DISC: a Dataset for Integrated Sensing and Communications in mmWave Systems

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***Abstract*—This paper presents DISC, a dataset of millimeter-wave channel impulse response measurements for integrated human activity sensing and communication. This is the first dataset collected with a software-defined radio testbed that transmits 60 GHz IEEE 802-11ay-compliant packets and estimates the channel response including scattered signals off the moving body parts of subjects moving in an indoor environment. The provided data consists of three parts, for more than 2 hours of channel measurements with high temporal resolution (0.27 ms inter-packet time). DISC contains the contribution of 7 subjects performing 5 different activities, and includes data collected from two distinct environments. Unlike available radar-based millimeter-wave sensing datasets, our measurements are collected using uniform packet transmission times and sparse traffic patterns from real Wi-Fi deployments. We develop, train, and release open-source baseline algorithms based on DISC to perform human sensing tasks. Our results demonstrate that DISC can serve as a multi-purpose benchmarking tool for machine learning-based human activity recognition, radio frequency gait analysis, and sparse sensing algorithms for next-generation integrated sensing and communications.**

***Index Terms*—Integrated Sensing and Communication, millimeter-wave, human activity recognition, gait identification, micro-Doppler, dataset.**

I. Introduction

DESPITE the huge interest towards Integrated Sensing And Communication (ISAC) systems working in the Millimeter-Wave (mmWave) frequency band, there is a lack of public datasets in this regard. Thus, it is hard for researchers to develop and *validate* signal processing or Machine Learning (ML)-based ISAC algorithms beyond simulation environments. Unlike widely studied Wi-Fi sensing in the sub-6 GHz band, mmWave ISAC lacks affordable commercial devices, tools for the extraction of Channel State Information (CSI) [1], so it has mostly relied on simulation tools [2]. Indeed, most of the experimental works in the field use mmWave radar devices which employ specifically optimized waveforms for each application and are inapt for communications [3]. Moreover, each work typically uses a different dataset and baseline algorithms. With the rising importance of Deep Learning (DL) for radio signal processing, it becomes key to foster easier comparison to state-of-the-art algorithms on common data. This is especially true since physical-layer radio signals are cumbersome to collect and store, due to the high sampling rates and data volume.

Challenges. In light of the above discussion, we identify two main unaddressed challenges we solve with the dataset and algorithms presented in this paper. First, there is a lack of datasets that contain radio signal traces to be used for the design and validation of mmWave ISAC algorithms. Key aspects are the size and diversity of such datasets, as most wireless sensing applications require data-hungry DL models to extract complex features from the reflected signal while generalizing to different environments and sensing subjects. Moreover, the data traces should present the typical characteristics of ISAC systems that can not be found in radar datasets, such as *(i)* diverse, irregular, and sparse traffic patterns, and *(ii)* the usage of standard-compliant communication waveforms. Existing efforts in this sense are limited to simulation tools that lack the complexity and hardware impairments of real measurements [2].

Second, open-source benchmark signal processing and DL algorithms to perform sensing applications are needed. These should encompass the variety of ISAC applications, such as people localization and tracking, Human Activity Recognition (HAR), and gait identification. Moreover, challenging sensing scenarios characterized by resource-constrained channel acquisition and diverse multipath environments should be investigated, building on public baseline algorithms. Solving these challenges is a key enabler for ISAC research, which has been identified as a core feature of next-generation 6G mobile networks [4] and Wireless Local Area Networks (WLANs) [5].

DISC. In this paper we present DISC [6], a mmWave ISAC dataset containing Channel Impulse Response (CIR) measurements from standard-compliant Single Carrier (SC) IEEE 802.11ay packets. The CIR sequences contain backscattered copies of the transmitted packets on people moving in an indoor environment. We solve both open challenges by *(i)* providing a large-scale dataset of realistic channel estimates to perform human sensing tasks, called DISC, containing 60 GHz IEEE 802.11ay Wi-Fi channel estimates including different people, environments, and traffic patterns [6], and *(ii)* making a set of benchmark algorithms for people tracking, human activity recognition, and sparse micro-Doppler (μD) spectrum estimation available to the community, open-sourcing their code implementation.

