Human Activity Recognition Using a Low Cost, COTS Radar Network

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***Abstract*—Wireless sensor networks have been a subject of much interest as a means for wide area surveillance. Typically, sensors such as acoustic, seismic, infrared, magnetic, and ultrasonic sensor have been employed to date. Radar, although possessing important advantages such as being able to operate in all weather conditions and nighttime, has not much been used in these systems due to their high power requirements, high cost, and large size. Recently, however, low-cost, COTS radar nodes have been developed that enable their application as part of a wireless surveillance network. In this work, the BumbleBee Radar developed by Samraksh Company is used as part of a wireless radar network to monitor the activities of a human moving within the sensing region of the network. The human micro-Doppler signature measured by the BumbleBee radar is shown for a variety of activities and used as a basis for recognition. Various schemes for fusing sensor data are explored.**

I. INTRODUCTION

Wireless sensor networks (WSNs) have been a subject of much interest as a means for wide area surveillance. Typically, inexpensive sensors such as acoustic, seismic, infrared, magnetic, and ultrasonic sensors have been employed to date. Indeed, at a workshop conducted by the US Army Research Laboratory [1], it was stated that *"It is not practical to rely on sophisticated sensors with large power supply and communication [demands]. Simple, inexpensive individual devices deployed in large numbers are likely to be the source of battlefield awareness in the future."* Radar, although possessing important advantages such as being able to operate in all weather conditions and nighttime, has not much been used in these systems due to their high power requirements, high cost, and large size.

Recently, however, low-cost COTS radar nodes have been developed that enable their application as part of a wireless surveillance network. One such radar is the BumbleBee Radar [2] developed by Samkrash Company in 2008 [3]. The BumbleBee Radar is a 5.8 GHz coherent, pulse Doppler radar capable of making measurements at a relative accuracy of about 3 mm for targets lying within a sensing region of 1.5 m to 9.5 m, possessing a radial velocity of 2.6 cm/s to 2.6 m/s, and a maximum Doppler frequency of 100 Hz. Most human motion falls within the operational constraints of the BumbleBee radar.

To date there have been just a few works that have employed the BumbleBee radars. In 2010, researchers from Johns Hopkins University used the BumbleBee to track a non-cooperative target based on radial velocity measurements with an Extended Kalman Filter (EKF) [4]. This work was implemented by researchers from Michigan Technological University [5], who found that the EKF worked well for linear trajectories, but exhibited degraded performance over non-linear paths.

The BumbleBee, however, is capable of providing much more target information than just radial velocity, as users are able to directly access the raw data measured by the radar. Researchers at Ohio State University [6] extracted the micro-Doppler signatures of targets, and used them as a basis for classification between humans and dogs. Micro-Doppler has been used as a basis for target identification in many works [7-8], with important applications to pedestrian safety using automotive radar networks [9]. In 2010, van Dorp and Groen used human micro-Doppler as a basis for classifying human arm swing with a COTS FMCW radar network [10].

The objective of this work is to investigate the application of cheap radar sensors, such as the BumbleBee, which provide a measure of human micro-Doppler of much poorer quality (lower signal-to-noise ratio, SNR) than conventional military radars, for the purpose of human activity recognition. The micro-Doppler signature for several different human activities (walking, running, and crawling) is presented. The quality of the spectrograms as measured from a network of BumbleBee Radars is assessed by conducting experiments with the network nodes placed at a variety of aspect angles relative to the target motion. Methods for selecting and fusing sensor data for optimal classification performance are discussed.

This work was supported in part by EU FP7 Project No. PIRG-GA-2010-268276 and TUBİTAK Kariyer Project No. 113E105.

II. BUMBLEBEE RADAR

A. Technical Specifications

The Bumblebee radar (Figure 1) is a battery-operated, coherent, pulsed Doppler radar for wireless sensor network applications. Communication between nodes is accomplished using TelosB Tmote motes running on TinyOS 2.x. The center frequency of the BumbleBee radar is 5.8GHz, while its internal antenna possesses a conical coverage angle of 60°. Targets with speeds ranging from 2.6 cm/s to 2.6 m/s can be detected at a maximum distance of 10 m. The Bumblebee board provides two outputs as an in-phase signal (I) and quadrature phase signal (Q), which are periodically sent to the Host PC at a frequency of approximately 185 Hz.

