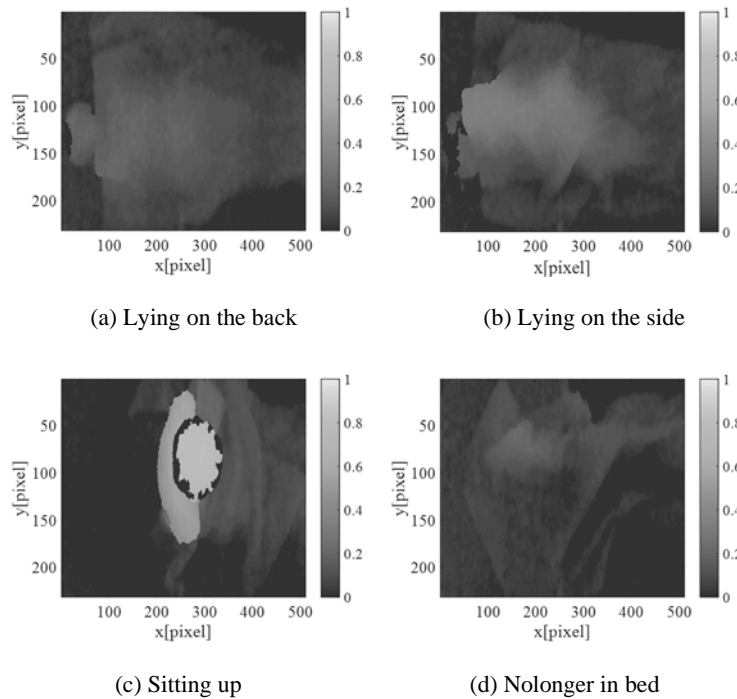


Fig. 3. Examples of height data for the four cases with a thin quilt covering the subject. One pixel equals 4.5 mm and the color bar unit is meters.

Table 1. Calculated volumes, maximum heights, and spaces for the four cases with a thin quilt covering the subject.

		Mean	Standard deviation	Minimum value	Maximum value
Volume ($\times 20.25 \cdot 10^3 \text{mm}^3$)	Lying on back	9511	1553	7355	13734
	Lying on side	10485	1329	7980	13319
	Sitting up	13080	1819	10979	17344
	On longer in bed	4880	1127	2722	6395
Space ($\times 20.25 \text{mm}^2$)	Lying on back	40719	10957	25780	61276
	Lying on side	41783	8312	30183	57494
	Sitting up	38579	6296	24418	49843
	On longer in bed	5085	3679	1196	12529
Maximum height ($\times 10^3 \text{mm}$)	Lying on back	0.152	0.0347	0.115	0.216
	Lying on side	0.2377	0.0241	0.157	0.281
	Sitting up	0.7304	0.0287	0.682	0.808
	On longer in bed	0.1021	0.021	0.071	0.157

Table 2 shows the Wilks coefficients for the case of a thin quilt covering the subject.

Table 2. Wilks coefficient for each combination in the case of a thin quilt.

	Volume	Space	Maximum height
Volume			
Space	0.07820		
Maximum height	0.00385	0.00176	

The lowest coefficient was obtained for the combination of maximum height and space. Therefore, optimal linear discriminant functions (OLDFs) were made with these data.

3.2. Thick Quilt

Fig. 4 shows examples of the height data for the four cases with a thick quilt covering the subject. Table 3 shows the calculated volumes, maximum heights, and spaces. Although the data show similar behavior as the thin quilt case, some differences were noted. In the thin quilt case, the maximum heights for the case with the subject no longer in bed were smaller than those for other cases, whereas in the thick quilt case, the maximum heights for the case with the subject no longer in bed sometimes became larger than those for the cases with the subject lying on the back and lying on the side. This is because the thick quilt left on the bed has a large volume itself.