The dataset consists of three parts. The first one, DISC-A, contains more than 1 hour of IEEE 802.11ay CIR sequences including backscattered signals from 7 subjects performing 4 different activities in front of the ISAC transceiver. This part is characterized by uniform packet transmission times, with a granularity of over 3 CIR estimates per millisecond, yielding extremely high temporal resolution. The second part, DISC-B, contains 40 minutes of CIR sequences obtained at uniform packet transmission times, with 1 to 5 subjects concurrently,

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freely moving in the environment and performing 5 different activities. Moreover, in this second part, we use the directional transmission capabilities of our testbed to allow the estimation of the Angle of Arrival (AoA) of the backscattered signal, which enables *tracking* the subject across time. DISC-B also includes data collected in a different test environment, to offer the opportunity to test the generalization capabilities of DL-based sensing algorithms. In the third part, DISC-C, we use open-source data on Wi-Fi traffic patterns to tune the inter-packet duration and collect more realistic *sparse* CIR sequences. The resulting CIR measurements, for a total of 9 minutes, are collected with a single subject performing the same 4 activities included in the first part.

Usage. We envision our dataset and algorithms being used to train and validate new fine-grained sensing approaches. Possible use cases include, but are not limited to, tracking of multiple subjects, extraction of the μD signatures of human movement from the CIR [7], which enables DL-based HAR [3], and person identification from individual gait features [8]. In addition, advanced ISAC problems such as the sparse reconstruction of sensing parameters from irregularly sampled signal traces, domain adaptation from regularly sampled signals to sparse ones, and target tracking under missing measurements can also be tackled using DISC [9]. Moreover, DISC is aligned with ISAC standardization efforts by the 3GPP, IEEE 802.11bf, and ETSI, which have shown interest in modeling human-related propagation characteristics of the channel [4]. In this sense, the availability of experimental data involving reflections on human subjects can support the channel modeling effort.

The paper is organized as follows. In Section II-A we discuss the necessary preliminaries regarding the IEEE 802.11ay CIR, while in Section II we present the experimental setup including the ISAC Software Defined Radio (SDR) testbed and the parameters of the experiments. Section III contains an overview of the dataset and in Section IV we discuss possible research problems that can be addressed by using it. Finally, in Section V we present results obtained with the proposed benchmark algorithms on DISC. Concluding remarks are given in Section VII.

II. Experimental testbed decription

In this section, we describe the experimental setup used to collect the dataset, including the ISAC testbed, the system parameters, and the collection environment.

A. Physical layer system operation and parameters

Our dataset contains CIR measurements collected according to the IEEE 802.11ay standard [10], using a SC waveform in single-input single-output mode. The CIR contains the complex channel gains for different delays. The delay resolution of the system is given by $\Delta\tau = 1/B$ with $B = 1.76$ GHz being the bandwidth of the transmitted signal, spanning an IEEE 802.11ay channel. As a result, the delay resolution of the system is given by $\Delta\tau = 1/B = 0.568$ ns. In IEEE 802.11ay the communication is highly *directional*, thanks to the use of

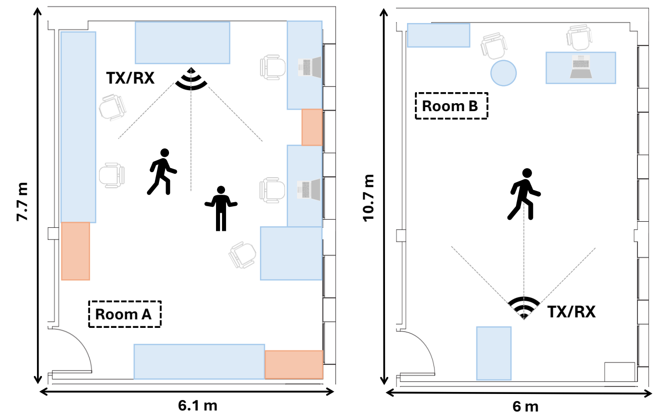


Figure 1: Data collection environments.

phased antenna arrays with narrow Beam Patterns (BPs). In addition, *in-packet* beam tracking is supported [10], which allows switching the BP within a single packet. The different BPs used illuminate targets located in the environment differently, thus introducing diversity that can be exploited to compute the AoA of the propagation paths with high accuracy, see, e.g., [11]. From the beamwidth of the BPs, one can obtain the angular resolution of the system, $\Delta\theta$, which is approximately 8°. Beam tracking is done by appending a specific field of pilot symbols, called TRN field, to the packet. A TRN field is composed of a tunable number of TRN units, each formed by 6 complementary Golay sequences of type a ("Ga") and b ("Gb") Golay sequences of 128 $\pi/2$ BPSK modulated samples, for a total of 768 samples [10]. At the receiver, the signal corresponding to each TRN unit is correlated with the known pilot sequence to estimate the CIR [12]. Note that exploiting TRN fields with different BPs for sensing is also featured in IEEE 802.11bf, so DISC can be used to test its physical layer sensing capabilities.

