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Dual ultra-wideband (UWB) radar-based sleep posture recognition system: Towards ubiquitous sleep monitoring

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A R T I C L E I N F O

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A B S T R A C T

Sleep posture monitoring is an essential assessment for obstructive sleep apnea (OSA) patients. The objective of this study is to develop a machine learning-based sleep posture recognition system using a dual ultra-wideband radar system. We collected radiofrequency data from two radars positioned over and at the side of the bed for 16 patients performing four sleep postures (supine, left and right lateral, and prone). We proposed and evaluated deep learning approaches that streamlined feature extraction and classification, and the traditional machine learning approaches that involved different combinations of feature extractors and classifiers. Our results showed that the dual radar system performed better than either single radar. Predetermined statistical features with random forest classifier yielded the best accuracy (0.887), which could be further improved via an ablation study (0.938). Deep learning approach using transformer yielded accuracy of 0.713.

1. Introduction

Obstructive sleep apnea (OSA) is a common sleep breathing disorder with a prevalence ranging from 9% to 38% which increased with advancing age [1]. Poor sleep quality by OSA reduces the quality of life, results in excessive daytime sleepiness, and has been an independent risk factor for motor vehicle accidents [2–4]. It was estimated that OSA produced a healthcare cost of USD$30 billion, workplace productivity loss of USD $86.9 billion, and accidents or injuries cost of USD $6.5 billion per year in the United States [5]. Other co-morbidities of OSA include cardiovascular disease, stroke, metabolic syndrome, and premature death [2,5].

Poor sleep posture or inadequate support might induce pressure on the soft tissues of the cervical region [6]. Supine sleep posture aggravates OSA since gravity induces a posterior prolapse of the tongue and soft palate against the pharyngeal wall, while a prone position affects respiration through pressure on the thorax [7]. On the contrary, lateral posture alleviates the problem by enlarging the retropalatal and retroglossal airways [8]. Sleep posture is a modifiable risk factor of sleep apnea and sleep posture training was proven to improve sleepiness, psychometry, hypopnea, and oxygen desaturation [9]. Therefore, posture recognition or tracking is one of the important sleep assessment components for estimating the severity and rehabilitation progress of patients with sleep breathing disorders [10].

Different types of sleep monitoring systems have been developed for examining sleep postures and behaviors. Pressure measuring mat and indentation bars were exploited for sleep posture or behavior characterization with machine learning [11–13] and were used to evaluate sleep quality [13]. Nevertheless, the optical approach was preferable since it is less expensive, more robust, and nonintrusive [14,15]. A traditional sleep test involves video-camera taping of the whole sleep process and annotated behaviors manually [16]. This approach was adopted together with polysomnography (PSG) to investigate sleep-related leg movement and breathing disorders [16]. The frequency of posture changes was also counted in a labor-intensive manner by watching the video records of sleep [17]. Recently, advanced algorithms, machine learning and deep learning models were applied to classify sleep postures on Red-Green-Blue (RGB) or Red-Green-Blue-Depth (RGB-D) camera images/videos with satisfactory performance [18–20]. Nonetheless, the optical approach is affected by occlusions (such as a blanket, and caregivers), variations in ambient light [21], and privacy concerns [22].

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Radar or radiofrequency signal could be a potential solution to the problem and has been used in previous studies. CW radar is the most common type of radar which sends and receives frequency signal continuously [23]. However, it's incapability to differentiating heartbeat and respiratory signals restrains the application of vital sign monitoring. FMCW shares similar weakness, which cannot separate the heartbeat and respiratory signals. It is also vulnerable to noise from random body movement and radar incoherence induced micro-doppler signature [24]. Ultra-wideband Radar (UWB) radar have been proposed to monitor and measure vital signs and body movements [25,26]. It allows multi-objects detection and range estimation with lower energy [24]. Although it is a strong candidate for sleep assessment, multi-radar and multi-modality applications are not popular.

Machine learning and deep learning techniques have been previously applied to radar signals for classification. Islam, et al. [27] measured breathing pattern by fast Fourier transform feature extraction, followed by support vector machine (SVM), while another research group proposed XGBoost, logistic regression, and random forest on UWB signal to predict respirational diseases [28]. For deep learning methods, there are two major classifier types including convolutional neural network (CNN) and time series-based classifiers. For CNN classifiers, the one-dimensional series of radar signal will be stacked into a two-dimensional matrix, and further duplicated thrice to mimic a red-green-blue (RGB) image input [29]. For the time series-based classifier, every signal frame will be treated as an input and sequentially fed into the model [30]. Long-short-term memory (LSTM) is the most common classifier due to its capability to reduce vanishing gradient problem [31]. Besides, due to rising popularity on attention-based transformer model, attention layer technique has been integrated with LSTM to improve model performance [32].

