In-bed posture classification using pressure sensor data and spiking neural network

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***Abstract*— Observing and evaluating sleeping positions is crucial in the treatment of cardiovascular episodes, pressure ulcers and respiratory diseases. Therefore, in-bed posture recognition systems become necessary at home as well as in hospitals. Many studies have shown that the use of gravity sensors in combination with the second generation of neural network (NN) architectures are extremely effective in assessing and classifying sleeping positions. However, the disadvantage of the second generation NN architecture is that it is quite energy-intensive. While the third NN generation - Spiking Neural Network (SNN) is projected to solve the power consumption problem while providing an equal performance or even better performance than the old ones. Surprisingly, none of the studies consider combining SNN in sleeping position classification based on pressure sensor assessment. In this paper, we propose the development of a converted CNN-to-SNN network for sleeping posture recognition algorithm supported by preprocessing technique. Experimental results confirm that our proposed method can achieve an accuracy of nearly 100% in 5-fold as well as 10-fold cross-validation and 90.56% in the Leave-One-Subject-Out (LOSO) cross-validation for 17 sleeping postures, which greatly surpasses the previous method performing the same task. Furthermore, the power consumption of our SNN model is 140 times lower than that of the published CNN model.**

Keywords*— *Sleeping posture recognition, pressure sensor data, spiking neural network

I. INTRODUCTION

In-bed posture recognition plays a vital role in sleep studies. It not only supports the need for the detection of bad habitual sleep positions but also allows doctors to diagnose esophagus problems earlier. Indeed, the sleep position is strongly related to the obstructive sleep apnea syndrome [1]. Sleeping on the right side has a higher risk in relation to developing transient lower esophageal sphincter relaxation [2], which is a major cause of nocturnal gastroesophageal reflux. In a clinic environment, lying on the same position for a long period of time can cause pressure ulcers for bed-ridden patients. Caregivers must regularly change the patients' posture in order to prevent injuries to their skin and underlying tissue. As a result, autonomous sleeping posture recognition is useful for detecting the wrong sleeping position and reminding patients to change their sleeping position.

In the past, there have been many solutions to recognise sleeping postures, such as using colour vision sensors, radiofrequency signal or wearable devices. Colour vision sensor-based solutions [3, 4], capture the map to determine presence, orientation, and body parts accurately. However, the main drawback of these techniques is that they violate the patient's privacy. The radiofrequency signal-based solution [5], avoids the violation of the patient's privacy but requires two devices at each side of a bed and these are only able to detect some specific postures. Wearable device-based approaches [6, 7], make people feel uncomfortable due to the requirement to wear the equipment all day. To overcome these limitations, pressure-sensing mattresses that produce image imprints of the human body are becoming increasingly popular. Their primary benefit is that they do not necessitate the installation of additional equipment within clinics. Furthermore, they also protect the personal privacy of patients during the monitoring and treatment stage.

In recent years, the second Neural Network generation has become attractive to researchers in their quest to develop the best solution for pressure sensor data-based sleeping posture classification. In 2016, [8] introduced a model based on the Deep AutoEncoder, which consists of a three-layer encoder to extract feature maps and a categorisation decoder. The model, which can be considered as a real-time method, achieved an impressive accuracy of 98.1 % on the 5-postures classification. Following that, [9] demonstrated an artificial neural network training with the data of four postures by 12 subjects. This model includes two layers followed by Tanh and Softmax activation, respectively. The given system obtained an accuracy of 97.9 % on the testing dataset.

Along with the evolution of Convolution Neural Networks, a CNN model was published by [10] in 2019. The pressure images in this model come through convolution blocks combined with Batch Normalization, MaxPool, and LeakyReLU in order to get the important characteristics of each frame. Then, the two classifications are used to define the subjects and their sleeping postures independently. The research shows 99.9 % and 87 % accuracy with 3 and 17 classes, respectively. In 2020, [11] took advantage of self-supervised learning to solve the challenge of sleeping recognition at three levels: sleep position recognition, sleep stage recognition, and insomnia detection with multi-sensor data. This notable method achieved 99.55% accuracy in the three-classes dataset.

