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Optimising for Dense Deployments in Commercial Ambient Human Sensing with WiFi CSI

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***Abstract*—WiFi Channel State Information (CSI) is widely-used in research for human sensing applications, yet its actual deployment in commercial real-time applications remains sparse with few examples. Existing demonstrations in research literature predominantly rely on specialised deployments of a single sensing apparatus, which cannot efficiently be used in large-scale deployments. Additionally packet loss is common which leads to an over-reliance on interpolation for missing points. Addressing these gaps, this paper presents a low-cost, and scalable solution for CSI-based human sensing, tailored for high performance and consistent operation in residential environments.**

Our approach leverages ESP32 hardware which is renowned for its high availability and low-cost compared to popular CSI collection solutions. We define a methodology for remotely collecting CSI data from multiple sensors concurrently over WiFi, by employing a single beacon for traffic generation while CSI data is gathered over a separate channel. We further optimize this process using DEFLATE compression on CSI payloads to minimize airtime contention during transmission. This proposed system has been evaluated through a series of experiments designed to assess its viability, scalability, and environmental adaptation capability. Notably, we demonstrate the system's capability to support 30 sensors sampling CSI data at over 90Hz simultaneously, with additional projected capacity. This validation has been conducted across two distinct residential environments, affirming the adaptability and effectiveness of our approach for high-performance CSI sensing in real-world scenarios.

***Index Terms*—wifi sensing, commercialisation, deployability**

I. INTRODUCTION

Radio-frequency (RF) sensing technologies continue to present unique opportunities for passive human sensing, allowing for contactless and non-invasive monitoring of locomotion and behaviour. RF sensors can offer several advantages over vision-based or wearable sensors which are commonly employed in these applications. One of the primary benefits is their ambient approach to sensing, which is preferable for both users and engineers. This privacy-focussed approach allows for the deployment of sensors which blend into a home environment and don't require physical interaction from the user. However, the choice of hardware solution used can affect deployment and scaling capacity. As this approach to sensing is relatively modern, the hardware landscape has not yet matured, leading to limited options with pros and cons. Therefore, careful consideration must be taken when selecting the appropriate hardware solution for a given application.

For instance, the Intel IWL5300 wireless chipset remains prevalent in modern CSI sensing research, despite its deprecation several years ago. This reliance on outdated hardware poses significant challenges to the scalability of CSI sensing solutions intended for deployment in real-world environments. Running a CSI collection system continuously also presents its own set of challenges. Ensuring consistent sampling of the channel is critical for obtaining reliable data, while managing interference levels in traffic generation is paramount for accurate measurements. Additionally, deploying an optimal number of sensors to achieve spatial diversity without overwhelming the system is another issue.

We address these challenges by leveraging a unique approach to traffic generation and remote sensing using ESP32 hardware, known for its low cost and widespread availability. First, a single central beacon is used to generate a continuous stream of packets. Our sensors then collect and feed back the CSI measurements from the beacon to a hub using a dedicated access point. This effectively distributes the airtime usage across two channels, while reducing the impact of transmission on injection consistency. Additionally, we employ batching and compression to reduce airtime consumption, further enhancing our capacity to accommodate numerous sensors simultaneously.

Our aim was to continuously collect CSI data from each sensor at a target rate of 100Hz, facilitating high-precision applications such as localization. This sampling rate aligns with the requirements of various applications and with a subset of public CSI sensing datasets. Employing a lower sampling rate may restrict the range of applications compatible with the data collected. This approach enables flexible dataset generation at will, supporting labelling and fusion from external sources. Furthermore, the redundancy afforded with a 100Hz target can be traded off in scenarios requiring reduced capacity or improved power and wireless efficiency.

We conducted two sets of experiments to evaluate both our system's viability and scalability. The paper is structured as follows: First related work is reviewed, focusing on CSI data capture and compression in similar setups. Then, we detail our methodology, system design, and scalability approach. Finally, our experiments and results are discussed, demonstrating the impact of our contributions, before drawing conclusions.