The objective of this study was to develop an UWB dual radar system for sleep posture recognition. We endeavored to classify four common sleep postures (supine, log left, log right, and prone) with different combination of modeling techniques. In short, we compared the traditional machine learning and deep learning approaches. For the traditional machine learning approach, we evaluated different feature extractors, including baseline (no extraction and input the original signal), predetermined statistical features, and deep feature extractors, on different classifiers. For the deep learning approach, the deep learning models streamlined the feature extraction and classification under unsupervised learning.

2. Materials and Methods

2.1. System Configuration

Two UWB short-range impulse radar transceiver system-on-chips (XeThru X4M03 v5, Novelda, Oslo, Norway) were used. Each sensor consisted of a fully programmable system controller and an antenna at a center frequency of 7.29 GHz or 8.748 GHz. A module connector was bundled to allow detailed configurations to suit our purpose, as shown in Table 1.

Table 1
Configurations of the UWB radar devices.

Parameters	Values
Transmitter Frequency (Tx)	7.29 GHz
Pulse Repetition Frequency	15.188 MHz
Sampling Frequency	23.328 GHz
Range of Elevation angle	-65° to $+65^{\circ}$
Range of Azimuth angle	-65° to $+65^{\circ}$
Bin Length	0.00643 m
Detection Range	1.30 - 1.8 m (top radar) 0.40 - 0.9 m (side radar)
Bin Resolution	78 bins per radar frame
Frame Rate	20 frames per second
Transmission Power	6.3 dBm

As shown in Fig. 1, the top radar was hung on a light boom, which was 2.1 m from the ground resembling the height of household ceiling. The side radar was positioned 0.9 m from the ground using a tripod at the right side of the participant. The distance from the side radar to the participant was set according to the specification of detection distance requirement of the UWB radar. The two sensors were placed orthogonally over a hospital bed (1.93 m × 0.84 m × 0.5 m with mattress). A center frequency of 7.29 GHz was chosen due to lower power consumption. The detection range of each radar was adjusted to encompass the region of interest. The two radars were connected to the same computer in dual channel and sent the radiofrequency data at the same time.

2.2. Data Collection and Pre-processing

We recruited 18 healthy young adults (12 males and 6 females) in this study from the university. Their mean age was 22 (SD: 1.33, range 19 to 25). Their average height and weight were 168 cm (SD: 12.1 cm, range 153 to 180 cm) and 61.6 kg (SD: 12.2 kg, range 45 to 81 kg), respectively. We collected 720 samples (18 participants × 4 postures × 10 repetitions). Exclusion criteria included physical disability, obesity, pregnancy, or any cardiorespiratory problems. Participants were also excluded with difficulties in maintaining or switching specific postures in bed.

All participants signed an informed consent after receiving an oral and written description of the experiment before the start of the experiment, which was approved by the Institutional Review Board.

Participants were instructed not to wear any clothing or accessories with metallic components (such as belt with metallic buckle). During the experiment, they were asked to lie on the bed with pillow support, in the order of (1) supine, (2) left lateral, (3) right lateral, and (4) prone recumbent postures (Fig. 2). Before the recording started, the participants were given sufficient time to adjust their postures and they were free to place their limbs that complied to the instructed postures. Participants are required to maintain their posture when started. Each posture was recorded for 20 seconds and repeated ten times.

Each radar produced 78 bins per samples at 20 frames per second, while the last 10 seconds of the recording were extracted for analysis because the posture of the participants became steady after some time. After concatenating the data of the two radars, a complete set of data for one posture contained 31,200 data samples (78 bins/frame × 20 fps × 10 seconds × 2 radars). Thereafter, direct current (DC) suppression, in which each set of frame data is deducted by its mean value, was applied to eliminate DC noise. Besides, background suppression, in which each set of bin data is deducted by its mean value, was applied to eliminate environmental noise [33]. Fig. 3 illustrates the radar signal of one representative participant. Processed data would proceed to feature extraction and modeling.

2.3. Feature Extraction and Modeling Approach

In total, we evaluated 24 modeling approaches. As shown in Fig. 4, four of them were deep learning approaches, while 20 of them were traditional machine learning approaches. Traditional machine learning approaches involved four classifiers on five feature extraction strategies (baseline, predetermined statistical features with and without ablation study, and two deep feature extractors).