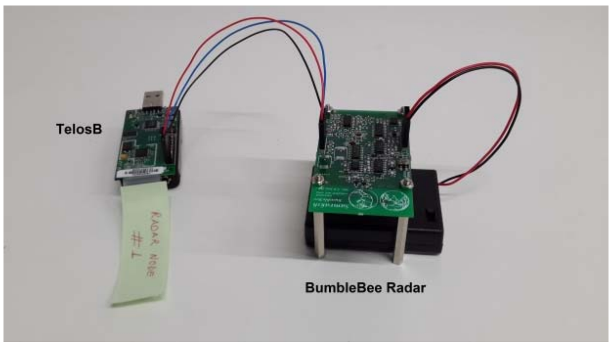


Figure 1. BumbleBee radar and TelosB mote comprising a single source node in the experimental WSN.

Aside from the center frequency, documentation provided on the BumbleBee radar provides little information about critical parameters of the transmitted chirp signal, such as bandwidth or chirp slope, pulse duration, and pulse repetition frequency (PRF). Thus, the BumbleeBee radar was characterized by making measurements of the transmitted waveform using 700 MHz - 18 GHz horn antenna and feeding the received signal to spectrum analyzer. The frequency domain signal measured by the spectrum analyzer is shown in Figure 2. The envelope of the received signal spectrum is that of a sinc function and corresponds to the Fourier transform of the time-domain pulsed Doppler envelope. Thus, the bandwidth of the LFM waveform was measured to be 240 MHz. Using the pulse analysis module of the spectrum analyzer, the transmitted waveform was measured, as shown in Figure 3. From this measurement, it was found that the pulse duration was 40 ns, while the pulse repetition frequency (PRF) was 2 MHz.

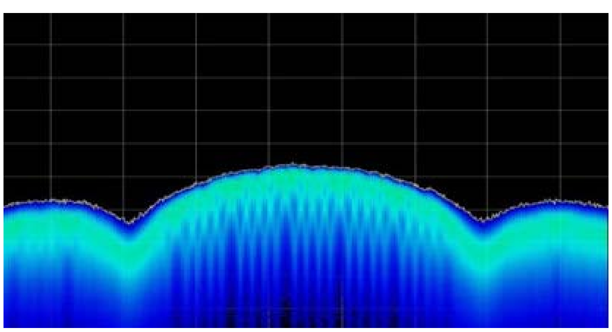


Figure 2. Measured frequency spectrum of the received signal (power versus frequency).

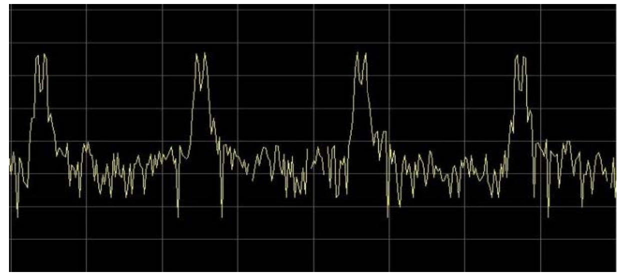


Figure 3. Time-domain measurement of pulse Doppler waveform transmitted by BumbleBee radar (amplitude versus time).

B. Data Acquisition

The signal received by the BumbleBee radar is sent to a computer for subsequent processing using two TelosB motes, a sink node connected to the computer and a source node connected to the BumbleBee radar. The *WirelessRadarDataCollect* application provided by the Samraksh Company is used to program the wireless motes while the sink node is defined via the *basestation* function provided by TinyOS.

The raw data sent to the PC as a message packet includes a header, comprised of the destination address, link source address, message length and group ID, as well as the handler ID, counter, and I and Q data. An example message packet is shown in Table 1. This data is ported into MATLAB, where the I/Q data is stripped from the message packet and the complex signal $C = I + jQ$ is formed.

