Human Sleep Posture Recognition Based on Millimeter-Wave Radar

Conference Paper · September 2021

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Abstract—In this paper, we propose a robust human sleep posture recognition method via multidimensional feature representation and learning based on millimeter-wave (mmw) radar. Firstly, through time-frequency processing of the radar echo signal reflected by the human body, the range spectrum, Doppler spectrum, range-Doppler spectrum, azimuth angle spectrum and elevation angle spectrum of the estimated target are obtained. By setting a fixed frame window length and splicing the above feature spectrums, 5 single-channel 2D radar features are obtained, and combining them in parallel can get a variety of different multi-channel 2D radar feature representations. Finally, a lightweight multi-channel convolutional neural network (CNN) with Inception-Residual module (IRM) is designed to learn and classify multidimensional features. Extensive experiments were carried out using the developed mmw radar system, and a large amount of data was obtained to train and test the classifier. The results show that the proposed sleep posture recognition method can effectively distinguish different sleep postures and achieve better robust performance and generalization compared to other methods.

Index Terms—Sleep posture recognition, mmw radar, multidimensional feature representation, convolutional neural network, Inception-Residual module.

I. INTRODUCTION

In recent years, non-contact intelligent perception and recognition based on microwave radar technology has made breakthrough progress, which has important application value in these application scenarios, such as smart home [1], augmented reality-virtual reality (AR-VR) [2], human health monitoring [3], human behavior recognition [4], sleep monitoring [5], etc. At present, the continuous monitoring of sleep quality during sleep has received more and more attention [6], [7]. Research studies have shown that sleep quality is closely related to the state [8] and changes [9] of sleep postures. Continuous sleep postures monitoring can improve the quality of life while reducing the burden of nursing staff. Through continuous data collection and big data analysis, it will be fed back to users for health analysis, for bedridden patients, babies, the elderly, etc.

There are two main methods for monitoring vital signs of human sleep: contact and non-contact methods, which mainly realize physiological parameter perception (such as breathing rate, heart rate and blood pressure, etc.) and behavior recognition (such as turning over, getting in and out of bed, etc.). For the contact method, clothing (such as clothes [10], belts [11], etc.) or wearing wearable device (bracelets, watches [12], etc.) are used, through embedded motion sensors (accelerometers [13], gyroscopes [14], etc.) and biosensors (electroencephalography (EEG) sensors [15], heart rate sensors [16], blood pressure sensors [17], etc.) to realize the perception of body movement status and physiological parameters during sleep. For the non-contact method, it is mainly based on camera imaging [18], thermal imaging [19], depth imaging [20], WiFi [21], acoustic wave [22] and radar sensing [23], [24]. For camera imaging [18], you can use a simple camera to detect breathing frequency and body movement information during sleep with certain privacy violations and good light conditions. For thermal imaging [19], a thermal imager or infrared camera is used to detect the temperature changes due to breaths and body movement. Depth imaging [20] is a good alternative to cameras to avoid an invasion of privacy while it is costly. WiFi [21] can be applied to sleep posture detection while it requires a pair of WiFi devices to be placed at two sides of the bed and only works for limited postures. In [23], a millimeter-wave radar with one transmitter and one receiver is used, and the machine learning method of decision tree is used to implement the training and test of the classifier on the time-frequency domain statistical feature data corresponding to human sleep postures. However, the angle features cannot be measured and the only available radar echo features are statistical features and received signal strength (RSS). The recognition ability and expansion of human sleep action categories are limited, thus they cannot adapt to the

complex human sleep posture movement process. However, compared with other non-contact sensing methods, radar has incomparable advantages such as non-privacy intrusion, resistance to occlusion, and independence from light conditions. It can not only monitor vital signs during sleep but also identify body movement information.

This paper draws on the multidimensional feature hand-gesture recognition method in the article [25], and proposes a millimeter-wave radar-based human sleep posture recognition method based on multidimensional feature representation and learning. In [25], its Plain CNN only contains 3 convolutional layers and 2 fully connected layers. Based on the lightweight CNN, this article adds the IRM, which significantly improves the classification performance and generalization. The remainder of the paper is organized as follows. Section II presents the methodology. Experimental results and analysis are shown in Section III, which illustrates the effectiveness of the proposed method. Finally, we draw some conclusions in Section IV.

