Highly Generalized Sleep Posture Recognition Using FMCW Radar

Yicheng Yao
Aerospace Information Research Institute (AIR),
Chinese Academy of Sciences (CAS)
School of Electronic, Electrical and Communication Engineering (EECE),
University of Chinese Academy of Sciences (UCAS)
Beijing, China
yaoyicheng19@mails.ucas.ac.cn

Lirui Xu
AIR, CAS
EECE, UCAS
Beijing, China

Pan Xia
AIR, CAS
EECE, UCAS
Beijing, China

Hao Zhang
AIR, CAS
EECE, UCAS
Beijing, China

Lidong Du
AIR, CAS
Beijing, China

Xianxiang Chen
AIR, CAS
Beijing, China

Zhen Fang
AIR, CAS
EECE, UCAS
Personalized Management of Chronic Respiratory Disease,
Chinese Academy of Medical Sciences
Beijing China
fangzhen@aircas.ac.cn

2023 IEEE 19th International Conference on Body Sensor Networks (BSN) | 979-8-3503-3841-6/23/$31.00 ©2023 IEEE | DOI: 10.1109/BSN58485.2023.10330941

***Abstract*—Identifying users' sleep posture is significant in reducing sleep apnea events and avoiding postoperative pressure sores. Past studies have identified sleep posture by installing cameras, installing sensors on mattresses, or letting users wear wearable devices. However, the camera-based method is usually affected by light intensity or coverage and can invade users' privacy. The method based on contact sensors will affect the comfort of users' sleep. The use of radar can solve the problem of cameras and contact sensors, but previous studies need to collect data from new users for calibration to maintain high performance. In this work, we use FMCW radar to estimate the position image of the user in space. We propose a multi-task learning sleep posture recognition model based on a neural network, which uses the radar position image to estimate the user's sleep posture. In addition, we use mix-up data enhancement to improve the model's generalization. We collected data from 17 subjects to train and test our model. The proposed method can achieve 0.935 sleep posture recognition F1 score without collecting new user calibration data.**

***Index Terms*—sleep posture recognition, FMCW radar, multi task learning**

I. Introduction

Sleep posture greatly impacts on people's health, and wrong sleep posture will lead to the aggravation of some diseases. Proper sleep posture has been shown to improve the stability of the upper airway during sleep and reduce the symptoms of obstructive sleep apnea (OSA) [1]. Previous studies have shown that lateral posture can relieve the symptoms of patients with OSA [2]. In addition, sleep posture monitoring is also necessary to prevent pressure sores in elderly and postoperative patients, and infrequent posture changes may increase the risk of pressure sores [3]. Therefore, monitoring the sleep posture of patients is of great significance in health monitoring and clinical nursing.

Automatic sleep posture recognition is mainly divided into contact methods and non-contact methods. The contact method identifies sleep posture by wearing wearable sensors on subjects or by installing sensor arrays on mattresses. For example, Chang et al. use three-axis acceleration information to detect sleep posture [4]. However, the method of wearing wearable sensors can affect sleep comfort and may lead to equipment failure due to power supply problems. Yousefi et al. uses flexible pads containing 2048 force sensors to collect pressure data on the bed and use machine learning classifiers to classify sleep postures [5]. This method may also affect the comfort of users. Non-contact methods usually use infrared, or depth cameras to identify sleep posture. Mohammadi et al. [6] uses infrared cameras to obtain human sleep images and transfer the pre-trained ResNet model to the sleep posture recognition task. Li et al. [7] use a deep multi-stream convolution neural network to process depth images and analyze sleep posture. However, vision-based methods need to obtain human body images, which will invade users' privacy. In addition, the system's performance may degrade when the user's body is obscured.