The I/Q data supplied by the BumbleBee radar are not raw data containing the fast-time samples of the received signals, but rather data that has already been range processed. The slow-time, fast-time data matrix obtained for the pulsed Doppler radar is pulse compressed along fast-time so as to yield a peak at the target location. Then, for each pulse, this peak is extracted so as to form a slow-time slice containing the Doppler information of the target. It is this slice which is supplied as I/Q data by the BumbleBee. Thus, the time interval between each data point corresponds to the pulse repetition interval (PRI) of the radar.

Since the data supplied has already be range processed on-board the BumbleBee platform, this sensor is only able to supply users with 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 radars were "not designed to be used as ranging radar." For the purposes of activity recognition, however, the slow-time slice (i.e. I/Q data provided) is exactly what is needed to compute the target's spectrogram, as explained in the next section.

Table 1. Example message packet from the wireless data collection application of TinyOS.

Header	Handler ID	Counter	Node ID	I	Q
00 FF FF FF FF 1A 00	EF	1B B3	01	0A DD	0B 07

III. MICRO-DOPPLER ANALYSIS

When the transmitted signal of a coherent radar system interacts with a moving target, the carrier frequency of the signal is shifted by an amount related to the translational radial velocity, which can be computed from the Doppler shift:

$$f_D = \frac{2 f_c v \cos\theta}{c} \ , \tag{1}$$

where f_c is the transmitted frequency, v is the target velocity, θ is the aspect angle, and c is the speed of light. Mechanical vibrations or rotations of parts of a target induce additional frequency modulations in the return signal, which generate sidebands about the target's Doppler frequency that are known as *micro-Doppler* [11]. Examples of sources of micro-doppler include the rotating wheels on a vehicle, spinning blade of a helicopter, or revolution of the treads of a tank.

Humans also generate a micro-Doppler signature due to the complex periodic limb motions that occur during the execution of any activity. In fact, the bi-pedal nature of human beings results in unique patterns that can be used to differentiate human signatures from those of animals. Moreover, the micro-Doppler signature of humans engaged in varying activities is also distinguishably different.

Although many possible time-frequency transforms can be used to visualize the micro-Doppler signature, in this work, spectrograms are employed. Spectrograms are defined as the square magnitude of the short-time Fourier transform (STFT) of a signal. Mathematically, if the STFT of a discrete time signal $x[n]$ is given by:

$$X(m,w) = \sum_{-\infty}^{\infty} x[n] w[n-m] e^{-j\omega t} \tag{2}$$

the spectrogram may be expressed as

$$spectrogram(m,w) = |X(m,w)|^2. \tag{3}$$

A. Micro-Doppler Measurement of Corner Reflector

As an initial test of the micro-Doppler measurement using the BumbleBee radar, a corner reflector that was tied to a string and hanged from the ceiling of the laboratory was slightly pushed to induce a damped oscillating motion. The corner reflectors swinging was measured by the BumbleBee radar and used to generate a spectrogram showing the corner reflector's micro-Doppler signature (Figure 4). The spectrogram clearly reflects the damped oscillations of the corner reflector.

Notice that the spectrogram suffers from a band of clutter residing between +/- 5 Hz. To eliminate this clutter, a 5th order Chebyshev high-pass filter with a cutoff frequency of 5 Hz and roll-off of 40 dB per decade was designed and applied to the complex raw data, I + jQ. After filtering the complex signal, the spectrogram without clutter (Figure 5) is generated.

