Bed Posture Classification using Noninvasive Bed Sensors for Elderly Care

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Abstract. This study proposes bed posture classification using a Neural Network and a Bayesian Network for elderly care. The data are collected in a hospital. The on-bed postures are analyzed into five types, those are, out of bed, sitting, lying down, lying left, and lying right, by using signals from a sensor panel (composed of piezoelectric sensors and pressure sensors). The sensor panel is placed under a mattress in the thoracic area. To eliminate the effect of weight and the bias between different types of sensors, the sensing data are normalized into a range of 0 to 1 by the unity-based normalization (or feature scaling) method. In addition, a Bayesian Network is adopted to estimate the likelihood of consecutive postures. The results from both a Neural Network and Bayesian Network estimation are combined by the weighted arithmetic mean. The experimental results yield the maximum accuracy of posture classification when the coefficient of Bayesian probability and a Neural Network are set to 0.7 and 0.3 respectively.

Keywords. Posture classification, Noninvasive bed sensor, Elderly care, Neural Network, Bayesian network

1. Introduction

The proportion of elderly in Thailand population is increasing rapidly that has increased the needs of geriatric care. It is reported that the percentage of single elderly is rising from 3.6 in 1994 to 10.4 in 2014 because of the gradual change of social structure. The 39% of elderly are injured in falling down by stumbling over an obstacle and 7.8% of them are hospitalized [1]. Elderly in nursing care homes and hospitals have a high risk of injury when they attempt to get out of bed in order to go to the bathroom. The patient's safety is significant for nursing intervention [2]. To prevent a falling down from a bed, one of the effective approaches is the ability in classifying human's on-bed gestures, and

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then provides enough time to assist his/her movement. Such a monitoring system will help to reduce the burden of nurses and caregivers.

In addition, hospitalized elderly normally has a higher risk of losing skills of activity in daily life, due to the less mobility. The elderly is usually restricted to a bed with cables and tubes [3]. However, a noninvasive sensor is proved to be appropriate to monitor the elderly behavior because of the general concern of the activities in daily life.

In the past few years, it is significant that the majority of bed posture classification methods had been proposed by using noninvasive sensors [4-20]. S. Nukaya et al. demonstrated the relationship between sensor signals and movement on a bed [4, 5] and A. Gaddam et al. conducted an experiment on the influence of weight's position to the sensor signal [6]. Both of the studies used four sensors attaching to each leg of a bed. The commercially available pressure mat system is used to monitor patients on a bed for the privacy reason, unlike the one with camera [7-12]. Many studies use pressure mat for sleep posture classification. Some studies use force sensing array [13-16]. However, those studies require a large number of sensors which are not practical. Therefore, some studies propose approaches to reduce the number of sensing array [14, 16]. For example, C. Hsia et al. d use Bayesian classification based on kurtosis and skewness with 16 long narrow sensors for bed posture classification [16]. H. Yamaguchi et al. determined whether or not a patient in a bed using fuzzy inference technique [18, 19]. M. Cholewa and P. Glomb introduced gesture classification using Hidden Markov Model and Bayesian Network with a set of sensors [20].

In the following sections, section 2 and section 3 discuss the past research in the literature review and the details of sensing equipment respectively. Section 4 described our approaches in posture classification. Section 5 shows the experimental results and section 6 finally concludes the results.

2. Literature Review

In the previous works, there are some studies proposed for bed posture classification [4-20]. S. Nukaya et al. used four spot sensors attaching to each legs of a bed. Each spot includes two types of sensor i.e. force sensors and piezoceramic sensors. They measured movement on bed from the integrated signal of four spot sensors [5]. In [7-12], the pressure mat is provided in their experiment. Those studies have applied different techniques to classify sleep posture. M. B. Pouyan et al. considered eight postures by using binary pattern matching [7]. Sarah Ostadabbas et al. used Gaussian Mixture Model (GMM) to detect the posture [8]. J. Liu Jason et al. proposed a pictorial structure method [10]. A machine learning approach for posture classification using Principle Component Analysis (PCA), Support Vector Machine (SVM), and Deep Neural Network (DNN) were introduced in [9, 11-15]. The force sensing array were used in some studies [13-16]. The minimum number of sensors in aforementioned studies is 16 sensors in C. C. Hsia et al. [16]. They use Bayesian classification with kurtosis and skewness technique. 16 long narrow sensors have been applied on a bed [16]. Although those of studies have shown promising results of posture classification, their approaches require a large number of sensors. They are costly and not so practical in the real applications. M. Cholewa and P. Glomb use some other sets of sensor i.e. finger bend, accelerometer and pitch/roll. The probabilistic models such as Hidden Markov Model (HMM) and Bayesian Network are applied for posture classification [20]. The set of sensors needs to attach to the body, especially the finger bend. Hence, it is not appropriate for elderly because the elderly will gradually lose their body functions by the restriction of the cables or tubes [2]. H. J. Lee uses SVM with RBF kernel to estimate postures on a bed with 12 electrodes of ECG measurement [17]. It is also not proper for elderly use either. H. Yamaguchi et al. use fuzzy inference technique to determine whether the patient is in a bed or not [18, 19]. The proposed approach can just only detect whether the patient is going to get out of bed.

