Beyond 5G White Paper
Supplementary Volume
"Sensing Technologies"

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XG Mobile Promotion Forum

【Revision History】

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1.0	2024.3.7	Initial version	

Preface

In our published white paper “Beyond 5G White Paper ~Message to the 2030s~”, we researched what are required in various industries in the Beyond 5G era, then we proposed “Further enhancement of specific 5G features” as key features for Beyond 5G. To address these key features, Target Key Performance Indicators (Target KPI) for Beyond 5G have been derived, and as quantitative Target KPI related with “Sensing”, sensing accuracy/resolution with order of centimeter (and more) has been introduced, which is much higher than that with order of meters in 5G.

The Third Generation Partnership Project (3GPP) has initiated discussions on Integrated Sensing and Communication (ISAC) for the secondary use of radio waves. Defined use cases include the detection of human and animal intrusions in indoor/outdoor environments and understanding the status of automobiles and automatic guided vehicles. Sensing technologies utilizing radio waves have found widespread applications in detecting the distance and direction of objects, among other functionalities. With the current rapid advancements in Artificial Intelligence (AI) and Machine Learning (ML), their application scope continues to broaden, particularly in shape, motion, and gesture detections.

Sensing technologies can be considered in both aspects of Beyond 5G advancement through sensing as well as sensing with Beyond 5G. First, let us consider the sensing for Beyond 5G. Sensing of wireless environments in Beyond 5G wireless communications is performed while transmitting data, and making this sensing more accurate is essential for improving performances of the wireless communications. The sensing data obtained here can be used not only for the wireless communications, but also for various applications as mentioned above. Next, let us consider Beyond 5G for the sensing. The use of high-frequency radios including millimeter-wave and terahertz bands is also expected to realize high-precision spatial sensing and localization (including positioning) by taking advantage of their properties. Such sensing is provided by the wireless communications (fixed and movable base stations) and optical communications. A basic principle of the wireless sensing is to characterize the status and behavior of a target object as radio propagation characteristics in wireless channels; a Received Signal Strength Indicator (RSSI) and Channel State Information (CSI) are useful as feature information for the wireless sensing. CSI-based sensing is crucial for integrating communication and radar sensing. Many studies have shown its adaptability for various sensing tasks. However, the CSI-based sensing faces an open issue: how information in physical space (sensing environment) is reflected in CSI observations. To address this, further research is needed to better understand the relationship between the physical space and the CSI observations.

In addition to such wireless sensing, network architecture to collect and process large amounts of data from cameras, Light Detection And Ranging (LIDAR), and other sensors, as well as sensing of real space as a digital twin are also expected.

However, there are still major challenges in the practical implementations for the design and evaluation of ISAC as a core technology in the Beyond 5G system. First and foremost, a theoretical framework is necessary to analyze and evaluate the performance of current ISAC solutions to identify the benefits and any short comings. Current design of the ISAC system calls for the baseband and RF hardware to be functionally shared and as a trade-off, the impact of distortion parameters on sensing performance needs to be carefully considered. The challenge for the joint waveform design is the very different KPIs for communication and sensing where optimizing both might not be so straight forward.

ISAC in the mobile communication network provides great opportunities and benefits for synchronized multi-static sensing where the technology challenges here would lie in the synchronization to achieve the optimum fusion sensing results. Concretely, current Global Navigation Satellite System (GNSS) fail to provide pico-second level synchronization accuracy to base stations, and new space-time synchronization should be provided with that level of accuracy, enabling the phase-locked synchronization in the millimeter wave between the base stations.

To tackle these challenges and realize new use cases, there are a lot of research and development activities on the sensing technologies in Japan. In this white paper, these research and development activities and their results with a lot of figures are shown as follows:

- "CSI-Based Device-Free Sensing Using Deep Learning with 5G NR 28 GHz Band" describes an overview of device-free sensing technology, which detects target object without the need for mobile terminals, utilizing deep learning. It further introduces the effectiveness of this technology by experiments using a radio testbed equipped with the physical layer specifications of the 28 GHz-band 5G NR.

- "Indoor Experimental Evaluation of Device-free Localization Schemes Using Channel State Information in Distributed Antenna Systems" describes a real-time channel state information (CSI)-based device-free localization scheme for distributed antenna systems, where CSI feedback frames are collected and used as a dataset for machine learning (ML)-based localization. Experimental results confirms that the localization scheme is effective for detecting a target in an indoor environment.