For deep learning approach, two convolutional based ResNet50 and DenseNet121 model [34,35], and two sequential based LSTM and Transformer model were used [36,37], in which the feature extraction and classification functions were streamlined within the unsupervised model. Pre-processed raw data were input into the deep learning models after pretrained by ImageNet [38,39].

For traditional machine learning approach, we needed to decide the combination of feature extractors and classifiers. Logistic regression, random forest, XGBoost, and SVM were chosen as classifiers. For the feature extractors, we considered predetermined statistical features and deep feature extractors (ResNet50 and DenseNet121), while a baseline

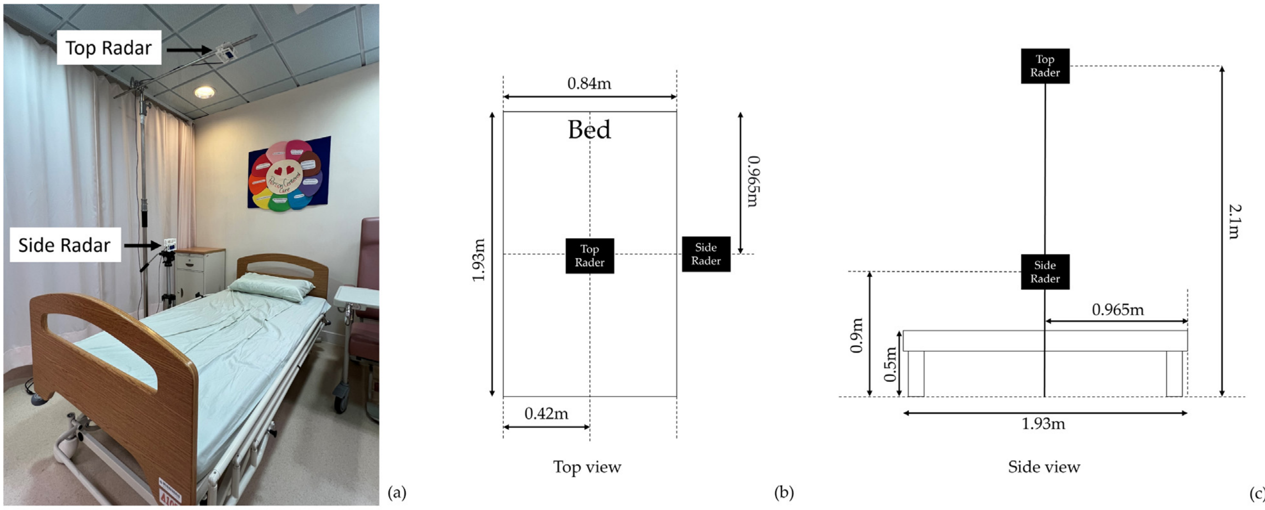

Fig. 1. System setup illustrating the top and side UWB radars positioned orthogonally over the bed.

