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# Datasets for Human Activity Recognition with Integrated Sensing and Communications in Wi-Fi

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## Abstract

Wi-Fi sensing has gained significant attention for its non-intrusive nature and the widespread availability of Wi-Fi-enabled devices that can be leveraged for sensing. Given the complexity of wireless propagation, sensing applications are increasingly relying on machine learning tools, which allow effectively extracting meaningful features from the radio measurements. However, developing robust, domain-adaptive algorithms that perform well across diverse environments remains challenging, requiring extensive datasets with rich diversity in terms of environments, subjects, and configurations. In this view, here we present and release two comprehensive datasets for human activity recognition (HAR) through Wi-Fi consisting of the channel state information (CSI) and beamforming feedback information (BFI) collected through commercial IEEE 802.11ac devices in both line of sight (LoS) and non-line of sight (NLoS) scenarios in different days. The first dataset entails traces related to 20 activities with six subjects across six different setups. The second dataset focuses on simultaneous multi-subject activity classification, with three individuals performing distinct activities concurrently. Our datasets are the first that also provide corresponding BFI measurements — a newly investigated and appealing primitive for Wi-Fi sensing given its ease of collection procedure. Overall, the datasets contain about 240 GB of CSI data and 230 GB for BFI.

## Introduction

With the pervasive adoption of Wi-Fi, Wi-Fi-based HAR has emerged as a transformative, non-intrusive method for interpreting human movements [1]. The intuition behind Wi-Fi sensing is that humans act as obstacles to the propagation of radio signals in the environment. Specifically, when encountering the human body, the radio waves undergo reflections, diffractions, and scattering that make the signals collected at the Wi-Fi receiver differ from the transmitted ones. Wi-Fi sensing aims at detecting the changes in the Wi-Fi signals and associating them to the way the subject stays/moves in the environment, thus realizing device-free monitoring solutions. This passive sensing approach enables a wide range of practical applications. In smart homes and assisted living environments, Wi-Fi-based HAR can support fall detection, remote health monitoring, and early identification of abnormal behavior. In intelligent buildings and workplaces, it can enable occupancy analytics and activity-aware automation to improve energy efficiency and comfort. In security-sensitive settings, it can assist in intrusion detection without requiring cameras or wearable devices. Reliable HAR is therefore essential to enable timely intervention, automation, and personalized services while preserving user privacy. Unlike conventional HAR systems, Wi-Fi-based HAR requires no specialized wearable devices, making it a highly attractive, scalable solution for real-world deployment. Recent advances in machine learning have propelled Wi-Fi-based HAR to new levels, enabling the detection and classification of increasingly complex human activities. However, the development of robust, domain-adaptive algorithms that perform well across diverse environments remains a critical challenge to leverage Wi-Fi-based HAR's full potential.

Addressing this challenge necessitates the availability of large, diverse datasets that reflect a rich variety of real-world conditions, including variations in environment, subject, spatial configurations, and other contextual factors. Without such datasets, it becomes exceedingly difficult to train models that generalize effectively without overfitting specific and narrow conditions. The need for high-granular, diverse data has become even more pressing as Wi-Fi-based HAR moves closer to practical deployment in smart-home scenarios, also thanks to the IEEE 802.11bf standardization efforts.

However, most publicly available datasets for Wi-Fi-based HAR consists of channel frequency response (CFR) traces collected through the legacy IEEE 802.11n standard, over limited bandwidths of 20 or 40 MHz [2–5]. These datasets typically cover only a few simple activities, restricting their applicability to developing models capable of handling complex scenarios or adapting to diverse environments. Moreover, relying on CFR data presents some challenges, as CFR extraction from commercial devices requires firmware modifications, creating accessibility issues that hinder real-world applicability.

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Recently, beamforming feedback information (BFI) has been increasingly investigated as a surrogate for the CFR to perform sensing [1]. BFI is the compressed channel feedback that Wi-Fi stations (STAs) transmit to the access point (AP) during standard IEEE 802.11ac/ax beamforming procedures to enable multiple-input multiple-output (MIMO) transmissions. This information is transmitted without encryption and, in turn, is easily decodable once collected through traditional network analyzer tools that do not require firmware modifications. Additionally, as illustrated in Fig. 1, CSI traces must be extracted locally at each sensing device through firmware modifications, whereas BFI is naturally broadcast as part of the channel sounding process. Finally, since BFI reports from multiple STAs are transmitted over the air, they can be recorded simultaneously with a single monitoring device. These characteristics make BFI a practical and scalable sensing primitive for real-world Wi-Fi deployments.

