Micro-Doppler-Based Human Activity Classification Using the Mote-Scale BumbleBee Radar

Bahri Çağlıyan and Sevgi Zübeyde Gürbüz

***Abstract*—Human activity recognition is an emerging technology for many security, surveillance, and health service applications utilizing wireless sensor networks (WSNs). However, the exploitation of radar in WSNs has been only recently made possible through the development of small, low-power, and low-cost wireless radar motes, such as the BumbleBee radar developed by the Samraksh Company. This letter explores the capacity of using the BumbleBee radar for indoor human activity classification based on micro-Doppler signatures. The electromagnetic measurements of the signal transmitted by the BumbleBee radar are made to fully characterize the sensor and its limitations. A database of the multiperspective micro-Doppler signatures measured from the BumbleBee radar is compiled to analyze the classification performance and limitations due to the dwell time and the aspect angle. Within the operational constraints delineated, it is shown that the BumbleBee radar can be used to discriminate between walking, running, and crawling, even under variable conditions.**

***Index Terms*—Classification, human activity recognition, human micro-doppler, wireless radar networks (WSNs).**

I. INTRODUCTION

HUMAN activity recognition is an emerging technology for many applications including surveillance, search and rescue, pedestrian safety, smart homes, and health services, which may exploit wireless sensor networks (WSNs). To date, many types of sensors, such as acoustic, seismic, magnetic, ultrasonic, and infrared sensors, have been used for human activity recognition and classification. However, because radar can be operated in all weather conditions and during nighttime, radar possesses key advantages for remote sensing applications. Nevertheless, the high power requirements, high cost, and large size of most radar systems have, for the most part, precluded the use of radar in wireless sensing systems.

Recently, however, several companies have developed low-cost, low-power, and commercial-off-the-shelf radar systems that are capable of being used as part of a WSN. One such radar is the BumbleBee radar developed by the Samraksh Company for research purposes in 2008 [1]. Unlike conventional radar, the BumbleBee radar is designed to be compatible at a systems level with small battery-powered nodes. The BumbleBee radar is a 5.8-GHz coherent pulse-Doppler radar system capable of providing measurements at a relative accuracy of about 3 mm for targets lying within a sensing region. According to its data sheet, it responds to radial velocities between 2.6 cm/s and 2.6 m/s, which are speeds typical of human motion. As such, the BumbleBee radar is advertised as a viable sensor for simple motion detection, robust intrusion detection using velocity estimation, velocity-based motion tracking, and vibration monitoring.

There have been just a few works that have employed the BumbleBee radar. In 2009, BumbleBee radar systems were used for human-activity-level monitoring for the case where there are two or more humans in a network area [2]. In 2010, researchers from John Hopkins University, Baltimore, MD, USA, developed an extended Kalman filter (EKF) for tracking noncooperative targets based on radial velocity measurements from a WSN comprised of BumbleBee radar systems and TelosB motes [3]. This algorithm was also implemented by researchers from Michigan State University, East Lansing, MI, USA [4], who found that the EKF worked well for linear trajectories but exhibited degraded performance over nonlinear paths. The first work to investigate micro-Doppler signatures extracted from BumbleBee data was done by Kizhakkel [5]. However, most recently, researchers have also exploited BumbleBee radar systems for the detection of eye blinking to investigate and assess the degree of fatigue and detect unconsciousness in drivers [6].

Several different types of radar systems have been investigated within the context of indoor sensing. In [7], a frequency-modulated continuous-wave software-defined radar system was used to extract three different activity metrics, which are then used to quantitatively describe the amount of activity in a corridor. In [8], a bistatic three-frequency continuous-wave radar system was proposed for activity classification and multiple target tracking. In a simulation environment, Doppler signatures from multiple people are shown along with localization results; however, no classification results are presented. Ultra-wide band (UWB) radar [9], [10] has been also investigated for activity recognition, whereas both UWB and noise radar systems [11] have been demonstrated to be capable of detecting human breathing in through-the-wall environments. Although the BumbleBee radar does not possess thru-the-wall sensing or breathing detection capabilities, it does possess advantages in size and wireless networking that make it a unique sensor for indoor activity classification applications.

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B. Çağlıyan is with the Department of Electrical and Electronics Engineering, Faculty of Engineering, TOBB University of Economics and Technology, 06520 Ankara, Turkey (e-mail: bcagliyan@etu.edu.tr).

