Towards Accurate Sleep Monitoring: Detecting Bed Events Using Millimeter-Wave Technology

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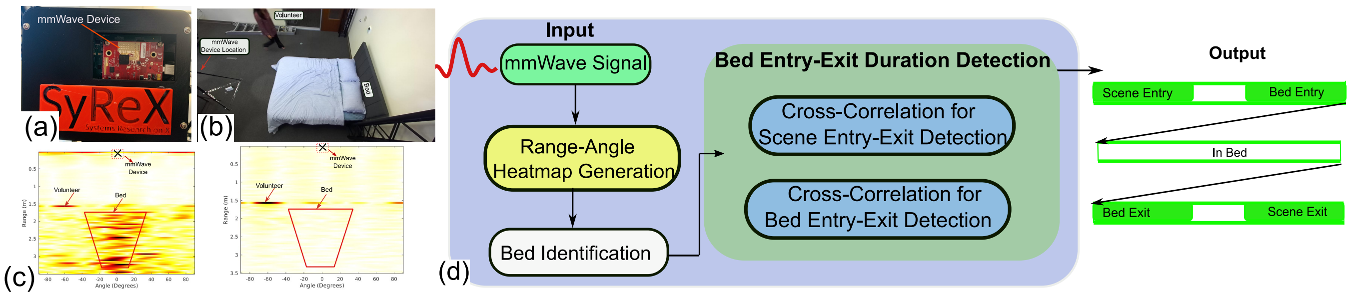

Figure 1: *(a) A millimeter-wave (mmWave) device; (b) A volunteer entering the scene captured from the camera's point of view; (c) MmWave reflection from a volunteer entering the scene: (left) Unfiltered Range-Angle heatmap showing various reflections; (right) Dynamic Range-Angle heatmap highlighting the reflection from the moving volunteer; (d) Our system design.*

ABSTRACT

We propose a millimeter-wave (mmWave) wireless signal-based sleep monitoring system aimed at providing information about a person's sleep by detecting sleep events, such as bed entry and exit times, as well as the duration of bed stay. It overcomes the limitations of existing vision-based systems by operating in low-light conditions without invading privacy. It uses spatial-temporal information and signal processing techniques to determine the duration, and our preliminary results indicate that our system can accurately detect bed events.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**.

KEYWORDS

Millimeter-Wave; Sleep Monitoring; Bed Events

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1 INTRODUCTION

Sleep plays a crucial role in overall health and well-being. Monitoring sleep behavior has a significant impact on healthcare for prevention, recovery, and the effective treatment of various health conditions. For instance, approximately 1 in 5 strokes occur during sleep, known as "wake-up strokes," where patients discover symptoms upon waking [1]. In these cases, treatment must be administered within a few hours of symptom onset. However, determining the exact time of stroke occurrence is challenging for those who wake up with symptoms. Similarly, nocturnal seizures, occurring during sleep, affect about 20% of epilepsy patients. These seizures often go unnoticed, leading to potential injury and inadequate treatment adjustment [2]. Given that humans spend one-third of their lives sleeping and the well-recognized importance of sleep, understanding and monitoring sleep behaviors has become a significant research focus in healthcare. The standard procedure for sleep monitoring is overnight polysomnography, performed in a hospital or sleep lab. However, this requires an

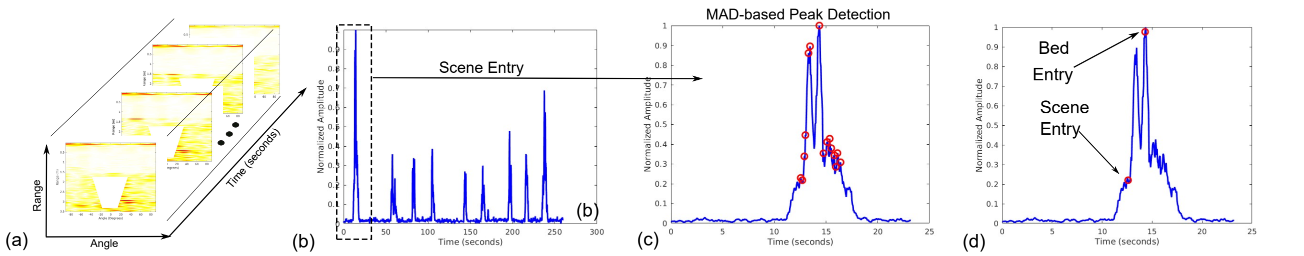

Figure 2: *(a) Our input range-angle heatmap with masked bed region; (b) Normalized cross-correlated data; (c) MAD-based peak detection automatically applies threshold and detects peak; (d) Detected scene-entry and bed-entry times.*

