Dataset: Channel state information for different activities, participants and days

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ABSTRACT

In our current society, unobtrusive sensing has become an important tool to monitor the physical world, as it is easy to use and privacy-aware. Remote sensing is a new and heavily researched technology based on the analysis of radio signals. A particular field research in this area is the analysis of channel state information with the raw signal, as this contains the most information. While most research focuses on analysis of individuals or clustered data, little to no research has gone into the analysis of channel state information of multiple people over multiple days for different and comparable activities. This dataset contains data of nine different participants over three different days, with an two participants repeating the activities over an additional three days. The dataset is available at the 4TU.ResearchData under the *CC BY-NC-SA* license [4].

CCS CONCEPTS

• **Computer systems organization** → Sensor networks; • **Networks** → Wireless local area networks; • **Human-centered computing** → Ubiquitous and mobile computing.

KEYWORDS

datasets, channel state information, human activity recognition, device-free sensing, 802.11n, data stability

1 INTRODUCTION

There is an increasing demand to monitor and control the world unobtrusively. This is supported by evolving technologies; enabling smaller and smarter solutions with better performance than current solutions. These techniques are often applied to humans; be it for security, safety or health reasons. This is not exclusive to humans either, as animals and structures are continuously observed through these pervasive systems. One could think of structural or vehicle health monitoring for preventive maintenance, the tracking of animals and poachers, and the security in a city centre.

For these situations in which continuous monitoring is required, two techniques are currently superior: audiovisual technologies and wireless sensor networks. Audiovisual technologies are based on video and sound. These are accurate and interpretable by humans, yet they are considered privacy invasive. This means these technologies can often not be used due to privacy concerns. Wireless sensor networks are the more privacy-aware alternative, as it becomes harder for humans to interpret the signals. Furthermore, they are considered to be unobtrusive as they often consider of small sensors, barely causing any impairment to the user. However, they are in fact still obtrusive physically, as sensors often need to be worn on and in the body.

Remotely sensing the human body is the only way to achieve true unobtrusive sensing. In order to achieve this, current research has shifted to remote sensing [1, 2, 8, 12]: analysing how activities and/or events affect the environment. An increasingly popular technique used for remote sensing is based on channel state information. Channel state information takes advantage of the multipath effect and provides information regarding the propagation of traces from the transmitter to the receiver, measured over different subcarriers and antenna pairs.

Human activity recognition is a field often tackled by this new idea of remote sensing. Research has shown that measuring physiological signals [5, 7, 9, 10] and general activity recognition [1, 5, 6, 11] can all be achieved through channel state information. The user-friendliness of remote systems is higher, as no wearables are required. Another incentive is the sense of privacy as it is more likely people would feel more comfortable with no cameras, microphones or wearables (Hawthorne effect).

1.1 Uniqueness of the dataset

Clearly labeled datasets with proper metadata including channel state information are hard to find, as they are often not shared. The ones that are shared are often lacking documentation or metadata. Furthermore, collecting varied data from multiple participants over multiple days is often challenging due to time constraints and availability.

This dataset is unique in that data is collected from nine different participants over three days, while two participants also repeated the experiments over the course of a total of three days. It allows researchers to test their model on i) same participant (50 trials per activity), ii) different participants on the same day, iii) different participants over different days and iv) same participants over different days.

2 DATA COLLECTION

2.1 Hardware and software

A dedicated transceiver node was designed for this research, consisting mainly of a Gigabyte Brix IoT. The hardware of the Brix was modified to fit an Intel Ultimate Wi-Fi Link 5300 NIC (Figure 1). The Intel NIC was chosen in order to use the open CSI platform by D. Halperin *et al.* [3]. Effort was put into using micro-PCs, but these were not stable enough in combination with the Intel 5300. This is likely due to the Intel 5300 being heavily outdated hardware. The specifications of the final design can be found in Table 1 and the final solution can be found in Figure 1.

Table 1: Hardware specifications Gigabyte Brix IoT

Component	Specifications
Processor	Intel Apollo Lake N34500
RAM	1x HyperX 8GB DRR3L-SO DIMM 1866 MHz
Hard drive	Transcend MTS800 SSD 128 GB (M.2 2280)
Graphics card	None
Wireless adapter	Intel N Ultimate Wi-Fi Link 5300
Size	165x105x27mm
Operating System	Ubuntu 14.04.4

The software developed for the receiver node was essentially a wrapper, allowing CSI collection for custom duration and sampling rate (depending on the activity). The node initiated the collection by pinging the access point. The access point replied to the node and for this reply the channel state information (amplitude and phase) over 30 subcarriers was recorded. Therefore, the sampling rate is not necessarily the number of frames measured per second, but rather the number of pings sent from the node to the access point.

