SleepGuardian: An RF-Based Healthcare System Guarding Your Sleep from Afar

Yu Gu, Yantong Wang, Zhi Liu, Jun Liu, and Jie Li

Abstract

The ever accelerating process of urbanization urges more and more population into the swelling cities. While city residents are enjoying an entertaining life supported by advanced informatics techniques like 5G and cloud computing, the same technologies have also gradually deprived their sleep, which is crucial for their wellness. Therefore, sleep monitoring has drawn significant attention from both the research and industry communities. In this article, we first review the sleep monitoring issue and point out three essential properties of an ideal sleep healthcare system, that is, realtime guarding, fine-grained logging, and cost-effectiveness. Based on the analysis, we present SleepGuardian, a Radio Frequency (RF) based sleep healthcare system leveraging signal processing, edge computing and machine learning. SleepGuardian offers an offline sleep logging service and an online abnormality warning service. The offline service provides a fine-grained sleep log like timing and regularity of bed time, onset of sleep and night time awakenings. The online service keeps guarding the subject for any abnormal behaviors during sleep like intensive body twitches and a sudden seizure attack. Once an abnormality happens, it will automatically warn the designated contacts like a nearby emergency room or a close-by relative. We prototype SleepGuardian with low-cost WiFi devices and evaluate it in real scenarios. Experimental results demonstrate that SleepGuardian is very effective.

Introduction

Sleep is crucial for the wellness of human beings. According to the latest report of the U.S. Bureau of Labor Statistics (BLS), employed persons aged 25 to 54 spend an average of 8.8 hours working and 7.8 hours sleeping [1]. During sleep, the human body remains in an anabolic state to restore both the muscular and nervous systems vital to the body and cognitive function. Individuals with sleep time deviating from the population norm are at risk of various sleep disorders like Sleep Disorder Breathing (SDB), Sleep Behaviour Disorder (SBD), Restless Leg Syndrome (RLS), and Periodic Limb Movement in Sleep (PLMS). These disorders may be serious enough to interfere with normal physical, mental, social and emotional functioning, especially hazardous for the elderly.

Sleep Monitoring

Sleep disorders are shown to be diagnosable via a fine-grained sleep history log represented in terms of still postures and in-place motions [2]. The log contains information like timing and regularity of bed time, onset of sleep, night time awakenings, time of waking up in the mornings, day time naps, day time sleepiness, and so on. It is very challenging to acquire such long-term logs since manual collection is quite time-consuming and labor-intensive. Therefore, the automatic sleep monitoring system arises as an emerging topic and draws more and more attention from both the academic and industrial communities.

In Fig. 1 we present a representative framework for an ideal healthcare system leveraging cloud computing, edge computing, and big data processing. An ideal system should bridge between users and social healthcare services in a realtime manner. Healthcare data harvested by distributed and heterogeneous in-home healthcare systems should be timely transmitted, stored and processed in clouds via either wired or high-speed wireless networks like 5G, depending on specific circumstances. Therefore, cloud computing, which relies on the rich computing power on the cloud, emerges as an efficient and reliable approach. Moreover, edge computing is also needed in time-sensitive applications, since edge computing will greatly accelerate processing the data at the proximity and thus ensure prompt medical response for users. Big data analysis on the collected healthcare data is essential for better diagnosis and treatment. In particular, an ideal sleep monitoring solution should possess the following properties,

Realtime Sleep Guarding: The system should provide a realtime guarding service so that any abnormalities, defined upon applications, can be captured, reported and handled in time.

Fine-grained Status Logging: A fine-grained sleep history log should be automatically and accurately generated and recorded, so that it can be promptly analyzed to aid diagnosis.

Cost-Efficiency and Privacy-Preserving: Sleep monitoring is long-term in essence. To maintain a continuous and fine-grained sleep log for accurate diagnosis, it is unreasonable to rely only on the monitoring service provided by hospitals. Therefore, the system should be cost-effective and affordable for the general public to support daily usage. Moreover, the privacy issue is another