In recent years, radio frequency sensors has been widely studied in health monitoring, such as motion recognition [8] and physiological parameter monitoring [9]. The characteristics of non-contact monitoring and privacy protection of radio frequency sensors make them suitable for sleep posture monitoring. Yue et al. [10] proposed a sleep posture recognition system based on radio frequency (RF). They used a neural

This work was supported by the National Key Research and Development Project 2020YFC2003703, 2020YFC1512304, 2018YFC2001802, CAMS Innovation Fund for Medical Sciences (2019-I2M-5-019), and National Natural Science Foundation of China (Grant 62071451).

network to analyze the position heat map obtained by radar to identify sleep posture. However, their approach requires collecting data from new users to calibrate their models in order to maintain high performance in the use of new users. Liu et al. [11] proposed a sleep posture recognition system based on RFID. They used RFID to obtain user breathing signals in different directions to infer their sleep posture. The sleep posture recognition accuracy of their system is 98.94%. However, their system's sleep posture recognition accuracy dropped to less than 40% in tests for new users. Due to users' individual differences, the reflection of RF signals by different users is different. Therefore, a robust sleep posture recognition system is needed to reduce the impact of individual differences on the model's performance.

In this work, we propose a highly generalized sleep attitude recognition system based on FMCW radar. We propose a deep learning sleep posture recognition model based on multi-task learning and train the model with a data enhancement method to maintain high performance among new users. This method can realize high-precision sleep posture recognition without calibrating the model with new user data.In particular, this paper provides the following contributions:

1) We propose a sleep posture recognition system based on multi-task learning to improve the model's generalization by using domain knowledge of multiple tasks.
2) We propose a data augmentation method that combines geometric transformation and sample mixing to improve the model's performance.
3) We collected the data of 17 users for training and testing the model, and the proposed model achieved 0.935 F1 score of sleep posture recognition in the test of new users.

II. Radar System

A. Radar Device

In this work, we used TI's IWR6843ISK radar sensor. The sensor has three transmitting antennas and four receiving antennas, which can transmit and receive frequency-modulated continuous wave signals from 60 GHz to 64 GHz [12]. The azimuth field of view of the sensor is 120 degrees, and the elevation field of view is 30 degrees. We use Minimum Variance Distortionless Response (MVDR) to estimate the direction of arrival of the signal and obtain high-quality azimuth heat map [13]. Figure 1 shows the radar azimuth heat maps corresponding to the four sleep postures.

B. Pre-Processing

For the azimuth heat map, we calculate the mean value of the angle corresponding to each range coordinate and obtain the range distribution map. We select the range coordinate with the maximum value as the position of the human body to extract the region of interest. We extract the signals of 25 range coordinates before and after the human body position coordinates in the azimuth heat map. We use Min-Max normalization to normalize the value of the azimuth heat map to between 0 and 1.

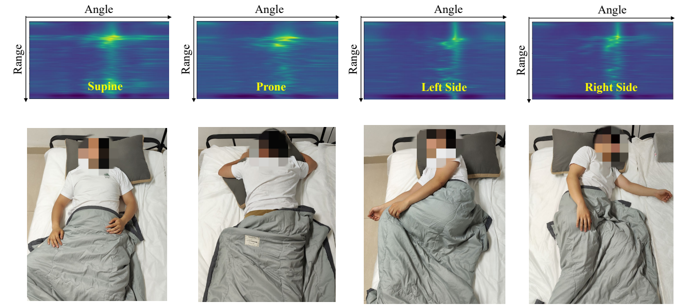

Fig. 1. Radar azimuth heat maps corresponding to the four sleep postures.

III. Sleep Posture Recognition Model

A. Model Overview

We aim to build a highly generalized sleep posture recognition system to identify new users' sleep posture recognition accurately. Figure 2 shows the proposed sleep posture recognition model. The model includes feature extractor F_e, decoder F_d, and sleeping posture predictor F_p. The feature extractor is composed of a ResNet network structure [14] based on 2D convolution to extract the spatial features of the azimuth heat map. The decoder is constructed by a 2D transposed convolution layer to reconstruct the features into the azimuth heat map. The predictor is an MLP [15] that predicts the sleep posture according to the features extracted by the feature extractor. The model performs the prediction task and reconstruction task simultaneously, making effective use of the knowledge of the two tasks and improving the generalization of the model.

