Neural Network based Bed Posture Classification enhanced by Bayesian Approach

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***Abstract*— This paper describes bed posture classification by using a Neural Network model for elderly care. Data collected from a sensor panel (composed of piezoelectric sensors and pressure sensors), which is placed under a mattress in the thoracic area, we use Neural Network for posture classification. Bayesian approach is used for estimating the likelihood of consecutive postures. The sensing data are normalized into a range of 0 to 1 by the unity-based normalization (or feature scaling) method for eliminating the bias between the different types of sensors. Also, the accumulated signal data in one second time slots (120-inputs set) can improve the coverage of the trained model. The results from Neural Network and Bayesian network estimation are combined by the weighted arithmetic mean. Our proposed technique is applied to elderly patient data with five different postures i.e., out of bed, sitting, lying down, lying left, and lying right. This resulted in 91.50% accuracy when the proportion of coefficient for Neural Network and Bayesian probability is 0.3 and 0.7 respectively.**

Keywords—Posture classification, Neural Network, Bayesian network

I. INTRODUCTION

A commercially available pressure mat system is widely used in the field of medicine and nursing for on-bed posture classification. This system is used to monitor the posture of a patient on a bed for the privacy reasons, unlike a system with a camera [1-6]. Bed posture classification is a significant approach for preventing accident around a bed. Those studies have applied various different techniques, for example, binary pattern mating, Gaussian mixture model, and pictorial structure [1, 2, 4]. In addition, machine learning approaches such as Principle Component Analysis (PCA), Support Vector Machine (SVM), and Deep Neural Network (DNN), are also introduced in [3, 6-10]. Some studies are proposed by using force sensors distributed on a bed [8-11]. However, all of those techniques require a large number of sensors which are not practical for daily use. Therefore, we can see some studies proposing approaches to decrease the number of sensing array [8, 10]. The minimum number of sensors in aforementioned studies is 16 sensors reported by C. C. Hsia et al. [10]. They use Bayesian classification based on kurtosis and skewness techniques. Besides, some studies use other types of sensor for human’s gestures recognition, e.g. electrode, ultrasonic sensor, air pressure, finger bend, accelerometer [11-17]. S. Nukaya et al. [12, 13] and Gaddam et al [14] used four sensors attaching to each leg of a bed. Both of the studies demonstrate the relationship between sensor signals and pressure on the bed. H. J. Lee uses 12 electrodes of ECG to estimate postures on a bed with SVM and RBF kernel techniques [11]. M. Cholewa and P. Glomb use the sets of sensor i.e. five fingers bend, three accelerometers, and two pitch/roll. The probabilistic models such Hidden Markov Model and Bayesian Network are applied [17]. Although those of studies have shown promising results of bed posture classification, their approaches require a large number of sensors. They are costly and not so practical in the real applications. Only two sensors, i.e. ultrasonic sensor and air pressure are used in H. Yamaguchi et al [15, 16]. They use fuzzy inference technique to determine whether a patient is in a bed or not [15, 16]. However, the proposed approach can just only detect whether a patient is going to get out of bed.

In this paper, Neural Network is introduced for bed posture classification. Rather than using a large number of pressure

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sensors array or other types of sensors, only four sensors i.e. two piezoelectric and pressure sensors are used for data acquisition. Unity-base normalization (or feature scaling) is adopted for eliminating the weight effect and the bias between different types of sensor. In addition, Bayesian Network is adopted to estimate the likelihood of consecutive postures

In the following sections, section II provides the details of the experiment methods. Section III describes our approaches in posture classification. Section IV shows the experimental results and Section V finally concludes the results.

II. EXPERIMENTAL METHOD

A. Sensor Panel

The sensor panel is set under the mattress in the thoracic area, as shown in Fig.1. It is a ready-made sensor panel provided by AIVS Co., Ltd. The panel consists of two types of four sensors i.e. two piezoelectric sensors and two pressure sensors. Each pair of them is embedded on each side of the panel. The sampling rate of each sensor is 30 Hz. The control device output the series of packages of the sensing data. A data package contains 45 bytes which are 8 bytes of header and 3 bytes of ender. The sensing data are then formed a package of 34 bytes between header and ender, where first two bytes contain the sensor's ID, and other 32 bytes are the signal data. The signal data are divided into 4 parts, 8 bytes for each sensor, in the sequence of left piezoelectric signal, left pressure signal, right piezoelectric signal, and right pressure signal. Fig.2 depicts the detail of the data structure. The magnitude of each sensor is 256, which piezoelectric and pressure signals have range of values as -127 to 128 and 0 to 256, respectively

Signals from sensing panel can be used to distinguish posture where the panel place in such Fig. 1. For instance, the both sides of sensors are activated in the lying down posture due to applied the pressure of the body on both sides, while in the posture of lying left or right, 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 is the very low signals from all sensors.

