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Evaluation of a commodity force sensor for building a low-cost bedsore prevention mat

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ABSTRACT

Bedsores are a common disease in patients who stay in the same position for a long period of time. Regular reposition must be done to prevent the problem. Accordingly, several tools are used to reduce bedsores. The Internet of Things and the machine learning technology have made it possible to make a number of smart kits using different sensors and artificial intelligence. This research evaluated the possibility of using a commodity force or pressure sensor, and the machine learning technology to build a budget-smart mat that can monitor patients and alert the caretaker to prevent bedsores. The experiment results showed that a force sensor is a potential candidate for making a smart tool that can be used to reduce bedsores for bedridden patients in hospitals or at homes.

Keywords: bedsores; pressure ulcers; bedsore prevention

1. INTRODUCTION

Bedsores, which are also known as pressure ulcers or decubitus ulcers, are injuries to the skin and the underlying tissue resulting from prolonged pressure, shear, or friction on the skin such as at the heel, sacrum, scapula, and ischium. Bedsores occur in patients with medical conditions that limit their ability to change positions or those who stay for a long time on a bed or chair and can barely move in a hospital or a nursing home. Bedsores can cause intense pain and lead to various diseases, such as depression and infection, and some of which can be lethal. Jiang et al. showed that, in 39,952 patients from 12 hospitals in China, the prevalence rate of pressure ulcers was approximately 1.58% (Jiang et al., 2014).

For bedsore prevention, patients must be frequently repositioned every 2 h or more often. Anti-bedsore mattresses, which are composed of individual cells with a variable cycle airflow that circulates in them, stimulate the skin by reducing pressure on it. These mattresses should be used in combination with regular patient repositioning.

While in the hospital, nurses or a patient's relatives may reposition the patient. In the case of patients staying at home, the caregivers are responsible for taking care of the patient and repositioning him/her to prevent bedsores. However, the patients may not be regularly repositioned, which may lead to bedsore symptoms. An equipment that can warn caregivers about patient repositioning when necessary and monitor how well the caregivers take care of the patient may be used to reduce bedsores in patients.

The equipment used for protection against bedsores deploys sensors that have been developed for years. Donald Kress (1985) filed a patent for sensors that protect against bedsores. These sensors were placed around the areas most vulnerable to bedsores. Manohar and Bhatia (2008) discussed the difference between resistive bend sensors and pressure sensors in patient bed application. Each unit of the former covered more area of measurement than a single piece of the latter. Hence, it requires a less complex interfacing circuit to obtain data from a smaller number of sensors needed to be implement on a bed. The authors also observed two different types of resistive bend sensors (i.e., unidirectional and bidirectional sensors). The sensor interfacing circuit was designed to accommodate up to 64 unidirectional sensors or 32 two-input bidirectional sensors. Meanwhile, Yip et al. (2009) developed a budget 17×22 cm^2 mat composed of 99 sensors. This mat can be placed under the body or the mattress to collect information regarding the pressure exerted by the body.

Yousefi et al. (2011) developed a sensor that can determine the sleeping posture of a patient to see if the patient has received proper repositioning. They claimed that their system could perform a prediction when the patient would get a bedsore with a 97.7% accuracy. Farve et al. (2014) proposed a system that uses 64 pressure sensors and 64 heat sensors on a 40×50 square centimeter mat. The system would give real-time information from these sensors. Consequently, it would analyze the data and alert the caregivers to help reposition the patient accordingly. A different type of sensor, called "smart rubber," (SR) was used by Misaki et al. (2014) to incorporate the active support surface mattress. The sensor is a sheet of 256 pressure sensing points laid in 16×16 matrix. They implemented two sheets to cover the main areas and detect the patient body pressure. Underneath the sheets are an array of two-balloon air cells installed, which the tension of the individual cell is actively changed according to the associated sensing area.

Apart from the abovementioned in-bed pressure sensing methods, Liu and Ostadabbas (2017) developed a vision-based method to track the posture of a bedridden person using a regular webcam equipped with a commodity laptop computer. The experiment successfully detected in-bed posture and provided certain reports for caregivers. However, this setting is still limited under certain contexts and need further research to tackle important issues, such as those for person under blanket, poor light condition detection, etc.