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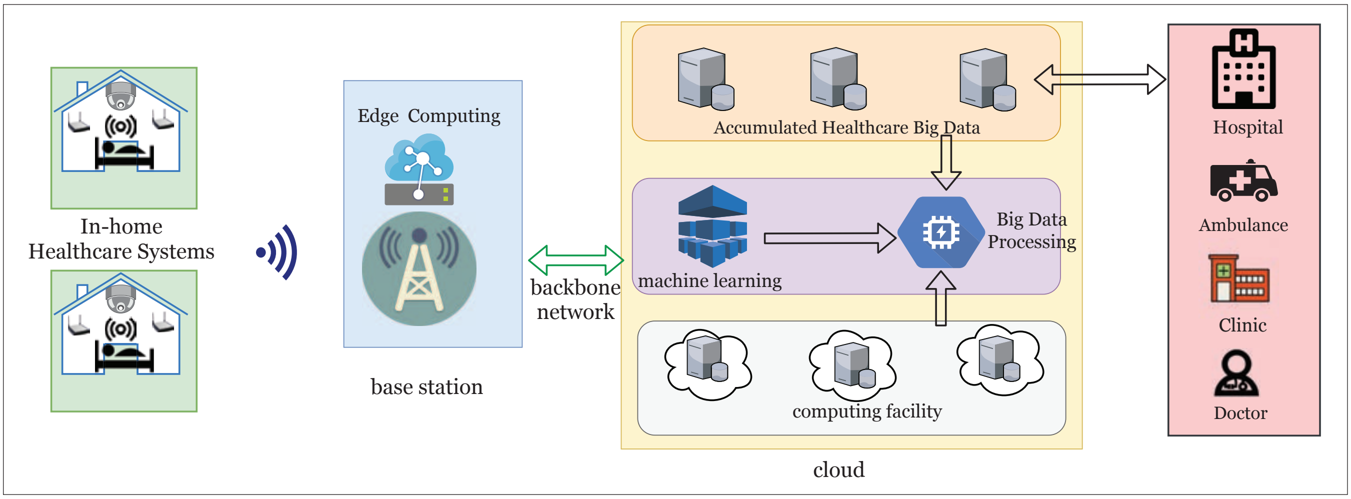


FIGURE 1. Our proposed framework to bridge between users and social healthcare services. Distributed in-home healthcare systems are connected through base stations which leverage the edge computing to ensure prompt medical response for emergency. The accumulated healthcare big data in the clouds demanding for big data anaylsis for better diagnosis and treatment.

major concern, since current mainstreaming sensor-based solutions are contact or even invasive, which could make users unconformable during sleep and lead to biased data.

Current Solutions

Actigraphy (ACT) has been accepted as a valid tool for this sleep history logging problem by the American Sleep Disorders Association (ASDA) in 1995 [3]. It refers to methods using wristband-like devices to monitor and collect data generated by body movements. Several such commercial products are already available in the open market such as Mi Band and Fitbit. ACT is considered as a low-cost solution that can provide a fine-grained sleep log. However, due to the volume and capacity constrains, it usually possesses little realtime communication and processing abilities. Moreover, ACT in the shape of wearable devices could be obtrusive for disturbing sleep.

Some recent research tries to improve the usability of ACT by attaching sensors to the objects where people lie on rather than the people themselves, for example, force sensing resistor sensors on the staves of the bed [4] or polyvinylidene fluoride (PVDF) film sensors on a mattress [5]. But such settings usually have mobility and coverage issues. Other research like vision systems [6, 7, 8] could be contactless but still obstructive due to the coverage issue: illumination and line-of-sight (LOS) restrictions. Also, vision-based approaches inherently raise privacy concerns for the general public.

Radio Frequency (RF) signal that is transparent to users emerges as a new paradigm for sleep monitoring in a "telepathic" way [9]. Patwari *et al.*, presented some pioneering work by exploiting the Received Signal Strength (RSS) of RF signal for extracting respiration rate [10]. Since RSS is a coarse-grained indicator that could easily be affected by the varying electromagnetic environment, researchers soon tend to Channel State Info (CSI) of RF signal instead. Liu *et al.*, designed Wi-Sleep leveraging multiple pairs of transmitter-receiver antennas for detecting sleep postures and rollovers [11]. Later, a similar CSI-based work is proposed to track abnormal breathing like sleep apnea [12]. Recently we designed Sleepy [13], a CSI-based realtime healthcare system providing offline status logging.

Existing research during the last few decades has provided solid progress on this topic. But much effort is still required since most current solutions possess some major shortcomings facing the above desired properties, e.g, relying on sophisticated hardware, lack of online processing ability, privacy concerns, and so on.

Our Contributions

To this end, we extend our previous work Sleepy [13] by endowing it with online processing ability via edge computing and finer recognition granularity via machine learning. The rationale of using edge computing and machine learning is to shorten system response time by keeping computing at the proximity of data, and to enhance system resolution through predictive analytics on data, respectively. To the best of our knowledge, it is a first-of-its-kind solution fulfilling the aforementioned essential properties for an ideal healthcare system, that is, realtime guarding, fine-grained logging, cost-effectiveness and privacy-preserving [14].

