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Through-Wall Multi-Human Detection and Localization using Ultra-Wideband Impulse Radar (UWB-IR)

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Abstract

Efforts to maximize the ability of Ultra-Wideband Impulse Radar (UWB-IR) technology to detect human presence through walls have progressed for years. This study optimized the human-detection capability of UWB-IR for people counting and localization behind walls through signal-processing techniques. These techniques include Clutter Suppression, Noise Reduction, Filtering, Digital Downconversion (DDC), Frame Differencing, Peak Detection, and Clustering. The system was evaluated across 15 unique test scenarios involving human subjects positioned behind walls made of plywood and concrete. Accuracy was assessed by comparing the estimated number of people and their positions with ground-truth data. The average count accuracy for both plywood panel and concrete wall is relatively high, with an overall percentage accuracy of maximum percentage error of 16%. In contrast, distance estimation is better for plywood panel, with a maximum percentage error of 10.85%. Overall, this study achieved Multi-Human Detection, People Counting, and Human Localization with an average accuracy of at least 92.11% across all delimitations considered.

Keywords: human localization, multi-human detection, people counting, through-the-wall sensing, ultra-wideband impulse radar

1. Introduction

Human detection and sensing behind obstacles and through walls have been of great interest over the years, particularly in medical monitoring, military applications, positioning, search and rescue, law enforcement, security and surveillance, and consumer analytics. A wide array of technologies has been developed to address these needs, including Wi-Fi-based systems, motion and pressure sensors, and thermal imaging (Teixeira *et al.,* 2010). Among these technologies is the radar systems, particularly Ultra-Wideband (UWB) radar, which are widely recognized for their capability to detect human presence and vital signs through walls without requiring physical contact or a direct line of sight (Li *et al.*, 2021).

Radar systems operate by transmitting electromagnetic waves that reflect off objects and return to the source (Revankar *et al.*, 2017), enabling detection of presence, position, movement, and, in some cases, physiological signals such as respiration and heartbeat (Uzunidis *et al*., 2024). The UWB radar is wireless high data rate transmission technology of extremely wide bandwidth, that provides a safe, low power, low system complexity, non- contact, non-invasive detection of body networks (Zhao *et al.*, 2017). These features make it especially suitable for non-invasive, non-contact detection in complex environments, including through-wall scenarios (Perotoni *et al.*, 2024).

Initially developed for military applications due to its ability to "see through" trees and underneath ground surfaces (Liang *et al.*, 2018), UWB radar has since evolved into a versatile tool for civilian use, including indoor localization, victim detection in disaster zones, and building health diagnostics (Perotoni *et al*., 2024).

Despite these advances, challenges remain in extending UWB radar applications to multi-human detection and real-time localization behind varying wall materials such as wood and concrete. These capabilities are crucial in emergency and search-and-rescue operations, where timely and accurate information about human presence can save lives (Zhang and Xia, 2016). Thus, this study aims to develop a system for multiple human detection and distance estimation through walls using Ultra-Wideband Impulse Radar (UWB-IR) and to evaluate its performance under varying wall conditions.

2. Methodology

2.1 Conceptual framework

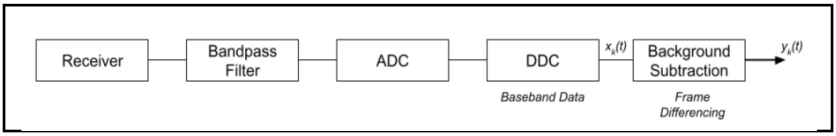

Figure 1. Block diagram of the system implementation

The raw data is acquired from a Xethru X4M06 UWB-IR transceiver directed at a defined number of human subjects positioned behind a wall. These received signals consist of both target reflections and unwanted echoes from static objects in the testing environment, such as walls, ceilings, beams, and furniture. These static components, collectively referred to as clutter, are suppressed via background subtraction to isolate the dynamic elements associated with human presence (Sharma *et al.,* 2017).

The output radar data are then subjected to a signal-processing chain using the devised algorithm, which includes a Bandpass Filter, Clutter Removal and Noise Reduction, Digital Downconversion, Background Subtraction (Frame Differencing), Peak Detection, and clustering.