Sen et al. (2018) proposed a patch of wireless, autonomous, and powered sensor system. This patch has a force sensor and a temperature/humidity sensor. One or more patches can be placed at the at-risk skin areas to monitor the contact pressure. Specific machine learning algorithms would provide an alert to the caregiver to prevent the bedsore formation.

This study evaluated the use of commodity force sensors to develop a bed mat that can monitor patient movement or repositioning. The mat can be put under the mattress to monitor the change in mattress pressure. Hence, it can be determined if the patient has been repositioned or not. The system can alert the caregivers if the patient has not been repositioned in a period of time. The system can also record the amount of times the patient has been repositioned. This mat can be produced as a budget equipment to reduce bedsores to patients.

2. MATERIALS AND METHODS

2.1 Materials

2.1.1 Commodity force sensor

FSR402 (Interlink Electronics, 2020) is a simple-to-use and robust polymer thick film that is a cost-effective device for use in various kinds of force sensors available in the market. It comes with an 18.28-mm diameter rounded-shape sensing area and a 56-mm tail length (Figure 1). It can sense the applied force in the range of 100 g to 10 kg. Each costs 4-7 USD in internet marketplaces. Accordingly, FSR402 is considered as a candidate in this evaluation.

Figure 1. FSR402 with 18.28-mm diameter, 56-mm tail length

The sensor is basically a variable resistor that exhibits decrease in resistance when the applied force on the sensing surface is increasing. Figure 2 presents the relationship between the applied force (grams) and the resistance (kΩ) of the device.

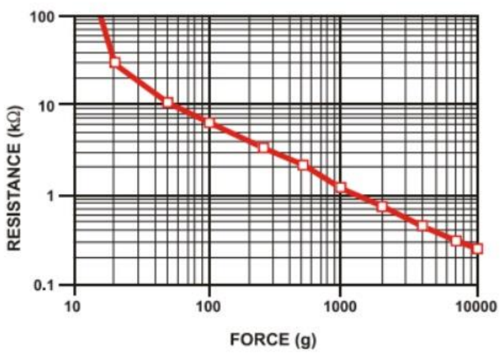

Figure 2. FSR 402-force curve (Electronics Interlink, 2020)

2.1.2 Microcontroller interfacing

For this experiment, a versatile and cost-effective microcontroller development board equipped with an ESP32-WROOM32 was chosen. This chip is a SoC with low-power dual-core 32-bit microprocessor and WiFi and bluetooth built-in (Espressif, 2020). WiFi was a selected communication medium for wirelessly delivering the acquired data from the force sensor array to the compute unit. The development board, called Node-32S (Ayarafun, 2020), provided 32 GPIO ports, although not enough for attachment to every sensor in the array, can simply use a few multiplexer modules to handle numbers of sensors. The schematic diagram in Figure 3 depicts 40 force sensors wired to the controller board to obtain the experiment data from the bed. Each sensor label in Figure 3 is represented in Figure 4. In addition, three multiplexers were used for interfacing all sensors that grouped into 15, 15, and 10 sensors attached to Mux1, Mux2, and Mux3, accordingly. The multiplexer module is CD74HC4067 (Texas Instruments, 2003), a 16-channel analog multiplexer/demultiplexer that can select any module input and tunnel it through the output.

Each sensor module displayed in Figure 4 is a simple voltage divider circuit equipped with FSR-402, a variable resistor symbol shown in the Figure, and a 220Ω resistor.

This configuration provides the corresponding voltage value on the sensor output up to the weight applied to the sensor. The more force is applied on FSR-402, the lesser the resistance becomes (Figure 2), resulting to more voltage on the output. This analog voltage value can be acquired to indicate the tendency of more weight or less weight applied on a certain sensor. Continuously, the sensor output value of each sensor will be available to the corresponding input port of the particular multiplexer, waiting to be delivered through a common pin designated as COM of the enabled multiplexer selected by the microcontroller. Once the certain signal arrives at the microcontroller, it is converted to digital representation ranging from 0 to 4095 (12-bit ADC).