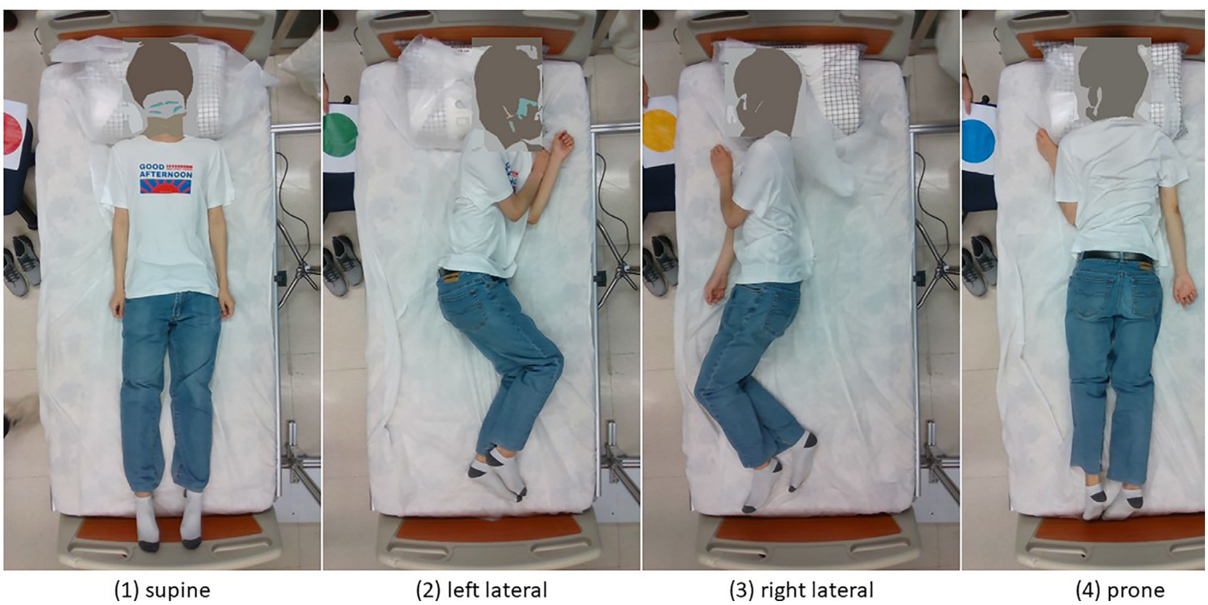

Fig. 2. Illustration of the four recumbent postures: supine, left lateral, right lateral, and prone.

model was also formed without any feature extraction (i.e., using the pre-processed raw data). It shall be noted that, unlike the deep learning approach, ResNet50 and DenseNet121 were used as deep feature extractors only without utilizing the classifier functions. There were 11 predetermined statistical features, including mean, median, variance, standard deviation, kurtosis, maximum, minimum, sum, differential entropy (ΔE), skewness, and slope sign change (SSC) [40,41].

To optimize the model, an ablation study was conducted on the two best classification models using predetermined statistical features. The least critical feature was identified by evaluating the accuracy change when leaving one feature at a time. The process continued to remove the second and third feature until the accuracy converged. Fig. 4 shows a flow chart for the data signal, feature extraction, and machine learning models.

2.4. Model Training and Evaluation

Two subjects were sampled as testing set, the remaining 16 subjects were as training and validation set. For classification models in the traditional machine learning approach, randomized grid search with stratified 5-fold cross-validation was applied for hyperparameter tuning. Table 2 shows the list and value of the hyperparameters. For the deep learning models, each sample was triplicated and stacked to imitate the input data format before feeding into the models. We implemented 4000 epochs of training, with early stopping at 100 epochs, to compare validation accuracy and testing accuracy in each epoch and obtain the final weight.

Accuracy, which was defined by the fraction of correct predictions over the total number of predictions on testing set, served as the primary evaluation outcome for the models.

3. Results

3.1. Traditional Machine Learning Approach

Table 3 presents the summary of accuracy of the models among traditional machine learning approach. Using dual radar data produced better accuracy with an average improvement of 0.180 using the pre-

