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Diagnosis of the Hypopnea Syndrome in the Early Stage

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Abstract — **Hypopnea syndrome is a chronic respiratory disease that is characterized by repetitive episodes of breathing disruptions during sleep. Hypopnea syndrome is a systemic disease that manifests respiratory problems, however, more than 80% of Hypopnea syndrome patients remain undiagnosed due to complicated polysomnography. Objective assessment of breathing patterns of an individual can provide useful insight into the respiratory function unearthing severity of Hypopnea syndrome. This paper explores a novel approach to detect incognito Hypopnea syndrome as well as provide a contactless alternative to traditional medical tests. The proposed method is based on S-Band sensing, peak detection algorithm and sine function fitting for the observation of breathing patterns and characterization of normal or disruptive breathing patterns for Hypopnea syndrome detection. The proposed system observes the human subject and changes in the channel frequency response caused by Hypopnea syndrome utilizing a wireless link between two monopole antennas, placed 3m apart. Accuracy of the proposed method is established through comparison with commercial respiratory sensor. The experimental results show that this technique has the potential to open up new clinical opportunities for contactless and accurate Hypopnea syndrome monitoring in a patient friendly and flexible environment.**

Keywords — **Hypopnea syndrome, respiration sensor, early warning, biomedical engineering, machine learning**

I. INTRODUCTION

Sleep is an essential survival skill and has great significance to human health. Sleep not only affects the productivity and physical vitality of a person but is also related to many diseases including diabetes, depression, and even stroke and heart failure [1]. Therefore, sleep function monitoring has a high medical value.

Hypopnea syndrome is a common illness that occurs when throat muscles intermittently relax and block the airway during sleep [2]. It is characterized by repetitive episodes of shallow or paused breathing during sleep and is usually associated with a reduction in blood oxygen saturation. These episodes of paused breathing typically last 20 to 40 seconds. Signs and symptoms of sleep apnea include excessive daytime sleepiness, loud snoring, breathing cessation during sleep, abrupt awakening due to respiratory disorders, such as hypopneas, apneas, and choking. Back in the days, Hypopnea syndrome was considered as a sleep habit accompanied by snoring, but it is now regarded as a serious clinical disorder. Several studies indicate that a high percentage of patients suffering from Hypopnea syndrome remain unidentified, which can greatly affect their routine life and might create severe health complications, such as reduced work performance. Furthermore, evidence suggest that Hypopnea syndrome is related to systemic diseases, such as cardiovascular diseases and glucometabolic impairments as well as various pediatric complications, such as psychological and behavioral disorders, nocturnal enuresis, and growth-related disorders [3]. Greater association to Hypopnea syndrome not only brings cardiovascular problems and neurological disorders, it can also cause sudden death in case of severe breathing obstruction [4]. Timely detection of Hypopnea syndrome through observation of respiratory disorder episodes is therefore of vital importance in personal healthcare.

Polysomnography is a standard method for the diagnosis of Hypopnea syndrome. It is based on a comprehensive recording of bio-physiological changes occuring during sleep. The test is typically a full night study performed on a patient in a laboratory environment by medical experts. The PSG monitors observe heart, lung and brain activity, breathing patterns, arm and leg movements, and blood oxygen levels in the form of electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), electromyography (EMG), and oxygen saturation (SpO2). Though Hypopnea syndrome can be objectively assessed and monitored by these signals, the subjects are often uncomfortable by deploying electrodes and wearing bands on their bodies during this long procedure. Moreover, the data can only be obtained in institutions or hospitals equipped with dedicated devices [4].

There are many reported attempts that have tried to utilize alternative physiological signals to overcome the drawbacks of polysomnography [5-7]. One of the examples includes spectral analysis of snoring sounds to detect Hypopnea syndrome [7]. However, accuracy and feasibility of such methods is always in question.

With the recent developments, wireless sensing has opened the doors for sleep monitoring systems leveraging various sensors, such as audio, image, force and temperature [8-18]. Most of these wireless systems are contact-oriented require wearable sensors worn by the patient to acquire adequate precision levels in a clinical setting. Use of smartphones' accelerometer and audio recordings to monitor sleep disorders is proposed in [8-10]. However, use of such systems in a clinical application is yet not established. Behar et al. have studied a wearable system composed of an armband sensor, a face-worn microphone and a wrist-worn oximeter connected to the smartphone for the sleep apnea detection [9]. Force sensors deployed under the mattress top have also been used to detect the heart rate, sleep pattern,

snoring, or respiration rate [11-15]. Martinez et al. have investigated a wireless sensor system to detect respiratory rate using received signal strength indicator [16]. However, this system requires 15 to 20 sensor nodes to achieve high classification accuracy. Video recordings of sleep patterns through camera-based optical approach is adopted to detect the breathing pattern via video recordings is discussed in [17] and [18]. Cost effective-ness of polysomnography technique using split-night sleep monitoring is considered in [19]. However, availability of the equipment at clinics restricts its wider availability and flexibility to the patient, as they have to spend the night in a hospital environment. Though wearable technologies have emerged as a potential solution to monitor the patients unobtrusively, outside clinical settings, they limits patients comfort due to requirement of a number of body-worn sensors.