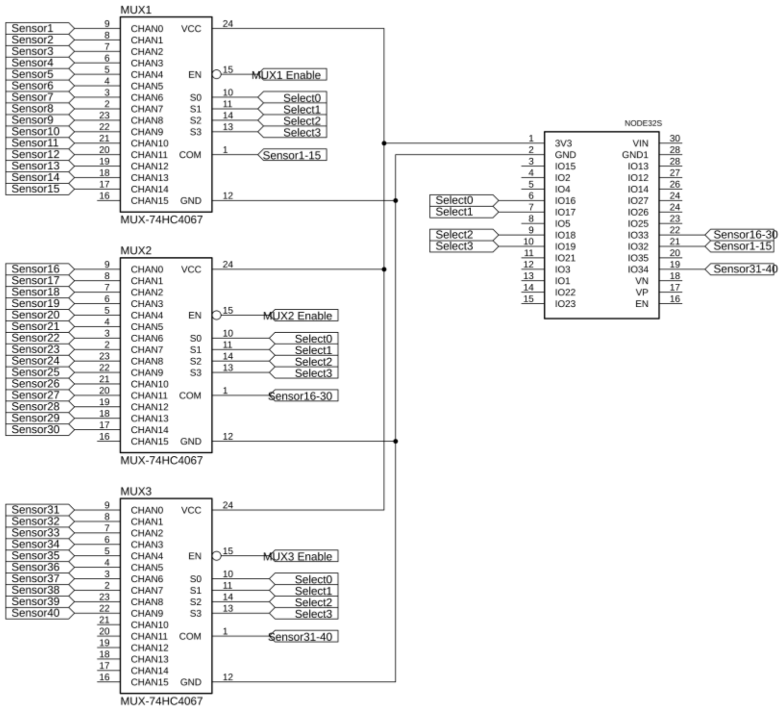

Figure 3. Schematic diagram of the data acquisition subsystem

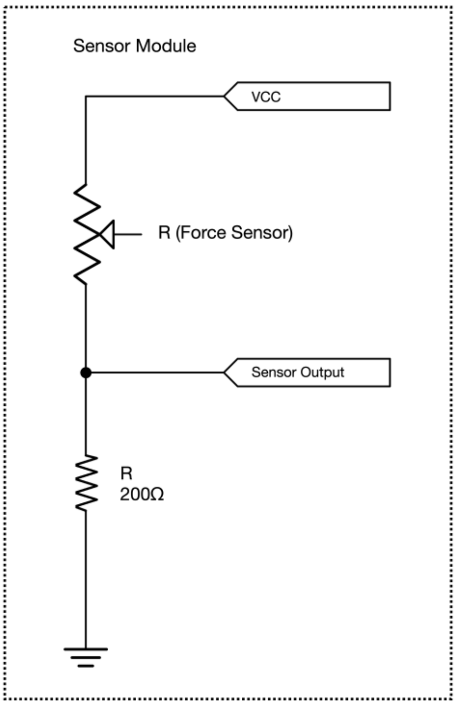

Figure 4. Each sensor module

2.2 Experiments

2.2.1 Data read from sensors

The FSR402 sensor was evaluated on how well it could detect force and how to calibrate each sensor separately. The sensor has a small receiving area for obtaining weight. The researchers could not find the object with a sufficient weight, but that was small enough to fit in the small receiving area of the sensors. Thus, even bigger than the receiving area, a 20-lbs dumbbell was put above the center of the receiving area of the sensor instead. The results showed that the different sensors would read different values. When the weight moved a little bit, the force read by the same sensor always changed. Calibrating all sensors was almost impossible.

However, we still need to determine whether the object is still or moving. A 20-lbs dumbbell and a person were used as the objects. The sensors were laid on the mat and put under a 1-inch thick mattress. The sensor layout will be shown in the next section. With the 20-lbs dumbbell, the data of only six sensors with 10 cm distance between them were read every second for demonstration (sensors N1–N6) (Figure 5). The numbers read from each sensor represented the converted signal ranging from 0 to 4095, as mentioned in Section 2.1.2. The results showed that without calibration, each sensor can show the change when the object is moving.

The first 12 lines in the upper square frame show the data for a stable object. The reading data changed little over time. The object was moving in the next 9 s (lower square frame), and the data were dramatically churned.

A person was used as an subject (i.e., a man has weight 64 kg and is 164 cm tall) in Figure 6. The first 12 lines illustrate a still subject. The last nine lines present a moving subject. Only sensors N4 and N5 sensed force. The result showed a similar pattern to the dumbbell.

Conclusively, if the value changes to over 50 in each second, an subject movement happens over the particular sensor.

