Information Modelling and Knowledge Bases XXXVI
Y. Kiyoki et al. (Eds.)

doi:10.3233/FAIA241587

Evaluation of Bed Sensor Panel Positions for Bed Position Classification Toward Fall and Bedsore Prevention

Waranrach VIRIYAVIT [a], Somrudee DEEPAISARN [b, 1], Thatsanee CHAROENPORN [c] and Virach SORNLERTLAMVANICH [c]
[a] *Faculty of Informatics, Burapha University*
[b] *Sirindhorn International Institute of Technology, Thammasat University*
[c] *Asia AI Institute (AAII), Faculty of Data Science, Musashino University*
ORCiD ID: Waranrach Viriyavit https://orcid.org/0000-0002-5192-8998, Somrudee Deepaisarn https://orcid.org/ 0000-0001-7647-6345 , Thastsanee Charoenporn https://orcid.org/ 0000-0002-9577-9082 , Virach Sornlertlamvanich https://orcid.org/ 0000-0002-6918-8713

Abstract. The increasing elderly population necessitates increased geriatric care. However, a shortage of caregivers leads to a risk of falls and bedsores in the elderly, both of which result in severe injuries. Whilst wearable devices, and vision sensors have been adopted for monitoring. However, these sensors come with limitations, impacting comfort and privacy for the elderly. To address these challenges, non-intrusive sensing devices integrated into the environment offer promising value for continuous elderly activity monitoring. This study uses a panel sensor embedded with four sensors, consisting of two piezoelectric sensors and two pressure sensors. It is placed beneath the mattress. The position classification encompasses five distinct positions: off-bed, sitting, lying in the center, lying on the left side, and lying on the right side. To find the best position for placing the panel, the positions of the panel and the combination of panel sensors positions are evaluated for five-bed positions classification. As a result, the best position for a sensor panel was in the middle of the bed (position No.3), with an accuracy of 97.12%. This suggests the panel sensor should be placed at 123.5 cm, measured from the top of the bed. Moreover, in the case of placing two-panel sensors, the most effective arrangement comprises placing one-panel sensor placed at the the bed-top (position No.1) and the other in the middle of the bed (position No.3), yielding accuracy 99.93%.

Keywords. Bed position classification, Bed sensor, Non-constraint sensing, Elderly care, Neural Network

1. Introduction

Falls among the elderly population can result in severe injuries, hospitalization, and even fatalities. Thailand faces a high rate of mortality resulting from falls among the elderly, with a 40.4% risk of death or disability [1]. Additionally, approximately 10% of patients develop bedsores in Thailand [2]. These issues pose both physical and financial challenges to the healthcare sector. Preventing falls and bedsores requires continuous

[1] Corresponding Author: Somrudee Deepaisarn, somrudee@siit.tu.ac.th.

monitoring, but Thailand has a shortage of care workers, with only 11.1% available for the elderly [1]. Continuous monitoring systems can assist caregivers by alerting them when the elderly need to get out of bed or lie in the same positiofor over two hours.

Various studies have explored fall detection and bedsore prevention systems. Fall detection systems typically rely on posture monitoring and impact detection to notify caregivers when the elderly attempt to exit the bed without assistance. Many types of monitoring systems, including pressure mats, infrared sensors, cameras, and wearable devices, are employed [3–31]. Although wearable devices are effective, they may cause discomfort and exhibit inconsistencies[3]. Camera-based systems can be seen as invasive, which causes feelings of insecurity. Non-contact sensing devices, like sensors attached to beds, have been used to detect bed exits. However, this can only detect if the patient is in bed or not; it is insufficient for fall prevention due to an accident related to the bed's edge. Pressure sensor mats are commonly used to monitor patient's position in bed to prevent bedsores [23–31]. However, larger mats designed for fall detection, while accurate, can be expensive and impractical in some situations. Some studies have explored using fewer sensors, such as 16 long narrow sensors [30] or even employing 12 electrodes [32] to determine a person's position in bed. In order to enhance behavioral monitoring, it is important to integrate both fall detection and bedsore prevention systems. Our previous approaches used only four sensors within a bed sensor panel to classify five different positions, aiding in the detection of individuals leaving or changing their positions while sleeping, as reported in [20] and [12]. However, the best position for placing the panel has not been evaluated. Therefore, this study proposed to find the best position for placing the panel for five positions classification. Moreover, in the case of placing two-panel sensors, combination input features are evaluated.

