On Goodness of WiFi based Monitoring of Vital Signs in the Wild

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Abstract—WiFi channel state information (CSI) has emerged as a plausible modality for sensing different human vital signs, i.e., respiration and body motion, as a function of modulated wireless signals that travel between WiFi devices. Although a remarkable proposition, most of the existing research in this space struggles to withstand robust performance beyond experimental conditions. To this end, we take a careful look at the dynamics of WiFi signals under human respiration and body motions in the wild. We first characterize the WiFi signal components - multipath and signal subspace - that are modulated by human respiration and body motions. We extrapolate on a set of transformations, including first-order differentiation, max-min normalization and component projections, that faithfully explains and quantifies the dynamics of respiration and body motions on WiFi signals. Grounded in this characterization, we propose two methods: 1) a respiration tracking technique that models the peak dynamics observed in the time-varying signal subspaces and 2) a body-motion tracking technique built with a multi-dimensional clustering of evolving signal subspaces. Finally, we reflect on the manifestation of these techniques in a practical sleep monitoring application. Our systematic evaluation with over 550 hours of data from 5 users covering both line-of-sight (LOS) and non-line-of-sight (NLOS) settings shows that the proposed techniques can achieve comparable performance to purpose-built pulse-Doppler radar.

Index Terms—WiFi Sensing, Channel State Information, Sleep Monitoring, Real-World Evaluation

1 INTRODUCTION

Respiration rate and body motions are critical indicators of an individual’s general state of health. They carry meaningful insights to assess different cardiovascular, neurological, and psychiatric functions of the human body and play an essential role in early diagnosis of various medical conditions, including sleep apnea, asthma, nausea, and several others. Most of the technologies that can monitor respiration and body motions simultaneously are invasive and require the subject to be connected to the measuring equipment, e.g., a respiratory inductance plethysmography belt or multiple wearable sensors. While these instruments certainly offer medical-grade insights, they are not suitable for long-term usage due to their poor ergonomics that hinder long-term assessment. Several other less obtrusive methods have been proposed for tracking vital signs, for instance, Actigraphy [1], [2], [3], [4], [5], [6], [7] and EEG [8] based techniques. However, these methods still require body contact, which is something people are often not comfortable with [9].

Naturally, contact-less vital signs monitoring technologies have attracted significant interest, which mainly include Audio [10], [11], [12], Video [13], [14], Bed sensors (e.g., Ballistocardiography (BCG), pressure and/or motion sensors based techniques) [15], [16], [17], [18], [19], [20] and RF sensing based techniques - e.g., mmWave, Frequency Modulated Continuous Wave (FMCW) radar, Pulse-Doppler radar, RFIDs and WiFi based techniques [21], [22], [23], [24], [25], [26], [27], [28]. RF-based techniques are by far some of the least intrusive methods, both in terms of privacy and convenience of use. Radar-based techniques can monitor breathing and other movements reasonably well, however, their operation often requires line-of-sight (LOS) which leads to deployment complexity and significant directivity issues. In contrast, WiFi, and in particular channel state information (CSI) signals of WiFi have emerged as an attractive modality to track respiration and body motions [29], [23], [22], [30], [31]. The fundamental principle of these works is to model the variation of wireless signals modulated by the respiration and motion of a human body. These works have shown the remarkable ability to re-purpose WiFi signals to track vital signs; however, unfortunately, often under constrained and controlled settings with strict assumptions. For example, the techniques proposed in existing works have been designed based on controlled experiments often performed on the same subject, where they require the subject to lie down in between or very close to both transmitter (TX) and the receiver (RX) to ensure line-of-sight (LOS) scenarios. Their techniques rely on trial-and-error based positioning of WiFi transceivers and signal processing methods to track vital signs, which often leads to high dependency on multiple, environment-dependent parameters that are difficult to tune in real life. Such techniques may be suitable for controlled short-duration lab experiments. However, their suitability cannot be generalized to different individuals, environments, positioning of WiFi transceivers, LOS/NLOS situations, and to natural in-home monitoring scenarios.

Building on the existing WiFi based vital signs monitoring works and recognizing their aforementioned limitations, in this work, we take a close look at the dynamics of WiFi, human respiration, and body motions in the wild. Extrapolating on a set of transformations including first-order...
differentiation, min-max normalization and component pro-
jections, first, we analyze the impact of respiration on the
multipath components of WiFi signal to quantify the effect of small breathing movements on the CSI signals. Second, we analyze the impact of respiration on WiFi signals sub-
space to quantify how breathing affects the spatio-frequency
subspace formed by multiple TX-RX antennas (MIMO) and
Orthogonal Frequency Division Multiplexing (OFDM) sub-
carriers very differently compared to other bodily motions
(such as slight head or limb movements). Collectively, these
characterizations enable us to develop two robust methods
for tracking respiration and body motions without any
constraints. Moreover, these techniques eliminate user- and
environment-specific calibration efforts and as such, allow
us to build a system that can track vital signs using design-
time training data obtained from only a few configurations
and users.

We systematically evaluate our methods by first taking
sleep monitoring as a case study, where we collected more
than 550 hours (80 nights) of data from 5 users at their
respective apartments in real-world full-night sleep moni-
toring settings. Our experiments covered both line-of-sight
(LOS) and non-line-of-sight (NLOS) scenarios such that 55%
of our dataset corresponds to NLOS deployment scenarios,
and 45% to LOS. Second, we develop a system named
Serene that implements our proposed methods to track vital
signs during sleep. We evaluate Serene’s performance in
terms of breath rate error, number of motion false positives
that occur in a user’s environment while the user is sleeping,
and breath signal outage during which Serene cannot track
subject’s vital signs but the ground truth device can. Our
results demonstrate that the proposed techniques were able
to track respiration rate with an average error of <1.19
breaths per minute (BPM). However, the breath rate error
varied between 0.34 BPM to more than 5 BPM depending
upon the time of night as a user’s sleep posture and distance
from the sleep monitor can change during sleep. Serene
experienced 20 false positive motion events on average
every night, which can be attributed to activity of other
house residents while a user is sleeping. Although the total
duration of such events during any night stayed below
10 minutes on average and below 37 minutes 95% of the
time, yet we observed motion false positives of more than
60 minutes (1 hour) in total during one of the nights in
our dataset. Serene experienced an average nightly breath
signal outage of 6.38 minutes. Such outages arise due to
subjects rolling over in bed to a different position and/or
sleep posture that makes it difficult for Serene to pick up
the subjects’ chest movements for a while. Figures 1(a) and
1(b) show how Serene tracks breathing and body movement
during a full night’s sleep of a subject, when the WiFi sleep
monitor was placed on a table close to the subject’s bed and
the router was placed in their TV lounge.