N1	N2	N3	N4	N5	N6
144	129	244	0	266	0
144	144	246	0	288	0
144	136	256	0	268	0
144	144	256	0	272	0
145	138	256	0	262	0
153	146	240	0	268	0
176	138	256	0	268	0
147	147	256	0	280	0
154	144	266	0	268	0
152	140	260	0	272	0
148	144	272	0	272	0
144	144	256	0	265	0
80	0	2	0	0	0
0	40	0	0	0	0
0	0	0	0	0	0
0	206	0	64	0	0
0	0	0	0	0	282
0	0	0	0	0	0
0	24	0	0	0	500
0	208	0	0	0	402
0	324	0	0	0	332

Figure 5. Example data read from six sensors

N1	N2	N3	N4	N5	N6
0	0	0	308	344	0
0	0	0	304	342	0
0	0	0	310	346	0
0	0	0	309	346	0
0	0	0	304	340	0
0	0	0	313	336	0
0	0	0	304	336	0
0	0	0	304	344	0
0	0	0	313	340	0
0	0	0	300	341	0
0	0	0	304	352	0
0	0	0	308	342	0
0	0	0	0	0	0
0	0	0	112	56	0
0	0	0	0	90	144
0	0	0	28	0	0
0	0	0	0	0	0
0	0	0	20	0	0
0	0	0	0	8	0
0	0	0	0	234	0

Figure 6. Example data read from a human as the subject

2.2.2 Mat layout

Other parameters also affect the sensors. Sensing force becomes easier if a small piece of cardboard is put under the sensor. Moreover, putting the sensor under a thin mattress (e.g., yoga mat) made it such that the sensor could not read as good as that when putting it under a 1-inch thick mattress. Thus, the mat was placed under the 1-inch thick mattress.

First, 90 sensors were used in an area with 60 cm width and 180 cm length, laying sensors in 18 rows with five sensors in each row at 10 cm distance for each sensor. Subsequently, the layout was tested by repositioning a subject on the mat. The layout was tested using two people: one male with 173 cm height and 65 kg weight and another person with 184 cm height and 94 kg weight.

The subjects were repositioned in the same manner as in the recommended repositioning method. The subjects changed position from supine to lying on the left and right and *vice versa* for a number of times. The result showed that only approximately 40 sensors out of 90 sensed the pressure from the mattress (Figure 7). Therefore, only 40 sensors could be used, which were enough to determine when a patient needs to be repositioned. Figure 8 illustrates the new sensor layout. Figure 9 depicts the configuration of the sensors underneath the bed mattress in the experiment.

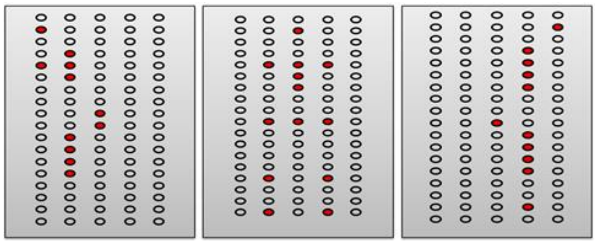

Figure 7. Position of the sensors that sensed pressure

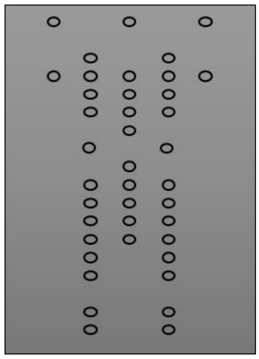

Figure 8. Sensor layout

Figure 9. (a) Wired sensor mat, (b) mattress and sensors lie beneath, and (c) mattress above the mat

2.2.3 Mat test

The mat was evaluated by the following steps: first, the data from all the sensors were collected; second, value 1 or 0 was given to each moving/stable status; third, the values from all the sensors in the same time frame for machine learning were summarized: different models were trained in machine learning; and finally, the selected machine model will be tested in a real-time experiment. Figure 10 summarizes the evaluation process.