S. Z. Gürbüz is with The Scientific and Technological Research Council of Turkey (TUBİTAK) Space Technologies Research Institute, 06800 Ankara, Turkey, and also with the Department of Electrical and Electronics Engineering, Faculty of Engineering, TOBB University of Economics and Technology, 06520 Ankara, Turkey (e-mail: szgurbuz@etu.edu.tr).

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In this letter, the capability and performance limitations of the BumbleeBee radar to recognize a variety of human activities in an indoor environment are investigated. First, in Section II, the BumbleBee radar is characterized as a radar system by measuring signal parameters in a laboratory. Next, in Section III, the micro-Doppler signatures for walking, running, and crawling are computed from BumbleBee data. The classification performance based on a multiperspective data set is accomplished to quantify the relationship between the dwell time, the aspect angle, and the correct classification rate. The classification performance of the BumbleBee radar is assessed for a representative indoor experiment. In Section IV, the potential applications of the BumbleBee radar are discussed, along with the future work.

II. BumbleBee Radar

A. Technical Specifications

The BumbleBee radar is a 5.8-GHz coherent and low-power pulse-Doppler radar system that has been designed for use with small battery-powered wireless motes and is thus suitable for use in WSN applications. According to the user manual [12], the BumbleBee radar is capable of providing measurements at a relative accuracy of 3 mm for targets lying within a circular sensing region of 10 m in radius. The antenna is an onboard radiator with a 60° conical pattern.

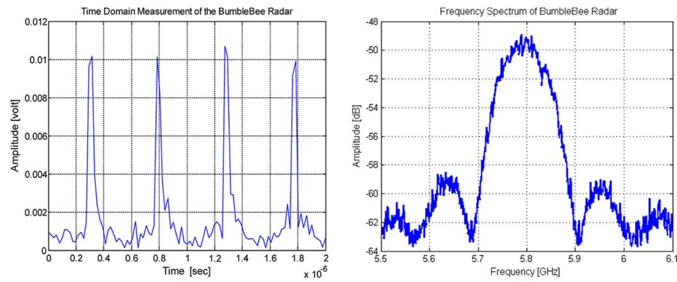
The BumbleBee radar and the TelosB Tmote work together with the TinyOS 2.x operating system to provide a data downlink to a remotely located host computer. The sensor outputs data on two channels providing the in-phase (I) and quadrature-phase (Q) output signal components, which are used to form the complex signal $C = I + jQ$.

The I/Q data outputted by the BumbleBee radar represent the peak of the matched filtered data acquired for each pulse. Thus, the time interval between each data packet corresponds to the pulse repetition interval (PRI) of the radar. As a result, this sensor is only able to supply users with the Doppler and velocity information pertaining to the target. No access is supplied regarding the target range. Indeed, it is for this reason that the user manual itself states that the BumbleBee radar systems were "not designed to be used as ranging radar." For the purposes of activity recognition, however, the matched filter output (i.e., the I/Q data provided) is sufficient for computing the spectrogram representation of the target's micro-Doppler signature and is thus not a limitation for this application.

B. Sensor Characterization

Aside from the basic information, such as the transmit frequency, the BumbleBee documentation provides little information about critical system parameters affecting the performance, such as the bandwidth, the pulse duration, and the PRI. Thus, the laboratory measurements of the transmitted waveform were made using a 700-MHz–18-GHz horn antenna and by feeding the signal to a real-time signal analyzer. As a practical consideration, it was found that better results were obtained when the BumbleBee radar was operating at least one wavelength (5.2 cm) away from any large metal objects, particularly the batteries.

The time-domain and frequency-domain measurements of the transmitted signal are shown in Fig. 1(a) and (b), respectively. Using the pulse analysis mode of the signal analyzer, the pulse duration was measured to be 40 ns, whereas the pulse repetition frequency was found to be 2 MHz. In the frequency domain, the envelope of the received signal is that of a sinc function and corresponds to the Fourier transform of the time-domain pulsed Doppler waveform. The bandwidth of the transmitted signal was measured to be 240 MHz.



(a) (b)

Fig. 1. (a) Time-domain and (b) frequency-domain measurements.