In this paper, we evaluated the best position for placing the bed sensor panel, which is set under the mattress on the bed. This study focuses on five distinct positions: off-bed, sitting, lying center, lying left, and lying right. These five positions can be used to alert caregivers in monitoring and providing care for the elderly.

The paper is organized as follows: Section 2 provides details on the materials and methods employed for bed position classification. Section 3 presents the classification results and discussion. Finally, Section 4 is the conclusion section.

2. Materials and Methods

2.1. Equipment

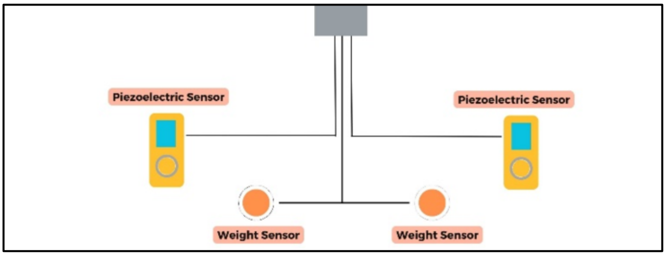


Figure 1 Panel Sensor[20]

The data for this study was collected using a sensor panel (manufactured by AIVS Co., Ltd., Japan) consisting of four sensors, as described in detail in a prior study by [20,33]. This sensor panel is equipped with a pair of pressure sensors and a pair of piezoelectric sensors, which are symmetrically arranged on the panel, as depicted in Figure 1. The piezoelectric signal values have a dynamic range of 256, covering a range from -127 to 128, while the pressure signal values range from 0 to 256. These sensors operate at a sampling rate of 30 Hz.

2.2. Data Collection

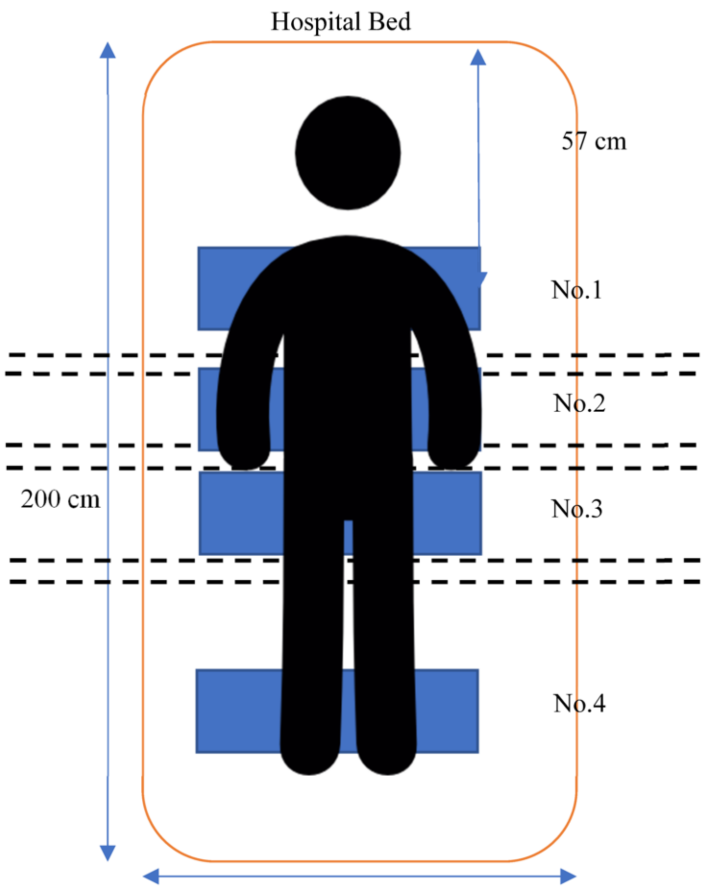


Figure 2 Positions of the four sensor panels placed under the bed mattress.