In this paper, we investigate a non-invasive system based on S-band sensing to monitor the sleep apnea. The novelty of this work lies in the development of an accurate and efficient monitoring technique that provides continuous, contactless and patient-friendly solution. Usability and accuracy of the proposed system is established through a comparative study with standard commercial respiratory sensors.

II. SYSTEM DESIGN

The proposed method primarily uses sensing technique that works at S-band. Details of the system architecture are discussed in this section.

A. Basic System Architecture

The proposed sensing system makes use of a wireless link between two antennas positioned at two sides of the human subject, as illustrated in Figure 1. The two antennas are placed around the chest and are visually in a straight line, enabling them to establish a Line-of-sight (LOS) link. The distance between the two antennas is kept at 3m to replicate a typical patient monitoring system in a wireless environment.

This sensing platform is an in-house system and consists of a spectrum analyzer (E8600), vector network analyzer (Agilent E8363B), antennas, software-defined radio, RF generator, and desktop workstation equipped with network adaptor. This system can work at a number of frequencies depending on the operating band of the antennas. For our work, we have selected the S-band frequencies of 2.4GHz-2.48GHz due to their wide usage in healthcare applications and added benefits discussed in the proceeding section.

The system employs monopole antennas at the transmitting and receiving ends. This selection of the antennas is based on a two-fold approach; making the system universal by using widely available standard type of antennas and decreasing the antenna's effect on the sensitivity of the system. Along with the antenna, the emitter includes RF generator, coaxial cable and connector.

Figure 1–Experiment setup for detecting sleep apnea.

The propagation mechanism of RF signals between the transmitter and receiver is complex and can take both Line-of-sight (LOS) and Non-line-of-sight (NLOS) paths, as shown in Figure 2. The LOS path refers to the signals propagating in a direct path with no blockade by the human subject. The walls of the room are covered with RF absorbing material to get rid of these scattered components. It not only simplifies the overall system model but also improves the accuracy through better detection of minute chest movements due to breathing and accompanying spatial changes in the channel response.
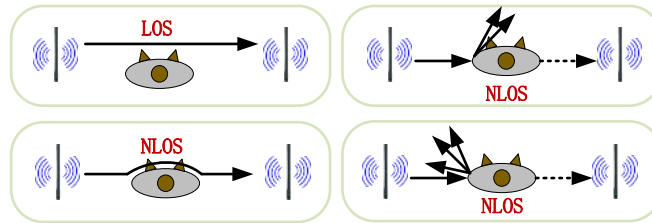

Figure 2– Radio propagation modes for sleep apnea detection.

B. *Wireless Channel Information at S-Band*

The proposed system observes the wireless channel between the transmitter and receiver and note down any sudden variations as a result of change in breathing pattern to detect the sleep apnea episodes. A group of 30 OFDM subcarriers carrying the channel information is used and can be exported to the user. Each of the exported data packets contains both the amplitude and phase information for a particular subcarrier:

$$H(f_n) = |H(f_n)| e^{j\angle H_n} . \tag{1}$$

Where, $H(f_n)$ represents the wireless channel information for n^{th} subcarrier at the central frequency,

f_n, $|H(f_n)|$ is the amplitude information, and $\angle H_n$ describes the phase response.

The rationale behind using the S-band sensing is based on the argument that the wireless channel information retrieved using S-Band sensing technique is a superior metric as compared to other techniques, such as received signal strength indicator as it presents a fine-grained information of the wireless channel and is more efficient for small-scale multipath fading [20]. The core idea of using wireless channel information is to monitor the breathing pattern of the human subject and identify sleep apnea episodes by keeping track of any minute changes in the channel response. S-band sensing is sensitive enough to record these small changes but the received signal strength indicator only provides the received power levels and fails to note down the effects induced by small chest movements caused by breathing irregularities. Moreover, reflections and scattering of the radio frequency (RF) signal caused by the chest movements affect different subcarriers differently. S-band sensing technique enables examination of each of the subcarriers while the conventional received signal strength indicator only presents average power that can potentially overlook these small changes.

From each wireless channel information (WCI) packet, a *30 × 1* matrix in the form of channel frequency response (CFR) can be extracted. Each row of the WCI matrix describes one subcarrier. If CFR_m represents the channel frequency response of mth packet received, then:

$$CFR_m = [\![h^1(m), h^2(m), h^3(m), \ldots, h^{30}(m)]\!], \tag{2}$$

where $h^i(m)$ denotes the CFR of the subcarrier i, at time m. To examine the time history of CFR_m, total number of CFR_m recorded at various time intervals are combined and expressed as:

$$CFR = [\![CFR_1, CFR_2, CFR_3, \ldots, CFR_k,]\!]. \tag{3}$$

Here, CFR is a *30 × k* matrix, where *k* describes the total number of packets received using network adapter and represents the change in the wireless channel over the observed time duration.