III. Micro-Doppler Signature Analysis

In this letter, activity recognition is accomplished by classifying the human micro-Doppler signatures computed from BumbleBee radar measurements. Micro-Doppler [13] is a term that refers to the frequency modulations, or sidelobes, that appear about the main Doppler shift when a target exhibits vibration or rotation in addition to translational motion. Oftentimes, these modulations may be used to identify different types of targets. For example, the rotating wheels of a vehicle, the turning propellers of a plane, the spinning blade of a helicopter, and the revolving treads of a tank all possess visually distinguishable micro-Doppler signatures [14]–[16].

Humans also generate a unique micro-Doppler signature due to complex periodic limb motions that occur during the execution of any activity. In literature, micro-Doppler signatures have been successfully used to discriminate not only between vehicles and humans [17], and animals and humans [18] but also different human activities [19], [20]. However, most of these works do not consider the impact of operational constraints, such as the dwell time and the aspect angle, on the classification performance. In fact, both factors have a significant impact on the classification performance because they affect the degree to which accurate feature estimates may be extracted from human micro-Doppler signatures.

A. Measured Human Micro-Dopper Signatures

Although many time–frequency transforms are available for micro-Doppler signature representation, this letter uses the popular spectrogram representation, which is defined as the square magnitude of the short-time Fourier transform of a signal, to capture the time–frequency variations of the target return. Once the spectrogram is computed from the measured I/Q data, a fifth-order Chebyshev high-pass filter is applied to remove the effects of clutter, which appears as a strong return between $+5$ and -5 Hz [21].

To facilitate precise measurements of the target speed, aspect angle, and dwell time, measurements were collected with the aid of a treadmill located indoors at the TOBB University of

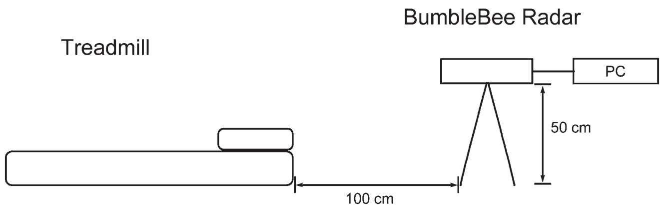


Fig. 2. Experimental setup used to measure human micro-Doppler signatures using a single BumbleBee radar system.

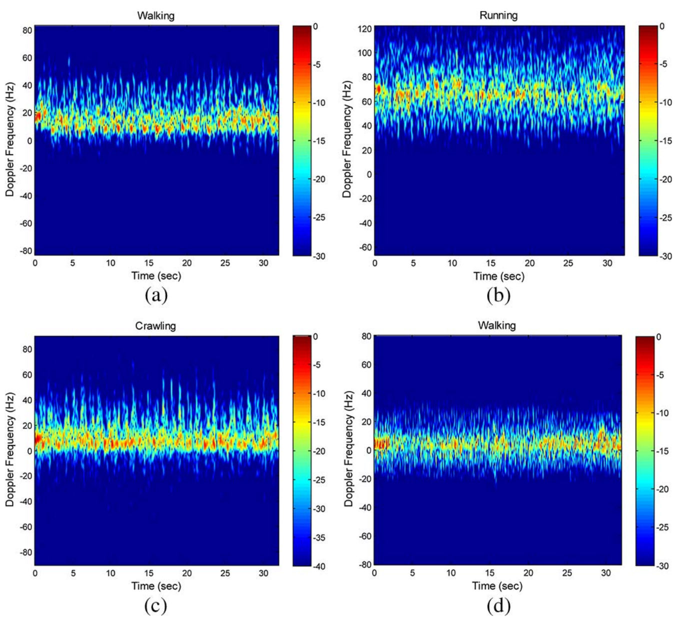


Fig. 3. Spectrograms of a human (a) walking, (b) running, and (c) crawling toward the radar (0° aspect angle), and (d) walking nearly tangential to the radar LoS (75° aspect angle).

Economics and Technology (ETÜ) Radar Systems Laboratory. As shown in Fig. 2, the BumbleBee radar was placed 1 m away from the treadmill at an elevation of 50 cm above the ground. The test subjects engaged in walking, running, or crawling were then illuminated by the radar and the spectrograms computed from the measured I/Q data.

