# Demo Abstract: Occupancy and Activity Monitoring with Doppler Sensing and Edge Analytics

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## ABSTRACT

We demonstrate an occupancy detection and human activity monitoring system using low-cost motion sensing, edge computing and wireless networking devices. We design a dual Doppler sensor to achieve high signal sensitivity and wide sensing range. We develop signal filtering, detection and machine learning algorithms on an embedded computer to generate classification result in real-time. We also implement web services to enable users to access signal and room state via a wireless network. Compared with conventional occupancy sensors, the dual Doppler system has higher detection rate, and also has the capability of detecting activities even for multiple people.

## 1. INTRODUCTION

Occupancy sensing and human activity monitoring has many internet of things (IOT) applications such as smart home, patient monitoring, and security. Different applications have different requirements and challenges. Due to the privacy concern, our patient discharge application requires detecting human presence in typical hospital rooms without using any cameras. In addition, it requires high detection rate, even if patients are sleeping in bed. We design a dual Doppler sensing system with low-cost hardware and edge analytics to meet these requirements.

The recent study in [1] developed a Doppler sensor to detect the presence of a person by monitoring human vital signs, e.g., respiration and heartbeat. However, the single Doppler sensor uses directional antenna to sense human motion, and thus has limited field of view. For example, a Doppler sensor installed on the room ceiling with its antenna facing down towards a bed can detect subtle respiration motion of a person lying in the bed, as shown in the middle plot of Figure 1. However, the same Doppler sensor cannot detect a person walking two meters away from the bed. Similarly, a Doppler sensor facing sideways can detect a person walking, as shown in the high variation signal in the bottom plot of Figure 1, but it cannot distinguish respiration motion from empty-room noise. To solve this problem in our occupancy monitoring work, we design a dual Doppler sensing system with one Doppler sensor antenna facing directly towards the bed, and the other antenna facing towards the room so that we can achieve high sensitivity to human motion, i.e., respiration motion, as well as wide sensing range. In this work, we develop filtering, detection and classification algorithms to classify three states: empty-room, a person walking in room, a person sleeping in bed.

In addition, the dual Doppler system can be configured to monitor activities of multiple people located at different areas. The state-of-the-art network-based sensing approach [2] uses received signal strength measurements from a wireless network to monitor the respiration of a single person. However, that approach cannot easily be scaled to multiple people monitoring. Since the Doppler system uses directional antenna, two Doppler sensors can monitor two different areas by pointing antennas to two directions. The Doppler system can include even more Doppler sensors, but we only demonstrate two sensors in this demo.

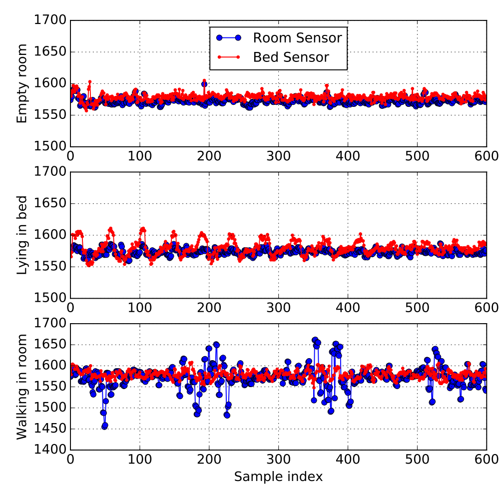


Figure 1: Dual Doppler signals from three states: empty-room (noise), walking in room (high variation on room sensor) and breathing in bed (periodic change on bed sensor).

## 2. METHOD AND SYSTEM

The Doppler hardware system is composed of two Doppler



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sensors and an embedded computer beaglebone black. The analog outputs of the Doppler sensors are passed to the analog-to-digit converters on the beaglebone black, on which we run our data acquisition and signal analytics algorithms. The system architecture is shown in Fig. 2. We explain the Doppler sensing and edge analytics here.

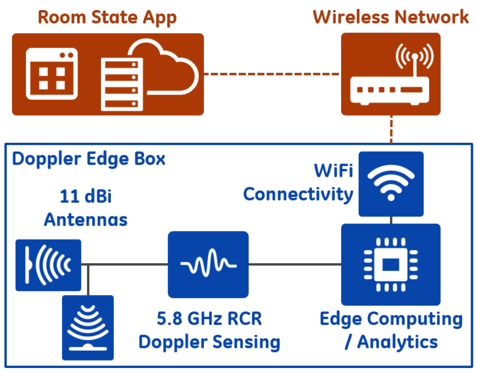


Figure 2: Demo system architecture.

