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FMCW Radar-based Sleep Posture Monitoring Through Logic and Deep Learning Methods

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***Abstract*—In this study, we introduce a non-invasive approach for sleep posture monitoring based on Frequency-Modulated Continuous Wave (FMCW) radar. In contrast to prior research, our method employs a novel logic-based approach to analyze sleep postures during the entire sleep process using only one radar device. The inspiration behind our proposal is the observations made regarding the downsampling calculation, which allows the Range, Doppler, Azimuth, and Elevation-Time (RT, DT, AT, and ET) map to focus more on breathing movement. Subsequently, a logical approach is proposed based on these data to recognize supine, prone, and side postures, and then further separate side postures into left and right postures. In addition, a custom Convolutional Neural Network (CNN) model is designed to compare the results with the performance of the logic-based method. Our evaluation was conducted using data collected from 10 subjects, which showed promising results. The logic-based method demonstrates high accuracy, achieving an overall accuracy of 98.11% for 3-category classification and 94.79% for 4-category classification. For the CNN-based approach, our model attains an accuracy of 93.25% in 4-category classification under subject-independent evaluation. Compared to the CNN-based method, the logic-based method provides better accuracy, but the CNN-based approach has the advantage of real-time applicability. These results underscore the effectiveness of our non-invasive FMCW radar-based sleep posture monitoring system.**

***Index Terms*—FMCW radar, sleep posture, logic, deep learning, CNN, WRTFT.**

I. Introduction

Sleep accounts for almost one-third of our lives, and some improper sleep postures may also be fatal for some specific patients. Therefore, sleep posture monitoring is of great importance for analyzing the quality of sleep and improving overall quality of life. Traditionally, previous research heavily relied on cameras [1] [2], pressure sensors [3] [4], and wearable devices [5] [6] for sleep posture recognition. However, these conventional methods exhibit inherent limitations, particularly in scenarios with low light, concerns about privacy intrusion, potential discomfort from the pressure sensor array, and disturbances caused by wearable devices. In response to these challenges, Radio Frequency (RF) technology was considered as a promising alternative.

Several RF-based devices have been explored for sleep posture monitoring in prior research. Some studies have utilized wireless sensor networks, such as Wi-Fi [7] [8] transmitters and receivers as their monitoring devices. While others have employed radar sensor, like pulse radar [9], continuous wave (CW) radar [10] [11], ultra-wideband [12] [13] radar, Impulse Radio (IR)-UWB radar [14], and Frequency-Modulated Continuous Wave (FMCW) radar [15] [16] [17]. Comparing different RF-based options, although most of them got good results, they each have their limitations. Wi-Fi sensors typically require a device pair for transmission and reception. Pulse radar requires higher energy levels to ensure wave reflection and reception. On the other hand, FMCW radar has the advantage of integrating both transmitting and receiving antennas on a single PCB board and continuously emitting waves with lower energy requirements. In terms of multiple target recognition, FMCW radar outperforms CW radar because of its frequency modulation over time, simplifying the process of identifying multiple targets. Consequently, FMCW radar was adopted as the sensor for this study.

Several studies have utilized radar for sleep posture recognition or joint location estimation on the bed. One impressive work [11] achieved a 100% accuracy using two Doppler radars and employing logic based on I and Q signals from both radars. For the study based on FMCW radar, [15] employed an azimuth range heatmap and a fully connected neural network to recognize four sleep postures, achieving a relatively high accuracy of 94%. Building upon this, [16] incorporated additional radar data, including Doppler, range, and elevation angle, and employed a convolutional neural network (CNN) with iterative reweighted multivariate (IRM) regression to train their model. Their objective was to identify common activities associated with sleep postures, ranging from TO (Turning Over) to WAB (Wake Arms on Bed), achieving an overall accuracy of 87.2%. A more recent work [17], conducted in 2023, which is Argosleep, used raw data from two FMCW radar sensors and trained a CNN model to estimate the positions of 21 major joints. Remarkably, they achieved a mean absolute error (MAE) of only 6.22 cm.

However, these studies exhibit several major problems. Some studies have relied on the use of multiple radar devices, which may present practical challenges in terms of cost, implementation complexity, and user convenience. Furthermore, most of the studies only rely on simple clutter removal, which can only filter the reflection from the static

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things. However, in real-world scenarios, there are often dynamic elements such as vibrating furniture, including desktop PCs, refrigerators, and fans, which can introduce unwanted interference into the received radar signals.