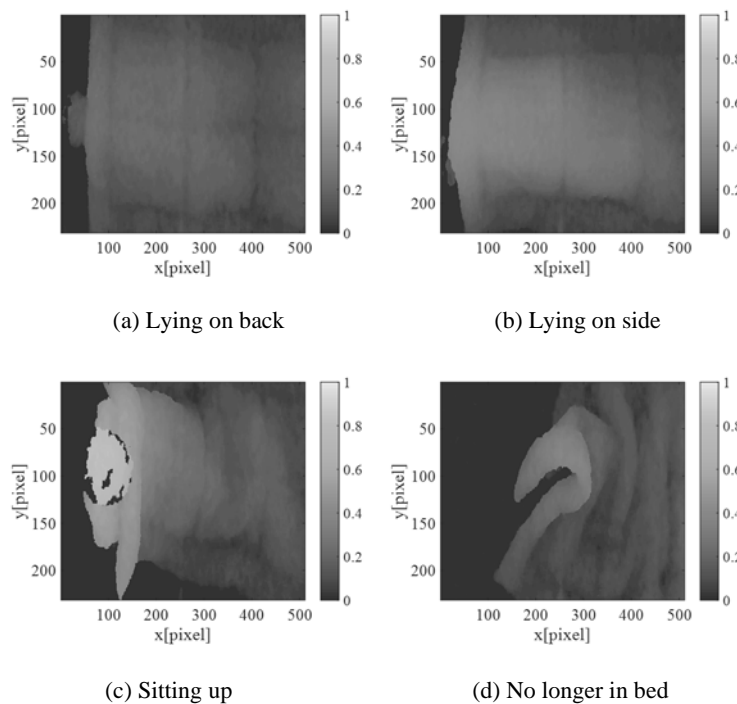


Fig. 4. Examples of height data for the four cases with a thick quilt covering the subject. One pixel equals 4.5 mm and the color bar unit is meters.

Table 3. Calculated volumes, maximum heights, and spaces for the four cases with a thick quilt covering the subject.

		Mean	Standard deviation	Minimum value	Maximum value
Volume ($\times 20.25 \cdot 10^3 \text{mm}^3$)	Lying on back	20682	3201	15862	27076
	Lying on side	23811	3639	20043	31391
	Sitting up	23168	4745	16318	30149
	No longer in bed	13401	1223	10650	14772
Space ($\times 20.25 \text{mm}^2$)	Lying on back	17892	15502	0	41430
	Lying on side	42728	10448	27794	63198
	Sitting up	36267	12185	16579	56404
	No longer in bed	6273	4467	2750	14231
Maximum height ($\times 10^3 \text{mm}$)	Lying on back	0.0173	0.0418	0.136	0.263
	Lying on side	0.3125	0.0725	0.245	0.521
	Sitting up	0.7233	0.0333	0.661	0.786
	No longer in bed	0.2137	0.0489	0.167	0.308

Table 4 shows the Wilks coefficients for the thick quilt case. The lowest coefficient was obtained for the combination of maximum height and space. Therefore, OLFs were made with these data.

Table 4. Wilks coefficient for each combination in the case of a thick quilt.

	Volume	Space	Maximum height
Volume			
Space	0.22658		
Maximum height	0.01975	0.01531	

4. Discrimination

First, the depth data was captured by the depth sensor. Second, the maximum height and space (volume) were calculated. Third, the discriminant functions were calculated. Finally, the conditions of the subjects were determined.

Table 5 shows the results of the OLDA judgment for experiments conducted using a thin quilt. For the cases with the subject lying on the back or lying on the side, good judgments were obtained; however, some judgments were incorrect.

Fig. 5 shows the depth image where the subject was lying on the back but judged as lying on the side. Such results are due to the space being increased as the quilt was spread wide.

Table 5. Confusion matrix for the thin quilt case (%).

	Lying on back	Lying on side	Sitting up	No longer in bed
Lying on back	98.33	1.67	0.00	0.00
Lying on side	1.67	98.33	0.00	0.00
Sitting up	0.00	0.00	100.00	0.00
No longer in bed	0.00	0.00	0.00	100.00

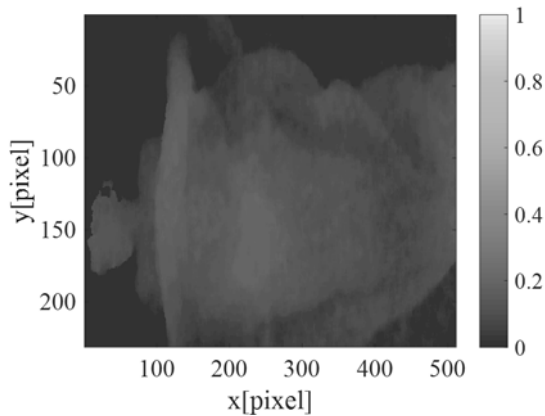


Fig. 5. Depth image of a subject lying on the back and covered with a thin quilt, which was misjudged as a subject lying on the side. One pixel equals 4.5 mm and the color bar unit is meters.

Fig. 6 shows the depth image where the subject was lying on the side but judged as lying on the back. Such results are due to the space being decreased as the quilt was narrowed. The judgement accuracy was 100 % for the cases with the subject sitting up or no longer in bed. Therefore, the system performed well when detecting the situations wherein the subject is sitting up or no longer in bed.