C. Experimental Workflow

The usability of the proposed system is established through performance comparison with a standard respiratory sensor. Thus, the experimental workflow has two main components:

1. Normal breath detection using both the S-band sensing technique and an invasive breathing sensor.
2. Hypopnea syndrome detection through wireless channel information and an invasive breathing sensor.

The respiratory sensor also helps to identify the specific frequency that should be chosen, which is a key step in sleep apnea detection.
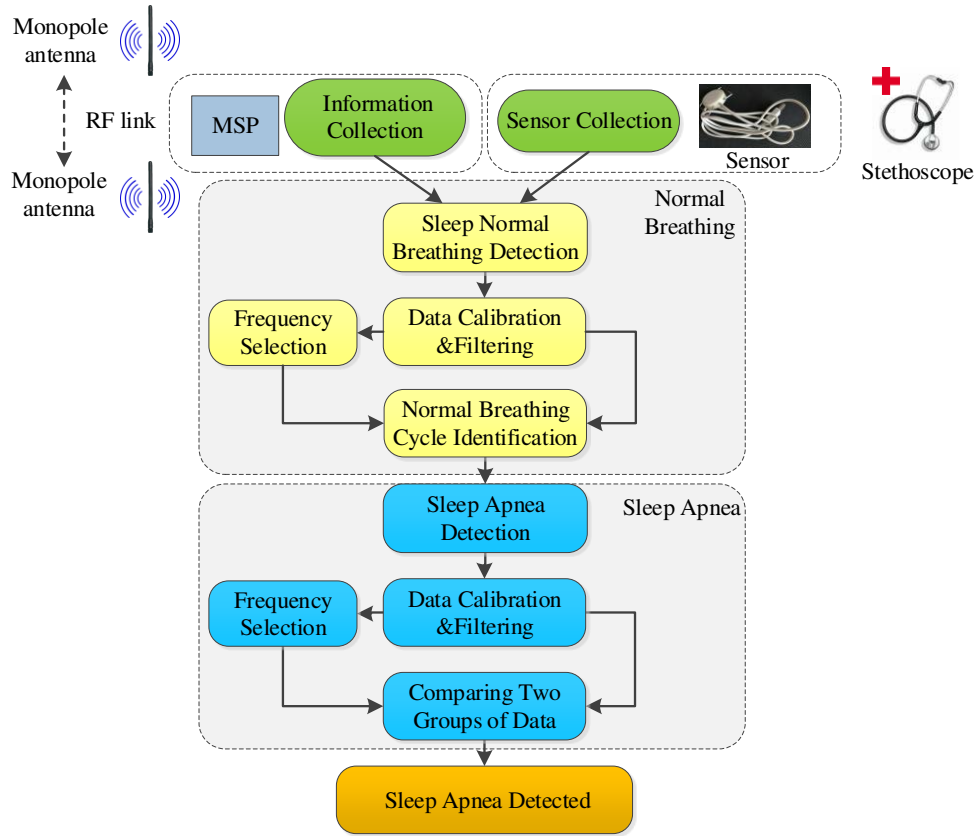
Figure 3– Experimental work-flow.

Raw wireless channel information recorded by S-band sensing technique is first calibrated and filtered, as shown in Figure 3. The wireless channel information measurements are then examined for changes that occurred due to small chest movements associated with varying breathing pattern. If any changes are recorded, all of the 30 subcarriers are analyzed to look for any abnormalities in the breathing pattern. In case of no sudden disturbances in the breathing pattern due to chest movements, the wireless channel information data would remain constant for the period of observation, inferring an absence of sleep apnea. A comparison between the two data sets would result in the detection of the Hypopnea syndrome.

