



## Data Article

## Millimeter-wave radar based sleep posture transition dataset: SPT



Jinjun Liu<sup>a</sup>, Shaoqi Li<sup>b,\*</sup>, Naji Alhusaini<sup>a,\*</sup>, Wei Li<sup>b</sup>, Liang Zhao<sup>a</sup>, Pengfei He<sup>b</sup>

<sup>a</sup> Chuzhou University, 1528 Feng Le Avenue, Chuzhou, Anhui, China

<sup>b</sup> Anhui University, 111 Kowloon Road, Hefei, Anhui, China

## ARTICLE INFO

## Article history:

Received 10 February 2025

Revised 9 March 2025

Accepted 11 March 2025

Available online 15 March 2025

Dataset link: [sleep posture transition dataset \(Original data\)](#)

## Keywords:

Radar sensing

Sleep monitoring

Human activity recognition

Non-contact measurement

Biomedical signal processing

Health informatics

## ABSTRACT

In recent years, millimeter-wave radar technology has been widely used for non-invasive recognition and tracking of sleep postures due to its advantages of high accuracy, contactless operation, and ability to penetrate clothing. In order to promote the development of this field and to address the lack of large-scale, high-quality sleep posture transition datasets, this paper proposes a publicly available millimeter-wave sleep posture transition dataset. The dataset contains 20 volunteers (15 males and 5 females) aged between 19 and 25 years, with heights ranging from 1.55 m to 1.80 m and weights between 45 kg and 90 kg. Each participant performed seven different body position transition maneuvers in a preset order, yielding a total of 1400 samples. During the experiment, participants' postural changes were captured by a millimeter-wave radar system mounted on the side of the bed. This dataset provides valuable support for the optimization of sleep posture recognition algorithms, analysis of nocturnal behavioral patterns, and health monitoring.

© 2025 The Authors. Published by Elsevier Inc.

This is an open access article under the CC BY-NC license (<http://creativecommons.org/licenses/by-nc/4.0/>)

\* Corresponding authors.

E-mail addresses: [e22301245@stu.ahu.edu.cn](mailto:e22301245@stu.ahu.edu.cn) (S. Li), [naji@chzu.edu.cn](mailto:naji@chzu.edu.cn) (N. Alhusaini).

Specifications Table

Subject	Computer Sciences
Specific subject area	Millimeter-wave radar for non-invasive sleep posture transformation recognition and tracking.
Type of data	Raw:Raw radar data (.bin format) Image:Radar heat map (.png format)
Data collection	Data were collected using a millimeter-wave radar system (Texas Instruments IWR6843ISK-ODS) with a data acquisition board (DCA1000 EVM FPGA), a sensor carrier card (MMWAVEICBOOST), and control software (mmWave Studio). The radar was placed 1.5 m above the ground, aligned with the bed. Twenty volunteers (19–25 years, 45–90 kg) performed seven predefined posture transitions in a fixed order, each repeated 10 times, totaling 1,400 samples. A 10–15 s rest period was given between transitions. Volunteers started in a supine position at the bed center to ensure full radar coverage.
Data source location	Institution: laboratory of Chuzhou University Region: Anhui Country: China
Data accessibility	Repository name: Kaggle Data identification number: <a href="https://doi.org/10.34740/kaggle/dsv/10813077">https://doi.org/10.34740/kaggle/dsv/10813077</a> Direct URL to data: <a href="https://www.kaggle.com/dsv/10813077">https://www.kaggle.com/dsv/10813077</a>
Related research article	none

1. Value of the Data

- The dataset can be used to train and evaluate deep learning models for automatic sleep posture transition recognition. By improving non-invasive sleep monitoring technology, it supports applications such as smart sleep environments and intelligent healthcare solutions. Similar to how ECG datasets have contributed to heart rate monitoring in wearable devices, this dataset aids in refining millimeter-wave radar-based sleep tracking for real-time posture detection.
- By analyzing large-scale sleep posture transition data, researchers can identify patterns linked to sleep disturbances, posture-related discomfort, and long-term health effects. This dataset facilitates the study of sleep disorders, much like existing sleep datasets have helped in understanding conditions such as insomnia and sleep apnea. It supports public health initiatives by providing data for targeted interventions, such as posture-based sleep recommendations for individuals prone to sleep-related musculoskeletal pain.
- This dataset contributes to advancements in millimeter-wave radar technology and non-invasive health monitoring. It serves as a benchmark for improving radar-based sensing, similar to how thermal imaging datasets have enhanced human activity recognition. By integrating radar-based posture tracking into smart home products and wearable health devices, the dataset paves the way for real-time sleep assessment technologies that operate without physical contact.
- Open access to this dataset fosters collaboration across disciplines such as sleep medicine, biomedical engineering, and artificial intelligence. Similar to how medical imaging datasets have enabled global advancements in disease detection, this dataset provides a shared resource for sleep research. It enhances the comparability of findings across different studies, driving progress in sleep science, health monitoring, and smart sensing technology on an international scale.