Researchers are increasingly interested in exploring the tradeoffs between CSI- and BFI-based approaches, as each sensing primitive has unique strengths and limitations that can significantly impact performance. Despite its potential, no existing datasets include BFI for HAR, thereby limiting the possibility of investigating these trade-offs.

To address this critical gap, we introduce two comprehensive datasets[1] featuring concurrently captured CSI and BFI data. The datasets are collected from IEEE 802.11ac networks operating with 80 MHz channels. Specifically curated for multi-environment and multi-orientation HAR tasks, the datasets capture a diverse set of activities, concurrent multi-subject scenarios, and a wide range of environmental conditions, addressing the need for diverse data that facilitates the development of adaptive and accurate Wi-Fi-based HAR. Parts of these datasets correspond to the data collection campaigns used in our prior studies [1, 6], where they were employed to evaluate sensing algorithms. In this article, we combine these data collection efforts and provide their complete documentation and public release as a reusable resource for the community.

**Summary of the Datasets Features.** The datasets contain about 240 GB of CSI data and 230 GB of BFI data, divided as follows.

**Dataset 1:** This dataset captures BFI and CSI data concurrently for 20 different human activities performed by 6 individuals in three distinct environments — office, classroom, and kitchen — over 6 days, including three different device orientations in the kitchen. Three stations were used in each environment. The ground truth is acquired through synchronous video capture from a fixed camera. Data was collected under both LoS and NLoS conditions.

**Dataset 2:** Expanding on Dataset 1, this dataset introduces simultaneous multi-subject scenarios, where three individuals perform different activities concurrently. Data is collected in three different environments over 6 days, including three different subject orientations in each of the environments. Since multiple subjects act simultaneously in each recording, Dataset 2 focuses on activity recognition under concurrent motion rather than increasing the number of distinct participants. Data collection entails three Wi-Fi stations and synchronous video capture from a fixed location for ground truth. This dataset enables research on simultaneous multi-subject HAR using CSI and BFI in diverse and complex environments.

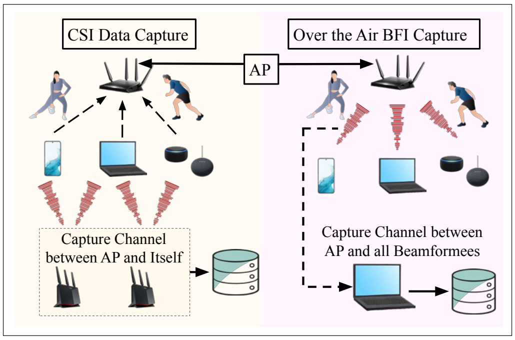


FIGURE 1. Overview of CSI (left) and BFI (right) data capture. CSI traces are extracted from devices' memory using modified firmware, while BFI traces are captured over the air from commercial devices through traditional network analyzer tools.

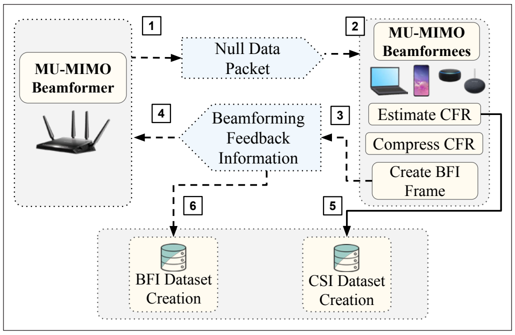


FIGURE 2. CSI estimation and BFI frame generation during MIMO channel sounding (Steps 1-4). CSI datasets are obtained by accessing the internal device memory and extracting the estimated channel (Step 5). BFI datasets are obtained by capturing the BFI traces transmitted over the air (Step 6).

