A Novel Approach for Radar-Based Human Activity Detection and Classification

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Abstract—In this paper, we propose a novel approach for real-time radar-based human activities detection and classification. In this approach, first, the radar transceiver is mounted on the room's ceiling leading to considerable variations of the relative received power as the subject perform the different activities. Second, to exploit the different activities' dynamics (i.e. evolution in the time domain), radar data is registered over a long period (around 8 seconds) leading to distinctive signatures corresponding to the different activities. Then Machine Learning (ML) techniques are used for these activities' classification. The obtained results demonstrate that this approach performs well both in millimeter Wave (mmWave) and in the sub-6GHz bands. We even obtained better results in the sub-6GHz band with an average classification accuracy of 95.7% compared to 89.8% obtained in the mmWave band.

Keywords—Human activity detection; radar; heatmap; mmWave; sub-6GHz; machine learning

I. INTRODUCTION

While for long years the radar technology was limited to military and high-end professional applications (e.g. aircraft/automotive industry), the recent advances in Integrated Circuits (ICs) and the impressive growth of processing power combined with Machine Learning (ML) techniques open the door to novel radar applications including user sensing/localization, gesture recognition, vital signs (e.g. breathing and heartbeat) sensing [1-9]. Indeed, the open literature is rich of signal processing techniques for human activity (e.g. walking, sitting and falling) detection and classification based on radar data mainly using range-doppler features hence leading to positioning the radar transceiver in front of the subject. As an example, in [8] range-doppler maps are considered as a feature, and both k-Nearest Neighbors (kNN) and Support Vector Machine (SVM) classifiers were tested.

Multiple radiofrequency (RF) bands, including millimeter Wave (mmWave) band and sub-6GHz are considered for radar applications. The mmWave radars cover mainly the 77GHz band for automotive applications, and the 60GHz Industrial, Scientific, and Medical (ISM) band. The mmWave bands provide a very fine range resolution (thanks to the availability of a large frequency spectrum). Moreover, they allow the miniaturization of high gain antenna arrays for improved angular resolution and clutter rejection. However, they suffer from high propagation losses, obstacle blockage, prohibitive cost (components and manufacturing) and high-power consumption. Meanwhile, lower frequency bands present better propagation and penetration characteristics at a lower overall cost. However, they are less suited for antenna array miniaturization and the available spectrum at these frequencies is a tenth of mmWave bands' one (rather few hundred MHz), leading to ten times worse range resolution.

In this paper, a novel approach for radar-based human activity detection and classification is proposed. This approach is suitable for both mmWave and sub-6GHz radar bands. Furthermore, it uses low computation ML techniques, hence it can be integrated in many Consumer Electronics (CE) devices including TVs, set top boxes, gateways and Internet of Things (IoT) devices.

The rest of the paper is organized as follows: in section II, the experimental setup and data collection process are described. Then, the real-time detection and classification method is presented in section III. Finally, the paper is concluded in section IV.

II. EXPERIMENTAL SETUP AND DATA COLLECTION

A. Experimental Setup

Fig. 1 shows the experimental setup. As it can be seen, the radar transceiver is mounted on the room's ceiling at a height of 2.7m from the floor. In this room, three different human activities are monitored namely: walking back and forth in the room (called walking), walking into the room and sitting under the radar system (called sitting), and finally walking into the room and falling on ones knees on a sofa under the radar system (called falling). The mounting of the radar on the room's ceiling has the following advantages. First, it has a good coverage of the room space hence it can follow the subject as he moves around the room. Second, when the subject performs a certain activity below the radar transceiver, the relative received power will change significantly leading to a good sensitivity. Indeed, the radar received power (P_r) is given by:

$$P_r = \frac{P_t . G_t . G_r . \lambda^2 . \sigma}{(4\pi)^3 R^4} \quad (1)$$

where P_t is the transmitted power, G_t and G_r are respectively the transmitting and receiving antennas' gain, λ is the free-space wavelength, σ is the target's Radar Cross Section (RCS) and R is the target's range.

Let us take the example of a falling event of a subject of 1.75m. When the subject is standing below the radar, the radar-subject's head distance is around 0.95m. When the subject falls, the radar-subject's back distance will suddenly increase to around 2.4m. Thus, looking at the radar received power equation given in (1), and assuming all the other factors including the target's RCS are fixed, it can be inferred that the received power will reduce by more than 16dB. Hence, it is pertinent to consider the time variations of the target's range and reflected power as features for different activities detection and classification.

