Motion Detection over 5G through Sensing Signal Disturbance Analysis leveraging COTS platform

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***Abstract*—This study presents a system-level investigation aimed at reliably detecting human movement in indoor environments using antenna signal quality indicators derived from a commercial off-the-shelf (COTS) private 5G mobile network deployment. The equipment utilized is capable of emulating a fully integrated telecommunications system, supporting the Integrated Sensing and Communication (ISAC) standard.**

The primary objective is to evaluate whether common measurements such as Channel Quality Indicator (CQI), Modulation and Coding Scheme (MCS), and Signal-to-Noise Ratio (SNR) can effectively indicate human presence and movement. Experimental results demonstrated that human motion events within the line-of-sight (LOS) path resulted in measurable and repeatable signal degradation. Specifically, SNR values were found to decrease by up to 31.9%, while in more pronounced cases, reductions exceeding 41.5% were recorded. Simultaneously, downlink MCS values dropped sharply from index 10–12 (corresponding to 16-QAM modulation with moderate coding rates), dropped sharply to near zero, as the system adapted in real time to the deteriorating channel conditions.

A strong positive correlation between signal degradation and link adaptation was confirmed, with a Pearson correlation coefficient of approximately r = 0.92 observed between SNR and MCS. Furthermore, a correlation of r = 0.84 was recorded between SNR and CQI. During the evaluation, SNR, CQI, and MCS measurements provided the most significant variations associated with human movement scenarios, particularly when the LOS was obstructed.

Keywords— Motion Detection, 5G, Sensing Signal Analysis.

I. Introduction

Wireless communication has come a long way in the past decade. While faster and more reliable connections remain its primary function, new opportunities are emerging in less conventional areas such as motion sensing.

With the rise of 5G, new tools have become available that enable existing infrastructure to be used not only for data transmission, but also for sensing and interpreting changes in the physical environment. Specifically, physical layer features in 5G networks exhibit a remarkable sensitivity to environmental changes. Even minor movements, such as a person walking through the signal path, can cause subtle but detectable disturbances in signal propagation, which are reflected in standard connection metrics like the CQI, MCS, and SNR [1].

This work investigates whether standard 5G signal quality metrics—readily accessible on commercial devices—can be effectively utilized to detect human motion in a LOS scenario. An efficient and accessible method for motion detection is introduced, based solely on 5G signal characteristics, without the need for custom sensing hardware or specialized signal processing.

A commercial off-the-shelf (COTS) platform [2] and a standard smartphone connected to a private 5G network are utilized, promoting a straightforward, easily deployable, and hardware-agnostic proposed methodology. The ability to detect motion passively using already deployed infrastructure opens a wide range of possibilities: non-intrusive security monitoring, non-contact healthcare monitoring (e.g., fall detection) [3], [4], and improving safety or efficiency in industrial environments minimizing obtrusiveness not relying on cameras or any wearable devices.

II. Related Work

The idea of using wireless signals as sensors is not entirely new. Several studies have demonstrated the feasibility of detecting motion or activity by analyzing how wireless signals behave under certain conditions. However, most existing approaches rely on custom hardware or complex signal processing, which limits their practical application, especially when lightweight and easily deployable solutions are required. Many methodologies depend on accessing detailed signal-level information, such as Channel State Information (CSI), often requiring specialized antennas, modified firmware, or dedicated radio hardware.

While such setups can be highly effective in controlled lab environments, they pose challenges for real-world deployment where scalability, cost, and ease of installation are critical concerns. In the context of 5G networks, there has been growing interest in leveraging signal properties beyond traditional data transfer. Previous works have employed deep learning techniques to enhance communication channel

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estimation, aiming to improve accuracy under challenging conditions. Respective knowledge can also be required for indoor localization to achieve a high accuracy [5].

Previous studies proposed alternative Adaptive Modulation and Coding (AMC) strategies that operate without relying on CQI feedback. The selection of MCS value or CQI index is highly sensitive to SNR. And with different channel models used in simulations or different channel conditions experienced during tests, the mapping between MCS/CQI to SNR varies. In fact, differentiated SNR-to-MCS or SNR-to-CQI mapping LUTs are obtained via simulations [6].