3. Sensing Equipment

3.1. Sensor Panel

Figure 1. Position of sensor panel on a bed

In our approach, we use the ready-made sensor panel of AIVS. The panel is equipped with two types of sensor i.e. two piezoelectric sensors and two pressure sensors. Each pair of them is embedded on each side of the panel. The panel is simply set beneath the mattress in the thoracic area, as shown in Figure 1. Placing the panel in such position, the signals from both pairs of sensors can be used to differentiate postures on a bed. For example, lying down posture, the pressure of the body applies on both sides of the sensors while lying left or right posture, only one side of the sensors is activated. In sitting posture, the activations of pressure sensors are low but the signals from piezoelectric sensors are still detected in contrast to out of bed posture which the very low signals from piezoelectric sensors can be detected.

3.2. Data Structure

Header	Sensors address	Piezo right	Weight right	Piezo left	Weight left	Ender
8 byte	2 byte	8 byte	8 byte	8 byte	8 byte	3 byte

Figure 2. Image of the data structure

The magnitude of sensors is 256. The range of values is -127 to 128 and 0 to 256 for piezoelectric and pressure, respectively. The sampling rate of each sensor is 30 Hz. The control device outputs a package of 45 bytes of data each time. The data package contains 8 bytes of header and 3 bytes of ender. Between the header and the ender, the data from the four sensors are formed in 34 bytes where the first two-bytes contains the sensor ID, and other 32 bytes are signal data. The signal data are divided into 4 parts containing 8 bytes for each sensor in the sequence of left Piezoelectric signal (P_l), right Piezoelectric signal (P_r), left pressure signal (W_l) and right pressure signal (W_r). Figure 2 depicts the detail of the data structure.

4. Approach for Posture Detection

4.1. Recognition using Neural Network

To recognize postures on bed, we use the four inputs from the control device, i.e. left Piezoelectric signal (P_l), right Piezoelectric signal (P_r), left pressure signal (W_l) and right pressure signal (W_r). These four inputs are passed through a Neural Network as shown in Figure 3.

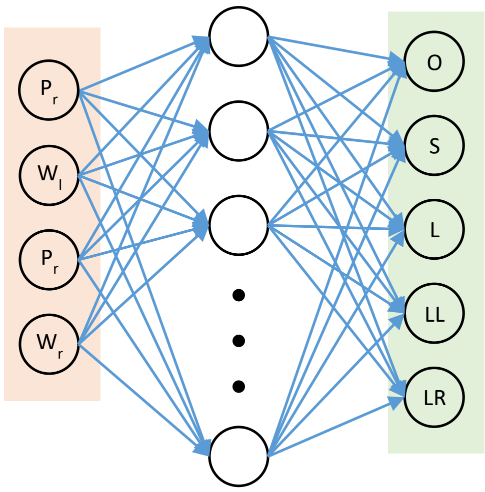


Figure 3. Neural Network diagram of four input signal types, where O is out of bed, S is sitting, L is lying down, LL is lying left, LR is lying right

We apply unity-based normalization to eliminate the bias of weight from different bodies and different types of sensor. All sensor data are normalized by Eq. (1) [21].

$$X_i = \frac{x_i - min}{max - min} \quad (1)$$

Where x_i is the sensor data in ith sequences, X_i is the normalized value, *min* is the minimum value, and *max* is the maximum value of the collection.