We denote by T the (tunable) Inter-Frame Spacing (IFS), i.e., the time interval between two subsequent channel estimation instants using pilot signals from different packets. For reliable μD extraction using the Short Time Fourier Transform (STFT) without aliasing [11], it is advisable to set T to a value that allows capturing the range of velocities typically covered by human movement in indoor environments. These can reach up to ±5 m/s for running or other fast movements [8]. In our dataset, when the IFS is constant, we set it to $T = 0.27$ ms, which is suitable to capture $v_{\max} = \pm c/(4 f_o T) \approx \pm 4.48$ m/s. When using a STFT window $W = 64$, one obtains a velocity resolution of $\Delta v = c/(2 f_o W T) \approx 0.14$ m/s. In the sequences with irregular inter-packet time, instead, this is determined by realistic traffic patterns of real Wi-Fi access points, as described in Section III. We use periodically transmitted in-packet beam tracking frames with a variable number of TRN units, depending on the part of the dataset considered, and antenna beams covering a Field-of-View (FoV) of $[-45°, 45°]$.

B. Data collection environments

The experiments included in DISC-A, most of DISC-B, and DISC-C are performed in a laboratory of 6.1 × 7.7 me-

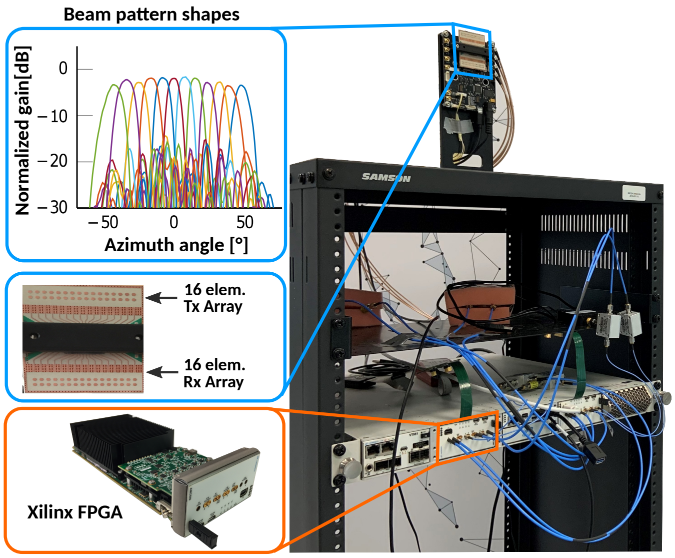


Figure 2: Testbed used in the data collection.

ters (room A) with a complex multi-path environment due to additional scattering and reflections caused by furniture, computers, screens, and a wide whiteboard, as shown in Fig. 1 on the left. The testbed is positioned at one of the two shorter sides of the room, oriented towards the whiteboard. This leaves sufficient space for the subjects to move and perform the different activities included in the dataset. On the right of Fig. 1 we show the second room used in our dataset (room B), which is a 10.7×6 meeting room. DISC-B includes CIR measurements collected in room B to allow testing ISAC algorithm across different environments.

C. Full-duplex ISAC testbed implementation

To collect the dataset, we implement a mmWave ISAC testbed using the open-source mm-FLEX platform [13] as a baseline design. The baseband processor is based on Vadatech slot cards, integrating a Xilinx UltraScale Field Programmable Gate Array (FPGA), multi-Giga-sample AD/DA converters, 20 GB of RAM, and a high-end microprocessor. The mmWave front-end includes a Sivers EVK06002 development kit with 60 GHz up/down converters to implement IEEE 802.11ad/ay channels. It integrates phased arrays including 16 antenna elements for both the transmitter (TX) and the receiver (RX) Radio Frequency (RF) chains. These are equipped with phase shifters, enabling analog beamforming. The main components of the testbed are shown in Fig. 2.