The overall signal processing is described in Figure 1, where the downconverted baseband signal $x_k(t)$ undergoes frame differencing to remove motion-induced changes, yielding $y_k(t)$, which is then analyzed for peak signatures corresponding to individual human reflections. These peaks are subsequently clustered based on distance and amplitude to confirm a human presence behind a wall and estimate both the number of people present and their respective distances from the radar. This conceptual framework is shown in Figure 2.

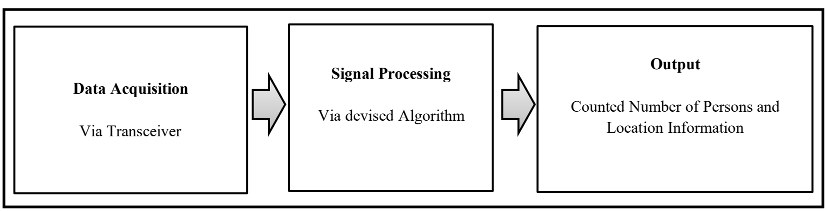

Figure 2. Conceptual framework of the study

2.2 Experimental Setup

This study comprises 15 distinct experimental setups, each with varying numbers of participants, inter-subject spacing (denoted as distance R), and the distance between the wall and the participants. For each setup, the UWB-IR transceiver is positioned at two fixed distances from the wall: 0.5 m and 1.0 m. Tests were conducted across two wall types—plywood panel and concrete—to evaluate system performance under different material conditions.

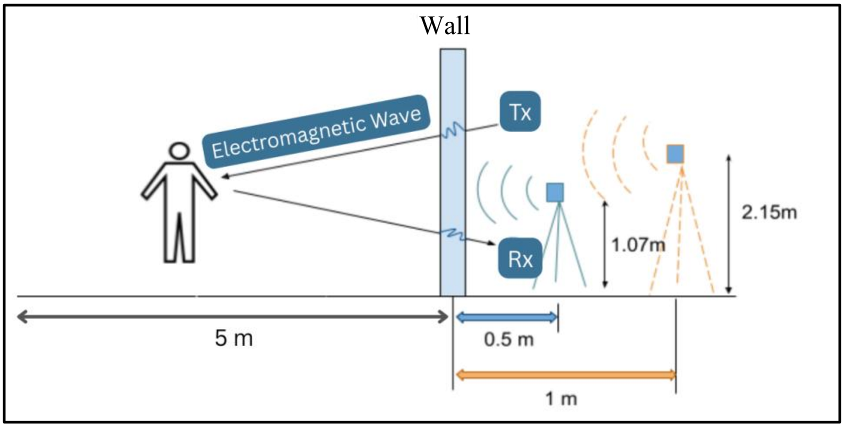

Figure 3. Physical setup of the study

As shown in Figure 3, the device is set up at two different heights and distances from the wall, with respect to its angle of elevation and azimuth of 65 degrees (as described in Table 1). At a 0.5 m distance from the wall, the device was elevated at 1.072 m, and at a 1.0 m distance, it was set at 2.145 m. The effective detection range was limited to 5.0 m behind the wall; therefore, any echoes received beyond 5.0 m will be considered false detections, based on the initial testing results discussed in the scope and delimitation. For human localization, the minimum distances between one person and another, and between one person and the wall, are set to 0.5 m to ensure distinct radar reflections.

2.3 Analysis of Signal

To accurately detect human presence and remove clutter from the received signal, conventional frame differencing, a background-subtraction technique, is employed, as shown in Figure 4. The difference plot in Figure 5 shows that the amplitude of the static reflections is significantly reduced, if not eliminated, after frame differencing. This subtraction process yields the data y_{dif} for peak detection and clustering.