From the properties of the panel sensor, where the sampling rate is 30 Hz, to accumulate the signal data in one second, there needs 30 x 4 = 120 data signals as described in Eq. (2).

$$X = \{x_1, x_2, x_3, \dots, x_{120}\} = \{Pl_1, Wl_1, Pr_1, Wr_1, Pl_2, Wl_2, Pr_2, Wr_2, \dots, Pl_{30}, Wl_{30}, Pr_{30}, Wr_{30}\} \quad (2)$$

4.2. Probabilistic Model

We apply a Bayesian Network [22] to estimate next possible postures. This can depress the noise of signals which can be caused by other activities in the uncontrolled environment. The probability of the consecutive posture can be estimated by the former *n* postures and current signals, as shown in Eqs. (3) and (4).

$$P(S, P) = P(S)P(P|S) = P(P)P(S|P) \quad (3)$$

$$P(S, P) = P(P_i|P_{i-1}, P_{i-2})P(S|P_i) \quad (4)$$

Where P_i, P_{i-1} and P_{i-2} are posture in i^{th} sequences. S is the current set of signals consisting of four sensor signals (P_l, W_l, P_r, W_r). We convert the continuous value of the signal data to nominal value by dividing the signal into three levels i.e. low, middle, and high. In the range of piezoelectric signal, 0-25 is defined as low, 26-50 is defined as middle, and 51-100 is defined as high. In range of pressure signal, 0-35 is defined as low, 36-70 is defined as middle, and 70-100 is defined as high. Probability of the consecutive posture is shown in Figure 4.

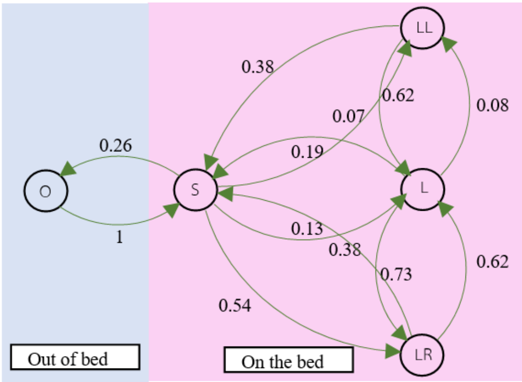


Figure 4. State transition of 5 postures

We apply the combination of the results from a Neural Network and a Bayesian network to classify the posture as shown in Eq. (5).

$$\alpha N + \beta B = C \tag{5}$$

Where, N is Neural Network probability, B is Bayesian probability, C is classes and α, β are the coefficient where the sum of α and β is 1.

5. Experiment and Results

5.1. Data Collection

The data are collected from two rooms in which a bed is equipped with a set of sensor. 3 elderly patients whose ages are between 60 and 85 participate in the experiment. The data of two subjects are collected from room 1, and another subject from room 2. For posture labelling, the collected data includes the signals from the sensors and the video. Total data are taken for 459 hours. The targeted posture labels are annotated by observing the captured video. Followings are the posture labels defining the 5 classes.

- O: Out of bed
- S: Sitting
- L: Lying down
- LL: Lying left
- LR: Lying right

5.2. Evaluation

5.2.1. Posture Classification by Neural Network

To be able to evaluate the coverage of the trained model, the evaluation is conducted in four categories, i.e. subject A, subject B, combination of subject A and B in the same room, and the combination of data from two rooms. We prepare a clean dataset by eliminating the possible noise of the signal. As a result, the selected dataset consists of 2,000 sets (5 postures x 400 sets) from each subject, and 5,335 sets (5 postures x 1067 sets) in case of the data from two rooms. The features of input are defined in the types of 4 inputs, 120 inputs, 4 inputs with normalized signal, and 120 inputs with normalized signal. We split the dataset into 70% for training and 30% for testing.

Table 1 shows the result of feature evaluation test. The overall performance on the 120 inputs with normalized signal can reach 100% of accuracy and the trained model can also work well in all situations. In total, the model based on the normalized signal can provide a better result.

Table 1. Input features

Dataset	Input			
	Raw signal data		Normalized signal data	
	4 inputs	120 inputs	4 inputs	120 inputs
A (Room 1)	99.3	99.8	99.6	99.9
B (Room 1)	99.5	100	100	100
A + B (Room 1)	97.6	98.2	98.2	98.8
Room 1 + Room 2	97.2	98.1	98.5	100

5.2.2. Posture Classification by the Combination of Neural Network and Bayesian Network

We extended our experiment on the single subject A from the data size 2,000 to about 300,000 to evaluate the tolerance of our trained model. In the very large and unclean dataset, it can include many signal errors and expected noises. To eliminate the unexpected result of the output posture from the Neural Network model, we adopt a Bayesian network to estimate the likelihood of the consecutive posture. The results from both a Neural Network and Bayesian network estimation are combined by the weighted arithmetic mean. We evaluate the coefficient (α, β) of the weighted arithmetic mean in Eq. (5) for both Neural Network and Bayesian outputs by varying the value of α and β applying on the dataset of subject A. α is coefficient of Neural Network probability, and β is coefficient of Bayesian probability. The result of accuracy corresponding to the variation of the coefficient is tabulated in table 3.