The key is to leverage RF signals (more specifically, WiFi) other than ACT or vision as the source for sleep monitoring. RF signal is insensible for human beings, making it an ideal option for this user-centric application. Also, SleepGuardian is cost-effective for using only low-cost off-the-shelf WiFi devices.

But RF signal is usually considered to be vulnerable to environmental interference caused by either humans or devices, so the main design challenge of SleepGuardian is *how to accurately characterize the still posture and in-place motion in terms of RF signal?*

Our response to the challenge is to build SleepGuardian on a Gaussian Mixture Model (GMM) based approach, which can adaptively model the still posture and in-place motion in Channel State Information (CSI) extracted from WiFi signal sent to monitor a sleeping subject. Specifically, we show that the energy feature of the wireless channel follows the GMM when describing the

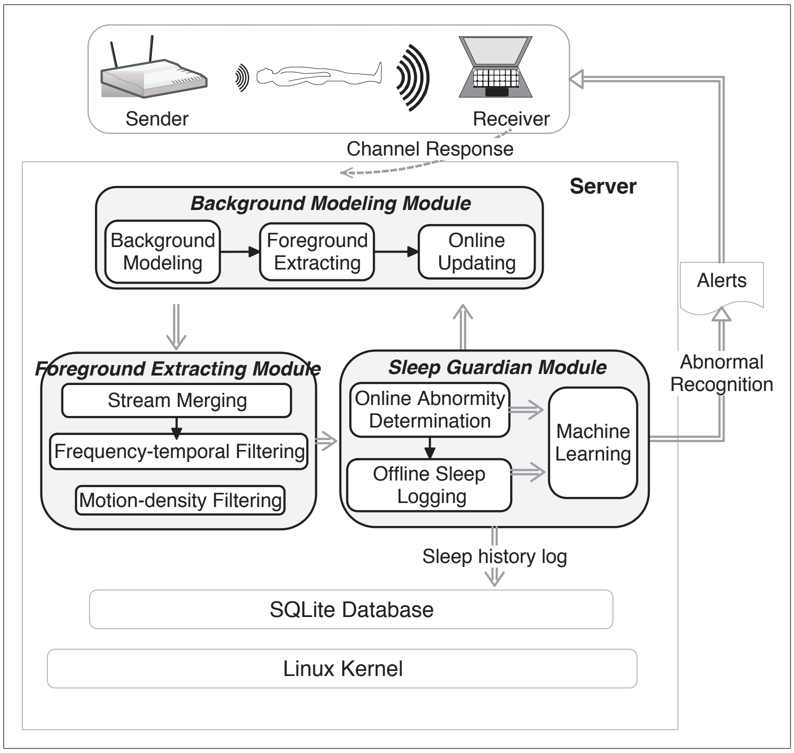


FIGURE 2. System overview of SleepGuardian.

sleep status of a person. Therefore, inspired by the foreground extraction method commonly-used in Computer Vision (CV), we design a similar approach in signal processing where the in-place motion is modeled as foreground and still postures as background in channel response. This approach possesses two major merits: 1) it needs no site-dependent calibrations, and 2) it needs no target-dependent training.

By processing the rich sleep status data offered by GMM, SleepGuardian provides an offline logging service and an online warning service. The offline service provides fine-grained information describing the sleep status of a person in terms of sleeping postures and in-place motions. It can even detect which parts of your body move via machine learning. The online service explores edge computing to guard the subject for any abnormal behaviors like intensive body twitches from a nightmare, a sudden seizure attack or falling off the bed, in a realtime manner. Once an abnormality happens, it will automatically warn the designated contacts like a nearby emergency room or a close-by relative.

We prototype SleepGuardian with low-cost off-the-shelf WiFi devices and verify its performance from different dimensions like the environment, scenario, sampling time, gender, and body shape in terms of detection rate (DR), recognition rate (RR), missing rate (MR) and mean absolute error (MAE). Experimental results demonstrate that SleepGuardian is very effective and reliable as a low-cost home-use healthcare system for sleep monitoring.

The remainder of this article is organized as follows. We present our system design of SleepGuardian in the next section, following by the performance evaluation. Finally, we conclude our work.