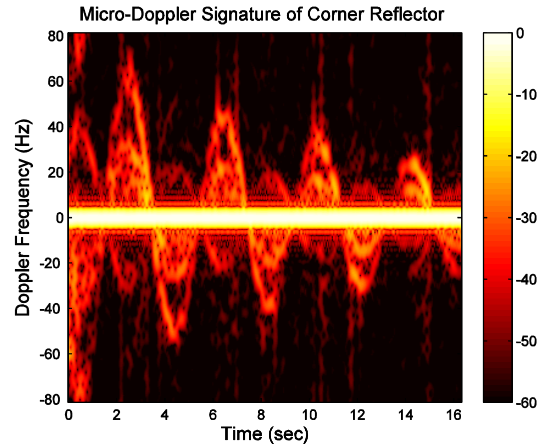


Figure 4. Micro-Doppler signature of the corner reflector with clutter.

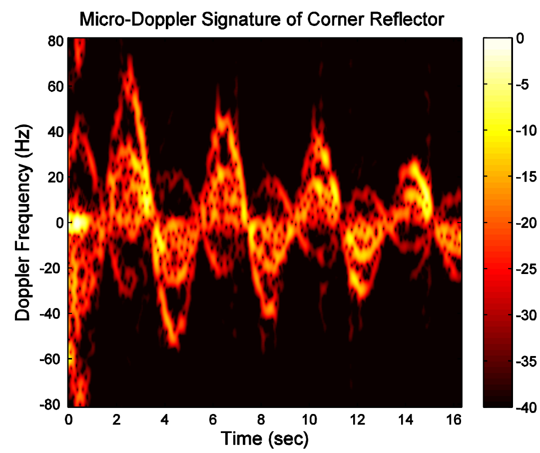


Figure 5. Micro-Doppler signature of the corner reflector without clutter.

B. Micro-Doppler Measurements of Human Activities

A variety of human activities were measured using the BumbleBee radar with the aid of an experimental setup located at the TOBB ETU Remote Sensing Laboratory. Micro-doppler signatures were collected over extended periods of time using a treadmill. The BumbleBee radar was position 70 cm away from the treadmill at an elevation of 50 cm above the ground, as illustrated in Figure 6. Measured spectrograms for walking, running, and crawling are shown in Figure 7, (a)-(c), respectively.

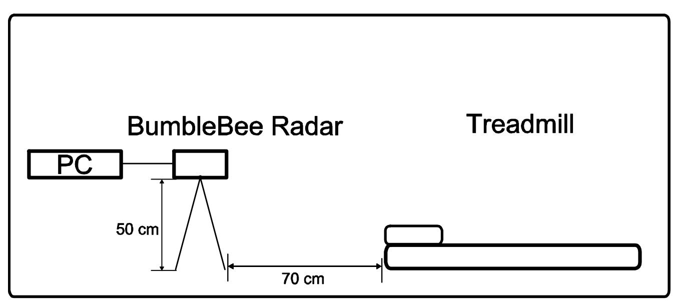
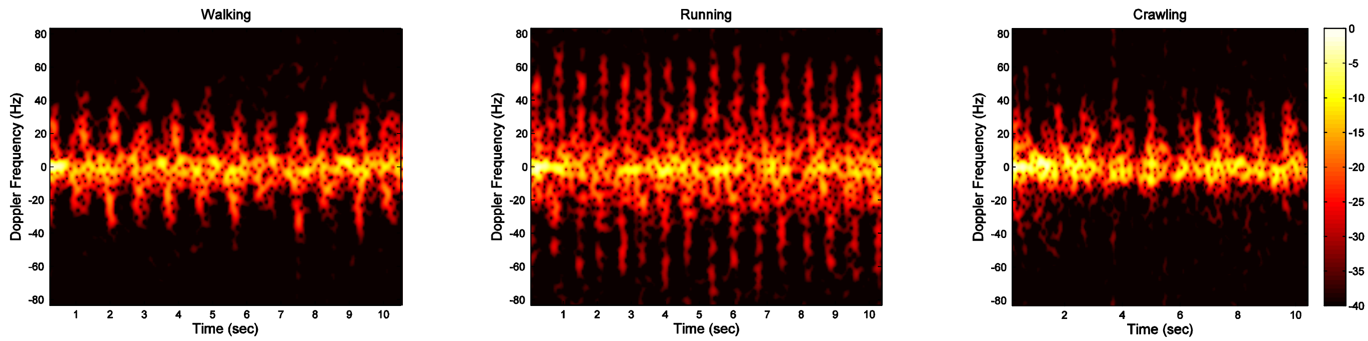


Figure 6. Experimental setup used to measure human micro-Doppler using a single BumbleBee Radar.