We found that, in case of the very large and unclean dataset, the accuracy in Table 2 decreased comparing to the clean and small dataset in Table 1. The result of using only a Neural Network (α=1, β=0) on subject A in Table 2 is 90.49 while the result on subject 1 in Table 1 is 99.9.

Table 2. Result of Neural Network and Bayesian network combining

α	β	Accuracy rate
1	0	90.49
0.7	0.3	90.67
0.5	0.5	91.02
0.3	0.7	91.50
0	1	78.59

By the way, the accuracy increases when the value of coefficient for Bayesian probability is increased. The accuracy is raised up to the highest value of 91.50 when the proportion of coefficient for Neural Network is 0.3 and Bayesian probability is 0.7 as shown in Table 2. The result confirms that Bayesian network is effective for eliminating the expected consecutive postures.

Figure 5 (a) shows the matrix confusion of 5-postures classification using only Neural Network. The accuracy of lying right posture detecting is noticeably low comparing to others. We found that there are confusions between lying right, lying down, and sitting. This is because the subject usually gets out of bed and returns to bed on the right-hand side of the bed. It is normal to observe that the subject has a trend to stay on the right-hand side of the bed.

Target class

output	Out of bed	Sitting	Lying down	Lying left	Lying right
Out of bed	94.0	6.0	0.0	0.0	0.0
Sitting	4.7	93.2	0.2	1.8	0.1
Lying down	0.0	0.9	95.3	1.3	2.6
Lying left	0.0	0.1	0.5	99.4	0.0
Lying right	0.0	11.9	17.5	0.0	70.6

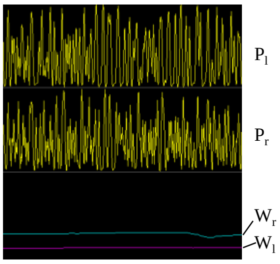
(a) Results of coefficient α=1 and β=0

Target class

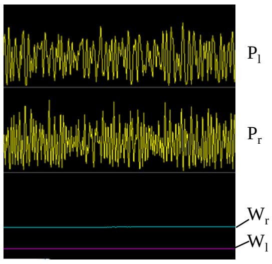
output	Out of bed	Sitting	Lying down	Lying left	Lying right
Out of bed	94.1	5.9	0.0	0.0	0.0
Sitting	4.3	93.7	0.2	1.7	0.1
Lying down	0.0	0.9	95.4	1.1	2.7
Lying left	0.0	0.1	0.5	99.3	0.1
Lying right	0.0	11.1	13.9	0.0	75.0

(b) Results of coefficient α=0.3 and β=0.7

Figure 5. Confusion matrix of 5-postures classification using the combination of Neural Network and Bayesian network



(a) Sitting posture



(b) Lying right posture

Figure 6. Similarity of the signal patterns between sitting posture and lying right posture

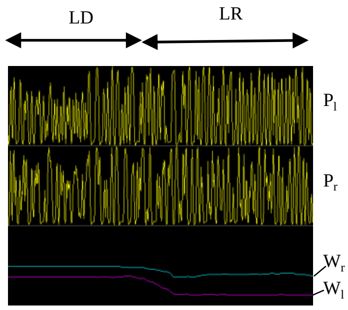
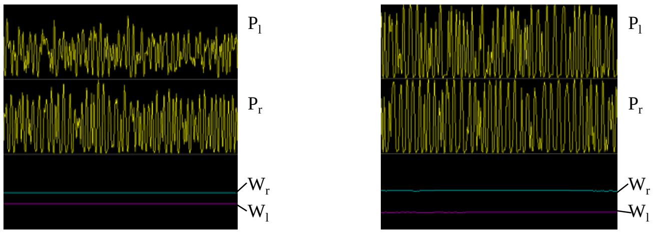


Figure 7. Signal pattern of changing posture of lying down (LD) to lying right (LR), where the top yellow line is the signal of piezoelectric sensor on left side, the second yellow line is the signal of piezoelectric sensor on the right side, pink line is the signal of pressure on the left side, and blue line is the signal of pressure on the right side

Considering the signal patterns shown in Figure 6, it is the case that the signal pattern of sitting posture looks similar to the one of right lying posture. This is because the subject gets on/off the bed on the right side of the bed, and the subject sits on the right side of the bed before getting on/off the bed. Therefore, our Neural Network may predict wrongly by confusing between these two postures. Figure 7 shows the case that the subject changes the posture of lying down to lying right but our Neural Network gives the result of sitting posture. This case can be solved by applying Bayesian probability. Figure 4 shows the probability of changing posture from lying down posture to lying right posture is 0.73 which is much higher than the one to sitting posture which is 0.19. Therefore, instead of giving the result of sitting posture, our combined model (Eq. (5)) can estimate the correct posture.