Despite the fact that the second Neural Network generation provides the sleeping posture classification solutions with high accuracy, there are two problems with it. The first problem is the computation cost. The deeper neural network model represents a higher computation cost. Therefore, to accelerate the computation speed, GPU is commonly used in both training and inference. The second problem is the power consumption. Due to the capability to perform large-scale matrix multiplication operations, GPUs are able to efficiently improve the speed of Neural Networks. However, GPUs suffer from high power consumption. Therefore, the development of Neural Network based sleeping posture classification is still an open challenge.

In recent years, many researchers have been focusing on a new generation of neural network named Spiking Neural Network (SNN). SNN is constructed to biologically emulate the human brain processes information [12]. In the brain, neurons communicate with each other by sending trains of action potentials, also known as spike trains. SNN mimics that mechanism so that a neuron is calculated only when a new input spike arrives. As a result, it turns the networks into an energy-saving mode which is suitable for implementation on hardware devices. Surprisingly, none of the studies explore the application of SNN in the sleeping posture classification.

Taking advantage of the ability of the Spiking Neural Network to decrease power consumption, as mentioned above, we proposed a SNN based classification method in classifying in-bed postures. We first apply a median filter based preprocessing technique to reduce noise of the pressure images. The preprocessed images are fed into a spiking neural network which is derived from a CNN-to-SNN conversion procedure.

The remainder of this paper is organised as follows. Section II indicates the background of the pressure sensor data and Spiking Neural Network. Next, the proposed method is described in the Section III. In Section IV, the experimental results including the environment setup, accuracy, and especially power consumption are discussed and compared to the existing approaches. Section V summarizes our study and provides some future orientations.

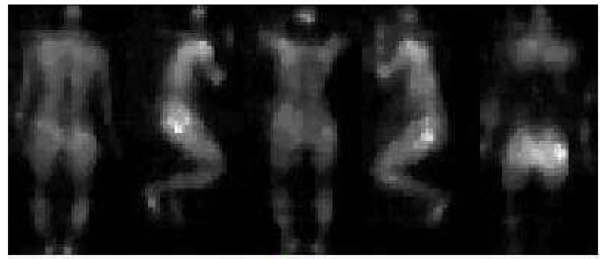
II. BACKGROUND

A. *Pressure sensor data based sleep posture classification*

Pressure sensor map data is a type of dataset measured using one or many types of pressure sensors with a certain sampling rate. The output of this measuring usually is formed in a grid of the 2-D matrix. Some typical types of the pressure sensor are DPS368 – Infineon Technologies, LPS33W – MEMS pressure sensor, and a series of Honeywell Basic Pressure Sensors. While the typical systems of grid pressure sensors are the pressure sensor maps of Kitronyx or Vista Medical FSA SoftFlex.

In published studies, Viriyavit et al. [13] collected the data from a small number of piezoelectric sensors and pressure sensors which is presented as a method for recognising the five postures of elderly patients. The authors applied the min-max normalization function in the raw data to reduce the weight bias from the various bodies and types of the sensor then pass them into their proposed neural network. Unlike the work of Viriyavit et al, the usage data in [14] uses a hydraulic bed transducer placed underneath the mattress to classify four major postures from 58 different subjects. Furthermore, in [10], the pressure data were collected utilising Vista Medical FSA SoftFlex. After preprocessing a 3x3 median filter, the data were fed forward to their proposed networks.

(a)



(b)

Fig 1. Several samples of the Pmatdata
(a): raw samples, (b): pre-processed samples

B. *Spiking Neural Network*

Inspired by the behavior of the biological neural network, spiking neural networks (SNNs) are inherently more biologically plausible and offer the prospect of event-driven hardware operation. The spiking neuron only processes input when a binary spike signal arrives. There are several types of neuron models namely McCulloch and Pitts, Hodgkin-Huxley, Perceptron, Hindmarsh–Rose, Izhikevich, Integrate-and-Fire (IF), Leaky Integrate-and-Fire (LIF), the Spike response model (SRM), and generalized Integrate-and-Fire. Most of these are more oriented to computing rather than biological purposes.

