Long Short-Term Memory for Bed Position Classification

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***Abstract*—This paper describes an approach for bed position classification by using 2 stacked layers of Long Short-Term Memory approach. The data is collected from the sensor panel which consists of 2 types of sensors, i.e. piezoelectric and pressure sensors. The raw data has been classified into 5 classes. It also has to go through the min-max scaling normalization on a fixed range between 0 and 1. The data is assembled to fit a one-second interval of the 30Hz sensor sampling rate. The model has been experimented by changing the number of hidden nodes of the model in 128, 80 and 50 nodes. The result is 91.70% of accuracy which is good enough comparing to the previous works.**

Keywords— bed position classification, LSTM, piezoelectric sensor, pressure sensor, elderly care.

I. Introduction

A human has to go through one natural phenomenon which is aging. Because of that, their daily activities and capabilities will decrease gradually over time when getting older. Elderly people usually have a sleep disorder which will eventually increase the bed fall accident while they are sleeping [1, 2]. Due to the above mentioned incident and their privacy, many approaches are proposed to solve this problem with unobtrusive devices such as sensor panels or sensor mats [3]. Those devices are better than cameras that can violate the elderly's privacy [4, 5].

Bennett et al. [6] use the Kinotex fiber-optic pressure sensors mats. They use 2-D support vector machines (SVMs) and linear classification to monitoring 3 in-bed positions such as lying, sitting and standing which can get a good result but the downside is that they have to use many pressure sensors in order to get those body positions. Ostadabbas et al. [5] use a pressure sensor mat to eliminate the risk of pressure ulceration and reposition the patient according to schedule. Each pressure point on mats is used to form a pressure image and then applied 2D Gaussian mixture model for in-bed posture classification and limb detection. Even they can get a good result yet their approach still relies on many pressure points to properly combine into the image.

The pressure-sensitive sensor mat produced by NITTA Corporation is tested with SVM, Naïve Bayes, Random Forest, and Neural Network (NN) by Minehura et al. [1] in order to classify 9 sleeping positions. The result from SVM is better than 3 others. Due to the arm postures between sleeping in log position and yearner position, it affects the model to misclassify those positions. Moreover, Foubert et al. [7] work with a pressure sensor array to recognize lying and sitting positions. They make a comparison between SVM, Neural Network and k-nearest neighbor and can get acceptable results from 5 out of 8 selected postures. For Townsend et al. [2] use the output from the pressure sensor array to calculate the center of gravity signal to extract the rollover positions. The rollover positions are recorded with 5 different placements of a pressure sensor array under the bed mattress. The data are applied to a decision tree technique for rollover detection; however, there is a limitation to the recorded data between rollover positions and many types of non-rollover positions for classification, and the experiment is done by a healthy volunteer in a non-sleep situation.

An effective approach from Viriyavit et al.[8] use Neural Network and Bayesian Network for bed posture classification with a sensor panel which consists of only 4 sensors and can get a good result as well. After reviewing the previous work, we notice that the bed positions often occur in sequence, i.e. lying to sitting to out of bed. Therefore, we propose the use of Long Short-Term Memory (LSTM) approach which has the potential to include the sequential information to make a better prediction for the current position [9].

In this research, we use the data from previous work and apply it with stacked LSTM to classify the bed position. In Section II, we describe briefly about the equipment and data preparation. Section III, we describe the proposed approach. Section IV, the result and discussion related to the previous works are presented.

II. Equipment and Data Preparation

A. Equipment

The sensor panel is made of a plastic plate which consists of two kinds of sensors, i.e. pressure and piezoelectric. Each type of sensor is placed symmetrically on the left and right side of the panel, as shown in Fig. 1. The length of the panel is 60 cm and the width is 18 cm. In operation, it is placed under the mattress in the thorax area of the patient. The sensors collect the signal in the sampling rate of 30 Hz ranging from -127 to 128 for the piezoelectric sensors and 0 to 255 for the pressure sensors.