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II. Related Work

The majority of CSI research with off-the-shelf commercial hardware is performed using the Intel IWL5300. The chipset itself was released in 2008 and it is no longer in production. Despite this, research using it is still regularly published. This is largely due to the availability of open source sensing research and the accurate CSI collection solution released by Daniel Halperin in 2011 [6]. State-of-the-art functional applications have been achieved using this hardware, ranging from movement detection and activity recognition, to environment mapping and water pressure monitoring [1]. Its primary limitation is that it cannot be deployed in any meaningful scale, due to its deprecation and inflexible hardware deployment requirements. More recently, Broadcom's modern 802.11ac chipsets used in the Raspberry Pi 3B+/4 and ASUS RT-AC86U have been used [4]. These chipsets are still in production and can be deployed at lower-cost than the IWL5300. An open source CSI sensing toolkit has also recently been released for use with Intel's 802.11ax chipsets [8], however relatively few research outputs have been developed using them. They also still require a host computer to operate them. In contrast, the ESP32-C6 is a SoC developed by Espressif which contains both a 2.4GHz 802.11ax radio, and a dual-core microprocessor onboard. This is an increasingly popular solution for CSI collection [7], which is well-suited to large-scale hardware deployments. It is both low-cost and has a smaller power profile compared to all other hardware options. The most significant tradeoff made in using the ESP32 is its lack of MIMO antenna support, which prevents its use in sensing applications which employ more than one antenna. Regardless of the hardware options, CSI data must be of a similar quality to that seen in other datasets in order to be useful in the development of new sensing applications. A key constituent of CSI data quality is the frequency of the measurements, or transmission rate.

Demonstrating state-of-the-art deep learning approaches to CSI sensing, SenseFi [11] serves as a public benchmark for four CSI datasets. These datasets employ CSI transmission rates of 1kHz (Widar 3.0, UT-HAR) and 500Hz (EfficientFi, Caution). Evaluations of the sensing applications developed with these datasets commonly involve downsampling the data to assess its impact on system performance. Widar 3.0 found a 4% decrease in accuracy when downsampling from 1kHz to 250Hz. Similarly, [10] observed minimal performance reductions going from 1kHz to 50Hz for a respiration monitoring application. [3] also demonstrated comparable human activity recognition performance could be achieved at both 100Hz and 10Hz. Capturing data at 100Hz allows for an efficient compromise between high and low sampling rates.

Capturing CSI data continuously, even at 100Hz, has overheads. The consistency of the target transmission interval is reliant on the wireless environment being clear, as contention between devices on similar channels can interrupt or block outgoing transmissions. One potential approach to reducing the impact of contention is to employ compression. Compression has been used in CSI sensing research before, including works by Yang [12] and Barahimi [2]. Both Yang and Barahimi applied approaches to compression which could be performed onsite, with both the decompression and sensing applications being employed in the cloud in real-time. Yang's EfficientFi employs a deep neural network to compress data at edge, achieving a significant reduction in the data rate required to transmit the same CSI data. However, their work is demonstrated using a single CSI collection setup covering a single room. They did not investigate how the reduced overhead from their compression approach could be used to incorporate additional sensors simultaneously, thus potentially enhancing environmental coverage or spatial diversity. This gap forms the basis for our work.

III. Method

The purpose of our system is to collect CSI data within residential environments for dataset generation and the development of real-time sensing applications. While the implementation of a CSI collection system for real-time sensing itself is not a novel concept, a commercially-viable solution must overcome the limitations of typical collection systems through novel means. The novel components of our approach include the use of a central beacon for traffic generation with many sensors measuring CSI for the same frames, a separate access point for feeding back CSI measurements, and a batching process with compression. When these components function effectively, the system's performance will scale efficiently with the addition of more sensors and will be adaptable to diverse environments.

The experiments performed in this work were designed to demonstrate the system's response to changes in the number of sensors and compression settings employed, and the environment in which it was deployed. We measured performance in response to these configuration changes in order to evaluate the system's viability and scalability.

First, we explain the decisions behind our system design. Then we define the metrics we measure to observe variations in performance. Finally we detail the methodology for our experiments exploring viability and scalability of the system.

A. System Design

Typical CSI collection setups make use of the CSI collected from the traffic between two WiFi devices communicating as part of a managed network. The device collecting the CSI is also typically directly connected to the ingest system. These limitations affect the scalability of this approach which directly affect its suitability for use in commercial environments. We designed this collection system to overcome these limitations and scale as needed to focus on supporting commercial usage.