II. METHODOLOGY

This paper proposes a robust multidimensional feature representation and learning method based on millimeter-wave radar for human sleep posture recognition, which mainly includes three parts: frequency modulated continuous wave (FMCW) radar signal model, radar feature extraction and representation and lightweight convolutional neural network with IRM. Fig. 1 is the overall flow chart of the system.

A. FMCW Radar Signal Model

The normalized transmitted signal of FMCW radar is [26]

$$S_T(t) = e^{j2\pi\left(f_c t + \frac{K_s}{2} t^2\right)} \tag{1}$$

where t denotes the fast time within a chirp (a frequency modulation period), $-(T_s/2) <= t <= (T_s/2)$, f_c and $K_s = B/T_s$ denote to the center frequency and frequency slope within a chirp, where B and T_s denote the bandwidth and the duration time of a single chirp, respectively.

If the range of the assumed moving point target is R, the signal received by the radar is [26]

$$S_R(t) = \sigma \cdot e^{j2\pi\left((f_c+f_D)(t-\tau)+\frac{K_s}{2}(t-\tau)^2\right)} \tag{2}$$

where σ is proportional to the radar cross section, antenna gain and range attenuation, $\tau = 2R/c$ denotes the time of flight, c is the speed of light, $f_D = 2v_r/\lambda$ denotes the Doppler frequency shift, and v_r is the radial velocity. Fig. 2 is the illustration of a FMCW radar signal model.
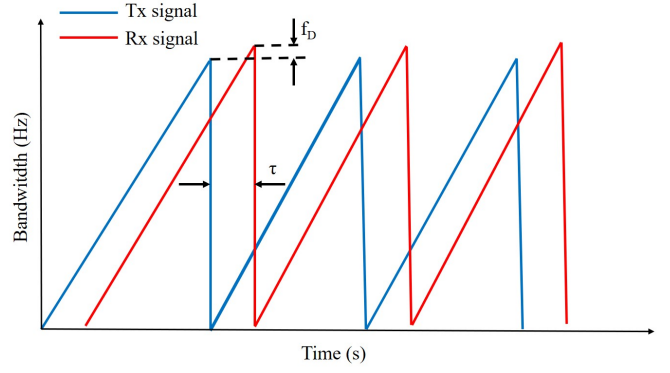

Fig. 2. Illustration of a FMCW radar signal model.

The intermediate frequency (IF) signal of the FMCW radar after mixing the received signal and the transmitted signal and low-pass filtering is [26]

$$\begin{aligned} S_{IF}(t) &= S_T^*(t)S_R(t-\tau) \\ &= \sigma \cdot e^{-j2\pi\left[f_c\tau - f_D(t-\tau)+\frac{K_s\tau}{2}(2t-\tau)\right]}. \end{aligned} \tag{3}$$

B. Radar Feature Extraction and Representation

Samples of the IF signal of the FMCW mmw radar can be arranged into a 3-dimensional tensor called radar data cube, which contains all the information provided by the radar device for a given time frame. The frequency shifts of interest, which reveal the target range, velocity and angle, can be extracted after applying a discrete Fourier transform (DFT) along the fast time, slow time and spatial dimension (beamforming). Fig. 3 is illustration of radar signal processing and radar feature extraction for human sleep posture recognition.
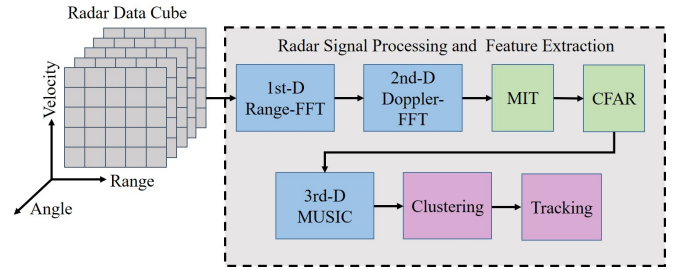

Fig. 3. Illustration of radar signal processing and radar feature extraction for human sleep posture recognition.

If there are multiple targets, their frequency domain range can be resolved by performing a range fast Fourier transform (Range-FFT) on the IF signals from all targets. The Doppler frequency shift is composed of a series of chirp frames, and then the range Fourier transform and Doppler Fourier transform (Doppler-FFT) can be performed on the frame time or slow time IF signal sampling data to obtain the range-Doppler maps [27].

