A Study of Bed-Leaving Prediction by Using a Pressure-Sensitive Sensor

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Abstract. Currently in care facilities, a bed-leaving sensor is often used in preventing falls of care receivers during the night. However, these current sensors are usually designed to detect the motion of care receivers getting out of bed and therefore, there are cases in which the care receiver has already fallen from the bed, by the time the sensor had reacted to the movement. It is common knowledge that a person frequently changes position while sleeping. In this research, we focus on the frequency of changes in sleep positions and aim to realize a method for precise prediction of care receivers' attempt in getting out of bed sufficiently before the actual action occurs. We employed the automatic classification method of sleeping positions in the pressure-sensitive sensor, with consideration to privacy of the research subjects, and identified nine types of sleeping positions that are common, with 80.9% accuracy. These results are reported in this paper.

Keywords: Elderly care · Fall prevention · Sleeping position · Pattern recognition

1 Introduction

1.1 Background

Japan is now an extremely aging society. With the growth of the aging population, the number of the people with dementia also increases. In 2012, 15% of the elderly over 65 years old are reported to have dementia which means that about 462 million elderly people in Japan are living with dementia. The elderly with brain disorders such as dementia develop sleep disorders with extremely high frequency. Symptoms of dementia that most frequently appear are sleep-related disorders: irregular sleep-wake patterns such as insomnia, day-night reversal and delirium. Such cases are often accompanied with behavioral disorders, such as violence, wandering, impatience, and excitability. As a consequence of these symptoms, family members and caregivers become exhausted.

In order to support such care of dementia patients during the night, fall preventive movement sensors are often used. Roughly speaking, there are three types of fall preventive movement sensors. The first type of sensor is the mat type in which the sensor is laid next to the bed which detects the pressure on the mat when the care receiver steps onto it. This type of sensor is durable and easy to handle for the nursing staff since it is

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less likely to cause false alarms. However, the wiring for the sensor, being also laid next to the bed, can potentially cause care receivers to trip over it resulting in fall accidents. Another problem that may arise with use of the mat type sensor is that the sensor reacts when the nursing staff is closer to the bed in order to aid the care receiver. These things mentioned above, are the problems of the mat type sensors. The second type is the clip type sensor which is the easiest and the most inexpensive option. The clip is attached to the clothing of the care receiver and connected to the sensor switch. When the care receiver gets out of the bed, the sensor is activated, allowing the caregiver to know that the care receiver is in danger of falling. However, because the care receiver often detaches the clip by him/herself it causes a malfunction in the sensor system. The third type of sensor is the type using infrared light. The body movement of the care receiver blocks out the infrared light from the emitter to the light receiving section. This type of sensor is flexible but expensive compared to the other types of sensors. All of the sensors mentioned above, are only designed to detect the moment when the care receiver's action of getting out of bed occurs. Therefore, in principle, they all have the same problem in that, it is often too late to assist the care receiver's action in getting up when the caregiver responds to the sensor call.

We are researching the method for predicting the action of the care receivers getting out of the bed rather than detecting it. In order to implement such a sensor system, we focus on the sleeping position. Due to the fact that, the action of turning over in bed occurs between REM sleep and non-REM sleep [1], we assume that the prediction of waking up can be achieved by monitoring the sleeping positions.

In this paper, we present the results of experimenting with the automatic classification of nine typical sleep positions by using the pressure-sensitive sensor, with consideration to privacy of the experiment subjects.

1.2 Related Work

As a bed leaving prediction method, a method for identifying sleep posture using a pressure sensor has been studied [2]. In this study, sleeping attitude is classified by extracting features from body pressure data obtained from a pressure sensor and using a discriminator such as SVM (Support Vector Machine) [3]. Since the design of the feature quantity greatly affects the discrimination rate, it is regarded as important matter to discover whether or not it is possible to find an effective feature quantity in this machine learning method. As a new approach to this problem, in recent years, Deep learning has attracted attention. As a feature of Deep learning, it is said that it is possible to automatically learn feature quantities designed by humans. It has been reported that the learning model constructed using CNN (Convolution Neural Network), being one of the deep learning techniques has higher accuracy in comparison to the conventional image recognition field method [4].