Typically, a hospital bed comprises four adjustable sections for lifting the patient. In order to determine the suitable placement, four areas were used, as depicted in Figure 2. The sensor panels were positioned in the center of each bed section, except for the top section, which was situated horizontally at chest level. The top sensor panel (position

No.1) is located approximately 57 cm from the top of the bed, corresponding to the area around the back of the supine posture for Thai people [34]. The size of the hospital bed is 200 x 90 cm.

As outlined in [33], the signal data is labeled using synchronized video, with five-position classes and an additional class for other situations. The classes are off-bed (O), sitting(S), lying center(C), lying left(L), lying right(R), and other that is any position that does not fit the previous five positions.

The dataset was collected from nine healthy people, aged 22 to 39, weighing between 55 and 80 kg, and heights between 156 and 170 cm. The subjects are instructed to follow a sequence of action on the bed: off-bed (O), sitting(S), lying center(C), lying left(L), lying right(R), lying center(C), sitting(S), off-bed(O). They switched positions approximately every 30 seconds, and each person repeated this sequence six times, resulting in six trials per person.

2.3. Position Classification Model

In order to classify a position on the bed, we adopt signal data obtained from the sensor panel, which includes the left piezoelectric signal (P_l), right piezoelectric signal (P_r), left pressure signal (W_l), and right pressure signal (W_r), are used as the input for the neural network. These four inputs are passed through the neural network as defined in equation (1)

$$X = [\, P_l, W_l, P_r, W_r] \tag{1}$$

When considering the combination of two-panel sensors, we incorporate the signals from both sensors. Since each panel provides four signals, this results in a total of 8 input features, as defined in equation (2).

$$X = [\, P_{l1}, W_{l1}, P_{r1}, W_{r1}, P_{l2}, W_{l2}, P_{r2}, W_{r2}] \tag{2}$$

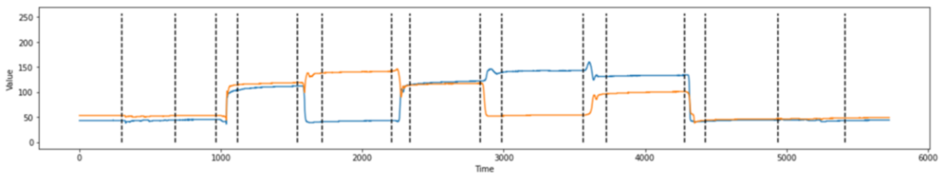
In the experiment, we employ a neural network model which includes one hidden layer with 10 hidden units of rectified linear unit (ReLU) activation function. We adopt a categorical cross-entropy loss function to train the model. To robust generalization and prevent overfitting, K-fold cross-validation is used. Our dataset has 9 subjects; therefore, 9-fold cross-validation is performed in which test set is one subject dataset. The dataset is split into 10% for the validation set. For each fold, models are trained over 100 epochs; the best model weights result from the lowest validation set loss during the 100 epochs of training and are saved for testing.

3. Results and Discussion

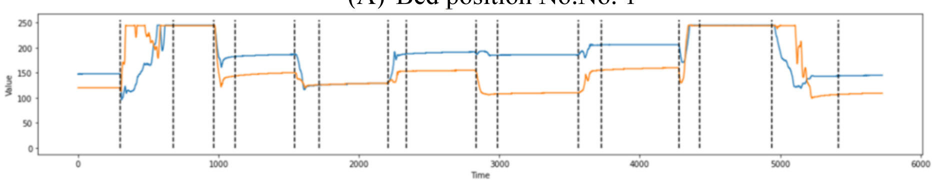
3.1. Evaluation Placing Position of the Bed Sensor Panel

Table 1 Classification accuracy and F1-score for different panel positions.

