2022 4th International Conference on Communications, Information System and Computer Engineering (CISCE)

Recognition of Human Sleep Pressure Posture Image Using Deep Residual Networks

Hailin Gao
Chongqing University of
Posts and Telecommunications,
Chongqing, China
Chongqing Institute of Green and
Intelligent Technology, Chinese
Academy of Sciences,
Chongqing, China
Email: ghl_rick@163.com

Dapeng Wei
Chongqing Institute of
Green and Intelligent Technology,
Chinese Academy of Sciences,
Chongqing, China
Chongqing Institute of Graphene,
Chongqing, China
Corresponding Author: Dapeng Wei
Email: dpwei@cigit.ac.cn

Fuping Yang
Chongqing University of
Posts and Telecommunications,
Chongqing, China
Email: yangfp@cqupt.edu.cn

2022 4th International Conference on Communications, Information System and Computer Engineering (CISCE) | 978-1-6654-9848-7/22/$31.00 ©2022 IEEE | DOI: 10.1109/CISCE55963.2022.9851077

Abstract*—Good sleep is essential for people. Sleep posture has been widely studied as a means of evaluating sleep quality. This paper proposes a sleep posture recognition method based on a deep residual network. The computational complexity is reduced by introducing residual blocks and omitting the complex manual feature extraction process. An unconstrained intelligent mattress system based on a flexible pressure sensor array is developed, which provides a comfortable and high-resolution solution for long-term sleep monitoring. Five testers conducted test experiments on the smart mattress to simulate the real sleep scene. The experimental results show that our method can accurately identify the seven categories (sitting, right trunk type, right fetal type, supine, left trunk type, left fetal type, and prone), and the overall recognition rate is 98%. The results showed that the system performed well in sleep research, which provided a basis for subsequent pressure ulcer prevention and drop warning. Our research provides a set of solutions and ideas for the follow-up study of intelligent mattress systems.

Keywords-sleep posture recognition; convolutional neural network; sleep posture image; intelligent mattress system.

I. Introduction

Sleep posture plays a vital role in evaluating sleep quality and preventing bedsores. The study of sleep posture can help patients adjust sleep posture to a great extent to prevent bedsores, in recent years has been the attention of researchers. At present, the developed sleeping posture recognition technology can be mainly divided into three categories : (1) visual feature extraction based on images and videos collected by the camera [1];(2) recording the real-time data of the person under test based on the wearable device [2]; (3) extracting tactile information based on mechanical pressure sensor system [3]. Image-based sleep posture recognition has been widely studied due to its simple use and low acquisition cost, however, the visual field is subject to light and dark interference and is easy to leak privacy, so it constitutes a huge challenge that needs to be solved by researchers. Wearing-based devices can also make testers feel foreign during sleep and vulnerable to movement, thus reducing the accuracy of sleep posture recognition. In contrast, sleep posture recognition based on tactile information has a higher cost than the first method, but it has the advantages of real-time, non-privacy, and good concealment.

At present, there are many studies on human sleep posture recognition. Nuksawn et al. [1] photographed the static sleep posture pictures and dynamic videos of the human body with high-definition cameras and used the SVM-RFE method to identify sleep posture. This method has hidden dangers of light interference and privacy disclosure. Chang et al. [2] proposed a multi-modal sensor system for wound assessment and pressure sore care, but the multi-modal sensor must be fixed on the human body, which brings a sense of restraint and is vulnerable to large-scale action. In recent years, uncon-strained sleep posture recognition has been widely concerned by researchers. A large number of flexible sensors based on force-sensing resistors (FSR) are embedded in mattresses to recognize sleep posture without affecting people's sleep. In the existing intelligent mattress system, there are few sensors, high data acquisition difficulty, and low image resolution. A. Kitzig et al. [4] put four sensors around the bed, due to the small number of sensors that need to be as close as possible to the four sensors, making the monitoring greatly limited. Xu et al. [5]proposed a sleep posture recognition method based on matching. An intelligent mattress with 8192 FSRs was designed, and the recognition rate of 6 postures was 91.21%. The third method is adopted in this paper. Based on the non-invasive identification system of mechanical sensors, the measured personnel can have no abnormal feelings, which is convenient for our long-term monitoring and subsequent research. The contributions of this paper are summarized as follows:

1. We propose a sleep posture pressure recognition algorithm based on residual neural networks is proposed. By constructing multi-layer residual blocks [6] to identify the pressure data, the complex manual feature extraction is avoided and the classification effect is improved.
2. We developed a non-binding intelligent mattress data ac- quisition system based on a flexible pressure sensor array, which can effectively obtain the pressure distribution of the whole body area of the

Authorized licensed use limited to: American University of the Middle East. Downloaded on May 01,2025 at 12:21:07 UTC from IEEE Xplore. Restrictions apply.

tested person, and develop the data display software on PC combined with the model.

The paper is organized as follows: Section II introduces the data preprocessing, residual neural network model, and data acquisition system. The experimental results are introduced in Section III and compared with other methods. Section IV gives conclusions and further work.

II. Method

A. Data Pre-processing

The pressure data of people's sleeping posture contain abundant information. Our original data are composed of 64 rows and 32 columns of the flexible sensor array, namely 64 × 32 sensing units. By collecting the electrical signals feedback from each flexible sensor, the pressure simulation value is converted into a digital value by a digital circuit, and then uploaded to the PC for data processing and classification identi. We filtered out some abnormal pixel error pressure data. This is because of the high frequency of data acquisition, the adjacent frame difference is not big, and the packet using UDP protocol does not guarantee data integrity. In addition, even if no one is lying on the mattress, the system will have some noise. A threshold of 800 is set, and the pressure value below the threshold will be filtered as noise. The pressure value of each device is set as $a_{i,j}(1 \le i \le 64, 1 \le j \le 32)$. The formula is as follows:

$$a_{i,j} = \begin{cases} a_{i,j} & a_{i,j} \ge 800 \\ 0 & a_{i,j} < 800 \end{cases} \qquad (1)$$

The original data of each frame is a 64 × 32 matrix, which records the pressure value of each point in the sleep posture. This value is converted from analog signal to digital signal by an ADC circuit. To make the image smoother, we first use bilinear interpolation to amplify the image by 20 times and then use a kernel size of 55 × 55 Gaussian filters. We set the pixel value range between 0 and 255, and normalize the pixel value to the range of 0-1 because the input value of our network is between 0-1. To facilitate model input, we fill the image into 64 × 64 pixels by zero-filling. The image of sleeping pressure is shown in Fig.1.

Figure 1. Preprocessed Right Trunk Sleeping Image.

B. Sleep Posture Recognition Algorithm

With the vigorous development of convolutional neural network (CNN) [7], it extends from images to various related fields, providing many schemes for recognition research. The convolution layer helps CNN automatically extract the feature information of local regions, without the need for complex feature extraction in the field of machine learning. The MatNet for sleep posture recognition proposed in this paper is based on ResNet-18 [6]. As shown in Figure 2, the key of the ResNet model is the residual block as Figure 3. The residual block can effectively prevent the gradient disappearance and gradient explosion with the increase of network layer number, and also accelerate the training speed of the network.

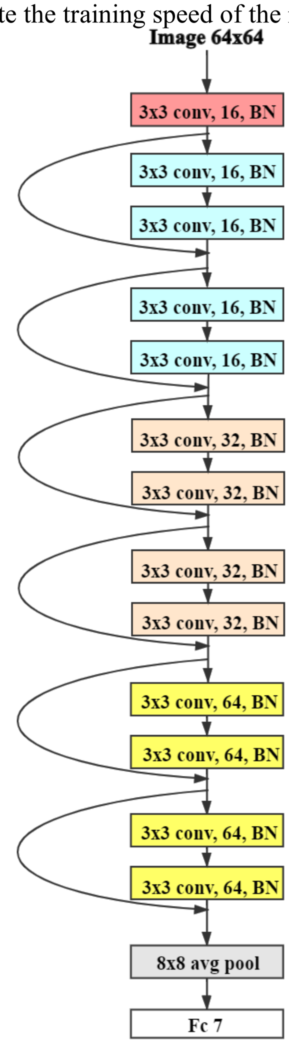

Figure 2. Network Structure of Sleep Posture Recognition Algorithm.

