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Automatic Detection of Turning Over in Bed with Protection of Privacy Using Four Low-resolution Thermal Sensors to Support Nursing Care

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Abstract Turning over in bed, especially turning over at night, is a vital human unconscious behavior. Clinically, this movement disperses pressure between the body and bed, thus preventing bedsores. Several devices, such as acceleration and pressure sensors, can count turning overs automatically; however, they often require installation on the patients or in the bed. The simplest and noninvasive method to count turning overs is to record and count on video images, but this method cannot protect privacy. Images obtained using thermal sensors have been used to protect privacy; however, there are no reports of counting turning overs automatically using low-resolution sensors. We developed a novel device equipped with four low-resolution thermal sensors, with each sensor recording only an 8×8-pixel thermal image. The original data can protect patient privacy because the resolution is only ~28.8×28.8 cm per body, which is the lowest resolution compared to previous reports using thermal images. Using four sensors simultaneously enables us to collect sufficient data for automatic identification. We first used the bilinear interpolation method employed in a previous report to count turning overs; however, the results were unsatisfactory because turning overs produced extremely subtle changes in the original data compared with postural changes such as falls. After several attempts, we finally developed a unique identification program that interleaved all data from four sensors and then identified turning overs using residual neural network-18. Using the new system, the accuracy, recall, and precision of counting turning overs in bed improved to approximately 90% with an acceptable computation load in an experiment conducted on volunteers. This study demonstrated the feasibility of our device to count turning overs in clinical settings by the new identification program using four 8×8-pixel thermal images per frame, which have sufficiently low resolution to protect patient privacy.

Keywords: turning overs, privacy, thermal sensors, low-resolution, ResNet

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1. Introduction

Several countries are facing the challenges of a super-aging population. Japan recorded the highest proportion of older individuals aged over 65 years in 2017, which is predicted to increase continuously to 38.4% in 2065 [1]. Allocating caregivers at appropriate times and locations to provide tailored services according to the characteristics of individuals is the most important strategy in actual area-based medicine [2]. Immobility causes bedsores, and the risk is often unrecognized [3] imposing a significant burden not only on the patients but also the entire healthcare system. The social impact is so severe that the United States has set reduction in the prevalence of bedsores as a component of the Healthy People 2010 initiative [3, 4].

Bedsores often develop because older individuals are repositioned only a small number of times. A 2-h interval for repositioning, widely known as “Kosiak’s rule", is recommended. However, Kosiak et al. [5, 6] merely showed that in dogs and other animal models, if a pressure greater than 200 mmHg is applied continuously on the same area of the skin, necrosis starts and may develop into bedsore within 2 hours. In nursing science, a study demonstrated that skin erythema and ischemic changes can occur in healthy human adults in less than 2 h on a standard mattress [7]. Another study reported no difference in the development of new lesions when patients were repositioned every 2 h versus every 3 h on a standard mattress, or every 4 h versus 6 h on a viscoelastic foam [8]. Although repositioning is certainly important to prevent bedsores, there are no detailed studies on pressure ulcer interventions. The specific groups of individuals who require caregiver-assisted repositioning and the minimally required frequency in clinical settings have not been clearly elucidated [9].

Our study focused on turning over in bed, especially nocturnal turning over, which is an important human unconscious behavior. Clinically, turning overs disperse pressure between the body and bed, thereby preventing bedsores [6]. Therefore, counting turning overs could be a quantitative method to evaluate the risk of developing bedsore, and may also help estimate the appropriate frequency of caregiver-assisted repositioning.

Although devices using acceleration sensors [10] and pressure sensors have been developed to count turning overs [11], they generally require installation on the patient or the bed. Assessing the movements of patients on video images may be the simplest and most accurate method for classifying movements without additional invasive device. However, acquisition of video images often induces a sense of intrusion and/or discomfort for individuals, and is still considered undesirable despite the increasing acceptance of using video images. Nevertheless, video images always pose a risk of compromising privacy [12] when using the data for analysis, and they cannot capture the movements at night. To meet strict hospital confidentiality requirements, low resolution images should be used. In a study that used a single 8×8 sensor, the requirement was apparently satisfied, but the method could only distinguish large postural changes (sitting still, standing still, approaching the sensor, and moving away from the sensor) [13]. To date, no study has counted nocturnal turning overs using thermal images while protecting patient privacy.