To tackle these problems, our approach aims to utilize a single FMCW radar for posture classification based on logic, while still maintaining a reliable level of accuracy. Our approach uses a special calculation to extract the chest location and movement information from the subject. By leveraging a single radar device, we provide a more practical and cost-effective solution for posture detection in sleep monitoring applications.

Overall, the proposed solution effectively overcomes the challenges of the requirement of multiple radar devices and reflections from other interference reflections. To summarize, this paper makes the following contributions:

- Using a downsampling calculation method that filters other interference, including vibrating furniture or moving limbs, only captures information related to respiratory movements, including location and Doppler.
- Employing a logic-based approach using a single radar device for sleep posture recognition, which offers a more practical and cost-efficient solution for sleep posture monitoring.

The remainder of this paper is structured as follows. Section II provides an in-depth explanation of the proposed sleep posture classification method. Section III offers insight into the experimental setup and protocol employed in our research, and Section IV presents the evaluation results and accompanying discussions. Section V concludes the paper with a comprehensive summary, as well as a prospective future work.

II. Sleep Posture Monitoring Method

In this section, a comprehensive overview of the sleep posture classification pipeline is presented. As depicted in Fig. 1, the pipeline is mainly separated into three steps: namely data pre-processing, target data extraction, and sleep posture classification.

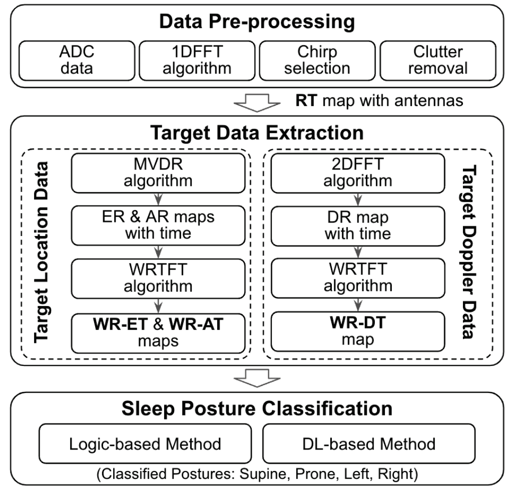

Fig. 1. Sleep Posture Monitoring Pipeline.

A. Data Pre-processing

The first stage in the overall pipeline is data pre-processing, where the radar data is prepared for further analysis. The core signal of FMCW radar is a waveform called a chirp, which is a sinusoid whose frequency increases linearly over time. The basic transmitting unit of FMCW radar is a frame that contains a constant number of chirps according to the configuration. After transmitting and receiving the chirps, the transmitted and received chirps are combined to create an Intermediate Frequency (IF) signal, which still remains in the analog domain. This IF signal will be further converted by the Analog Digital Converter (ADC) to form the ADC raw data. A One-Dimensional Fast Fourier Transform (1DFFT), also called range-FFT, is subsequently applied to extract the range information. This step segments the collected data into discrete distance intervals, often referred to as "range bins". Since radar sends multiple chirps per frame, we only select one chirp for each frame that still meets the requirements of our proposed solution and may provide further information that may fit our proposal. Furthermore, clutter removal is incorporated to eliminate reflections from static objects in the environment, such as floors, walls, and furniture. Because the radar used has 12 virtual antennas, the final output of this stage is the filtered RT map with respect to each antenna.

B. Target Data Extraction

In the second stage of our method, more advanced processing techniques are employed to extract detailed information. Unlike conventional studies, our approach involves a difference from utilizing all chirps within a frame for data calculation. Instead, we selectively extract one chirp per frame and leverage a two-second data interval for comprehensive data computation. This approach enables us to primarily capture information related to respiratory movements, including location and Doppler data.

The left part is to detect the location information of the target. To achieve this, the Minimum Variance Distortionless Response (MVDR) algorithm is used to implement beamforming. This process scans each Angle of Arrival (AoA), allowing us to extract the angle information of the target by the higher energy in the spectrum. This will enable the precise localization of targets within the radar's field of view by using range-azimuth-elevation coordinates. The output of the MVDR algorithm is the Elevation-Range (ER) and Azimuth-Range (AR) map with time. To emphasize the dynamic changes in AoA over time, the AR and ER maps with time were further fed into a Weighted Range-Time-Frenquency Transform (WRTFT) algorithm [12]. The final output of this task is the Weighted Range (WR)-Azimuth-Time (AT) and Elevation-Time (ET) maps.