(a) (b) (c)

Figure 7. Spectrograms of human activity measured by the BumbleBee Radar: (a) walking at 2 km/hr, (b) running at 5 km/hr, and (c) crawling at 1 km/hr.

IV. Activity Recognition with a Radar Network

Human activity recognition with the BumbleBee radar was also tested in the context of a wireless sensor network of four BumbleBee nodes simultaneously measuring the micro-Doppler of a human activity. From the perspective of classification, the primary difference between the single sensor and network/multiple sensor observations is that of observation angle. As the aspect angle between the line-of-sight to the radar and the direction of target motion increases, the radial velocity component observed by the radar decreases. As a result, the Doppler shifts measured also decrease and the overall Doppler spread of the spectrogram decreases to the point where at 90 degrees extracting meaningful features for classifications becomes nearly impossible.

Thus, one of the key tasks of a radar network tasked with activity recognition is to decide upon which sensor is offering data of sufficient quality that classification decisions should be based upon that data. To assess the suitability of spectrograms as a function of aspect angle, four Bumblebee radars place at different angles about the treadmill. Each BumbleBee radar was paired with a TelosB mote to be able to send data wirelessly to the sink node connected to the computer. A system block diagram for the wireless sensor network is shown in Figure 8. Each node was placed 2 m away from the position of the test subject standing upon the treadmill. The angular position of each sensor were adjusted at -30°, 0°, 60 °, and 90 ° relative to the front view of the test subject. The positioning of the sensor network is illustrated in Figure 9.

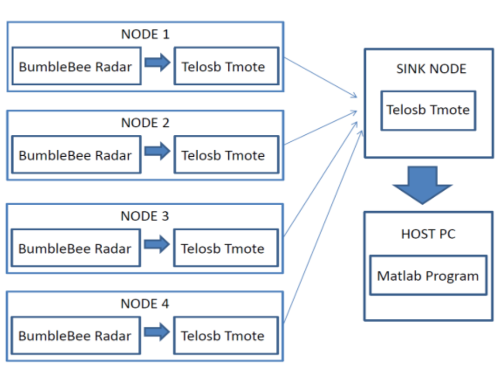


Figure 9. System block diagram of the WSN.

The spectrograms measured by each sensor for walking, running, and crawling are given in Figures 10-12. As in the single sensor case, there are visible differences in the spectrograms obtained for different activities, as well as variations due to the differences in aspect angle. From each measured spectrogram, a finite number of features will be extracted and used to classify the measured returns. For N nodes extracting M features, a total of N*M features are estimated by the network. However, to maximize classification performance, not all of these features are required – only those made by the sensor with the best estimates.

In this work, Principle Component Analysis (PCA) is utilized as a measure of the quality of feature estimates obtained from each sensor. In particular, three features are extracted from each measured spectrogram: (1) the bandwidth

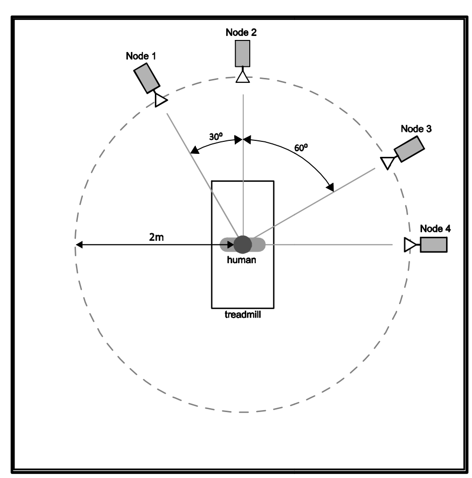


Figure 9. Positioning of the wireless radar network around the test subject standing upon the treadmill.