Therefore, the objective of this study was to develop a device equipped with thermal sensors and a computer program to detect patients' nocturnal turning overs while maintaining privacy. We encountered challenges in balancing privacy protection with accuracy of image recognition using thermal sensors. We also found that counting turning overs using low-resolution sensors had difficulties that could not be resolved using previous methods; such as residual heat on the bed that did not correspond to the body, only subtle movements detected during turning over compared with postural changes, and presence of blankets interfering with temperature change [14]. In this study, we developed for the first time a device capable of acquiring four low-resolution thermal images (8×8 pixels) that distinguished only the head, torso, and limb movements of a person. We succeeded to achieve accurate counting of turning overs using a residual neural network (ResNet) program trained on unique datasets.

2. Materials and methods

2.1 Study design

The study protocol (UMIN 000040549, R2004-001) was approved by the Institutional Review Board of Okayama University (14000045) before study initiation. Only volunteers who were aged ≥ 20 years and could understand and sign informed consent forms were enrolled. All subjects provided written informed consent.

We enrolled 20 healthy volunteers. Data from 16 of the 20 volunteers were successfully collected, and data from the remaining 4 volunteers were not collected because of device errors (**Fig. 1**).

2.2 System

The sensor component of the original device consisted of four low-resolution thermal sensors (Grid-EYE AMG8833, Panasonic Industry Co., Ltd., Japan). Each thermal sensor provided a field of view of 60° and had a resolution of 8×8 pixels. The four thermal sensors were positioned side-by-side, with a distance of 10 cm between two sensors in close proximity. One general video camera (FIT0701, Zhiwei Robotics Corp., China) was

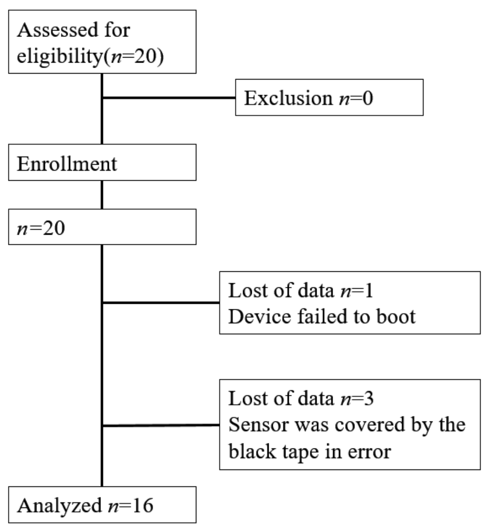

Fig. 1 Diagram of the clinical trial. Data from 16 of 20 volunteers were collected successfully.

added at the center to collect ground truth data for system evaluation of this study. Power was supplied by a commercially available USB port (**Fig. 2a**). The sensors were connected to an Arduino mini board (Arduino Uno R4 WiFi, Arduino S.R.L., Italy) and a Raspberry Pi 3 (Raspberry Pi 3 Model B+, Raspberry Pi Ltd., UK) to send the collected data via wireless LAN to a mini-PC (NUC, Next Unit of Computer) (**Fig. 2b**). Consequently, four low-resolution image data and one video image were obtained simultaneously from the device set on the ceiling (**Fig. 3**).

The environment of the dark hospital room was simulated using the same bed, blanket, and pillow. The volunteers were told to turn over in bed anytime they want, and the device collected the thermal image data of the bed for 30 min at a height of 200 cm, which was the same height as the hospital room. Hence, one pixel covered an area of approximately 28.8 cm × 28.8 cm (**Fig. 4**).

2.3 Evaluation and identification programs

For evaluation, we set each frame at 0.1 s and defined a time window of 50 frames, equivalent to 5 s per window. The true turning over timestamps were manually confirmed from the ground truth data collected by the video camera at the center. If the window included the movement of a turning over and the identification program classified it as "turned over", the result of identification was defined as true positive (**Fig. 5**).