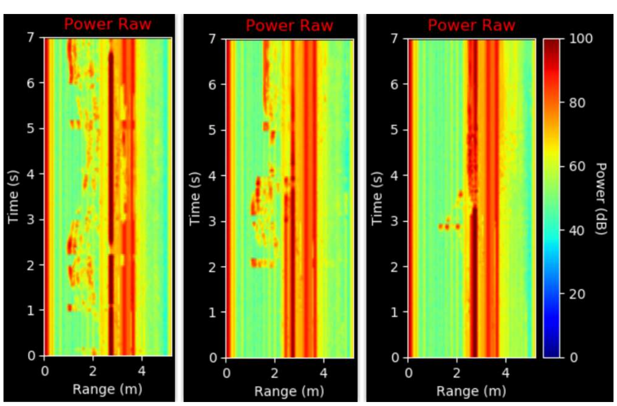
Fig. 1. Experimental setup with the two radar modules mounted on the room's ceiling

B. Data Collection Process

Two different radar modules were used for data acquisition. The first one is the short-range radar reference design TIDEP-0095 [10] based on the AWR1642 chip from Texas Instruments (TI). This single chip outputs a Frequency Modulated Continuous Wave (FMCW) signal with 4GHz available bandwidth leading to a range resolution of 3.8cm.

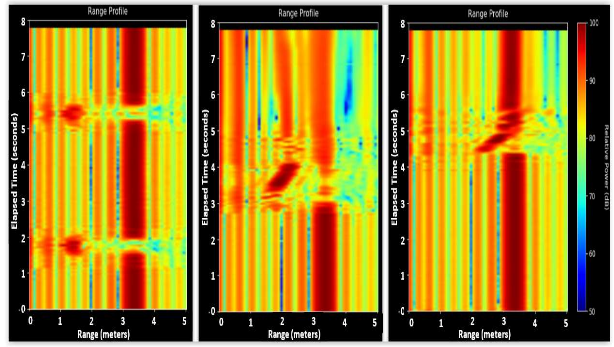
The second used module is the Software Defined Radio (SDR) reference design SDR-KIT 580AD2 [11] from Ancortek. This module outputs a FMCW signal with 400MHz typical bandwidth leading to a range resolution of 38cm.

Fig. 2 shows examples of the range-time-power signatures of three activities using the TI reference module. As it can be noticed, the three activities have visually different signatures, meaning that they can be easily discriminated. Fig. 3 show examples of the range-time-power signatures of the same three activities using the Ancortek reference module. As predicted, one can easily see that these signatures have lower range resolution (wider vertical lines) compared to those of Fig. 2. However, the three signatures are still visually different, and they can be detected and classified with good performances as it will be shown in the next section.



(a) (b) (c)

Fig. 2. Example of range-time-power heatmaps of three indoor human activities for mmWave band.(a) Walking, (b) Sitting, and (c) Falling



(a) (b) (c)

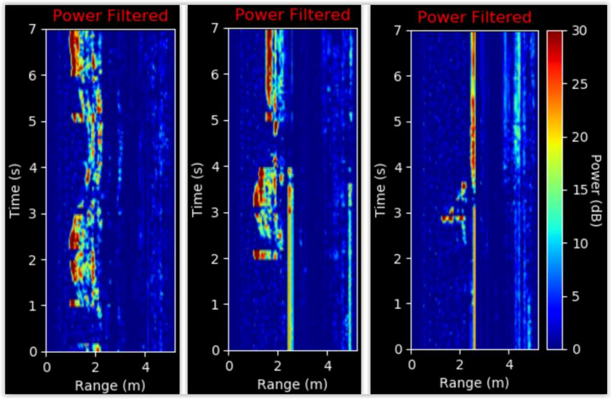
Fig. 3. Example of range-time-power heatmaps of three indoor human activities for sub-6GHz band. (a) Walking, (b) Sitting, and (c) Falling

III. Real-Time Detection and Classification Method

To be able to focus on the useful data, we first apply a background subtraction on the different signatures. Fig. 4 shows the signatures from Fig. 2 after performing the background subtraction. It can be noted that the self-reflection and the static clutter, including the ground effect, are minimized. Hence, the three activities are more distinctive. The same process is applied to the sub-6GHz heatmaps of Fig.3.

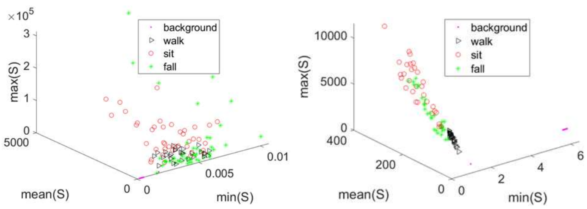
Then, after converting each heatmap signature matrix from dB to linear values, we used two different approaches based on ML techniques to classify the filtered signatures corresponding to the three activities. One additional class (called background) was added, as a default class corresponding to the background scene when there is no activity in the room. This class prevents the ML processing from false detections i.e. when the current activity does not correspond to any of the three activities.