Figure 1 describes the wireless CSI system developed and tested in this work:

Traffic Generation: We use an ESP32 operating in monitor mode to transmit bespoke WiFi frames through injection, which can be observed by other monitor mode devices. This

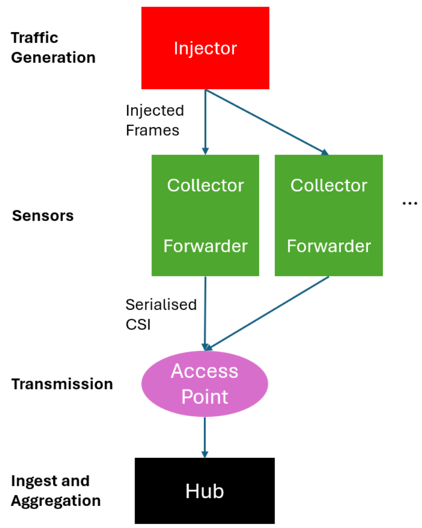

Fig. 1. System diagram for WiFi-based CSI collection at scale.

allows the sensors to gather CSI from a single central beacon, reducing overall system costs, power usage, and complexity. This stream of generated traffic is transmitted over a low-volume WiFi channel determined through a density sweep on boot. The injector may optionally be connected over Ethernet to feed back telemetry. Only one injector is used in each of our test environments.

Sensors: Each sensor is comprised of 2 ESP32 modules working in tandem; a Collector, and a Forwarder. The Collector operates as a WiFi monitor mode device to collect CSI for the frames generated by the Injector. These frames and their metadata are then serialised using Google's protobuf format, which are transmitted to the Forwarder over SPI. The Forwarder maintains a WiFi connection with the Access Point, which is used to transmit the protobufs to a UDP server running on the Hub. The Forwarder may also batch many frames from the Collector into one buffer, which reduces the frequency of transmissions. The size of these buffers can then be reduced by applying compression, further reducing airtime usage and increasing system capacity. The only physical connection required is for power. In our test Environment 1, at least one sensor is deployed in each room.

Transmission: An Access Point (AP) is used to operate a managed mode network to feed back data from each of the Forwarders. This AP operates on a separate 802.11 channel to that of the Injector, which reduces contention between the Sensors and Injector.

Ingest and Aggregation: A host system is used to run a UDP server to receive data from the Forwarders. This ingest server handles incoming CSI protobufs which can then be stored, visualised, and used for sensing applications.

This approach can be used to employ sensors across the entire home as a collective sensor network, akin to an inverse antenna array. While room-specific sensing precision may be reduced, on paper scalability in both sensor count and throughput is improved by necessitating only one traffic stream for CSI generation. In operation this system generates a stream of traffic and collects the associated CSI data from multiple sensors simultaneously to a server.

B. Performance Evaluation

The key metric in evaluating a system for collecting continuously-sampled CSI is how much CSI it gathers in a given second or the **Ingest Rate**, measured in Hz. In a theoretically perfect implementation of the system this would be equal to the number of Sensors multiplied by the Injector's target transmission rate. This is 100Hz for all experiments in this work. In figures, the unit for this axis is labelled as % for readability.

In real-world scenarios the maximum possible ingest rate is almost never met, as packet loss is commonplace with WiFi. We practiced provenance to audit the data collection process, and highlighted likely points of failure in the system:

- **Injector**: The WiFi driver may fail to inject frames, referred to as **Dropped Frames**. These manifest as a reduction in ingest rate on all sensors simultaneously. We run the Injector over Ethernet to track dropped frames at injection through telemetry.
- **Sensor**: Injected frames may fail to reach the Collector, or may not be transmitted at the Forwarder stage. These are both separate potential points of failure.
- **Ingest**: UDP packets may be dropped if the Ingest server cannot process them faster than they are received.

We primarily used **Ingest Rate** in monitoring the performance of the system, while also considering the impact of **Dropped Frames** where present.

Next, we discuss the methodology used in each of our experiments.

C. Viability

The viability of the system refers to its ability to function as defined in Section III-A. Thus we planned to implement each component and test it in a residential environment to demonstrate wireless CSI collection with multiple sensors operating simultaneously. The end-to-end performance of the system was monitored both to establish viability, and observe consistency over longer capture periods.

D. Scalability

Scalability in this context refers to both the ability to deploy many sensors simultaneously, and the ability to apply this approach to sensing in unique residential environments.