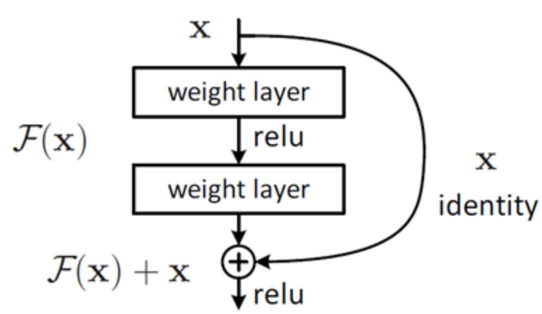

Figure 3. Residual Unit Structure Diagram.

The residual block is divided into two parts: the direct mapping x_i and the residual $F(x_i, W_i)$. The direct mapping corresponds to the right curve part of Figure 3, and the weight layer refers to the convolution operation. The residual block is defined as:

$$x_{i+1} = x_i + F(x_i, W_i) \qquad (2)$$

Authorized licensed use limited to: American University of the Middle East. Downloaded on May 01,2025 at 12:21:07 UTC from IEEE Xplore. Restrictions apply.

If the number of features of x_i and x_{i+1} is inconsistent, it is necessary to add a 1 × 1 conv layer to the direct mapping part for dimension elevation and dimension reduction, which is expressed as:

$$x_{i+1} = h(x_i) + F(x_i, W_i) \quad (3)$$

Table I summarizes the network architecture. The image of sleeping pressure is input to the network, and the resolution is 64 × 64 pixels. Firstly, enter the initial convolution layer, reduce the size of the input feature map and increase the number of input channel features, and then pass multiple residual blocks. When the step size is 2, the number of features doubles. Batch normalization and ReLU layer are connected behind each convolution layer. The obtained feature vector is output to the full connection layer to obtain the last layer of the classification task.

TABLE I.
NETWORK ARCHITECTURE. FOR EACH LAYER TYPE, WE SPECIFY THE KERNEL SIZE AND OUTPUT FEATURE MAPPING.

Layer Type	**Parameter**	**Output Size**
conv	3 × 3, 16, stride(1, 1)	16 × 64 × 64
Res block	$\begin{pmatrix} 3\times3, & 16 \\ 3\times3, & 16 \end{pmatrix}\times 2$	16 × 32 × 32
Res block	$\begin{pmatrix} 3\times3, & 16 \\ 3\times3, & 16 \end{pmatrix}\times 2$	32 × 16 × 16
Res block	$\begin{pmatrix} 3\times3, & 16 \\ 3\times3, & 16 \end{pmatrix}\times 2$	64 × 8 × 8
Avg pool	8 × 8, stride(1, 1)	64 × 1 × 1
liner	64	7

C. Data Set

We evaluate the network on the SLEEP POS dataset, which is obtained from the data collected by our system. The data acquisition process only needs to lie flat or in other postures on the smart mattress. We collected the original sleep pressure measurement data of 100 healthy researchers, named P01 to P100. Each person collected 7 groups of sleep data, including sitting, right trunk type, right fetal type, supine, left trunk type, left fetal type, and prone position. Each posture collected about 4 frames of data with an obvious difference, that is, each person has about 28 frames of original data, a total of 2800 frames.

D. Data Acquisition System

The data acquisition system consists of the sensor array, data acquisition board, main control board, and data bus. The sensing area is 180 cm × 80 cm. A sensor array with a length of 80 cm and a width of 2.1 cm is composed of 32 flexible pressure sensors. The distance between the two arrays is 1cm as shown in Figure 4. When the data are collected, the sensor will be fed back to the data acquisition circuit board under pressure. At the same time, the data are stored in the register, waiting for the collection instructions of the main control board to be issued and then sent to the main control board through the RS422 data bus.