The measured sample spectrograms are shown in Fig. 3 for a human walking, running, and crawling directly toward the radar and walking at an aspect angle of 75°, i.e., nearly tangential to the radar line of sight (LoS). Notice that the aspect angle has a significant impact on the micro-Doppler signature [21]. Most noticeably, the overall Doppler bandwidth in the 75° signature is much smaller than at 0°, yielding a "squishing" effect on the micro-Doppler signature. The reason for this effect is that the radar measures radial, not absolute, velocity. As the observed motion becomes increasingly tangential to the radar LoS, the measured radial velocity and, hence, the Doppler shift, increasingly decrease. As will be shown in the next sections, the aspect angle is a key factor limiting the performance.

B. Multiperspective Analysis of Minimum Dwell Time

A database is comprised of the micro-Doppler signatures measured for ten different test subjects engaged in three different activities (walking, running, and crawling) over a duration of 64 s and for 7 different aspect angles between 0° and 90°. Each 64-s measurement was divided by 8 to obtain data collects of 8 s, which is the longest dwell time considered in this letter. Thus, the database is comprised of a total of $10 \times 3 \times 8 \times 7 = 1680$ 8-s-long micro-Doppler signatures. To the signatures of a shorter dwell time, these signatures are further divided, increasing the total signature count accordingly.

The signatures in the database are classified by first extracting features from the micro-Doppler. Ten different features are considered in this letter as follows:

- the mean torso Doppler;
- the minimum value of the lower envelope;
- the maximum value of the lower envelope;
- the mean value of the lower envelope;
- the minimum value of the upper envelope;
- the maximum value of the upper envelope;
- the mean value of the upper envelope;
- the bandwidth of the torso return;
- the peak-to-peak (total) bandwidth; and
- the (outer) bandwidth between the envelope means.

All ten features were then used as inputs to a two-nearest neighbor $(k\mathrm{NN} = 2)$ classifier.

To learn the operational limitations of the BumbleBee radar, the dependence of the classification performance on the dwell time (i.e., the duration over which a subject is observed) and the aspect angle is studied. Fig. 4 shows the classification rates achieved using a $k\mathrm{NN} = 2$ classifier for differing dwell times when the subject moves at four different aspect angles, i.e., 0°, 45°, 75°, and 90°, respectively. Under nearly ideal operating conditions, i.e., a long dwell time with the target moving toward the radar (0° aspect angle), almost perfect activity recognition is achievable. When the dwell time drops below about 1 s, however, the activity is being observed for such a short period of time that accurate features are no longer estimable from the spectrogram, resulting in a drop in the classification performance.

As the aspect angle increases, however, the smaller radial velocity component also causes a degradation in the performance. When the target approaches the radar at a 45° angle, at least 3 s of data is required to achieve close to 100% classification. At an angle of 75°, the subject should be observed for at least 5 s. At 90°, the spectrogram has become very compressed in the Doppler that meaningful classification is quite challenging. In one study, classification rates as low as 40% have been reported for tangential motion [22]. For the BumbleBee radar, even with 8 s of data, at most 70% correct classification of running is possible.

Another way of visualizing the effect of subject motion is to consider the degradation in the performance as a function of the angle for a dwell time of 1 s, which is a duration seen to be sufficient for nearly 100% classification when the radial velocity measured is maximum (see Fig. 5). Here, it may be seen that, beyond 75°, a drastic drop in the classification performance is incurred. This result shows that, although the data sheet for the BumbleBee radar states the antenna beam width to be 60°, a sufficient fraction of the radar return can be received through the antenna sidelobes to allow classification, albeit with degraded confidence. Thus, for indoor monitoring applications, the BumbleBee radar should be positioned such that the intended targets primarily move at most with a 75° aspect angle relative to the radar LoS.