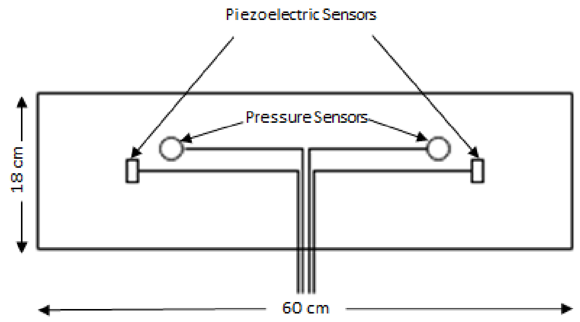

Fig. 1. Sensor Panel

B. Data Collection

The signal data generated from those sensors are sent via the Bluetooth box to the M2M box as shown in Fig 2. After that, the data from the M2M box are sent to the computer which saves the signal data in the comma-separated value (CSV) format.

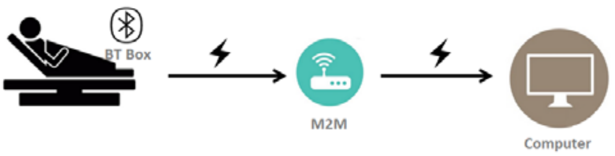

Fig 2. The process flow of collecting the data

C. Data Preprocessing

The structure of the data collected is organized into 5 columns. Column 1 to column 4 are the data from each sensor that it starts from PR: Piezo-Right, WR: Weight-Right, PL: Piezo-Left, WL: Weight-Left and the last column is the label of the bed position as shown in (1).

$$D = \{PR, WR, PL, WL, Label\} \qquad (1)$$

For annotated the data, we install the camera for recording the movement of the patient on the bed. We observe the video and synchronize with the recorded signal to decide the targeted position. However, recording the video is against the patient's privacy. Therefore, we obtain a consent from the patient with a formal agreement to maintain personal privacy.

The signal data and video footage are collected from a patient whose age is more than 60 for 120 hours. The predefined 5 classes of bed position are used for annotation. The annotated labels are represented by the number as described in Table 1.

The total dataset is more than 390,000 samples that use for this experiment which consists of out of bed, sitting, sleep at the center, sleep left side, and sleep right side. The numbers of data for each position are around 44,000, 32,000, 90,000, 4,800, and 220,000 respectively. The total data are divided into 3 parts for training, validation, and testing with 60%, 20% and 20% proportion of the total data.

TABLE I. Five Classes of Bed Position

Bed Position	Tagging Label
Out of Bed	1
Sitting	2
Sleep Center	3
Sleep Left	4
Sleep Right	5

D. Data Accumulation

The sensor panel records the signal in 30Hz of sampling rate, we accumulate the data before we use it in our model by transforming the 30 of data points into 1 second which is equal to 30 x 4 sensors = 120 data points as described in Fig. 3.

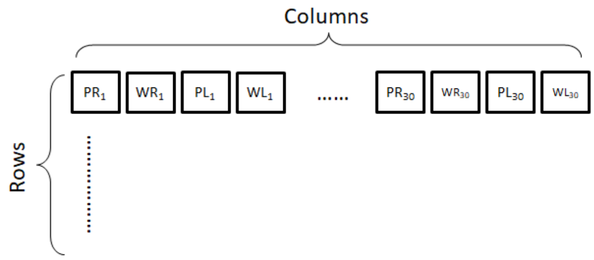

Fig. 3. Data accumulated structure

E. Data Normalization

Before the data can pass through the model, we need to mitigate some factors that might affect the signal such as the weight of the patient, the weight of the mattress, and different types of sensors. Hence, we apply for the off-set number with min-max scaling normalization on a fixed range from 0 to 1 [10].

$$X_{norm} = \frac{(X_t - min)}{(\max - min)} \qquad (2)$$

X_t is the signal point at time tth, X_{norm} is normalized value, min is the minimum off-set value and max is the maximum off-set value.