In what follows, we first position our work against the
existing body of research. Then we present the character-
ization of the dynamics of respiration and body motion
concerning modulated WiFi signals. The signal processing
steps and implementation details are then discussed. We
then explain our data collection and deployment configura-

tions, followed by the evaluation reports. We conclude the
paper by discussing a sleep efficiency monitoring applica-
tion and highlight the limitations of WiFi based vital signs
monitoring in the wild.

2 RELATED WORK

2.1 Respiration, Body Movements and Sleep

Previous works have shown that breathing and body move-
ments during sleep are closely related to sleep quality in
humans [32, 2, 33]. These studies show that respiratory
dynamics vary over sleep stages, which means that respira-
tory activity can be used to separate sleep stages [32]. For
example, Dafna et al. evaluated whole night sleep based on
sleep-awake classification using audio recordings of breathing
sounds [33]. They captured and quantified variations in
breathing features such as periodicity and consistency, and
showed that these features contribute to distinguishing
between sleep and wake epochs. Our work is motivated by
such studies, where our goal is to first develop a robust
and generic scheme to extract breathing and limb/body
activity related vital signs using CSI signals obtained from
COTS WiFi devices, and then evaluate it in practical sleep
experiments.

2.2 Sleep Monitoring Technologies

Several sleep monitoring techniques have been proposed in
the past which use different sensing modalities, such as in-
ear [34], inertial sensors (Actigraphy) [35], [1], [2], [3], [4], [5],
[6], [7], EEG [8], Audio [10], [11], [12], Video [13], [14], Bed
sensors (e.g. Ballistocardiography (BCG), pressure and/or
motion sensors based techniques) [15], [16], [17], [18], [19],
[20] and RF sensing based techniques (e.g. mmWave, Fre-
quency Modulated Continuous Wave (FMCW) radar, Pulse-
Doppler radar, RFID and WiFi based techniques) [27], [28],
[21], [22], [23], [24], [25], [26]. For brevity, we will only
discuss some of the closely related recent works on contact-
less sleep monitoring, which include some sound, radar and
WiFi CSI based techniques.

Lullaby [36] tracks various environmental factors, sound,
light, temperature, and motion that help users assess the
quality of their sleep environments. iSleep [10] uses the
built-in microphone of the smartphone to detect the events
that are closely related to sleep quality, including body
movements, cough and snore, and infers quantitative mea-
sures of sleep quality. Sleep Hunter [37] uses actigraphy
and acoustic events to predict sleep stage transitions by
smartphone. Toss-N-Turn [38] uses features such as sound
amplitude, acceleration, light intensity, screen proximity,
battery and screen states, etc. to track a subject’s sleep qual-
ity. However, Audio based techniques are privacy invasive,
and therefore, often avoided as sleep is a private activity.

RF sensing based techniques are by far the least intrusive
methods for monitoring sleep, both in terms of privacy and
convenience of use. DoppleSleep [21] is another unobtrusive
sleep sensing system which uses short-range Doppler radar
to perform sleep stage classification (Sleep vs. Wake and
REM vs. Non-REM). Vital-radio [25] develop an FMCW
based system which is shown to accurately track a person’s
breathing and heart rate without body contact, from dis-
tances up to 8 meters. Based on the same system, [39] pro-
poses a deep learning architecture to perform 4-stage sleep

1. The dataset and deployment settings will be made public.
stage classification. More recently, authors of \cite{20} proposed algorithms to achieve multi-person identification and breath monitoring based on the same FMWC hardware. Although the aforementioned radar based techniques do fairly well in terms of monitoring vital signs during sleep. However, they require dedicated hardware and spectrum, adding cost, scalability, and/or RF regulation hurdles. These factors prevent their large-scale and long-term deployment. WiFi signals based sensing has recently emerged an approach to low-cost and easily adoptable long-term sleep monitoring, as the widespread use of WiFi capable devices (e.g. smart-home assistants, smart-phones, etc.) has made WiFi signals the most ubiquitous form of sensing in homes requiring no additional hardware costs. Multiple WiFi CSI based schemes have been proposed for tracking vital signs during sleep \cite{29, 23, 24, 30, 31}. The key limitation of the existing works is that they have only been evaluated with short-duration mock sleep experiments in very controlled settings. This makes the applicability of their techniques and findings quite limited in practical sleep monitoring scenarios. For example, the techniques proposed in existing works have been designed based on controlled experiments often performed on the same subject, where they require the subject to lie down in between and/or very close to both transmitter (TX) and the receiver (RX) to ensure line-of-sight (LOS) scenarios. Their techniques rely on trial-and-error based positioning of WiFi transceivers and signal processing methods to track vital signs, which often leads to high dependency on multiple, environment-dependent parameters that are difficult to tune in real world. Such techniques may be suitable for controlled short-duration lab experiments. However, their suitability cannot be generalized to different individuals, environments, positioning of WiFi transceivers, LOS/NLOS situations, and to natural in-home full-night sleeping scenarios.