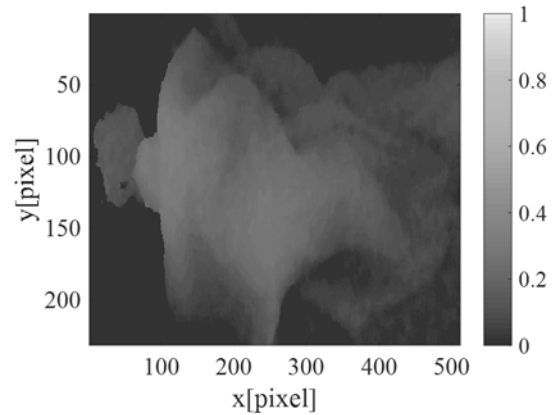


Fig. 6. Depth image of a subject lying on the side and covered with a thin quilt, which was misjudged as a subject lying on the back. One pixel equals 4.5 mm and the color bar unit is meters.

Table 6 shows the results of OLDA judgment in the thick quilt case. Some cases of the subject lying on the back were misjudged as the subject no longer in bed. Comparing with the case of thin quilt, accuracy decreased for the cases of the subject lying on the side, and the incidences of misjudgments that indicated the subject was lying on the back increased.

Table 6. Confusion matrix for the thick quilt case (%).

	Lying on back	Lying on side	Sitting up	No longer in bed
Lying on back	43.33	18.33	0.00	38.33
Lying on side	21.67	78.33	0.00	0.00
Sitting up	0.00	0.00	100.00	0.00
No longer in bed	0.00	0.00	0.00	100.00

Fig. 7 shows the depth image where the subject was lying on the back but judged as no longer in bed. Such results occurred because the quilt narrowed and the space decreased. Fig. 8 shows the depth image where the subject was lying on the side but judged as lying on the back. Such results occurred because the quilt narrowed and the space decreased. The judgement accuracy was 100 % for cases with the subject sitting up or no longer in bed. Therefore, this system performs well when detecting the situations

wherein the subject is sitting up or no longer in bed. The error rate for the thick quilt case is higher than that for the thin quilt case. When a thick quilt is used, judgement becomes difficult, because the differences in the space and height become small between the three cases of the subject lying on back, lying on the side, and no longer in bed.

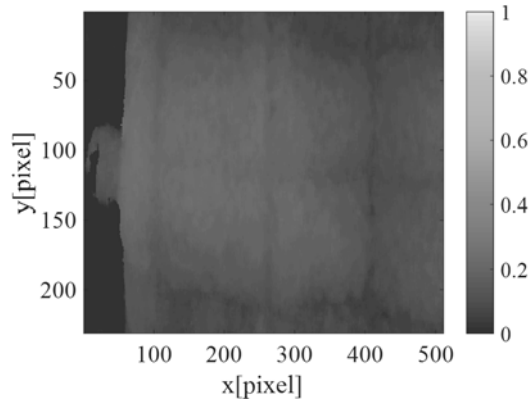


Fig. 7. Depth image of a subject lying on the back and covered with a thick quilt, which was misjudged as a subject on longer in bed. One pixle equals 4.5 mm and the color bar unit is meters.

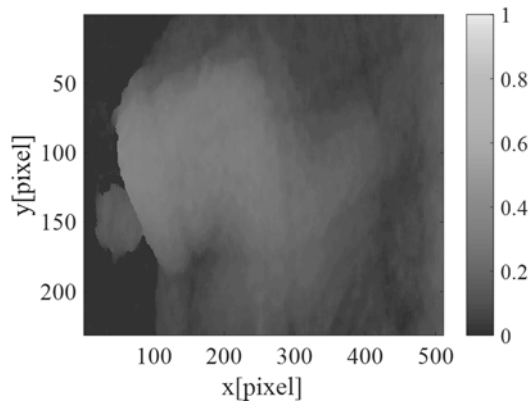


Fig. 8. Depth image of a subject lying on the side and covered with a thick quilt, which was misjudged as a subject lying on the back. One pixle equals 4.5 mm and the color bar unit is meters.

5. Judgment of Using a Combination of a Thin Quilt and a Thick Quilt

5.1. Judgement Using Two Variables

Different quilts are used depending on the season or climate. Therefore, we next considered whether the system could perform well independent of the quilt thickness with one discrimination function. Table 7 shows the Wilks coefficients for the cases using a combination of a thin quilt and a thick quilt. The lowest coefficient was obtained for the combination of maximum height and space.

Table 7. Wilks coefficient for each combination in the case of a combination of thin and thick quilts.