III. RESULTS AND DISCUSSION

A. *Benchmark Study*

A benchmark study is carried out first to establish the usability of S-band technique for breathing pattern monitoring. Figure 4 shows the raw amplitude data obtained using S-band sensing technique for 30 subcarriers over a period of 60 seconds when the subject was breathing normally. The measurements were taken when the patient was lying straight, facing upwards. Clear variances and some wave-like pattern can be observed in the observed data.
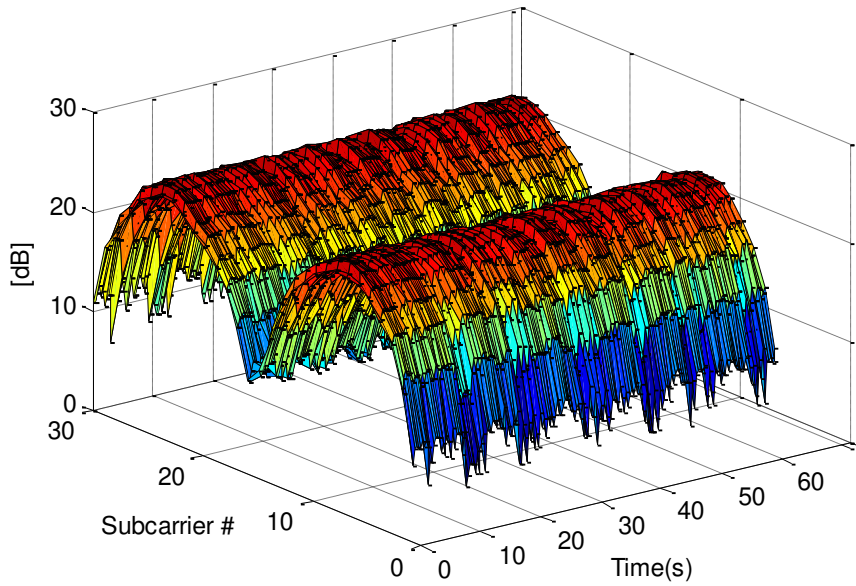
Figure 4 – 3-D illustration of the raw data obtained for normal breathing.

To examine the breathing pattern, further processing of the CFR amplitude data is needed. The first step is to perform filtering. Figure 5(a) shows the raw amplitude of all the 30 subcarriers in 2-D. It can be seen that there are some abrupt changes in all the subcarriers. To track clear breathing behavior, these abrupt change points must be eliminated.
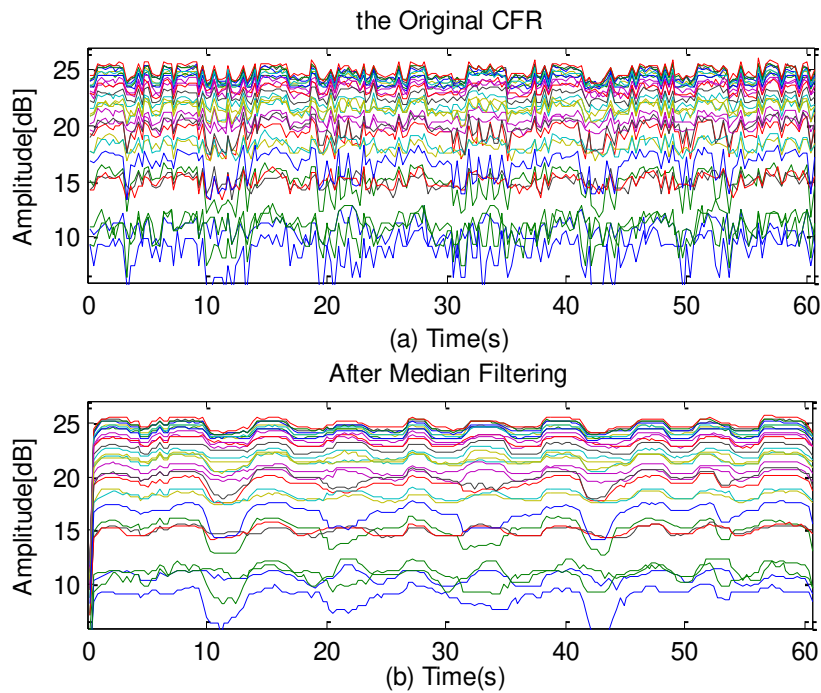
(a) Raw CFR from all the 30 subcarriers.

(b) CFR data after applying selective weight median filtering.

Figure 5 – Variances of 30 sequences of normal breathing.

The selective weight median filter is used to remove the abrupt change points. The choice of this filter is based on the fact that it is a highly effective elimination method for the impulse noise [21], appearing in Figure 5(a). The conventional filters like Chebyshev or Butterworth, are not appropriate to remove such high-frequency noise as they blur the rising and falling edges of the signal which are critical for identifying the sleep apnea episodes in this study. Figure 5(b) shows a much cleaner CFR data for the 30 subcarriers after using the selective weight median filtering.

We will now discuss the process of characterizing normal and abnormal breathing.