## Background and Related Work

Both CSI and BFI based sensing systems leverage the channel estimation mechanism defined in the IEEE 802.11ac/ax standards [7] to sound the physical environment, as illustrated in Fig. 2. During this process, Wi-Fi stations estimate the channel in response to sounding packets broadcast by the AP. CSI-based systems directly use the resulting uncompressed CFR, whereas BFI based systems rely on a compressed representation of this estimate that is fed back to the AP to enable MIMO transmissions. From a sensing perspective, these two primitives provide different levels of channel abstraction while relying on the same underlying sounding procedure. CSI provides fine-grained channel measurements across subcarriers and MIMO links, enabling detailed modeling of multipath dynamics and subtle motion patterns. However, extracting CSI from commercial devices often requires firmware modifications, which limits ease of deployment. BFI, in contrast, represents a compressed version of the channel response that is regularly transmitted over-the-air as part of standard beamforming feedback procedures. This makes BFI easier to capture in practice without modifying any device, although the compression leads to a less fine-grained channel representation compared to raw CSI. Importantly, although BFI is compressed, the feedback parameters capture the dominant spatial structure

CSI-based systems directly use the resulting uncompressed CFR, whereas BFI based systems rely on a compressed representation of this estimate that is fed back to the AP to enable MIMO transmissions.

[1] The datasets are publicly available at: https://ieee-dataport.org/documents/csi-bfi-har-wi-fi-datasets-human-activity-recognition


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CSI-based systems directly use the resulting uncompressed CFR, whereas BFI based systems rely on a compressed representation of this estimate that is fed back to the AP to enable MIMO transmissions.

of the MIMO channel that governs beamforming. Human motion perturbs multipath propagation by modifying the amplitudes, phases, and spatial correlation of propagation components over time. These variations influence the channel's dominant spatial directions, which are reflected in the temporal evolution of the quantized beamforming angles across the subcarriers. As a result, BFI-based sensing retains activity-discriminative spatial and temporal dynamics, making it physically meaningful in addition to being practical. Nevertheless, our experimental validation (Section V) shows that BFI-based HAR can achieve accuracy levels comparable to CSI-based approaches in the considered environments, despite relying on more compact channel representation. By jointly providing both CSI and BFI traces, our datasets enable systematic exploration of the tradeoff between measurement detail and deployment practicality.

Specifically, in a multi-user multiple input multiple output (MU-MIMO) system, the beamformer (AP) triggers the channel estimation procedure at the beamformees (STAs) by periodically transmitting an null data packet (NDP), i.e., a frame that does not contain any user payload data and is used exclusively for channel estimation (see **Step 1** in Fig. 2). This estimation process, commonly referred to as *channel sounding* which allows the receiver to measure how the wireless channel modifies the transmitted signal. Each NDP contains predefined long training fields (LTFs), i.e., orthogonal frequency-division multiplexing (OFDM) symbols specified in the IEEE 802.11 standard [6]. Hence, these symbols are known a priori to the Wi-Fi beamformees and are used to estimate the wireless channel response. Since its purpose is to sound the channel, the NDP *is not beamformed* by the AP. This is particularly advantageous for sensing purposes since the resulting CSI estimation is not affected by inter-stream or inter-user interference. The LTFs are transmitted over the different beamformer antennas in subsequent time slots, thus allowing each beamformee to estimate the CSI of the links between its receiving antennas and the beamformer transmitting antennas. The NDP is received and decoded by each STA (**step 2** in Fig. 2) to estimate the channel over each pair of transmitting (TX) and receiving (RX) antennas, for every OFDM subcarrier. This produces a per-subcarrier MIMO channel estimate for each transmit–receive antenna pair that is referred to as CSI or CFR. The estimated CFR can be extracted from the device's memory through different tools like Atheros CSI tool, Linux 802.11n CSI tool, Nexmon-CSI, and AX-CSI [8].

Before feeding back the estimated CSI to the AP, each beamformee applies the IEEE 802.11 beamforming feedback compression procedure to reduce the overhead of channel reporting. This entails decomposing the channel matrix using singular value decomposition (SVD) and representing the resulting right unitary matrix through a sequence of Givens rotations (see [9], Chapter 13). The corresponding parameters are expressed as beamforming angles and identified by the $\phi$ and $\psi$ symbols. To reduce channel occupancy, these angles are quantized using a standard-defined number of bits and included in the compressed BFI frame. The frame is then transmitted to the AP, which reconstructs the corresponding right unitary matrix for precoding. Since MU-MIMO requires fine-grained channel sounding — every around 10 milliseconds to account for user mobility, it is fundamental to process the BFI in a fast manner at the AP. For this reason, and since cryptography would lead to excessive delays, the angles are currently sent unencrypted. Therefore, the BFI reports are exposed to and can be recorded by any device that can access the wireless channel.