The FMCW mmw radar sensor has multiple receiving antenna channels placed in azimuth and elevation, where beamforming method is used to solve for the angle of each
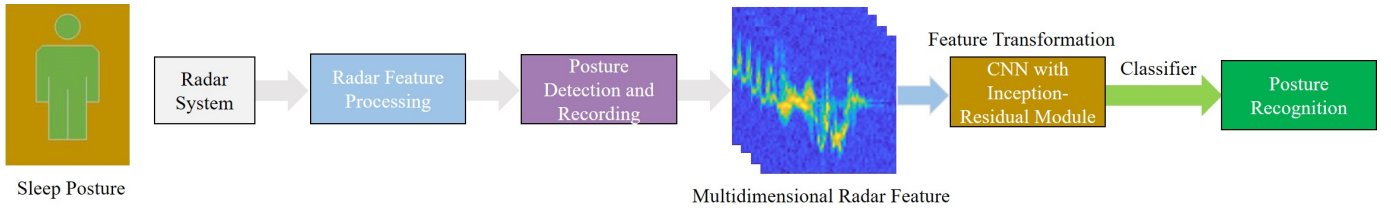
Fig. 1. Overall human sleep posture pipeline depicting feature transformation through CNN with Inception-Residual Module model to enable posture classification and recognition.

scattering point. After Range-FFT and Doppler-FFT processing are performed, followed by moving target indication (MTI) to discriminate a moving target against the static clutter points. To detect the scattering points from a noisy background, the constant false alarm rate (CFAR) detection of the range-Doppler spectrum distribution can obtain the distance indexes and velocity indexes of the single target. The Doppler distribution corresponding to the target distance index and the distance distribution corresponding to the target velocity index, respectively. The distribution is spliced by frame time to obtain Doppler spectrum and distance spectrum. Combining multiple azimuth or elevation virtual channels, complex amplitudes corresponding to the same distance index and velocity index, using the multiple signal classification (MUSIC) algorithm, the azimuth or elevation angle distribution can be obtained, and the azimuth or elevation angle spectrum can be obtained by splicing them according to the frame time.

The density-based spatial clustering of applications with noise (DBSCAN) [28] method is used to cluster these detected target scattering points. Finally, a Kalman filter [29] is applied to track the target to obtain spatio-temporal continuous spectral features [25].

C. Convolutional Neural Network with IRM

In this paper, based on the small pixel size of the radar feature image, the feature area is symmetrically distributed up and down or left and right, a 56-layer lightweight convolutional neural network is designed, as shown in Table I below, the input is multi-channel 2D images whose size is 64×64, and sent to the 3 convolutional layers with the convolution kernel sizes of 5×5, 3×3 and 3×3. The shallow features are extracted by increasing the number of channels of the feature maps, and then sent to 3×3 maximum pooling layer for downsampling, and then the obtained feature maps are sent to the self-designed IRM, as shown in Fig. 2, connecting two IRMs in series, followed by a fully connected layer, and finally a softmax layer.

It can be seen from Fig. 2 that the IRM has both the Inception network structure [30] and the Residual network structure [31]. The Inception module is shown in Fig. 5, combining the convolutional layers of 1×1, 3×3 and 5×5 and the maximum pooling layer of 3×3 constituting 4 parallel branches, which increases the width of the network and increases the adaptability of the network to the scale. The receptive fields of different branches are different and integrate the multi-scale

TABLE I
THE OUTLINE OF THE PROPOSED NETWORK ARCHITECTURE.

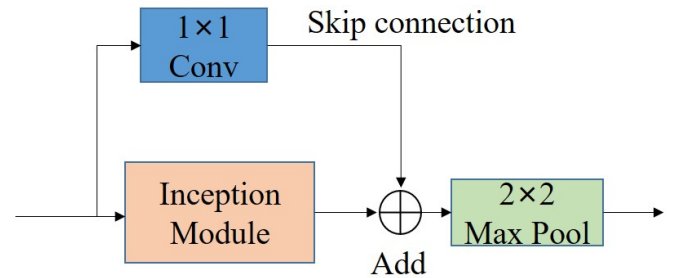| Layer(Type)	Filter Edge Size	Parameters
input	-	0
conv1	5	6464
bn1	-	128
relu1	-	0
conv2	3	73856
bn2	-	256
relu2	-	0
conv3	3	295168
bn3	-	512
relu3	-	0
max pool	3	0
2 × the IRM	As in Fig. 2	128864+96096
fc	-	3936264
softmax	-	0
Total Parameters	-	4537608