Afterwards, the receiver node would synchronise with a server (a Raspberry Pi with an external hard drive) and store the files in a logical order on the hard drive. Synchronisation was done using the same network between activities. The files were automatically converted by the Raspberry Pi from .dat to .mat and .h5 to analyse them through MATLAB and Python. The Raspberry Pi was located within the same room, but at a safe distance away from the nodes.

Figure 1: Inside of the Gigabyte Brix IoT (receiver node) with the Intel 5300 NIC

2.2 Data acquisition

2.2.1 Experimental setup. In order to produce a dataset that is reminiscent of day-to-day living, an actual (small) living room was used in student housing. The living area is approximately 379x345cm and enclosed by two concrete walls (379cm), a full glass wall (305 cm) and an "open space", partly blocked by a hard plastic toilet box (179cm), leading into the kitchen and sleeping area. The total dimensions of the studio are 861x345cm (Figure 2).

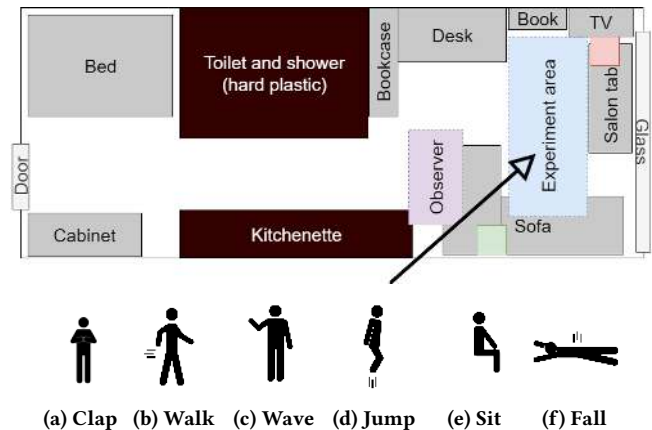(a) Clap (b) Walk (c) Wave (d) Jump (e) Sit (f) Fall

Figure 2: Layout of the experiment studio, including visualization of performed activities. Transmitter and receiver are the red and green square, respectively.

The setup consisted of a custom Gigabyte Brix IoT connected to an access point (TP-LINK AC1750). The distance between the transmitter and receiver was approximately 250cm, where the access point was located on a table (50cm off the ground) and the receiver node was located on a shelf on the wall (160cm off the floor). Furthermore, there was a laptop to monitor the status of the nodes and a screen showing experiment instructions and progress to the participants. The room also contained a yoga mat to indicate the perfect location to perform activities. Also located in the room were a L-shaped sofa, table (with a plant), TV (and furniture), desk (with a chair), and a bookcase with books. All of these were either in the line-of-sight between the nodes or within the immediate vicinity of the either the node or the access point.

2.2.2 Connectivity. There are different connectivity options using the Linux CSI Tool [3]. The two main ones are using a WiFi network (which this dataset used) or the 802.11n injection mode. For this dataset, the node initiates the transmission by pinging the access point. The access point then returns a frame for which the channel state information is captured. The most important incentive to use an existing WiFi network, was that it was important to replicate a real-life setting. Injection mode requires more modifications to the access point and a continuous transmission (thus causing a lot of interference on the specified GHz band). The rate at which the node was pinging the access point was 20 Hz. This low frequency was chosen over higher frequencies used in past works [11], as real-life solutions should not flood the network. A 2.4 GHz network was used, as this is still the most available one in most homes. Frames

were transmitted at 48 Mbps using 64QAM(1/2) using mostly 3x3 MIMO for 5 seconds. After each 5 seconds, there was a 1 second buffer to flush the data. Note that this does not mean that 100 traces were recorded per second, as frames get lost.

2.2.3 Participants. A majority of papers using channel state information for activity recognition focus on either a single participant or generalizing all data. Nine participants were selected with strongly different characteristics when it comes to height and weight. The dataset does not contain this information due to the participants not willing to share confidential information. The 9 participants were spread over the course of 3 days, meaning there were three participants on each day. However, due to availability constraints, participants were welcomed at any time and therefore there is no consistency between recording times throughout the days (see Table 2).