The performance of the program was evaluated using the following metrics:

Accuracy is the proportion of correctly classified cases, both positive and negative, of the total number of cases. It was calculated using the following equation:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision is the proportion of predicted positive cases that are truly positive. It was calculated using the following equation:

$$Precision = \frac{TP}{TP+FP}$$

Recall is the proportion of actual positive cases that are correctly identified by the model. It was determined

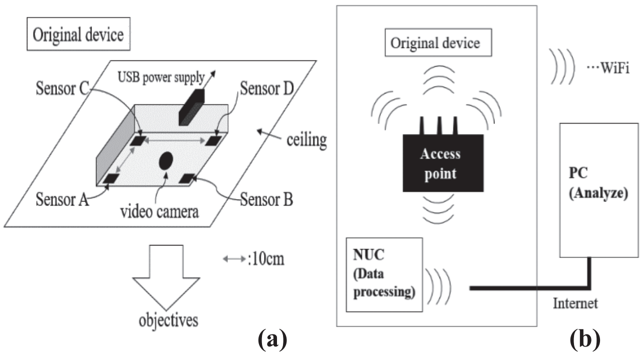

Fig. 2 Device and configuration. (a) Four thermal sensors in the corners (sensor A-D) collect data from four directions. (b) Data are sent via Wi-Fi, stored in a NUC, and analyzed by a PC.

Fig. 3 Examples of collected data. 8×8 thermal sensor data of 2×2 arrayed sensors and the relevant video image. Four sensors observed the same object but showed differences because of their directions.

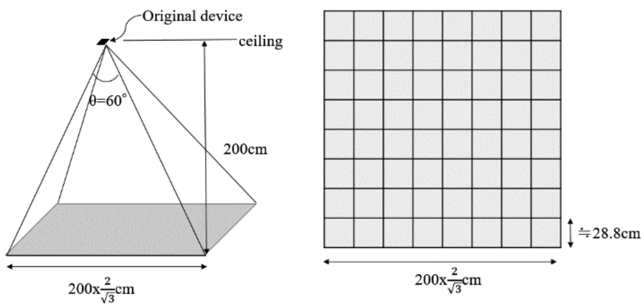

Fig. 4 Area covered by one sensor. One pixel covers an area of approximately 28.8 cm ×28.8 cm from a height of 200 cm.

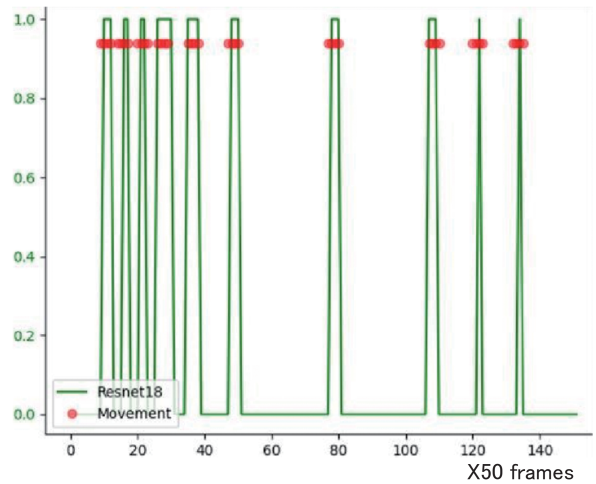

Fig. 5 Automatic detection of turning overs. Turning overs can be automatically detected using the device. Circle: actual turning over confirmed by the video camera, line: value of ResNet-18, the threshold of 1.0 is judged to be turning over.

using the following equation:

$$Recall = \frac{TP}{TP + FN}$$

where TP = true positives, TN = true negatives, FP = false positives, and FN = false negatives.

For identification programs, the Z-score (as detailed below) was used as a simple mathematical measure to identify turning overs. Recurrent neural networks (RNNs) and ResNet (18 and 50) were adopted as neural network programs (**Table 1**). For the machine learning analysis, we randomly selected 7 of 16 cases as a training set, 5 as the validation set, and 4 as the testing set.

2.3.1 Z-score

The temperature at frame i (T_i) of a pixel was assumed to be linear ($T_i = T_{i-1} + \Delta$). We defined (x, y) using the same method of interleaving explained in section **2.3.3**. The Z-score method first smoothed Δ using the Kalman filter [15], then calculated the fittest plane that satisfied (x, y, $\Delta_{x,y}$) at frame i, obtained the angle (θ) of inclination of the plane [16], and finally calculated Z_i using the mean, variance and the angle of every frame.

$$Z_i = (\theta - \mu)/(\sigma)$$

where μ is the mean, and σ is the standard deviation of θ calculated from all frames.

If Z-score of the maximum angle was > 2.0 in a window, this window was considered turning over.

2.3.2 RNNs

A total of 200 frames were sequenced, and the sum of the maximum pixel-wise differences across all frames was used as input. Data size was (200, 256). For the RNN model [17], the hidden size was set at 2048, and the number of layers was four. The model learned and evaluated the results for every 50 frames. The threshold was set at 1.0.