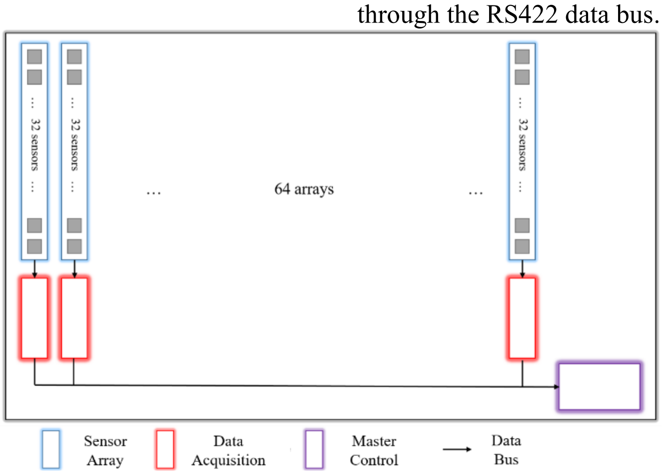

Figure 4. Frame Diagram of Data Acquisition System.

The main control module and data acquisition module designed in this paper are all based on the STM32F407VET6 microcontroller. The STM32 microcontroller has complete functions, low prices, and rich data, which helps to improve development efficiency. There are 64 data acquisition modules, the frequency is 500 Hz. The main control board

Authorized licensed use limited to: American University of the Middle East. Downloaded on May 01,2025 at 12:21:07 UTC from IEEE Xplore. Restrictions apply.

uses UDP protocol to communicate with the PC. Compared with the reliable connection of TCP, UDP uses a connectionless way to make the packet more portable and flexible and has better real-time performance.

III. Experiment and Results

A. Experiment

To evaluate the performance of the system, we conducted experiments to verify its feasibility. There were five participants in this experiment, and their sleeping posture information was not included in the data set. To simulate the real sleep scene, the experimenters carried out the test experiments in seven postures. Each posture was maintained for 30 min. During this period, different shapes of the posture and different positions on the smart mattress can be changed at will, to verify the robustness of the system. According to the correct duration of the posture recognition on PC during this period, the recognition rate of the posture is calculated as Figure 5.

As shown in table II, we note that the overall recognition effect of MatNet for people with lightweight is slightly lower than that of normal weight. This is because the pressure characteristics of people with lightweight in some areas are not obvious, and may even be filtered out as noise by the system. In addition, during the experiment, we also found that the left trunk type was easy to be identified as the prone position when the body tilt angle was large, and the prone position was easy to be identified as the left when the right leg was lifted to lose pressure. Therefore, the two postures were easily confused in the identification. The lateral trunk type and the fetal type are affected by the degree of curling of the body, and two postures are also confused during the experiment, but the duration is usually shorter. There is a big difference between sitting and other postures, so the recognition rate can reach 100% stably.

TABLE II
SUBJECTS INFORMA TION AND CLASSIFICA TION ACCURACY.

No.	**Gender**	**Age**	**Height (cm)**	**Weight (kg)**	**Sitting**	**RTrunk**	**RFatal**	**Supine**	**LTrunk**	**LFatal**	**Prone**	**Accuracy**
1	male	23	166	65	100%	98%	99%	100%	97%	99%	98%	99.00%
2	female	24	159	49	100%	95%	97%	99%	95%	93%	100%	97.28%
3	male	32	165	63	100%	96%	97%	100%	97%	98%	100%	98.29%
4	male	29	179	75	100%	95%	97%	99%	97%	96%	99%	97.57%
5	female	26	160	55	100%	99%	97%	99%	96%	95%	99%	97.86%

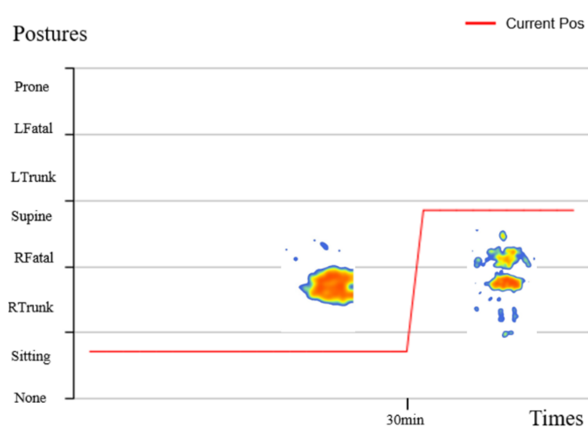

Figure 5. Prediction of Postures.