The right part of the step is dedicated to the extraction of the target movement information. To accomplish this, the Doppler-based computation is employed. Leveraging the Range-Time (RT) information obtained in the previous step, the data is further processed using a Two-Dimensional FFT (2DFFT), also known as Doppler-FFT, to generate Doppler-Range (DR) maps over time. Similar to the approach taken in the extraction of location data, following the 2DFFT, the DR maps with time are subsequently fed into the WRTFT algorithm, to analyze the dynamic change in Doppler characteristics over time, which is the WR-DT map.

C. Sleep Posture Classification

The final stage is to classify the four sleep postures. The radar data used are maps of WR-DT, RT, WR-AT, and WR-ET, as shown in Fig. 2, in which S represents supine, R represents right, P represents prone, and L represents left. To address this classification, our study employed two distinct methods: logic-based and Deep Learning (DL)-based approaches, shown in Fig. 3 and Fig. 4, respectively. The logic-based method utilizes the features of radar data in different maps, whereas the DL-based method relies on the learning ability with labeled data.

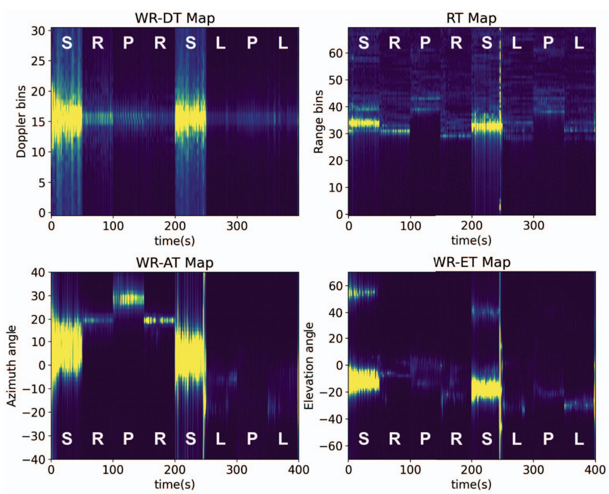

Fig. 2. Example of WR-DT, RT, WR-AT, WR-ET maps.

1) Logic-based Method: The proposed logic involves obtaining the DR and AR maps over time. To visualize and then find the features of change in Doppler, azimuth angle, and elevation angle. WRTFT is used to derive the WR-DT and WR-AT matrix (P_{dt} and P_{at}). In addition, the RT matrix (P_{rt}) is extracted from a single channel to obtain the RT information. After incorporating Doppler information into the DT map through weighted adjustments (resulting in wP_{dt}), a subject location can be determined using the dominant angle bin ($< Ap_k >$) and the nearest peak in the range profile ($< Rp_k >$). From the observation of the maps, it can be seen that the maps from the supine posture always have the highest power with a relatively unstable formation. Therefore, the power of the WR-DT map is analyzed by calculating the standard deviation of each second of data and subsequently computing the mean across all seconds within each posture. The outputs are gathered in $< Md_k >$. The power of the RT and WR-AT maps are focused on the map data surrounding the

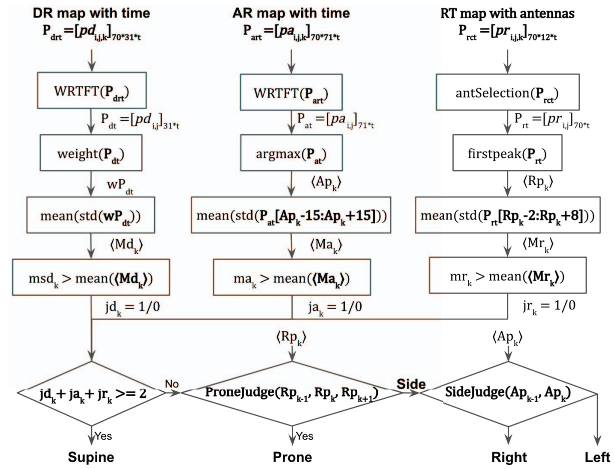

Fig. 3. Logic-based Method Flowchart.

dominant angle bin $< Ap_k >$ and the nearest range bin $< Rp_k >$ which is $[< Ap_k > -15, < Ap_k > +15]$ and $[< Rp_k > -2, < Rp_k > +8]$, then doing the same analysis process, the outputs are gathered in $< Ma_k >$, and $< Mr_k >$ respectively.