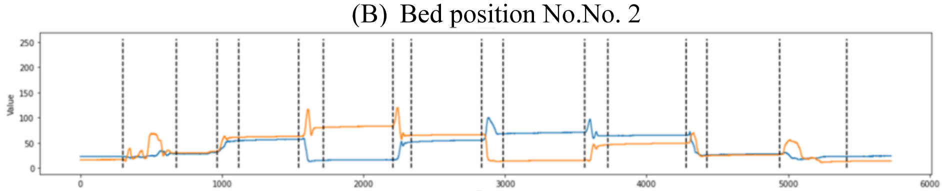
Bed sensor Position	F1-Score (%)					Accuracy (%)
	Off-bed	Sitting	Center	Left	Right	
No.1	83.30 (8.28)	79.27 (7.84)	**98.07 (3.63)**	**99.12 (2.59)**	**96.80 (6.07)**	91.70 (2.11)
No.2	98.50 (2.86)	96.58 (3.44)	97.18 (3.80)	94.35 (8.63)	96.55 (4.67)	96.84 (3.68)
No.3	**99.25 (1.49)**	**97.37 (3.36)**	97.54 (3.83)	95.12 (10.18)	95.05 (9.24)	**97.12 (4.34)**
No.4	95.70 (3.60)	89.67 (5.85)	95.83 (3.48)	89.04 (20.30)	90.49 (11.16)	92.79 (4.94)



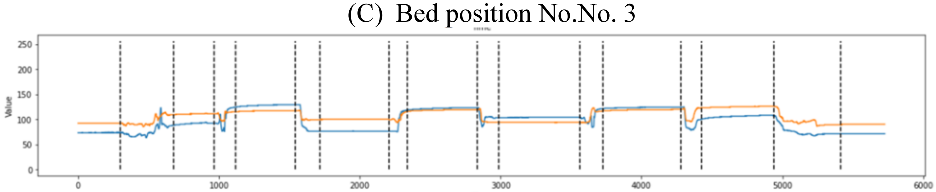
(A) Bed position No.No. 1



(B) Bed position No.No. 2



(C) Bed position No.No. 3



(D) Bed position No.No. 4

Figure 3 Signal of the pressure sensor of subject No.1, where blue is the right pressure signal, and orange is left pressure: (A) signal of bed position No.1, (B) signal of bed position No.2, (C) signal of bed position No.3, and (D) signal of bed position No.4.

In comparison to the different positions of the sensor panel, position No.1 excels in capturing lying positions, i.e., center, left, and right, as F1-score of 98.07%, 99.12%, 96.80%, respectively. This indicates that when it comes to detecting activities related to lying down in different areas of the bed, position No.1 demonstrates remarkable accuracy. Conversely, position No.3 outperforms the other position in terms of detecting off-bed and sitting, with an F1-score of 99.25% and 97.37%, respectively. These results imply position No.3 provides the most precise and reliable results to determine whether someone is off-bed or sitting.

Overall, positions No.3 yields the highest accuracy compared to the other positions. This indicates that position No.3 is the top-performing choice among the sensor panel positions. The superior performance of position No.3 can be attributed to its strategic placement in the middle of the bed. This location allows it to capture and detect movements on the bed, particularly excelling in identifying off the bed and sitting.