For the data collection, we configure the Analog-to-Digital/Digital-to-Analog (AD/DA) converters to operate at 3.52 Gsps sampling frequency. We enable fast antenna beam reconfiguration capability during the transmission of a packet to estimate the CIRs using different BP shapes in the same packet. To provide the required ISAC functionality, we enhance the testbed with new features, including full-duplex capability, synchronization between TX and RX datapaths, and variable IFS to emulate real traffic patterns.

We modified the testbed to support CIR data collection with variable IFS, supporting Wi-Fi traffic patterns. Further details regarding this aspect and how to implement full-duplex capabilities are given in [6].

To enable AoA estimation techniques [13], we measure the BPs in the codebook of the Sivers kits in a semi-anechoic chamber, with a granularity of 0.5° [13]. For the experiments, we select a subset of BPs that covers uniformly the FoV of the antenna, which are shown in Fig. 2.

As part of DISC, we provide the bitstream and executable software for the baseband processor, as well as MATLAB© scripts to generate packets and process captured data from the testbed [6].

III. DISC OVERVIEW

In this section, we provide a high-level overview of the DISC dataset. DISC is available at [6], together with extensive documentation, and is complemented by a code repository containing Python code to process the data and replicate our benchmarks in Section V. Informed consent was obtained from all the subjects involved in the data collection.

DISC consists of three parts, detailed in the following.

1) DISC-A: Uniform IFS, forward-looking, multiple subjects. The first part of the dataset, termed DISC-A, contains 433 CIR sequences for a total of over 1 hour of time. Such sequences are collected with uniform IFS $T = 0.27$ ms and contain the contribution of 7 different subjects performing 4 activities: *walking*, *running*, *sitting down/standing up*, and *waving hands*. Each sequence is collected with a single subject present in room A. Channel estimation is performed by appending a single TRN unit to each transmitted packet, using a BP pointing forward, along the antenna boresight.

2) DISC-B: Uniform IFS, multiple BPs, multiple subjects moving freely and concurrently. In the second part of the dataset, we provide over 40 minutes of CIR sequences collected with the same uniform IFS used in DISC-A. However, in DISC-B we append 12 TRN fields to each packet, steering the BP in each of them to scan the whole field of view of the antenna. This enables the estimation of the AoA of the signals, and hence to localize and track subjects in the environment.

The CIR sequences in DISC-B are collected across 7 different days. A first set of CIR sequences contains a single subject moving freely in the room and performing one of 5 possible activities: *walking*, *running*, *sitting down/standing up*, *waving hands*, and *standing still*. A second set of sequences contains multiple subjects *concurrently* present in room A (up to a maximum of 5 subjects), in different locations, and performing different activities. This part of the dataset also includes measurements obtained with a *second* ISAC transceiver, located 1.8 m from the main one. This can be leveraged to explore sensing algorithms that exploit multiple points of view on the environment. Finally, DISC-B provides data collected in room B, to enable testing ISAC algorithms across different multipath environments.

3) DISC-C: Non-uniform IFS, multiple BPs, a single subject moving freely. In the third part of DISC, we provide sparse CIR measurements collected according to the traffic patterns of real Wi-Fi Access Points (APs). To collect such measurements, we exploit the configurable IFS provided by our testbed and schedule the packet transmissions using the public `pdx/vwave` dataset [14]. This contains real traffic traces captured in different environments using sub-6 GHz Wi-Fi APs. For our experiments, we select representative traces of three types of real-life environments: a computer science department, a library, and an internet cafe. In addition to the packet transmissions contained in the `pdx/vwave` traces, the sparse sequences contain additional transmissions (*injections*) following the protocol described in [9].

In DISC-C, we collect data in room A, using the same channel estimation procedure used in DISC-B, i.e., transmitting 12 TRN units with different BPs for AoA estimation. A single subject is present in each CIR sequence, performing the same 4 activities of DISC-A.

Note that, in the dataset collection, each subject was asked to perform one of the pre-defined activities given above. However, each subject performs the activity in a unique way, introducing subject-specific diversity. For all the three parts of DISC, we provide (i) the raw CIR measurements as multi-dimensional arrays in MAT-file format (`.mat`) and (ii) pre-computed μD spectrograms that can be readily used to develop ML-based HAR or person identification algorithms.

IV. Envisioned use cases

We identify and discuss five main possible use cases for the dataset.

