Open Radar Initiative: Large Scale Dataset for Benchmarking of micro-Doppler Recognition Algorithms

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Abstract—In this paper, we discuss an "open radar initiative" aimed at promoting the sharing of radar datasets and a common framework for acquiring data. The framework is based on widely available and affordable short-range radar hardware (automotive FMCW radar transceivers). This framework and initiative are intended to create and promote access to a common shared dataset for the development and benchmarking of algorithms. While this is the norm for image processing and speech processing research, there has been reluctance in the radar community so far to create common datasets of shared data, often due to justified intellectual property or security classification reasons. Notable exceptions do exist, such as the MSTAR dataset of SAR images, which enabled great progress across the radar research community for a number of years. With this initiative, we hope to stimulate discussion and, with time, changes of practice in the radar research community. The main contribution of this work relative to previously shared datasets of radar data is that the proposed framework consists of a complete, integrated and replicable hardware and software pipeline, allowing users to not only download existing data, but also to acquire their own data with a compatible format that allows expansion and enrichment of the common dataset.

I. INTRODUCTION

Radar sensors are capable devices for many applications, spanning from gesture recognition with the Google Soli radar [1] or similar other short-range platforms, to long-range surveillance radars [2] and even space observation radars [3]. Because of the large span in applications, radar system configurations vary greatly, but they still have a lot in common such as the basis of their signal processing. Many radar signal processing tasks can benefit from machine learning and emerging, data-driven processing approaches. In recent years, many papers have been presented on machine learning and artificial intelligence for both classification [4], [5] and detection [6]. This is far from an exhaustive list, for a good overview, the reader is advised to read the review paper by Patel et. al. [7]. Because

much of radar research is focused on military or proprietary automotive applications, most of the datasets are collected using bespoke radar sensors and the datasets are not published due to intellectual property and classification issues. Because of this, it is hard to compare the performance of different algorithms and approaches. Consequently, it is difficult to point out major findings in the research contributions and development of algorithms is therefore slowed down.

This problem has been addressed in the community of machine learning for optical images or speech processing by having shared datasets for algorithm development and benchmarking. This has allowed the community to compare results on common datasets and also share some approaches in achieving these results - resulting in major leaps in algorithm performance. The ubiquity of camera sensors has eased the collection of data for these domains, but large annotated datasets are still a valuable asset that is shared with the community.

However, in the radar community, there are a few commonly available datasets, some of them publicly shared by the authors of this paper with the idea of supporting classification challenges [8]–[10]. A great example of a publicly available dataset is the MSTAR dataset [11] that researchers have used for algorithm development for years. In some cases, researchers have even published both radar configuration, results, and datasets such as Ritchie [10] and Roldan [12]. The initatives are commendable, but a shortcoming of these approaches is that it is difficult to reproduce or expand the dataset, as the hardware is closed source and/or the data is already processed. Other initatives are providing frameworks for processing of radar data, such as PreSenseRadar [13] and PyRapid [14], but no public datasets have been published along with these efforts.

The "open radar initiative" discussed in this paper attempts to bridge the gap between some of these publications, by proposing:

- An open hardware radar platform that is commercially available and affordable for a large variety of users.
- An open source framework for interfacing with the hardware
- A publicly available dataset to be used as a common benchmark for algorithm development

And thereby aiming to offer a framework for generating a large-scale database of radar data in support of a wide range of applications, including defense, security, and commercial applications, as well as research areas, such as:

- Classification
- Detection
- Signal processing
- Tracking
- Radar resource management

By providing commonly available radar hardware with open-source software and datasets, the platform can be shared across institutions and research communities with a unified file format.

The remainder of this paper is organized as follows. Section II describes the components of the proposed common radar platform. Section III describes the vision of the datasets. Sections IV and V discuss the initial datasets shared as part of the launch of this initiative, and possibilities for its further expansion.

