Poster: mmSleep: Monitoring Sleep Posture from Commodity Millimeter-Wave Devices

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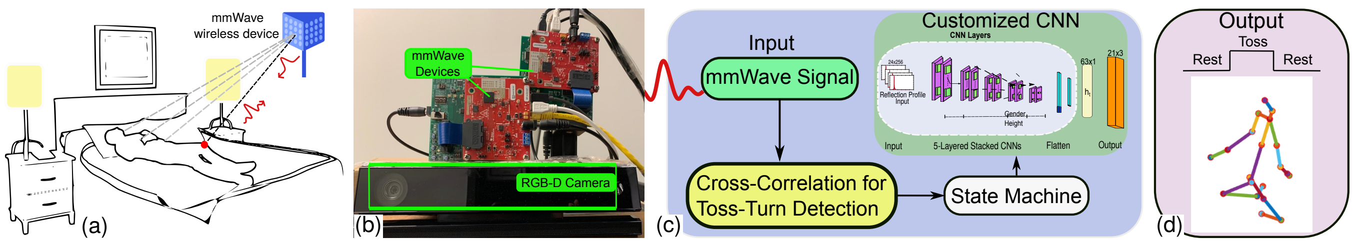

Figure 1: *(a) A mmWave device captures reflected signals from a sleeping person using multiple antennas; (b) Experimental set up for* mmSleep*; (c) System design for* mmSleep*; (d) Output from* mmSleep*.*

ABSTRACT

We propose *mmSleep*, a millimeter-wave (mmWave) wireless signal based sleep posture monitoring system that can assist in tracking 3D location of body joints of a person during sleep. *mmSleep* overcomes the limitations of existing vision-based sleep monitoring and can work under low-light without being privacy-invasive. *mmSleep* uses a customized Convolutional Neural Network to learn diverse sleep postures, and our preliminary results show that *mmSleep* can consistently predict 3D joint locations with high accuracy.

CCS CONCEPTS

• Human-centered computing → Ubiquitous and mobile computing systems and tools; **• Computing methodologies → Machine learning approaches**.

KEYWORDS

Millimeter-Wave; Sleep Posture Monitoring; Toss-Turn; Convolutional Neural Network

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1 INTRODUCTION

Sleep is essential and critical for the proper functioning of the human body, and sleep deprivation has been linked with different chronic diseases, such as Diabetes, Obesity, Stroke, Depression, and Alzheimer's disease [1]. Due to the well-recognized importance of sleep, monitoring its quality continuously and non-intrusively in a privacy-noninvasive manner has become an important research area. *One way to monitor sleep is by estimating the sleep posture of a person* [2].

We sleep in different postures throughout the night, such as fetal, lateral, supine, *etc.* [2]. To avoid fatal consequences of improper sleep posture and facilitate physicians in monitoring a patient, fine-grained sleep posture monitoring system is required. Current in-clinic monitoring approaches require a patient to stay overnight, ask them to wear sensors on the body, and embed sensors on the bed, which could be costly and cumbersome. So, there is a need for an at-home monitoring system that can record fine-grained spatio-temporal changes of the body throughout the night.

Existing at-home solutions are based on either wearables or vision or low-frequency wireless signals. Wearable-based approaches bring discomfort to sleep, and many people may forget to wear them before sleep, whereas vision-based approaches are privacy-invasive and are limited by the dark bedroom conditions and occlusion due to the blanket. Wireless-based solutions can provide only broad coarse-grained categories of postures, and are unable to provide the fine-grained 3D location of body joints due to the fundamental limit of resolution in low-frequency wireless devices. High-frequency millimeter-wave (mmWave) wireless signals in ubiquitous 5G-and-beyond commodity devices can offer a higher-resolution and could potentially provide fine-grained information.

However, monitoring sleep postures with mmWave signals is challenging for two reasons: (1) Due to the problems of signal specularity, high signal absorption, and presence of clothing, most of the transmitted mmWave signals do not reach back to the receiver. So, the device will have inadequate information about the body parts. (2) Compared to the vision-based systems, images generated by the mmWave system have extremely low-resolution. Due to the limited number of antennas and bandwidth on commodity devices, there will be a large point spread in the mmWave images, which eliminates higher frequency components critical for posture monitoring, such as joints and body contour.

To this end, we propose *mmSleep*, a deep learning based approach that models the relationship between sleep postures and mmWave signals using a data-driven approach, and overcomes the fundamental challenges to enabling fine-grained sleep posture monitoring. *mmSleep* has two design components: (1) A cross-correlation based toss-turn detection module to classify the sleeping period as either rest or toss-turn states; and (2) A deep learning framework that predicts the 3D location of body joints during the rest state. Our preliminary results show that *mmSleep* predicts the 3D joint locations for a different sleeping postures with a median error of 6.22 cm and 90^{th} percentile error of 12.12 cm, and consistently outputs ground truth looking sleep postures.