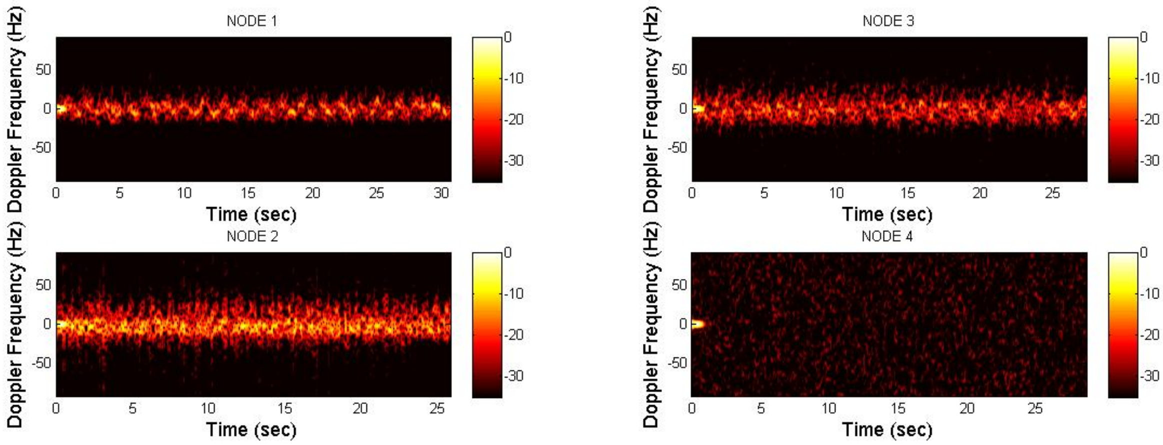


Figure 10. Spectrograms measured by Nodes 1-4 for a human walking at 2 km/hr upon the treadmill.

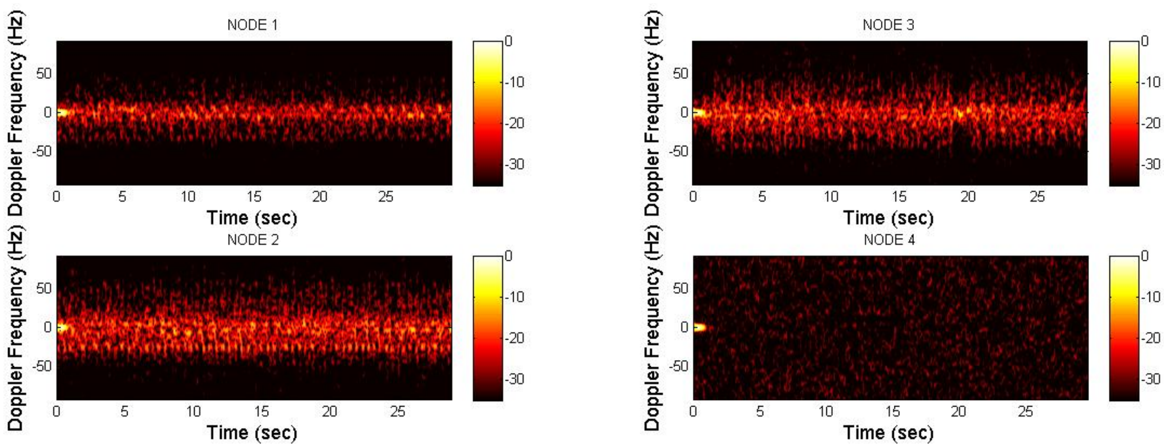


Figure 11. Spectrograms measured by Nodes 1-4 for a human running at 5 km/hr upon the treadmill.