II. COMMON RADAR PLATFORM

Choosing a common radar platform is challenging. To achieve widespread use this platform would need to be affordable, capable, flexible, and widely available. The radar has to be affordable so that many institutions can acquire the hardware. It also has to be flexible and capable, so that it can be used for many different applications. Many different hardware platforms were considered for the common radar platform with varying affordability, capability, flexibility and availability. Automotive radar sensors provide highly capable and versatile radar solutions in a small and affordable package. Therefore, they provide a great starting point for a common radar platform. The "open radar initiative" is primarily focused on the datasets, but the platform provides a good opportunity for the radar community to contribute. Code and usage examples are therefore made available open-source to encourage contribution and sharing.

A. Description of the components

The proposed radar platform utilizes radar evaluation modules from Texas instruments (TI)[1]. TI supplies a rich variety of

[1]The "Open radar initiative" is not affiliated or funded by Texas instruments.

radar modules accompanied by both documentation and examples. These modules are also widely available. The common radar platform proposed in this paper consist of:

- TI AWR2243Boost radar evaluation board
- TI DCA1000 Data Acquisition board

The radar module is highly flexible and capable, as explained later on in the section. Coupled with a real-time acquisition board, it is possible to capture raw analog-to-digital converter (ADC) samples from the radar. With an extensive set of parameters and the ability to capture raw ADC data, the platform can be used in multiple modes for different research purposes. For more details, check the GitHub repository associated with this initiative [15].

B. Radar Platform

The radar module itself is an integrated circuit containing a full radar transceiver including signal generator, RF transmit and receive, down-conversion and sampling. A block diagram of the TI AWR2243 chip is shown in Figure 1. For detailed information on the radar chip itself, the reader is advised to read the datasheet [16]. Some of the key parameters of the platform are:

- 4 Receive channels, 3 Transmit channels
- 76-81 GHz carrier frequency, up to 5 GHz bandwidth
- Flexible chirp generation
- Up to 40 Msps sampling per channel
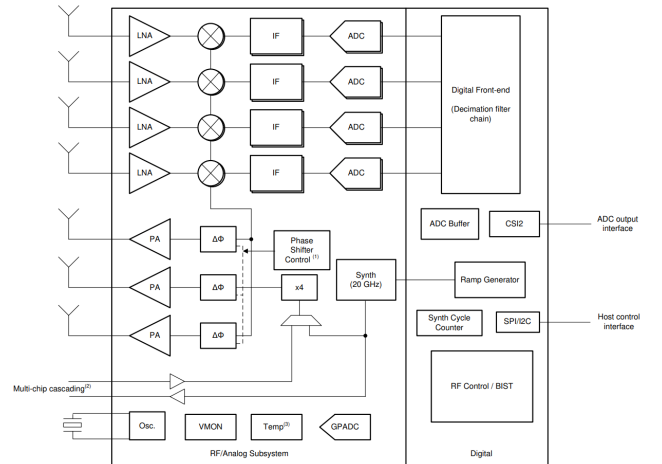- Raw data stream via TI DCA1000

Figure 1: Block diagram of the TI AWR2243 transceiver chip from the datasheet [16]

C. Platform setup and configuration

TI provides extensive software to set up and evaluate their mmWave devices called "*mmWaveStudio*". This software is at the moment only available on Windows operating systems. For details on the setup parameters and configuration, interested readers are referred to the user manual for *mmWaveStudio*. To be able to setup the device from a Linux operating system, one

of TI's mmWaveLink examples was ported to work with Linux operating systems. This ported setup code is made available as part of the proposed "Open Radar Initiative". Detailed installation instructions and a user manual are available at the GitHub repository [15]. A simplified functional flowchart of the radar setup is shown in Figure 2.

Figure 2: Flowchart of the setup.

The radar parameters are set using a text file in the same folder as the code to set up and configure the radar.