Fig. 4. The structure of Inception-Residual module.

information together. And it adds a 1×1 convolutional layer in front of the 3×3, 5×5 convolution layers and after the 3×3 maximum pooling layer to compress the model parameters and reduce calculation. Skip connection is one of the main ideas of Residual network design. By connecting a 1×1 convolutional layer to the Inception module to form a skip connection, which can solve the problem of gradient disappearance and gradient degradation caused by the increase of the number of network layers during the training process.

III. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experiment Environment

To evaluate our human sleep posture recognition architecture, we develop a real-time FMCW mmw radar system. As shown in Fig. 6, the system consists of two functional
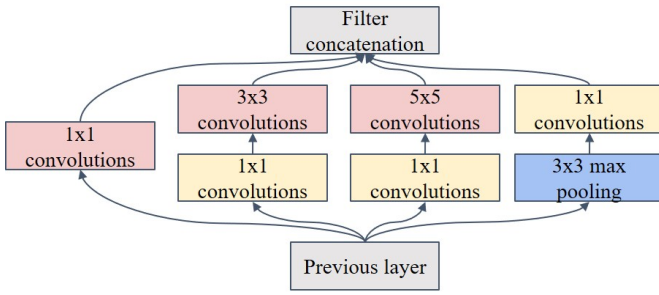
Fig. 5. The structure of Inception module.

Fig. 7. Block diagram of the real-time FMCW mmw radar system.

modules: an mmw radar evaluation board (TI's AWR1642-BOOST ODS development board) and a real-time high-speed data-capture adapter. The data-capture adapter captures raw ADC data from the radar chip by the low-voltage differential signaling (LVDS) interface and outputs raw data to a PC for further processing by a USB3.0 interface. The PC controls the radar system and performs the remaining radar feature extraction, multidimensional radar feature representation and deep learning classification. Block diagram of the real-time FMCW mmw radar system is shown in Fig. 7. As shown in Fig. 8, the real-time FMCW mmw radar system is placed on the side of the bed, where the horizontal distance between the sensor and the bed is 1.5 m to 5.44 m and the vertical distance between the sensor and the bed is 0.5 m. This setting makes the field of view (FOV) of the sensor slightly larger than the bed surface area to ensure that the sleep posture can be fully captured.

Fig. 8. Experimental environment setup.

parameters for the radar system are listed in Table III, which is calculated based on the procedure to determine the optimal configuration in [25].

TABLE II
PARAMETERS LIMITED BY THE RADAR HARDWARE.

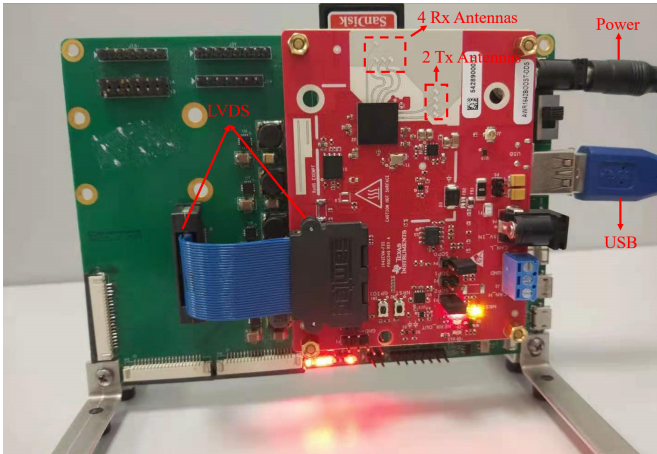| Radar Parameters	Values	Units
N_{TX}	2	-
N_{RX}	4	-
maximum sweep frequency range	77-81	GHz
B_{max}	4	GHz
r_{m-max}	20	m
K_{s-max}	150	MHz/μs
F_{s-max}	15	MHz
F_{s-min}	2	MHz

Fig. 6. Illustration of FMCW mmw radar experimental system based on TI's AWR1642-BOOST ODS development board.