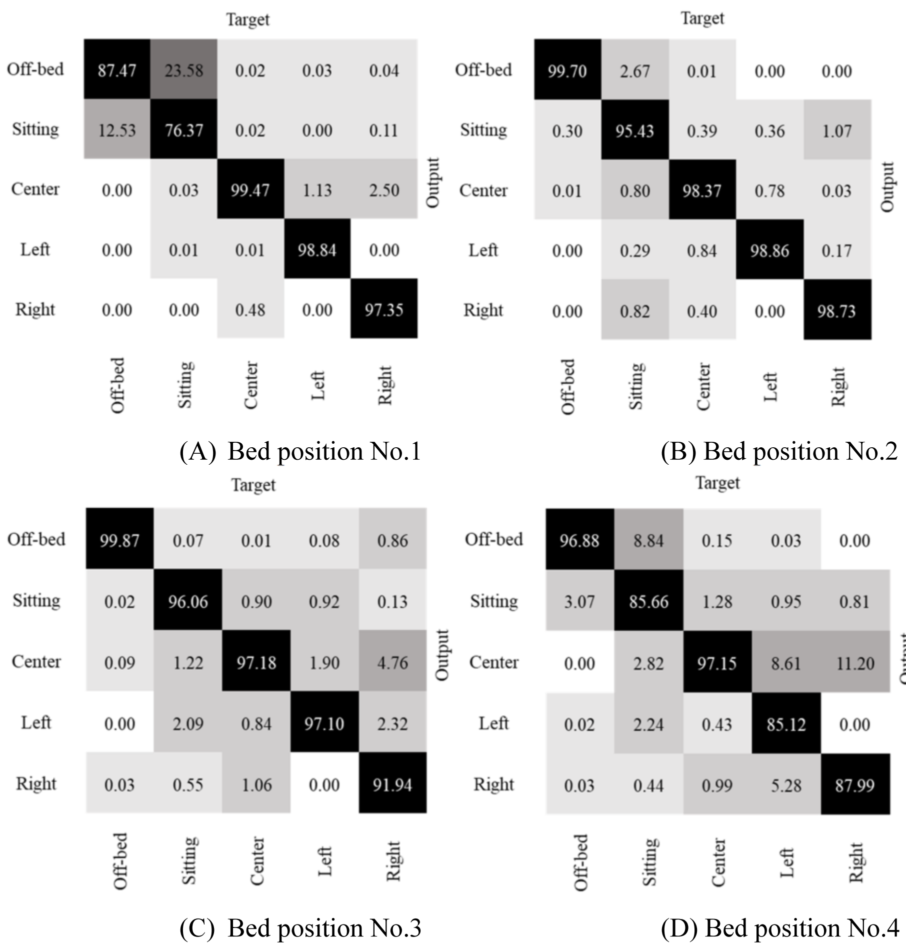


Figure 4 Confusion matrix of NN model with a single timestep of different panel positions.

Figure 3 displays signal data from five-bed positions, with blue representing the right pressure signal and orange representing the left pressure signal. The dashed black line marks the position where a pressure change is observed. The sequence of bed position is followed in Section 2.2. In position No.1, the signal of off-bed and sitting position exhibits notable similarities; both the right and left pressure sensors remain inactive, with only the piezoelectric sensors being different. Consequently, the signals for off-bed and sitting positions become ambiguous to classify. The accuracy for the off-bed position was 87.47%, while the sitting position was 76.37%. This indicates a 5.32% error rate in classifying off-bed as sitting and a 10.54% error rate in classifying sitting as off-bed, as depicted in Figure 4 (A). Meanwhile, position No.3 outperforms the other, as tabulated in Table 1. This superiority is attributed to the subjects sitting on position No.3; the pressure sensors register significantly higher activation, as indicated in Figure 3 (C). Consequently, it becomes feasible to distinguish the pressure signals associated with sitting from those linked to the off-bed position. No.Position No.4 exhibits the lowest accuracy due to the less activation of sensors in different bed positions, as shown in Figure 3 (D).