2. Background

In today's fast-paced society, where work stress and daily responsibilities are ever-increasing, ensuring quality sleep has become an integral aspect of maintaining a healthy lifestyle. Medical research consistently emphasizes that adults should aim for 7 to 9 h of sleep per night to support optimal physical and mental well-being [1]. Achieving this recommended sleep duration is

linked to numerous health benefits, including enhanced cognitive function, improved mood, and reduced risk of chronic conditions [2]. However, recent studies highlight that sleep quality is not solely determined by duration but also significantly influenced by sleep posture.

Sleep posture plays a critical role in overall sleep quality and health. Poor sleeping positions have been associated with various health issues, such as snoring, sleep apnea, and musculoskeletal discomfort, including neck and back pain [3]. These issues can compromise sleep quality, leading to fragmented or insufficient sleep, which in turn negatively affects daytime functioning and long-term health outcomes [4]. Therefore, accurate identification and monitoring of sleep posture are crucial components of effective health management and disease prevention.

The importance of sleep posture monitoring is particularly pronounced for vulnerable populations, such as long-term bedridden patients and the elderly. Regular changes in sleep posture are essential for these individuals to prevent complications like pressure ulcers or bedsores, which arise from prolonged immobility and sustained pressure on specific body areas [5]. Automated monitoring systems that accurately track sleep posture transitions enable healthcare providers to intervene promptly, adjusting patients' positions to mitigate the risk of skin damage and associated complications [6].

Traditional methods for sleep posture monitoring, such as video surveillance or wearable sensor patches, have limitations, especially in terms of comfort and usability. These contact-based methods can be intrusive, potentially disturbing the natural sleep environment, and may not be feasible for all patients, particularly those with restricted mobility. This underscores the need for non-contact, non-invasive technologies capable of real-time monitoring without interfering with the sleeper [7].

Millimeter-wave radar technology has emerged as a promising solution to these challenges. Unlike traditional methods, millimeter-wave radar can continuously collect detailed posture transition data without physical contact, making it suitable for a wide range of users, including those who are immobile or sensitive to touch [8]. This technology operates effectively regardless of ambient lighting conditions and can penetrate clothing and bedding, providing accurate posture data even in the presence of body occlusion. By capturing continuous time-series data, millimeter-wave radar not only identifies static sleep postures but also tracks transitional phases with high precision, reducing errors associated with ambiguous posture definitions [9].

The continuous monitoring capabilities of millimeter-wave radar provide valuable insights into sleep patterns and nocturnal activities, supporting both healthcare professionals and users. For clinicians, this technology enhances the ability to assess and manage patients' sleep-related health conditions more accurately [10]. For users, it offers actionable information about their sleep behavior, enabling personalized adjustments to improve sleep quality [11]. Moreover, the non-invasive nature of this technology ensures minimal disruption to the sleep environment, fostering a more natural and restful sleep experience.

In conclusion, the collection and analysis of sleep posture transition data hold significant potential for advancing intelligent health monitoring systems. Millimeter-wave radar technology represents a transformative approach to sleep posture monitoring, offering real-time, non-contact solutions that enhance sleep quality and support personalized health management interventions. This advancement opens new avenues for improving sleep hygiene and overall well-being, making it a valuable tool in the pursuit of healthier lifestyles.

### 3. Data Description

The Fig.1 shows the overall flow of the sleep posture transition experiment using millimeter-wave radar. In this experiment, millimeter-wave radar sensors are used to capture the transition states between different sleep positions, and the raw radar data collected are stored as .bin format files. These raw data are then processed by a series of advanced signal processing algorithms to extract key features associated with the position transitions, and finally thermogram data are generated and stored in .png format. These heatmap data are used to further analyze the dy-

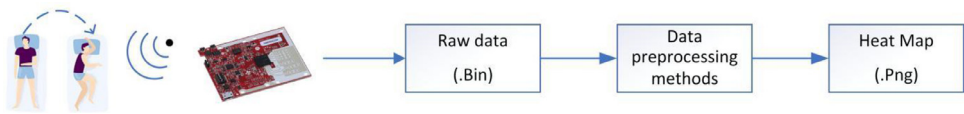


Fig. 1. Radar data acquisition and processing flow.

namic patterns of body position changes during sleep posture transitions, providing important feature support for subsequent sleep posture recognition tasks.