III. Methodology

Long Short-Term Memory or LSTM is a type of Recurrent Neural Networks (RNN) with the capability to cope with long term dependency [11, 12] as a solution to a gradient explosion during the long backpropagated leaning process of RNN [13]. LSTM is commonly used for classification of the time-series [14]. The mechanism of LSTM is described as a unit that allows the data to pass through with little modification [15]. Each unit has 3 gates: (1) forget gate uses to decide what value needs to remember or forget inside the unit. (2) input gate uses to decide how much value needs to update inside the unit and (3) output gate uses to decide what value the unit going to output. Fig. 4 is the representation of the LSTM unit where x_t is the input data, h_{t-1} is the hidden value from the previous unit, C_{t-1} is the memory cell from the previous unit. h_t is the hidden output value and C_t is the output memory cell.

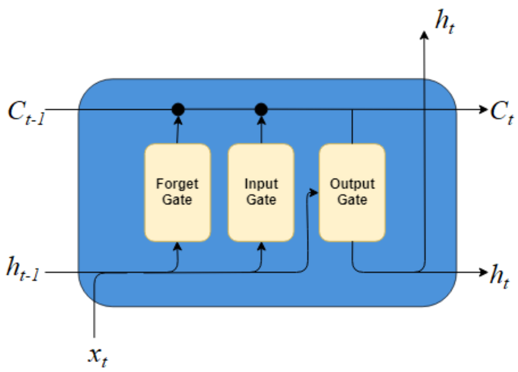

Fig. 4. LSTM Unit [12]

Stacked LSTM is a stable approach for solving the sequence prediction problem [9] and is used on the fraudulent transaction and temporal dependence in EEG [16, 17]. Therefore, we propose the approach of 2 stacked layers of LSTM with Softmax activation function since we work on classification problem and body position on the bed usually happen in sequence. Fig. 5 shows the process flow of the experiment.

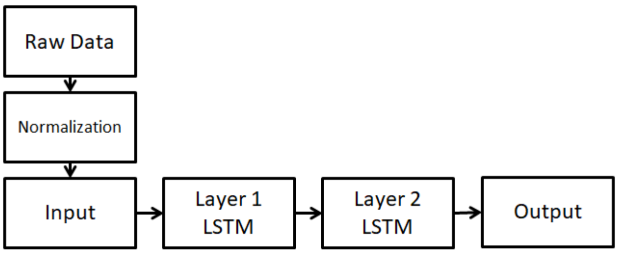

Fig. 5. Process Flow for Experiment

IV. Result and Discussion

A. Result

We test with 3 different experiments. The first experiment starts with 128 hidden nodes, 6000 batch size. We input the data into LSTM and allow it to process for 300 epochs. We can achieve overall accuracy at 92.73% on the testing set. Yet, it still has some weak points for its prediction as shown in Fig 6. The accuracy for sitting and sleep left side are moderately low from our expectation. For sitting position, it has only 72% correctly predicted while 20% is wrongly predicted as sleep right position. Also, 84% is predicted correctly and 11% is incorrectly predicted.

Fig. 7 is the result of reducing the hidden node to 80 while other factors remain the same. We can see that the overall accuracy is reduced to 92.43%. But, there is a significant improvement for sleep left position from 84% to 95%. Unfortunately, the sitting position gets a decrease from 72% to 65%.

After the hidden node is reduced to 50, the sitting position, which is the lowest prediction position, has significant improvement. It increases back from 65% to 83% and the wrongly predicted position is decreased from 20% to 13% while maintaining the other positions with each accuracy of more than 90% and overall accuracy at 91.70% as described in Fig. 8.