3.2. Evaluation Combination of Placing Bed Panel Sensor Position

Table 2 Classification accuracy and F1-score of varied

Bed sensor Combination	**F1-Score**					**Accuracy (%)**
	Off-bed	**Sitting**	**Center**	**Left**	**Right**	
No.1 and No.2	98.30 (3.16)	98.16 (3.95)	99.53 (14.10)	99.68 (9.53)	99.34 (19.64)	98.99 (2.26)
No.1 and No.3	**99.96 (0.09)**	**99.91 (0.21)**	**99.84 (0.49)**	99.69 (0.94)	**99.98 (0.06)**	**99.93 (0.19)**
No.1 and No.4	93.09 (7.61)	90.45 (12.30)	97.92 (3.06)	98.44 (2.38)	95.68 (6.39)	95.17 (5.41)
No.2 and No.3	99.59 (1.22)	99.17 (2.48)	99.39 (1.81)	**99.82 (0.52)**	99.56 (1.28)	99.41 (1.77)
No.2 and No.4	98.09 (5.41)	97.95 (5.39)	99.07 (2.61)	99.78 (0.44)	98.90 (3.20)	98.76 (3.33)
No.3 and No.4	98.03 (2.77)	96.42 (5.53)	96.27 (6.74)	98.68 (2.33)	96.50 (4.94)	97.03 (4.37)

Table 2 presents the outcomes obtained from an analysis of various input features gathered from two-bed panel sensors. The aim was to determine the most effective combination of these features in accurately classifying different bed positions. Overall, the combination of input features from positions No.1 and NNo.3 achieved the highest accuracy as tabulated in Table 2.

From Table 1, position No.3 outperforms in distinguishing off-bed and sitting positions. In contrast, position No.1 has superior performance in detecting lying positions, i.e., lying center, lying left, and lying right. Therefore, it is clear that the combination of input features derived from position number 1 and position number 3 emerges as a robust and effective choice for accurately classifying bed positions. This combination leverages the strengths of each position, capitalizing on the strengths of position number 1 for off-bed and sitting detection and those of position number 3 for accurately identifying lying positions.

3.3. Comparative with other studies

Evaluating our performance against other approaches is quite difficult due to disparities in the dataset, the number of bed positions, and the sensors used. In order to provide a comparison, we focus on the lying position. Table 3 summarizes the results for lying positions. Our approach achieves 99.7% accuracy in classifying three sleep positions: lying center, lying left, and lying right. Our approach, using a total of eight sensors, outperforms various others except [30] using 16 sensors.

Table 3 Comparison of sleep position classification algorithms

Accuracy (%)	#of position	# of sensor	Approach
98.1	5	2048(32×64)	[23]
98.4	3	1728 (64x27)	[24]
90	4	171 (19 × 9)	[25]
97.9	4	1728 (64 × 27)	[26]
97.7	5	2048(32×64)	[35]
97	8	2048	[28]
83.5	6	56	[29]
100	3	16	[30]
99.7	4	512(16×16)	[31]
98.4	5	12	[32]
95	3	4	[12]
95.8	3	4	[20]
99.7	**3**	**8**	**Ours**

4. Conclusion

The study also found that the best positions for the sensor panel were in the middle of the bed (position No.3). This information provides valuable insights for developing more effective and efficient methods for preventing falls and bedsores in different settings such as home use. Consequently, it is recommended that the sensor panel be positioned at location No. 3, situated approximately 123.5 cm from the top of the bed. Moreover, in the case of positions No.1 and No.3 outperform in all bed positions. This suggests that for enhanced accuracy, the panel sensors should be placed both at the top (position No.1) and middle (position No.3) of the bed.

References

[1] National Statistical Office. The 2014 survey of the older persons in Thailand. 2014.

[2] Khumnual P, Chuayunan N, Detupkarakul S. Effects of a clinical practice guideline for the prevention of pressure sores in at-risk patients at Phayao Hospital (in Thai). Hua Hin Sook Jai Klai Kangwon Journal. 2018;3(2):89–101.