The dataset consists of two main parts: the first part is the raw radar data file, and the second part is the heat map file after signal processing. For the raw radar data files, users can apply different signal processing methods according to their specific needs so as to extract features and data results that meet the research objectives. As for the processed radar heatmap files, users can directly use these heatmap data for model training to further improve the performance and accuracy of the sleep posture recognition model.

3.1. Heatmap data presentation

In order to better understand and utilize this dataset, we selected two typical thermogram samples for display: micro-Doppler thermograms and distance-time thermograms. These thermograms not only visualize the physical properties under different sleep posture transition modes, but also provide researchers with valuable visual references that can help develop more accurate human motion detection algorithms. The experiment encompasses the following types of sleep posture transitions: supine to side-lying (SUSI), side-lying to supine (SISU), supine to prone (SUPR), prone to supine (PRSU), side-lying to prone (SIPR), prone to side-lying (PRSI), and side-lying to side-lying (SISI). These transition modes cover common posture changes during sleep, offering comprehensive data support for studying the physical characteristics of different posture transitions.

Fig. 2 shows the distance-time heatmaps for seven different sleep posture transition modes. In these heatmaps, the horizontal axis represents time (seconds), the vertical axis represents distance (meters), and the color intensity reflects the frequency of target changes relative to the radar position. These images vividly depict the dynamics of the distance between the human body and the radar sensor as it performs specific translational maneuvers. For example, in

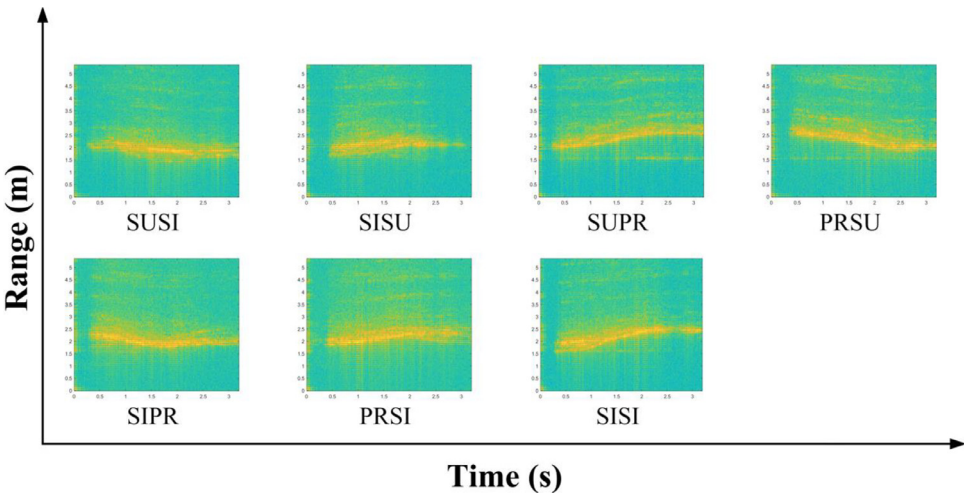
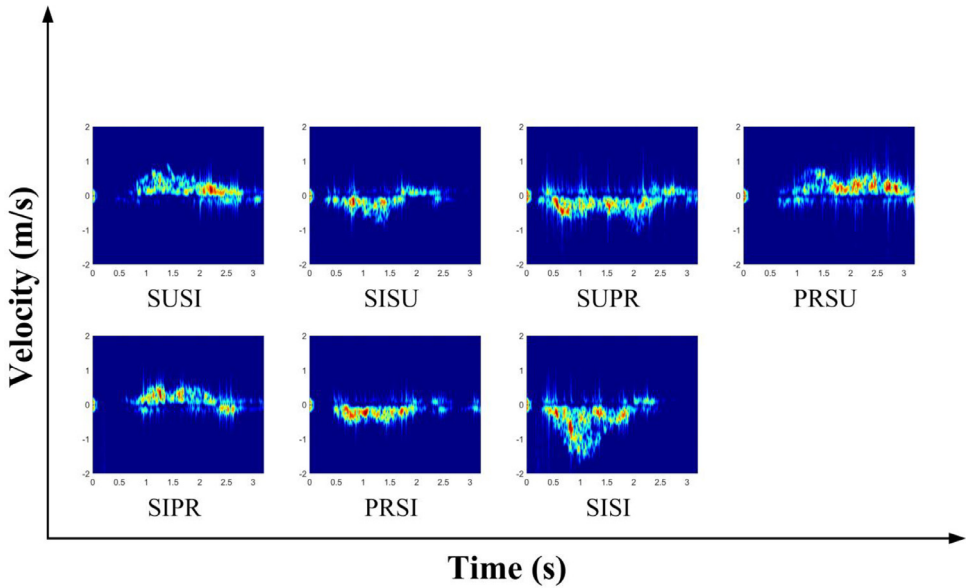


Fig. 2. Sample distance-time heatmap in different sleep posture transition modes.