From Figure 5(b), we can see that most of the 30 subcarriers have conspicuous periodic oscillatory patterns correlated with breathing, whereas the rest are messy. The channel giving most clear information of breathing pattern with most obvious wave-like pattern after the filtering process is considered as the most 'suitable' for the detection of the Hypopnea syndrome. Based on this, we selected the time history of the 26th subcarrier as shown in Figure 6.
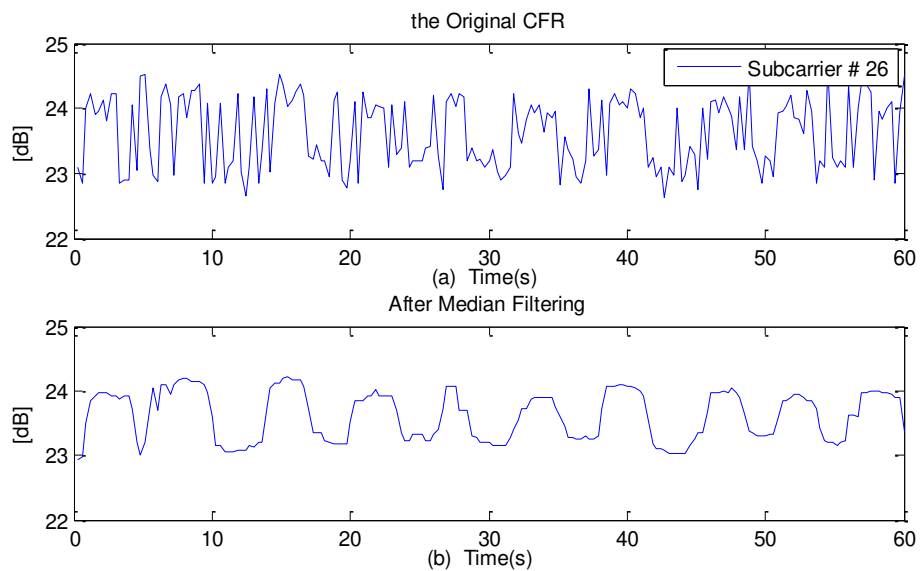

Figure 6 – Time history of the 26th subcarrier and corresponding filtered data for 60 seconds duration.

The data for the chosen individual subcarrier is analyzed for a sample of 60 seconds. Figure 6(a) shows the normal breathing of a person lying in a straight position. Signs of breathing are clearly evident due to fluctuations in amplitude information. Figure 6(b) shows the CFR values after applying the median filter.

the Original Data
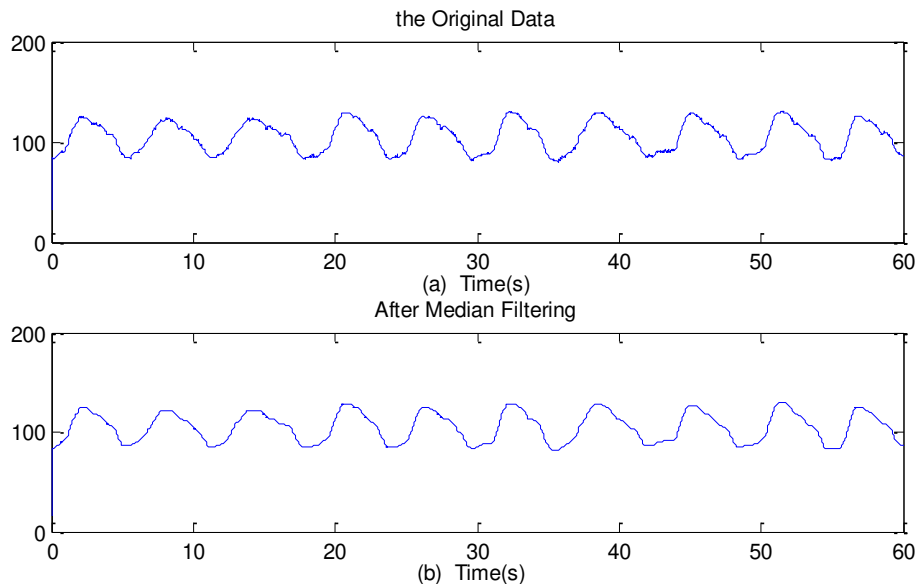

(a) Time(s)

After Median Filtering

(b) Time(s)

Figure 7–Normal breathing obtained using breathing sensor

Figure 7 presents a comparison of the filtered breathing pattern obtained using S-band sensing technique with that recorded using a breathing sensor. The filtered breathing patterns shown in Figures 6(b) and 7(b) indicate that over the period of 60 seconds, a total number of 10 breathing cycles were obtained. This comparison also helps to select the specific frequency for detection. It establishes the ability of S-band sensing to successfully record a clear breathing pattern.

To analyze the accuracy of S-band sensing technique, the Sine function fitting algorithm is used to compare the results of the two detecting methods in Fig. 8. The S-band sensing technique has observed 10 complete breathing cycles. Value of ω is 4.989e-05 for S-band technique, which is equal to b1.
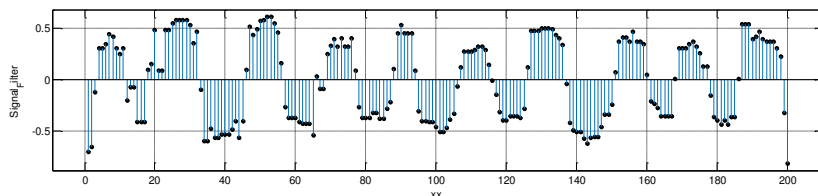
General model Sin1:
$$f(x) = a1*\sin(b1*x+c1)$$
Coefficients (with 95% confidence bounds:)
    a1 = 24.07   (-268.9, 317.1)
    b1 = 4.989e-05 (-0.01589, 0.01599)
    c1 = 1.762   (-61.01, 64.54)