The logic-based method identifies the supine (S) posture using the mean value of the sleep record as a trigger. The current posture data (msd_k, ma_k, mr_k) is compared with the mean value of all the posture data of the sleep process ($< Md_k >$, $< Ma_k >$, $< Mr_k >$). When at least two of the current posture data parameters exceed their respective mean values, the posture is classified as Supine (S), while other postures are temperately considered as Prone (P). To further distinguish between the Prone (P) and Side posture is based on the change in the nearest peak range. If this range gets closer, the posture is considered as a side posture because the shoulder is closer this time. Subsequently, the side posture is separated into Left (L) and Right (R) postures based on the change in azimuth angle.

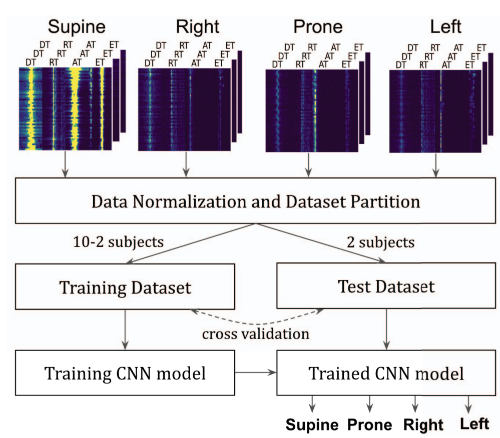

Fig. 4. DL-based Method Flowchart.

2) Deep Learning-based Method: After designing the logic-based method, we want to further compare the results

TABLE I
CNN ARCHITECTURE AND SETTING

Layers	Parameters
Input	$50 * (31(D) + 70(R) + 71(A) + 71(E))$
Conv1D	32, 3, activation = relu
MaxPool1D	pool_size = 2, strides = 2
Conv1D	64, 3, activation = relu
MaxPool1D	pool_size = 2, strides = 2
Flatten	-
Dense	64, activation = relu
Dropout	0.5
Dense	32, activation = relu
Dropout	0.5
Dense	classes, activation = softmax

of the classification based on Deep Learning (DL).

As depicted in Fig. 4, the DL-based approach in our study capitalizes on the 2D vector format of the data resembling an image. Given this similarity, Convolutional Neural Network (CNN), known for its proficiency in image recognition, is employed. Before initiating the deep learning process, data preprocessing and dataset partitioning are performed. During preprocessing, the DT, RT, AT, and ET data are normalized individually and then combined into a unified 2D matrix. The matrix is further saved in its original numerical format within a CSV file for each sleep posture.

As illustrated in Table I, the input data for the CNN model is matrix data structured as $50\times$ (31(D)+70(R)+71(A)+71(E)). The architecture of the model comprises two convolutional layers interspersed with two max pooling layers. The max pooling layer is a pooling operation that calculates the maximum value for patches of a feature map and uses it to create a downsampled (pooled) feature matrix, leaving only robust features. To avoid overfitting during model training, a dropout layer with a 0.5 ratio is employed. Subsequently, dense layers are used to learn the relationships between the high-level features extracted by the pooling layers using a ReLU activation function. The final dense layer is sized according to the number of sleep postures learned, and each value represents the possibility of classifying the current input to the specific posture, using the softmax activation function.

As for dataset partitioning, various window sizes (WS), sliding window sizes (SL), and different combinations of the data were experimented with. To train the CNN model, a subject-independent method is used. The data from 8 subjects were used for training, and the data from the remaining 2 subjects were used for testing. The subject-wise cross-validation is further conducted to evaluate and compare the accuracy of the parameters and data used.

III. EXPERIMENT SETUP AND PROTOCOL

In this section, the experiment scene, devices used in the experiment, and data collection protocol are presented.

The FMCW radar utilized in this study is the IWR6843ISK-AOP [18] board by Texas Instruments (TI), coupled with a data-capture adapter, the DCA1000EVM [19]. A summary of the most important data collection parameters is presented in Table II. In terms of the configuration, the radar provides a range resolution of 0.04m, allowing for a fine detection of the target location. The radar system is connected to a PC running the TI mmWave Studio application [20] for raw data acquisition. The PC is equipped with an Intel Core i7-12700 CPU and an NVIDIA RTX 3060 GPU, along with 32GB of RAM. Subsequently, the collected data is processed and analyzed using a custom Python program within our laboratory.