In general, the way neurons in a network biologically connect to each other through links or synapses which represent the network topology or network architecture. Spiking network architecture can be classified into three general categories. The first type is the feed forward network, where the data processing is fixed, data flows from input to output and it is completely one-way with no feedback connections. By contrast, the next category is the recurrent network. In this type, each neuron or group of neurons interacts through reciprocal (feedback) connections which allow it to manifest dynamic temporal behavior. A final type of network architecture is the hybrid network that combines the two architectures above [15].

III. METHODOLOGY

Our proposed approach includes two major steps. First, we apply a pre-processing technique on the raw pressure sensor data. Then, we feed the processed data into a SNN model to implement the classification. The SNN model is derived from a CNN-to-SNN conversion algorithm.

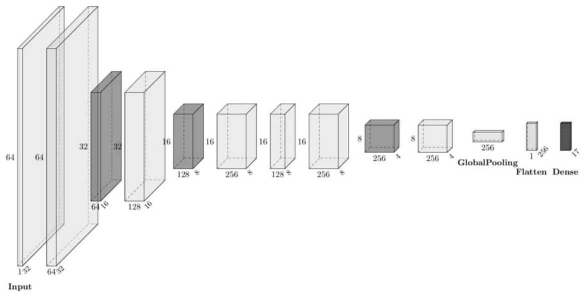


Fig 2. The proposed network architecture

A. Preprocessing techique

In this study, we utilised the Pmatdata dataset [16] to train and test our proposed approach. Generally, the pressure sensor data were collected from 13 individuals (from S1 to S13) in 17 different lying postures with the sampling rate at 1 Hz. A system named Vista Medical FSA SoftFlex was used for this data acquisition. In this system, the mattress consists of 2048 1-inch square sensors and the output sensor grid is organized with a 32 x 64 resolution. In addition, due to the physical characteristics of the pressure sensor, obtained data can vary in the range of 0-1000. The data subject included 6 people at the age of 19-26 and 7 people at the age of 27-34 with their height and weight were 170-186 cm and 63-100 kg, respectively. Table I presents the detail of classes in the Pmatdata dataset.

To apply image processing techniques, a sliding window with the size of 3 was used to combine each consecutive 3 frame of the sequence into a 3-channel image. Then, a Spatio-temporal 3x3x3 median filter was implemented on this 3-channel image to lessen the noise caused by occasionally failing pressure sensors during the sampling data stage. Next, the filtered outputs were normalized into the range of 0 – 255. Figure 1 presents several samples of the pressure sensor data, before and after, using the proposed preprocessing technique.

B. Spiking Neural Network based classification model

The CNN-to-SNN conversion procedure includes four steps. We firstly design a CNN model and then train the proposed CNN model. Next, we convert the trained CNN model to an equivalent SNN model. Finally, we adjust the post-synaptic filter and scale firing rate to achieve the best model.

TABLE I. 17 CLASSES OF THE PMATDATA DATASET

Class	Icon	Name	Class	Icon	Name
1		Supine	10		Supine Knees up
2		Right	11		Supine Right Knee up
3		Left	12		Supine Left Knee up
4		Right 30º Body-roll	13		Right Fetus
5		Right 60º Body-roll	14		Left Fetus
6		Left 30º Body-roll	15		Supine 30º Bed Inclination
7		Left 60º Body-roll	16		Supine 45º Bed Inclination
8		Supine star	17		Supine 60º Bed Inclination
9		Supine Hand Crossed			

1) Proposed CNN model

Since the performance of the converted SNN model will drop rapidly when the CNN model goes deeper [17], we focused on the shallow network architecture. The proposed CNN model in this work is based on the Darknet 19 [18] and its modification in [19- 20]. In our proposed model, we only utilise the first 9 layers of the Darknet 19 model and modify them by increasing the number of filters. Additionally, the max-pooling layer is replaced by the average pooling layer since the computation of the average pooling layer in spiking neurons is easier to implement than that of the max pooling layer [21]. Some extra layers consisting of a global average pooling layer and a fully connected layer with 17 neurons are added into the proposed model. The details of our proposed network architecture are shown in Figure 2 and table II.

2) CNN model training

In this work, the Sparse Cross Entropy loss function is employed as the main error function. To simplify the CNN-to-SNN conversion, the activation function of the convolution layer is the ReLU function. The ReLU function not only has a constant derivative to avoid the vanish and explosion gradient but also has a fast computation. The Adam algorithm with a learning rate of 0.001 is used for the training process in 10 epochs. To enhance the robustness of the SNN model after conversion, the additive Gaussian noise is added during the CNN training.