## Existing HAR Datasets

Several datasets collected using IEEE 802.11n compliant devices operating with 20 or 40 MHz bandwidths have provided an essential foundation for HAR research. For example, the *WiAR* dataset [3] includes 16 activities across three indoor environments with 10 different subjects. The dataset provides both Wi-Fi Received Signal Strength Indicator (RSSI) and CSI data over a 20 MHz bandwidth, considering a single transmitter and three receivers. Similarly, the *Widar3* dataset [4] supports gesture recognition, providing data for 15 gestures across three environments with 16 subjects, relying on 20 MHz bandwidth data captured through IEEE 802.11n devices. The *Human AR* dataset [10], collected at 40 MHz, expands on this dataset by covering 6 activities in three environments, capturing CSI data estimated by IEEE 802.11n devices. However, this dataset still lacks the environmental and subject variability necessary for developing adaptive HAR algorithms. The *ReWiS* dataset [11] marks an improvement with the collection of 80 MHz channel data in three environments through IEEE 802.11ac devices in a multi-antenna setup. Although ReWiS offers higher resolution CSI data, it remains limited to four activities and two subjects, which restricts its applicability.

Further advancements in environmental and hardware diversity can be seen in more recent datasets. For example, the dataset by Meneghello *et al.* [14] offers enhanced domain diversity by using IEEE 802.11ac devices to collect CSI data across seven environments, including LoS and NLoS scenarios with obstructions, providing data from 13 volunteers for seven different activities. Similarly, the *WiMANS* dataset [12] captures multi-user activity in various environments and includes synchronized video, offering a robust foundation for multi-user identification, localization, and activity recognition applications across nine activities and three environments. However, this work is based on 20 MHz channel data and, in turn, reaches a limited granularity in CSI data.

Importantly, none of the available datasets provide BFI data, which has been a recent primitive of interest for different Wi-Fi sensing tasks including HAR. Addressing these limitations, the datasets introduced in this paper provides an unprecedented level of diversity across environments, participants, and activities with corresponding CSI and BFI data from IEEE 802.11ac devices operating with 80 MHz bandwidth. We provide two comprehensive datasets: **Dataset 1** entails both CSI and BFI data while 20 different activities were performed by six subjects across six environments and device orientations, collected over multiple days in both LoS and NLoS scenarios, with three spatially diverse sensing devices; **Dataset 2** expands on this by including simultaneous multi-subject scenarios, with three individuals


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| Dataset | Days per env. | Envs | People | Concurr. subject | Activities | Primitive | Sensing devices | Video Ground Truth | Standard | BW (MHz) |
|---|---|---|---|---|---|---|---|---|---|---|
| AR [2] | 1 | 1 | 6 | 1 | 6 | CSI | 1 | No | 802.11n | 20 |
| WiAR [3] | 1 | 3 | 10 | 1 | 16 | RSSI, CSI | 3 | No | 802.11n | 20 |
| Widar3 [4] | 1 | 3 | 16 | 1 | 15 | CSI | 1 | No | 802.11n | 20 |
| Human AR [10] | 1 | 3 | 1 | 1 | 6 | CSI | 1 | No | 802.11n | 40 |
| ReWiS [11] | 1 | 3 | 2 | 1 | 4 | CSI | 1 | No | 802.11ac | 80 |
| EfficientFi [5] | 1 | 1 | 20 | 1 | 6 | CSI | 1 | No | 802.11n | 40 |
| WiMANS [12] | 1 | 3 | 6 | Up to 5 | 9 | CSI | 1 | Yes | 802.11n | 20 |
| WiSense [13] | 1 | 2 | 10 | 1 | 6 | CSI | 1 | No | 802.11n | 20 |
| CSI dataset [14] | 1-5 | 7 | 13 | 1-10 | 7 | CSI | 3 | No | 802.11ac | 80 |
| **Our Dataset 1** | 6 | 6 | 6 | 1 | 20 | CSI, BFI | 3 | Yes | 802.11ac | 80 |
| **Our Dataset 2** | 3 | 9 | 3 | 3 | 20 | CSI, BFI | 3 | Yes | 802.11ac | 80 |

TABLE 1. Comparative summary of existing public Wi-Fi HAR datasets. For each dataset, the following characteristics are summarized: no. days of collection in each environment ("env."), no. different environments and no. people considered, no. subject simultaneously moving in the environment ("concurr."), no. activities, sensing primitive(s), no. concurrent sensing devices, Wi-Fi standard, and bandwidth ("BW").

performing different activities simultaneously in 9 different environments and device orientations.