[3] Ibrahim A, Chaccour K, Hassani AHE, Andres E. Bed-Fall Detection and Prediction: A Generic Classification and Review of Bed-Fall Related Systems. IEEE Sensors Journal. 2021 Mar;21(5):5678–86.

[4] Asbjørn D, Jim T. Recognizing Bedside Events Using Thermal and Ultrasonic Readings. Sensors. 2017 Jun;17(6):1342.

[5] Bauer P, Kramer JB, Rush B, Sabalka L. Modeling bed exit likelihood in a camera-based automated video monitoring application. In: 2017 IEEE International Conference on Electro Information Technology (EIT). 2017. p. 056–61.

[6] Chang WJ, Chen LB, Ou YK, See AR, Yang TC. A Bed-Exit and Bedside Fall Warning System Based on Deep Learning Edge Computing Techniques. In: 2021 IEEE 3rd Global Conference on Life Sciences and Technologies (LifeTech). 2021. p. 142–3.

[7] Chen TX, Hsiao RS, Kao CH, Liao WH, Lin DB. Bed-exit prediction based on convolutional neural networks. In: 2017 International Conference on Applied System Innovation (ICASI). 2017. p. 188–91.

[8] Chiu SY, Hsieh JC, Hsu CI, Chiu C. A Convolutional Neural Networks Approach with Infrared Array Sensor for Bed-Exit Detection. In: 2018 International Conference on System Science and Engineering (ICSSE). 2018. p. 1–6.

[9] Härmä A, ten Kate W, Espina J. Bed exit prediction based on movement and posture data. In: IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI). 2014. p. 165–8.

[10] Hata Y, Yamaguchi H, Kobashi S, Taniguchi K, Nakajima H. A human health monitoring system of systems in bed. In: 2008 IEEE International Conference on System of Systems Engineering. 2008. p. 1–6.

[11] Inoue M, Taguchi R, Umezaki T. Bed-Exit Prediction Applying Neural Network Combining Bed Position Detection and Patient Posture Estimation. In: 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2019. p. 3208–11.

[12] Sao S, Sornlertlamvanich V. Long short-term memory networks for bed position classification. 2019 [cited 2023 Feb 18]; Available from: https://digital.library.tu.ac.th/tu_dc/frontend/Info/item/dc:175940

[13] Song KS, Nho YH, Kwon DS. Histogram based fall prediction of patients using a thermal imagery camera. In: 2017 14th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI). 2017. p. 161–4.

[14] Shinmoto Torres RL, Ranasinghe DC, Shi Q, Sample AP. Sensor enabled wearable RFID technology for mitigating the risk of falls near beds. In: 2013 IEEE International Conference on RFID (RFID). 2013. p. 191–8.

[15] Wickramasinghe A, Ranasinghe DC, Fumeaux C, Hill KD, Visvanathan R. Sequence Learning with Passive RFID Sensors for Real-Time Bed-Egress Recognition in Older People. IEEE Journal of Biomedical and Health Informatics. 2017 Jul;21(4):917–29.

[16] Yamaguchi H, Nakajima H, Taniguchi K, Kobashi S, Kondo K, Hata Y. Fuzzy Detection System of Behavior before Getting Out of Bed by Air Pressure and Ultrasonic Sensors. In: 2007 IEEE International Conference on Granular Computing (GRC 2007). 2007. p. 114–114.

[17] Wu CL, Chien YW, Fu LC. Monitoring bed activities via vibration-sensing belt on bed. In: 2017 IEEE International Conference on Consumer Electronics - Taiwan (ICCE-TW). 2017. p. 85–6.

[18] Youngkong P, Panpanyatep W. A Novel Double Pressure Sensors-Based Monitoring and Alarming System for Fall Detection. In: 2021 Second International Symposium on Instrumentation, Control, Artificial Intelligence, and Robotics (ICA-SYMP). 2021. p. 1–5.