D. Data reception and logging

The software shared within this initiative contains little processing software, but provides the convenience of being able to read and parse UDP packets, raw data logging and reading back raw data. The data transmitted from the TI radar platform is in the form of user datagram protocol (UDP) packets, where each packet contains raw ADC data sampled in the radar. The first part of the processing is UDP packet reception and data combination to form a structure of raw data that fulfills the requirements. The data reception and logging process are described in the block diagram in Figure 3. These utilities are available at the GitHub Repository [15]. For more signal processing examples, the reader is encouraged to be inspired by PreSenseRadars examples [13] or refer to conventional radar textbooks like "Principles of modern radar" by Richards [17]
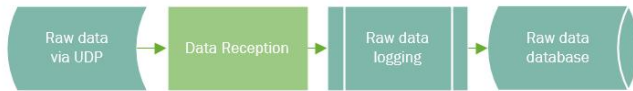

Figure 3: Data logger block diagram

III. OPEN DATASET

Large open datasets like "Openimages" [18] have revolutionized the field of machine learning on optical images. It is therefore likely that a well-designed, large and open dataset will help advance the field of machine learning on radar data as well. As mentioned in the introduction, radars can be used for multiple purposes and in multiple modes. As a consequence, not all data is relevant for every situation. Put quite simply, data from hand gestures might not be beneficial for ground surveillance purposes and vice versa, but the machine learning algorithms and approaches might be with some proper adjustments.

Some data will likely be suitable for classification, others for detection, and some other data for interference mitigation. An open dataset would therefore need to allow for multiple

usages and data types to be really impactful and valuable to the radar research community. It is worth underlining the fact that a well-designed dataset is needed and not just a large dataset. A good dataset needs to have high-quality labelling, well documented data acquisitions and a variety of targets. Additionally, the dataset has to allow for users of the dataset to access and in case alter the raw data processing, to develop and investigate optimal pre-processing and representation.

The dataset for this initiative contains raw data and annotated extracted signatures of multiple targets and classes. The following two sections will introduce the two first contributions to the dataset:

- Outdoor moving object dataset
- Activity classification dataset

These two datasets are a first contribution and there will likely be more datasets available in the future. They will also likely be expanded with time to address imbalance or to increase the dataset quality. The datasets, their statistics and examples of usage are available at a GitHub Repository [15].

IV. OUTDOOR MOVING OBJECT DATASET

This dataset has been collected with a stationary radar observing different types of moving targets such as people walking and cycling. The primary goal of the dataset is to use classification techniques to be able to distinguish the classes. The dataset has been collected outdoor with both collaborative and non-collaborative targets and currently has four classes, namely person, bicycle, unmanned aerial vehicle (UAV) and vehicle. The samples include labels corresponding to "classification" in the NATO AAP-6 [19] and meta-labels corresponding to "recognition".

(i) Spectrogram of a person   (ii) Spectrogram of a bicycle

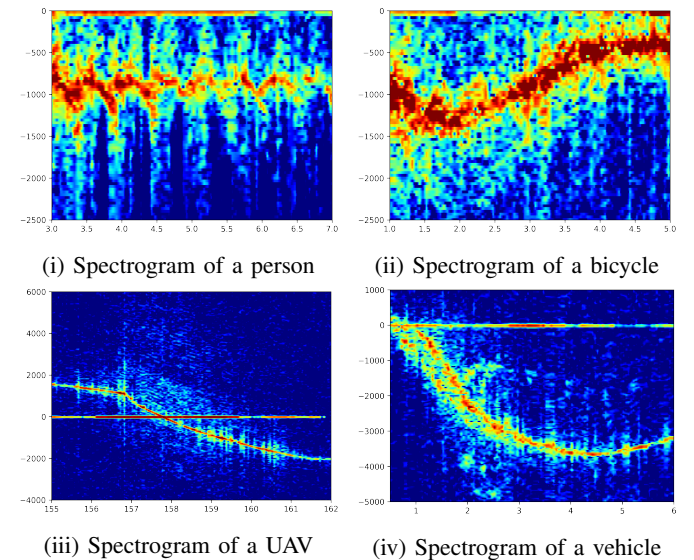(iii) Spectrogram of a UAV   (iv) Spectrogram of a vehicle

Figure 4: Example of signatures from the dataset. The y-axis denotes Doppler-frequency in Hz and the x-axis is time in seconds.