B. Feature Extractor

The proposed feature extractor is a 2D convolution residual neural network. The feature extractor has four residual blocks to extract the spatial feature z of the input azimuth heat map x_{input}:

$$z = F_e(x_{input}) \tag{1}$$

The size of the convolution kernel in the feature extractor is 3 × 3, and the number of channels of the four residual blocks is 32,64,128,256, respectively. In addition, the dimension of the feature is reduced by setting the convolution step size to 2.

C. Decoder

The proposed decoder consists of four 2D transposed convolution layers, which are used to restore the spatial feature z to the original input azimuth heat map x'_{input}:

$$x'_{input} = F_d(z) \tag{2}$$

We use the mean square error (MSE) as the reconstruction loss of the decoder to evaluate the difference between the reconstructed azimuth heat map and the original azimuth heat map:

$$L_{rec} = ||x'_{input} - x_{input}||_2^2 \tag{3}$$

The feature extractor and decoder are optimized by MSE loss to learn the input information. The feature extractor extracts

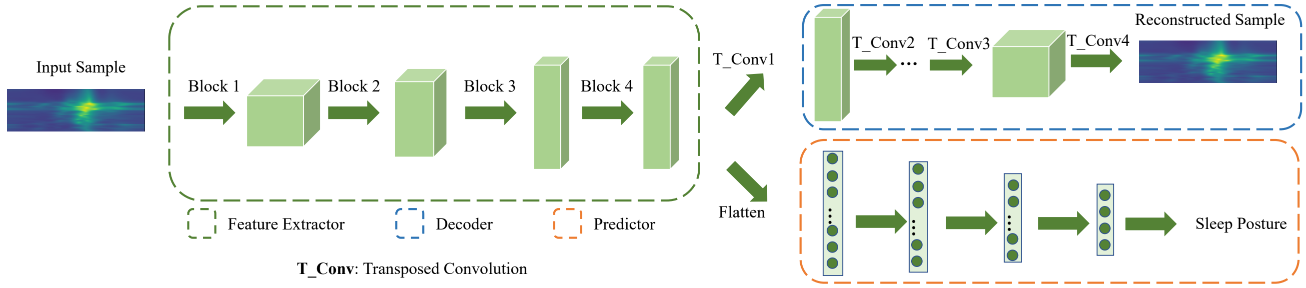

Fig. 2. The proposed multi-task learning framework.

the compressed representation of the azimuth heat map, and the spatial features contain the spatial information used to reconstruct the azimuth heat map.

D. Predictor

The predictor is a MLP with 4 layers. The predictor takes the spatial feature z as input to predict the user's sleep posture:

$$y^{'} = F_p(z) \tag{4}$$

Where $y^{'}$ is the sleep posture label. We use the Softmax layer to obtain the prediction probability of sleep posture and use cross entropy (CE) as the classification loss to evaluate the accuracy of sleep posture prediction:

$$L_{cls} = -\sum_{c=1}^{4} y^{'}(c)\log(y(c)) \tag{5}$$

Where c is the class index, $y(c) = 1$ indicates that the current sample belongs to class c. We use CE loss to optimize the model so that the features extracted by the feature extractor contain information that can distinguish sleep postures and predict sleep postures based on these features using the predictor.

We use two losses to optimize the model, and the total loss of the model is as follows:

$$L_{total} = L_{cls} + \alpha * L_{rec} \tag{6}$$

Where α is the weight coefficient. In this work, we set α to 0.5. Two losses are used to optimize the model during model training, and the model simultaneously learns classification tasks and reconstruction tasks. Through multi-task learning, the decoder and predictor can share information and complement each other to improve the accuracy of sleep posture recognition. In addition, multi-task learning can reduce the risk of overfitting the model on a task, thus improving the model's generalization ability.