### 2.1 Doppler sensing

The dual Doppler sensors are modified from a commercial range-controlled radar sensor originally designed for home security [1]. Each Doppler sensor operates at 5.8 GHz ISM band with a 11 dBi directional antenna. The Doppler sensor detects motion by multiplying reflected radio signal $r(t)$ with transmit signal $s(t)$ through a mixer:

$$m(t) = r(t) \times s(t)$$

where $s(t) = A_0 \cos(2\pi f_0 t + \phi_0)$, $r(t) = A_1 \cos(2\pi f_1 t + \phi_1)$, $A_{0,1}$, $f_{0,1}$ and $\phi_{0,1}$ are magnitude, central frequency and phase for the transmit and receive signals.

Applying trigonometric identiy, we have:

$$m(t) = \frac{A_0 A_1}{2} \{ \cos[2\pi(f_1 - f_0)t + \phi_1 - \phi_0] + \cos[2\pi(f_1 + f_0)t + \phi_1 + \phi_0] \}$$

Then $m(t)$ is passed to a low-pass filter, which removes the high frequency term $f_1 + f_0$, and only keeps the Doppler shift term $\Delta f = |f_1 - f_0|$:

$$d(t) = \frac{A_0 A_1}{2} \cos(2\pi \Delta f t + \phi_1 - \phi_0)$$

Finally, $d(t)$ is the Doppler signal that is sensitive to human motion. If there is no motion, $\Delta f = 0$ and $d(t)$ becomes time-invariant.

### 2.2 Edge Analytics

Once we obtain the Doppler signal, we implement a finite state machine (FSM) filter and a threshold-based detector for occupancy detection. The variance of Doppler signal during a time window is used to measure the variation caused by human motion. The baseline variance without any human motion can be quantified by collecting data offline when no person is present in a room. Then during online period, the variance of a windowed Doppler signal is compared with the baseline variance for occupancy detection. To make the occupancy detection more robust, we implement a FSM to filter out noise and false detection. Specifically, two counters - occupy counter ($\alpha_1$) and empty counter ($\alpha_0$) are used for the state transition between the occupied state and the empty state. If the occupancy detection result is positive (human detected), the occupy counter $\alpha_1$ will increase by one, and the empty counter $\alpha_0$ will be clear to zero. If no human presence is detected, $\alpha_0$ will increase one count, and $\alpha_1$ be set to zero. If the occupy counter $\alpha_1$ is above a predefined threshold, the state transition is triggered from the empty state to the occupied state. The same rule applies to the state transition from the occupied to the empty state using the empty counter $\alpha_0$. Note that we also use a logic OR operator to fuse the detection result from each sensor: if any one of the Doppler sensors detects human presence, the final detection is positive (room occupied); only if all sensors detect no human presence, the final result is negative.

Once we detect occupancy, we further classify two activity states: breathing and walking. From Fig. 1, we see that if a person is breathing normally, the Doppler signal shows a periodic change pattern. Thus we calculate the Doppler power spectral density (PSD) from the Doppler signal, and use the peak frequency of PSD as one classification feature. We also choose features used in [1] to build a feature vector. Then we apply support vector machine (SVM) to classify different human activity states. Note that we can also use SVM to directly classify three states: empty room, breathing and walking. However, we choose to use FSM filter to obtain a robust room occupancy detection result first.

Finally, we use the container-based framework of the Predix from GE Digital to support our embedded software. Our software system has the following modules: data acquisition, analytics, and communication. The data acquisition and analytics modules perform our edge computing tasks and feed a queue of time-series datagrams to be sent using the communication module. For communication out of the embedded sensor, we use the Predix framework to securely send the time series data and display the classification and activity updates to users.

## 3. DEMONSTRATION PLAN

The hardware components of the Doppler system are all inside a plastic box. In the demo, we plan to place the Doppler box on a table, and point two antennas to different directions to cover a room corner of about 2m by 2m area. The demo system can detect if the area is empty, and also detect walking and breathing activities of up to two people. If they are within two meters range from the antennas, and they keep stationary with regular respiration, their respiration rates can also be calculated. We use a WiFi router to set up a local wireless network, so that we update the state every 20 seconds and display the result on our room state app. We also provide a URL address to people, so that they can see real-time Doppler signal with activity state from a webpage on their own mobile devices.

## 4. REFERENCES

[1] C. Graichen and et al. Unobtrusive vital signs monitoring with range-controlled radar. In *IEEE SPMB*, 2012.

[2] N. Patwari and et al. Monitoring breathing via signal strength in wireless networks. *IEEE Transactions on Mobile Computing*, 13(8):1774–1786, Aug 2014.