3 Understanding the Relationship between Vital Signs and WiFi CSI

3.1 Overview of WiFi CSI

WiFi devices measure the Channel State Information (CSI), which characterises the surrounding wireless channel across bandwidth and multiple antennas. The Orthogonal Frequency Division Multiplexing (OFDM) communication scheme used in IEEE 802.11a/n/ac divides the wireless channel’s bandwidth into multiple modulated subcarriers. To correct for channel frequency-selectivity (or equivalently the delay spread in time-domain) and maximise the link’s capacity, WiFi devices continuously track changes over these subcarriers in terms of CSI values, which are then used to adapt transmission power and rates in real time. CSI values are the Channel Frequency Response (CFR) at per subcarrier granularity between each transmit-receive (Tx-Rx) antenna pair. When a user is breathing, the chest and body movements change the constructive and destructive interference patterns of the WiFi signals. The CSI values are sensitive enough to measure these breathing movements, as CSI measurements can be obtained at high sampling rates and from multiple different OFDM subcarriers of each TX-RX stream. For example, the driver of the Intel 5300 WiFi NIC, which we use to implement our scheme, reports CSI values on 30 OFDM subcarriers \cite{40} for each TX-RX antenna pair for every CSI measurement. This leads to 30 matrices with dimensions \( M_t \times M_r \) per CSI sample, where \( M_t \) and \( M_r \) denote the number of transmit and receive antennas respectively. Such high dimensional data allows us to recover detailed information about the vital signs even if the breathing and body/limb related movements only incur small changes in the CSI.

3.2 Impact of Breathing on WiFi Multipath

Next, we present our first analysis that is aimed at understanding the effect of small breathing movements on the WiFi multipath and CSI signals. Based on this analysis, we design Serene’s signal processing pipeline to robustly extract breathing waveforms in an individual and environment independent manner. Our analysis shows that if we differentiate (i.e. by taking first order difference) the CSI signals from each WiFi subcarrier, and then max-min normalize the CSI signal projection corresponding to variations due to breathing, we can robustly extract the waveform corresponding to user’s breathing motion in an environment and individual independent manner, as long as the user sleeps close to the WiFi receiver. Such proximity requirement is easy to satisfy during real-life in-home sleep scenarios by either mounting receiver on the headboard of a bed frame or placing it on a table nearby. Note that differentiation generally degrades signal-to-noise ratio, unless the differentiation algorithm includes smoothing that is carefully optimized for the application at hand. Therefore, we introduce a combination of low-pass filters (i.e. median, exponential moving average, and Butterworth filters.
We experimentally design these filters such that signal-to-noise ratio is sufficiently good for a reasonable quantitative measurement of the sleep related vital signs. The max-min normalization is performed after the filtering process to estimate the breath rate ( \( \text{(4.3.2)} \) ). At the basis of our analysis is a closed form expression, which we derive using time-varying Channel Frequency Response (CFR) of Wi-Fi channel. The time-varying CFR corresponding to a Tx-Rx antenna pair for a subcarrier with wavelength \( \lambda \) can be quantified as:

\[
H(f, t) = H_s(f) + \sum_{i=1}^{N} \frac{K}{D_i(t)^2} e^{j\frac{2\pi D_i(t)}{\lambda}}
\]

In the equation above, \( N \) is the number of multipath reflections of the transmitted signal at the Rx end, \( D_i \) represents the distance traveled by \( i^{th} \) multipath reflection, and \( K \) is an environment dependent proportionality constant. \( H_s(f) \) is the static component of CFR corresponding to all non-user multipath reflections, while the second term on the right hand side corresponds to the dynamic component of CFR, represented as \( H_d(f, t) \), while the user is breathing and/or moving during sleeping. Now, let us assume that user is sleeping at a distance \( D_{0, i} \) from the router, and \( d_i(t) \) is the change in distance traveled by \( i^{th} \) reflected path due to breathing. To make our scheme resistant to static changes in the environment, we first eliminate \( H_s(f) \) by differentiating the above equation with respect to \( t \), and substitute \( D_i(t) = D_{0, i} + d_i(t) \) to get:

\[
H'(f, t) = \frac{d}{dt} \left[ \sum_{i=1}^{N} \frac{k}{D_{0, i}^2} \left(1 + \frac{d_i(t)}{D_{0, i}}\right)^{-2} e^{j\frac{2\pi(D_{0, i} + d_i(t))}{\lambda}} \right]
\]

As \( d_i(t) \) is caused by motion due to breathing in the order of a few centimeters, whereas \( D_{0, i} \) is usually in the order of meters (i.e. \( d_i(t) \ll D_{0, i} \)), we can expand the negative polynomial \( \left(1 + \frac{d_i(t)}{D_{0, i}}\right)^{-2} \) via binomial series expansion. After performing binomial expansion, discarding the \( \frac{d_i(t)^m}{D_{0, i}^m} \) terms with \( n = 4 \) or higher, and doing some algebraic manipulations, we get the following expression for \( H'(f, t) \):

\[
H' \approx ke^{\frac{j2\pi D_{0, i}}{\lambda}} \times \left[ \sum_{i=1}^{N} d_i(t) \left(-\frac{2}{D_{0, i}^3} + \frac{2\pi d_i(t)}{\lambda D_{0, i}^2} + \frac{4\pi d_i(t)}{\lambda D_{0, i}^3} \right) e^{j2\pi d_i(t)} \right]
\]

After converting the term inside summation into polar coordinates, and discarding the \( \frac{d_i(t)^m}{D_{0, i}^m} \) terms with \( n = 4 \) or higher, we get the following simplified expression for \( H'(f, t) \):

\[
H' \approx \left[ \frac{2\pi k}{\lambda D_{0, i}^2} \right] \left[ 1 + \left( \frac{\lambda}{\pi D_{0, i}} \right)^2 \right] \times e^{\frac{j2\pi D_{0, i}}{\lambda}} \times \left[ \sum_{i=1}^{N} d_i(t) e^{j2\pi d_i(t)} + jA_i \right]
\]

Here, \( A_i = tan^{-1} \left( \frac{\pi D_{0, i}}{\lambda} \left(1 - \frac{2}{D_{0, i}} \right) \right) \). Figure 2(a) shows variation of \( A_i \) with \( d_i(t) \), as \( d_i(t) \) varies from 1cm to 20cm (typical range for motion due to human breathing is 1-5cm [32]), for different router-receiver distances \( D_{0, i} \) ranging from 3m - 10m (i.e. which is typical for regular home use cases).