**Fig. 3.** Sample microDoppler thermograms in different sleep posture transition modes.

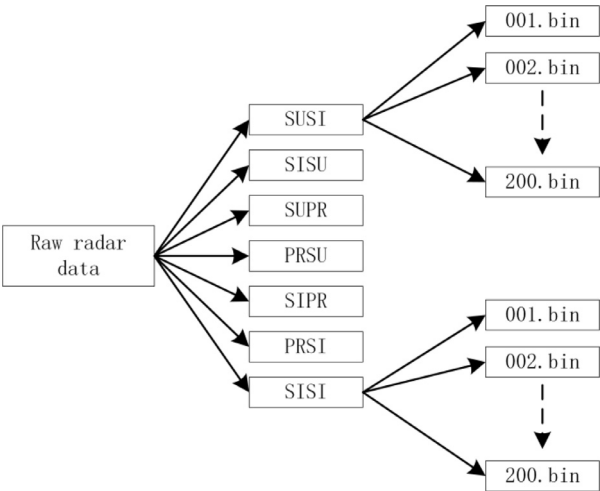
the SISU mode, the heatmap shows a distinct round-trip path that begins with a gradual decrease and subsequent increase in distance, graphically reproducing the process of rolling over from one side to the other. By comparing the heat maps of different modes, the unique spatial displacement characteristics of each can be found, which is important for recognizing sleeping posture transition modes.

Fig. 3 shows the micro-Doppler heatmaps for seven different sleep posture transition modes. The horizontal axis of each heat map represents time (seconds), the vertical axis represents velocity (m/s), and the color depth reflects the change in signal strength. By observing these thermograms, the velocity trends specific to each mode can be clearly identified. For example, in the SUSI mode, a gradual increase in velocity from zero to a peak and then a slow decrease can be seen, which reflects the complete transition cycle from rest to action and back to rest. Velocity change characteristics varied between modes, providing key clues to distinguish between various sleep transitions.

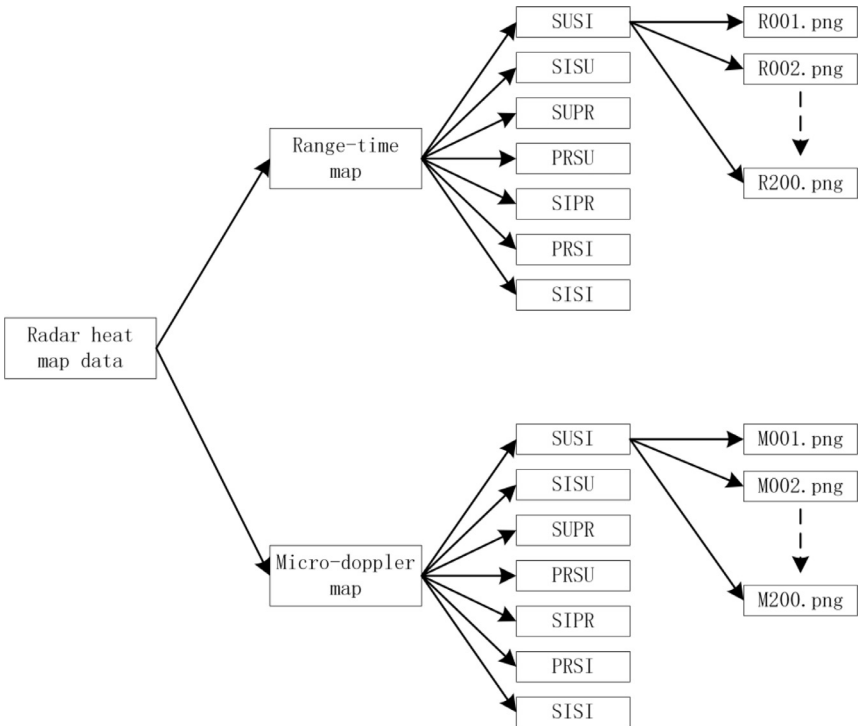
### 3.2. Data file description

This dataset focuses on the information recorded by millimeter-wave radar about transitions between different sleep postures, aiming to advance the development of human motion detection and sleep quality monitoring technologies. The whole dataset is carefully organized into two main categories: raw radar signals and processed thermogram data. For the raw radar signals, the data are stored in .bin file format, which contains the radar echo information in hexadecimal form; these files are categorized according to the seven different modes of attitude transitions (SUSI, SISU, SUPR, PRSU, SIPR, PRSI, SISI) and stored in corresponding subdirectories, and each subdirectory contains multiple .bin files with names consisting of three digits (e.g., 001.bin), which represents the specific experiment or sample number. The structure of the raw radar data storage in the first part of the dataset is shown in Fig. 4.