overnight stay and is not practical for long-term continuous monitoring. Therefore, an at-home monitoring system that can track sleep behavior is desirable for long-term use, as it would help healthcare providers gain valuable insights for early detection, timely intervention, and personalized treatment for various medical conditions.

One important parameter in monitoring sleep behavior is bed entry and exit duration [3]. These specific times, when the user gets into and out of bed, are extremely valuable in sleep studies as they provide insights into sleep duration and can help identify sleep disorders that involve frequent bed entry and exit [4]. Current at-home solutions rely on wearables, vision, or low-frequency wireless signals. Wearable-based methods can be uncomfortable and disruptive to sleep, and there is a risk that users may forget to put them on before bedtime. Vision-based approaches raise privacy concerns and are hindered by poor visibility in dark bedrooms and obstructions like blankets. Existing low-frequency wireless-based solutions can address these challenges as they can perform effectively in complete darkness and can penetrate blankets. However, due to the inherent resolution limitations of low-frequency wireless devices, their localization error is higher, often measured in meters, making them unreliable for detecting specific actions like bed entry and exit. In contrast, high-frequency millimeter-wave (mmWave) wireless signals in ubiquitous 5G-and-beyond devices provide finer resolution. The shorter wavelengths of mmWave signals allow for high spatial resolution, enabling precise position estimation. Further, mmWave signals can penetrate through the blankets, and work under zero visibility.

However, accurately estimating bed entry and exit times using mmWave reflected signals is challenging for two reasons: (1) Signal specularity and various objects in the room, such as bed, result in only a small portion of the signals returning to the receiver, providing limited information about body parts and positions. (2) Additionally, individuals may move near the bed without actually entering it or may shift significantly while in bed without exiting. This makes it challenging to accurately determine the exact times of bed entry or exit.

To address this, we propose a sleep monitoring system that leverages range-angle heatmaps (RAMaps) generated from mmWave reflected signals to accurately detect bed entry and exit events. Our system first generates RAMaps and maps the bed's geometry in the RA plane to establish a spatial reference for tracking movement. It then employs a cross-correlation and peak detection module to identify significant changes in the RAMaps, detecting when a person enters the monitored area and gets into the bed, as well as when they exit the bed and leave the area.

We design and prototype our system using a 77–81 GHz mmWave transceivers (TI IWR1443BOOST), to collect the reflected mmWave signals, and an RGB-D camera (ZED2i) to collect the ground truth time information (Figure 1[a–b]). Our preliminary results indicate that our system predicts the duration of bed entry, exit, and stay with median errors of 0.35, 0.63, and 0.97 seconds, respectively.

2 SYSTEM DESIGN

Our system, illustrated in Figure 1(d), first locates the bed by converting 3D mmWave reflections into a 2D RA plane in the azimuth direction. This enables tracking a person's movement toward or away from the bed, allowing accurate detection of bed entry and exit. We identify these events by detecting high-frequency spatio-temporal changes in RAMaps and using cross-correlation to distinguish dynamic movements from the static environment. Isolating the bed location ensures precise determination of entry and exit durations. However, strong specular reflections from human movement near the bed pose significant challenges. These intense reflections interfere with the effectiveness of standard cross-correlation methods. To address this, our work employs a customized peak detection algorithm to detect bed entry and exit times.