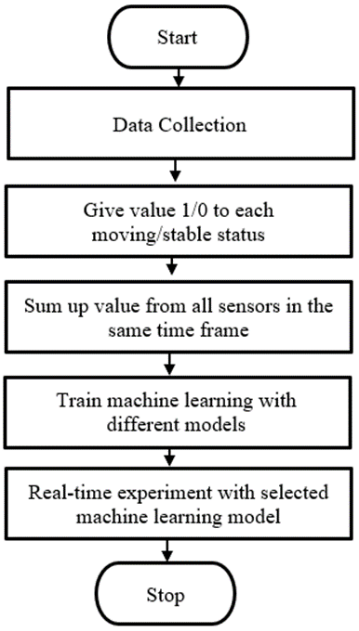

Figure 10. Evaluation processes

In data collection, the subject was a male with 176 cm height and 64 kg weight. The values from 40 sensors were recorded every second. The subject was stable and regularly changed position. The time the subject remained stable varied from 30 to 60 s and again changed position. The overall collected data from all 40 sensors amounted to 8644 records. The flowchart in Figure 11 shows how the human subject changes his position in the test.

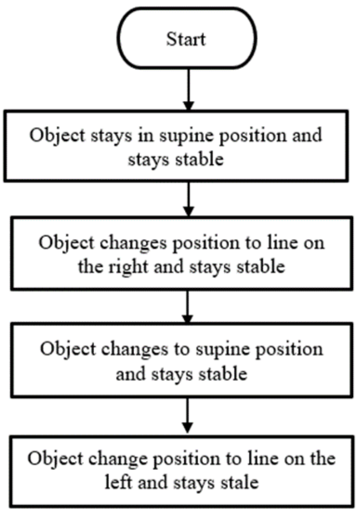

Figure 11. Data collection process

If the force read from each sensor changes to more than 50, the subject over that sensor changes its position, and a value of 1 is given to that sensor, while the stable sensors have a 0 value.

Figure 12 depicts the summed up numbers of the sensors that detected change in data. In this example, only six sensors were used to demonstrate our method. In the 1st second, no sensors sensed force. In the 2nd second, four sensors (i.e., N1, N2, N3, and N5) read the force, and the sum became 4 because the value changed to more than 50. At the 3rd second, only four sensors sensed weight. The force read did not sufficiently change; hence, the subject was stable. The sum of the changed sensors was 0, as well as was the next second. In the 5th second, only two sensors (i.e., N1 and N3) sensed force, and the value change was enough to detect movement. However, even though sensors N2 and N5 did not detect force, the values still changed to more than 50 from the previous second. Thus, value 1 was given to sensors N1, N2, N3, and N5, making the sum 4.

N1	N2	N3	N4	N5	N6	Sum
0	0	0	0	0	0	0
152	140	260	0	272	0	4
148	144	272	0	272	0	0
144	144	256	0	265	0	0
80	0	2	0	0	0	4
0	40	0	0	0	0	1
0	0	0	0	0	0	0
0	206	0	64	0	0	2
0	0	0	0	0	282	3
0	0	0	0	0	0	1
0	24	0	0	0	500	1
0	208	0	0	0	402	2
0	324	0	0	0	332	2
0	320	0	0	0	320	0

Figure 12. Example data from six sensors

2.2.4 Machine learning

Sensor data may vary from the sensor location and value; hence, the major challenge is how the system makes the decision that the object, especially human subject, is moving or still. When the subject moves, the system should be smart enough to distinguish if the subject has changed its position or just moved, but remained in the same position after that. The decision-making solution is complicated, but machine learning can be used to resolve this challenge.

However, the smart decision-making system is beyond the scope of the research at this phase, but will be our goal in the future works. At this phase, an uncomplicated machine learning process is used to separate between only two stages (i.e., stillness and movement of the human subject) to demonstrate the machine learning capability.

Thus, a large part of the data acquired from the experiment will be categorized as trained using a machine learning model, namely Scikit-learn (Pedregosa et al., 2011), which is a machine learning library for Python. The rest will be used for testing accordingly.

3. RESULTS

The experiment showed 8644 records saved for the machine learning process. In the training method, Scikit-learn was used for the machine learning process defined as follows:

• The subject above the sensor is moved when the data change to over 50 in each second.
• Value 1 is given to every sensor detecting movement.
• Value 0 is given to every stable sensor.
• Use a 5-s time frame to calculate the frame slides for every second
• Sum up the value of every sensor in the time frame. A value equal to or over 15 means subject repositioning happened over the entire mat of 40 sensors.

Accordingly, 15 sensors were used because it was approximately one third of the 40 sensors on the mat. Figure 13 shows the example results of five time frames. SumN states the summation of the value in each time frame. StatusSumN denotes that the subject is moving because the SumN value is equal to or over 15.