Goodness of fit:
    SSE: 31.72
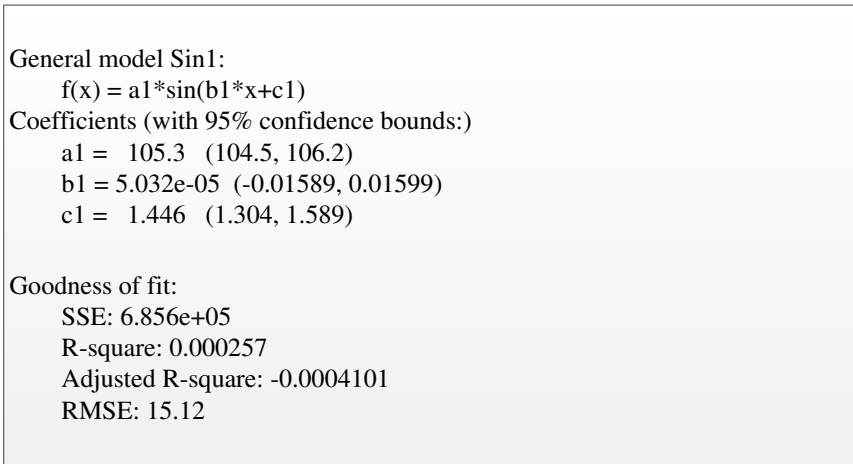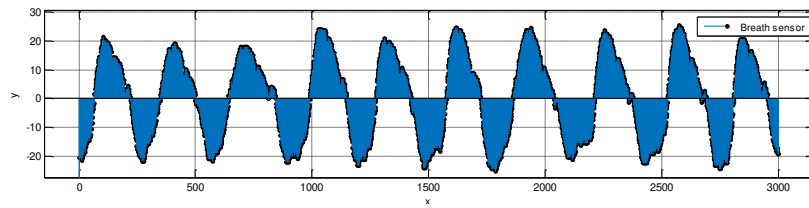   R-square: 0.001354
    Adjusted R-square: -0.008784
    RMSE: 0.4013

(a)

```
General model Sin1:
    f(x) = a1*sin(b1*x+c1)
Coefficients (with 95% confidence bounds:)
    a1 =   105.3   (104.5, 106.2)
    b1 = 5.032e-05  (-0.01589, 0.01599)
    c1 =   1.446   (1.304, 1.589)


Goodness of fit:
    SSE: 6.856e+05
    R-square: 0.000257
    Adjusted R-square: -0.0004101
    RMSE: 15.12
```

(b)

(a) Normal breathing obtained using S-band sensing technique.

(b) Normal breathing obtained using breathing sensor.

Figure 8–Sine function fitting for normal breathing.

Sine function fitting results for the respiratory sensor in Figure 8(b) also have 10 complete breathing cycles with ω = 5.032e-05, which is equal to b1. Comparing the two observations, regardless of intuitive or calculated results, the observations of detecting normal breathing have close agreement. This show that S-band sensing technique and the designed measurement system has a good ability to detect breathing patterns.

B. *Sleep Apnea Detection*

Acquisition of the data is in-line with the benchmark study for this part of the experiment. Raw wireless channel information is obtained with the human subject lying straight. The subject first breathes normally, then stops breathing for a while to mimic sleep apnea episode and then starts breathing normally again. Figure 9 illustrates the raw data for this experiment in 3-D.
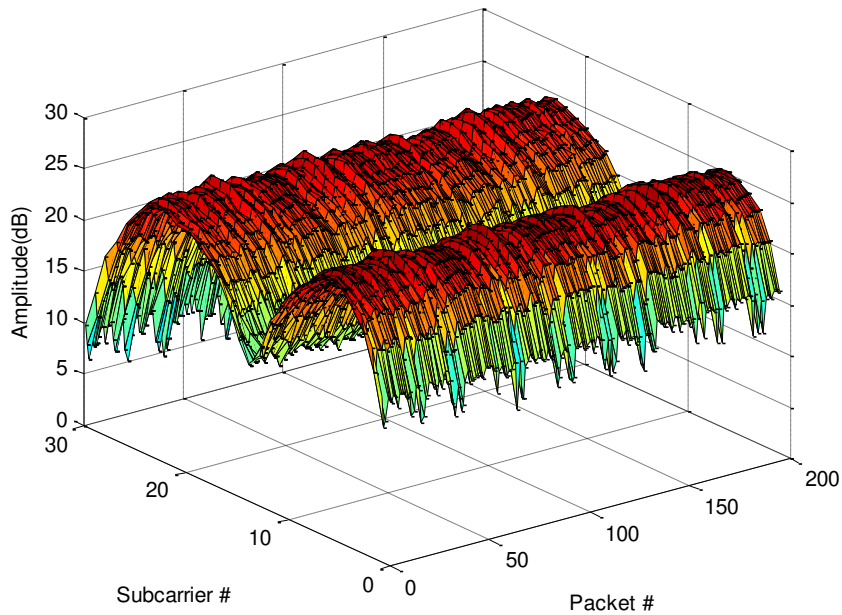
Figure 9–Raw data recorded for Hypopnea syndrome.