	Volume	Space	Maximum height
Volume			
Space	0.34977		
Maximum height	0.02913	0.02251	

Table 8 shows the judgement results for cases using a thin and thick quilt combination. The judgment accuracy decreased compared with the accuracy of using only a thin or a thick quilt. In particular, cases of the subject lying on the side were misjudged as the subject sitting up. Fig. 9 shows the depth image when the subject was lying on the side but was judged as sitting up. Such results occurred because the subject was overweight and the height increased when the subject was lying on the side.

Table 8. Confusion matrix for a combination of thin and thick quilts (%).

	Lying on back	Lying on side	Sitting up	No longer in bed
Lying on back	48.33	26.67	0.00	25.00
Lying on side	21.67	78.33	0.00	0.00
Sitting up	0.00	0.00	100.00	0.00
No longer in bed	0.00	0.00	0.00	100.00

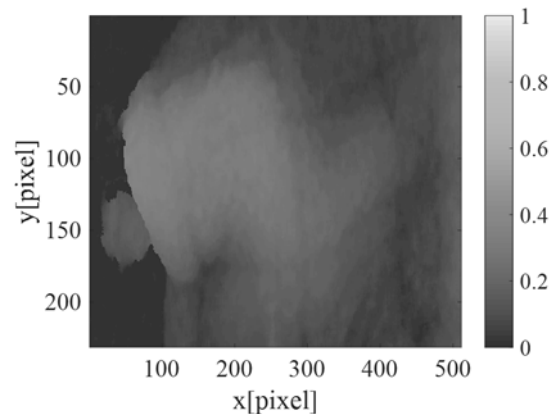


Fig. 9. Depth image of a subject lying on the side and covered with a thick quilt, which was misjudged as a subject sitting up. One pixle equals 4.5 mm and the color bar unit is meters.

5.2. Judgement Using Three Variables

As shown above, the judgment is affected by subject size and quilt thickness. Therefore, we introduced the data of the initial condition (the subjects lying on back first)—volume, maximum height, and space. These were measured only once,

when the subject or the quilt was changed. The data for the three variables were analyzed using OLDfS. The smallest coefficient was obtained for space, maximum height, and initial volume.

Table 9 shows the judgment results using three variables. The judgment accuracy significantly improved. This system performed well when used to detect situations wherein the subjects were sitting up or no longer in bed. Although, the data for four variables were also analyzed, better results were not obtained.

Table 9. Confusion matrix using three variables (%).

	Lying on back	Lying on side	Sitting up	No longer in bed
Lying on back	94.17	5.83	0.00	0.00
Lying on side	9.17	90.83	0.00	0.00
Sitting up	0.00	0.00	100.00	0.00
No longer in bed	0.00	0.00	0.00	100.00

The reported detection rate of the dangerous action (almost falling) using neural networks is 84 % [21]. The detection rate of the dangerous action (lying on side, sitting up, and no longer in bed) in this system is 97 %. Although the situations of the dangerous action differ, a better detection rate is obtained in this system. The reported detection rate for the get-up event using the multi-kernel learning framework is 98.76 %, and the frame rate is 10 fps [22]. A same level of the detective rate is obtained by OLDA. The frame rate of this system is 30 fps, which is limited by the frame rate of the Kinect sensor. Our system enables high-speed operation

6. Conclusions

In this paper, we proposed a system for monitoring patients in a coma. The system uses a depth sensor with an infrared projector and the discrimination results are based on simple OLDA. The system is capable of detecting the behaviors of a person awakening and a person no longer in bed. The obtained data were analyzed by OLDfS. The detection rate when the subject was covered by a thin quilt and was lying on the back, lying on the side, sitting up, or no longer in bed was 99.2 %; thus, the system has high reliability and practicality. The detection rate was 80.4 % when using a thick quilt and 80.8 % when using a combination of a thin and a thick quilt. However, the rate improved to 96.3 % using the data of the initial condition of the subject.

We believe that the system will be useful for monitoring patients in a coma or patients who are sleeping due to anesthesia who must occasionally be left unsupervised. This technique has higher accuracy than passive camera-based image-processing systems and is more durable than mat sensors. Although, its

accuracy depends on the subjects' physique and quilt thickness, accurate results are obtained by measuring these values. For further verification, investigation using more samples is required.

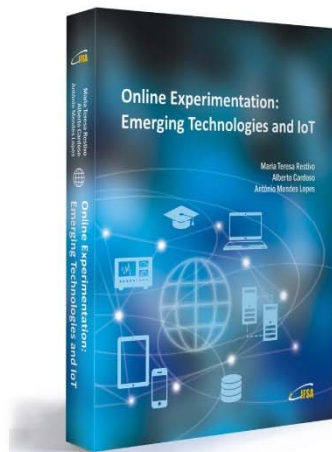
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