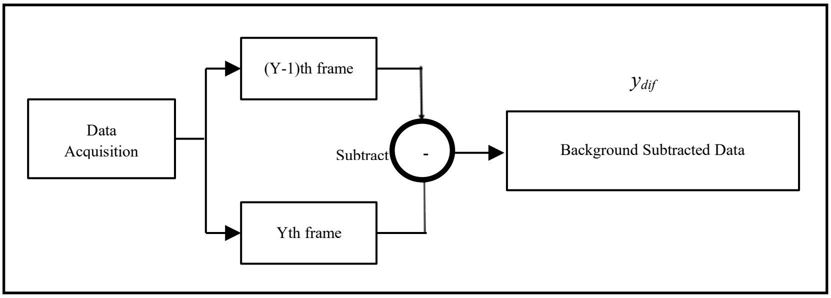

Figure 4. Data subtraction flow

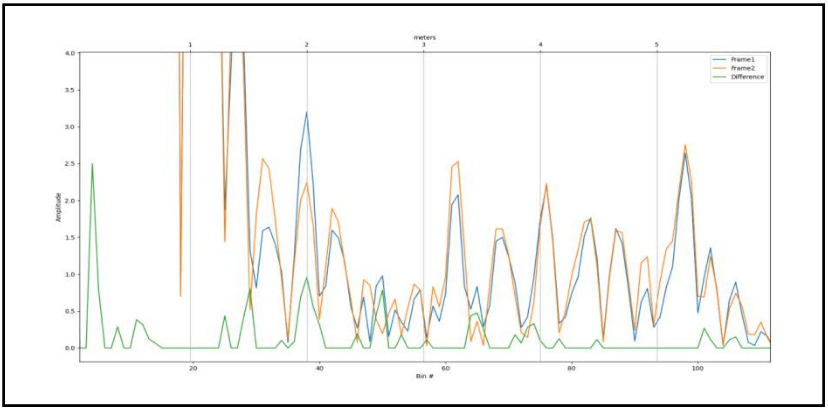

Figure 5. Frame difference plot

The output data y_{dif} is processed using the proposed Multi-Human Detection Algorithm, which is adapted from the method presented in (Choi *et al*., 2017), as illustrated in Figure 6. Unlike the original approach, this study performs peak detection on y_{dif} prior to applying the clustering procedure.

Peak detection was applied to identify candidate reflections indicative of human presence. Peaks are identified inside a signal based on the defined peak properties set. By comparing the surrounding values of any sample whose two direct neighbours have a smaller amplitude, a peak or a local maximum is identified. For flat peaks (more than one sample of equal amplitude wide), the index of the middle sample is only returned. This step will return all the peaks of possible human presence and store it in another 1-D array. This array will contain the amplitude of each peak and its corresponding distance in meters.

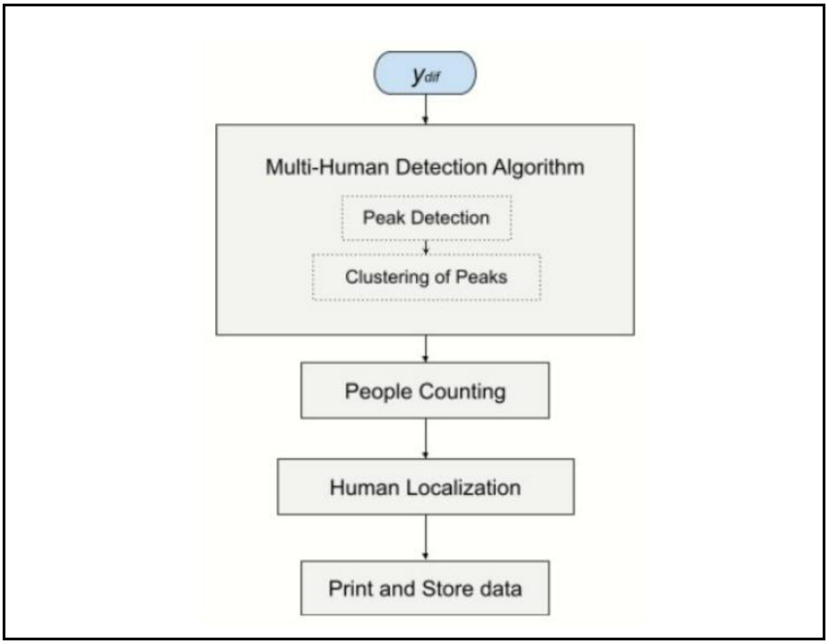

Figure 6. Signal analysis flowchart

To improve detection accuracy and minimize false positives caused by residual noise and multipath effects, the identified peaks were further processed using a rule-based clustering technique. This approach groups reflections using calibrated amplitude and distance thresholds specific to wall types and compensates for signal attenuation with distance.

While the clustering algorithm is deterministic, its operation is conceptually similar to density-based methods such as DBSCAN, as it effectively isolates valid targets without requiring prior knowledge of the number of human subjects (Wu *et al*., 2022).

2.4 Ground Truth Validation

To validate system output, participant locations were predefined using floor markers placed at known intervals. Manual annotations were used to compare estimated distances, and detection counts with actual ground truth, allowing computation of localization error and detection accuracy. The percent accuracy *%A* was calculated using Equation 1 as:

$$\%A \;=\; 100 = \left|\frac{Tv - Ov}{Ov}\; x\; 100\right| \tag{1}$$

where *Tv* is the theoretical value and *Ov* is the observed value.