These are relevant targets for a ground-based radar system, but also to some degree relevant for other applications such as pedestrian detection for a smart vehicle. Samples of spectrograms from each of the classes are shown in Figure 4. The target signature is distinguishable in sections where the signal to noise ratio (SNR) is high. This section describes the generation of the dataset and its class distribution.

A. Data collection

Because the data is collected with both collaborative and non-collaborative targets some of the data will therefore be fairly clean spectrograms, whereas some will be collected in a more cluttered environment. The data has been collected by FFI, TU-Delft and the University of Alabama using the common radar platform.

The radar has been configured to use one transmit antenna and all four receive antennas. The pulse repetition frequency (PRF) constant with a high PRF of 33 kHz, resulting in an unambiguous velocity of 30 m/s, sufficient to capture most moving ground vehicles. The dataset was configured to collect 1008 pulses per Coherent Processing Interval (CPI), resulting in approximatly 30.5 ms CPI. The range resolution was varied, to allow for the collection of vehicles at longer ranges and still stay within the data streaming limitations of the capture card. Full descriptions of the waveforms and the configuration files used are available on the Github page [15]. Two different radar sensors were used for the collections, the AWR2243Boost and the AWR1843Boost.

B. Dataset generation

After recording, the signatures have to be extracted. The process of signature extraction is explained in Figure 5. The signal processing pipeline takes the real ADC data from the radar and generates detections with their associated Doppler spectra attached. These detections are passed to the tracker that produces an association log for each target, essentially associating all the detections on the tracked target. Combining these associations with their detections and Doppler spectra produces a long spectrogram comprised of Doppler spectra of consecutive CPI's originating from the target. These long spectrograms can then be split into smaller spectrograms of the desired duration for classification.
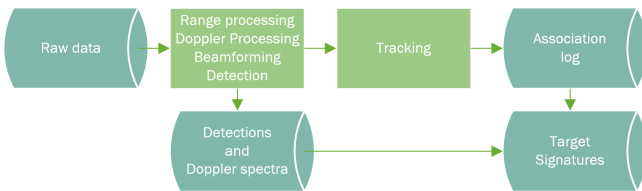

Figure 5: Flowchart of the target signature generation.

C. Signal processing pipeline

The signal processing pipeline consists of several steps in the process of converting raw samples to a beamformed range-Doppler data cube.

1) Range profile generation: The first step in the signal processing chain is to generate a range profile, which is a Fourier transform in the fast time domain for a frequency modulated continuous wave (FMCW) radar [17]. In the frequency domain of a FMCW radar, the beat frequency is proportional to the range of the target. A Hamming window is applied prior to range profile generation.

2) Beam forming: The beam forming of a radar signal is performed in the array element domain, and may be implemented with a Fourier transform. However; a Fourier transform based beamformer will not utilize even space sampling in the azimuth domain, which is a non-desirable property. Using steering vectors, an arbitrary sample space may be used; although, the processing may not use efficient algorithms such as the fast Fourier transform (FFT).

The steering vector for a uniform linear array (ULA) [20], is defined as

$$\boldsymbol{a}_{ULA}(\theta) = g(\theta) \begin{bmatrix} 1 & e^{-jkd\cos(\theta)} \dots e^{-j(L-1)kd\cos(\theta)} \end{bmatrix} \quad (1)$$

Where θ is the pointing direction of the steering vector, k is the wave number and defined as $2\pi/\lambda$, L is the number of antenna elements and d is the distance between antenna elements.