As mentioned about machine learning, 6916 sets or approximately 80% record data were picked up for training, and 1729 sets out of 8644 sets (approximately 20%) were picked out for testing. Eleven models were used to classify only two classes: still and move. The test results showed that eight models, namely Nearest Neighbors, Linear SVM, RBF SVM, Decision Tree, Random Forest, ANN-BFGS, ANN-SGD, and AdaBoost, gave 100% accuracy. Meanwhile, Naive Bayes and Quadratic Discriminant Analysis exhibited 96.58% accuracy. Only LAD provided 94.15% accuracy.

	A	B	C	D	E
1		N	SumN	statusSumN	
2		0	0	0	
3		0	0	0	
4		0	0	0	
5		0	2	0	
6		0	17	1	
7		0	29	1	
8		0	35	1	
9		2	43	1	
10		15	45	1	
11		12	30	1	
12		6	18	1	
13		8	12	0	
14		4	5	0	
15		0	3	0	
16		0	3	0	
17		0	3	0	
18		1	3	0	
19		2	10	0	
20		0	18	1	
21		0	33	1	
22		0	40	1	
23		8	41	1	
24		10	37	1	
25		15	29	1	
26		7	14	0	

Figure 13. Example of the time frames

Figure 14 shows the confusion matrix testing results from Scikit-learn. The summation of numbers in the bracket must be 1729.
• The value in the top left indicates that the subject in reality is still, and the machine predicts that the subject is still (actual = prediction).
• The value in the top left indicates that the subject in reality is still, and the machine predicts that the subject is moving (actual ≠ prediction).
• The value in the top left indicates that the subject in reality is moving, and the machine predicts that the subject is still (actual ≠ prediction).
• The value in the top left indicates that the subject in reality is moving, and the machine predicts that the subject is moving (actual = prediction).

In a real-time experiment, a linear support vector machine was deployed as the model because it fits the binary class. Every second, the controller on the mat sent real-time data to the server via WiFi. A human was used as the subject. The subject would remain in the same position for approximately 30 s and change position after that. Consequently, the result showed a 100% accuracy.

4. DISCUSSION

Some limitations in this step of the research must be noted. First, the position of each sensor on the mat was not used in the training. Thus, even though the system can determine whether the subject is moving or still, it cannot state whether the subject has actually been repositioned. The system cannot determine the difference if the subject moves and remains in the same position afterwards.

Second, the system cannot decide if the subject had moved enough to prevent bedsores because a patient's weight may be supported in the same skin region after moving.

Third, only a 1-inch thick mattress was used in the experiment. Thus, a different mattress thickness or softness may affect the results. In addition, only two human subjects were employed in this experiment, and they were fairly tall. If the subject small, the weight and the height may also affect the system. Thus, further experiments and machine learning training are needed.

```
Nearest Neighbors
100.0
[[829   0]
 [  0 900]]

Linear SVM
100.0
[[829   0]
 [  0 900]]

RBF SVM
100.0
[[829   0]
 [  0 900]]

Decision Tree
100.0
[[829   0]
 [  0 900]]

Random Forest
100.0
[[829   0]
 [  0 900]]

ANN lbfgs
100.0
[[829   0]
 [  0 900]]

ANN sgd
100.0
[[829   0]
 [  0 900]]

AdaBoost
100.0
[[829   0]
 [  0 900]]

Naive Bayes
96.58762290341237
[[770  59]
 [  0 900]]

LAD
94.15847310584152
[[829   0]
 [101 799]]

QDA
96.58762290341237
[[770  59]
 [  0 900]]
```

Figure 14. The testing result from different algorithms

5. CONCLUSION

In conclusion, the evaluation showed that the commodity force sensor is a potential sensor that can be used to make a budget-smart mat that protects patients with bedsore risk. The mat is convenient and easy to use because it can be put under the mattress. Patients, nurses, caregivers, and the patient's relatives can benefit from the ability to alert and record patient repositioning. Even though more sensors are better, the experiment showed that approximately 40 sensors are enough to detect a moving body. This can dramatically reduce the number of necessary sensors and the production cost in the future. Nevertheless, other factors may also affect how the sensors work, and these include the mattress thickness or the patient size. Therefore, further research and experimentation on the factors affecting the mat and machine algorithms are important for the future work.

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