Higher MCS indices are associated with increased spectral efficiency; however, their application is limited to scenarios with high-quality signal conditions. Therefore, under degraded signal conditions, the selected MCS level is correspondingly reduced [7]. The relationship between SNR, CQI, and MCS plays a critical role not only in communication performance but also in environmental sensing. In a static environment, the SNR at the User Equipment (UE) remains relatively stable, leading to a consistent CQI report and a corresponding stable MCS selection.

However, when a human subject moves within the signal path, the resulting physical obstruction and multipath effects cause variations in the observed SNR. Therefore, monitoring abrupt or systematic variations in SNR, CQI, and MCS can serve as an effective method for passive motion detection using standard 5G communication parameters [8]. In contrast to prior studies that often require custom hardware or specialized signal processing, the approach proposed in this paper relies solely on standard 5G signal quality metrics accessible through commercial devices.

III. 5G Testbed and Evaluation Methodology

To better illustrate the area of focus, the physical topology of the laboratory, as shown in Figure 1, was designed. The circles in the diagram indicated the areas in which the 5G measurements were conducted.

Additional details regarding the topology shown below: starting from the bottom of the diagram, on the right-hand side, a mobile phone was connected via 5G to the callbox. On the left side, there was a 5G router (CPE gateway), which received its signal wirelessly over 5G and can provide internet access via wired ethernet e.g., to a computer or local device. While the 5G router is not the main focus of this paper, it is worth noting that it will be used in future work as part of a more extended setup. For the scope of this study, the specific focus was placed on the link between the mobile phone and the callbox.

Right at the heart of the setup was placed the AMARI callbox [9], [10], which was connected to the laboratory's internal network using a Cat 6a UTP Ethernet cable. From there, all the traffic was routed out to the internet. To keep things secure, the entire network was protected by next-generation Layer 7 firewalls. These did not just handle basic filtering but also guarded against serious threats like DDoS attacks. On top of that, the laboratory operated with its own autonomous system (AS) using BGP, which gave direct and stable access to the internet. That setup proved beneficial, especially when measurements were conducted that required consistent connectivity or working remotely through a VPN without interruptions.

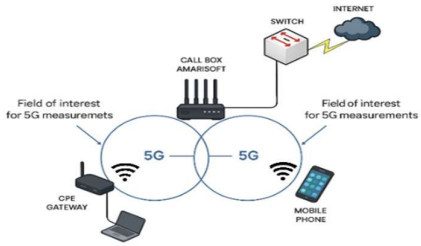

Figure 1: Physical topology of the laboratory

The following equipment was used and integrated into the laboratory infrastructure for this research:

a) AMARI Callbox Mini. The AMARI callbox is a compact solution for testing 4G and 5G devices, functioning as a 3GPP-compliant eNB/gNB and EPC/5GC. It supports functional and performance testing and offers a single cell configuration up to 20 MHz with 2x2 MIMO.

It is compatible with a range of technologies, including NB-IoT, LTE-M, LTE, RedCap, and 5G SA. Although not all features were used in this study, it's worth noting that the device also supports capabilities relevant to future experiments, such as LTE-M operation in both FDD and TDD for CAT-M1, connectivity NB-IoT support Up to 500 concurrent active UEs, maximum throughput of 200 Mbps downlink and 75 Mbps uplink. Inter-eNB/gNB handover functionality (using two callboxes).

b) Samsung Galaxy A14 5G Dual SIM, a straightforward but fully compatible smartphone used as the mobile receiver. This device supports multiple 5G bands (2, 5, 66, 77 Sub-6/mmWave) and includes several built-in sensors like, accelerometer, gyroscope, proximity sensor, compass, and barometer.

c) Teltonika TRB500 5G LTE CPE Gateway was utilized in the laboratory setup. This compact and energy-efficient industrial gateway supports 5G Sub-6GHz SA/NSA with a maximum throughput of 2.1 Gbps downlink and 900 Mbps uplink, and is capable of reporting key signal parameters such as RSSI, SINR, RSRP, and RSRQ.

It is worth noting that among the metrics analyzed, only SNR is measured in decibels (dB), as it represents a physical ratio of signal power to noise power. In contrast, CQI and MCS are dimensionless indices. CQI is an integer value typically ranging from 0 to 15, reflecting the estimated channel quality at the receiver (table 1).