The primary issue affecting the system's ability to scale increasing numbers of sensors is the available WiFi airtime. There is finite time available for each sensor to transmit

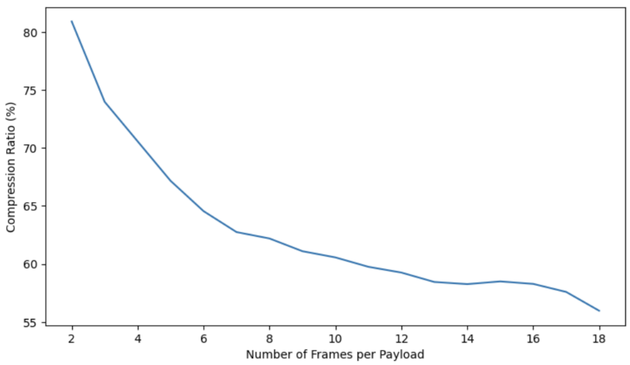

Fig. 2. Mean compression ratio against the number of CSI frames in a payload.

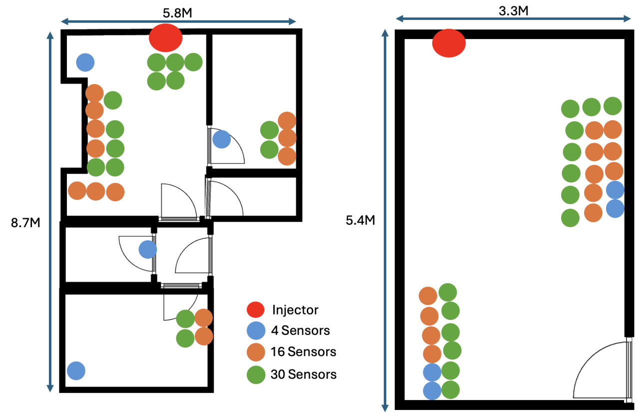

Fig. 3. Floorplan for environments 1 and 2 with labelled sensor locations.

their payloads to the AP. The available airtime can fluctuate dynamically due to shared channels and varying levels of traffic from other WiFi devices. The system's capacity and performance are inherently tied to the wireless environment.

We use a relatively high transmission rate of 100Hz, allowing us the capacity to adjust resource usage as needed in response to fluctuating airtime availability. Each sensor attempts to feed back up to 100 available CSI measurements in a given second. The simplest approach to remote data collection is to transmit a CSI payload over WiFi to the AP for each CSI measurement. However $n * 100$ is unsustainable for more than a few sensors at once. Data ingest systems typically employ some form of batching to overcome this issue. However this alone does not solve the airtime issue, as larger frames take longer to transmit.

Our solution is to apply compression to CSI packet payloads to reduce the number and size of transmissions from sensors to the AP. As each sensor collects CSI measurements the Forwarder buffers them to be compressed into a single payload. We chose the DEFLATE compression algorithm, due to Zlib's efficient performance on embedded hardware. Figure 2 shows the average compression ratio achieved on a Forwarder. As the number of frames added to the buffer increases, the overall reduction in payload size falls, plateauing between 14 and 16 frames. Initial tests were concluded at 18 frames, as the size of each frame exceeded the threshold for IP fragmentation which causes larger packets to be split at the protocol level. Batching and compression reduces payload size, airtime consumption, and the number of transmissions. This improvement is expected to enhance system performance in all environments. We tested the system in 2 unique environments in this work.

Figure 3 shows annotated floorplans for the 2 environments used in our experiments. Environment 1 is a flat in a densely populated apartment building, while Environment 2 is in a detached house in a rural location. Sensor locations are marked successively for experiments where 4/16/30 sensors are used. Given the vastly different wireless environments of these settings, we expected performance discrepancies between the two. We aimed to establish the optimal compression configuration by performing data collection in both environments while adjusting the number of frames per payload.

IV. Experiment

This section describes the system implementation and experiments performed to assess the real-world viability and scalability of our CSI collection system in residential environments. In each experiment the system was assembled and operated to collect CSI for a set period of time. The variables we adjusted were the number of sensors and number of frames per payload. The **Ingest Rate** and **Dropped Frames** were measured during this period. The implementation of the system is detailed as described in the system diagram in Figure 1.

Injector: An Olimex ESP32-POE-ISO was configured to inject truncated 802.11n beacon frames with a target interval of 10ms. MCS4 was used with short guard interval at 20dBm. In Environment 1, channel 4 was used for injection, with Environment 2 using channel 12.

Sensors: 2 Espressif ESP32-C6-DevKitC boards running ESP-IDF v5.1.1 were connected over the HSPI/SPI2 bus. Forwarder using 802.11ax for transmission.

Compression: miniz [5] with DEFLATE level 10 was used.

Transmission: Ubiquiti U6-Enterprise running a 2.4GHz 802.11ax access point on channel 1 (both environments).

Hub: A Raspberry Pi 4 with 2GB RAM on Debian 11, running a Rust-based UDP server to process incoming protobuf data from sensors.