Table 2: Timesheet participants per day (GMT+1), each experiment took 1 hour

		Day 1			Day 2			Day 3			Day 6		Day 7		Day 8	
		1	2	3	4	5	6	7	8	9	6	8	6	8	6	8
	11:30				■											
	13:00					■										
	14:00							■								
Times	15:00	■														
	16:00		■													
	17:30						■	■								
	19:00								■					■		
	20:00		■							■	■				■	
	21:00											■	■			
	22:00														■	

2.2.4 Activities. The performed activities were full-body activities to visibly change the channel state information to the human eye. Minor activities (such as hand gestures) or physiological signals (such as heart rate) do not cause enough disturbance on the channels to differentiate them using the human eye. For the analysis of impact on the channel state information, it was thus more beneficial to consider these activities. The activities include clapping, walking, waving, jumping, sitting and falling (see bottom of Figure 2). Jumping was excluded from the experiments for the two participants performing over multiple days due to health concerns.

2.2.5 Days. Experiments were conducted over multiple days to investigate WiFi signals changing throughout and over days, due to external influences. These influences include other wireless networks (on the same channel), mobile devices and physical changes in the environment (such as furniture being replaced). As this research focuses on the use of a wireless network, rather than the 802.11n injection mode, stability over days is captured.

2.3 Dataset

The dataset is available at the 4TU.ResearchData under the *CC BY-NC-SA* license with the DOI *10.4121/uuid:42bffa4c-113c-46eb-84a1-c87b6a31a99f* [4].

2.3.1 Overview. Each experiment contained 5 or 6 activities, where each activity contains of 50 trials.Each trial took 5 seconds, resulting in 250 seconds for the each activity. This means the total time each experiment captured data was 1500 seconds. This is excluding the

buffer periods between trials. Per second, 20 pings were initiated, meaning ideally 5000 frames were recorded per activity. A visualization of the data can be found in Figure 3 for all activities. Note that these are chosen as they are quite distinctive. Depending on the participant and day, trials may include more or less distinctive activities as shown here. Each trace also contains more information regarding noise and antennas [3].
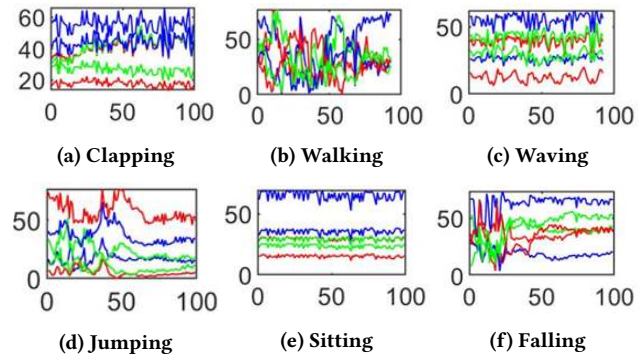

Figure 3: Visualization of the amplitude (x-axis) for 1 subcarrier and 6 antenna pairs (3x2 MIMO) over 100 frames (y-axis)

2.3.2 Metadata. Data was collected from November 13, 2018 through November 20, 2018. Files are ordered in a clear manner, spread over different folders per day. The naming of the files is done in the following fashion:

$$./day<n>/<p>\_<a>\_<t>.<dat|mat>$$

where $n \in \{1, 2, 3, 6, 7, 8\}$ for days, $p \in \{1, 2, 3\}$ for participants, $a \in \{clapping, walking, waving, jumping, sitting, falling\}$ and $t \in \{1..50\}$. Note that participants are denoted from 1 to 3, depending on the day, unlike Table 2 where participants are numbered from 1 to 9.

Except for falling, all activities were monitored continuously. This means that the data contains a lot of different phases of each of the activities and that no starting point is comparable. For example in waving, a trace could start with the participant moving the hand from left to right, but also with the participant moving the hand from right to left. This increases the diversity in the dataset.

For $d = \{1, 2, 3\}$, participants were instructed to perform the activities more freely. This meant participants were allowed to change the way they performed activities throughout the experiments and walk freely in the experiment area. This was most noticeable for $d = 2$.