CQI	Modulation	Code Rate	MCS Index	Spectral Efficiency (bps/Hz)
0	—	—	—	— (outage)
1	QPSK	~0.15	0–1	~0.15–0.3
4	QPSK	~0.44	4	~0.88
7	16-QAM	~0.37	10	~1.48
9	16-QAM	~0.6	12–14	~2.4–2.8
13	64-QAM	~0.8	20–22	~4.8–5.5
15	256-QAM	~0.93	27–28	~7.4

Table 1: CQI–MCS–Modulation–Coding Rate Mapping

MCS indicates a specific modulation and coding scheme, chosen by the system based on the reported CQI, and is also expressed as an index rather than in physical units (table 2). All CQI and MCS readings in this study were derived from the Amarisoft 5G callbox platform and may reflect implementation-specific mappings within the standardized 3GPP-defined ranges.

MCS Index	Modulation	Approx. Coding Rate	Spectral Efficiency (bps/Hz)
0	QPSK	~0.12	~0.3
4	QPSK	~0.38	~0.88
10	16-QAM	~0.48	~1.92
11	16-QAM	~0.51	~2.04
12	16-QAM	~0.55	~2.22
20	64-QAM	~0.75	~4.5
27	256-QAM	~0.93	~7.4

Table 2: MCS Index Mapping to Modulation and Spectral Efficiency (5G NR)

The methodology is described in the following section, including the procedures used for real-time signal value collection and observation. Conclusions drawn from the collected data are presented, along with planned future research directions.

IV. Experimental Results and Analysis

To gain a deeper understanding how human motion affects 5G signal quality, a practical lab experiment was set up. A commercially available 5G callbox was positioned on one side of the space, and a standard smartphone was placed about five meters away on the opposite side. This setup ensured a clear LOS between the two devices, as shown in Figure 2. During the tests, a person walked through the LOS to simulate obstruction and observe how it influenced the signal. The system captured signal changes in real time using the callbox's built-in interface, which displayed key physical layer indicators such as SNR, CQI, and MCS.

Each time the LOS was blocked—whether by a person or temporary objects like chairs or whiteboards—the system immediately reflected changes in signal quality. Most notably, both SNR and CQI values dropped, pointing to increased signal loss and reduced channel reliability. The system responded by lowering the MCS level to maintain a stable connection and avoid excessive block errors. In response, the system adaptively reduced the MCS level to maintain link robustness and control the Block Error Rate (BLER) [11]. These changes remained as long as the obstruction was present and quickly returned to normal once the LOS was restored. To make sure the findings were reliable and not just isolated incidents, the entire experiment was repeated more than 20 times under identical conditions. Across all runs, the behavior was consistent, strengthening confidence in the reproducibility and reliability of the results. The experiment demonstrates that typical 5G signal quality metrics—SNR, CQI, and MCS—can be used as practical indicators of human movement, even without any additional sensors or custom hardware. The ability of the system to react in real time to changes in the environment shows the potential of using existing infrastructure for passive motion detection.

As shown in Figure 2, the experiment took place in an indoor lab to reduce external interference and allow precise control over conditions. The LOS served as the main path for radio signals between the callbox and the smartphone. The subject crossed the LOS multiple times, and additional objects were also introduced at intervals to further test how sensitive the signal metrics are to environmental disruptions.

To maintain a stable connection and accurate data throughout the testing, the smartphone was set up to transmit and receive continuously during the measurements. At the time of data collection, the measured downlink rate was around 114 Kbps, and the uplink rate was 7.93 Kbps. These modest but consistent data flows kept the latency very low—estimated to be well under 10 milliseconds—which was important for capturing rapid signal changes with high precision as motion occurred. Every time the LOS was interrupted, fluctuations in SNR, CQI, and MCS were immediately detected and visualized on the callbox interface. These measurements form the basis for the motion detection capability demonstrated in this study.

The results showed that whenever the LOS was blocked, SNR levels dropped noticeably—likely due to greater path loss and signal scattering. In response to these drops, the UE reported lower CQI values, reflecting the degraded channel conditions. As a result, the system lowered the MCS to maintain a stable link and avoid higher block error rates. This dynamic interplay among SNR, CQI, and MCS not only confirmed the occurrence of physical movement but also provided quantifiable evidence of motion.