We observe that changes in \( d_i(t) \) do not significantly affect the value of \( A_i \). Moreover, the impact of \( d_i(t) \) on \( A_i \) decreases even further as the distance between receiver and the router it is connected to increases. Therefore, we can safely approximate \( A_i \approx tan^{-1} \left( \frac{\pi D_{0, i}}{\lambda} \right) = A_{0, i} \) and write \( H'(f, t) \) as:

\[
H' \approx \left[ \frac{2\pi k}{\lambda D_{0, i}^2} \right] \left[ 1 + \left( \frac{\lambda}{\pi D_{0, i}} \right)^2 \right] \times e^{\frac{j2\pi D_{0, i}}{\lambda} + jA_{0, i}} \times \left[ \sum_{i=1}^{N} d_i(t) e^{j2\pi d_i(t)} \right]
\]
The first term on right hand side of the equation above stays constant when receiver is placed on some surface, e.g., a desk/table, and is not moving. We write amplitude of CFR i.e. \(|H'(f, t)|\) as:

\[
|H'(f, t)| \approx C_{0, 1} \left| \sum_{t=1}^{N} d'_t(t)e^{2\pi di(\frac{t}{4})} \right|
\]

(3)

The waveform \(\left| \sum_{t=1}^{N} d'_t(t)e^{2\pi di(\frac{t}{4})} \right|\) corresponds to the variations due to breathing. The proportionality term \(C_{0, 1}\) in breathing samples extracted from \(|H'(f, t)|\) corresponding to different placement of receiver can be easily eliminated via max-min normalisation. Figure 2(b) shows extracted and processed single breath samples from a user for seven slightly different receiver placement configurations close to the user, while the router was in subject’s TV-lounge (router-receiver distance >10 meters).

### 3.3 Impact of Breathing and Body/Limb Movements on WiFi Signal Subspace

Next, we present our second analysis that is aimed at understanding how breathing affects the signal subspace formed by WiFi subcarriers compared to other bodily movements. Today’s MIMO and OFDM based WiFi devices use many frequency subcarriers and multiple transmit-receive (Tx-Rx) antennas for data communication. The MIMO system between the OFDM subcarriers and the Tx-Rx antennas, forms a multidimensional array which effectively represents a high-dimensional mathematical space. Contained in this space is the signal subspace along frequency and spatial dimensions [41]. The key intuition behind our model is that while a user is sleeping, the signal subspace along these dimensions is affected by both breathing and body/limb motion. When there is no body/limb motion, there is only one dominant time-varying component in the subspace, which corresponds to breathing. However, more components along these dimensions evolve (i.e. show considerable variations) during other body/limb activity e.g. during roll overs or arm/leg movement. Based on this principle, Serene isolates breathing from limb motion without requiring any environment-dependent calibrations.

To model this in Serene, we track the top dominant components in the CSI signal subspace using Principal Component Analysis (PCA). Figure 3(a) shows power values in top 5 PCA projections of the CSI signals corresponding to multiple sleep epochs during a sleep experiment, where the dotted lines correspond to epochs with motion events—highlighted in Figure 3(b). We observe that in the absence of any body/limb activity, the top-most PCA projection is enough to track breathing as it is the only major motion occurring in the environment. However, during body/limb movements, multiple lower PCA projections also show significant variations. Based on this phenomena, we accurately detect and then discard the CSI values corresponding to any body/limb activity by tracking variations in the lower PCA components (e.g. 3, 4 and 5) using a multi-dimensional clustering technique, which we discuss in §4.2.

### 4 CSI Signal Processing Architecture

To obtain CSI data in real-time during sleep, we develop a client-server based mechanism to communicate the CSI values extracted from WiFi NIC to a Python based CSI processing server. Based on our discussion in §3 we take first order difference of the incoming CSI data and then take its amplitude i.e. \(|H'(f, t)|\) for further processing. From now onward, we use the term “CSI” to denote \(|H'(f, t)|\).

CSI data is collected in 30 second epochs, which is typically the partitioning convention followed by most sleep monitoring systems. Next, we first perform basic low-pass filtering for removing bursty noise due to hardware noise and isolate the signal of interest i.e. to extract human motion related frequencies only. Second, we perform PCA on the low-pass filtered CSI streams for dimensionality reduction and automatic distinguishing of CSI variations due to body movements from those of breathing in different subcarriers based on our discussion in §3.3. This avoids the need for complex trial-and-error based subcarrier selection procedures used in previous works [23], [22]. Third, we harmonise the filtered CSI data corresponding to each 30s sleep epoch into uniformly sampled and consistent measurements via down-sampling. Fourth, we robustly detect body movements by tracking lower PCA projections of CSI signals using a clustering-based event detection technique. Finally, we first detect the presence of breathing using a power threshold, and then perform further band-pass filtering to extract the signal corresponding to breathing. Figure 4 shows our system architecture. Next, we briefly discuss Serene’s noise removal process.