System Design

System Overview

Figure 2 shows the system architecture of SleepGuardian. The WiFi signal periodically emitted by the sender flows through the target subject and reaches the receiver. The attenuated signal described by channel response contains rich descriptions of the subject like still postures and in-place motions via the multi-path and fading effects. To retrieve fine-grained sleeping information from the signal and offer offline/line monitoring services, the receiver leverages three modules to process CSI data (channel response), that is, the background modeling module, foreground extracting module and sleep guardian module.

Background Modeling Module: This module aims to build an adaptive model for still postures (background) in terms of channel response. It leverages GMM to process raw CSI flows from different receiver antennas.

Foreground Extracting Module: This module targets extracting in-place motions (foreground) from background for further analysis. It removes counterfeit foreground caused by system glitches and surrounding interferences via the continuity feature of the physical motion in both frequency and time domain.

Sleep Guardian Module: This module provides the offline logging and online warning services by further processing the background and foreground information provided by the above two modules. More specifically, it logs the duration of different still postures, and the start-time and duration for the offline services and identifies the abnormal behavior based on the intensity of the in-place motion.

Background Modeling Module

CSI Visualizing: The incoming CSI data stream should be visualized first. We partition the stream into consecutive windows with length T, containing N samples for each subcarrier [15]. Then each frame contains $M \times N$ pixels, where M is the number of subcarriers. Each pixel $P_{m,n}$ in a frame is the CSI amplitude of subcarrier m collected within the nth time window (t_n) and the color of each pixel is determined by mapping its amplitude value to a predefined colormap.

Background Modeling: Within one frame, each pixel is modeled by a mixture of K Gaussian distributions. The probability that a certain pixel has a value (dBm) x_t at time t can be written as,

$$p(x_t) = \sum_{i=1}^{K} w_{i,t} \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\mu_{i,t})^T \Sigma^{-1}(x_t-\mu)} \quad (1)$$

where $w_{i,t}$ and $\mu_{i,t}$ are the weight and the mean value of the i-th Gaussian component at t, respectively.

If an incoming pixel does not fit in the background model, it is likely to be the foreground. More specifically, if this pixel is more than 2.5 standard deviations away from any of the B distributions in the background model, it is marked as the foreground.

Online Updating: Different sleeping postures constitute different backgrounds in our GMM based foreground extraction method. To accurately distinguish foregrounds from changing backgrounds, online updating is essential:

The initial weight and variance of K distributions are set to $1/K$ and 1.5, respectively.

If none of the K distributions match the current pixel, the model is updated by replacing the distribution with the *least fitness value* using a new Gaussian distribution whose mean is set to the value of the current pixel while using an initial weight ($1/K$) and variance (1.5). Then, we normalize the weights of all K distributions.

Otherwise, we update the weight of all K distributions as follows:

$$w_{i,t} = (1-\alpha)w_{i,t-1} + \alpha M_{i,t},$$
$$M_{i,t} = \begin{cases} 1 & \text{if } i \text{ is the first match distribution;} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where α is a pre-defined learning rate.

Then, we normalize the weight of all K distributions and update the first matched distribution as follows,

$$\mu_{i,t} = (1 - \rho)\mu_{i,t-1} + \rho x_t,$$
$$\sigma_{i,t}^2 = (1 - \rho)\sigma_{i,t-1}^2 + \rho(x_t - \mu_{i,t})^2 \quad (3)$$

where $\rho = \alpha/w_{i,t}$ is a temporary parameter and α is set to 0.01.

The online updating gives our system the ability to adapt to background changing without extra calibrations or target-dependent training. Detailed information about the GMM model can be found in our previous work [13].

Foreground Extracting Module

This module processes foregrounds in two steps, that is, enhancing the real foregrounds via stream merging and removing the counterfeit ones via two filters.

Stream Merging: Our preliminary experiments suggest that the motion of different body parts has varying degrees of impact on different antennas. Therefore, we should merge the CSI data in all the antennas to enhance the impact of motions following a simple rule: one pixel marked as a foreground on any antenna remains so in the merged frame. Otherwise, it is a background.

Stream merging enhances the real foregrounds but also brings more counterfeit ones, which are likely caused by two reasons: device interference and human interference. The former is usually caused by system glitches or other wireless devices competing for the same channel, while the latter is caused by nearby human beings.