This process ensured objective performance evaluation, in line with recent validation practices in UWB-based human sensing studies (Li *et al*., 2021; Perotoni *et al*., 2024).

2.5 Graphic User Interface (GUI)

A simple Graphic User Interface (GUI), as shown in Figure 7, was used for this study to show the signal graph, number of people counted and their detected locations. The graph shows the frame difference between two signals, and the peaks in red dots are the points where people are located.

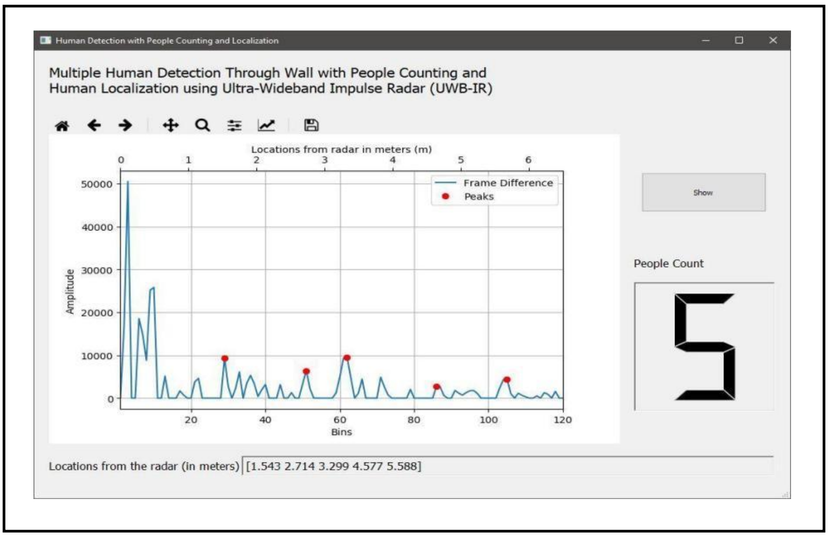

Figure 7. Simple graphic user interface of the study

3. Results and Discussion

3.1 Experimental Setup

To test the performance of the presented method, several experiments are carried out in different arrangements of people behind a wall. The experimental setup parameters for the experiments are shown in Table 1. These parameters remained the same throughout all the test cases.

Table 1. Experimental setup settings

Parameters	Value
Sampling Rate	23.238 GS/s
Frequency Band	6 to 8.5 GHz
Center Frequency	7.29 GHz
Pulse Repetition Frequency (PRF)	15.1875 MHz
Radiation Power	68.85 μW
Antenna	Directional patch
Opening Angle	65 degrees azimuth and elevation
DAC Range	150 (min=949, max=1100)
Pulse per step	26
Frames per second	10
Iterations	64
Duty Cycle	95%

Figure 8 shows the experiment environment with the used radar module, both implemented in a concrete and a plywood panel. In these setups, we collected experimental data on the number of people present and their distance information behind the wall.

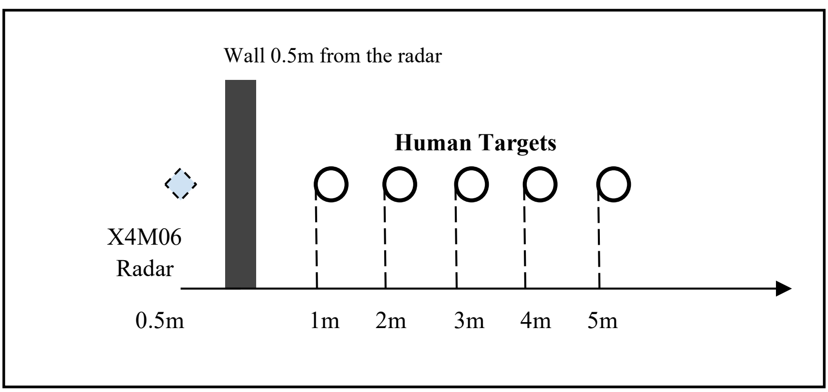

Figure 8. Sketch map

3.2 False Alarm and Missed Detection

False alarm happens when the devised algorithm detects a peak and identifies it as a human presence when there is none. Conversely, missed detection happens when the devised algorithm finds no peak reflection when there is an actual person present.