Estimating Bed Geometry: To accurately extract the information about a person's movement, we generate RAMaps (See Figure 1[c]). Our mmWave device, with 3 transmitters and 4 receivers, captures signals from 12 virtual channels. Once we generate RAMaps, we identify the bed's location within them. Our setup includes a bed fixed within the mmWave device's field of view (FoV). We measure the angle

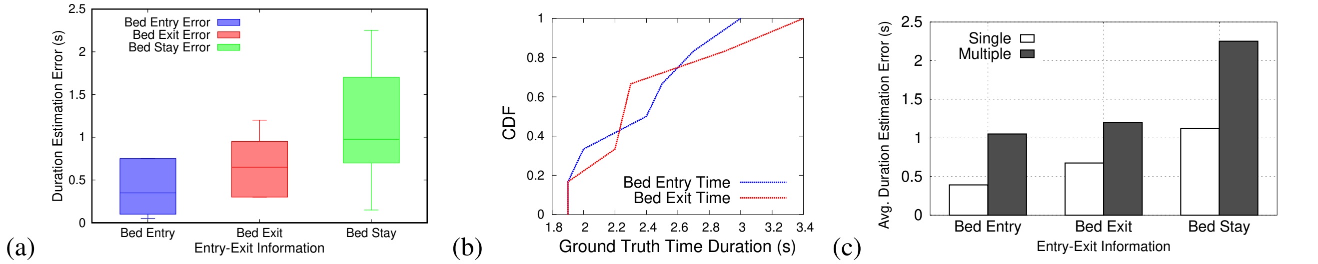

Figure 3: *(a) Box plot for the duration estimation error for bed entry, bed exit, and bed stay; (b) Distribution of ground truth bed entry and exit times; (c) Comparison of average duration error between single and multiple volunteers.*

between the vertical and RA planes as 59.98°. To transform the bed's corner points from the spatial domain to the RA plane, we project these points onto the RA plane.

Detecting Bed Entry-Exit Duration: To identify segments where a person enters or exits the bed, we first detect the timestamps for scene entry and exit. A person will enter the bed only after appearing in the scene and will leave the scene only after exiting the bed. Knowing these timestamps helps narrow down the search duration for bed entry and exit.

Initially, we mask the bed area and suppress values within the bed region, causing activities outside the bed region to appear as large-scale events. We then amplify the changes during out-of-bed events and distinguish them from bed events by applying cross-correlation between successive RAMaps of the reflected signals. Suppressed bed activities show minimal changes, resulting in small peaks, while out-of-bed movements create two sharp peaks for entry and exit. We segment these peaks from their onset to their conclusion, smooth the data with a window size of 10, normalize it, and apply Mean Absolute Deviation (MAD) for adaptive thresholding [5] (See Figure 2[a–d]). MAD is a robust statistical measure for peak detection and adaptive thresholding that quantifies the average absolute deviation of data points from their median.

After detecting scene entry and exit timestamps, we then determine the bed entry and exit timestamps by suppressing the surrounding values and retaining only those within the bed geometry. Using a similar approach as before, we determine the person's bed entry and exit times.

3 PRELIMINARY RESULTS

We evaluate the performance of our system by collecting data from six volunteers of diverse ages. We instruct the volunteers to start walking from the starting point within the mmWave device's FoV, enter the bed, perform a few toss-and-turn movements, exit the bed, and finally leave the FoV at the endpoint. Our ground truth is from our Zed2i camera synchronized with the mmWave device. We manually review all the frames to determine the start and end times. Figure 3(a) shows the box plot for the duration estimation errors for bed entry, exit, and stay, with median errors of 0.35, 0.63, and 0.97 seconds, respectively.

Further, we simulate a patient scenario with two volunteers assisting another to enter and exit a bed while walking slowly. Figure 3(c) shows that the average duration estimation error for the multiple-person scenario is 1.05, 1.2, and 2.25 seconds for bed entry, bed exit, and bed stay, respectively. These increased errors occur because helpers enter and exit the FoV before and after the patient, causing stronger reflections. The ground truth durations for single volunteers are 2.4 and 2.5 seconds, compared to 10.8 and 10.7 seconds for multiple volunteers (see Figure 3[b]). Despite this, our system can still detect these events effectively

4 CONCLUSION AND FUTURE WORKS

We propose a sleep monitoring system that utilizes contactless mmWave devices to detect when a person enters and exits their bed. Our system aims to provide reliable information about a patient's sleeping patterns to assist physicians. In the future, we plan to expand the system's capabilities to monitor various in-bed events, including vital signs and sleep stages.

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