3) CNN-to-SNN conversion

The CNN-to-SNN transformation algorithm by Hunsberger et al. [21] was utilised in our work to achieve the SNN based in-bed posture classification model. Theoretically, the model parameters of the convolution neural network can be mapped to the spiking neural network. Therefore, we can use a pre-trained CNN model to map it to a SNN model. There are four things to do when converting the CNN model to the SNN model. The first thing is to reform the convolution operation as simple connection weights (synapses) between pre-synaptic neurons and post-synaptic neurons. The second thing is to reform the average pooling operation as a simple connection weight matrix. The next thing is to replace the CNN neuron with the ReLU activation function to the SNN neuron with the Spiking ReLU activation function. Each Spiking ReLU neuron is modeled as a rectified line and its activity scales linearly with the current. This occurs unless the current is less than zero, at which point the neural activity will stay at zero [22]. The final thing is to add post-synaptic filters to the output of spiking neurons to filter the incoming spikes before passing the resulting currents to the other SNN neurons since these filters can remove a significant portion of the high-frequency variation produced by the spikes [21].

TABEL II: DETAIL OF THE PROPOSED CNN MODEL

Layer	Filters	Size/strides	Input	Output
1 conv	64	3/1	64x32x1	64x32x64
2 avg pool		2/2	64x32x64	32x16x64
3 conv	128	3/1	32x16x64	32x16x128
4 avg pool		2/2	32x16x128	16x8x128
5 conv	256	3/1	16x8x128	16x8x256
6 conv	128	1/1	16x8x256	16x8x128
7 conv	256	3/1	16x8x128	16x8x256
8 avg pool		2/2	16x8x256	8x4x256
9 conv	256	3/1	8x4x256	8x4x256
10 global avg pool		2/2	8x4x256	4x2x256
11 flatten			4x2x256	2048
12 fully conc			2048	17

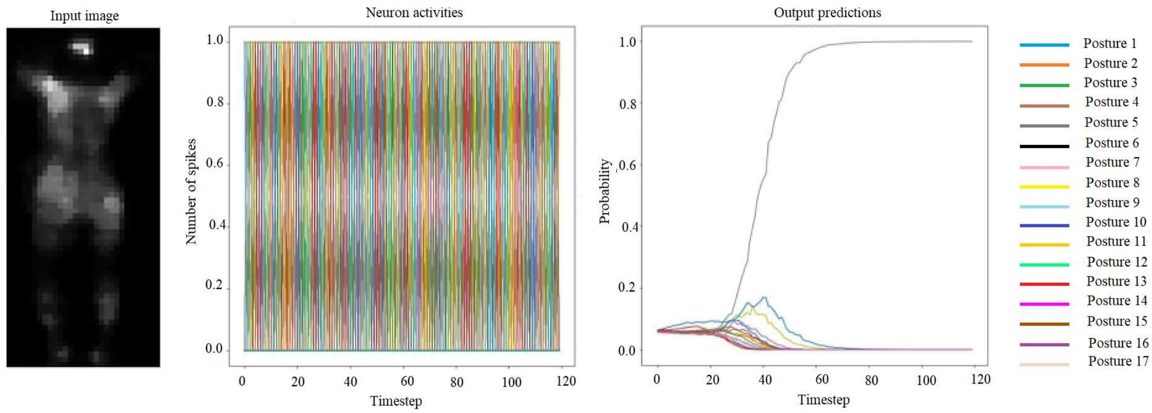


Fig 3. Output of neuron activities and network prediction

TABLE III. A COMPARISON BETWEEN MODEL TRAINING WITH AND WITHOUT PREPROCESSING STEP

Method		**Accuracy on the LOSO validation dataset (%)**													
		S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**	**S11**	**S12**	**S13**	**Average**
SNN	**With pre-processing step**	**81.75**	**85.50**	**100.0**	**100.0**	**100.0**	**66.0**	**100.0**	**84.75**	**85.25**	**100.0**	**85.0**	**100.0**	**89.0**	**90.56%**
	Without pre-processing step	81.75	85.50	83.75	75.00	100.0	65.50	100.0	84.75	85.25	99.00	84.75	83.75	85.50	85.73%
CNN	**With pre-processing step**	82.04	69.45	93.80	93.65	94.72	84.89	92.89	88.82	88.88	100.0	94.62	95.17	94.31	90.25%
	Without pre-processing step	86.68	74.91	89.91	97.60	100.0	81.83	91.01	82.6	82.50	100.0	88.10	87.88	81.67	88.05%