We provide a comparative summary of the existing public Wi-Fi HAR datasets in Table 1. The table highlights the unique features of our datasets, including broader domain diversity, enhanced activity, and participant variability. Moreover, a unique feature of our datasets is the concurrent collection of CSI and BFI data. Unlike previous datasets that rely solely on CSI, BFI offers a more practical approach to Wi-Fi sensing that does not require firmware modifications, making it suitable for real-world deployments. Thus, our datasets allow researchers to evaluate the relative strengths of CSI and BFI based approach, contributing to a more comprehensive understanding of Wi-Fi-based HAR and enabling practical applications that seamlessly integrate with existing Wi-Fi infrastructures.

## Experimental Setup and Data Collection Campaigns

The three data collection environments are depicted in Fig. 3, where we highlight their spatial layouts and furniture configurations. In the kitchen scenario, we consider multiple device orientations to examine the impact of spatial diversity. We will indicate with "Orientation 1" the initial placement, while "Orientation 2" and "Orientation 3" are obtained by moving all sensing device by respectively 20° and 40° clockwise with respect to the center of the subject moving area. This corresponds to a relocation of approximately 2 and 4 meters with respect to the initial position. These variations introduce controlled spatial and environmental diversity, which is essential for assessing the generalization capability of activity recognition models.

**CSI Network Setup and Equipment.** We set up an 802.11ac MU-MIMO network operating on channel 42 with center frequency $fc$ = 5.21 GHz and 80 MHz bandwidth. This allows sounding $K$ = 234 subcarriers, i.e., 256 available subcarriers on 80 MHz channels minus 14 control subcarriers and 8 pilots. The 802.11ac AP (referred to as *CSI AP*) serves three STAs (referred to as *CSI monitors*) as depicted in Fig. 3 in green. The AP is implemented with a Netgear Nighthawk X4S AC2600 router. For the CSI extraction, three IEEE 802.11ac-compliant Asus RT-AC86U routers (referred to as *CSI monitors*) equipped with the Nexmon CSI extraction tool ([15]) have been deployed. To have a 3 × 3 MU-MIMO network, the CSI AP is enabled with $M$ = 3 antennas whereas the CSI monitors are set up to sense the channel through $N$ = 1 antenna over $N_{ss}$ = 1 spatial stream each.

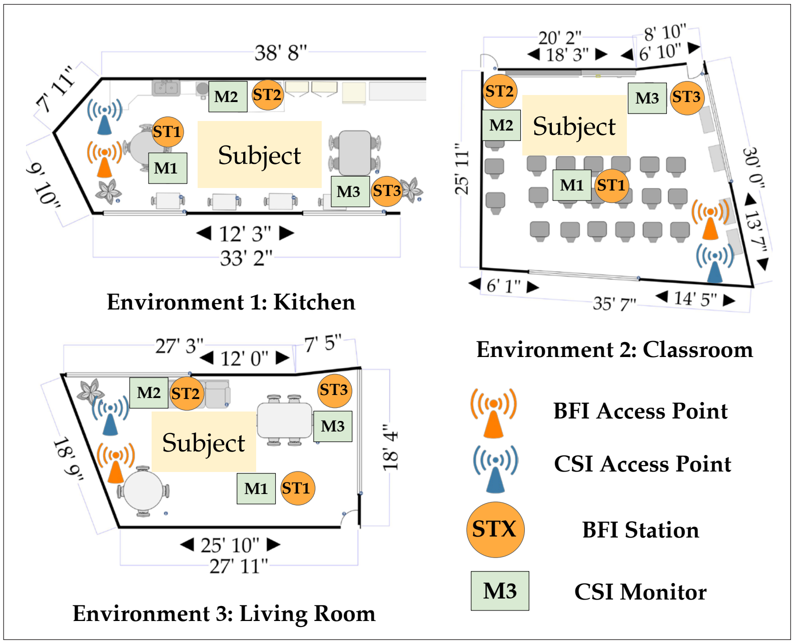


FIGURE 3. Experimental setups for CSI and BFI data collection campaigns. The yellow area is where the subject moves. Three different device orientations have been considered in the kitchen scenario.