B. Data Collection

The data are collected in the hospital from an elderly patient whose age is more than 60. For posture labeling, the collected data includes the signals from the sensors and the video. Total data are taken for 120 hours. The targeted posture labels are annotated by observing the captured video synchronized to the signal data. Followings are the posture labels defined in five classes.

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

Fig. 1. Position of sensor panel on the bed

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

Fig. 2. Image of the data structure.

C. Dataset

1) Evaluation of Feature Input

The selected dataset consists of 20,500 sets (5 postures x 4,100 sets) from a single subject. The features of input are evaluated in four type inputs, i.e., 4 inputs, 120 inputs, 4 inputs with normalized signal, and 120 inputs with normalized signal. The 4 inputs are include left Piezoelectric signal (Pl), right Piezoelectric signal (Pr), left pressure signal (Wl) and right pressure signal (Wr). The 120 inputs. The dataset is split into 70% for training and 30% for testing.

2) Estimation of Bayesian Probaility

The dataset is extended on the total data from the size of 20,500 to about 390,000 to evaluate the tolerance of our trained model. The more than 300,000 sets of data are composed of the posture types of out of bed, sitting, lying down, lying left, and lying right. The size of the postures is about 44,000, 32,000, 90,000, 4,800, and 220,000, respectively.

3) Evaluation of Coefficient of Nerual Network and Bayesian Network

To evaluate the coefficient of the weighted arithmetic mean for both Neural Network and Bayesian outputs, the ratio the combination of the weight of both outputs are varied as shown in table III. Then, we apply on the total dataset (more than 390,000 sets).

III. POSTURES CLASSIFICATION APPROACH

A. Feature Input in Neural Network

1) Raw Data

a) 4 inputs

The four inputs from the control device, i.e., left Piezoelectric signal (Pl), right Piezoelectric signal (Pr), left pressure signal (Wl) and right pressure signal (Wr) as described in (1).

$$X=\{x_1, x_2, x_3, x_4\} = \{Pl_1, Wl_1, Pr_1, Wr_1\} \quad (1)$$

The four signals are passed through the Neural Network as shown in Fig. 3.

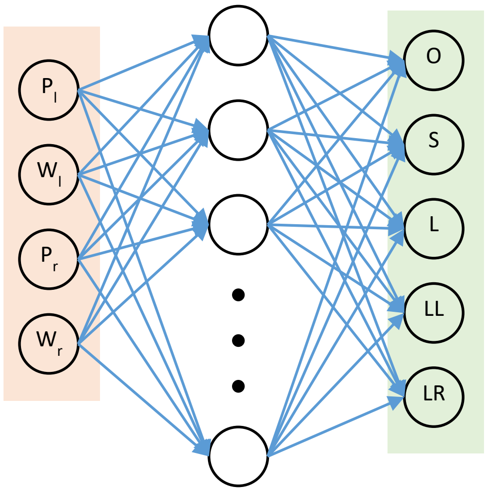

Fig. 3. Neural Network diagram of four input signal types, where O is out of bed, S is sitting, L is lying down, LL is lying left, LR is lying right

a) Acumulated data

From the property of the sensors, 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 (2).

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

2) Normalized Data

Unity-based normalization is applied to eliminate the bias of weight from different body and different types of sensor. All sensor data are normalized by (3) [18].

$$Y_\iota = (X_\iota\text{-}min/max\text{-}min)\qquad(3)$$

Where *Xi* is the sensor data in i[th] sequences, *Yi* is the normalized value, *min* is the minimum value, and *max* is the maximum value of the collection.

B. Bayesian Network Estimation

The Bayesian network [19] is adopted to estimate the next possible posture. This depresses the noise of the signal 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 the current signal, as shown in (4) and (5).

$$P(S, P) = P(S)\, P(S|P)=P(P)P(P|S)\qquad(4)$$

$$P(S, P) = P(P_i|P_{i-1},P_{i-2})P(S|P_i)\qquad(5)$$

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 (Pl, Wl, Pr, Wr). The continuous value of signal data is converted to the nominal value by dividing the signal into three levels i.e. low, middle, and high from normalized data. In the range of the piezoelectric signal, 0.0-0.25 is defined as low, 0.26-0.50 is defined as middle, and 0.51-1 is defined as high. In range of pressure signal, 0.0-0.35 is defined as low, 0.36-0.70 is defined as middle, and 0.70-1 is defined as high.

C. Combination of Neural Network and Bayesian Network

To eliminate the unexpected result of the output posture from the Neural Network model, we adopt Bayesian network to estimate the likelihood of the consecutive posture. The results from both Neural Network and Bayesian network estimation are combined by the weighted arithmetic mean show in (6).

$$\alpha N+\beta B = C\qquad(6)$$

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.

