Poster Abstract: Non-invasive Human Activity Monitoring using a Low-cost Doppler Sensor and an RF Link

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ABSTRACT

This paper presents a non-invasive human activity monitoring system with a low-cost Doppler sensor and a pair of radio frequency (RF) sensors. This radio-based system combines the strengths of two sensing modalities: fine granularity from a Doppler sensor and large sensing coverage from an RF link. The system is capable of detecting subtle human motion such as breathing, as well as walking in a large area. We deploy the system and perform experiments in a 5.5 m by 7.5 m room to classify four activities. Experimental results show that the average classification rate is 90%, 31% more accurate than a single Doppler system.

Categories and Subject Descriptors

C.3 [**Special-purpose and application-based systems**]: Real-time and embedded systems, Signal processing systems

General Terms

Design, Experimentation, Measurement

Keywords

Activity recognition; Doppler; Radio frequency

1. INTRODUCTION

Human activity monitoring is a very important topic in many applications such as security, remote monitoring for elder care, and demand controlled ventilation and lighting for smart facility. In this work, we focus on monitoring vital signs and common activities for hospitalized patients.

Traditional activity monitoring methods use sensor tags such as inertial measurement unit (IMU), or fingertip attached to human body to monitor their activities. However, these systems and methods require user cooperation, and often cause discomfort to users. Computer vision-based methods provide a non-cooperative way of human activity monitoring, but they suffer from the privacy issue, which limits their use in many applications.

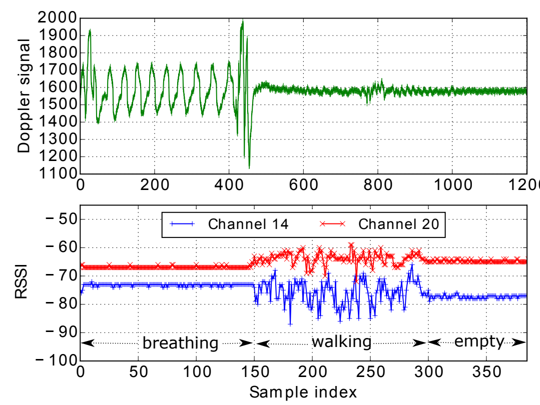

Figure 1: Doppler and RSSI time series from different activities.

As RF sensors and networks become more pervasive, radio-based methods are becoming a promising way of detecting, locating people [1], and even recognizing human activity [3]. In this paper, we investigate radio-based tag-free human activity monitoring. We design a low-cost low-power Doppler sensor modified from a commercial-off-the-shelf (COTS) range-controlled radar [2] to monitor a person's motion within its field of view. To solve the limited detection range problem of the Doppler sensor, we integrate a pair of COTS RF sensors to cover a large area. By integrating two radio sensing modalities, the system is capable of recognizing human activity with both high accuracy and large coverage in a non-invasive way.

2. METHOD AND SYSTEM

The Doppler sensor is modified from a commercial Doppler motion sensor originally designed for home security. The hardware modification is made such that the Doppler sensor is sensitive enough to detect subtle motion due to breathing and heart beat [2]. The Doppler sensor operates at 5.8 GHz, and we set the sampling rate to be ten Hz. We use two TI CC2531 radios to create an RF link. We use a wireless basestation and a time division multiple access (TDMA) protocol to collect received signal strength indicator (RSSI) between two radios from 16 frequency channels at 2.4 GHz

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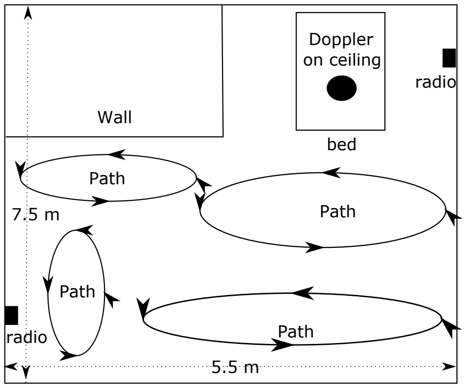

Figure 2: Experimental testbed layout.

ISM band [1]. The sampling rate is set to be three Hz on each channel. We connect the output of the Doppler sensor and the basestation to a single board computer, on which we perform data acquisition, data fusion and activity classification.

The Doppler signal and the RSSI on an RF link are complimentary with respect to sensing human motion. We can see this from the example shown in Fig 1. When a person is breathing in bed, the Doppler signal clearly shows the periodic pattern of the respiration motion. However, the RSSI time series do not show such pattern due to their coarse granularity. When a person is walking in the room, the Doppler sensor cannot always capture the motion: the signal has high variation when the person is close to the sensor (Doppler sample index from 780 to 810), but the variation is negligible when the person walks far away from the sensor. Theoretically, the Doppler sensor has a range loss inversely proportional to range to the fourth power ($1/R^4$), while the one-way radio communication range loss is inversely proportional to range squared ($1/R^2$) in the free space. Fig 1 clearly shows that the RSSI measurements from two frequency channels are both highly variable when a person is walking in the room.

For our patient monitoring application, we classify the following four activities: 1) breathing in bed, 2) turning in bed, 3) walking in room, and 4) no vital signs (empty bed and room). In the classification, we choose the Doppler features used in [2], such as: the mean and standard deviation of the Doppler signal, the peak frequency of the Doppler power spectral density (PSD). In addition, we use two more features: the averaged variance of RSSI over all frequency channels, and the variance of the PSD peak frequencies (each peak frequency is from a short-time window divided from the Doppler signal). After we use these features from the Doppler signal and RSSI to build a feature vector, we use support vector machine (SVM) with a radial basis function kernel to classify four human activity states.

3. EXPERIMENTS AND RESULTS

We perform experiments in a 5.5 m by 7.5 m mock hospital room with an adjustable hospital bed. We deploy the Doppler sensor on a ceiling-mounted rail above the bed, and we plug two radio nodes to the power outlets on the walls. The experimental layout is shown in Fig 2. Note that the Doppler sensor may be deployed at a different location and angle to cover a relatively larger area, but it cannot cover the entire room based on our measurements.

	breathing	turning	walking	empty
breathing	7	3	0	0
turning	0	10	0	0
walking	0	0	10	0
empty	0	1	0	9

Table 1: Confusion matrix from SVM (ten tests for each activity).

We recruit two human subjects to perform ten tests (each occurs for two minutes) for each of the four activities. For the breathing in bed activity, we ask them to breathe normally in bed with three orientations facing upwards, right and left. For the turning in bed case, human subjects turn their bodies from one side to the other randomly in bed. They also walk along different paths at different locations in the room, as shown in Fig 2. Note that we do not perform individual training for walking at each location, or breathing with each orientation. Instead, we can use walking at certain locations as training data to test walking at other locations. Compared with the recent activity recognition work [3], our system removes the location-dependent training requirement. That is, our system does not need to perform extensive training for each user orientation or each possible location in a room.

We use leave-one-out cross validation method to evaluate the performance of our system. The confusion matrix from our 40 tests is shown in Table 1. The average classification rate is 90%. If only the Doppler sensor is used, the classification rate is 55%. We deploy two RF nodes at three other locations, and we achieve 31% performance improvement on average, compared with the single Doppler system.

4. CONCLUSIONS AND FUTURE WORK

We design a low-cost activity monitoring system by combining a Doppler sensor with a pair of RF communication nodes. The integrated sensing system is capable of classifying four human activity states with high accuracy. One important future topic is to explore other ways of deploying the Doppler sensor and the RF radios. We plan to investigate more features from the RSSI and Doppler signal. We also plan to perform experiments with more human subjects, and investigate more machine learning algorithms in the future.

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