1) People tracking: Estimating the position of people across time serves as an enabler for a vast number of applications including people flow control, remote healthcare, and intrusion detection, among others. In ISAC, people cause scattering components that are detected as energy peaks in the channel response and can be used to localize and track people across time. People tracking is particularly challenging in multitarget scenarios, where multiple people are concurrently moving in the same indoor space. This is especially true for mmWave signals, which are easily blocked by the human body and are thus prone to mutual occlusion among the subjects. DISC-B contains CIR sequences collected in such challenging multitarget situations, with up to 5 subjects.

Moreover, under sparse traffic patterns, people tracking algorithms deserve additional attention as not having regularly sampled measurements can degrade the tracking accuracy. Standard methods based on the Extended Kalman Filter (EKF) applied to the range-angle position measurements may need to be adapted [11]. DISC-C allows designing and validating new people tracking methods based on ML and traditional signal processing.

2) μD reconstruction: Human movement causes a complex superposition of multiple Doppler shifts on the received signal, caused by the different body parts, i.e., a μD effect. Such μD can be extracted from a sequence of uniformly spaced CIR estimates, as shown in [11], by applying STFT. The resulting spectrogram serves as a feature of human movement that can be used for downstream tasks such as HAR and person identification.

In the more realistic case where the CIR estimates are not uniformly spaced, standard STFT would yield a corrupted μD spectrogram. Therefore, more advanced μD extraction should be applied, see for example the one in [9], based on Compressed Sensing (CS). For further details on μD signatures, including how to extract them from uniformly sampled and sparse measurements, we refer to [9, 11].

Using DISC-C, which contains CIR measurements collected with real IFS from Wi-Fi traffic, one can develop and test novel sparse reconstruction algorithms to extract μD signatures of the subjects' movement. As a benchmark solution, we refer to [9]. This is an important research direction to enable ISAC in realistic scenarios where the inter-packet duration is dictated by communication rather then by the sensing performance.

3) Activity recognition in ISAC: Our dataset provides the opportunity to validate HAR ML algorithms on the CIR data. A ML classifier can be trained to distinguish between different activities performed by the subjects, based on suitable features extracted from the CIR such as the μD signatures of the movement. A common signal feature that is used for HAR is the μD spectrogram, which can be computed as detailed in point 2).

4) Gait-based identification in ISAC: By selecting the measurements containing the walking activity from the 7 subjects in DISC-A, one can train and validate classifiers to perform subject identification based on their gait. A typical way is to extract the μD signature of the gait for each person and train a classifier to learn subject-specific patterns that reveal their identity. This is a challenging task that requires fine-grained feature extraction capabilities and is typically performed with DL methods. Ours is the first dataset to enable such task with IEEE 802.11ay CIR sequences, which makes it substantially different from existing mmWave radar datasets.

5) Domain adaptation to sparse data: A more challenging task entails training the classifiers on the uniformly sampled data, and then testing it on the sparse CIR measurements. This requires a higher generalization capability as the reconstructed μD signatures from sparse data have a lower (and varying) resolution. Domain adaptation techniques could be applied to solve this problem.

In the next section, we provide benchmark results for use cases 1), 2), 3), and 5), since they represent the most widely studied ISAC applications.

V. Example results

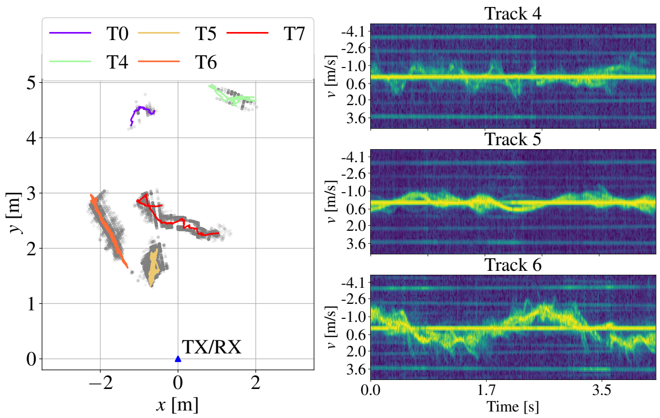
This section presents benchmark algorithms and example results based on DISC. We release their code implementation on GitLab, the link is provided at [6].