#### 4.1 Noise Removal

Commodity Wi-Fi NICs report noisy CSI values, both due to hardware limitations (such as low resolution Analog to Digital Converters (ADCs)) and due to changing transmission power and rates. We use a combination of median filter and an exponential moving average filter to get rid of such bursty noise and spikes in CSI time series. After this basic filtering step, we further remove any high frequency variations in CSI signals using Butterworth low-pass filter. Variations due to movement during sleep cause low frequency variations, typically under 5 Hz [42]. We use Butterworth low-pass filter for separating these variations from higher frequency noise in CSI values. Due to maximally flat amplitude response of Butterworth filter, its application on CSI time series does not distort the shape of CSI variations due to body motion. Our scheme samples CSI values at a nominal frequency \(F_s = 800\). With this in mind, we use cut-off frequency \(\omega_c = \frac{2\pi f_s}{F_s} = 0.0125\ rad/s\) for Butterworth filtering. We apply the same filter on CSI timeseries of all the subcarriers, making sure that every CSI stream experiences the same phase distortion and group delay introduced by the filter.

Based on our experimental results, we observed that filtered CSI waveforms still retain some noisy variations which are not related to activity/breathing. We avoid any further low pass filtering on CSI streams as it can lead to loss in details of variations due to activity/breathing behavior. To remove such noise, we utilize the fact that the CSI variations in CSI streams of multiple subcarriers in each Tx-Rx antenna pair are correlated. We apply PCA on CSI obtained from all subcarriers and all Tx-Rx pairs, and retain only the waveforms that represent the most common variations in all the subcarriers, i.e., the variations due to breathing and/or...
body movements during sleep. That is, signal subspace-based filtering enables our scheme to automatically obtain the signals that are representative of the monitored vital signs only. PCA also reduces the dimensionality of data by discarding the principal components unrelated to the vital signs i.e. the noise subspace. Finally, we rearrange the multi-dimensional filtered CSI data corresponding to each 30s sleep epoch into consistent length samples (600 in our current implementation) via down-sampling, performing zero-padding where necessary. Although we have partitioned the incoming CSI data into 30s epochs, we concatenate data from consecutive epochs for real-time tracking of vital signs (e.g. breathing) which we discuss later in this section.

### 4.2 Tracking Body Movements

As discussed earlier, today’s MIMO and OFDM based WiFi devices use multiple frequency subcarriers and Tx-Rx antennas for data communication. The MIMO system between the Tx-Rx antennas, and the OFDM subcarriers, form a multidimensional tensor along space-frequency axes. Contained in such tensor is the signal subspace we wish to track for breathing and body motion. We observed that when there is no body/limb motion, there is only one dominant, time-varying component in the signal subspace, which corresponds to breathing. PCA sorts different principal components in descending order of their variation. During sleep, the signal subspace is rather quiet and breath is captured in the top PCA projection of the CSI time series. However, we observed that during episodes of other body movements—e.g. during roll overs or arm/leg movement—more signal subspace components evolve, since body movements cause more pronounced variations in the spatial-frequency subspace compared to faint breathing movements.

#### 4.2.1 Body Movements Detection Approach

To robustly distinguish body activity/limb motion from breathing, we propose to use a multi-dimensional hyper-ellipsoidal clustering on the lower PCA projections of CSI data. At a high-level, we can think of this clustering method as a high-dimensional generalization to a Gaussian outlier rejection technique whereby measurements few sigma’s away from the mean are deemed erroneous. Specifically, let $R_k = \{r_1, r_2, \ldots, r_k\}$ be the first $k$ samples of CSI vectors containing values from the selected signal subspace—we use PCA projections 3, 4 and 5 in our current implementation. Each sample $r_i$ is a $d \times 1$ vector in $\mathbb{R}^d$, where $d$ is the number of signal subspace components. This hyper-ellipsoidal technique clusters the normal data points (i.e. when there is no body movement in the environment), and any points lying outside the cluster are declared as outliers. The boundary of the cluster (a ‘hyper-ellipsoid’ in this case) is related to a distance metric which is a function of mean $m_{R,k}$ and covariance $S_k$ of the incoming signal subspace components $R_k$. We use the Mahalanobis distance metric, $D_r$, for which the cluster is arrived at according to the following [42]:

$$e_k(m_{R,k},S_k^{-1},t) = \{r_i \in \mathbb{R}^d \mid \sqrt{(r_i - m_{R,k})^T S_k^{-1} (r_i - m_{R,k})} \leq t\}$$

$$D_r = \text{Mahalanobis distance of } r_i$$

where $e_k$ is the set of normal data points whose Mahalanobis distance, $D_r < t$ and $t$ is the effective radius of the hyper-ellipsoid. The choice of $t$ depends on the distribution
4.3 Tracking Breath

Human breath involves motion of chest and lungs during inspiration (when air enters the lungs) and expiration (when air is blown out from the lungs) [32]. These motions are often periodic (e.g. in case of healthy subjects [32]), and therefore, cause periodic variations in WiFi channel which we can extract using CSI data. In the absence of other body movements, the first PCA projection of CSI data would be able to capture these variations due to breathing. However, as these minute variations are often embedded in noise, and because human subject might not be in proximity of the RX device, we can not always assume that breathing signal exists in a particular sleep epoch. Therefore, to robustly track breathing, we propose the following signal processing pipeline.

4.3.1 Bandpass Filtering

To extract the periodic variations in CSI due to breathing, we apply a Butterworth bandpass filter on the first PCA projection. We choose the filtering parameters of this filter according to the fact that breathing rate of humans (including adults as well as newly born babies) ranges between 10 - 40 breaths per minute (BPM) [32]. This step removes any non-breathing related noise present in the signal.

4.3.2 Measuring Breathing Rate

We design our system to measure breathing rate in terms of breaths per minute (BPM). We measure the rate over a window of two sleep epochs in length, which moves over concatenated data from multiple consecutive sleep epochs. To report BPM every second, we move this window over the concatenated data every second (i.e. 20 samples a time).