E. Data augmentation

To enhance the generalization ability and improve the model's performance, we used data augmentation methods that combine geometric transformations and sample mixing. Firstly, we translated the azimuth heat map along the range and angle coordinate axes to simulate the user's signal when the range and angle changed. Secondly, we use the mixup data enhancement method to enhance the input signal. For two samples (x_i, y_i) and (x_j, y_j), the new samples are generated as follows:

$$\widetilde{x} = \lambda x_i + (1-\lambda)x_j \tag{7}$$

$$\widetilde{y} = \lambda y_i + (1-\lambda)y_j \tag{8}$$

where $\lambda \in [0,1]$ is the weight coefficient. By applying geometric transformations and mixup enhancement to the signal, data diversity can be increased, thereby improving the performance and generalization of the model.

IV. Experimental Setup

A. Dataset

We conducted data collection research using FMCW radar in the laboratory. The radar was installed above the subject's head and facing downward at an angle. The dataset includes 17 subjects, four females and 13 males. We collected continuous 5 seconds of signals as one sample, and we calculate an azimuth heatmap based on a sample. The data set contains a total of 1400 samples. After collecting each sample, we asked the subject to change direction or posture to collect the following sample. We provided subjects with quilts as coverings. We asked the subjects to collect data in their habitual posture during data collection.

B. Model Evaluation

We used leave-one-subject-out (LOSO) cross-validation in the experiment to test the model's performance in new users. We trained the model using data from 16 users and tested the model using data from the remaining one user. To evaluate the performance of the proposed model, we used the F1 score as the evaluation metric:

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{9}$$

V. Results and Discussions

The performance of the proposed sleep posture recognition model is shown in Table I. Table I shows the F1 scores for four sleep posture recognitions and the average F1 score. In addition, we tested the model's performance on the same users and new users. The proposed model has an F1 score of 0.935 in the test of new users and an F1 score of 0.960 in the test of the same users, as shown in Table I. When testing the model with data from the same users, the users in the test set are the

TABLE I
F1 SCORES OF THE MODEL IN SAME USER'S TEST DATA AND NEW USER'S TEST DATA.

Test People \ Posture	Supine	Prone	Left Side	Right Side	Mean
Same People	0.961	0.960	0.929	0.990	0.960
New People	0.942	0.929	0.900	0.969	0.935

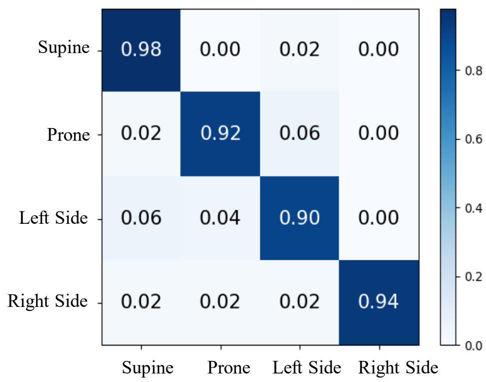

Fig. 3. The confusion matrix of the model.

same as those in the training set, so the model performs better. However, when testing the model with data from new users, the model's performance will be challenged due to differences in body shape and sleeping posture among each user.

In order to better analyze the accuracy of sleep posture recognition of the model, we show the confusion matrix of the model in Figure 3. The confusion matrix shows that the classification performance of the supine posture is the best, and the classification performance of the prone and left-side postures is poor. Unlike images, radar signals can only obtain the range and angle information of the target relative to the radar. Therefore, the radar signal contains less information that can be used to distinguish sleeping postures, and the model may be confused when distinguishing different sleeping postures.

We conducted ablation experiments to demonstrate the effectiveness of the proposed multi-task learning method and data augmentation method. Table II shows the results of the model ablation experiments. We demonstrated the model's performance after removing a certain module in the ablation experiments. As shown in Table II, compared with the model that does not use multi-task learning and data augmentation, the F1 score of the model using multi-task learning is increased by 0.013. In addition, the F1 score of the model using only data augmentation is increased by 0.054 compared to the model that does not use any module. The F1 score of the model using both multi-task learning and data augmentation is increased by 0.09 compared to the model that does not use any module. The results of the ablation experiments demonstrate that multi-task learning and data augmentation can effectively improve the performance and generalization ability of the model.