The FMCW mmw radar equipment has 2 transmitted antennas and 4 received antennas. It supports a maximum frequency modulation bandwidth of 4 GHz from 77 GHz to 81 GHz. The main parameters of the radar are as follows, the feature length is set to 64 frames, the chirp number of per frame is 128, the sampling point number of each chirp is 64, and the frequency range is 77-81 GHz. The parameters limited by the radar system hardware are listed in Table II and the configuration
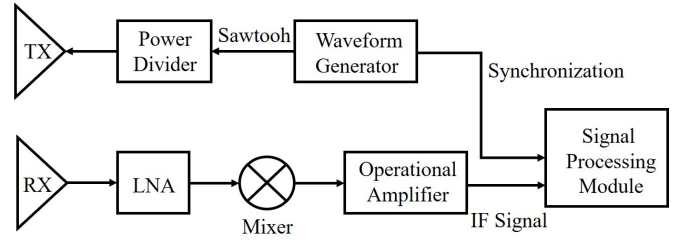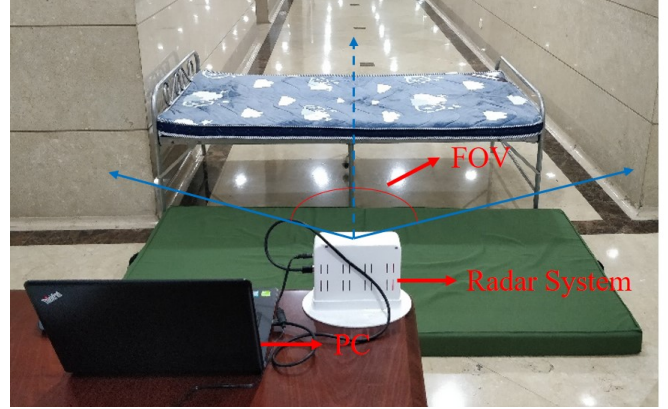
B. Human Sleep Posture Data Set Construction

The designed 8 kinds of human sleep-related postures are shown in Fig. 9, including (a) turning over near the radar, (b) turning away the radar, (c) getting out of bed, (d) going to bed, (e) getting up, (f) lying down on the bed, (g) waving in bed, (h) walking around the bed. Three experimental objects performed different human sleep postures within the field of view of 5 m from the radar. According to the process in section 2.1, 100 groups of 8 human sleep postures were obtained, and radar features were extracted from the raw radar data. The following 5 types of single-channel 2D radar feature images including Channel Average Range-Time-Map (CA-RTM), Channel Aver-

TABLE III
RADAR CONFIGURE PARAMETERS FOR HUMAN SLEEP POSTURE
RECOGNITION.

Radar Parameters	Values	Units
f_{rate}	40	Hz
N_{chirp}	128	-
N_{adc}	64	-
B	3.525	GHz
λ	3.8	mm
f_c	79.215	GHz
F_s	3.515	MHz
K_s	96.8009	MHz/μs
r_{max}	5.4430	m
r_{res}	0.0484	m
v_{max}	3.9978	m/s
v_{res}	0.1249	m/s

TABLE IV
COMPARISON OF MODEL GENERALIZATION AFTER TRAINING OF 2D
RADAR FEATURES OF DIFFERENT CHANNELS.

Radar Features	VA(%)	OA(%)	AA(%)	Kappa(%)
CA-RTM(1)	97.5	55.6	55.8	49.48
CA-DTM(2)	95.0	71.9	72.15	67.93
CA-RDTM(3)	91.2	79.1	79.01	76.06
EATM(4)	83.8	57.4	57.46	51.4
AATM(5)	86.2	65.4	65.3	60.48
2+4+5	95.1	82.9	82.88	80.47
3+4+5	94.4	79.5	79.48	76.55
2+3+4+5	**98.8**	**87.2**	**87.21**	**85.35**
1+2+3+4+5	92.5	72.9	73.08	69.12