**BFI Network Setup and Equipment.** ~BFI data has been collected simultaneously with the CSI frame capture. For this purpose, we set up a Wi-Fi network consisting of one AP (beamformer) and three STAs (beamformees) co-located with the CSI collecting network in the same environments, as depicted in Fig. 3 in orange. The AP and the STAs are implemented through Netgear Nighthawk X4S AC2600 routers with $M$ = 3 and $N$ = 1 antennas enabled respectively for the AP and each of the STAs to have the same setup as CSI network. The three STAs are served with $N_{ss}$ = 1 spatial stream each to form a 3 × 3 MU-MIMO system. According to the IEEE 802.11ac standard [7], four beamforming feedback angles (two $\phi$ and two $\psi$) are needed to represent each of the 3 × 1 channels between the AP and the STAs. In our setup, the angle quantization process uses $b_\phi$ = 9 bits and $b\psi$ = 7 bits for the feedback angles $\phi$ and $\psi$ respectively.


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| Set | Env. | Dev. | LoS/NLoS | Concur. subject | Subject |
|---|---|---|---|---|---|
| **HAR-1** | Kitchen, Orient. 1-3 | M1, M2 | LOS | X | P1 – P6 |
| **HAR-2** | Kitchen, Orient. 1-3 | M3 | NLOS | X | P1 – P6 |
| **HAR-3** | Classroom | M1, M2 | LOS | X | P1 – P6 |
| **HAR-4** | Classroom | M3 | NLOS | X | P1 – P6 |
| **HAR-5** | Living room | M1, M2 | LOS | X | P1 – P6 |
| **HAR-6** | Living room | M3 | NLOS | X | P1 – P6 |
| **HAR-7** | Kitchen Orient. 1-3 | M1, M2 | LOS | 3 | P1 – P3 |
| **HAR-8** | Kitchen Orient. 1-3 | M3 | NLOS | 3 | P1 – P3 |
| **HAR-9** | Classroom Orient. 1-3 | M1, M2 | LOS | 3 | P1 – P3 |
| **HAR-10** | Classroom Orient. 1-3 | M3 | NLOS | 3 | P1 – P3 |
| **HAR-11** | Living room Orient. 1-3 | M1, M2 | LOS | 3 | P1 – P3 |
| **HAR-12** | Living room Orient. 1-3 | M3 | NLOS | 3 | P1 – P3 |

TABLE 2. Organization of the two HAR datasets.

**Data Collection Campaigns.** For both the datasets, we collect the CSI and BFI data simultaneously with different subjects performing 20 different activities, namely, *jogging, clapping, push forward, boxing, writing, brushing teeth, rotating, standing, eating, reading a book, waving, walking, browsing phone, drinking, hands-up-down, phone call, side bends, check the wrist (watch), washing hands, and browsing laptop*. The activities have been chosen to represent a broad range of human motions, including both stationary and dynamic actions, to test the system's ability to differentiate between subtle and vigorous movements. We collect both the CSI and corresponding BFI data for 300 seconds for each of the subjects performing each of the above-mentioned activities within the colored zone of each of the environments as presented in Fig. 3. In **Dataset 1**, activities are performed by a single subject at a time and six subjects were involved in total, whereas in **Dataset 2**, three subjects perform the activities simultaneously.

Each CSI trace is stored as a time-ordered complex matrix, where each row corresponds to one CSI sample and the columns represent the monitored OFDM subcarriers (242 in our setup) across the available antenna links. Similarly, each BFI trace is organized as a time-ordered structure indexed by packet time and subcarrier, with four beamforming feedback angles per subcarrier in our 3 × 3 MU-MIMO configuration. The number of CSI and BFI samples depends on the capture duration and the sounding rate. In our experiments, CSI is sampled at approximately 150 Hz, while BFI reports are collected at approximately 10 Hz.

To establish a ground truth, synchronized video streams of subjects performing each activity were recorded from a fixed location covering the entire activity area. The cameras were positioned to ensure full visibility of movements with minimal occlusion, capturing the subject's entire body. The video streams were timestamped to precisely align with BFI and CSI data frames, enabling accurate labeling of each activity. Both video and Wi-Fi captures (CSI and BFI) are initiated via a single execution script on the same host machine, ensuring a shared system clock. Timestamps are generated with millisecond-level resolution, and the execution delay between processes remains within a few milliseconds.