A. People tracking

From the raw IQ samples available in the dataset, it is possible to perform localization and tracking of people in the environment. This is achieved by using the CIR estimates collected over time, which must be processed in three steps explained in [11]: *(i)* subtraction of the background channel response caused by static objects, *(ii)* estimation of the targets' distances and angles with respect to the ISAC device, and *(iii)* using a tracking algorithm (e.g., a Kalman filter) to estimate each person's movement trajectory across time. The

Table I: Benchmarks for ML models.

Dataset	Activity	F1-score
DISC-A	Walking	0.996
	Running	0.974
	Sitting/standing	0.947
	Waving hands	0.928
DISC-B	Walking	0.993
	Running	0.976
	Waving hands	0.894
	Sitting/standing	0.961
	Standing still	0.926
DISC-C	Walking	0.765
	Running	0.742
	Sitting/standing	0.773
	Waving hands	0.021



(a) Trajectories of 5 subjects from DISC-B. Each subject performs an activity among the 5 present in the dataset. Grey dots represent measurements associated with tracks.

(b) μD spectrograms corresponding to T4, T5, ad T6, corresponding to activities *waving hands*, *sitting/standing*, and *running*. Each activity presents a unique pattern.

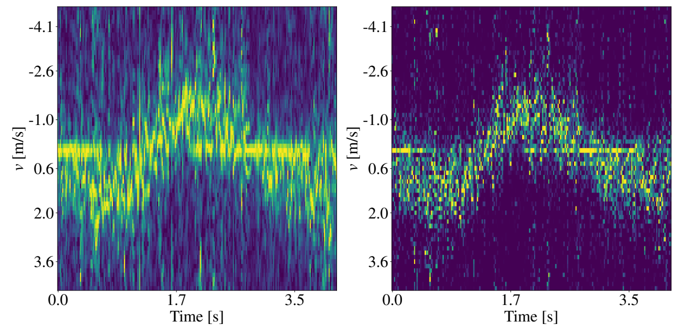
Figure 3: Example tracks obtained from a CIR sequence in DISC-B (a) and the corresponding μD spectrograms (b).

localization step (ii) is carried out using the magnitude peaks of the CIR estimates, which correspond to *observations* of the positions of the subjects in the surroundings. In step (iii), in our results we employ an EKF to track the physical position of each individual in the Cartesian space from the localization measurements. A constant velocity model is used to approximate the movement of the subject. The association between the observations from subsequent timesteps is done using the Nearest-Neighbors Joint Probabilistic Data Association algorithm (NN-JPDA) [15].

The results of this process are shown in Fig. 3a, in which 5 subjects are tracked obtaining 5 tracks (denoted by Tx where x is an identifier of the track) from an example CIR trace from DISC-B. Each subject is performing an activity: T0 *sitting/standing*, T4 *waving hands*, T5 *sitting/standing*, T6 *running*, and T7 *walking*. In the next section, we show that DISC allows extracting μD sequences from each track to recognize the activities performed by the subjects.

B. μD extraction

To provide a benchmark algorithm to extract μD spectrograms of human movement, we apply STFT to the CIR



(a)

(b)

Figure 4: μD spectrogram of a walking subject from irregular CIR measurements from DISC-C: (a) using STFT and (b) IHT [9].

sequences, as described in Section II-A, after localizing the target and extracting the CIR part corresponding to the target's location. For the STFT we use a Hamming window of $W = 64$ samples and normalize the resulting μD spectrogram column-wise in $[0, 1]$, using $\min - \max$ normalization. Thanks to the μD signatures, in Fig. 3b it is possible to differentiate between the different activities performed by each subject. We report the activities corresponding to T4-6, throughout 4 s. The resulting μD pattern is typical of each activity. As an example, for *running* (T6) it shows the strong contribution of the torso and the fainter one of the moving limbs.

As part of DISC-C, we also release μD spectrograms obtained from non-uniformly sampled CIR sequences, using the Iterative Hard Thresholding (IHT) algorithm as detailed in [9], and the corresponding code implementation. We report an example of spectrograms reconstructed with IHT in Fig. 4, in comparison with those obtained using standard STFT on irregularly sampled CIR data.

C. Human activity recognition

Different activities performed by subjects cause different, time-varying patterns in the Doppler shift of the received signal. These are contained in the phase of the CIR data, and are, in turn, reflected in the μD signatures. Therefore, it is possible to train DL models for multi-class classification problems that receive as input the μD signature and output the most likely activity performed by the subject. In the following, we present: 1) a basic benchmark to demonstrate the feasibility of μD-based activity recognition from the DISC dataset, and 2) a more advanced task in which the classifier is trained on uniformly sampled CIR data and tested on irregular and sparse communication traffic.