To measure breathing rate, we employ a peak detection based approach. First, we max-min normalize the signal so that parametrization of our peak detection algorithm can be easily generalized to different users. Second, robustly detect the number of peaks, we use three parameters, namely minimum peak prominence (MINPRO), minimum peak distance (MINDIST), and minimum peak strength (MINSTR). The prominence of a peak measures how much the peak stands out, due to its height and location, relative to other peaks around it. We tune MINPRO such that we only detect those peaks which have a relative importance of at least MINPRO. We tune MINDIST according to the fact that human breathing rate ranges between 10-40 BPM [32], so that redundant peaks are discarded. To further sift out redundant peaks, we only choose peaks of value greater than MINSTR times the median peak value. In our current implementation, we chose MINPRO = 0.025, MINDIST = 1.5 seconds and MINSTR = 0.6 which generalize well for different sleeping scenarios. To achieve accurate tracking of breathing rate, we perform parameterization of Serene’s breath estimation algorithm using ground truths obtained from a contact-less COTS Xethru X4M200 Breath/Motion sensor [43]. We perform this parametrization only during the design of our system and do not require any end-user calibration effort in the real-world deployments.

5 IMPLEMENTATION AND EVALUATION

In this section, we present the performance evaluation of our system after performing full-night sleep experiments in real-world settings. Next, we first discuss our hardware implementation and the experimental settings.

5.1 Hardware Implementation

We developed compact HummingBoard (HMB)-based small-sized nodes as sleep monitoring devices [44] which makes Serene easy to deploy. HMB nodes were equipped with the Intel 5300 NICs with modified drivers for extracting CSI information [40]. We used Linksys AC1200+ routers as transmitters in our deployments. Moreover, we developed a client-server software architecture—in C and Python respectively—capable of the real-time extraction and processing of CSI data throughout the night. For body movement and breathing rate ground truths, we deployed state-of-the-art pulse-doppler radar-based Xethru X4M200...
Breath/Motion sensors [43]. In terms of breathing rate accuracy, the X4M200 devices have been shown to perform very closely to a medical-grade, gold standard equipment (X4M200 has been shown to track breathing with up to 96% accuracy when compared to PSG) [45]. We chose a contactless sensor to record ground truths because the participants of our study were not comfortable wearing devices such as breath monitoring belts during their regular sleep. Moreover, the devices that require body contact generally tend to interfere with natural sleep of the users [9]. We utilize these ground truths in our system for: (1) the robust parametrization of our signal processing pipelines (e.g. breath tracking), (2) measuring breath tracking accuracies, and (3) measuring limb/body motion tracking accuracies.

5.2 Experimental Settings

We deployed our system in 5 apartments, where we collectively recorded more than 80 nights (~550 hours) of data from 5 different participants. The participants were graduate students aged between 23 to 32 years. The duration of data collection for each participant varied from 5 to 31 days. Figure 6 shows the real-world deployment scenarios for our sleep experiments. The numbers in circles specify user/environment IDs. Data collected from environments 2 and 3 corresponds to NLOS deployment scenario, and constitute 55% of our dataset. Data collected from environments 1, 4, and 5 corresponds to LOS deployment scenario, and constitute 45% of our dataset. To evaluate Serene’s vital signs tracking performance, we collected Xethru ground truth alongside CSI data for the environments 1, 2, 3 and 5. We evaluate both long-term (i.e. whole night) and short-term (i.e. specific short duration sleep windows during the night).

5.3 Breath Tracking Accuracy

We evaluate the accuracy of Serene’s breathing rate estimation in terms of BPM error. We define BPM error as the average mean squared error (MSE) between per second BPM values reported by Serene and the corresponding ground truth BPM values reported by X4M200 over a specific time window. We perform this evaluation on data collected from environments 1, 2, 3 and 5. We evaluate long-term and short-term (i.e. specific short duration). Figure 7(a) shows how Serene tracks breathing rate throughout the night in for 4 different
users, where we have plotted X4M200 ground truth side by side. We can observe that BPM accuracies vary during the night as a user’s sleep posture and distance from the sleep monitor can change during sleep. However, we also observe that Serene is able to track the overall increasing and decreasing trend in a subject’s breath during sleep fairly well when compared to Xethru’s ground truth.

![Figure 7(a)](image)

(a) CDF of overall and per-user BPM error.

![Figure 7(b)](image)

(b) Full night breath tracking.

![Figure 7(c)](image)

(c) Sleep posture experiments.

Fig. 7: CDF of overall and per-user breathing rate MSE compared to a Xethru X4M200 ground truth; Serene’s full-night breath tracking performance; and average BPM errors for short duration sleep experiments in different sleep postures.

Figure 7(a) also shows how BPM accuracy varies across subjects. For instance, the median accuracy was better than 1.12 BPM and 1.2 BPM for users 1 and 2, respectively. However, user 3’s median accuracy was a bit higher (i.e., 1.488), while the 95th percentile confidence was as large as 1.95 BPM. These slight variations across different users and environments occur due to differences in physiques, respiratory system morphologies and environmental deployment conditions. For example, environments 2 and 3 both correspond to NLOS scenarios, which leads to relatively lower BPM accuracies. Although the level of robustness and accuracy Serene achieves may not be comparable to contact-based high accuracy breath monitors, yet it is comparable to other commercial contact-less sleep monitoring products. Therefore, based on our results, we conclude that WiFi based sleep monitors can be robust and accurate enough for daily in-home use to gain insights into overall breathing trends during sleep. However, the accuracy may not be enough for medical grade sleep assessments.

### 5.3.2 Short-term Accuracy

Serene can achieve an error of as low as 0.34 BPM during certain parts of a full-night sleep. However, the errors can be more than 5 BPM depending upon the time of night as a user’s sleep posture and distance from the sleep monitor changes during sleep. In Fig. 7(b), we notice that there are certain time windows during the night where Serene matches Xethru’s performance very closely. To know how many times such time windows occur during different nights in our dataset, we divide each night into small 15 minute time windows and compute the MSE of per second BPM estimate in those windows. Figure 8(a) shows the CDF plots for 6 different full-night sleep experiments corresponding to users 1, 2 and 3. From Fig. 8(a), we observe that in the case of User 1, Serene experienced a breathing rate error of only 0.34 BPM in one 15 minute window during Night 6. Moreover, error in more than 50% of the time windows remained below 0.84 BPM during Night 6. Similarly, for other users, we observe that in multiple time windows during a full-night sleep, BPM error stays under 1 BPM. This shows that Serene does fairly well when compared to controlled short-duration sleep experiments performed in recent CSI based sleep monitoring studies. Also, figure 7(c) shows average BPM errors for controlled 10 minute sleep experiments in different sleep postures. We observe that Serene achieve an error of less than 1 BPM for most sleep postures even in NLOS scenarios. The errors were as low 0.55 BPM in LOS scenarios. However, we also observed errors approaching 5 BPM during certain time windows that can be attributed to changes in the user’s sleep posture and distance from the sleep monitor during sleep.