Frequency-Temporal Filtering: This filter deals with the device interference. It leverages a basic fact: human motions usually last for a period of time, leading to the temporal correlations of foregrounds. Also, human motion changing the signal propagation paths usually affects multiple subcarriers, resulting in the frequency correlations of foregrounds. However, a device interference is brief, random and scattered. Therefore, any foreground segment at time t meeting either of the following criteria will be marked as background:

- It lasts less that τ seconds
- It affects less than p of all subcarriers,

where τ and p are set to 0.1 and 70 percent in SleepGuardian, respectively.

The abnormality is application-dependent. For instance, an abnormality of an infant could be an unusually high frequency of motions, implying that they are awake feeling uncomfortable on the bed and the parents should be warned.

Motion Density Filtering: This filter handles the human interference. It is built on a general investigation: a non-line-of-sight (NLOS) human motion usually leaves a much lighter impact on channel response than its LOS kind. Therefore, we use a sliding window of 0.5 s length and evaluate the density of foregrounds within the window. If its density is lower than d, all foregrounds within the current window will be marked as background. d is set to 0.4 in SleepGuardian.

Sleep Guardian Module

Offline Logging: This service estimates the duration of different sleep postures and the start time, duration and intensity of motions, based on which a fine-grained sleep log is generated including timing and regularity of bed time, onset of sleep, night time awakenings, time of waking up in the mornings, day time naps, and day time sleepiness. It even recognizes which part of the body moves via machine learning.

Online Guarding: This service keeps guarding the subject for any abnormal behaviors like intensive body twitches from a nightmare, a sudden seizure attack or falling off the bed. Once an abnormality happens, it will automatically warn the designated contacts like a nearby emergency room or a close-by relative.

The abnormality is application-dependent. For instance, an abnormality of an infant could be an unusually high frequency of motions, implying that they are awake feeling uncomfortable on the bed and the parents should be warned. For a person having a history of seizure, the abnormality could be a series of periodic motions lasting for a few minutes.

Implementation and Evaluation

Implementation

Prototype System: The prototype consists of two low-cost commodity MiniPCs (2.16GH CPU, 4GB RAM and 240GB SSD). One MiniPC is linked with one external antenna as the sender, sending 330 packages per second. The other MiniPC is equipped with three antennas as the receiver. They are both mounted with Intel Network Interface Controller 5300 (5GHz). Figure 3 shows such experimental setting. The distance between Tx and Rx2 is 110cm, while Rx1 and Rx3 are located left/right side of Rx2 with distance 120cm, respectively.

Sleep Guardian Application: Sleep is featured by inactivity, and thus SleepGuadian focuses on the motions, especially the abnormal ones, happening during sleep. To understand the key difference between the normal and abnormal motions, Table 1 lists most commonly-seen normal motions that could happen during sleep according to the involved body parts.

We developed a mobile application for users other than the monitored subject. Its interface

Body part	Motion	Head	Arm	Leg	Torso	Multiple 1	Multiple 2	Physical meaning
Head	Swing	100.0 %	0	0	0	0	0	Adjusting head position
Arm	Up and down	6.3 %	93.7 %	0	0	0	0	Adjusting the quilt
	Swing							Adjusting arm position
Leg	Bend	0	0	100.0 %	0	0	0	Adjusting leg position
	Stretch							
Torso	Twist	0	0	12.5 %	87.5 %	0	0	Lightening the tension
Multiple 1	Rollover	0	0	12.5 %	6.3 %	81.2 %	0	Changing postures
multiple 2	Stretch	0	0	0	0	0	100.0 %	Adjusting posture
Avg.							93.68 %	

TABLE 1. The confusion matrix of motion recognition via k-NN.

