Radar-based Dataset Development for Human Activity Recognition

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Human activity recognition (HAR) is an important research problem and considerable efforts have been made in the past two decades to develop successful solutions. Datasets developed for HAR serve as a baseline for evaluating new HAR algorithms and play a pivotal role in advancing the research efforts in this domain. Hundreds of datasets have been developed by various researchers which focus on different types of motions and activities [1]. In this context, most of the efforts have been invested in developing the datasets which contain either the video or clips of 2D images of different types of motions. Due to the advent of 3D sensors, modern datasets also contain the information of the motion as well as the depth [2].

There are several intrinsic challenges associated with image or video-based HAR. The HAR strategies developed based on visual datasets cannot work for challenging visibility conditions or in the absence of light. There are also privacy issues associated with image and video-based HAR.

These facts have motivated great interest to develop radar-based HAR methods [3,4]. Such efforts are still in their initial phase and generally exploit micro-Doppler analysis of radar signals reflected by the human body. The basic idea is that different human activities exhibit unique micro-Doppler signatures, which are typically characterized in the joint time-frequency domain, for their classification. With the availability of cost-effective radar systems, it is now easier to detect and classify human activities with a high resolution– thanks to the high Doppler sensitivity of millimeter-wave radar systems. Since the received micro-Doppler signals do not provide facial and other sensitive privacy information, radar-based HAR is much more easily accepted without privacy-related concerns.

In this abstract, we present a radar-based dataset for human activity recognition (Rad-HAR) that exploits continuous wave (CW) radar signals. Based on our knowledge, Rad-HAR is the first public dataset in this domain. We consider a simple scenario where one human subject is moving in front of the radar. For this purpose, we use the Ancortek SDR-KIT-2500 [5] software-defined transmitter-receiver system which consists of one transmit and one receive channels as shown in Figure 1. The radar module has a center frequency of 25 GHz and a bandwidth up to 2GHz; however, we only use a CW signal with carrier frequency of 25 GHz for the dataset development. The output power of the SDR-KIT-2500 radar module is 16 dBm. We provide the raw and processed micro-Doppler signals in DAT format which can be imported in several popular programming languages. Few examples of data processing are provided in MATLAB by exploiting time-frequency analysis techniques.

Figure 1. Ancortek SDR-KIT-2500 module [5].

Signal Model: Consider a human body as the collection of a set P of point targets, which are located in the front of the radar. The transmit signal by the radar is given by:

$$s(t) = A \exp(\mathrm{j}2\pi f_c t), \tag{1}$$

where A is the transmit signal amplitude, f_c is the carrier frequency, and t is the fast time. The instantaneous range of the pth point target with respect to the radar is:

$$R_p(t) = R_{0,p} + \int_{t_0}^{t} v_p(u) \cos\big(\varphi_p(u)\big)\, \mathrm{d}u, \tag{2}$$

where t_0 is the start time, $R_{0,p}$ is the initial range of the pth point target, whereas $v_p(u)$ and $\varphi_p(u)$ respectively denote the velocity and angle of the pth target at time instant u with respect to the radar.

Subsequently, the signal reflected by point target p can be expressed as:

$$r_p(t) = A_p(t)\exp\left(\mathrm{j}2\pi f_c(t-\tau_p)\right) = A_p(t)\exp\left(\mathrm{j}2\pi f_c\left(t-\frac{2R_p(t)}{c}\right)\right), \tag{3}$$

where $A_p(t)$ is the amplitude of the target echo at time t which depends on the transmit signal amplitude A, the range $R_p(t)$ and radar cross-section of the point target. Moreover, $\tau_p = 2R_p(t)/c$ is the time delay due to the round-trip range of the pth point target, and c is the electromagnetic propagation speed.

Using Eq. (3) and the known carrier frequency f_c, we can extract the baseband signal received due to the pth point target as follows:

$$\bar{r}_p(t) = r_p(t)A_c\exp(-\mathrm{j}2\pi f_c t) = B_p(t)\exp\left(-\mathrm{j}4\pi f_c\frac{R_p(t)}{c}\right), \tag{4}$$

where A_c is the amplitude of the demodulating carrier waveform and $B_p(t)$ is the baseband amplitude of the resulting received signal. The time-varying Doppler frequency due to the pth point target is expressed as:

$$f_{D,p}(t) = -\frac{2v_p(t)\cos\varphi_p(t)}{c}f_c = -2\frac{f_c}{c}\frac{\mathrm{d}}{\mathrm{d}t}R_p(t). \tag{5}$$

Since the human body is the collection of all point targets contained in the set P, the overall baseband signal corresponding to the entire human body can be represented by the collection signals from all these point targets, expressed as:

$$\bar{r}(t) = \int_{p\in P}\bar{r}_p(t)\mathrm{d}p = \int_{p\in P}B_p(t)\exp\left(-\mathrm{j}4\pi f_c\frac{R_p(t)}{c}\right)\mathrm{d}p, \tag{6}$$

and the corresponding Doppler signatures are given by:

$$\tilde{f}_D(t) = \int_{p\in P}f_{D,p}(t)\mathrm{d}p = -2\frac{f_c}{c}\int_{p\in P}v_p(t)\cos\varphi_p(t)\,\mathrm{d}p. \tag{7}$$