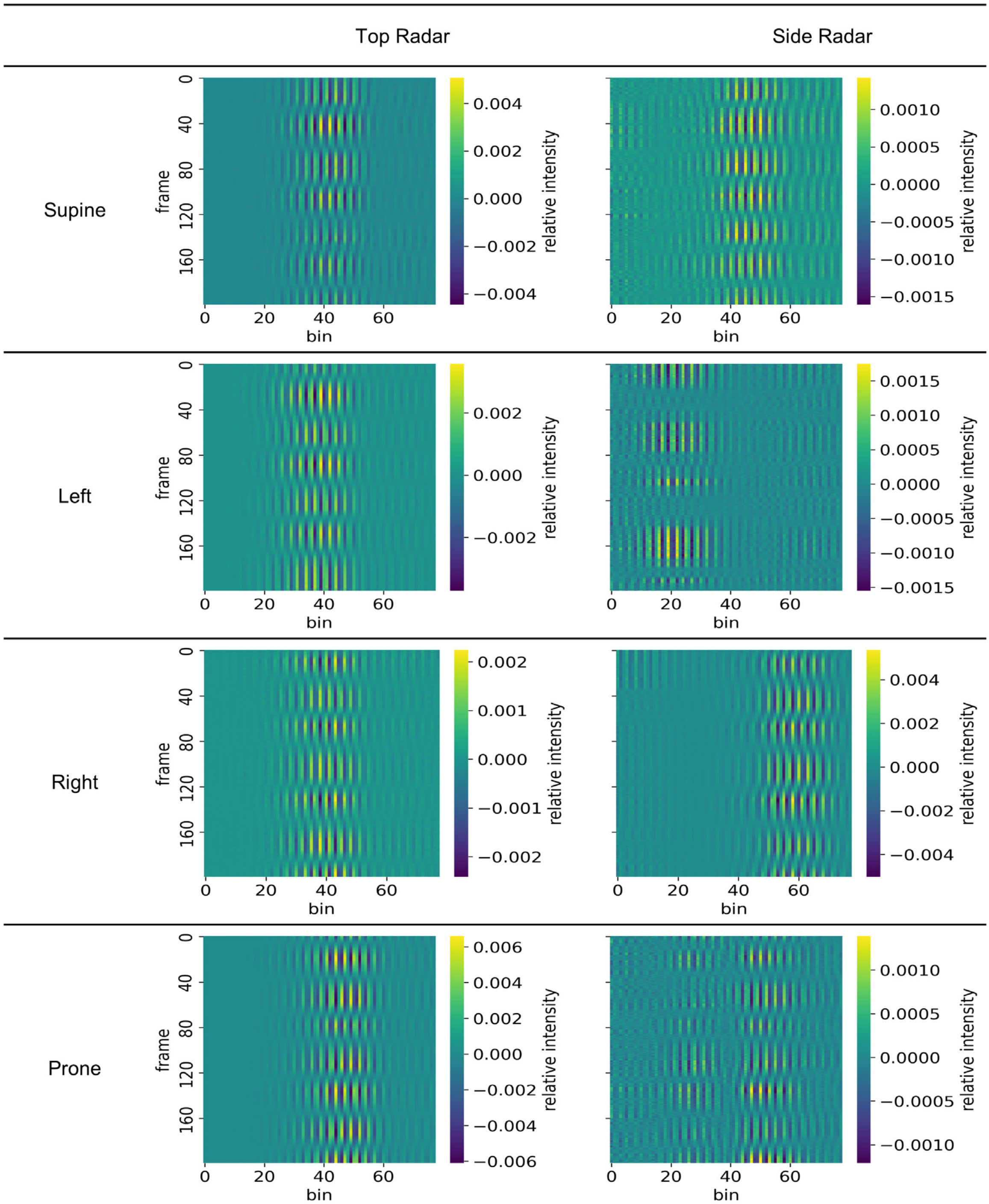

Fig. 3. Radar signal intensity function graph of the top and side radar of one representative subject of the four postures.

determined statistical features (before ablation), while that of random forest and XGBoost also performed better than logistic regression and SVM. Random Forest classifier with predetermined statistical features after ablation demonstrated the best performance, with an accuracy of 0.750, 0.750, and 0.938 respectively for top, side, and both radar input.

3.2. Deep Learning Approach

Table 4 presents the deep learning model accuracy. It should be noted that ResNet50 model did not converge for the single radar input. Overall, the performance of the deep learning models was not satisfactory and worse than the traditional machine learning approach. The accuracy was less than 0.600 for single radar input (either top or side). Using both radars, the highest accuracy attained by transformer is 0.713.

3.3. Ablation Study on Predetermined Statistical Features

Table 5 presents the model accuracy of the Random Forest and XGBoost with the first and second least important features improved. The model accuracy of random forest was improved when differential entropy and standard deviation were removed. All model performance was above 0.85 in the ablation study. Detailed accuracy summary for each feature of the ablation study is available in the supplementary information (Table S1).

