Poster: A Millimeter-Wave Wireless Sensing Approach for Sleep Posture Classification

Edward M Sitar IV; Sanjib Sur
Department of Computer Science and Engineering; University of South Carolina, Columbia, USA
esitar@email.sc.edu; sur@cse.sc.edu

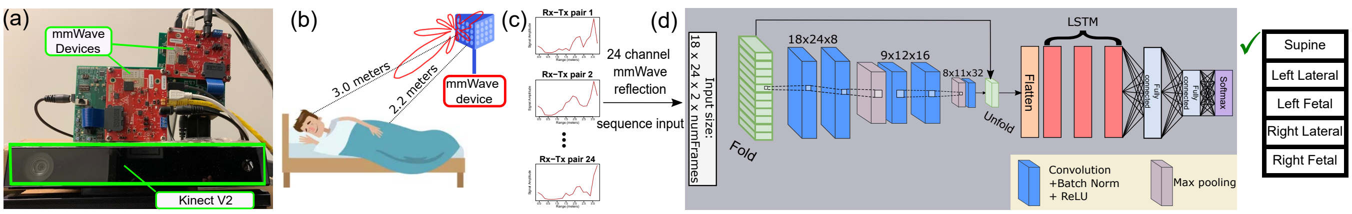

Figure 1: *(a) Data collection setup with two mmWave transceivers and an RGB-D camera; (b) Illustrative example of an individual sleeping in front of the mmWave device; (c) Reflected signals captured by multiple receive antennas in one frame; (d) Classification network architecture.*

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**; • **Computing methodologies → Neural networks**.

KEYWORDS

Millimeter-Wave; Sleep Posture Recognition; Deep Learning

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ABSTRACT

We spend one-third of our lives sleeping, and sleep quality plays an important role in our overall health. Sleep posture monitoring can help medical professionals prevent negative health outcomes associated with certain sleep postures. In this work, we propose using millimeter-wave wireless signals to classify the sleep posture using a supervised deep learning model and preliminarily evaluate the performance for 7 volunteers and 5 broad classes of postures.

1 INTRODUCTION

Sleep is an incredibly important part of our daily lives, and it plays a vital role in our health and well-being. Humans typically sleep in one of the broad categories of posture, such as supine, prone, right or left lateral, and right or left fetal. Certain sleep postures have been linked with negative health outcomes. For example, supine posture has been shown to be linked with respiratory issues, such as sleep paralysis and sleep apnea [1], which itself is a risk factor for cardiovascular complications, including strokes and hypertension [2]. What's more, individuals who subjectively categorize themselves as "poor sleepers" spent significantly more time in the supine or prone postures [3]. Automatically classifying and logging information about sleep posture throughout the night can help provide insights to medical professionals and individuals in improving sleep quality and preventing negative health outcomes.

The current gold standard for studying sleep is Polysomnography [4], but it requires very expensive hardware and is usually done in a lab setting, making it impractical for at-home use. Doctors can also ask patients, or their caretaker/partner, about their sleep postures, but it is usually an error-prone qualitative assessment. A vision-based system, using RGB-D or Infrared cameras, can allow a quantitative assessment [5, 6], but these systems invade the user's privacy, mostly rely on lighting conditions, and do not work if the subject is occluded behind blankets. Pressure mattresses [7] and wearable sensors [8] are other popular techniques; however, these approaches require additional hardware either on the bed or attached to the user's body, which may introduce sleep discomfort.

High-frequency millimeter-wave (mmWave) wireless signals provide a promising alternative for monitoring sleep postures. MmWave is well-suited for human posture monitoring since it works under low light conditions and occlusions, which are both likely scenarios for sleep monitoring. Additionally, mmWave is poised to become ubiquitous in next-generation wireless devices, such as home wireless routers, presenting an opportunity for wireless sensing to be integrated into user's networking devices without additional bulky and expensive hardware. MmWave is also favorable for the comfort and convenience of the user, as it does not require the user to have any sensors on their body or bed. Prior approaches based on Wi-Fi have been successful in classifying postures [9]; but mmWave operates at a higher frequency and ultra-wide bandwidth, so it will allow better range resolution and finer-grained posture monitoring.

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In this work, we propose a sleep posture monitoring system using only reflected mmWave signals received from commodity devices. Our key intuition is that *different sleep postures will introduce distinct signatures in the mmWave reflections*, and thus, we can use them directly for posture classification. At a high level, we use reflection signals captured by multiple receive antennas and design a deep learning model that exploits the spatial and temporal characteristics in the signal and classifies the sleep postures.