### 5.4 Naturally Occurring Motion False Positives

Serene experienced a median of 20 false positive limb/body motion events, which can be attributed to activity of other house residents while the user is sleeping. The total duration of such events stayed below 37 minutes more than 95% of the time. Radar and WiFi are both very sensitive to body motion. We observed from our experiments that whenever a user moves in their bed, both Serene and X4M200 successfully detect the motion event. However, we also observed scenarios where Serene detected body movements but the ground truth remained undisturbed (i.e., contained breathing signal only). We call such spurious movements detected by Serene as motion false
positives (MFPs), which we attribute to other movements present in the environment (e.g., when one of the occupants wakes up to get water, etc.). To understand how significant such MFPs can be in real-world deployments of a WiFi based sleep monitoring system, we evaluate the following two key metrics on the real-life dataset we collected using Serene: (1) the number and (2) duration of MFPs per night’s sleep.

Figure 9 illustrates the CDFs of these two metrics evaluated over more than 65 nights in our database. We observe that our system detected less than 56 MFPs occurrences for 95% of tested nights. Moreover, when we observe that when MFPs occur, their collective duration remains bounded under 37 minutes for 95% of the time, as shown in figure 9(b). Although the total duration of such events during any night’s stayed below 10 minutes on average and below 37 minutes 95% of the time, yet we observed motion false positives of more than 60 minutes (1 hour) in total during one of the nights in our dataset. Note that these MFPs do not signify any technical limitation of WiFi based sleep monitoring, as such motions occur naturally in home environments. Our results show that the number and duration of naturally occurring interference in WiFi signals due to activity of other residents is usually low during night time. Therefore, WiFi based sensing is suitable enough to be used for sleep monitoring during night time.

5.5 Breath Signal Outage

5.5.1 Detecting Outage in Breathing Signal

Serene experiences an average outage of less than 6.38 minutes, during which it cannot track any vital signs. We define the outage of our system as the event when variations due to breathing are not present in the CSI signal while the ground truth device (i.e., Xethru X4M200 in our case) is able to track breathing. To detect outage, our system first determines the noise floor of the environment using the first PCA projection. During real-time tracking, our system compares the average power of the signal, calculated over 7.5s windows of every 30s sleep epoch (i.e., $1/4^{th}$ of an epoch’s duration), with the determined noise floor. If the average power of the sleep epoch is not above the determined noise floor while X4M200 is still able to track breath, Serene signals outage. To assess Serene’s ability to continuously track vital signs (i.e., breathing and other limb/body activity) in real

3. To detect outage, we use the ‘absent’ signal that Xethru X4M200 provides when it cannot detect any motion in the environment.
life, we measure its per-night outage performance statistics. To achieve this, we follow the treatment of signal outage in wireless propagation literature. Specifically, we calculate two second-order statistics: level crossing rate (LCR), and average fade duration (AFD) \[46\]. LCR determines the rate at which outages occur during a full-night sleep, whereas AFD determines the duration of each outage. We analyze the LCR and AFD using the first PCA projection’s power with respect to the noise floor. LCR and AFD have been extensively studied in body area network (BAN) literature owing to the complex and non-stationary way in which a human body interacts with the wireless channel \[47\]. Next, we present a summary of the aforementioned statistics derived from our entire dataset. Figure \[10(a)\] shows LCR or outage rate calculated per hour across our sleep dataset. We can observe that on average, the breathing rate estimation introduced a design threshold to separate the two types of outage events. From the analysis of our dataset, we set such design threshold to 5 minutes, where we consider outage events longer than 5 minutes as a large-scale outages and vice versa. Figure \[10(b)\] elaborates on the statistical behavior of small-scale outage. On average, small-scale outage events lasted for 0.7 minutes, while the 95th percentile confidence outage duration is under 1.62 minutes. CDF of the duration of large-scale outage is shown in figure \[10(c)\]. Large-scale outage duration averaged around 6.38 minutes while its 95th percentile confidence is under 11.56 minutes, although durations in excess of 15 minutes can occur. Based on this analysis, we can conclude that WiFi based sleep monitors experience more outages compared to radar based monitors such as Xethru X4M200. However, we must mention that while collecting the dataset we suggested our subjects not to change the position of X4M200 so that their chest stays in X4M200’s line-of-sight. In real life scenarios, users can make mistakes while positioning such radar based sensors before going to sleep which may cause outages similar to the ones experienced by Serene.

6 Discussion

6.1 Limitations of WiFi Signals based Vital Signs Monitoring during Sleep

Our results show that WiFi based sleep monitoring can be significantly affected by changes in a user’s sleep postures and activity of other house residents while the user is sleeping. The breath rate error can vary between 0.34 BPM to more than 5 BPM depending upon the time of night as a user’s sleep posture and distance from the sleep monitor can change during sleep. Breath signal outages arise due to subjects rolling over in bed to a different position and/or sleep posture that makes it difficult to pick up the subjects’ chest movements for a while. False positive sleep motion events arise due to variations in CSI signals caused by other house residents of a sleeping user. However, average nightly duration of breath signal outages and motion false positives stayed under 6.38 and 10 minutes in our dataset, respectively. Therefore, we conclude that WiFi based vital signs monitors perform fairly well compared to pulse-Doppler radar based solutions and can be robust and accurate enough for daily in-home use to gain insights into overall breathing and body movement trends during sleep. However, the accuracy may not be enough for medical grade sleep assessments.