Therefore, such signal quality metrics can be effectively leveraged for passive motion detection, utilizing only standard features of a 5G communication system, without requiring dedicated sensing hardware. This experiment supports the broader vision of ISAC [12], where communication infrastructure is repurposed to enable situational awareness in a non-intrusive and cost-effective manner.

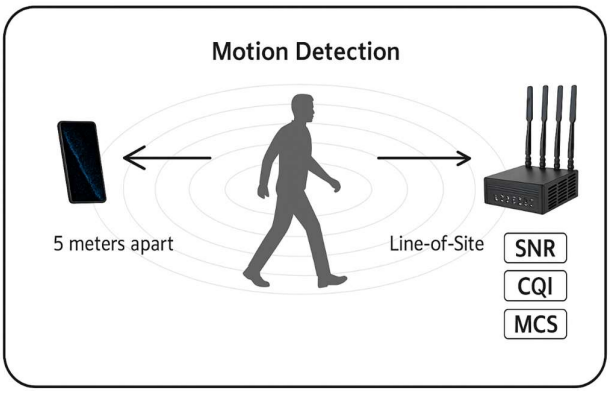

Figure 2: experimental setup

To systematically investigate the effect of human motion on uplink signal quality, multiple repetitions of the same experimental scenario were conducted under controlled conditions. Time-synchronized SNR measurements were collected across various uplink channel slots during each event in which a person crossed the LOS path between the mobile device and the callbox.

Figures 3 and 4 present two representative snapshots from separate motion events, each demonstrating a distinct but similarly significant degradation in SNR levels. Including both figures helps demonstrate that the changes in signal quality caused by motion were not random, but consistent and repeatable. This consistency adds weight to the argument that motion detection can rely on standard physical-layer indicators.

An important detail that emerged during testing was the role of the object's position relative to the devices. When the person or object moved closer to the smartphone rather than the callbox, the drop in signal quality was noticeably stronger. In those cases, the values of SNR, CQI, and MCS showed greater variation, which points to the receiver being more sensitive to nearby interference.

Examining Figure 3 around the 14:04:28 mark, where motion was detected, a significant drop in SNR appeared in the light blue line, which represents SNR 12, slot 9 of the uplink physical channel that carries Uplink Control Information (UCI). The specific SNR value fell to a low of 17.7 dB at this point. A reduction of approximately 31.9% in SNR was observed, with values decreasing from 26 dB to 17.7 dB. Such a sharp decrease indicates that the detected motion significantly affected the signal reception for this particular channel and time slot.

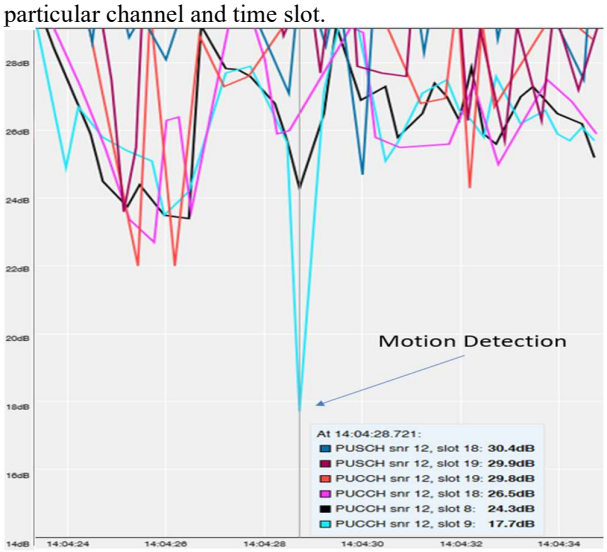

Figure 3: SNR variation during motion near the transmitter

Examining Figure 4, a continuation of the signal analysis presented in Figure 3, offers additional confirmation the impact of human motion on the quality of wireless signal reception in the uplink direction. The figure 4 displays the SNR behavior across multiple UCI-carrying physical uplink shared channel (PUSCH) slots during a controlled motion event. Around the 14:04:12 mark, a significant and sudden decrease in SNR is observed, particularly evident in the red line, which corresponds to PUSCH SNR for slot 19, where the value drops from 29.6 dB to approximately 17.3 dB within a very short time span. This drop represents a reduction of more than 41.5%, indicating a severe degradation in link quality caused by the obstruction of the LOS path.