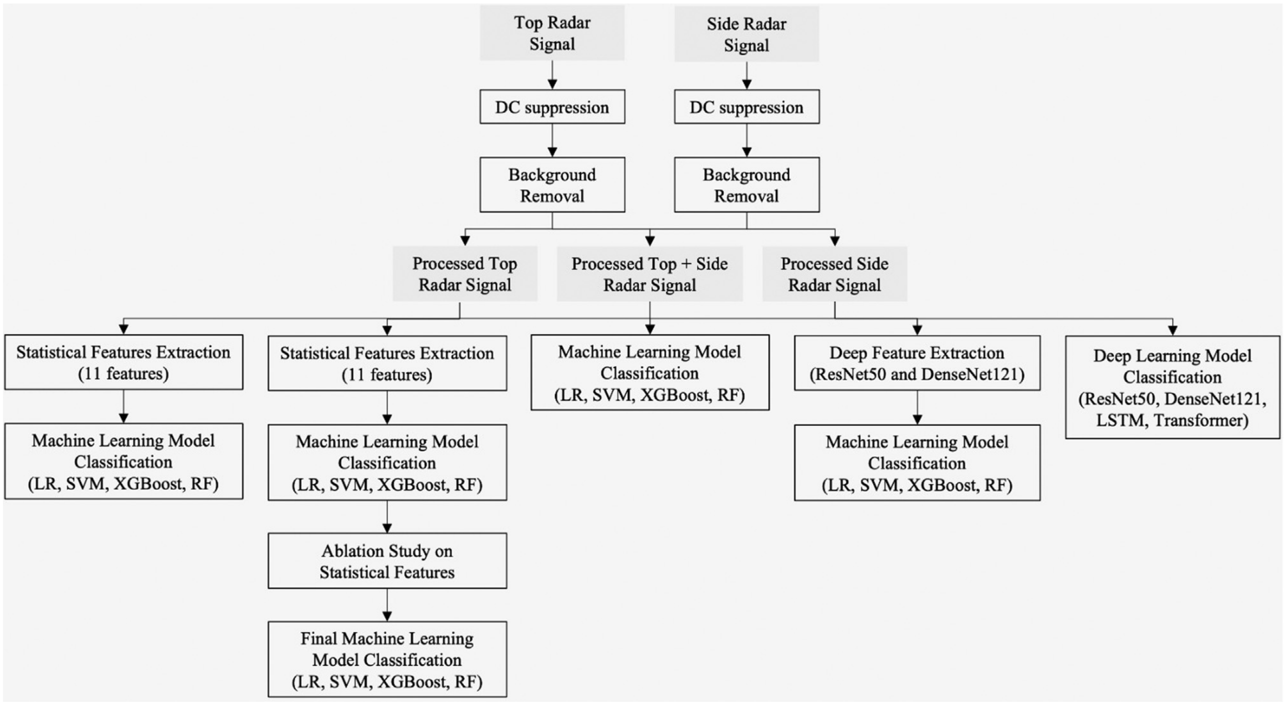

Fig. 4. Summary flow chart on data processing and feature extraction and modeling.

Table 2
Hyperparameters of the classification models in the traditional machine learning approach.

Model	Hyperparameter(s)	Value(s)
Logistic Regression	Solver	Nt-cg, Lbfgs, Liblinear
	C	Log-ud (10e^{-5} – 100)
Random Forest	No. of Estimator	200, 400, …,2000
	Max. No. of Features for Best Split	sqrt (Total No. of Features)
	Max. Depth	10,20, …,110
	Max. Sample Split	2, 5, 10
	Max. Sample Leaf	1, 2, 4
	Bootstrap	True, False
XGBoost	Min. Child Weight	1, 5, 10
	Gamma	0.5, 1, 1.5, 2, 5
	SSR of training instance	0.6, 0.8, 1.0
	SSR of Columns for Every Tree Constructed	0.6, 0.8, 1.0
	Max. Depth	3, 4, 5
Support Vector Machine	C	0.01 .1, 1, 10, 100, 1000
	Gamma	0.001, 0.01, 0.1, 1
	Kernel	Rbf, Poly, Sigmoid

Lbfgs: Limited memory Broyden-Fletcher-Goldfarb-Shanno algorithm; Liblinear: A Library for Large Linear Classification; Log-ud: Log-uniform distribution; Nt-cg: Newton-conjugate gradient algorithm; Rbf: Radial basis function kernel; Sqrt: Square root; SSR: Subsample Ratio; Poly: Polynomial Kernel.

3.4. Subgroup analysis on sleep postures

Confusion matrices and a subgroup analysis table are shown in Fig. 5, respectively on the best performing model (i.e., random forest) in ablation study. Overall, using both top and side radars, the left and right lateral postures had a better sub-classification accuracy (0.988 in both cases) than the supine (0.950) and prone postures (0.950).

4. Discussion

The innovation of this study lies on the application of the UWB dual radar system for sleeping posture classification, while the strengths of this system lie in the ability to remedy the variation problem of ambient light and its robustness without embedding sensors onto the bed. Based on the data collected from the radar, we utilized and evaluated different feature extraction and modeling techniques. Our results indicated that classification performance of model trained by the bi-radar system was better than that trained by a single radar (or channel) of the system. Moreover, traditional machine learning approach with predetermined statistical feature input (before and after ablation) was better than that with deep feature input and pure deep learning models streamline with deep features. While deep learning models are generally more reliable and without the need of feature justification, traditional machine learning techniques do not necessarily perform worse than deep learning models in many scenarios and could be computationally more efficient, especially with the lack of large dataset [42].