6.2 Sleep Scoring

To motivate the merits of WiFi based sleep monitoring, we present a few interesting insights on sleep quality gained from our data collection campaign. To achieve this, we take an actigraphy based approach towards sleep quality monitoring, where we classify the stage of each minute as sleep or awake period. Our approach is inspired by the classic light-weight actigraphy based method proposed in \[48\], which determines sleep-awake stage of a minute by taking into account body movement related information corresponding to the surrounding minutes. The activity sleep-awake scores determined by their technique have been shown to agree with EEG based sleep monitoring 94.46% of the time \[48\].

In our implementation, we adopt the following model from their work, which takes 4 previous minutes and 2 following minutes into account to classify stage of the current minute:

$$ s_m = \rho \times (w_{-4}a_{-4} + w_{-3}a_{-3} + w_{-2}a_{-2} + w_{-1}a_{-1} + w_0a_0 + w_1a_1 + w_2a_2) $$

where \( s_m \) is the average sleep-awake score for the current minute, \( \rho \) is a scaling factor, \( a_{-i}, a_0, a_{+i} \) are activity scores (normalized number of body movement events in each minute) for previous, current and following minutes, and \( w_{-i}, w_0, w_{+i} \) represent weights for the previous minutes, current minute and following minutes. If \( s_m \leq 1 \), the current minute’s stage is classified as sleep, and if \( s_m > 1 \), the current minute’s stage is classified as awake. In our implementation, we chose \( \rho = 0.125, w_{-4} = 0.15, w_{-3} = 0.15, w_{-2} = 0.15, w_{-1} = 0.08, w_0 = 0.21, w_1 = 0.12, w_2 = 0.13 \), as suggested by the authors of \[48\] for best results in their real-world deployments.

Next, we perform sleep assessments using the data corresponding to users 1 - 4. Our results show how Serene can provide users with actionable feedback on a per-night basis towards the long-term tracking and management their sleeping habits based on the aforementioned sleep scoring algorithm. Figure \[12\] shows three different metrics of sleep determined for 3 users over a period of more than 13 consecutive days, namely sleep efficiency, aggregate motion (in minutes) during sleep and sleep length. Sleep efficiency for each night of sleep was calculated using on our actigraphy based sleep scoring approach, which is defined as the ratio of actual time spent in sleep stages to total time spent in bed (i.e. \( T_{sleep}/(T_{sleep} + T_{awake}) \)). Figure \[11\] shows Sleep/Awake...
Fig. 10: Second-order statistics of breath estimation outage events. Outage rate and average outage duration mirror, respectively, their counterparts level crossing rate and average fade duration from wireless propagation literature.

Fig. 11: Example showing Sleep/Awake classification for full night’s sleep of a subject. Sleep efficiency was 62.1%.

Fig. 12: Sleep efficiency and body motion corresponding to 4 users and throughout 13+ consecutive nights.

classification performance for full night’s sleep of a subject, where sleep efficiency was determined to be 62.1%. As users manually started and ended each night’s data collection using our software, the sleep lengths were easily determined according to those end points. We observe interesting insights for these long term sleep metrics. For instance, we can see that User 1 experienced a noticeably restless 9th night which resulted in poor sleep efficiency. User 4 only slept for 1.25 hours, but as he was awake for only 4.156 minutes during that time, his sleep efficiency reaches 95%.

In terms of aggregate body motion statistics over nights and across subjects, we measured a median of 40 minutes with the 95th percentile being under 80 minutes as illustrated in the blue CDF in figure 13(a). On an individual basis, and considering user 2 and user 4 for instance, their median body movements were 36 minutes and 47 minutes, respectively. This insight is corroborated when inspecting the complementary CDF’s depicted in figure 13(b). Specifically, while both users 2 and 3 have a comparable maximum sleep efficiency of 96%, User 3’s sleep efficiency was lower than 80% on 3 different nights. Moreover, User 2 has a worst efficiency of 75%, whereas User 3 has worst efficiency of 63%. For the aggregate dataset, the median user population sleep efficiency was around 87%. The average sleep duration among these 3 users during this consecutive testing period was 7.32 hours. Note that the recommended sleep for ages 18-64 years is 7-9 hours [32].

7 CONCLUSIONS
In this paper, we evaluate the performance of WiFi based vital signs monitoring in the wild. We make two major contributions. First, we characterize the relationship between WiFi signal components (i.e. multipath and signal subspace) and human vital signs (i.e. respiration and body motions). Grounded in this characterization, we propose two methods: 1) a respiration tracking technique that models the peak dynamics observed in the time-varying signal subspaces and 2) a body-motion tracking technique built with a multi-dimensional clustering of evolving signal subspaces. Second, we extensively evaluate our proposed methods through real-world full-night sleep experiments conducted in 5 different apartments, where we collected more than > 550 hours (80 nights) of data from 5 users. Our results demonstrate that the proposed techniques were
able to track respiration rate with an average error of <1.19 breaths per minute (BPM). However, the breath rate error varied between 0.34 BPM to more than 5 BPM depending upon the time of night as a user’s sleep posture and distance from the sleep monitor can change during sleep. Co-located activity of other house residents also affects WiFi based vital signs monitoring. For example, our system experienced 20 false positive motion events on average every night, due to activity from co-located house residents while a user is sleeping. The duration of time during which respiration monitoring halted (i.e. estimation outage) was under 10 minutes on average per night. We conclude that WiFi based vital signs monitors can be robust and accurate enough for daily in-home use to gain insights into overall breathing trends during sleep. However, the accuracy may not be enough for medical grade sleep assessments.

Fig. 13: Overall and per-user CDF for motion duration and sleep efficiency.

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