2.3.3 ResNet

We uniquely sequenced the 200 frames and computed the maximum difference for every pixel. The processed data were then organized into two-dimensional (2D) arrays. The total number of pixels was (16, 16), by interleaving the data of each array on sets of four corresponding positions (**Fig. 6**).

$$For_{i=1\sim16} For_{j=1\sim16}\left(Max_{t=x\sim x+200}\left(Data_{i,j,t}\right) - Min_{t=x\sim x+200}\left(Data_{i,j,t}\right)\right)$$

Table 1 Parameters of the models.

	Input Data	Data Size	Threshold	Other parameters
Z-score	Sum of maximum difference	(1,1)	2.0	
RNN	Sequence the 200 frames and sum of maximum difference of every pixel	(200,256)	1.0	Hidden size: 2048 layers: 4
ResNet-18	Sequence the 200 frames and Maximum difference of every pixel in 50 frames	(16,16)	1.0	
ResNet-50	Sequence the 200 frames and Maximum difference of every pixel in 50 frames	(16,16)	1.0	

where (*i, j*) is the position of the interleaved data, and *t* represents the number of frames. The window size was set at 50 frames, and the threshold was 1.0, the same as that in the RNN model.

The 2D arrays are not real image but contain all collected data without modifications. We adopted ResNet-18 and ResNet-50 [18] for comparison.

Initially, we adopted bilinear interpolation to the original data according to a previous study [13] that used the same thermal sensor. However, this approach did not yield satisfactory results. After several attempts, we developed a program that was able to count turning overs with sufficient accuracy, by interleaving the data and then classifying turning overs automatically by ResNet.

3. Results

The healthy volunteers consisted of 5 men and 15 women. One volunteer was aged in the 40s, 5 were in their 30s, and 14 were aged in their 20s.

The total number of windows (5 s for one window) in the testing set was 936 for the four testing sets. Movements of turning over were included in 96 windows (10.26%). Confusion matrices were constructed according to the results of the identification programs (**Table 2**).

The accuracy, precision, and recall for counting turning overs evaluated using the Z-score method were 0.9049, 0.6000, and 0.2188, respectively, and those evaluated using the RNN method were 0.8932, 0.4697, and 0.3299, respectively. These results were suboptimal. There were more false negatives in these models if the number of turning over events increased. Conversely, the accuracy, precision, and recall for the ResNet-18 method were 0.9808, 0.9239, and 0.8854, respectively; and those for the ResNet-50 method were 0.9754, 0.9011, and 0.8542, respectively, showing dramatic improvement.

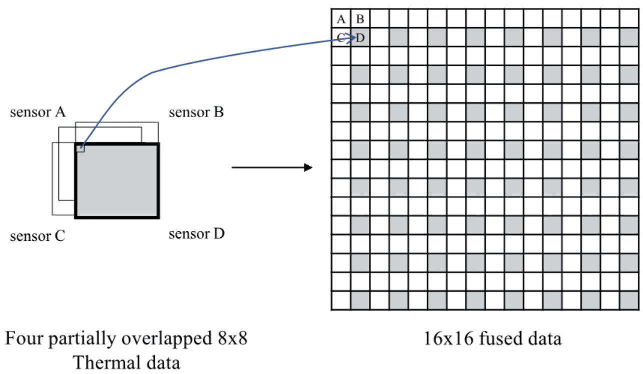

Fig. 6 Interleaving of data. Data obtained from the four sensors are placed sequentially based on their related positions (in the 16×16 matrix). The gray area shows the distribution of data from sensor D (8×8).
onfirmed by video camera, line: value by ResNet-18)

Table 2 Results of identification of turning overs.

Model					Z-Score				RNN				ResNet-18				ResNet-50			
Judgment					TP	FP	FN	TN	TP	FP	FN	TN	TP	FP	FN	TN	TP	FP	FN	TN
	G	H	W	A																
Case #2	F	154	47	30-35	5	0	54	91	14	0	45	91	57	4	2	87	57	3	2	88
Case #6	F	164	51	30-35	9	4	21	225	10	11	20	218	21	1	9	228	18	1	12	228
Case #7	M	174	79	30-35	7	0	0	262	7	5	0	257	7	2	0	260	7	5	0	257
Case #10	F	159	59	30-35	0	10	0	248	0	19	0	239	0	0	0	258	0	0	0	258
Total					**21**	**14**	**75**	**826**	**31**	**35**	**65**	**805**	**85**	**7**	**11**	**833**	**82**	**9**	**14**	**831**

TP: true positive, FP: false positive, FN: false negative, TN: true negative, G: gender, H: height (cm), W: weight (kg), A: age group (years)

Table 3 Performance metrics for the prediction models.