A. Viability

Setup: The system was assembled and operated in Environment 1 for 1 hour at a time. This process was repeated with 4/16/30 sensors, with compression first set to 15 frames per

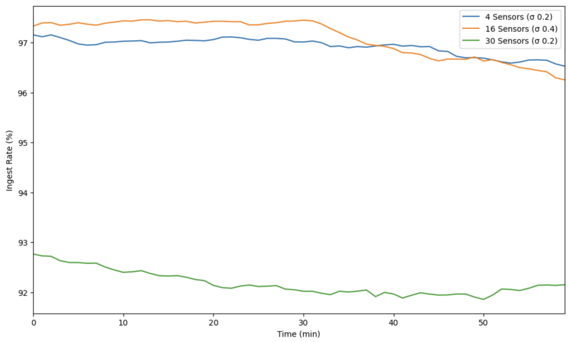

Fig. 4. Mean ingest rate and standard deviation per sensor count in Environment (15 frames per payload).

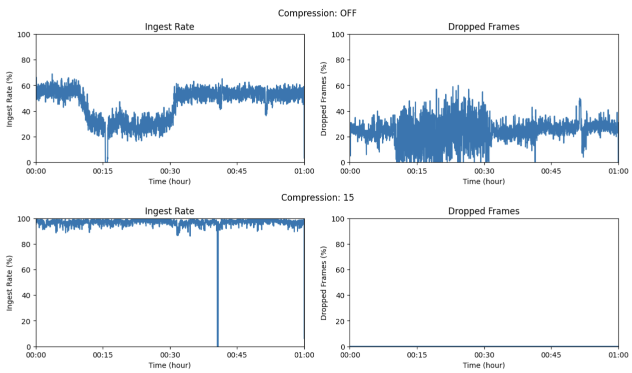

Fig. 5. Injector and mean collection performance metrics across 16 sensors in Environment 1 (toggling compression).

payload and then disabled. 15 frames was chosen for the viability tests, as this was shown to be the point where the compression ratio plateaued in Figure 2.

Results: Figure 4 shows the mean ingest rate across all sensors, plotted for the default configuration with 15 frames. The ingest rate remains largely consistent over a 1 hour period. With 30 sensors in operation, the rate drops by around 4Hz when compared with the captures with 4 and 16 sensors. While the rate observed with 16 sensors appears to drop in the second half of the capture, the drop is just over 1Hz and does not appear to indicate a significant reduction in system performance. The standard deviation is the same for 4 and 30 sensors, whereas a higher standard deviation (0.4) is observed for 16 sensors.

Figure 5 shows a full breakdown of each of our performance evaluation metrics, for the experimental runs using 16 sensors in Environment 1 with compression first disabled, and then set to 15 frames per payload. With compression disabled, the ingest rate does not exceed 65Hz, with a mean of 55Hz. The rate of dropped frames in this capture is relatively high, with a mean drop rate of 25Hz. The capture with compression enabled shows a much higher ingest rate with a mean of 95Hz. No frames were dropped at injection during this capture.

Discussion: The system demonstrates strong performance, aligning with our goal of achieving high transmission rates comparable to that of a 100Hz dataset. The observed performance degradation at 30 sensors of around 6Hz is deemed reasonable given the high throughput of CSI data.

Compression significantly impacts performance with larger numbers of sensors, with a substantial increase in dropped frames when compression is disabled. This phenomenon was consistent across all captures involving 16 or more sensors without compression. Further speculation is warranted regarding the root cause of this observation, although the excessive transmission rate of each sensor is likely to blame.

Instances where the ingest rate drops to 0Hz are relatively rare. However, the ingest rate from all sensors falls, it indicates a potential issue either with the injection of the frame or with the wireless environment. Further investigation into these occurrences is necessary to ensure system reliability and robustness.

B. Scalability

Setup: The system was deployed in both test environments with 4, 16, and 30 sensors used. Initially, compression was disabled, after which it was incrementally increased by 5 frames, ranging from 5 to 30 frames. We expected performance degradation beyond 18 frames due to IP fragmentation. Due to the increased number of captures and limited access to Environment 2, the capture period was reduced to 1 minute.

Results: Figure 6 shows the mean ingest rate across all sensors for multiple configurations captured in both test environments. The number of frames per compression payload is plotted along the x-axis. Both plots show greater than 90Hz ingest rate can be achieved in both environments with all sensor counts through the use of compression. A curve is observed across both plots, with performance quickly increasing as compression is enabled, before dropping as the setting exceeds 20 frames. In Environment 1, the performance for each sensor count does not converge until 25 frames. In Environment 2, performance quickly converges once compression is enabled, dropping as the threshold for IP fragmentation (18) is exceeded.