Multiple other PUSCH slots also show simultaneous drops during the motion interval, reinforcing the conclusion that signal disruption was not isolated to a single frequency-time resource but affected a broader range of uplink allocations. This pattern demonstrates that even brief physical obstructions, such as a human body passing through the LOS, can introduce considerable instability in channel conditions, which in turn affect link adaptation mechanisms.

The purpose of including both Figure 3 and Figure 4, despite their visual similarity, is to strengthen the repeatability and reliability of the results. While Figure 3 focuses on the motion-induced SNR drop occurring at 14:04:28, Figure 4 captures a distinct motion event that occurred earlier at 14:04:12, under comparable conditions. By showcasing multiple independent occurrences of motion-related signal disruption, it is demonstrated that the observed phenomena are not incidental or isolated. Instead, the consistent SNR degradation across different time slots and repetitions provides robust evidence supporting the claim that physical movement in the LOS directly influences uplink signal quality in measurable and predictable ways.

This comparative analysis across both figures enhances the statistical credibility of the findings and establishes a strong case for the feasibility of motion detection using uplink SNR data collected from standard 5G network parameters.

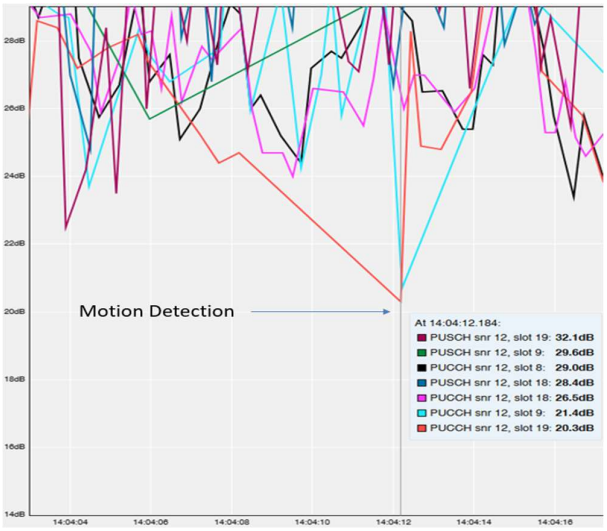

Figure 4: SNR variation during motion near the receiver

Figure 5 corresponds to a scenario where a person obstructs the signal for approximately 20 seconds (from around 14:04:14 to 14:04:34), the Downlink MCS (purple) experienced a sharp decrease from approximately 10–12 to nearly 0. The Uplink MCS (red) remained relatively stable. The Rank Indicator (RI, blue), was shown consistently at a low value, also dropped to zero and recovered alongside the Downlink MCS, indicating the impact of blockage on the number of useful transmission layers.

In order to quantify the correlation between the SNR, MCS, and CQI parameters, a Pearson correlation coefficient analysis was conducted. The Pearson coefficient r between two variables X and Y is mathematically expressed as:

$$r_{X,Y} = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}}$$

Where X and Y denote the mean values of $\overline{X}, \overline{Y}$ respectively, and n is the number of samples. In the presented scenario (Figure 5), time-synchronized samples of Downlink MCS, Uplink MCS, and associated SNR values were collected. By applying the Pearson correlation formula, a strong positive correlation was observed between SNR and MCS values, with a Pearson coefficient of approximately r = 0.92, indicating a 92% linear relationship between signal degradation and transmission quality adaptation during human motion events (table 3).

Metric	Mean (μ)	Standard Deviation (σ)	Min	Max	Units
SNR	23.6 dB	2.1 dB	17.7	30.4	dB
DL MCS	9.5	3.2	0	12	(Index)

Table 3: Summary of time-synchronized SNR and MCS samples collected during the motion event in Figure 5

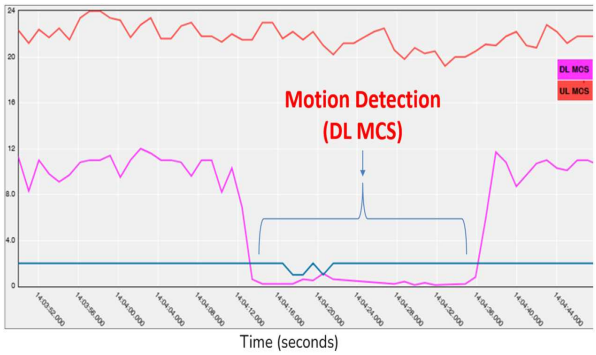

Figure 5: Downlink MCS decreases from 10-12 to 0

Figure 6 highlights a significant reduction in CQI (yellow), indicating a degradation of the communication channel. Subsequently, a decrease in MCS (orange) was recorded, representing the system's adaptation to maintain link reliability. The SNR (red) exhibited a transient increase, attributed to an attempt to enhance signal strength, before trending downwards in conjunction with CQI and MCS to confirm motion detection.