	Accuracy	Precision	Recall
Z-score	0.9049	0.6000	0.2188
RNN	0.8932	0.4697	0.3229
ResNet-18	0.9808	0.9239	0.8854
ResNet-50	0.9754	0.9011	0.8542

ResNet-50 required much higher computation load [329.41 million floating-point operations per second (FLOPs)] than ResNet-18 (139.66 million FLOPs) [18], although the evaluation metrics were not apparently improved (**Table 3**).

In this study, we showed the actual data to all the volunteers and asked whether they had any privacy concerns, to which all volunteers responded that they had absolutely no issues.

4. Discussion

We used low-resolution thermal sensors to count turning overs in bed, including nocturnal turning overs, while protecting patient privacy. Several studies have detected postures, movements, and health conditions using thermal sensors with protection of privacy (**Table 4**).

Table 4 Summary of previous studies.

Study	Device	Resolution	Objectives
[19]	FLIR Lepton 80x60 Thermal Array with Ultrasonic sensor	80×60	location and posture futures(laying, sitting, standing, or none), bedside falls, bed-entry and exit events
[23]	Seek CompactPRO with ReSpeaker Microphone Array (version 2.0)	320×240	influenza-like illness
[20]	The thermopile infrared sensor (multiple)	30×32	pose recognition (arm forward, arm side, arms down, bend and sitting)
[21]	Seek Thermal Compact PRO for iPhone	640×480	respirations
[24]	FLIR Lepton v3 sensor	213×120	posture (standing, lying, sitting, bending)
[22]	FLIR ONE camera	640×480	falls
[13]	AMG8833 IR array sensor	8×8	postures (sitting still, standing still, coming toward the sensor, going away from the sensor)

The systems described in those studies used extremely low-resolution sensors (e.g., 8×8 [13]) or relatively low-resolution sensors (e.g., 80×60 [19] and 30×32 [20]) to detect major postural changes. In contrast, systems with high-resolution sensors (e.g., 640×480 [21, 22], 320×240 [23], and 213×120 [24]) were used to monitor health conditions or detect precise postural changes. Higher resolution is generally required to recognize small changes in thermal sensor data, it may pose a risk of compromising privacy.

We prioritized protecting the privacy of the original data, because hospitals require strict confidentiality. We hypothesized that human movements are detectable if thermal images approximately 30×30 cm in size could be collected from major body parts such as the head, torso, and limbs. Moreover, previous reports provide evidence that this size can protect privacy [25]. Therefore, we adopted a thermal sensor of 8×8 pixels, which was the lowest resolution available when we started this project, and this sensor was able to detect the temperature for a pixel size of approximately 28.8×28.8 cm from a height of 200 cm (**Fig. 4**).

Based on the above assumption, we developed a system to detect turning overs accurately. A previous study [13] also used the same low-resolution sensor (Grid-EYE AMG8833) to classify postures (sitting still, standing still, approaching the sensor, and moving away from the sensor. However, counting turning overs in bed using low-resolution sensors presents difficulties [14]; such as residual heat on the bed does not correspond to the body, only subtle movements are detected during turning over compared with postural changes, and the presence of blankets interferes with temperature changes. To resolve these difficulties, we used four low-resolution sensors simultaneously and observed the object from different directions, increasing the dimensionality of the data aiming to obtain more accurate data without compromising privacy.

We then attempted to upscale the original data using methods such as bilinear interpolation as described in a previous study [13] and super resolution approach. However, these methods achieved only 30%-70% precision and recall. Finally, we developed interleaving data, which differ fundamentally from generating true images but include all the original data without upscaling, and applied ResNet to these unique data (**Fig. 3**). ResNet is widely used to learn and classify images, and is characterized by effective training of deeper networks through residual connections [18]. The window was set at 50 frames, representing 5 s. All data with a maximum difference of 200 frames were allocated to 2D data of (16, 16) for ResNet machine learning. Consequently, the device was able to detect turning over with extremely high accuracy. We believe that two major factors contributed to the success. First, the Grid-EYE AMG8833 sensors provide highly accurate temperature readings. Second, we did not upscale the original data before machine learning, unlike previous study [13]. The performance of ResNet-18 and ResNet-50 was comparable. ResNet-50, which has more parameters than ResNet-18, performs better in most image classification datasets. However, the input size of our data is small; hence, a model with excessive parameters tends to overfit rapidly.