1.3 Purpose

CNN has few application examples in fields other than image and speech recognition; however, its effectiveness is still unknown. Therefore, in this study, we aim to examine the optimal method for prediction of bed-leaving by comparing the accuracy of classification in sleep positions by adopting two methods, SVM and CNN.

2 Method

2.1 Support Vector Machine

SVM is currently one of the outstanding learning models in terms of recognition performance among many pattern recognition techniques. Support vector machine maps the learning pattern to another higher dimension space using a kernel trick. Based on the learning data, this method identifies a margin hyperplane that maximizes in the distances between individual data points.

2.2 Convolutional Neural Network

Many methods of deep learning have been proposed and various approaches have been studied also in the field of image recognition, but CNN is currently considered to be the most successful. CNN is an extension of the classical multilayered perceptron, but it is characterized by limiting the binding between neurons locally and sparsifying the interlayer bonds based on the findings in the structure of the visual cortex. More specifically, it has a structure in which a convolution layer responsible for local feature extraction of images and a pooling layer (subsampling layer) for summarizing features for each local region are repeated. Since the parameters of the convolution filter are shared at all places in the image, the number of parameters is greatly reduced as compared with a simple total coupled network. Moreover, by interleaving the pooling layer, it is possible to further reduce the number of parameters and at the same time add invariance to the parallel movement of the input, which is indispensable for general object recognition step by step. Intuitively, it can be interpreted that it is a network that co-occurrence of adjacent features on different scales while gradually lowering the input resolution, selectively giving information effective for identification to upper layers. Such an architecture based on repetition of convolution/pooling is from Japan, and Neocognitron [5] developed by Fukushima et al. was the first to appear. After that, based on the propagation method correcting errors, in the 1990's LeCun et al. [6] established a learning method that served as the technical basis of the CNN that is currently used today.

3 Experiment

We classified the sleeping position using the body pressure data obtained from the pressure sensor. Moreover, we compared the recognition rate of SVM and CNN, which are machine learning techniques, and decided the suitable learning model for the bed-leaving prediction.

3.1 Using Data

In this study, we used a pressure sensor system made by Tsuchiya Co., Ltd. to measure body pressure data. The textile type pressure sensor made from conductive fibers was soft and comfortable, even when placed on the bed. The size of the pressure sensitive area is 1840 mm × 800 mm, and there are 80 * 40 sensing points in the sheet. The sensor can output up to 12 frames of data per second. In this experiment, we placed the pressure sensor onto the bed, then placed the mattress cover over it, and fixed the sensor as shown in Fig. 1.

Fig. 1. Pressure-sensitive sensor placed on the bed

Sleeping Posture

It has been reported that there are six typical human sleeping positions [7] as shown in Fig. 2. Among these types of sleeping positions, the first three types are horizontally unsymmetrical, and the left side was distinguished from the right side. Therefore, there were nine types of sleeping positions in total that were subjected to this research.

1. Fetus position: Curling into the fetal position on the bed
2. Log position: Lying on one's side with both arms down by one's side
3. Yearner position: Lying on one's side with both arms out in front
4. Soldier position: Lying on one's back with both arms pinned to one's sides
5. Freefall position: Lying on one's front with one's hands around the pillow, and the head turned to one side
6. Starfish position: Lying on one's back with both arms around the pillow

Fig. 2. Typical sleeping positions

Participants

The number of the participants in this experiment was ten people and they ranged from 21 to 27 years of age. Every participant was healthy. Each participant performed the above nine types of sleeping position in their own manners. There were three trials in each position and as a result, we obtained 189 samples (21 samples per position $\times$ 9 positions) in total. First, we measured the initial pressure value and then, we instructed the participants to lie on the bed with the nine postures. We then at last, measured the pressure after checking the posture was stable.