3) Doppler spectrum processing: The second step in the signal processing chain is the Doppler processing, in order to separate moving targets from stationary clutter. Doppler processing is performed with a Fourier transform in the slow time domain, and is implemented with a FFT. A Blackman window is applied prior to Doppler processing.

D. Dataset statistics

As previously mentioned, a well designed dataset is just as important as a large dataset. This section will discuss some of the statistical aspects of the dataset at the time of writing. These number might have changed by the time the dataset is available to the public due to the inclusion of newer data.

Firstly, the dataset contains a total of 187.393 spectra from a total of four classes as shown in the Table I. This is large enough for many experiments, but more data will be added in the future. More importantly, the dataset is well distributed with regards to RCS and relative velocity, to make the classification a challenge. The vehicle category contains mostly medium-sized passenger cars, with some larger trucks and and lorries. The UAV category currently only contains small quadcopters like the DJI Phantom 4.

Class	Vehicle	Person	Bicycle	UAV
Samples	48321	69741	32433	36897

Table I: Number of samples in each class in the dataset.

There is a significant difference in RCS estimates distinguishing most of the targets, with different overlap within the classes

as shown in Figure 6. This means that a pure RCS-based classification will not give a 100% correct on this dataset.
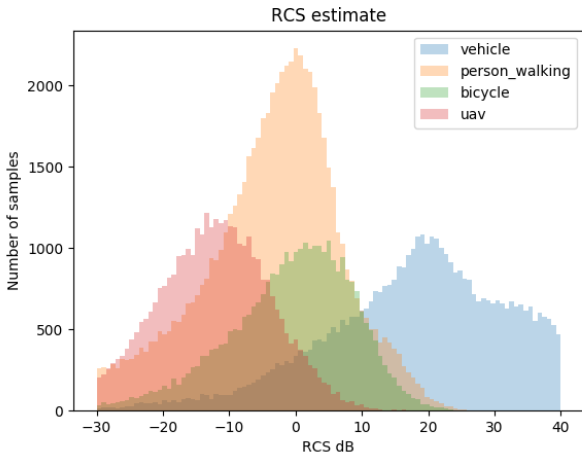

Figure 6: Histogram of the estimated RCS in the dataset, separated by class

The same is true for radial velocity, where there is a significant overlap between the classes as shown in Figure 7, again causing confusion for a simple classifier.
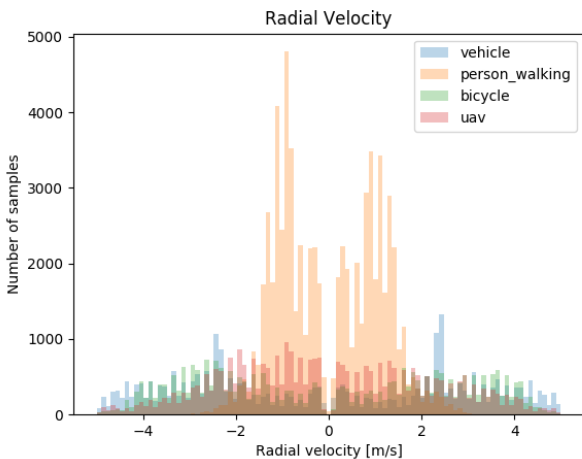

Figure 7: Histogram of the radial velocity of the classes in the dataset.

V. INDOOR HUMAN ACTIVITY CLASSIFICATION DATASET

In contrast with outdoor target recognition scenarios, indoor human activity classification scenarios typically involve finer-scale motion recognition, such as in assisted living application of fall detection [21], fall risk assessment, and gait analysis [22]. In these situations, the challenge requires discrimination of many types of similar, ambulatory signatures [23], [24] to differentiate normal walking from aided walking or abnormal walking, which could be indicative of fall risk.