B. Experimental Result

During the training process, we divide the dataset into the training set and test set with a ratio of 4 : 1. The sleep posture recognition algorithm model is trained and tested on the Pytorch platform. We used the Adam [8] optimizer and cross-entropy loss function to train 20 epochs, with the batch size of 64, the initial learning rate of 1×10^{-3}, and the learning rate of each five epochs divided by factor 3.

The MatNet recognizes sleep posture by extracting pressure distribution, so position information has little effect on recognition results. Fig. 6 shows the prediction rates of various postures by our recognition algorithm, and the overall prediction rate of postures reaches 97.14%, indicating that the model can classify these postures with high precision.

Authorized licensed use limited to: American University of the Middle East. Downloaded on May 01,2025 at 12:21:07 UTC from IEEE Xplore. Restrictions apply.

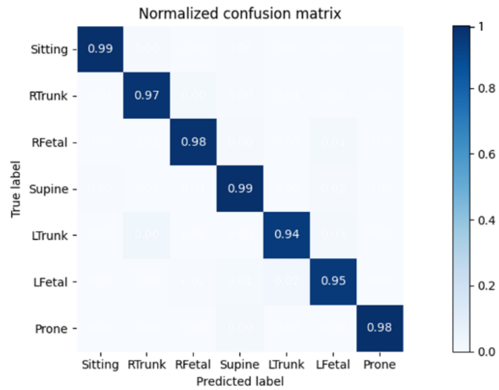

Figure 6. MatNet's Prediction of Postures.

Table III shows the comparison of our recognition algorithm with other models. Compared with other models, MatNet has the highest classification accuracy of 99.02%. CNN with only two-layer convolution has the fastest training speed, while the VGG network with 13-layer convolution has the slowest training speed. Although MatNet with residual has 13 layers of convolution, the training time is greatly shortened.

TABLE III
CLASSIFICATION ACCURACY OF DIFFERENT

Models	Model Description	Accuracy	Time
AlexNet	5 Conv + 3 MaxPool + 3 Fc	93.67	0.094
2-Layer CNN	2 Conv + 2 MaxPool + 1 Fc	94.09	0.043
VGG	13 Conv + 5 MaxPool + 3 Fc	98.59	0.56
MatNet	13 Conv + 1 AvgPool + 1 Fc	**99.02**	**0.095**

When the network depth increases, the performance of the network on the training set and the test set is not as shallow as the network, resulting in the disappearance or explosion of the reverse propagation gradient. If the gradient correlation is poor close to the white noise, the correlation between the reverse propagation gradient will become worse and worse, and the update of the gradient is similar to the effect of the deep network caused by random disturbance. When the residual is introduced, Skip Connection ensures that a part of the gradient sample does not return, and enhances the correlation between the gradients. The network obtains a function similar to the differential amplifier, which is more sensitive to the subtle changes in the output. The Skip Connection of the residual network accelerates the network training speed, and its short connection mechanism also reduces the gradient dispersion problem.

Table IV shows the research on sleep posture classification by different methods. These studies are based on smart mat- tresses with a large number of FSR sensors. Methods The classification accuracy of [9] is lower than other methods. Some methods such as [10] and [11] have higher accuracy, but there is no recognition and classification of supine and prone positions. The classification of these two positions has a great influence on the prevention of pressure sores. The method we used not only has a high recognition rate but also has rich postures. The supine and prone positions can also be well distinguished and display the measured person's overall pressure distribution in real-time.

TABLE IV
COMPARISON OF THE PROPOSED METHOD WITH EXISTING METHODS.

Author,Year	Algorithms	Number of Postures Classified	Accuracy
Liu et al., 2013 [9].	Minimum class residual classifier	6	83.03%
Pouyan et al., 2013 [10].	K nearest neighborhood	8,prone excluded	97.1%
Heydarzadeh et al., 2016 [11].	Deep Neural Networks	3,prone excluded	98.06%
Matar et al., 2020 [12].	Full connected networks	4	97.9%
Our Method	**ResNet**	**7**	**99.02%**

Authorized licensed use limited to: American University of the Middle East. Downloaded on May 01,2025 at 12:21:07 UTC from IEEE Xplore. Restrictions apply.