3.2 Data Set

Our data set for learning is the pressure data performed the following preprocessing. The pressure sensor used in this study, measures not only the body pressure but also the load of the mattress cover, on the sensor. Moreover, the measurement was unstable due to the influence power supply noise. In an attempt to solve these problems, we obtained plain body pressure data by the subtraction of the initial value from the average measurement. And after, above common processing, in order to convert the preprocessing data into a form suitable for each learning model, an input data set was created by using the method of feature extraction and image transformation.

Subtraction Processing

The measurement values indicate the increment of the pressure from the initial value at the start of measurement. Therefore, the plain body pressure value (as mentioned earlier) can be determined by the subtraction of the initial value from the average measurement value taking into consideration that, when a negative number appears by subtraction, the pressure value was set to zero.

Feature Extraction for SVM

From the preprocessing data, 29 features such as the pressure center and the ratio of the pressure area were extracted, and used as the features.

Image Transformation for CNN

A body pressure data has 3200 (40×80) pressure values. We standardized the pressure value from 0 to 255, regarded this pressure value as a pixel value and created an image of 40×80 pixels (Fig. 3).

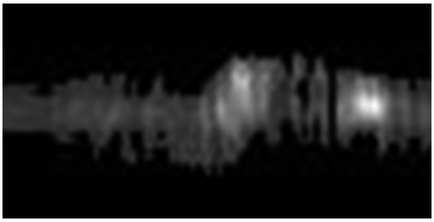

Fig. 3. A pressure image sample

3.3 Performance Evaluation

We classified nine classes of sleeping postures using preprocessed data sets. In this study, we used the "e1071" package of the R statistical software [8] for SVM classifier, and used the "Keras" [9] of CNN framework for CNN classifier. A simple CNN construction is shown in Fig. 4 and hyper parameter setting is shown in Table 1. We used 9-fold cross validation test for evaluating the classification rate of the classifiers.

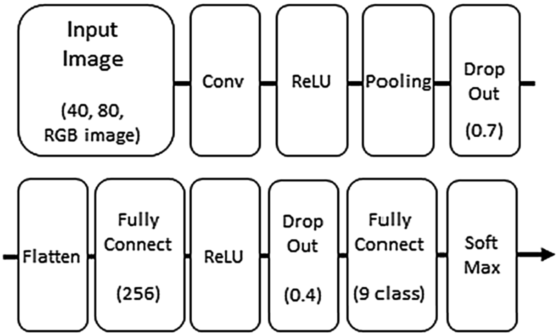

Fig. 4. A simple CNN construction

Table 1. Hyper prameter setting of simple CNN model

OS	Ubuntu 12.04 LTS
GPU	GeForceGTX1080
Backend	TensorFlow
Convolution layer	Kernel size 4 * 4 32 output channels
Pooling layer	MaxPooling Pool size 2 * 2
Epochs	300
Objective	Categorical_crosseentropy
Optimizer	Adam

4 Result and Discussion

In this section, we present the results of the classification rate of the classifiers, moreover tuned of CNN model.

4.1 Plain CNN Model

We classified nine classes of sleeping postures by using SVM and CNN classifier. Table 2 shows the averages of classification rate calculated by a 9-fold-cross-validation.

Table 2. Average of recognition rate

	SVM	CNN
Average	80.9%	71.1%

SVM achieved the best classification rate of 80.9%. As shown in Fig. 5, the difference of $\geq 30\%$ accuracy exists between the training data and the validation data. This indicates that over learning is occurring, and seems that the simple CNN structure is more effective. Therefore, to improve accuracy and to prevent over leaning, we performed the tuning of the CNN model.