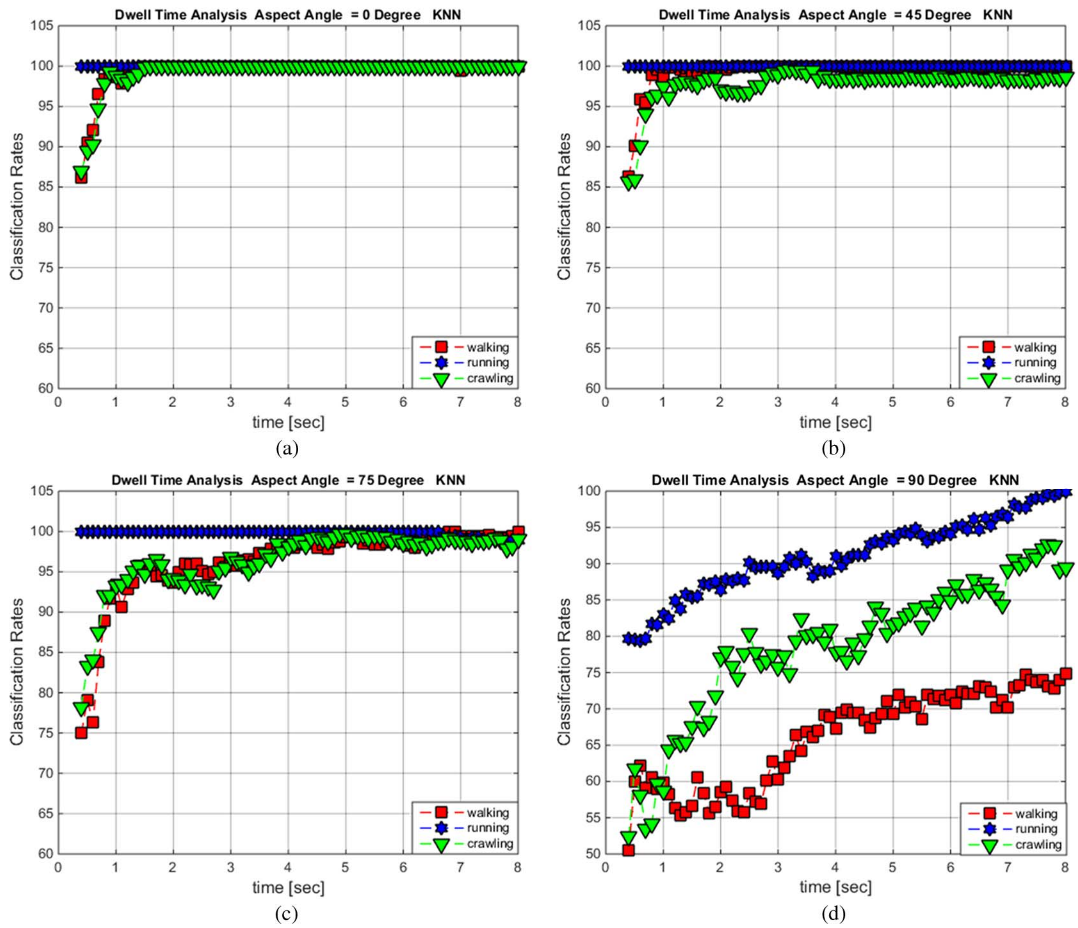


Fig. 4. Dwell time dependence of correct classification rates for varying aspect angles.

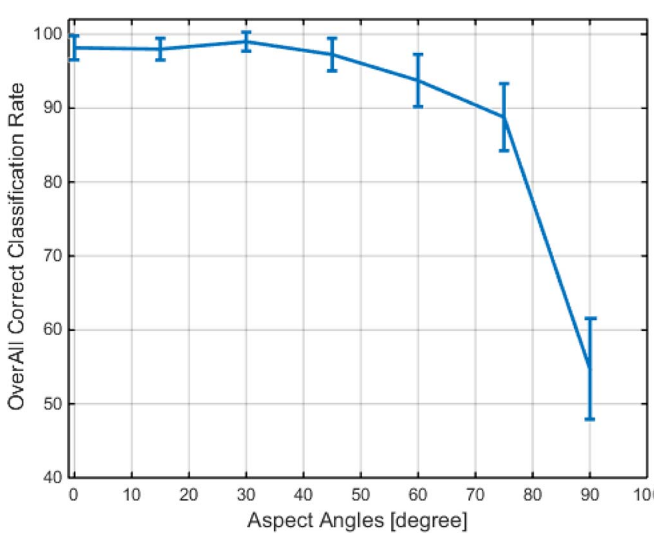


Fig. 5. Influence of the aspect angle on the classification performance for data with a dwell time of 1 s.

Due to the range limitations of the BumbleBee radar, depending on the speed of the target, the total dwell time over which data may be collected is also limited. A typical human crawling moves at a speed of approximately 0.3 m/s, whereas average walking, jogging, and running speeds are around 1.4, 2.8, and 6.7 m/s, respectively; the fastest sprinting speed in the world is about 12 m/s. Thus, in the best case scenario that the entire data collect occurs within the 5-m sensing radius, crawling, walking, jogging (light running), and running data for at most 16.7, 3.6, 1.8, and 0.75 s, respectively, may be obtained. For sprinting at 12 m/s, only 0.42 s of data may be collected.