IV. CONCLUSION

In this paper, a 2D-CNN method based on the pressure data of human sleeping posture is proposed to identify sleeping posture. The hardware design and circuit of the data acquisition system with 2048 sensor arrays are introduced. The intelligent mattress system can make the measured people fall asleep as usual. No abnormal feeling is convenient for longterm monitoring and recognition research. The experiment proved the advantages of using the residual neural network to extract features, and the accuracy reached 99.02%. Compared with other methods, higher classification accuracy and faster training are achieved. In the future, we will use the existing pressure characteristics to conduct drop warning training and bedsore research to improve the system function. In addition, we integrate the mattress system with the information obtained by other sensors, such as respiration and heart rate, to conduct a more comprehensive assessment of sleep.

ACKNOWLEDGMENT

This work was supported by Chongqing Talents Program(CQYC2020030146), Project of Chongqing Science and Technology B-ureau (cstc2019jcyj-msxmX0574, cstc2021ycjh- bgzxm0345), Chongqing Entrepreneurship and Innovation Support Program for Overseas Students, and Chongqing Key Laboratory of Artificial Intelligence and Service Robot ControlTechnology.

REFERENCES

[1] L. Nuksawn, E. Nantajeewarawat, and S. Thiemjarus, "Real-time sensor- and camera-based logging of sleep postures," in *2015 International Computer Science and Engineering Conference (ICSEC)*, 2015, pp. 1–6.

[2] M.-C. Chang, T. Yu, J. Luo, K. Duan, P. Tu, Y. Zhao, N. Nagraj, V. Rajiv, M. Priebe, E. A. Wood, and M. Stachura, "Multimodal sensor system for pressure ulcer wound assessment and care," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 3, pp. 1186–1196, 2018.

[3] H. Diao, C. Chen, W. Yuan, A. Amara, T. Tamura, J. Fan, L. Meng, X. Liu, and W. Chen, "Deep residual networks for sleep posture recognition with unobtrusive miniature scale smart mat system, " *IEEE Transactions on Biomedical Circuits and Systems*, vol. 15, no. 1, pp.111–121, 2021.

[4] A. Kitzig, E. Naroska, G. Stockmanns, R. Viga, and A. Grabmaier, "A novel approach to creating artificial training and test data for an hmm based posture recognition system," in *2016 IEEE 26th International Workshop on Machine Learning for Signal Processing (MLSP)*, 2016, pp. 1–6.

[5] X. Xu, F. Lin, A. Wang, Y. Hu, M.-C. Huang, and W. Xu, "Body-earth movers distance: A matching-based approach for sleep posture recognition," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 10, pp. 1–13, 07 2016.

[6] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.

[7] Y. Lecun and Y. Bengio, "Convolutional networks for images, speech, and time-series," *Handbook of Brain Theory & Neural Networks*, 1995.

[8] D. Kingma and J. Ba, "Adam: A method for stochastic optimization," *Computer Science*, 2014.

[9] J. J. Liu, W. Xu, M. C. Huang, N. Alshurafa, M. Sarrafzadeh, N. Raut, and B. Yadegar, "Sleep posture analysis using a dense pressure sensitive bedsheet," *Pervasive and Mobile Computing*, vol. 10, no. part_PA, pp. 34–50, 2014.

[10] G. Matar, J.-M. Lina, and G. Kaddoum, "Artificial neural network for in-bed posture classification using bed-sheet pressure sensors," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 1, pp. 101–110, 2020.

[11] M. Heydarzadeh, M. Nourani, and S. Ostadabbas, "In-bed posture classification using deep autoencoders," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2016.

[12] M. B. Pouyan, S. Ostadabbas, M. Farshbaf, R. Yousefi, M. Nourani, and M. D. M. Pompeo, "Continuous eight-posture classification for bed-bound patients," in *2013 6th International Conference on Biomedical Engineering and Informatics*, 2013, pp. 121–126.

Authorized licensed use limited to: American University of the Middle East. Downloaded on May 01,2025 at 12:21:07 UTC from IEEE Xplore. Restrictions apply.