## Datasets Organization

We structure the datasets into 12 folders, as summarized in Table 2. Folders labeled with `HAR-1` to `HAR-6` correspond to **Dataset 1** and are associated with HAR for a single subject present in the environment. Folders `HAR-7` to `HAR-12` constitute **Dataset 2** and contain data collected when multiple concurrent subjects are present in the environment. Each folder contains both CSI and BFI data, organized to capture the specific environment, device orientation, and LoS/NLoS configuration for subjects performing the different activities. To facilitate structured data access, each folder is organized into two sub-folders, labeled "csi" and "bfi," which separately store the CSI and BFI traces. For example, the folder `HAR-1` includes CSI and BFI data collected from sensing devices M1 and M2 in LoS conditions with the AP in the kitchen environment, recorded across three orientations (1, 2, and 3) of the devices. In this setup, a single concurrent subject performed all 20 different activities in each of the orientations.

Each trace filename follows the format `X_D_YY_ZZ`, where each component encodes specific details about the recorded activity, collection day, sensing device, and subject identity. The single-letter code `X` indicates the type of activity: jogging (A), clapping (B), push forward (C), boxing (D), writing (E), brushing teeth (F), rotating (G), standing (H), eating (I), reading (J), waving (K), walking (L), browsing phone (M), drinking (N), hands-up-down (O), phone call (P), side bends (Q), wrist movement (R), washing hands (S), and browsing laptop (T). The day of data collection is indicated by the numerical value `D` ∈ {1, ..., 6}. The component `YY` specifies the sensing device, with M1, M2, and M3 denoting devices for CSI traces, and S1, S2, and S3 representing devices for BFI traces. Finally, `ZZ` identifies the subject, with identifiers ranging from P1 to P6. To facilitate the use of the dataset, we provide a public GitHub repository[2] accompanying the dataset release detailing the dataset structure and data extraction process, and scripts. The repository documents the complete directory structure, file naming conventions, data formats, and includes representative example files and parsing scripts for both CSI and BFI traces. This allows researchers to inspect and test the data structure prior to downloading the full dataset from IEEE DataPort.

## Experimental Validation with a Learning Algorithm

To assess the relevance of our datasets in training and validating HAR algorithms, we consider the CNN-based approach for effective activity classification in [1]. The network consists of three convolutional blocks followed by a max-pooling layer. The output of the max-pooling layer is flattened, and the Softmax activation function is applied to generate a probability distribution over activity labels. Each convolutional block consists of two 2D convolutional layers, enhanced with batch normalization to stabilize training and ReLU activation to introduce non-linearity while mitigating gradient explosion or vanishing issues.

[2] https://github.com/Restuccia-Group/CSI-BFI-HAR


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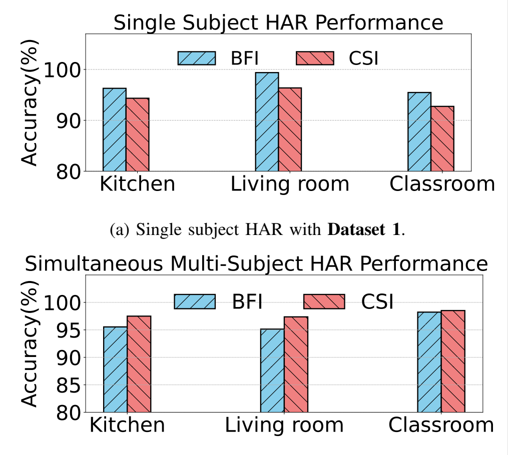
Figure 4a illustrates the performance of single-subject HAR using both CSI and BFI in **Dataset 1**. Across all environments, CSI- and BFI-based approaches achieve average accuracies of 94.48% and 97.04%, respectively, indicating clear activity separability within the proposed dataset. In the more challenging simultaneous multi-subject scenario shown in Fig. 4b, performance remains consistently high. On average, CSI achieves 97.79% accuracy and BFI reaches 96.30% across environments, confirming the robustness of the dataset even under increased spatial interaction and motion complexity.

We note that BFI slightly outperforms CSI in the single-subject case, while the opposite trend is observed in the simultaneous multi-subject scenario. This behavior follows from the different levels of granularity provided by the two sensing primitives. BFI captures a compressed representation of the channel that is sufficient to describe motion-induced variations from a single subject. In contrast, when multiple subjects move concurrently, the higher temporal resolution of CSI provides richer channel measurements that help the learning model better distinguish overlapping motion-induced channel variations.




(a) Single subject HAR with **Dataset 1**.