Discussion: The results indicate that good performance can be achieved in both environments with up to 30 sensors. Performance with 4 sensors and no compression is largely comparable to performance with compression. However, performance is notably lower with 16 and 30 sensors when compression is disabled. Compression significantly improves performance in both environments, thereby enhancing the scalability of the approach to accommodate more sensors in diverse environments.

The optimal compression setting across the two environments is 15 frames. Environment 1 favors higher compression sizes, while Environment 2 peaks with all sensor counts converging at 5 frames. Nevertheless, strong performance is

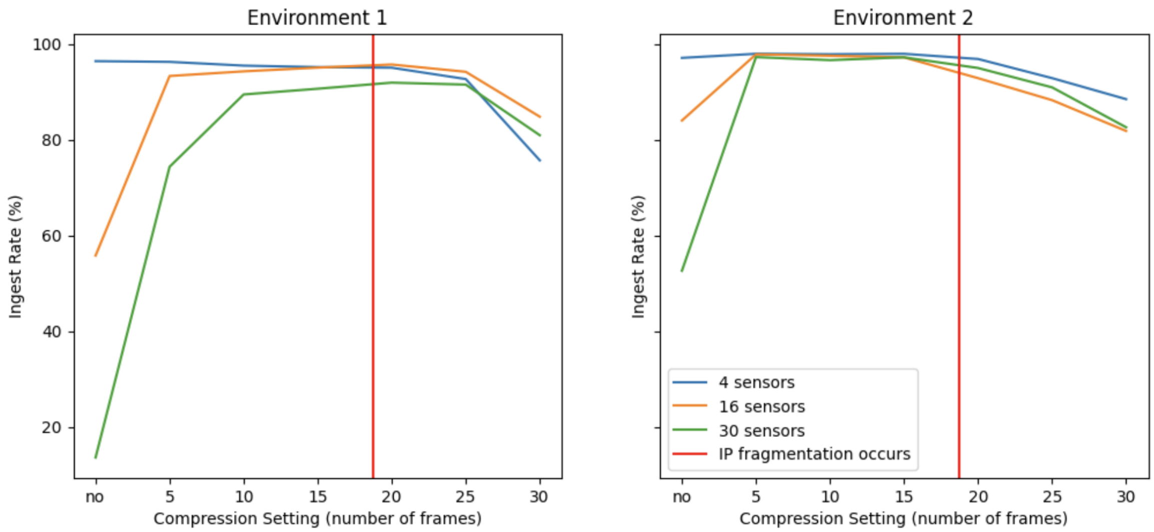

Fig. 6. Impact of deployment density and compression on ingest rate.

observed at 15 frames, suggesting this value may serve as a suitable baseline in unknown environments. Additionally, IP fragmentation is likely the cause of reduced performance beyond 25 frames; however, this phenomenon may not be consistent across different environments and could depend on other networking factors such as MTU. Environment 2 consistently outperforms Environment 1 in most captures, likely due to its quieter wireless environment with fewer neighboring WiFi devices. A calibration process may be necessary to select the optimal compression setting in unknown environments.

Given the robust performance observed with 30 sensors in either environment, speculation about the system's ability to scale further is warranted. This also underscores the built-in redundancy in the system, with potential for further efficiency improvements.

V. Conclusions

This paper proposes an approach to high-volume CSI collection with a focus on scalability and deployability. We have shown the system can scale to large numbers of sensors in 2 unique environments with diverse wireless backgrounds. With the same configuration, an average ingest rate exceeding 90Hz across both environments has been achieved while using 30 sensors. Implementing batching and compression on the sensors as they feed data back to the hub over WiFi is necessary to achieve consistent performance beyond smaller sensor counts. While an optimal compression setting can be derived for each environment, strong performance was achievable in both environments with a common setting of 15 frames per payload. This work shows high-volume CSI collection at scale can be achieved with low-cost, highly-available hardware. Thus the system can be employed to generate datasets at scale.

In future work we aim to perform a long-term study using our FitHomes research testbed, which incorporates motion and environmental sensor data from real-world residential environments [9]. This will allow us to establish the requirements of a possible calibration solution, and explore the impact of changing wireless conditions as we deploy CSI sensing systems at scale.

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