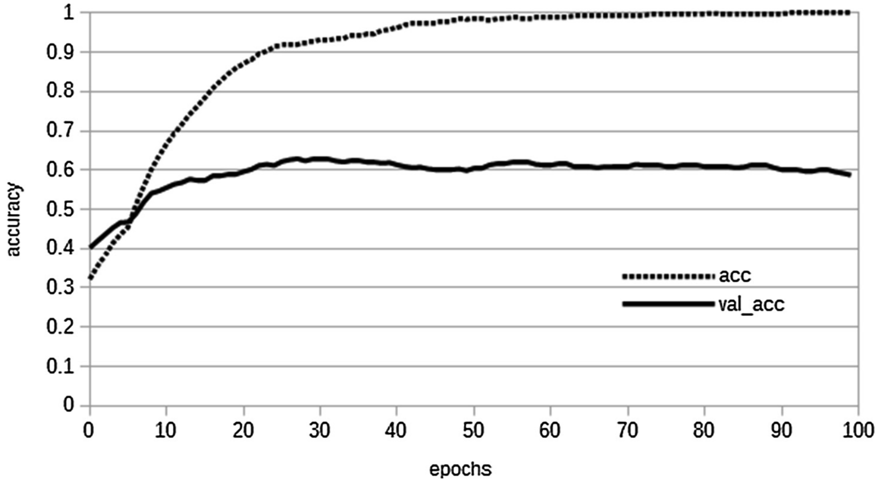

Fig. 5. Accuracy of simple CNN model

4.2 Tuning CNN

In order to find the optimal CNN model in classification of sleep posture, we compared the recognition ratio and training loss of six models as shown in Table 3. The configurations of six CNN models are outlined in Table 3, one per column. In the following, we will refer to these models by their names (A–F). The convolution layer parameters are denoted as “conv (number of channels, number of rows in kernel, number of cols in kernel)”. The ReLU activation function is not shown for brevity.

In the six models, the averages of the recognition rates and the learning situations were compared. Among the six models, model C possessed the highest recognition rate of 74.5% (Fig. 6).

Table 3. Configuration of 6 CNN models

A	B	C	D	E	F
(1Conv)	(2Conv)	(1Conv-2)	(2Conv-2)	(1Conv-3)	(2Conv-3)
Input (40 * 80 RGB image)					
Conv(32, 4, 4)	Conv(32, 4, 4) Conv(32, 4, 4)	Conv(32, 4, 4)	Conv(32, 4, 4) Conv(32, 4, 4)	Conv(32, 4, 4)	Conv(32, 4, 4) Conv(32, 4, 4)
MaxPooling					
Dropout (0.7)					
		Conv(32, 4, 4)	Conv(32, 4, 4) Conv(32, 4, 4)	Conv(32, 4, 4)	Conv(32, 4, 4) Conv(32, 4, 4)
		MaxPooling			
		Dropout (0.7)			
				Conv(64, 3, 3)	Conv(64, 3, 3) Conv(64, 3, 3)
				MaxPooling	
				Dropout (0.7)	
Flatten					
Fully-connect (512)					
Dropout (0.3)					
Fully-connect (9)					
Soft-max					

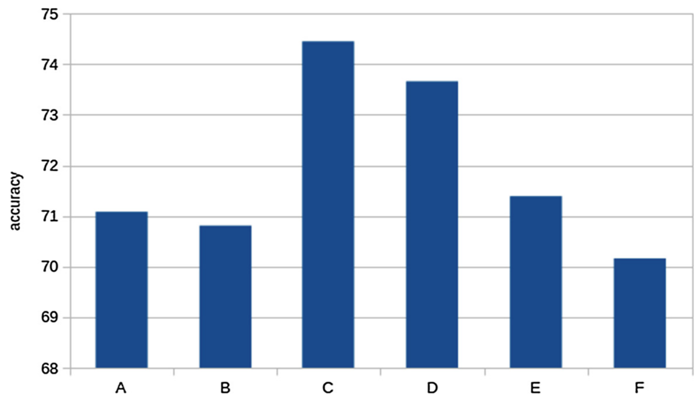

Fig. 6. The recognition rate of 6 models

The layer that had only one Convolution had better accuracy than the one that had two Convolutions, moreover it was thought that better accuracy was achieved by not to having more layers, but to keep it at two layers.