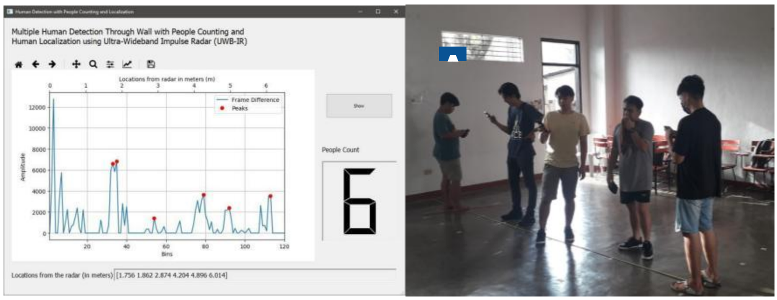

Figure 9. False alarm in GUI result and actual setup arrangement

Observing Figure 9, the first two peaks are detected for person A. This is because person A had moved around five (5) bins from his original standing position. This created a noticeable displacement, thus resulting in a thicker width and two peaks for the same person. It was later discovered upon reviewing the video recording during the testing process.

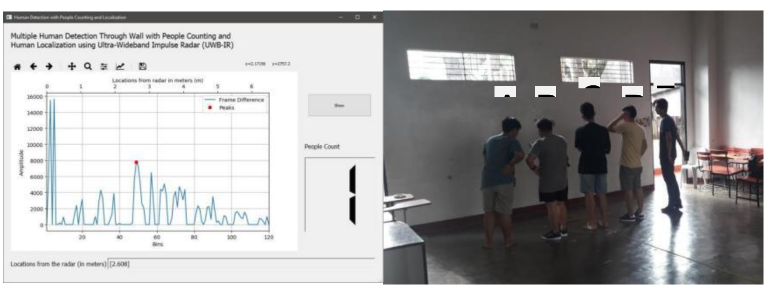

Figure 10. Missed detection in GUI result and actual setup arrangement

In the missed detection instances shown in Figure 10, the locations of the other four (4) participants are not detected because all five (5) persons are positioned at the same distance from the radar. As a result, only a single peak is observed.

This suggests that when multiple people occupy the same range from the radar, the detection won't be as accurate as in cases where individuals are at distinct distances.

3.3 People Counting

People counting is most accurate when individuals are located at different distances from the radar, when there is a maintained vertical distance of at least 0.5 m from the radar, when participants are standing and arranged from a distance of not less than 0.5 to the wall, and when participants stayed at rest and maintained minimal movements. Table 2 shows that the detection behind a Plywood Panel achieved an accuracy of not less than 85%, while a Concrete wall achieved an accuracy of not less than 84%. Overall, the performance error of People Counting shows a maximum percentage error of 16%.

Table 2. Comparison of count accuracy for two types of walls

Set	Manual Count	Wood				Concrete			
		0.5m		1m		0.5 m		1m	
		Detected Count	Accuracy (%)	Detected Count	Accuracy (%)	Detected Count	Accuracy (%)	Detected Count	Accuracy (%)
A	1	1	100	1	100	1	100	1	100
B	2	2	100	2	100	2	100	2	100
C	2	2	100	2	100	2	100	1	50
D	3	3	100	2	66.67	3	100	2	66.67
E	3	2	66.67	2	66.67	2	66.67	3	100
F	5	5	100	4	80	5	100	4	80
G	5	2	40	2	40	1	20	3	60
H	5	4	80	5	100	1	20	4	80
I	5	5	100	4	80	5	100	3	60
J	5	5	100	5	100	5	100	4	80
K	5	4	80	4	80	5	100	6	120
L	5	4	80	4	80	5	100	5	100
M	5	4	80	5	100	5	100	5	100
N	5	5	100	5	100	4	80	4	80
O	5	4	80	4	80	5	100	4	80
Average Accuracy		87%		85%		86%		84%	

3.4 Human Localization

The distance estimation behind a Plywood Panel achieved an accuracy of not less than 92.73%, while a Concrete wall achieved an accuracy of not less than 89.99%. Overall, the performance error of Human Localization shows a maximum percentage error of 10.85%.

As seen from the results in Table 3, the location estimation achieved better accuracy when tested behind a plywood panel than a concrete wall. Just as how the conditions stated in the counting affect the performance of the people counting, it was also evident in the results of distance estimation.