In the radar signal intensity function graph, the x-axis (bin) represented the distance from objects; y-axis represented the time; and the color scale represented the intensity of the signal (i.e., effective reflectance area). The sleep posture could be identified by the radar signal heatmap since the radars received different effective reflectance area at different distances under different postures. For example, the side radar could receive a larger effective reflectance area at a particular distance under left lateral posture because of the large and flat exposed area of the body back. In contrast, the right lateral posture might could have a lower signal strength because of the lower effective area by the forearms and knees. There were small wave patterns along the y-axis (time) because of the breathing-induced biomotion.

Amid traditional machine learning, we further optimized the model through an ablation study over the predetermined statistical features. Random forest and XGBoost performed better than logistic regression and SVM probability because they accounted for non-linear association better. We also chose to further optimize random forest and XGBoost because of the better performance. The maximum and minimum value of the radar bin across time were the most dominant affecting classification accuracy with a drop of 0.026 when removed. Maximum and minimum value, after suppression, indicated the relative signal strength of radar bin. The radar signal strength could represent the cross-sectional area at their focal region and might manifest different sleep postures.

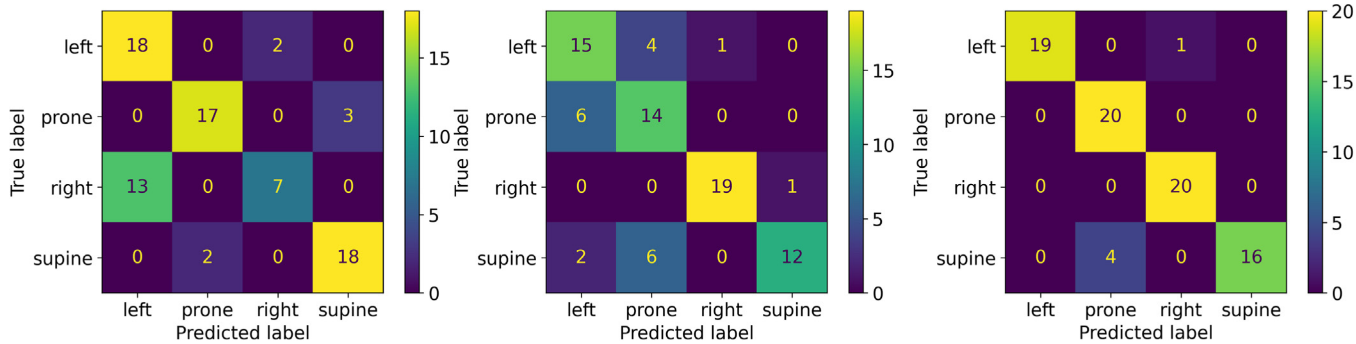

Fig. 5. Confusion matrix of random forest classification results of top radar only (left), side radar only (middle) and both (right) in the ablation study.

Table 3
Model accuracy of traditional machine learning approach using baseline pre-processed data, predetermined statistical features (before and after ablation) and deep feature extractors.

Classifier	Radar	Baseline	Predetermined Statistical Features		Deep Feature Extractor	
			Before Ablation	After Ablation	ResNet50	DenseNet121
LR	Top	0.263	0.588	0.600	0.625	0.625
	Side	0.325	0.713	0.762	0.738	0.787
	Top + Side	0.350	0.900	0.900	0.875	0.900
SVM	Top	0.312	0.625	0.650	0.600	0.537
	Side	0.250	0.750	0.662	0.688	0.500
	Top + Side	0.363	0.838	0.863	0.850	0.850
XGBoost	Top	0.487	0.725	0.713	0.637	0.650
	Side	0.738	0.750	0.775	0.800	0.787
	Top + Side	0.825	0.900	0.912	0.887	0.875
RF	Top	0.600	0.700	0.750	0.588	0.662
	Side	0.850	0.787	0.750	0.800	0.800
	Top + Side	0.887	0.900	0.938	0.875	0.925

LR: Logistic Regression; RF: Random Forest; SVM: Support Vector Machine.

Table 4
Model accuracy of deep learning models.

Model/Radar	Top	Side	Top + Side
ResNet50	0.225*	0.200*	0.487
DenseNet121	0.588	0.600	0.662
LSTM	0.463	0.512	0.562
Transformer	0.275	0.438	0.713

* The model did not converge in model training.; LSTM: Long Short-term Memory

Table 5
Classifier accuracy in the ablation study on predetermined statistical features (detailed information available in Table S1).

Classifier	Removed 1st Feature	Removed 2nd Feature	Accuracy
Random	ΔE	-	0.925
Forest	ΔE	SD	0.938
XGBoost	Skewness	-	0.912

ΔE: differential entropy; SD: Standard Deviation.