The dataset provides not only the raw radar signals, but also heat maps that have been processed to represent seven specific attitude transition modes. This allows researchers to directly utilize the heatmaps for analysis or to develop their own processing algorithms using the raw



**Fig. 4.** Dataset part 1: raw radar data storage structure.



**Fig. 5.** Dataset Part 2: Heat Map Data Storage Structure.

data. This dataset is intended to facilitate further research in the field of human motion detection and sleep quality monitoring. The second part of the dataset is the data-processed thermogram data, which is categorized into distance-time thermograms and micro-Doppler thermograms, and the storage structure of the second part of the dataset is shown in Fig. 5.

The second part of the dataset is dedicated to a detailed division of the processed thermogram data into two types of thermograms - distance-time thermograms and micro-Doppler thermograms. Each type of heat map corresponds to one of the seven specific sleep posture transition modes. These heat map data are stored in the form of PNG image files with the prefixes "R" and "M" for distance-time and micro-Doppler heat maps, respectively, followed by a three-digit sequence number (the "R" and "M" prefixes are for distance-time and micro-Doppler heat maps, respectively), followed by a three-digit sequence number (from 001 to 200). This design allows researchers to visualize and analyze the changes during various postural transitions to better understand human movement characteristics and their effects on sleep quality. In addition, since all the heat maps were generated according to a uniform standard, they are well comparable with each other, facilitating comprehensive analyses across samples and even across individuals. In conclusion, this part of the dataset provides a valuable resource for scientific research in related fields and is expected to promote more innovative results.

### 3.3. Data availability

The SPT dataset is publicly available and can be accessed by visiting the following: <https://www.kaggle.com/dsv/10813077>.

## 4. Experimental Design, Materials and Methods

### 4.1. Data collection process

To develop a robust and high-quality dataset for millimeter-wave radar-based sleep posture transitions, the experimental setup was meticulously designed to control both the conditions and the data collection process. The dataset comprises data from 20 healthy participants, including 15 males and 5 females. The participants' heights ranged from 1.55 meters to 1.80 meters, weights from 45 kilograms to 90 kilograms, and ages from 19 to 25 years. This specific age group was selected to maintain dataset representativeness while minimizing physiological variability related to age differences.

The millimeter-wave radar system was positioned on a table approximately 1.5 meters above the bed, ensuring the radar remained parallel to the bed surface. This arrangement minimized signal interference and accurately captured the participants' sleep posture changes. Before the experiment commenced, detailed instructions were provided to the participants to ensure they thoroughly understood the procedure and the required movements. At the start of the experiment, participants lay in a standard supine position at the center of the bed to ensure their entire body was within the radar's detection range (illustrated in Fig. 6). This standardized initial posture served as a consistent reference point for subsequent posture transitions, ensuring that the collected data was uniform and comparable across all participants.

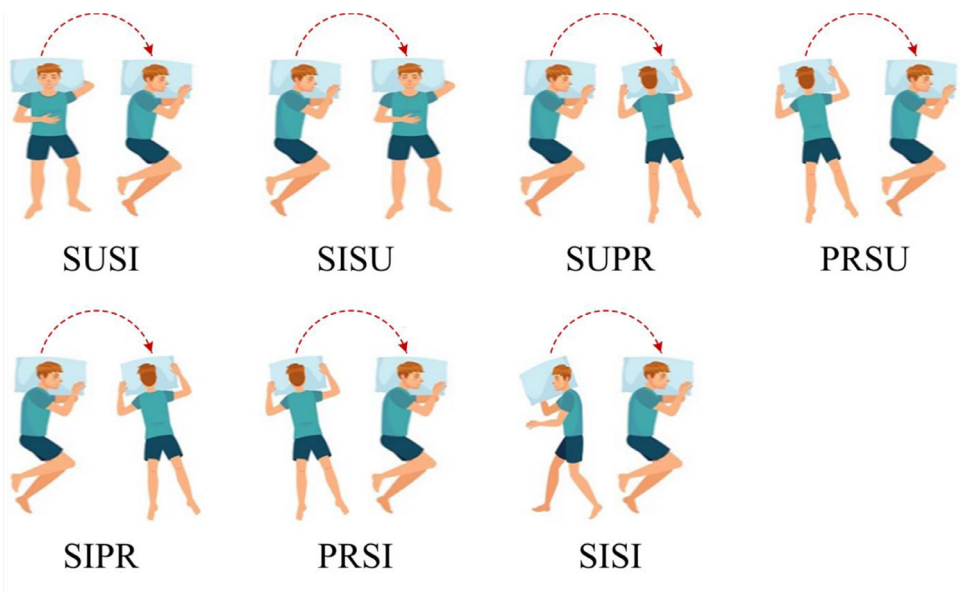
As shown in Fig. 7, volunteers performed 7 types of position transitions in a predetermined order: supine to side-lying (SUSI), side-lying to supine (SISU), supine to prone (SUPR), prone to supine (PRSU), side-lying to prone (SIPR), prone to side-lying (PRSI), and side-lying to side-lying (SISI). Between each postural transition, volunteers rested for 10 to 15 s and took four to five deep breaths to help the body return to a steady state and ensure that the radar system could accurately capture the characteristics before and after the postural change. In addition, deep breathing helped to reduce the volunteers' psychological stress, further improving the quality of the data.