(b) Simultaneous multi-subject HAR with **Dataset 2**.

FIGURE 4. Single subject and simultaneous multi-subject HAR performance with **Dataset 1** and **Dataset 2** in the three experimental environments using BFI and CSI as sensing primitives.

## Examples of Research Use Case

Our datasets provide a comprehensive resource for advancing Wi-Fi-based HAR, accommodating diverse scenarios, environments, and application needs. By including CSI and corresponding BFI data collected across multiple environments, orientations, propagation paths, and subjects, it supports the development of robust domain-adaptive algorithms capable of operating effectively in a variety of real-world settings.

Below, we outline some key use cases that illustrate the versatility of our datasets in enabling a wide range of HAR research use cases and the development of domain-adaptive and domain-independent algorithms.

**Pioneering Research on BFI based HAR.** Our datasets uniquely offer both CSI and BFI data, setting a new benchmark by including BFI — a rapidly emerging sensing primitive. Unlike CSI, which requires specialized firmware modifications to extract the information from commercial devices, BFI can be easily captured from any off-the-shelf Wi-Fi terminal, allowing researchers to explore firmware-independent HAR algorithms with minimal effort. This feature not only facilitates plug-and-play HAR application development but also enables the first comprehensive comparative analysis between CSI- and BFI-based approaches, advancing the understanding of their respective advantages and practical applicability in diverse, real-world environments.

**Domain Adaptation and Robustness Across Environments and Subjects.** The rich domain diversity in datasets is essential for developing domain-adaptive techniques that enhance model robustness across different environments and subjects. This adaptability is critical for real-world HAR applications, where environmental changes and the presence of different individuals can significantly affect performance. By including data from a wide variety of scenarios — such as the same subjects performing the activities in multiple environments and different subjects conducting similar activities under consistent conditions — researchers can develop models that generalize effectively across different settings. This level of adaptability supports plug-and-play HAR solutions that automatically adjust to new contexts and users, making them particularly valuable for applications in smart homes, healthcare, and public spaces. In such settings, models must maintain high accuracy despite variations, allowing for resilient and reliable sensing in real-world conditions.

**Adaptability Across Wi-Fi Devices.** Our datasets allow for the evaluation of HAR models trained on data from one device and used with data collected from other devices. By enabling device-agnostic sensing models, these datasets encourage research to enforce hardware independence, supporting the development of models resilient to hardware variability.

**Effect of Obstructions.** The datasets have been collected in scenarios where some sensing devices experience LoS transmission whereas others only collect NLoS signals. This allows researchers to assess the resilience of HAR systems to obstacles, which is key for applications requiring activity detection through walls or in cluttered environments.

**Impact of Device Locations.** Simultaneous data captures from multiple devices monitoring the same scene allow for an assessment of how transmitter and monitor positions affect HAR accuracy. This setup supports investigations into optimal placement configurations, enhancing HAR reliability across various layouts.

**Exploring Temporal, Frequency, and Spatial Diversity.** The datasets' breadth also supports novel research directions, such as examining the effects of temporal sampling on accuracy and identifying relevant subcarriers for specific tasks. This encourages in-depth exploration of factors that impact sensing performance, driving the development of refined, high-precision HAR models.

These use cases demonstrate the broad applicability of our datasets and their potential to support future advancements in Wi-Fi-based HAR, providing a benchmark for effective performance comparison.

Our datasets provide a comprehensive resource for advancing Wi-Fi-based HAR, accommodating diverse scenarios, environments, and application needs.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## Concluding Remarks

This article presents two comprehensive Wi-Fi-based HAR datasets, collected through IEEE 802.11ac devices operating with 80 MHz bandwidth channels. The datasets are expected to serve as benchmarks for domain-adaptive HAR models that work across diverse real-world scenarios. The first dataset provides CSI and BFI data for 20 activities performed by each of the six subjects in three different environments, including multiple orientations and LoS/NLoS conditions. The second dataset considers a multi-subject activity scenario, enabling multi-person recognition research in complex settings. Overall, we provide a total of approximately 240 GB of CSI and 230 GB of BFI data. By incorporating BFI as a rapidly emerging sensing primitive, our datasets support the development of scalable, domain-adaptive HAR algorithms and open up new research avenues for robust, firmware-independent Wi-Fi sensing applications. Being publicly available, this resource sets a strong foundation for advancing HAR adaptability across varying conditions and user contexts.

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