As the comparison shown in Table IV, it can be concluded that the CA-DTM and CA-RDTM performed better using the proposed lightweight CNN with IRM among single-channel 2D radar features. It can be inferred that the two single-channel 2D radar features compared with other single-channel 2D radar features contain more motion information about human sleep postures and have achieved more prominent results after training. At the same time, the two single-channel 2D radar features are combined with AATM and EATM in parallel to constitute 3-channel 2D radar features and the result has significantly improved after training and test. And the parallel combination of CA-DTM, CA-RDTM, AATM and EATM forms a 4-channel 2D radar feature, which has achieved the best prominent result. The validation accuracy (VA), the OA, the AA and the Kappa reached 98.8%, 87.2%, 87.21% and 83.35% respectively. But the 5-channel 2D radar feature has not achieved the theoretically best result and worsened. From the comparison results of the five single-channel 2D radar features, it can be seen that the CA-RTM feature has the worst representation ability for human sleep-related postures, which reduces the generalization of the model of the 5-channel 2D radar feature. It can be infered that a single-channel 2D radar feature with poor representation ability will reduce the generalization of the entire model.

age Doppler-Time-Map (CA-DTM), Channel Average Range-Doppler-Time-Map (CA-RDTM), Elevation-Angle-Time-Map (EATM), Azimuth-Angle-Time-Map (AATM) can be obtained respectively. And then different multi-channel 2D radar features can be obtained respectively. The data set of each feature is composed of 3 objects × 8 categories × 100 image samples.
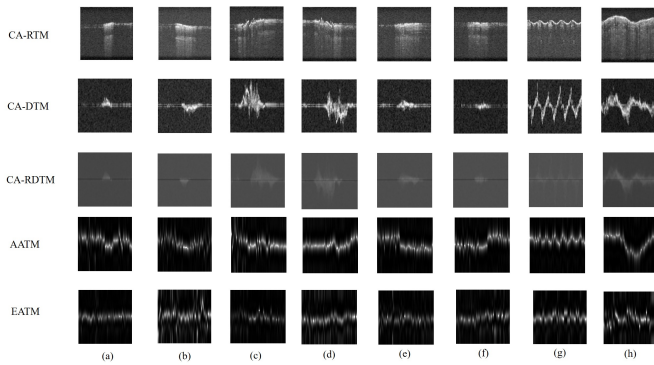

Fig. 9. Schematic diagrams of 5 basic single-channel 2D radar features of 8 human sleep postures.

C. Experimental Results

Set the corresponding channel number according to the different channel numbers of the 2D radar feature images of the input human sleep postures. The Adam optimization algorithm is used, the initial learning rate is 0.001, the learning rate drop factor is 0.9, the maximum number of epochs is 100, and the size of the mini-batch is 64, using GPU to accelerate training, in which the radar feature data set of one experimental object is used as the training set and the validation set (training set: validation set = 0.8 : 0.2), and the radar feature data set of the other two experimental objects is used as the test set to evaluate the different generalization of 2D radar feature images of the different channels and the generalization of different CNN models. To evaluate the performance of the proposed method, three common metrics are adopted, which are the overall accuracy (OA), the average accuracy (AA), and the Kappa coefficient (Kappa).

TABLE V
4 CHANNEL 2D RADAR FEATURE IMAGES (2+3+4+5) AFTER TRAINING
WITH DIFFERENT CNN STRUCTURES, THE MODEL GENERALIZATION
COMPARISON.

CNN Model	VA(%)	OA(%)	AA(%)	Kappa(%)
Plain CNN [25]	98.8	86.5	86.54	84.53
Inception V3 [32]	**99.4**	**87.2**	**87.72**	**85.34**
CNN with IRM	**98.8**	**87.2**	**87.21**	**85.35**

As the comparison shown in Table V, it can be concluded that the CNN with IRM designed in this paper has achieved better model generalization compared with the Plain CNN [25], and achieved almost the same test result as Inception V3 [32], and the model parameters are greatly reduced compared with Inception V3, which accelerates the model calculation and training process. And the memory occupied of the model is reduced by 5 times compared with Inception V3, which fully shows the superiority of the designed network structure.

IV. CONCLUSION

A robust human sleep posture recognition of multidimensional feature representation and learning method based on millimeter-wave radar is proposed in this paper. The designed multi-channel CNN with IRM can achieve good robustness to learn and classify multidimensional radar features of human sleep postures. By comparing a variety of different 2D radar features, it is found that their representation abilities of human sleep postures are different, resulting in different generalization performances. Through the parallel combination of multiple single-channel 2D radar features, the representation ability is enhanced, so the generalization performance also has a obvious improvement. In subsequent work, the research direction will be focused on the real-time sleep posture recognition of multiple persons.

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