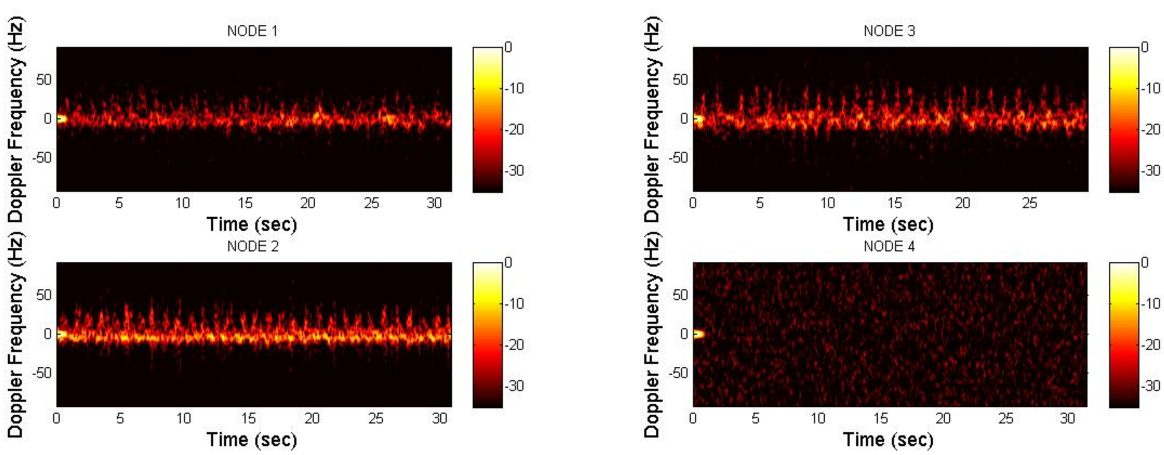


Figure 12. Spectrograms measured by Nodes 1-4 for a human crawling at 1 km/hr upon the treadmill.

of the torso oscillations, (2) the maximum value of the torso oscillations, and (3) the mean value of the torso oscillations. Thus, for a network comprised of four sensors, a total of 12 features were extracted. For the feature values to be accurate, the spectrograms derived by the treadmill experiment were shifted in accordance to the translational Doppler shift caused by the constant speed of motion. Thus, for Sensor 1, walking at a speed of 2 km/hr results in a Doppler shift of 3.31 Hz, while running at a speed of 5 km/hr results in a Doppler shift of 8.28 Hz and crawling at a speed of 1 km/hr results in a Doppler shift of 1.65 Hz.

The values of the eigenvalues computed by the PCA algorithm offer a metric of the contribution of a given feature to the classification problem. Thus, a high, positive eigenvalue is desired. The eigenvalues computed for each feature are given in Table 2 in respect to each different activity. Then, the eigenvalues corresponding to a given sensor are summed to obtain a score indicative of the overall quality of the features estimated by that sensor. Based on these scores, Sensor 2 provides the best feature estimates for walking and running, while Sensor 3 provides the best feature estimate for crawling. Sensor 2 is expected to provide good results as it is positioned directly ahead of the target, while Sensor 4 is expected to offer poor results as the radial velocities measured are quite low, degrading feature estimates.

Table 2. PCA eigenvalues computed for each feature extracted from the network and different activities.

		Activity		
Sensor	Feature	Walking	Running	Crawling
1	1	-28	17	-9.25
1	2	-8	-20.3	-1.88
1	3	-8.75	4	-0.5
Sensor 1 Score		**-44.75**	**0.7**	**-11.63**
2	1	64	42	-48
2	2	8.77	38	15.62
2	3	17.25	43	9
Sensor 2 Score		**90.02**	**123**	**-23.38**
3	1	47	68	148
3	2	0.77	-7.22	-6
3	3	16.25	42	20
Sensor 3 Score		**63.95**	**102.78**	**162**
4	1	25	-127	-91
4	2	1.225	-11.228	-7
4	3	-24.75	-80	-43
Sensor 4 Score		**1.475**	**-218.22**	**-141**

Conclusion

In this work, the capabilities of a recently developed, low-cost, COTS pulse-Doppler radar are explored. It is shown that the sensor is capable of making micro-Doppler measurements of sufficient quality that different human activities may be visually differentiated. Use of the radar in a wireless sensor network is explored, and a method for selecting the sensor in a network offering the best feature estimates for classification is proposed.

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