Multiple thermal sources and environmental changes can introduce noise in detection. The sensor requires data collected over a period of time for calibration and for distinguishing useful signals from noise. Also, turning overs in bed are gradual movements lasting a few seconds. Therefore, detection relies on thermal images collected over a certain time interval rather than a single frame. Each frame has a dimension of $(8\times8)\times(2\times2)$, and each turning over detection uses 200 consecutive frames. The dimension of a detection can reach 51,200, which is close to a 224×224 gray-scale image. For performance evaluation, we compared a neural network with a linear discriminant method based on z-score. The linear discriminant method failed to detect turning overs in many cases, whereas the neural network method achieved better performance.

As shown in **Table 2**, false-negative windows were more frequent in Cases #2 and #6. These cases exhibited very frequent turning overs (n = 59 and 30, respectively). Cases with fewer turning overs, such as Cases #7 (n = 7) and #10 (n = 0), had less false-negative windows. This result implies that there may be less false-negative windows in natural turning over frequencies, typically twice per hour [26].

Although this study was exploratory, gender and physique appeared to have little influence (**Table 3**), probably because our device acquired only thermal images of the upper body covered by a blanket. We also reviewed false-positive windows in the original video images and found that they were caused by small movements of hands and heads. This finding suggests that our device may detect turning overs more accurately in real-world clinical settings and may eventually be able to detect and classify small movements by learning from real patient data in the future.

As shown in **Table 3**, all models demonstrated high accuracy, but the Z-score and RNN models showed low precision, suggesting that the previous models had more false-positive windows. Our results show that ResNet models can overcome this limitation.

To date, no study has demonstrated that machine learning can detect turning overs using data from low-resolution sensors, such as 8×8 pixels. Our findings suggest a possibility that the device can generate new parameters for evaluating patients' individual and exact conditions by accurately identifying small movements other than turning overs, while protecting patient privacy.

There were some limitations in this study. Because of the COVID-19 pandemic, we recruited a small group of healthy and young volunteers, who probably performed turning over consciously to some degree, and apparently had a higher frequency of turning overs (**Table 2**). Therefore, in more natural environments with patients, the characteristics of the data will be different, and the prediction performance may change. In the future, we plan to evaluate this system by applying it to study actual turning overs of older individuals in hospital settings.

5. Conclusion

To our knowledge, this study is the first to automatically count turning overs in bed using extremely low-resolution thermal sensor images, which enable us to observe the patients even at night with protection of privacy. Although the resolution of one image of 8×8 pixels was sufficiently low for protection of privacy in hospitals, the resolution was too low to detect small postural changes such as turning over. By using multiple low-resolution sensors simultaneously, we were able to count turning overs. Using the ResNet-18 machine learning program, the accuracy, recall, and precision of counting turning overs were approximately 90%, indicating marked improvement over other previous methods. Further experiments may elucidate the appropriate frequency of turning overs needed to prevent bedsores using this system.

Conflicts of interest

The authors have no conflicts of interest directly relevant to the content of this article.

Ethics declaration

This study was conducted in accordance with the ethical principles of the Helsinki Declaration and after obtaining informed consent from each subject. The study was approved by the Institutional Review Board of Okayama University. Written informed consent for publication was obtained from the participant in **Fig. 3**, which was thought to be indispensable for the understanding of this report.