4) *Post-synaptic filter and scale firing rate adjustment*

After converting the CNN architecture to the SNN architecture and mapping their parameters, we need to adjust the post-synaptic filter and the scale firing rate to obtain the best SNN model. The post-synaptic filter is given by Equation 1. In this study, the decay time constant τ is experimentally chosen at 0.01. To increase or decrease the spike firing speed of SNN neurons, we adjust the scale firing rate. Theoretically, the scale firing rate parameter is used to make neurons spike more frequently by applying linear scale to the input of all neurons and then dividing their output by the same factor [23]. In this work, we set the scale firing rate at 50.

$$\alpha(t) = -\frac{t}{\tau}\, e^{-\frac{t}{\tau}} \tag{1}$$

IV. Experimental Results

A. *Experimental setups*

For the training stage, we set up our environment on a server with an Intel Xeon E5-2650 CPU, 32GB RAM, and RTX 2080 Ti GPU on a 64-bit Ubuntu 18.04 OS. For the validation stage, the SNN model was tested on two cross-validation scheme including k-fold and Leave-One-Subject-Out (LOSO). The k -fold validation scheme splits the data into k folds, where one-fold is utilised for testing and the rest for training. On the other hand, the LOSO validation scheme keeps one subject aside at each iteration for testing and the other subjects are adopted for training. In both validation scheme, we evaluated the accuracy for each testing set and then calculated the average accuracy on the whole dataset.

B. *CNN-to-SNN conversion results*

The proposed CNN model without data preprocessing stage: here we apply the preprocessing data function while training and evaluating the CNN model. In the two last experiments, we evaluated the converted SNN model with and without preprocessing function with fixed decay time constant and scales firing rate parameter (the decay time constant = 0.01 and the scale firing rate = 50). These experiments indicate that we gained better-averaged accuracy in both CNN and SNN models with preprocessing function than without this function in terms of the lying posture classification. Moreover, the use and non-use of the preprocessing technique had a great effect on the accuracy in the SNN models rather than CNN models. As shown in Table

TABLE IV. COMPARE ENERGY CONSUMPTION OF SNN AND CNN

Proposed method	**CNN**		**SNN**
Layer (type)	**CPU (J/inf)**	**GPU (J/inf)**	**Loihi (J/inf)**
input_2 (Input layer)	0	0	0
conv2d_1 (Conv2D)	0.011	0.00039	1.20×10^{-5}
average_pooling2d_1 (AveragePooling)	0	0	0
conv2d_2 (Conv2D)	0.33	0.011	8.80×10^{-6}
average_pooling2d_2 (AveragePooling)	0	0	0
conv2d_3 (Conv2D)	0.32	0.011	4.70×10^{-6}
conv2d_4 (Conv2D)	0.036	0.0013	1.50×10^{-6}
conv2d_5 (Conv2D)	0.32	0.011	3.50×10^{-6}
average_pooling2d_3 (AveragePooling)	0	0	0
conv2d_6 (Conv2D)	0.16	0.0057	8.90×10^{-7}
global_average_pooling2d (GlobalAvgPooling)	0	0	0
flatten (Flatten)	0	0	0
dense (Dense)	3.70×10^{-5}	1.30×10^{-6}	3.20×10^{-11}
Total Energy	1.18	4.13×10^{-2}	$\mathbf{3.16 \times 10^{-5}}$