### 4.2. Experiments materials

Each volunteer performed a total of 7 groups of movements in the experiment, with each group containing 10 samples. In order to simplify data processing and analysis, the left and



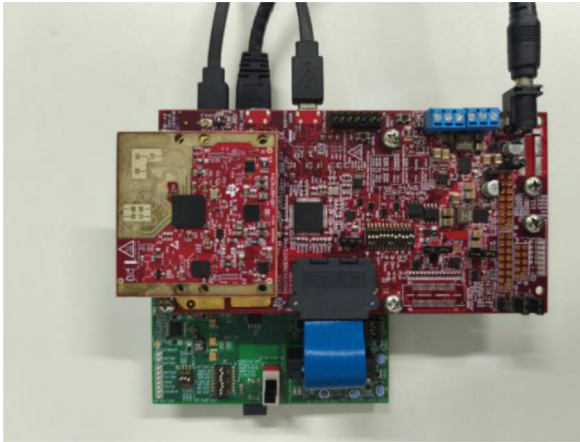
**Fig. 6.** Installation of the millimeter wave radar system during the experiment and test environment for volunteers.



**Fig. 7.** 7 Types of Sleep Posture Transition Schematic.

right side lying positions were uniformly categorized as side lying positions. After rigorous experimental design and manipulation, a total of 1,400 samples of data from 20 volunteers were collected. These data will help to reveal the different sleeping position transition patterns and their effects on sleep quality, providing solid data support for future sleep studies.

As shown in Fig.8, the millimeter-wave radar data acquisition system consists of three core modules: the millimeter-wave radar evaluation board (Texas Instruments IWR6843ISK-ODS), the millimeter-wave sensor bearer card platform (MMWAVEICBOOST), and the real-time high-speed data Acquisition Adapter (DCA1000). The IWR6843ISK-ODS evaluation board is the core component of the system, which generates and receives millimeter-wave signals through its built-in millimeter-wave radar chip.The MMWAVEICBOOST platform provides additional hardware support for the radar evaluation board, including power management and signal processing functions, which can significantly improve the overall performance and stability of the system. The



**Fig. 8.** Millimeter-wave Radar Evaluation Board.

DCA1000 adapter captures the raw ADC data from the radar chip through the Low Voltage Differential Signaling (LVDS) interface and transfers the data to the computer in real time through the USB3.0 interface, providing efficient and reliable support for subsequent data processing and analysis.

In order to adapt to the experimental requirements, the system is customized and configured. The antenna layout of the millimeter-wave radar includes one transmitting antenna and four receiving antennas. During data acquisition, 128 chirp signals are emitted cyclically for each frame of data, each chirp contains 512 sampling points, and 80 frames of data are recorded for each data acquisition. This configuration is able to accurately capture the subtle changes in human motion and meet the research requirements for sleep posture transition monitoring.

The raw radar data is stored in .bin files, with each file having a size of 81,920 KB. This size is determined by adjusting the radar acquisition parameters. The data acquisition of the millimeter-wave radar is performed in complex form, with both the I and Q channels being 16-bit. The radar is of the 1T4R type, meaning it has 1 transmitting antenna and 4 receiving antennas. Each chirp samples 512 points, and each frame contains 128 chirps, with a total of 8 frames of data collected. The data size for a single sample point is 32 bits, or 4 bytes. Based on the above parameters, the number of sample points is calculated as 20,971,520 (80 (number of frames)  $\times$  128 (number of chirps per frame)  $\times$  512 (number of sample points per chirp)  $\times$  1 (transmitting antenna)  $\times$  4 (receiving antennas)). Therefore, the size of the echo data is 83,886,080 bytes (20,971,520  $\times$  4 bytes). After processing, the final data size is 81,920 KB. By using the same equipment and hardware parameters, we can collect the same type of radar echo raw data again.