For $d = \{6, 7, 8\}$, participants were instructed to repeat the same experiments at approximately the same time each day. The participants performed the activities in the same order every day and an effort was made to replicate the appearance of each participant by making sure the outfit and hairstyle were the same throughout the experiments. Furthermore, an effort was made to replicate the activities in the same way by showing a video of the first day. Jumping was excluded from the list of activities.
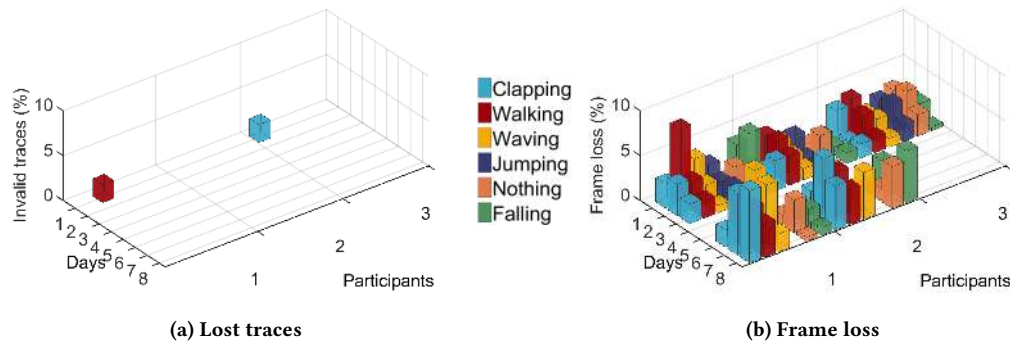
(a) Lost traces

(b) Frame loss

Figure 4: Visualization of received traces and frame loss within traces for days, participants and activities (in %)

2.3.3 Dataset analysis. During the statistical analysis, we denote the following notation for easy reference:

- $d \in \{1, 2, 3, 6, 7, 8\}$ as a given day d.
- $a \in \{clapping, walking, waving, jumping, sitting, falling\}$ as a given activity a
- $p = \{d, s\}$ where d is a given day and s the index for a specific participant on a d. Note that $p(2, 3) = p(6, 2) = p(7, 2) = p(8, 2)$ and $p(3, 2) = p(6, 1) = p(7, 1) = p(8, 1)$.
- $t \in \{1..50\}$ as a given trial t.

The dataset should contain 420000 frames when considering 5 seconds per frame with 20 Hz. However, it turns out the actual dataset consists of 407978 frames due to frame loss and corrupted files. Out of all files, only 2 traces had 0 frames (Figure 4a). This figure shows most experiments have at least a single recorded trace, with the exception for $d = 1, s = 1, a = walking, t = 50$ and $d = 1, s = 3, a = clapping, t = 41$.

For the remaining traces, 97.14% of the expected frames were collected, meaning 2.86% of all frames were lost. This is confirmed by Figure 4b, as an average loss of 3.05% per day, activity and participant can be found here. As these are averaged over multiple trials, there are some outliers. Figure 5 shows that while most trace lengths are in the range of [90; 110], some received fewer frames (as low as 20).

For the entire dataset there were always 3 receiving antennas (Nrx). However, for a total of 1782 traces the number of transmitting antennas was 2 instead of 3 (0.44%). For the rates, this was slightly different. The total range of rates can be split into two categories, low (< 278) and high (> 8468). Here, the high rates correspond to the 48 Mbps. There are 404254 traces with high rates, accounting for 99.09% of the dataset.

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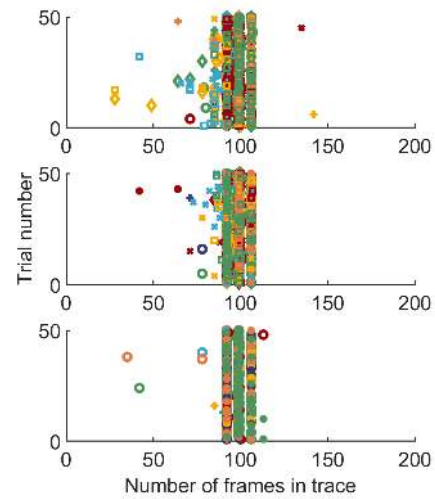

Figure 5: All received frames per trial for all participants (1=top, 2=middle, 3=bottom), days (1=○, 2=+,3=⋆, 6=◇, 7=✕, 8=□) and activities follow the same colour as Figure 4.

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