IV. Result and Discussion

A. Evaluate feature input in Neural Network

Table I shows the result of feature evaluation test. The overall performance on the 120 inputs with normalized signal can reach 98.3% of accuracy. The model based on the accumulated signal can provide a better result. The ambiguous signal in out of bed and sitting posture because some point of signals of both postures is quite similar. The sitting posture, the activations of pressure sensors are low as same as posture out of bed, but the signals from piezoelectric sensors are still detected.

To evaluate the tolerance of our trained model, the 5 fold cross validation is used. The data are divided into 5 sets. The results are tabulated in table II. The accuracy of results shows that our Neural Network model can be work on any dataset. This is because the accuracy of each set is approximately equal.

TABLE I. Input Features

Input			
Raw data		***Normalized signal***	
4input	***120input***	***4input***	***120input***
97.8	98.0	97.8	98.3

TABLE II. 5-fold cross validation

Dataset	**Number of set**				
	1	***2***	***3***	***4***	***5***
Training	97.9	98.0	97.9	98.8	98.7
Test	97.4	97.6	97.4	98.3	97.9

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	70.4

(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

Fig. 4. Confusion matrix of 5-postures classification using the combination of Neural Network and Bayesian network

B. Combination of Neural Network and Bayesian Network

From the evaluation of the coefficient (α, β) of the weighted arithmetic mean in (5) applying on the total dataset, the result of accuracy corresponding to the variation of the coefficient is tabulated in table III, where, α is coefficient of Neural Network probability, and β is coefficient of Bayesian probability. We found that, in the case of the very large dataset, the accuracy in table III decreased comparing to the small dataset in table I. The result of using only Neural Network (α=1, β=0) on total data in table III is 90.49 while the result in table I is 98.3. However, the accuracy raises up when the value of the coefficient for Bayesian probability is increased. The highest accuracy of 91.50, when the coefficient of Bayesian probability and Neural Network are set to 0.7 and 0.3 respectively, as shown in table III. The result confirms that Bayesian network is effective for eliminating the expected consecutive postures.

TABLE III. 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

Fig. 4 (a) shows the matrix confusion of 5-postures classification using only Neural Network. A confusion between lying right, lying down, and sitting is occurred because the subject usually gets out of bed and returns to the 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. These behaviors can affect the accuracy of the lying right posture. The of lying right posture is noticeably low when compared to others.

Fig 4 (b) shown the confusion matrix of five posture classification, where the proportion of coefficient for Neural Network is 0.3 and the Bayesian probability is 0.7. The result of lying right detection is significantly improved 4.6% of accuracy while no deterioration in other posture detection accuracy happens. This means that some less possible postures can be eliminated. For example, changing posture from lying right to lying left, or out of bed is not likely to occur rather than to lying down or sitting.

C. Comparative Evaluation with Other Approaches

Table IV summarizes the comparison result with previous studies in terms of the number of postures, the number of sensors, and accuracy. The performance is quite difficult to compare with other approaches due to the difference of equipment, the number of samples, and the target postures. Owing to other reports have been done on only the sleep posture on the bed, the accuracy includes only the accuracy of our three postures i.e. lying down, lying left, and lying right. The performance of our approach is 89.9% which can outperform only 4 from 11 approaches. In terms of practicality, our approach needs only four sensors which are low cost, and very handy for installation and maintenance.

TABLE IV. COMPARISON OF SLEEP POSTURE CLASSIFICATION ALGORITHMS

Ref	# of Postures	Accuracy (%)	Type of Sensors	# of sensors
[1]	8	97.1	Pressure sensors	2048
[2]	3	91.6	Pressure sensors	1728
[3]	5	97.0	Pressure sensors	360
[4]	3	89.8	Pressure sensors	8192
[5]	5	98.1	Pressure sensors	2048
[6]	4	99.7	Pressure sensors	512
[7]	5	97.7	Force Sensing Array	2048
[8]	6	83.5	FSR Sensors	56
[9]	9	94.05	FSR Sensors/Video	60
[10]	3	81.4	FSR Sensors	16
[11]	5	98.4	CC-electrodes	12
Ours	**3**	**89.9**	**Pressure sensors/piezoelectric**	**4**

V. . CONCLUSION

This paper has described the new bed posture classification method. Our proposed method achieves the highest accuracy of 91.5% with coefficient 0.7 and 0.3 for Neural Network and Bayesian probability, respectively. The proper ratio of the combination of the weight of the results from Neural Network and Bayesian probability can achieve high accuracy. The Neural Network approach is proposed to detect the five different postures by using the signals from the minimum number of piezoelectric sensors and pressure sensors. Bayesian Network probability is adopted to improve the performance of Neural Network. From the results, Bayesian Network can improve 4.6% of accuracy in the lying right posture. This means that Bayesian Network probability is an effective parameter for the posture classification. The accumulated the signal data in one second time slots (120-inputs set) can improve the coverage of the trained model. The normalized signal data can also eliminate the bias of different type of sensors. Comparing to other previous proposed methods, our approach needs only four sensors without losing much in performance. This is simple for installation and maintenance.

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