ResNet50, and DenseNet121 were used in our study to serve as deep feature extractor in the traditional machine learning approach and streamlined model in the deep learning approach because of their relatively low computational demands [43]. Therefore, they are feasible in the applications of wearable devices or the Internet of things (IoT) technologies. Moreover, our study found that DenseNet121 was superior to ResNet50 no matter they served as deep feature extractor or deep learning model. It was because its model architecture, which featured more layers and unique dense connectivity pattern, could be more efficient to identify dominating features using less samples [44]. LSTM and transformer, on the other hand, are sequential based models [45,46], which could be applied to time series alike radiofrequency data. Overall, sequential based models outperformed convolutional based models due to its capability to recognize state-to-state changes.

There were some similar developments in existing studies. An UWB 4-sleep-postures classifier using a Multiview learning approach via SleepPoseNet reached an accuracy of 73.7% [33]. Our dual radar system with random forest model using predetermined statistical features could achieve an accuracy of 93.8%. Besides, another research team utilized a dual-frequency microwave doppler radar to recognize three key postures of 20 participants with an accuracy around 80% to 90% [47,48]. The strength of our system was to apply radar impulse with extreme short emission period. Therefore, it has substantially less radiation than other radar technologies.

There were some limitations in this study. Our study adopted a dual radar approach by concatenating the data input, which might not be able to precisely locate the region of interest. A beamforming or beam steering using multiple radars could facilitate the tracking of the region of interest and thus may improve the efficiency and accuracy of the models [49]. In addition, radar has been placed on the right side only. The symmetrical property of the radar signal awaits further investigation. Furthermore, as a proof-of-concept, we only implemented a study with small sample size with data pooling. While some researchers might allow limited sample size in top-tier publication to compromise resource and feasibility during the early-stage of model or system development [50–54], scarcity of data for machine learning may suffer from overfitting, underfitting, non-convergence, and/or bias in accuracy estimates [50,55], since the small dataset may produce strong spurious patterns. Therefore, accuracy might be achieved or overly dependent on the tuning of model parameters or hyperparameters [50]. In fact, unlike sample size estimation in statistics, sample size determination for machine learning models designed for different data types is very challenging, especially the requirement on large and balanced class dataset could be difficult to be achieved in real-life [56]. Some studies proposed alternative solutions to accommodate the small sample size, such as data augmentation/synthesis, data fine-tuning, transfer learning, optimizing feature space, post-hoc curve fitting and nested-cross validation [50,55,57]. Future studies shall also consider collecting data from OSA patients and analyze their characteristics of postural behaviours.

The long-term goal of this research is to develop a comprehensive sleep surveillance system that can track sleep postures and behaviours. Our previous studies developed depth camera-based bed-exiting event monitoring [58,59] and sleeping postures classification under blanket conditions for the application in elderly care homes [20]. With the comprehensive sleep surveillance system, we can early detect signs such as waking spinal symptoms [60]. This study represents a milestone in establishing baseline parameters to classify postures using a dual radar system that could be incorporated to our existing system. Our future study will focus on the development of beamforming and beam steering using multiple radars. We will explore and develop other advance sleep monitoring applications, for instance, rapid eye movement tracking and sleeping postures classification under blanket conditions for the application in elderly care homes [20].

5. Conclusion

In this study, we proposed an UWB dual radar system to recognize common sleep postures using different feature extractions and modeling techniques. The innovation represents a starting milestone for OSA and related intervention assessment. Our results showed that overall prediction using dual radar was significantly better than single radar. Future studies may consider improve the accuracy of the model and systems by the implementation of radar beamforming and beam steering technology.

Author Statement

Derek Ka-Hei Lai: Software, Formal analysis, Investigation, Data curation, Writing – Original Draft Preparation. **Li-Wen Zha:** Software, Formal analysis, Investigation, Data curation. **Tommy Yau-Nam Leung:** Formal analysis, Investigation, Data Curation. **Andy Yiu-Chau Tam:** Methodology, Software. **Bryan Pak-Hei So:** Validation, Data Curation. **Hyo Jung Lim:** Data Curation. **Daphne Sze-Ki Cheung:** Validation, Resources. **Duo Wai-Chi Wong:** Concept, Methodology, Writing – Review and Editing, Project Administration, Funding Acquisition, Supervision. **James Chung-Wai Cheung:** Concept, Methodology, Validation, Resources, Writing – Review and Editing, Project Administration, Funding, Supervision

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Declaration of Competing Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.engreg.2022.11.003.

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