2 SYSTEM DESIGN

Since the reflection signals captured by a single antenna may not contain enough spatial resolution to differentiate the postures, we use multiple antennas along both the vertical and horizontal dimensions of the device. The device can be mounted in any corner of the bed room, like a regular wireless router. Since existing commercial mmWave routers do not provide raw reflections, we built a customized setup with two transceivers, each with 3 transmit and 4 receive antennas. The two transceivers are arranged with one physically rotated 90° *w.r.t.* the other. Such configuration enables us to measure the signal reflections from 24 individual receive channels in both azimuth and elevation planes. The devices collect reflections by transmitting FMCW chirps starting at 77 GHz, and linearly increasing frequency over a bandwidth of ≈1.6 GHz. We apply a Fast Fourier Transform (FFT) to the received signal and obtain the reflection of objects at different ranges from the transceiver. Each frame of mmWave reflections contains the signal phase and amplitude for each discrete range bin, with a resolution of 9.25 cm, for each of the 24 receiving channels. We further process the signal to remove reflections corresponding to objects beyond the fixed, known range of the bed. This amplifies the distinct posture signature and removes reflections from background objects, like walls. Figures 1(a–b) show the device and experimental setup. Figure 1(c) shows an example of the signal amplitude received across different ranges. The strongest reflection corresponds to the human body.

To classify the sleep posture, we design a customized Convolutional Neural Network (CNN) with Long Short-Term Memory (LSTM). We use a CNN based network design because CNNs have been previously shown to be highly effective at extracting spatial features from input data, and they are computationally less expensive than the matrix multiplications associated with dense layers [10]. The LSTM layers serve the purpose of learning any temporal variations in posture type. Figure 1(d) shows the network architecture.

Several convolutional blocks consisting of a 2D convolution layer followed by batch normalization and ReLU activation are used to extract the spatial features and acquire a feature vector from each input frame. Each convolution layer consists of 3×3 filters and has a stride size of 1×1, with an increasing number of filters for the deeper layers. In between sets of convolutional blocks, we apply a 2×2 max pooling with strides of 2×2 and 1×1 to reduce the size. This feature vector is then merged with the feature vectors of other frames from the same sample, flattened and passed through 3 LSTM layers with 128, 64, and 32 hidden units, respectively, and passed through two dense layers with sizes 20 and 5, where 5 corresponds to the number of output classes. Finally, we apply the Softmax function, which estimates the probability that the sequence of mmWave reflections belongs to each of the possible postures. Our network then outputs the posture with the highest predicted probability.

Table 1: *Classification metrics for the model.*

Number of frames	Accuracy (%)	MCC	F1-score
10	73.45	0.61	0.69
50	66.38	0.55	0.64
100	58.04	0.55	0.64

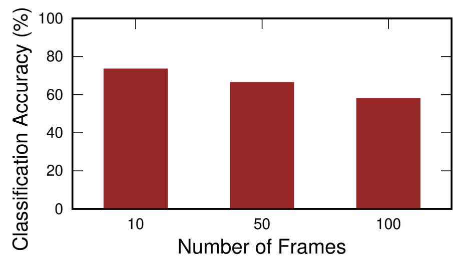

Figure 2: *Bar graph showing the network's classification accuracy when trained on a different number of frames per network sample.*

3 PRELIMINARY RESULTS

We collect an extensive dataset from 7 volunteers performing 5 distinct postures: Supine, left lateral, left fetal, right lateral, and right fetal. Our dataset consists of 112,586 frames of mmWave reflection signals. A co-located RGB-D camera captures ground truth depth images and is used to label the collected dataset. We collect our data for each volunteer over 11 trials of approximately 1500 frames per trial. In each trial, one individual lies in the bed within the field-of-view of the mmWave transceiver, and remains (almost) stationary in one posture for the duration of the sample. We train our classification model and evaluate it with several metrics: Classification accuracy, F1-score, and MCC. We also evaluate the performance of our model when training and testing with different numbers of sequential frames concatenated together. We use approximately 80% of the data for training and the remaining 20% for testing. To prevent overfitting in training, we partition the training and testing samples according to the trials that each sequence of frames came from.

Table 1 shows some key classification metrics of our posture recognition network when trained on a different number of frames per sample. Additionally, Figure 2 shows a bar graph of the classification accuracy when using a different number of frames per sample. We can see that the model performs the best when using fewer frames per sample. We believe this is due to the fact that with more frames per network sample, a lower number of training samples are available and a higher number of frames are retained at the LSTM layers, preventing optimal convergence of the network.

4 CONCLUSION AND FUTURE WORKS

In this work, we propose a wireless sleep posture monitoring system using mmWave. We experimentally show the feasibility of using this technology for multiple volunteers and sleep postures. In the future, we hope to expand our dataset to include a more diverse set of volunteers, and more types of sleep postures to provide finer-grained posture information to users over the course of a night. Also, in practice, an individual will change postures many times over the course of a night. So, we plan to explore methods to detect such events using the mmWave signal reflections. We believe such an automated system can enable high-quality at-home sleep monitoring with ubiquitous millimeter-wave devices.

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