In the first one, a Singular Value Decomposition (SVD) was applied. Then, min(S), mean(S), max(S) was selected as a 3D feature, where S is the singular values matrix. Fig. 5 shows the distribution of the different classes' samples in this case. As it can be seen, in the mmWave band, most of the classes' samples are well separated. However, the walking samples are spread among the fall and sit samples. Meanwhile, in the sub-6GHz band, all the classes' samples are well separated. Then, "MATLAB Classification Learner" was used to find the best classifier in each band. The best classifier, using cross-validation, was found to be Medium Gaussian SVM in both mmWave and sub-6GHz frequency bands. TABLE I. and TABLE II. show the confusion matrix for the two frequencies. The obtained average accuracy - calculated by taking the average of the confusion matrix's diagonal - is equal to 70.5% (respectively 95.7%) in the mmWave band (respectively sub-6GHz band).



(a) (b) (c)

Fig. 4. Example of filtered range-time-power heatmaps of three indoor human activities for mmWave band after background subtraction. (a) Walking, (b) Sitting, and (c) Falling



(a) (b)

Fig. 5. The distribution of the different classes using SVD. (a) In mmWave band and (b) in sub-6GHz band

TABLE I. CONFUSION MATRIX BASED ON MEDIUM GAUSSIAN SVM CLASSIFIER WITH SVD IN MMWAVE BAND

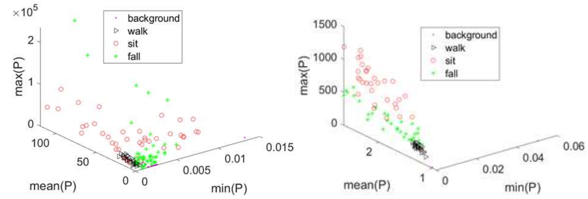
Ground truth \ Detected activity	Background	Walking	Sitting	Falling
Background	98%	0%	0%	2%
Walking	0%	47%	7%	46%
Sitting	0%	20%	53%	27%
Falling	0%	6%	10%	84%

TABLE II. CONFUSION MATRIX BASED ON MEDIUM GAUSSIAN SVM CLASSIFIER WITH SVD IN SUB-6GHZ BAND

Ground truth \ Detected activity	Background	Walking	Sitting	Falling
Background	97%	0%	0%	3%
Walking	0%	100%	0%	0%
Sitting	0%	0%	93%	7%
Falling	0%	3%	4%	93%

In the second classification approach, min(P), mean(P), max(P) were selected as 3D features, where P is the linear power matrix. Fig. 6 shows the distribution of the different classes in this case. Then, as for the first approach, by using the "MATLAB Classification Learner", the best classifier was found to be Linear SVM in mmWave band and Bagged Trees Ensemble in sub-6GHz band with an average accuracy of respectively 89.8% and 93.3%. TABLE III. and TABLE IV. show the confusion matrix of the two classifiers.

It is worth to notice that in both approaches, the sub-6GHz provides the best results despite it is lower range resolution.



(a) (b)

Fig. 6. The distribution of the different classes without using SVD. (a) In mmWave band and (b) in sub-6GHz band

TABLE III. CONFUSION MATRIX BASED ON LINEAR SVM CLASSIFIER WITHOUT SVD IN MMWAVE BAND

Ground truth \ Detected activity	Background	Walking	Sitting	Falling
Background	98%	0%	2%	0%
Walking	0%	97%	0%	3%
Sitting	0%	13%	78%	10%
Falling	2%	10%	2%	86%

TABLE IV. CONFUSION MATRIX BASED ON BAGGED TREES ENSEMBLE CLASSIFIER WITHOUT SVD IN SUB-6GHZ BAND

Ground truth \ Detected activity	Background	Walking	Sitting	Falling
Background	100%	0%	0%	0%
Walking	0%	100%	0%	0%
Sitting	0%	0%	90%	10%
Falling	0%	7%	10%	83%

IV. CONCLUSION

In this paper, we proposed a novel approach for radar-based human activity detection and classification. We tested the proposed approach using two different radar modules in the mmWave and sub-6GHz frequency bands. An average classification accuracy of 89.8% and 95.7% was obtained respectively in the mmWave and sub-6GHz bands. This means that the high range resolution provided by the mmWave module is not mandatory for obtaining good classification results, and lower cost, narrower bandwidth sub-6GHz band radar modules are well suited for numerous sensing applications where the range resolution is not paramount. We are currently trying to further improve the detection accuracy by using deep learning techniques.

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