Comparing these dwell times with the classification results shown in Fig. 4, it may be seen that, in scenarios where 5 m of the target motion are recorded, there is an ample dwell time to classify crawling and walking even at a 60° aspect angle. In the case of fast running, the performance varies between 80% and 100%, depending on the aspect angle. Only jogging is correctly classified at least 85% of the time over all angles.

Thus, for typical daily activities that would be expected in offices, the BumbleBee radar can be used to achieve high activity recognition rates. However, in scenarios involving high-speed motion or short dwell times, e.g., hospital personnel rushing to an emergency room, the performance can be noticeably degraded.

C. Indoor Activity Classification

As a final experiment, the BumbleBee radar was used to recognize the activities of random test subjects passing by or approaching the TOBB ETÜ Radar Systems Laboratory from the main corridor of the Technology Center building (see Fig. 6). The test subjects followed four primary paths along both directions as follows: 1) left and right along the main corridor;

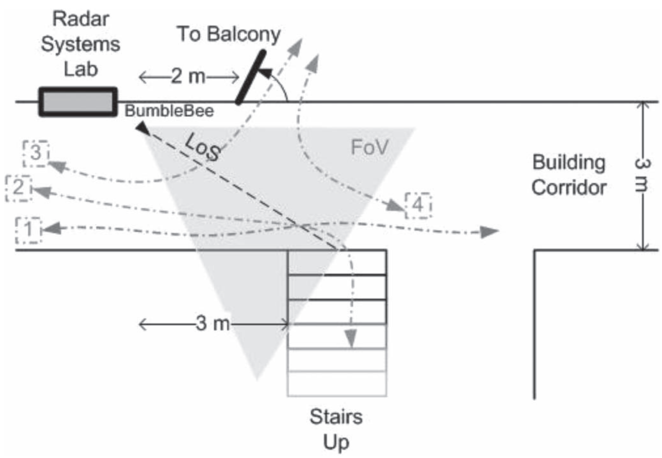


Fig. 6. Schematic showing the positioning of the BumbleBee radar, the LoS, the field of vision, and the paths followed by the test subjects relative to key walkways outside the laboratory entrance.

TABLE I
CONFUSION MATRIX OF THE CLASSIFICATION PERFORMANCE FOR THE CORRIDOR MONITORING EXPERIMENT

	Walking	Running	Crawling
Walking	89.9%	4.5%	5.6%
Running	11.8%	87.9%	0.3%
Crawling	6.5%	0.1%	93.4%
Sensitivity	0.90	0.875	0.925
Precision	0.837	0.94	0.925

2) back and forth from the stairs to the laboratory; 3) to and from the balcony to the laboratory; and 4) to and from the balcony to the opposite end of the main corridor. Paths were not marked. Just the to and from locations were stated to the subjects along with instructions to walk, run, or crawl. Thus, the data set collected involved activities with variations in the speed, the angle, the trajectory, and the dwell time.

The $k\text{NN} = 2$ classifier utilized was trained on 60% of the data and tested on 40%. Based on 80 micro-Doppler signatures for walking, 80 signatures for running, and 4 signatures for crawling obtained for 4 different test subjects, it was found that walking, running, and crawling could be correctly classified 90%, 88%, and 93%, respectively, with a precision over 0.83. Running and crawling have high precision over 0.9 as they represent the upper and lower extremities of the motion. These results are consistent with previous results when it is considered that many paths (particularly path #3) involved high aspect angles and dwell times ranging from less than 1 to at most 3 s. The confusion matrix for the classification results of the indoor measured data is shown in Table I.

IV. CONCLUSION

In this letter, the system characteristics of a BumbleBee wireless radar mote have been measured in a laboratory environment. The sensing limitations of the BumbleBee radar are investigated in terms of applicability to human activity recognition. Through the analysis of the performance dependence on the dwell time and the aspect angle, it is found that the best classification performance may be obtained when a subject is observed for at least 1 s at angles less than 75°. For a typical indoor scenario, classification rates over 88% were achieved despite the highly variable subject paths and the limited observation intervals. In future work, the application of the BumbleBee radar to indoor health monitoring and fall detection is planned.

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