TABLE II
RADAR PARAMETERS USED IN EXPERIMENTS

Parameter	Value	Unit
Operating Frequency	60-64	GHz
Chirp per frame	16	-
Frame per second	16	-
ADC samples	256	-
Range resolution	0.04	m
Azimuth FoV	+/-60	deg
Elevation FoV	+/-60	deg

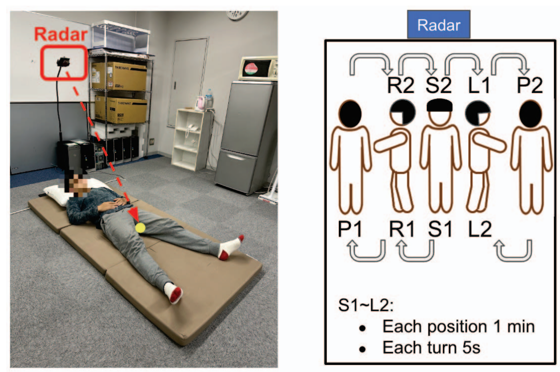

Fig. 5. Experiment Scene and Data Recording Protocol (S: Supine, R: Right, P: Prone, L: Left).

As depicted in Fig. 5, in this experimental setup, the radar was positioned at the head of the bed, approximately 1.35 meters away from the mattress, simulating an installation on the wall above the bed to provide an optimal viewpoint of the subject. The radar was oriented to face the center of the bed, with a tilt angle of 53 degrees.

The experimental procedures were conducted in our laboratory, involving 9 male participants and 1 female participant. During the experiment, participants were instructed to assume various body postures while lying on the bed, with each posture requiring them to maintain stillness for a duration of 1 minute. The experiment consisted of two main segments: one involving turning to the right and the other to the left. The "turning to the right" segment included one supine posture, two right-side postures, and one prone posture. Similarly, the "turning to the left" segment comprised one supine posture, two left-side postures, and one prone posture. As a result, each posture in the experiment was represented by a 2-minute data segment.

IV. Evaluation Results and Discussion

This section provides a summary of the accuracy results of the sleep posture classification achieved using the logic-based method and compares it with the DL-based results. Furthermore, an in-depth discussion is included.

A. Logic-based Method

Based on the logical framework outlined in Fig. 3, its performance is first evaluated using 3-category recognition, as depicted in Fig. 6. The results achieved an accuracy of 98.11% for the 3-category recognition. Notably, all supine postures in the experimental records were correctly identified. However, errors primarily occurred in distinguishing prone postures, which were occasionally misclassified as supine. A detailed analysis of each experiment highlighted a correlation with body mass; subjects with higher body mass exhibited more powerful breathing, leading to false recognition of prone as supine. Given the excellent results achieved through 3-category recognition, we extended our analysis to 4-category recognition, as shown in Fig. 7. The overall accuracy for 4-category recognition reached 94.79%. As the proposed logic focuses on distinguishing left and right from side postures, the recognition results for supine and prone postures remained consistent. However, errors in prone posture recognition also affected the accuracy of left and right recognition because the logic relies on changes in the azimuth angle and previous postures.

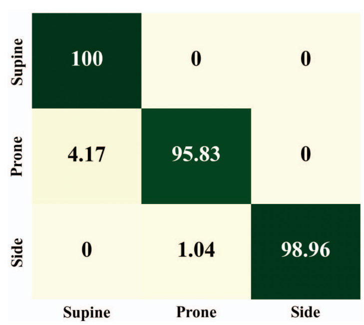

Fig. 6. Confusion Matrix for 3-category classification based on logic.

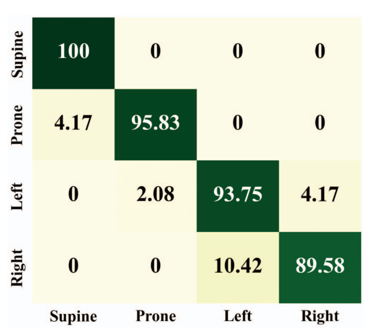

Fig. 7. Confusion Matrix for 4-category classification based on logic.