Acknowledgments

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References

1. Nakatani H: Population aging in Japan: policy transformation, sustainable development goals, universal health coverage, and social determinates of health. Global Health Med. **1**, 3–10, 2019.
2. Inoue N, Matsumura T, Sakai H: Area-Based Medicine in the Super-Ageing Society in Japan. J Med Invest. **67**, 40–43, 2020.
3. Duncan KD: Preventing pressure ulcers: the goal is zero. Jt Comm J Qual Patient Saf. **33**, 605–610, 2007.
4. Armstrong DG, Ayello EA, Capitulo KL, Fowler E, Krasner DL, Levine JM, Sibbald RG, Smith AP: New opportunities to improve pressure ulcer prevention and treatment: implications of the CMS inpatient hospital care present on admission indicators/hospital-acquired conditions policy: a consensus paper from the International Expert Wound Care Advisory Panel. Adv Skin Wound Care. **21**, 469–478, 2008.
5. Kosiak M: Etiology and pathology of ischemic ulcers. Arch Phys Med Rehabil. **40**, 62–69, 1959.
6. Kosiak M: A mechanical resting surface: its effect on pressure distribution. Arch Phys Med Rehabil. **57**, 481–484, 1976.
7. Knox DM, Anderson TM, Anderson PS: Effects of different turn intervals on skin of healthy older adults. Adv Wound Care. **7**, 48–52, 54–56, 1994.
8. Defloor T, De Bacquer D, Grypdonck MH: The effect of various combinations of turning and pressure reducing devices on the incidence of pressure ulcers. Int J Nurs Stud. **42**, 37–46, 2005.
9. Reddy M, Gill SS, Rochon PA: Preventing pressure ulcers: a systematic review. JAMA. **296**, 974–984, 2006.
10. Park H, Kim K, Kweon S-J, Gul O, Choi J, Oh YS, Park I, Je M: A wireless and wearable body-pressure-monitoring system for the prevention of pressure-induced skin injuries. IEEE Trans Biomed Circuits Syst. **17**(5), 889–899. 2023.
11. Yousefi R, Ostadabbas S, Faezipour M, Farshbaf M, Nourani M, Tamil L, Pompeo M: Bed posture classification for pressure ulcer prevention. Annu Int Conf IEEE Eng Med Biol Soc. **2011**, 7175–7178, 2011.
12. Alkhatib S, Waycott J, Buchanan G, Bosua R: Privacy and the Internet of Things (IoT) Monitoring Solutions for Older Adults: A Review. Stud Health Technol Inform. **252**, 8–14, 2018.
13. Newaz NT, Hanada E: A Low-Resolution Infrared Array for Unobtrusive Human Activity Recognition That Preserves Privacy. Sensors (Basel). **24**(3), 926, 2024.
14. Bound T: 2020 IEEE 26th International Conference on Embedded and Real-Time Computing Systems and Applications (RTCSA) RTCSA 2020.
15. Kalman RE: A New Approach to Linear Filtering and Prediction Problems. J Basic Eng. **82**, 35–45, 1960.
16. Söderkvist I: Using SVD for some fitting problems. University Lecture, 2009.
17. Elman JL: Finding structure in time. Cogn Sci. **14**, 179–211, 1990.
18. He K, Zhang X, Ren S, Sun J: Deep residual learning for image recognition. Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 770–778.
19. Asbjørn D, Jim T: Recognizing Bedside Events Using Thermal and Ultrasonic Readings. Sensors (Basel). **17**(6), 1342, 2017.
20. Burns M, Cruciani F, Morrow P, Nugent C, McClean S: Using Convolutional Neural Networks with Multiple Thermal Sensors for Unobtrusive Pose Recognition. Sensors (Basel). **20**(23), 6932, 2020.
21. Jakkaew P, Onoye T: Non-Contact Respiration Monitoring and Body Movements Detection for Sleep Using Thermal Imaging. Sensors (Basel). **20**(21), 6307, 2020.
22. Hsu WW, Guo JM, Chen CY, Chang YC: Fall Detection with the Spatial-Temporal Correlation Encoded by a Sequence-to-Sequence Denoised GAN. Sensors (Basel). **22**(11), 4194, 2022.
23. Al Hossain F, Lover AA, Corey GA, Reich NG, Rahman T. FluSense: A Contactless Syndromic Surveillance Platform for Influenza-Like Illness in Hospital Waiting Areas. Proc ACM Interact Mob Wearable Ubiquitous Technol. **4**(1), 1, 2020.
24. Guo Y, Chen Y, Deng J, Li S, Zhou H: Identity-Preserved Human Posture Detection in Infrared Thermal Images: A Benchmark. Sensors (Basel). **23**(1), 92, 2022.
25. Sirmacek B, Riveiro M. Occupancy Prediction Using Low-Cost and Low-Resolution Heat Sensors for Smart Offices. Sensors (Basel). **20**(19), 5497, 2020.
26. Matuura R, Furukawa K, Tanaka S, Aritomi R. Body posture on sleep onset and during nocturnal sleep. Jpn J Physiol Anthropol. **10**, 90–91, 2005.