To further quantify the relationship between signal quality and link adaptation mechanisms, a Pearson correlation coefficient analysis was also applied to the CQI and SNR parameters. As with the MCS–SNR study, time-synchronized samples of CQI and SNR were collected over the duration of the observed motion event in Figure 6. The Pearson correlation coefficient r was computed according to the formula:

$$r_{X,Y} = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2 \sum_{i=1}^{n}(Y_i - \overline{Y})^2}}$$

Where X and Y represent the sampled values of CQI and SNR, respectively, and n is the number of data points. The resulting correlation coefficient revealed a moderately strong positive linear relationship, with $r \approx 0.84$, indicating that 84% of the variance in CQI can be explained by the corresponding SNR values under the influence of motion-related disturbances (table 4). This supports the assertion that CQI reacts sensitively to dynamic changes in signal conditions, further validating its utility as an indicator for motion detection within 5G environments.

Metric	Mean (μ)	Standard Deviation (σ)	Min	Max	Units
SNR	24.1 dB	2.7 dB	17.7	30.4	dB
CQI	9.8	2.2	0	14	(Index)

Table 4: Statistical summary of the CQI and SNR samples used for Pearson correlation analysis.

In addition, log-based variations were also observable during periods of active motion detection. A key point to highlight is that CQI, MCS, and SNR values were monitored continuously in real time and recorded both as graphical outputs and in structured log formats. These logs can be further utilized by being fed into AI or machine learning models, with the goal of optimizing motion detection accuracy through automated classification and prediction mechanisms. This capability introduces the potential for future enhancements in non-intrusive, real-time sensing applications over commercial 5G networks using standard radio interface measurements.

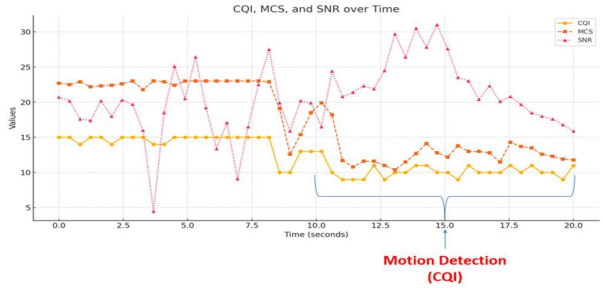

Figure 6: Significant reduction in CQI

V. Conclusion

This study investigated the feasibility of detecting human motion by monitoring variations in 5G signal quality metrics within a controlled indoor environment. Rather than employing specialized sensors or custom hardware, a standard mobile phone and a 5G callbox were used. Real-time signal data were captured through the system's built-in tools, confirming that motion detection can be achieved with minimal infrastructure. Significant sensitivity to environmental disturbances was consistently observed in the behavior of SNR, CQI, and MCS values. Specifically, SNR was found to decrease by up to 31.9% during motion events, and in more severe cases, drops exceeding 41.5% were recorded. Downlink MCS values were observed to fall sharply from 10–12 to nearly zero during LOS obstruction. A Pearson correlation coefficient of 0.92 between SNR and MCS, and 0.84 between SNR and CQI, demonstrated strong and consistent relationships between signal degradation and link adaptation. These results validate the use of standard 5G metrics as reliable indicators for passive motion detection. Future work will focus on the visualization of RSSI values through the callbox's remote APIs and a deeper investigation into other signal metrics is planned to boost accuracy and the overall system efficiency.

Currently, a range of configuration parameters is under evaluation, including the comparison of FDD and TDD, FR1 and FR2 frequency bands, and various MIMO configurations (such as 2x2 and 4x4), in conjunction with adjustments to bandwidth, to determine their effects on overall system efficacy.

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