TABLE III
Accuracy Results Across Experiment Types

Experiment type	WS	SL	Acc.
WS-wise (DREA)	15s	1s	90.03%
	20s	1s	91.55%
	30s	1s	**92.11%**
SL-wise (DREA)	30s	3s	91.52%
	30s	5s	**93.13%**
DRA	30s	5s	**94.38%**
DRE	30s	5s	87.3%
DR	30s	5s	64.38%
DA	30s	5s	64.38%
D	30s	5s	53.75%
R	30s	5s	77.5%

WS: window size, SL: sliding window size

B. Deep Learning Method

In the CNN approach, the model is trained using various window sizes (WS), sliding window sizes (SL), and subject-independent data. The results are presented in Table III, where D represents the WR-DT map, R denotes the RT map, E signifies the WR-ET map, and A represents the WR-AT map. From the results, it is observed that increasing the window size led to improved performance. Similarly, as the sliding window size increased, the results also demonstrated improvement. Regarding data combination, the DRA combination gives the best results, surpassing the performance achieved when using all four data sources. After extensive experimentation with WS-wise, SL-wise, and different data combinations, the optimal parameters are identified: a window size of 30 seconds, a sliding window size of 5 seconds, and the DRA data combination, resulting in an accuracy of 94.38%. To provide a comprehensive evaluation of the model under the optimal parameters, we employed an advanced 5-fold Cross-Validation (CV) approach. The resulting confusion matrix, depicted in Fig. 8, demonstrates an overall accuracy of 93.25%.

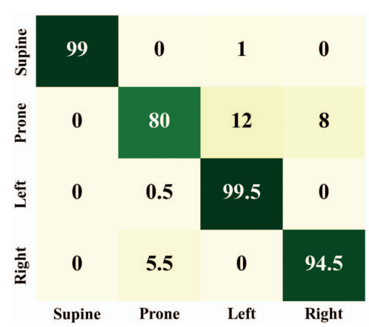

Fig. 8. Confusion Matrix for the Cross Validation Result Using DRA data with 30s WS and 5s SL.

C. Comparison Between Logic-based & DL-based methods

Upon comparing the outcomes achieved using the CNN approach, it is found that the logic-based approach achieved slightly higher accuracy in posture recognition, which is 94.79% for a four-posture classification task. Nevertheless, the CNN approach offers a distinct advantage in terms of real-time applicability. This is attributed to the configuration of a window size below 30 seconds and a sliding window size below 5 seconds, enabling swift posture recognition. In contrast, the logic approach necessitates post-recording analysis of the entire sleep session. Each approach possesses its own set of strengths and limitations, and the choice between them should follow the specific requirements of the intended application.

V. Conclusion and Future Work

In this study, an innovative sleep posture monitoring solution leveraging FMCW radar technology is introduced. Our primary contribution lies in the development of a novel calculation method for creating DT, AT, and ET maps that specifically focus on chest movement, including location and movement information. Additionally, this novel approach enables us to design a reliable sleep posture classification solution using just a single radar device based on a logic method. A CNN model is also designed to compare the performance of the logic-based method with that of the deep learning method. Finally, a comprehensive set of experimental evaluations was conducted to determine the reliability of the proposed approach.

The experimental results underscore the remarkable performance of our innovative approach, particularly in the sleep posture classification using logic-based methods, achieving good sleep posture classification based on logic-based methods, achieving an accuracy of 98.11% in 3-category classification and 94.79% in 4-category classification. In comparison, the DL-based approach also exhibited noteworthy results, with our model achieving an accuracy of 93.25% in a 5-fold cross-validation evaluation.

Although the results show the promising outcomes of this study, there are still limitations that future work should aim to improve. Currently, our logic-based posture recognition method faces challenges in effectively distinguishing between side postures (left and right). In addition, our current approach can only monitor the sleep posture of a single subject. To develop a comprehensive sleep posture monitoring system, it is necessary to address multi-subject scenarios in future research. In addition, to transition our system toward a marketable product, the development of a professional Graphical User Interface (GUI) is essential. The integration of cloud computing resources is also a logical step, ensuring usability and accessibility for widespread use.

References

[1] M. H. Li, A. Yadollahi, and B. Taati, "Noncontact vision-based cardiopulmonary monitoring in different sleeping positions," *IEEE journal of biomedical and health informatics*, vol. 21, no. 5, pp. 1367–1375, 2016.

[2] A. Ren, B. Dong, X. Lv, T. Zhu, F. Hu, and X. Yang, "A non-contact sleep posture sensing strategy considering three dimensional human body models," in *2016 2nd IEEE International Conference on Computer and Communications (ICCC)*. IEEE, 2016, pp. 414–417.