- “CSI2Image: CSI-to-Image Conversion using a Generative Model” describes how to convert CSI observations into RGB images corresponding to physical space using generative adversarial network (GAN) architecture. The generated RGB images intuitively show the relationship between the CSI observations and the physical space, and potentially help us to extract many environmental parameters for multi-purpose sensing system.

- “Use Cases for CSI Sensing with an Example of Pedestrian Movement Direction Identification” describes use cases for CSI sensing from the perspectives of commercial products and the author’s research, and specifically the effectiveness of pedestrian movement direction identification as one of the use cases for CSI sensing is verified by experimental evaluation with ML.

- “Integrated Sensing and Communication (ISAC)” describes a concept of ISAC, typical use cases, and two case studies of how to use ISAC to improve localization accuracy and perform millimeter-level imaging at the THz band using future portable devices. The research challenges to implementing ISAC in practice are discussed.

- “Space-Time Synchronization” describes that synchronization must not only be limited to time but also extend to space, entailing the sharing (synchronization) of spatial coordinate axes. The space-time synchronization is realized by three basic technologies, namely compact atomic clocks, wireless time synchronization, and cluster clock systems, which are explained briefly.

In conclusion, as we embark on the journey towards Beyond 5G technologies, the sensing technologies emerge as one of key elements in this technological evolution. Japan's endeavor to overcome the challenges to realize the sensing technologies, coupled with its commitment to research and development in this domain, positions it at the forefront of this next-generation communication revolution. This white paper aims to provide a comprehensive overview of the potential, challenges, and future directions of the sensing technologies for Beyond 5G, with a particular emphasis on their initiatives and advancements in Japan.

This White Paper was prepared with the generous support of many people who participated in the White Paper Subcommittee. The cooperation of telecommunications industry players and academia experts, as well as representatives of various industries other than the communications industry has also been substantial. Thanks to everyone’s participation and support, this White Paper was able to cover a lot of useful information for future business creation discussions between the industry, academia, and government, and for investigating solutions to social issues, not only in the telecommunications industry, but also across all industries. We hope that this White Paper will help Japan create a better future for society and promote significant global activities.

Satoshi Suyama
NTT DOCOMO, INC.

I. CSI-Based Device-Free Sensing Using Deep Learning with 5G NR 28 GHz Band

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Abstract— **Integrated Sensing and Communication (ISAC) is gaining attraction as it aims to bring added value to next-generation mobile communication networks. This paper offers an overview of the device-free sensing technology, which detects target object without the need for mobile terminals, utilizing deep learning. It further introduces the effectiveness of this technology based on our experiments conducted on a radio testbed equipped with the physical layer specifications of the 5G (NR) 28 GHz band.**

I-1. Introduction

The Japanese Cabinet Office has advocated “Society 5.0” to realize a human-centered society that balances economic advancement with the resolution of social problems through a system that highly integrates cyberspace and physical space [1]. This system leverages artificial intelligence (AI) and machine learning (ML) to analyze vast amounts of sensor data as big data in physical space, providing feedback to humans in various forms. Sensor data plays a pivotal role in Society 5.0 and requires efficient and cost-effective integration into cyberspace. In response to this need, the Third Generation Partnership Project (3GPP) has initiated discussions on Integrated Sensing and Communication (ISAC) for the secondary use of radio waves. Defined use cases include the detection of human and animal intrusions in indoor/outdoor environments and understanding the status of automobiles and Automatic Guided Vehicles (AGVs) [2].

Sensing technologies utilizing radio waves have found widespread applications in detecting the distance and direction of objects, among other functionalities. With the current rapid advancements in AI/ML, their application scope continues to broaden, particularly in shape, motion, and gesture detections [3][4]. This paper specifically focuses on device-free sensing as a method for detecting target objects without the need for mobile terminals. It introduces a Channel State Information (CSI)-based device-free sensing method that achieves high-precision location detection of target objects through the application of a Deep Neural Network (DNN). Additionally, we demonstrate the performance of the proposed method through the results of an indoor experiment conducted on a radio testbed, equipped with the physical layer specifications of the 5G (NR) 28 GHz band [5].