1) Basic classification benchmark: To provide a benchmark DL classifier, we developed a basic Convolutional Neural Network (CNN) model, composed of (i) six convolutional layers for feature extraction, with 3×3 kernel size, a stride of 2, and $8, 16, 32, 64, 128, 128$ feature maps, and (ii) a classifier with two fully connected layers with 64 and C neurons, respectively, where C is the number of activities in the HAR task. Dropout with probability 0.2 is applied before each fully connected layer during training.

We trained the model for 10 epochs on the μD signatures from DISC-A and DISC-B (see Section III) independently. In

Tab. I, we show the classification *F1 score*, defined as the harmonic mean of precision and recall, on the test set. In DISC-A, we include CIR sequences from subjects 1 to 5 in the training set, while subjects 6 and 7 are used for the validation and test sets, respectively. This is intended to demonstrate the possibility of generalizing to unseen subjects, thus testing the generalization capabilities of the DL classifier. In DISC-B, the validation and test sets are a randomly selected 10% fraction of the total dataset each.

Our results demonstrate the feasibility of performing HAR with radar-like accuracy using standard-compliant SC IEEE 802.11ay waveforms.From Tab. I, one can see that the most challenging activity to recognize in both datasets is *waving hands*. Indeed, this activity only involves the movement of arms, which do not cause strong scattering of the radio signal and are hence difficult to detect.

2) Generalization to sparse and irregular CIR data: The temporal irregularity and sparsity of CIR measurements obtained from normal communication traffic degrade the quality of the resulting μD spectrograms. Moreover, collecting data containing diverse temporal CIR estimation patterns is challenging and time-consuming. However, classifiers trained on CIR data collected at regular sampling times may not generalize well to irregular patterns, due to the reduced μD quality. To show this phenomenon, we train a CNN classifier like the one used in the previous section on DISC-B. Then, we test it on data contained in DISC-C, evaluating the generality of the learned features.

The results are shown in Tab. I. The sparsity of the data degrades the performance of the model in three of the activities (*walking*, *running*, and *sitting/standing*), which are however still recognizable with over 0.7 F1-score. For the last activity (*waving hands*), the model does not generalize enough to the new data. This activity is more challenging than the other three since it involves movements of the hands that cause weak signal scattering. This shows the importance of addressing the problem of *domain shift* and generalization in DL-based ISAC.

VI. Limitations and future work

While DISC serves as a valuable benchmark dataset for ISAC research, certain limitations present opportunities for further extensions and improvement.

Dataset size. DISC contains a sufficient amount of data to train and validate DL models for ISAC. However, compared to existing DL datasets in other fields (e.g., computer vision), its size is fairly limited in terms of total measurement time, which may limit the applicability of extremely large DL architectures.

Occlusion and interference. Although DISC captures two distinct indoor environments, five different activities, and up to five subjects moving simultaneously, acquiring data in more diverse settings, including the presence of obstacles in future work would enhance the value of the dataset.

Bistatic and multistatic CIR. As research moves towards *cooperative* ISAC networks, it is key to collect datasets including bistatic and multistatic CIR data, with multiple distributed ISAC TX and RX nodes. This is a critical aspect to be investigated by future work and ISAC datasets.

Irregular temporal patterns generalization. While DISC-C includes realistic Wi-Fi traffic patterns, its irregular and sparse nature introduces difficulties in μD extraction and classification, requiring adaptive signal processing techniques and domain adaptation strategies for DL architectures. Future research should focus on developing and evaluating algorithms that generalize across different inter-packet durations while maintaining robust sensing performance.

VII. Conclusion

In this paper, we presented DISC, the first ISAC dataset containing CIR sequences obtained using 60 GHz, standard-compliant, IEEE 802.11ay waveforms that contain backscattered signals on people moving in the environment. The provided CIR measurements include 7 subjects performing 5 different activities in 2 environments, and they are collected according to both uniform and real Wi-Fi traffic patterns, thus enabling the validation of a variety of ML and signal processing algorithms for ISAC. We presented benchmark algorithms for people tracking, μD extraction, and activity recognition under diverse channel estimation patterns, and made them available to foster further ISAC research.

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