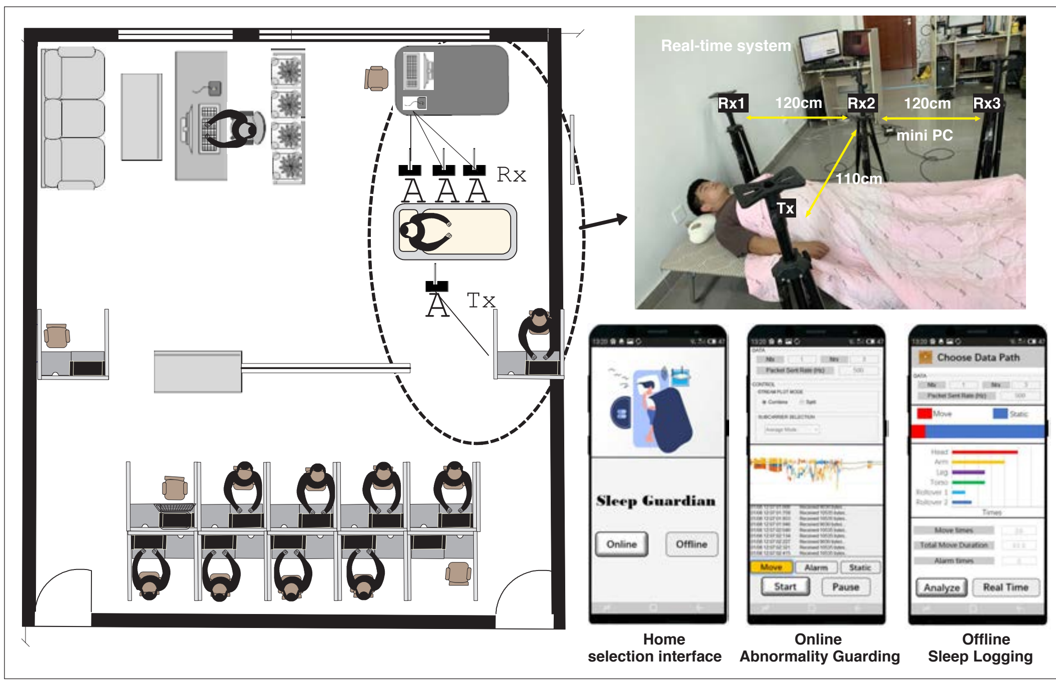


FIGURE 3. Our prototype SleepGuardian system in a 10 × 7 m^2 office.

is shown in Fig. 3. We provide two functions in the application: online abnormality guarding and offline sleep logging. The former focuses on real-time motion detection, while the latter records the number of motions during sleeping time.

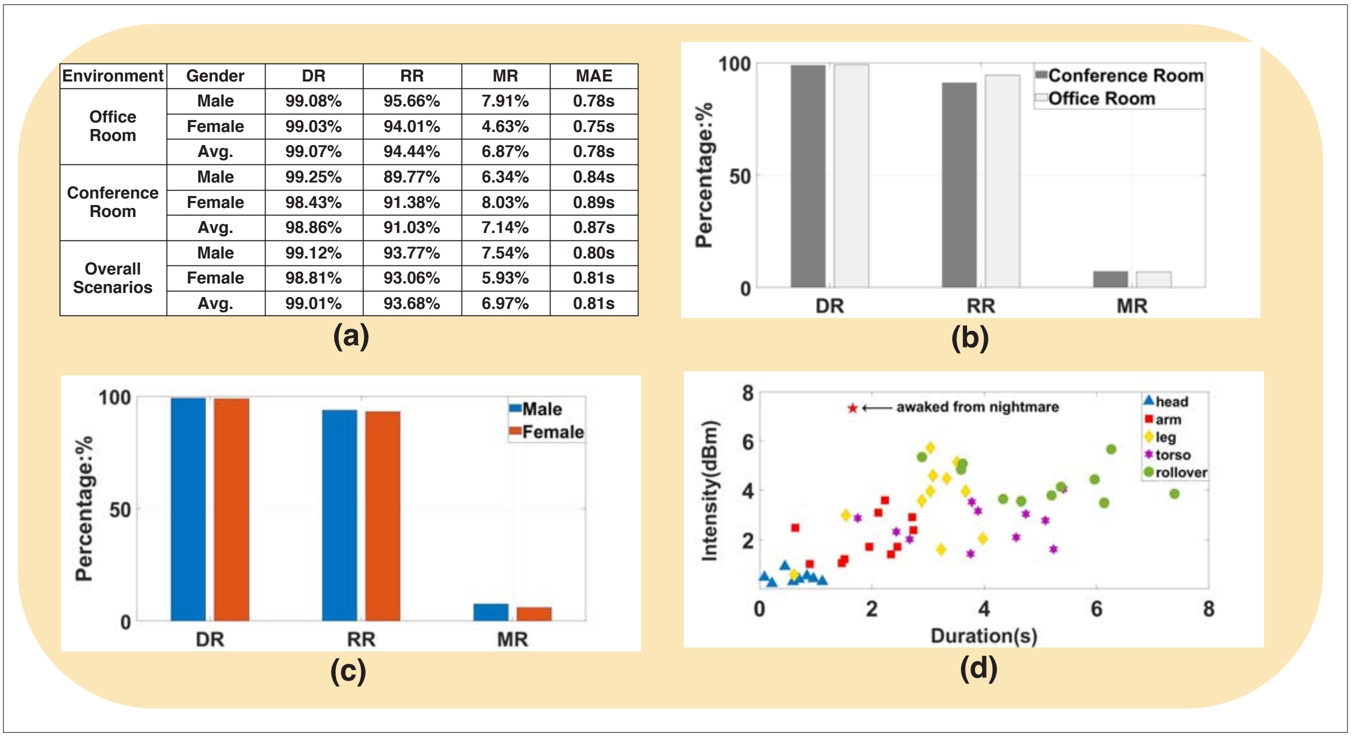
Online Abnormality Guarding: To ensure a prompt response to any emergency, we leverage edge computing deployed at the local server to detect any abnormal behaviors like intensive body twitches from a nightmare, a sudden seizure attack or falling off the bed. Once an abnormality happens, the server will issue an emergency warning to designated contacts via the mobile application. The interface of online abnormality guarding is shown in Fig. 3.