TABLE V. COMPARISON WITH OTHER METHODS

Author name, year	**Algorithm**	**Postures**	**Average accuracy (%)**			**Energy consumption**	**Model size (MB)**
			5-fold	**10-fold**	**LOSO**	**(J/inf)**	
Pouyan et al., 2013[25]	Binary pattern matching technique	8	-	97.1	-	-	-
Xu et al., 2015 [26]	kNN classification with a BEMD metric	6	-	-	90.78	-	-
Xu et al., 2016 [27]	kNN & Skew rate classifier with a BMED metric	6	-	-	91.21	-	-
Viriyavit et al., 2017 [12]	Bayesian probability and Neural Network classification	3	89.9	-	-	-	-
Enayati el al., 2018 [13]	Neural Network classification with PCA based 16 feature extractions	4	-	72	67	-	-
Davoodnia et al., 2019 [10]	CNN based feature extraction with Softmax classification	3	-	100	99.56	on GPU	-
		17	-	93.2	87	4.42 x 10^{-3}	
Doan et al., 2021 [31]	EfficientNet B0 based feature extraction with AM-Softmax classification	17	99.9	99.9	95.32	-	25.5
Our proposed method	**CNN-to-SNN conversion**	**3**	**100**	**100**	**99,94**	**on Loihi**	**15.8**
		17	**99.9**	**99.9**	**90.56**	$\mathbf{3.16 \times 10^{-5}}$	

III, the usage of our preprocessed dataset raised the average accuracy of about 2% and 5% in CNN and SNN respectively compared to the unpreprocessed one. The table also shows that SNN model achieved the highest averaged accuracy in the LOSO cross validation scheme with a mean accuracy of 90.56%. Figure 2 displays output results of the neuron activities and network prediction at the time-step of 120 ms.

C. Energy consumption of CNN and SNN models

To estimate the power consumption of the CNN and SNN models, we utilised the Keras-Spiking framework to simulate the operation of the CNN model on the Intel-I7-4960X processor and the Nvidia GTX Titan Black GPU and the converted SNN on the Intel Loihi neuromorphic processor [24]. Assuming that the Keras-Spiking only calculates the energy usage of internal model computations and the evaluated model can be fully converted to a spiking implementation for deployment on the mentioned devices [28-30], we obtained the power usage of the proposed CNN and SNN models on various devices, as shown in Table IV. It can be seen from Table IV that the Intel I7-4960X processor consumes the most power, about 28 times that of the Nvidia GTX Titan Black GPU. By contrast, running the SNN model on the Intel Loihi processor only uses a small amount of energy. This energy is lower 37341 times and 1307 times than that of the CNN model running on the Intel I7-4960X CPU and Nvidia GTX Titan Black GPU, respectively. Due to the operating mechanism of the SNN neuron, the SNN neuron is triggered only when it receives an input spike. Therefore, inactive neurons that do not have any input spikes can be put into low-power mode to save power.

D. Comparison with other methods

We summarised the experimental results of previous studies in Table V. It can be seen from this table that while the earlier studies obtained the high accuracy, they only considered a small number of postures (3-8 postures). Our work provides better results with more sleeping postures to classify (17 postures). Compare to the work of Davoodnia et al. [10], our method has approximately the same accuracy as theirs in terms of 3 basic posture classification. In addition, our work yielded a mean accuracy of 90.56% in LOSO validation scheme, which is 3.5% higher than the result of Davoodnia et al. on the same dataset and 17 posture classification task. Furthermore, the power consumption of our SNN model is 140 times lower than that of the Davoodnia et al. CNN model. Compare to the latest sleeping posture classification work of Doan et al. [31], despite our accuracy is lower than their accuracy about 4.76%, the size of our model is 39% smaller than that of their model in terms of 17 posture classification with LOSO validation scheme. In k-fold validation schemes, our proposed method achieves the high accuracy as the Davoodnia et al. and Doan et al.

V. CONCLUSIONS

This paper has proposed a novel approach for sleep posture recognition with the third generation of the neural network. The proposed method is a combination of a preprocessing technique and a converted CNN-to-SNN model. With an accuracy of 99.9% for k-fold cross-validation and 90.56% for LOSO cross-validation, our method achieves a state-of-the-art result for the classification of 17 postures on the Pmatdata dataset in terms of using Spiking Neural Network. The experimental results also reveal that our approach satisfies the power-saving solution of the old generation networks. In terms of future work, we suggest that this can focus on improving the accuracy of pressure datasets with over 17 classes and be ready for hardware integration.

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