The specific radar parameter configuration is shown in Table 1.

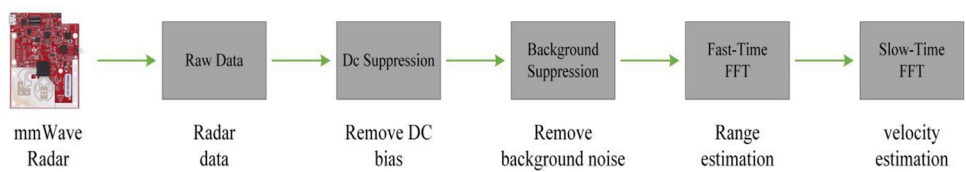
The range resolution (*RangeRes*) of a millimeter wave radar can be calculated as follows by the formula:

$$\text{RangeRes} = \frac{c}{2B} \quad (1)$$

Where B is the signal bandwidth determined by  $B = K_s \times T_c$ ,  $T_c = T_s \times \text{Nadc}$ ,  $T_s$  is the sampling interval of the radar signals, and Nadc is the number of ADC samples for each chirp. The above formula can be used to derive the radar's range resolution *RangeRes*, from which the optimal experimental observation distance can be determined. Since the radar acquisition system is installed at a distance of about 2 m from the bed surface, data within the range of 2 m to 4 m are prioritized in the processing of the distance dimension to ensure that the changes in the sleeping posture on the bed are accurately captured.

**Table 1**  
Detailed parameterization of the radar system.

Parameters	Values	Unit
$f_c$	60	GHz
$T_c$	102.4	us
B	3.854	GHz
$K_s$	5000	ksp/s
ADCStartTime	6	us
IdleTime	10	us
RampEndTime	110	us
Nadc	512	
Nchirps	128	
RangeRes	0.0418	m
VelRes	0.316	m/s



**Fig. 9.** Overview of the radar data processing steps, including DC bias correction, noise reduction.

The velocity resolution (VelRes) is determined by the following equation:

$$VelRes = \frac{\lambda}{2 \times T_c \times Nchirps} \tag{2}$$

Where  $\lambda = \frac{c}{f_c}$  is the wavelength corresponding to the center frequency  $f_c$ , and Nchirps is the number of chirps contained in one frame of signal. The velocity resolution VelRes of the millimeter wave radar is calculated to be related to  $T_c$  and Nchirps. Due to the relatively slow change of the human body's velocity during sleep posture transition, the velocity resolution is set to 0.316 m/s to ensure that it meets the experimental requirements, and the relevant parameter configurations are optimized based on the hardware performance limitations.

4.3. Data preprocessing methods

This research utilizes FMCW radar sensors to capture human movements critical for sleep posture transition analysis. The signal processing framework is depicted in Fig. 9. By transmitting a chirp signal, which is a linearly frequency-modulated continuous wave, the radar extracts the distance and velocity of targets. The received signal is mixed with the transmitted chirp to generate the radar's raw data.

Initial data processing involves removing DC bias and suppressing background noise to minimize unwanted interference. The raw data is structured as a matrix  $S[p, q]$ , where  $p$  corresponds to slow-time samples (related to velocity) and  $q$  to fast-time samples (related to distance). Fast-Time FFT and Slow-Time FFT are subsequently applied to derive range and velocity features. This pipeline, through noise reduction and Fourier transformation, enhances the radar signal's quality, enabling detailed analysis of sleep posture transitions.

Removing DC bias is vital for eliminating static noise components unrelated to the target. This involves computing the mean value along the slow-time axis of  $S[p, q]$  and subtracting it from the original data to yield  $S'[p, q]$ :

$$S'[p, q] = S[p, q] - \frac{1}{P} \sum_{p=0}^{P-1} S[p, q] \tag{3}$$

where  $P$  denotes the number of slow-time samples. This process effectively removes the DC component from each distance unit, preparing the data for further processing.

Following DC correction, background noise suppression is conducted to highlight dynamic target movements such as human motion. The mean value of  $S'[p, q]$  along the fast-time axis is calculated and subtracted, resulting in the refined signal  $T[p, q]$ :

$$T[p, q] = S'[p, q] - \frac{1}{Q} \sum_{q=0}^{Q-1} S'[p, q] \quad (4)$$

where  $Q$  is the number of fast-time samples. This step reduces background noise, emphasizing the dynamic features of the target.

Fast-Time FFT is applied to each column of  $T[p, q]$  (fast-time samples) to transform the time-domain signal into the frequency domain, extracting range information. The target distance  $d$  is computed as follows:

$$d = \frac{c \cdot f_b}{2K} \quad (5)$$

where  $c$  is the speed of light,  $f_b$  is the beat frequency, and  $K$  is the frequency modulation slope. The FFT result produces a Range-Time Map (RTM), visualizing the target's location changes over time.