Table 3. Comparison of distance accuracy for two types of walls

Set	Plywood Panel		Concrete	
	0.5m	1m	0.5m	1m
A	92.11	92.42	93.21	93.96
B	96.32	98.88	95.32	93.38
C	95.95	96.37	93.10	94.65
D	96.25	65.33	96.75	64.83
E	96.84	93.88	81.50	95.37
F	96.00	78.75	96.14	76.21
G	99.55	98.73	97.89	98.70
H	97.74	98.09	77.24	95.78
I	97.43	77.51	81.05	73.67
J	94.85	97.49	88.41	95.44
K	77.12	78.28	95.60	95.02
L	95.17	95.86	85.62	97.83
M	95.01	94.76	90.80	92.82
N	96.21	95.70	82.43	97.77
O	96.38	96.86	82.20	97.03
Average Accuracy (%)	94.86	90.59	89.15	90.83
	92.73 %		89.99 %	

While the system achieved promising localization accuracy, several error sources were identified. Multipath reflections can distort true location estimates, especially in metallic or cluttered environments. Additionally, interference from other RF sources may introduce spurious detections. To mitigate these, the radar was positioned at a height of 1.2 m to minimize ground and ceiling reflections, and experiments were conducted in controlled intervals to reduce RF interference.

4. Conclusion and Recommendation

This study presents an effective framework for detecting, counting and localizing multiple humans through two types of walls (plywood panel and concrete) using Ultra-Wideband Impulse Radar (UWB-IR) technology. By combining band-pass filtering, background subtraction, peak detection, and rule-based clustering techniques, the devised algorithm achieves an overall high detection accuracy of 92.11% at all delimitations considered, while mitigating environmental clutter and multipath interference. The experimental results demonstrate the capability of the proposed method to distinguish up to five human targets behind a plywood panel and a concrete wall with minimal localization error.

With these conditions, it has been found that the devised algorithm yields best results when the wall used was a plywood panel for a range up to five (5) meters from the radar. Moreover, both the count and distance estimation are accurate when persons do not share the same distance from the radar, when there is a maintained vertical distance of at least 0.5 m from the radar, and when participants are standing and arranged from a distance of not less than 0.5 m to the wall. System performance is also enhanced when subjects remain stationary with minimal movement, reducing signal variability and overlap in radar reflections.

Table 4. Performance Summary of the Proposed System

No. of Subjects	Detection Accuracy	False Alarm/Missed Detection Rate	Localization Error
1	97.0%	1-2%	0-7.73%
2	94.5%	2-3.5%	2.4-3.84%
3	92.0%	3-5%	4.64-19.21%
5	88.5%	5-6.5%	0.86-22.30%

As seen in Table 4, the system maintained a high detection accuracy across all test scenarios, with a peak of 97% for single-subject detection and 88.5% for five subjects. As the number of subjects increased, both the false-alarm and missed-detection rates increased slightly, indicating a mild degradation in performance in more complex scenarios. These results demonstrate the system's ability to detect multiple humans through obstructions such as walls, even as environmental complexity increases.

While the proposed system demonstrates high accuracy in through-wall multi-human detection, post-processing was time-consuming because of the complexity of evaluating 15 distinct test setups with varying parameters (e.g., person-to-person and device-to-wall separations). To improve scalability, adaptability, and operational efficiency, future work should focus on developing a more adaptive detection and localization framework through the integration of machine learning techniques, reducing reliance on manual processing and enabling the system to handle a greater number of subjects and more complex environments.

Further validation in diverse settings, including different wall materials, occlusions, and room layouts, is also recommended to assess system robustness under realistic conditions. Additionally, enabling real-time detection by reducing the current 10-second frame interval would enhance applicability in time-sensitive scenarios such as search and rescue. Explore hardware improvements, including the utilization of the 16-pin I/O interface of the X4M06 and the incorporation of additional antennas, may further enhance signal quality and spatial coverage.

Lastly, given that this is one of the initial attempts to integrate UWB-IR for through-wall multiple-human detection, these recommendations will help transition the proposed system toward a real-time, robust, and deployable solution suitable for emergency response and other indoor sensing applications.

5. Acknowledgement

We would like to give our deepest gratitude to the volunteer participants who wholeheartedly gave their time and presence to take part in this study amid the COVID-19 pandemic. This study would not be possible without their selfless act of generosity.

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