[3] A. Mineharu, N. Kuwahara, and K. Morimoto, "A study of automatic classification of sleeping position by a pressure-sensitive sensor," in *2015 International Conference on Informatics, Electronics & Vision (ICIEV)*. IEEE, 2015, pp. 1–5.

[4] M. Enayati, M. Skubic, J. M. Keller, M. Popescu, and N. Z. Farahani, "Sleep posture classification using bed sensor data and neural networks," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2018, pp. 461–465.

[5] K. Van Laerhoven, M. Borazio, D. Kilian, and B. Schiele, "Sustained logging and discrimination of sleep postures with low-level, wrist-worn sensors," in *2008 12th IEEE International Symposium on Wearable Computers*. IEEE, 2008, pp. 69–76.

[6] Z. Zhang and G.-Z. Yang, "Monitoring cardio-respiratory and posture movements during sleep: What can be achieved by a single motion sensor," in *2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*. IEEE, 2015, pp. 1–6.

[7] X. Liu, J. Cao, S. Tang, and J. Wen, "Wi-sleep: Contactless sleep monitoring via wifi signals," in *2014 IEEE Real-Time Systems Symposium*. IEEE, 2014, pp. 346–355.

[8] Y. Gu, X. Zhang, Z. Liu, and F. Ren, "Wifi-based real-time breathing and heart rate monitoring during sleep," in *2019 IEEE Global Communications Conference (GLOBECOM)*. IEEE, 2019, pp. 1–6.

[9] V. P. Tran and A. A. Al-Jumaily, "Non-contact doppler radar based prediction of nocturnal body orientations using deep neural network for chronic heart failure patients," in *2017 International Conference on Electrical and Computing Technologies and Applications (ICECTA)*. IEEE, 2017, pp. 1–5.

[10] K. Higashi, G. Sun, and K. Ishibashi, "Precise heart rate measurement using non-contact doppler radar assisted by machine-learning-based sleep posture estimation," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2019, pp. 788–791.

[11] J. E. Kiriazi, S. M. Islam, O. Borić-Lubecke, and V. M. Lubecke, "Sleep posture recognition with a dual-frequency cardiopulmonary doppler radar," *IEEE Access*, vol. 9, pp. 36 181–36 194, 2021.

[12] M. Piriyajitakonkij, P. Warin, P. Lakhan, P. Leelaarporn, N. Kumchaiseemak, S. Suwajanakorn, T. Pianpanit, N. Niparnan, S. C. Mukhopadhyay, and T. Wilaiprasitporn, "Sleepposenet: Multi-view learning for sleep postural transition recognition using uwb," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 4, pp. 1305–1314, 2020.

[13] D. K.-H. Lai, L.-W. Zha, T. Y.-N. Leung, A. Y.-C. Tam, B. P.-H. So, H.-J. Lim, D. S. K. Cheung, D. W.-C. Wong, and J. C.-W. Cheung, "Dual ultra-wideband (uwb) radar-based sleep posture recognition system: Towards ubiquitous sleep monitoring," *Engineered Regeneration*, vol. 4, no. 1, pp. 36–43, 2023.

[14] V. Nguyen, A. Q. Javaid, and M. A. Weitnauer, "Detection of motion and posture change using an ir-uwb radar," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2016, pp. 3650–3653.

[15] S. Yue, Y. Yang, H. Wang, H. Rahul, and D. Katabi, "Bodycompass: Monitoring sleep posture with wireless signals," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 4, no. 2, pp. 1–25, 2020.

[16] T. Zhou, Z. Xia, X. Wang, and F. Xu, "Human sleep posture recognition based on millimeter-wave radar," in *2021 Signal Processing Symposium (SPSympo)*. IEEE, 2021, pp. 316–321.

[17] A. Adhikari and S. Sur, "Argosleep: Monitoring sleep posture from commodity millimeter-wave devices," in *Proceedings IEEE INFOCOM*, 2023.

[18] T. Instruments. (2023, Jan) Iwr6843isk-ods. [Online]. Available: https://www.ti.com/tool/IWR6843ISK-ODS

[19] ——. (2023, Jan) Dca1000evm. [Online]. Available: https://www.ti.com/tool/DCA1000EVM

[20] ——. (2023, Jan) mmwave studio. [Online]. Available: https://www.ti.com/tool/MMWAVE-STUDIO