To derive velocity information, the STFT is applied to signals within each range unit, capturing motion characteristics over time:

$$V(\tau, f) = \sum_{n=-\infty}^{\infty} v[n] \cdot h[n - \tau] \cdot e^{-j2\pi f n} \quad (6)$$

where  $V(\tau, f)$  is the STFT output at time  $\tau$  and frequency  $f$ ,  $v[n]$  is the input signal, and  $h[n - \tau]$  is the window function. The relationship between Doppler frequency  $f_D$  and the radial velocity  $v_r$  of the target is given by:

$$v_r = \frac{f_D \cdot \lambda}{2} \quad (7)$$

where  $\lambda$  is the radar signal wavelength. Analyzing  $f_D$  results in a Doppler-Time Map (DTM), revealing the target's velocity characteristics over time.

## Limitations

None

## Ethics Statement

The authors confirm that all participants provided informed consent prior to data collection. No personally identifiable information was recorded, and all data was fully anonymized to protect participant privacy. The study adhered to ethical research practices, and no formal ethical committee approval was required under the regulations applicable to this work.

## CRedit Author Statement

**Jinjun Liu:** Methodology, Original draft preparation. **ShaoQi Li:** Data collection, Writing, Data processing, Writing- Reviewing and Editing. **Naji Alhusaini:** Validation. **Wei Li:** Supervision, Investigation. **Liang Zhao:** Data curation. **PengFei He:** Data curation and manuscript proofreading.

## Data Availability

[sleep posture transition dataset \(Original data\)](#) (Kaggle).

## Acknowledgement

This research is supported by the Science and Technology Plan Project of Chuzhou City, with project number 2023CI003.

## Declaration of Competing Interest

This study was conducted jointly by Anhui University and Chuzhou College. All data collection and analysis were conducted under strict scientific and ethical guidelines. The authors were not funded or influenced by any commercial company or interest group. None of the participants in the study were consultants, directors, or shareholders of any company, nor did they receive any compensation for the content of this study. Nor have they received any financial benefit from any related commercial entity. In addition, in the process of creating and using the dataset, laws and regulations related to privacy protection and data security were strictly adhered to in order to ensure the legally compliant use of the data. Should any competing interests arise after the submission of this paper, the corresponding author will immediately notify the journal and take appropriate measures.

## References

- [1] K. Ramar, R K Malhotra, K A Carden, et al., Sleep is essential to health: an American academy of sleep medicine position statement, *J. Clin. Sleep Med.* 17 (10) (2021) 2115–2119.
- [2] L. Matricciani, Y S Bin, T. Lallukka, et al., Rethinking the sleep-health link, *Sleep Health* 4 (4) (2018) 339–348.
- [3] S C Liew, T. Aung, Sleep deprivation and its association with diseases-a review, *Sleep Med.* 77 (2021) 192–204.
- [4] S. Mansfield, K. Obraczka, S. Roy, Pressure injury prevention: a survey, *IEEE Rev. Biomed. Eng.* 13 (2019) 352–368.
- [5] T. Paillard, Detrimental effects of sleep deprivation on the regulatory mechanisms of postural balance: a comprehensive review, *Front. Hum. Neurosci.* 14 (2023) 1146550.
- [6] D. Kirshner, K. Spiegelhalter, R T Shahar, et al., The association between objective measurements of sleep quality and postural control in adults: a systematic review, *Sleep Med. Rev.* 63 (2022) 101633.
- [7] S M M Islam, V M Lubecke, Sleep posture recognition with a dual-frequency microwave Doppler radar and machine learning classifiers, *IEEE Sens. Lett.* 6 (3) (2022) 1–4.
- [8] M. Piriyaikitakongkij, P. Warin, P. Lakhan, et al., SleepPoseNet: multi-view learning for sleep postural transition recognition using UWB, *IEEE J. Biomed. Health Inform.* 25 (4) (2020) 1305–1314.
- [9] B. Luo, Z. Yang, P. Chu, et al., Human sleep posture recognition method based on interactive learning of ultra-long short-term information, *IEEE Sens. J.* 23 (12) (2023) 13399–13410.
- [10] M. Fan, W. Brahim, X. Zhang, et al., Leveraging FMCW radar for monitoring on-bed states of human presence, posture, and motion, in: 2023 IEEE Smart World Congress (SWC), IEEE, 2023, pp. 1–8.
- [11] R. Robbins, A. Seixas, L. Walton Masters, et al., Sleep tracking: a systematic review of the research using commercially available technology, *Curr. Sleep Med. Rep.* 5 (2019) 156–163.