Offline Sleep Logging: To maintain a long-term sleep log, we explore machine learning to decode fine-grained movement information as well as the still posture (the corresponding interface is shown in Fig. 3). This function estimates the frequency and duration of each body movement, and records the alert times.

Evaluation Setting

To simulate real sleep, we recruited 15 participants (five females), whose age, weight, and height range from 20 to 27, 38kg to 95kg, and 1.60m to 1.82m, respectively. We have selected two typical environments, that is, a 10 × 7 m^2 office room, as shown in Fig. 3, and a 4 × 8 m^2 conference room. Each participant is asked to perform a specific sequence of six motions 10 times involving different parts of the body like head, arm, leg and torso while lying on the bed. A camera is used to record the scene simultaneously to serve as the groundtruth. Therefore, the dataset contains 15 (participants) × 6 (motions) × 10 (cases) × 2 (environments) = 1800 entries.

Evaluation Metrics: To quantify the performance of SleepGuardian, we focus on:
- Detection Rate (DR): the fraction of motions where SleepGuardian correctly detects among all the detected motions.
- Recognition Rate (RR): the fraction of motions where SleepGuardian correctly recognizes among all the detected motions.



Environment	Gender	DR	RR	MR	MAE
Office Room	Male	99.08%	95.66%	7.91%	0.78s
	Female	99.03%	94.01%	4.63%	0.75s
	Avg.	99.07%	94.44%	6.87%	0.78s
Conference Room	Male	99.25%	89.77%	6.34%	0.84s
	Female	98.43%	91.38%	8.03%	0.89s
	Avg.	98.86%	91.03%	7.14%	0.87s
Overall Scenarios	Male	99.12%	93.77%	7.54%	0.80s
	Female	98.81%	93.06%	5.93%	0.81s
	Avg.	99.01%	93.68%	6.97%	0.81s

FIGURE 4. System evaluation.

- Missing Rate (MR): the fraction of motions where SleepGuardian misses among all motions.
- Mean Absolute Error (MAE): the mean absolute error between the motion duration that SleepGuardian outputs and the groundtruth.

SleepGuardian first leverages GMM to detect a motion and then uses machine learning to recognize it. Therefore, DR and MAE are responsible for evaluating how precisely a motion can be detected by our system. MR is an important metric for online guarding since an undetected motion may lead to a severe consequence. RR is to evaluate how accurately a detected motion can be recognized by our system. It is key to offline logging.

Motion Classifiers: We tried several machine learning algorithms including k-NN, SVM and discriminant analysis for motion recognition, and selected k-NN due to its better performance.

Performance Evaluation

Overall Evaluation: Figure 4a presents the statistic results of the real-world experiment. SleepGuardian shows a satisfying performance by achieving 99.01 percent DR, 93.68 percent RR, 6.97 percent MR and 0.81s MAE on average.

In the following sections, we will interpret the results in terms of environments, genders, abnormal behavior and body parts.