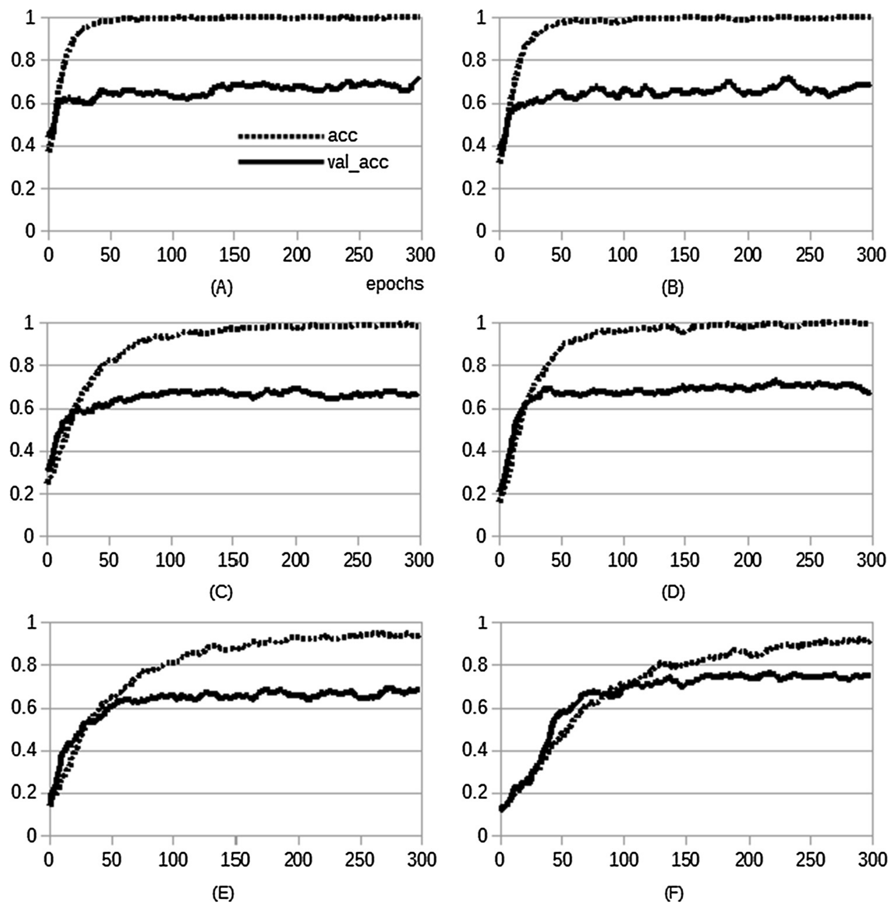

Fig. 7. Learning situation of 6 CNN models

As shown in Fig. 7, it is apparent that adding more layers reduces the process of over learning. Although over learning in model C was greater than in model F, over learning can be improved by increasing the data set in the future. Therefore, as a result, model C was the most suitable classifier model.

5 Conclusion

We classified nine sleeping positions by using the body pressure data obtained from the pressure-sensitive sensor. We compared the versatility of SVM and CNN by using the recognition rate calculated by a nine-fold cross validation test. As a result, the recognition rate of SVM was 80% while the recognition rate of CNN was 70%. Moreover, by tuning CNN, the recognition rate in the best model resulted to be 74%. In conclusion, this study has demonstrated that SVM was a more suitable method in comparison to CNN in classifying sleep posture by using pressure data.

6 Future Work

In this study, we performed an experiment with static pressure data. In order to detect the action of turning over in bed, we will classify sleeping position using dynamic pressure data. In addition, it is also necessary to measure pressure data not only of the young population but of the elderly population as well.

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