[19] Inoue M, Taguchi R. Bed Exit Action Detection Based on Patient Posture with Long Short-Term Memory. In: 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). 2020. p. 4390–3.

[20] Viriyavit W, Sornlertlamvanich V. Bed Position Classification by a Neural Network and Bayesian Network Using Noninvasive Sensors for Fall Prevention. Journal of Sensors. 2020 Jan 31;2020:e5689860.

[21] Zhao F, Cao Z, Xiao Y, Mao J, Yuan J. Real-Time Detection of Fall From Bed Using a Single Depth Camera. IEEE Transactions on Automation Science and Engineering. 2019 Jul;16(3):1018–32.

[22] Lu C, Huang J, Lan Z, Wang Q. Bed exiting monitoring system with fall detection for the elderly living alone. In: 2016 International Conference on Advanced Robotics and Mechatronics (ICARM). 2016. p. 59–64.

[23] Heydarzadeh M, Nourani M, Ostadabbas S. In-bed posture classification using deep autoencoders. In: 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2016. p. 3839–42.

[24] Ostadabbas S, Baran Pouyan M, Nourani M, Kehtarnavaz N. In-bed posture classification and limb identification. In: 2014 IEEE Biomedical Circuits and Systems Conference (BioCAS) Proceedings. 2014. p. 133–6.

[25] Tang K, Kumar A, Nadeem M, Maaz I. CNN-Based Smart Sleep Posture Recognition System. IoT. 2021 Mar;2(1):119–39.

[26] Matar G, Lina JM, Kaddoum G. Artificial Neural Network for in-Bed Posture Classification Using Bed-Sheet Pressure Sensors. IEEE Journal of Biomedical and Health Informatics. 2020;24(1):101–10.

[27] Yousefi R, Ostadabbas S, Faezipour M, Nourani M, Ng V, Tamil L, Bowling A, Behan D, Pompeo M. A smart bed platform for monitoring & Ulcer prevention. In: 2011 4th International Conference on Biomedical Engineering and Informatics (BMEI). 2011. p. 1362–6.

[28] Pouyan MB, Ostadabbas S, Farshbaf M, Yousefi R, Nourani M, Pompeo MDM. Continuous eight-posture classification for bed-bound patients. In: 2013 6th International Conference on Biomedical Engineering and Informatics. 2013. p. 121–6.

[29] Hsia CC, Liou KJ, Aung APW, Foo V, Huang W, Biswas J. Analysis and comparison of sleeping posture classification methods using pressure sensitive bed system. In: 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2009. p. 6131–4.

[30] Hsia CC, Hung YW, Chiu YH, Kang CH. Bayesian classification for bed posture detection based on kurtosis and skewness estimation. In: HealthCom 2008 - 10th International Conference on e-health Networking, Applications and Services. 2008. p. 165–8.

[31] Cruz-Santos W, Beltrán-Herrera A, Vázquez-Santacruz E, Gamboa-Zúñiga M. Posture classification of lying down human bodies based on pressure sensors array. In: 2014 International Joint Conference on Neural Networks (IJCNN). 2014. p. 533–7.

[32] Lee HJ, Hwang SH, Lee SM, Lim YG, Park KS. Estimation of Body Postures on Bed Using Unconstrained ECG Measurements. IEEE Journal of Biomedical and Health Informatics. 2013;17(6):985–93.

[33] Viriyavit W, Sornlertlamvanich V. Data Labeling Scheme for Bed Position Classification. In: Information Modelling and Knowledge Bases XXXI. IOS Press; 2020. p. 222–37.

[34] Faculty of Home Economics Technology, Rajamangala University of Technology Thanyaburi,. THAI STANDARD BODY SIZES [Internet]. [cited 2019 Jan 2]. Available from: http://www.fashion.rmutt.ac.th/download/KM/N56-0301-1-THAI-STANDARD-BODY%20SIZES.pdf

[35] 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;2011:7175–8.