Figure 10 shows the breathing pattern observations taken through the respiratory sensor for 120 seconds duration. The results indicate that the subject is breathing normally from 0 to 52 seconds. A constant level in amplitude for the next 26 seconds (from 52nd second to 78th second) reflects that the subject is experiencing a sleep apnea episode. A normal breathing pattern can be observed from the 78th second onward as the apnea episode is over.
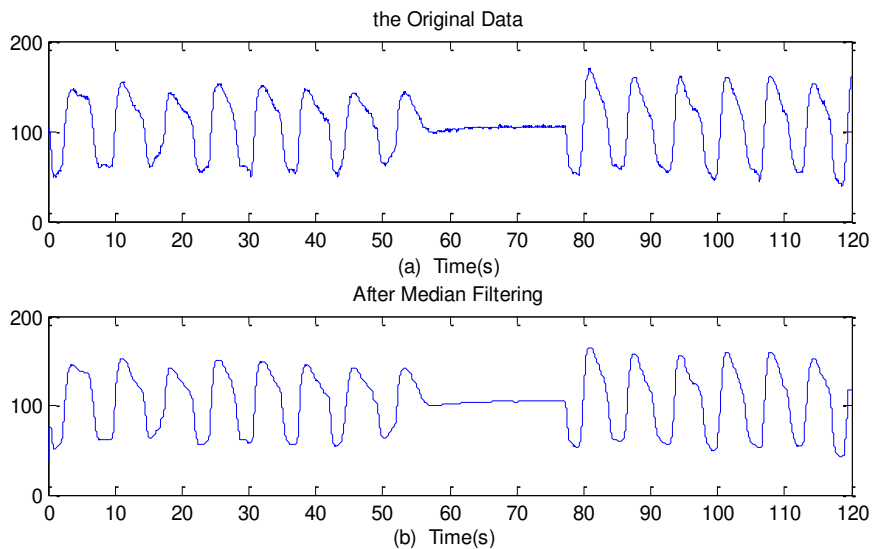

Figure 10–Sleep apnea detection using breathing sensor.

S-band sensing results are then analyzed for the sleep apnea measurements. Response for all of the 30 subcarriers is analyzed as shown in Figure 9. Figure 11(a) shows the raw variances of amplitude information for subcarrier # 30 over a period of 120 seconds. The fluctuation of wireless channel information data from 0 dB to 8 dB indicates the breathing pattern but a sleep apnea episode is not present as clearly as shown in Figure 10. To reduce the impulse noise, the median filter is applied obtaining a

clear sleep apnea episode from 52nd second to 78th second. This close agreement between the output of the respiratory sensor and S-band sensing further establishes the working of the proposed method as an efficient alternative.
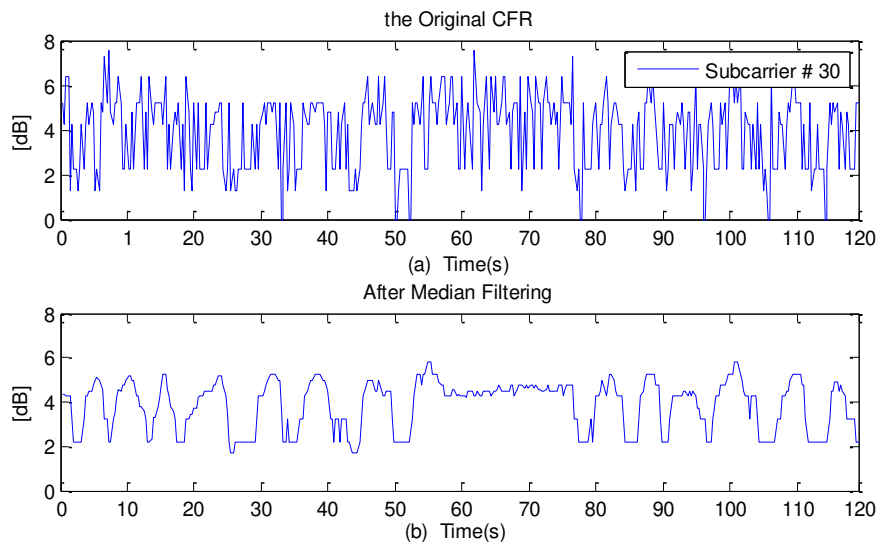

Figure 11 – Variances of amplitude for sleep apnea episode at subcarrier 30.