The assisted living/activity classification dataset is comprised of 11 different ambulatory gaits or activities as acquired from 6 different participants, who repeated each activity 10 times; namely, 1) walking, 2) picking up an object, 3) sitting on a chair, 4) crawling towards the radar, 5) walking on both toes, 6) scissors gait, 7) walking away from the radar, 8) bending, 9) kneeling, 10) limping with right leg stiff (i.e. no bending at the knee), and 11) walking with short steps (almost like a shuffle gait).

The activities were simultaneously recorded using three different RF sensors: 1) a TI IWR1443BOOST 77 GHz transceiver, set for 750 MHz bandwidth FMCW, 2) an Ancortek 25 GHz FMCW transceiver with 750 MHz bandwidth, and 3) a Xethru X4 ultra-wide band (UWB) impulse radar with roughly 3 GHz bandwidth between 7-10 GHz. A total of 60 samples per class were acquired for each sensor.

The micro-Doppler signatures for each activity were computed as the square modulus of the short-time Fourier Transform (STFT). Note that high-pass filtering for ground clutter removal was only applied on the 25 GHz FMCW and 7-10 GHz UWB sensors, and not the 77 GHz FMCW sensor. Due to the finer detail offered the higher millimeter wave transmit frequency, we have found that many deep neural networks (DNNs) actually perform better when the ground clutter not filtered out [25]. This is because the filtering operation removes not just the clutter, but also low-frequency signal components, which may be of interest in gesture recognition and other fine-scale problems, such as incurred in assisted living applications. Examples of the the micro-Doppler signatures from the dataset are given in Fig. 8.
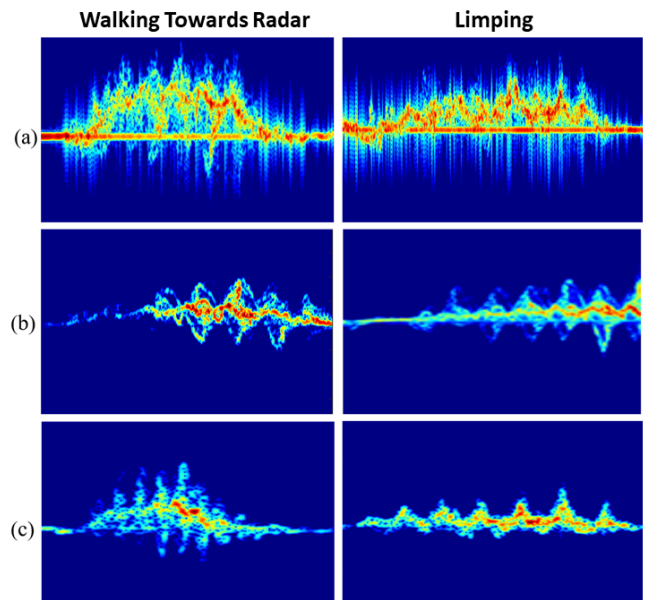

Figure 8: Sample micro-Doppler signatures for walking and limping as acquired using a) 77 GHz FMCW, b) 24 GHz FMCW, and c) 7-10 GHz UWB transceivers.

This data has been used to support research relating to cross-frequency training [26] and cross-modal fusion [27] in RF sensor networks, as well as distributed RF sensor fusion for sequential gait recognition [28].

VI. CONCLUSION

This paper has presented the "open radar initiative" an open-source end-to-end radar platform, providing radar, software and data supplied open-source to the radar community. This is different from previous publications and smaller shared datasets by providing a full pipeline for radar experimentation. All the code is made available online, along with a radar platform available for purchase and two challenging datasets to start the development and benchmarking of algorithms. The two datasets provided are interesting classification challenges in different settings and provide a starting point for the "open radar initiative" The hope of this initiative is to kick start a new collective joint distributed experimental setup and procedure to help generate more openly accessible radar data that can be published and shared across the community.

VII. ACKNOWLEDGEMENT

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