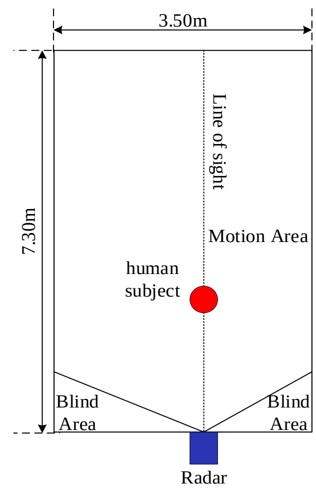


Figure 2. The lab environment in which the Rad-HAR dataset is acquired.

Dataset: The Rad-HAR dataset was acquired at Advanced Signal Processing Laboratory (ASP Lab) at Temple University. The data collection was approved by the Institutional Review Board (IRB) of Temple University. The layout of the laboratory is given in Figure 2. The dataset consists of six different types of human movements as shown in Table 1. These data due to the human movements are recorded at different sampling rates and stored as raw data in DAT file format. The data for each type of motion are placed in separate folders whose name also acts as the data label. These files contain the raw I/Q data in the form of complex sinusoids expressed in Eq. (6).

Table 1. The Rad-HAR dataset

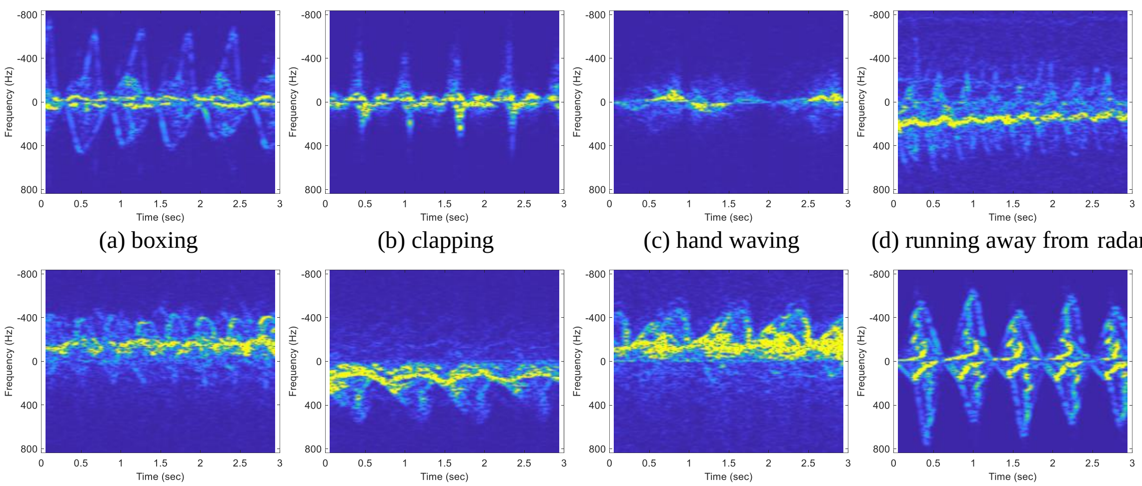
	Type of motion	Raw data length (sec)	Raw data sample rate (kS/sec)	Number of 3-second data segments
Facing towards the radar	Boxing	60/30	512	196
	Clapping	15/180	128/512	199
	Hand waving	60/30/15	512/512/128	199
	Piaffe/Mark time	15/300	128/512	199
	Running towards radar	3/6	128/128	50
	Walking towards radar	3/6	512/128	100
Facing opposite to the radar	Walking away from radar	6	128	50
	Running away from radar	6	128	97

The Rad-HAR dataset also contains processed data. The DC offset is removed because it mainly represents strong clutter near 0 Hz in the Doppler domain and obscure motion recognition. Furthermore, we clip the data of each class into three-second segments which can be readily employed to observe the

Doppler signatures in the time-frequency domain. We downsample all the processed data to 64 ksample/sec which is enough to capture the desired human motions. All the data are stored in the form of DAT files and provided as the part of the dataset.

The Rad-HAR dataset can be accessed at [6] under the “Resources” section.

Examples: In order to provide a demo of the Rad-HAR dataset, we represent the time-frequency characteristics of the received radar signals. The spectrogram computed for the first three second of the data in each class is shown in Figure 3. It is evident that each class has a unique Doppler signatures for them to be separately recognized. For motions that generate noticeable changes in the range between the target and the radar, such as walking and running, the spectrogram clearly reflects the propagation loss of electromagnetic signals which increases with the range. An example of the HAR performance on the Rad-HAR dataset by exploiting deep learning approaches can be found in [7].



(a) boxing (b) clapping (c) hand waving (d) running away from radar

(e) running towards radar (f) walking away from radar (g) walking towards radar (h) mark time

Figure 3. Spectrogram of different types of motions with respect to radar in Rad-HAR dataset

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