As shown in Figure 10, the breathing waveform can be approximated as a periodic sinusoidal wave. Hence, the number of the peaks of these sinusoidal waves determines their periodicity and their peak locations ascertain sleep apnea. Thus, we choose peak detection to monitor occurrence of the sleep apnea.

Standard peak detection algorithm is that the maximum is labeled as a peak for every set of three points. For sleep apnea detection, we introduced used two changes. First is to set a threshold on the minimum distance between two consecutive peaks. Since the maximal breathing frequency in an adult human is 18 breaths/min, we set a conservative threshold of 3.3 seconds. Second is to set a threshold on the minimum amplitude at which a peak is detected.
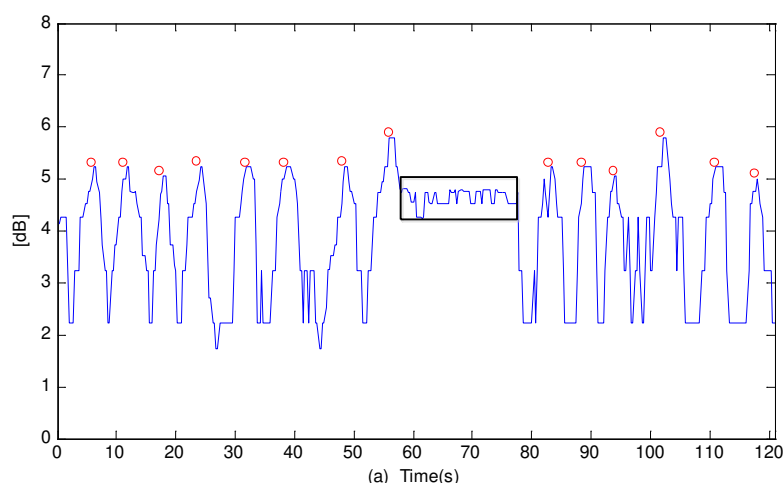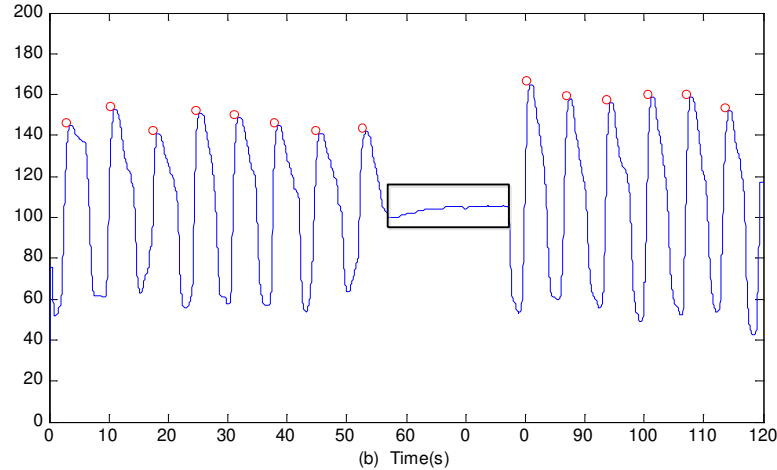
(a)Breathing pattern obtained using S-band sensing technique.

(b)Breathing pattern obtained using breathing sensor.

Figure 12 – Sleep apnea detection using peak detection algorithm.

Figure 12 shows that peak detection algorithm identifies correct peaks and the pause times. There are 14 peaks and one apnea in breathing pattern obtained using the S-band sensing technique. Also, the pause times are more than 10 seconds. The results agree excellently with that obtained using the respiratory sensor.

IV. CONCLUSION

A novel contactless monitoring system for breathing pattern observation and sleep apnea detection is presented in this paper. The proposed technique is based on S-band sensing system in an indoor environment and makes use of wireless channel information to observe breathing patterns and identify small changes in the channel response due to the chest movements caused by breathing abnormalities. The proposed system utilizes the median filtering to eliminate impulse noise in the observed data. A detailed measurement campaign is carried out to obtain the breathing pattern of a normal breathing human subject using S-band sensing technique and a standard respiratory sensor simultaneously to compare and establish the working of the proposed technique in benchmark study. Sine function fitting algorithm is used to analyze the detected results. A close agreement between the two results has established the accuracy of the proposed method. The proposed technique is then used to detect Hypopnea syndrome successfully. Similar peaks and pause times using peak detection algorithm observed for the S-band sensing and respiratory sensor for sleep apnea has further established the ability and accuracy of the proposed technique for Hypopnea syndrome detection. The experimental have shown that the proposed S-band sensing is an efficient alternative to traditional Hypopnea syndrome detection methods with added features of contactless, and patient friendly system exhibiting sufficiently high precision with good potential of early-warning Hypopnea syndrome detection for both clinical and home settings.

V. CONFLICT OF INTEREST

The authors declared that they have no conflicts of interest to this work.

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