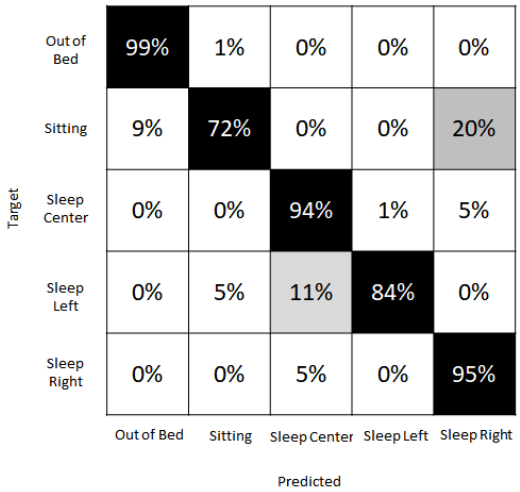

Fig. 6. Confusion Matrix for 128 hidden nodes

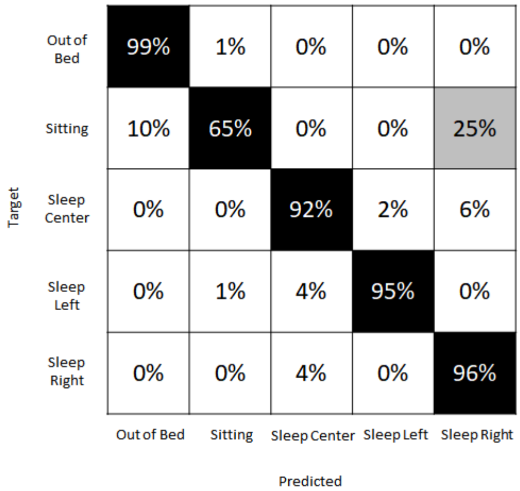

Fig. 7. Confusion Matrix for 80 hidden nodes

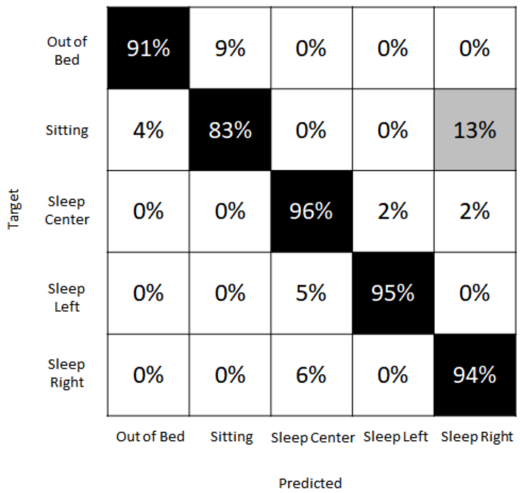

Fig. 8. Confusion Matrix for 50 hidden nodes

B. Comparative finding with previous work

Base on the result from the previous research, It shows 91.5% for the total accuracy [8] from the combination of Neural Network and Bayesian Network. For our proposed method can achieve a slight increase to 91.7%. Although the accuracy is likely the same, we can see a refinement of the sleep right position. NN and Bayesian Network has only 75% [8] while our method can predict up to 94%.

There are some improvement points from the previous work. We can use the built-in mechanism of LSTM to adjust its network and provide a moderate output rather than using the combination of 2 networks. Even we cannot outperform the previous approach, but we can see an improvement of sleeping right side position that NN and Bayesian Network hard to predict based on the same dataset.

As described from the previous work, the confusion of the prediction from sleep right, sleep center and sitting because the patient usually gets out of the bed and return back on the right side which has a side effect on prediction for those 3 positions.

V. Conclusion

This paper has shown some improvement from the previous work with an accuracy of 91.7%. As mention above, our proposed method cannot outperform the previous work but it shows some improvement which is worth to study. For example, we can reduce the workload from the combination of Neural Network with Bayesian Network and use the only LSTM. Moreover, this approach helps increase the prediction of sleep right position without losing much accuracy from other positions.

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