2 MMSLEEP SYSTEM DESIGN

mmSleep first identifies toss-turn events during a sleeping period by analyzing the reflected mmWave signals, and then, predicts the sleep posture only under the rest conditions. This is critical since predicting postures during a fast movement under a toss-turn event not only is challenging but also is less useful since toss-turn events span only a few seconds. Intuitively, a toss-turn event is associated with a high-frequency spatio-temporal change in the reflected signal and can be separated from almost static rest states by applying a cross-correlation between successive reflected signals. Once *mmSleep* identifies the start of a rest state, it aims to predict the 3D location of body joints from the mmWave signals. *mmSleep* trains a customized CNN with thousands of input-output pairs to map the relationship between the mmWave signals with the true joint locations. We design the CNN by incorporating the known height and gender of a person to generalize for variations in skeletal structure across multiple persons. At run-time, when the network is fully trained, *mmSleep* can predict the 3D joint locations with only the received mmWave signals (see Figures 1[c–d]).

CNN to Learn Input-Output Representation: CNN maps the relevant spatial features in the input mmWave signals and outputs the joint locations by using non-linear filters with convolution operations. To this end, we leverage multiple antennas from two mmWave devices to capture the reflected signals and gather coarse 3D environmental information. The devices are placed orthogonal to each other with 3 transmitters and 4 receivers on each of the horizontal and vertical axes, and can capture signals from 24 virtual channels (2×3×4). Thus, with a total of 256 range-reflection bins, we collect an input of size 24×256 corresponding to an instant of posture, which encompasses the signal reflections from the azimuth, elevation, and depth. Then, we design a multi-layered stacked CNN with S stacking in each layer, and explore a different number of layers, S, and network parameters to find the optimal network convergence. Furthermore, we increase the number of convolution filters from 8, 16, 32, 64, and 128 in each subsequent layer, and apply batch normalization and Leaky ReLU activation to ensure regularization and learn complex patterns. Then, we flatten the output and pass it through two dense layers of sizes 128 and 64 with ReLU activation. Finally, the output layer uses a linear activation with a layer size of 63 to predict the 21 key body joint locations (*i.e.*, 21 [x, y, z] values).

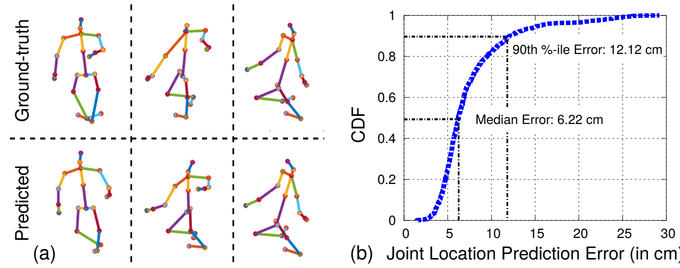

Figure 2: *(a) Top view of 3 sleeping postures. (b) CDF of absolute errors in joint localization.*

Loss Function: To ensure the optimal convergence of the network, we design the loss function as the sum of Euclidean distance, L_{ED}, between predicted and ground truth joint locations, defined as: $L_{ED} = \sqrt{\sum_{i=1}^{N}(F^i_{real} - F^i_{pred})^2}$, where N is the total number of joints, and F^i_{real} and F^i_{pred} represent the real and predicted i^{th} joint location, respectively.

3 PRELIMINARY RESULTS

We evaluate the performance of *mmSleep* by training with data collected from a single volunteer performing 5 different sleeping postures. We select 6500 frames for training and validation and test *mmSleep* on another 2000 frames. Each frame includes 3D location of 21 joints and multi-antenna mmWave signals. Furthermore, through hyperparameter tuning, we find that *mmSleep* works well with Adam optimizer, with a learning rate of $2{\times}10^{-4}$, batch size of 4, and epochs of 2000. Figure 2(a) shows some visual examples of predicted body joints, and statistical results in Figure 2(b) shows that *mmSleep* can predict the joint locations with a median and 90^{th} percentile errors of 6.22 cm and 12.12 cm, respectively, which are tolerable in practice.

4 CONCLUSION AND FUTURE DIRECTIONS

We propose *mmSleep*, a sleep monitoring system that can predict accurate sleep postures using commodity mmWave devices. We believe *mmSleep* can reliably assist physicians with richer, fine-grained information about sleep posture. In the future, we plan to improve the accuracy of our preliminary result by incorporating knowledge about joint hierarchy and conduct end-to-end field trials with multiple volunteers.

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