Similar to the case of similarity between sitting posture and lying right posture as explained above, our combined model can also solve the confusing case of lying down and lying right. There are also many cases that the signal pattern of lying down and lying right postures are similar as shown in Figure 8. By additionally applying the Bayesian probability, our combined model can correct the wrong result of Neural Network output as in the case of Figure 9. The probability of changing from sitting posture to lying right posture (0.54) is higher than to lying down (0.13).



(a) Lying down (b) Lying right

Figure 8. Similarity of the signal pattern between lying down posture and lying right posture

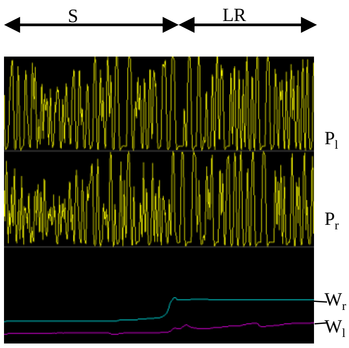


Figure 9. Signal pattern of changing posture of sitting to lying right, where the top yellow line is the signal of piezoelectric sensor on the left side, the second yellow line is the signal of piezoelectric sensor on the right side, pink line is the signal of pressure on the left side, and blue line is the signal of pressure on the right side

As a result, the result of combined model shown in Figure 5 (b) shows the significant improvement of the estimation of lying right posture, comparing to the Figure 5 (a) which does not include Bayesian probability. Applying the Bayesian probability to the Neural Network in a proper weight of combination, our new model can improve the result of posture estimation due to the confusing errors.

5.2.3. Comparative Evaluation with Other Approaches

It is quite difficult to evaluate the performance comparing to other previous approaches because of the difference in number of samples and equipment in use. To understand their performance and using environment, Table 3 summarizes the comparison result with other posture detection approaches in terms number of postures, accuracy, and number of sensors in use. Since other reports have been done on only the posture on bed, we then include only the accuracy of our three postures of lying down, lying left, and lying right. The performance of our approach is 89.9% which can outperform only three from 11 approaches. In terms of practicality, our approach needs only four sensors which is low cost, and very handy for installation and maintenance.

Table 3. Comparison of sleep posture classification algorithms

Ref	# of Postures	Accuracy (%)	Algorithm	Type of Sensors	# of sensors
[7]	8	97.1	Binary Pattern Matching	Pressure sensors	2048
[8]	3	91.6	GMM	Pressure sensors	1728
[9]	5	97.0	PCA+SVM	Pressure sensors	360
[10]	3	89.8	Pictorial Structure	Pressure sensors	8192
[11]	5	98.1	HoG+DNN	Pressure sensors	2048
[12]	4	99.7	SVM	Pressure sensors	512
[13]	5	97.7	PCA	Force Sensing Array	2048
[14]	6	83.5	Raw Data + SVM	FSR Sensors	56
[15]	9	94.05	Joint feature extraction and normalization +SVM+PCA	FSR Sensors/Video	60
[16]	3	81.4	Kurtosis+Skewness	FSR Sensors	16
[17]	5	98.4	SVM+RBF kernel	CC-electrodes	12
Ours	**3**	**89.9**	**NN+Bayesian propability**	**Pressure sensors/piezoelectric**	**4**

6. Conclusions

This study has described on-the-bed posture classification for the purpose of preventing the accident around the bed for the elderly care. The Neural Network approach is proposed to detect the five types of posture by using the signal from minimum number of piezoelectric sensors and pressure sensors. Bayesian network probability is adopted to improve the performance of a Neural Network by identifying the proper ratio of the combination of the weight. The accumulated the signal data in one second time slot (120-inputs set) can improve the coverage of the trained model. The normalized signal data can also eliminate bias of weight effect and different type of sensors. The results show that Bayesian network probability is effective parameter for the posture classification. The proposed method achieves an accuracy of 91.5% with coefficient 0.7 and 0.3 of a Neural Network and a Bayesian network probability respectively. Comparing to other previous proposed methods, without losing much in performance, our approach needs only four sensors which are simple for setting and maintenance.

Acknowledgement

This research is financially supported by Thailand Advanced Institute of Science and Technology (TAIST), National Science and Technology Development Agency (NSTDA), Tokyo Institute of Technology, Sirindhorn International Institute of technology, Thammasat University under the TAIST Tokyo Tech Program. The sensor panel and IP camera are supported by AIVS Co., Ltd, Japan. The videos and patient data are collected under the permission of the patients and acknowledgement of Banphaeo Hospital.

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