TABLE II
PERFORMANCE OF THE MODEL IN ABLATION EXPERIMENTS

Metrics \ Method	w/o M1 and M2	w/o M1	w/o M2	Full Model
F1 Score	0.845	0.858	0.899	0.935

M1: Data Augmentation M2: Multi-task Learning

VI. CONCLUSION

This study proposes a highly generalized sleep posture recognition model based on FMCW radar. The proposed method shows good results in four kinds of sleep posture recognition tasks. The model combines multi-task learning and data enhancement methods to realize highly generalized sleep posture recognition among new users. As far as we know, this is the first method to achieve high-accuracy sleep posture recognition without using new user data to calibrate the model. The proposed method shows the application potential of sleep posture recognition based on radar.

REFERENCES

[1] Neill, A. M., Angus, S. M., Sajkov, D., and McEVOY, R. D. (1997). Effects of sleep posture on upper airway stability in patients with obstructive sleep apnea. American journal of respiratory and critical care medicine, 155(1), 199-204.
[2] Lee, J. B., Park, Y. H., Hong, J. H., Lee, S. H., Jung, K. H., Kim, J. H., ... and Shin, C. (2009). Determining optimal sleep position in patients with positional sleep-disordered breathing using response surface analysis. Journal of sleep research, 18(1), 26-35.
[3] Gorecki, C., Closs, S. J., Nixon, J., and Briggs, M. (2011). Patient-reported pressure ulcer pain: a mixed-methods systematic review. Journal of pain and symptom management, 42(3), 443-459.
[4] Chang, Kang-Ming, and Shin-Hong Liu. "Wireless portable electrocardiogram and a tri-axis accelerometer implementation and application on sleep activity monitoring." Telemedicine and e-Health 17.3 (2011): 177-184.
[5] Yousefi, Rasoul, et al. "Bed posture classification for pressure ulcer prevention." 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, 2011.
[6] S. M. Mohammadi, S. Enshaeifar, A. Hilton, D. -J. Dijk and K. Wells, "Transfer Learning for Clinical Sleep Pose Detection Using a Single 2D IR Camera," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 290-299, 2021, doi: 10.1109/TNSRE.2020.3048121.
[7] Y. -Y. Li, Y. -J. Lei, L. C. -L. Chen and Y. -P. Hung, "Sleep posture classification with multi-stream CNN using vertical distance map," 2018 International Workshop on Advanced Image Technology (IWAIT), Chiang Mai, Thailand, 2018, pp. 1-4, doi: 10.1109/IWAIT.2018.8369761.
[8] Gurbuz, Sevgi Zubeyde, and Moeness G. Amin. "Radar-based human-motion recognition with deep learning: Promising applications for indoor monitoring." IEEE Signal Processing Magazine 36.4 (2019): 16-28.
[9] Shen, Hongming, et al. "Respiration and heartbeat rates measurement based on autocorrelation using IR-UWB radar." IEEE transactions on circuits and systems II: express briefs 65.10 (2018): 1470-1474.
[10] Yue, Shichao, et al. "BodyCompass: Monitoring sleep posture with wireless signals." Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies 4.2 (2020): 1-25.
[11] Liu, Chen, et al. "Beyond respiration: Contactless sleep sound-activity recognition using RF signals." Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies 3.3 (2019): 1-22.
[12] "Iwr6843isk", 2021, [online] Available: www.ti.com/tool/IWR6843ISK.
[13] Capon, Jack. "High-resolution frequency-wavenumber spectrum analysis." Proceedings of the IEEE 57.8 (1969): 1408-1418.
[14] He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.
[15] Baum, Eric B. "On the capabilities of multilayer perceptrons." Journal of complexity 4.3 (1988): 193-215.