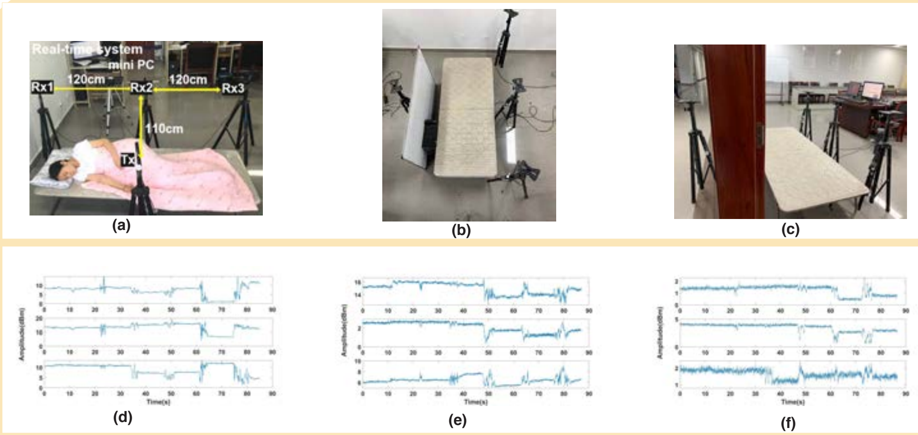
Environments: The office room is not only much larger than the conference room (70 m^2 vs 32 m^2), but also much more crowded and noisy with more people. However, such environmental differences make little impact on SleepGuardian, as shown in Fig. 4b. SleepGuardian achieves an average of 99.07 percent and 98.86 percent DR, 94.44 percent and 91.03 percent RR, 6.87 percent and 7.14 percent MR, and 0.78s and 0.87s MAE in the office room and the conference room, respectively. The performance difference is marginal for both environments.

Genders: Genders usually lead to differences in the body shape. For instance, the difference in weight of different genders can reach over twice in great in our experiments. However, SleepGuardian shows little performance variation between genders: it achieves an average of 99.12 percent and 98.81 percent DR, 93.77 percent and 93.06 percent RR, 7.54 percent and 5.93 percent MR, and 0.80s and 0.81s MAE for male and female, respectively.

Abnormal Behavior: The Sleep Guardian also effectively detects abnormal behaviors by analyzing the duration and intensity (defined as the absolute amplitude change per second) of each motion. Fig. 4d shows one real-world experiment, where a sudden sitting up from a nightmare is detected (red star in Fig. 4d). The sudden sitting up is isolated from normal motions, and thus easily identified by intensity. We can also observe that motions from the same body part tend to converge, for example, head movements that are marked by blue triangles, gather together in the 2 x 2 zone of the graph, owing to the short duration and small intensity during the normal sleeping time.

Body Parts: Table 1 illustrates the performance of motion classification. We can observe that SleepGuardian achieves an average accuracy up to 93.68 percent using the k-NN algorithm. Most of the normal motions can be identified with high accuracy; however, the rollover sometimes is misidentified as torso. Movement with multiple motions like rollover sometimes is misidentified as the movement of torso, because the intensity and duration of the torso movement are very similar to multiple movements.

In summary, the experimental results demonstrate that SleepGuardian is resilient to the envi-



	DR	RR	MR	MAE
LOS	99.01%	93.68%	6.97%	0.81s
NLOS with whiteboard	97.91%	89.36%	2.08%	1.07s
NLOS with Wall	97.82%	71.00%	16.67%	0.99s

(g)

FIGURE 5. Comparison of the performance in LOS and NLOS scenarios.

ronment, genders and body parts, and thus constitutes a promising solution for sleep monitoring.

Further Discussions

WiFi signal performs differently in LOS and NLOS scenarios. To study SleepGuardian's performance in NLOS scenarios, we perform extra experiments and the results are shown in Fig. 5. The experimental setup is the same as introduced earlier, with the only difference of adding a white board and a wall between the sender and the receiver to simulate the NLOS phenomenon. Figures 5a–5c list the evaluation environment and Figs. 5d–5f show the amplitude in each scenario. The overall detection performance is shown in Fig. 5g.

From the results, we can observe that the NLOS does affect the overall performance in terms of the DR, RR, MR and MAE, and the wall (which blocks the signal more) affects more than the whiteboard. Please note that the DR and RR in all three cases are all above 89 percent, indicating the SleepGuardian's ability to achieve satisfactory performance in the NLOS scenarios.

We are also interested in the theory behind, especially the optimal setup for the NLOS scenarios, which requires further efforts to explore and is left as future work.

Conclusion

In this article, we present SleepGuardian, a RF-based sleep monitoring system leveraging the off-the-self WiFi infrastructure. Unlike its rivals relying on specialized hardware or complicated training, it explores the channel characteristics and models the energy distribution over subcarriers as a Gaussian Mixture Model, which requires no calibrations or target-dependent training to detect normal or abnormal motions during sleep. SleepGuardian has been extensively evaluated in real environments from different perspectives and the results confirmed its reliability and efficiency. SleepGuardian can be seamlessly integrated in existing WiFi infrastructures, and thus constitutes a practical solution in the real world.

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