I-2. CSI-based device-free sensing using DNN

As outlined in the reference paper [6], the integration of DNN into radio communication networks is advancing, with sensing technologies using radio waves being fundamental to this progress. This paper introduces a device-free localization method, utilizing a DNN capable of detecting the location of a target object without relying on mobile terminals [7][8]. Fig. I-1 depicts a system model wherein the detection of objects such as humans or cars and their states is accomplished through the analysis of radio waves between Beyond 5G (B5G) base stations (BSs). The training data for this system includes the target object locations and CSI between B5G-BSs, serving as the physical information. CSI, obtained through reference signals and similar means, is vital information for demodulation processing in radio communication networks. A prediction model for the DNN, developed through supervised learning based on recurrent neural network architecture, is constructed using the locations of target objects and CSI. Subsequently, the location of the target object is determined through the prediction model and the acquired CSI. This detected location information can be stored in cyberspace as sensor data, thereby contributing to the enhancement of radio communication network quality.

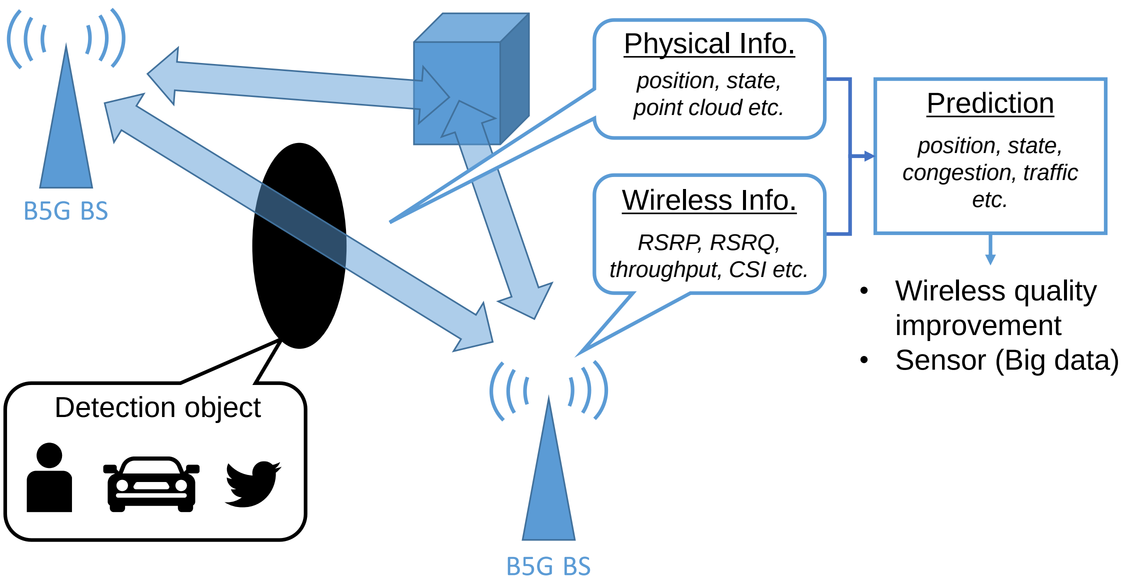

Fig. I-1 System model.

I-3. Experimental results

We demonstrate the effectiveness of CSI-based device-free sensing utilizing a 28 GHz radio testbed [5]. As depicted in Fig. I-2, the experimental setting comprises an indoor office with dimensions of 25 m × 15 m × 3.5 m and four columns. The radio testbed is configured to meet the physical specifications of 5G NR in the 28 GHz band, employing Multiple Input Multiple Output (MIMO) Orthogonal Frequency Division Multiplexing (OFDM) transmission with a 100 MHz bandwidth and a subcarrier spacing of 60 kHz. To enhance sensing accuracy, antennas for each BS are strategically distributed, as illustrated in Fig. I-2. The CSI for 6 × 2 MIMO-OFDM is acquired at 1-millisecond intervals through reference signals exchanged between BSs. The target object in this experiment is a human body phantom adjusted to match the dielectric constant of an actual human body in the 28 GHz band. Moreover, the phantom is mounted on an AGV for automated movement within the designated area, facilitating precise location information acquisition.

Fig. I-3 shows the cumulative distribution of the distance error between the detected location obtained from the proposed DNN-based method and the actual location. The predictive DNN model incorporates pre-acquired location information of the human body phantom and CSI from the BS. This figure highlights that the median location error for the human body phantom is approximately 0.6 m, with a root mean squared error (RMSE) of 1.1 m. While previous studies have demonstrated the effectiveness of location detection using Wi-Fi within sub-6 GHz bands, these results affirm the feasibility of location detection in the 28 GHz band.

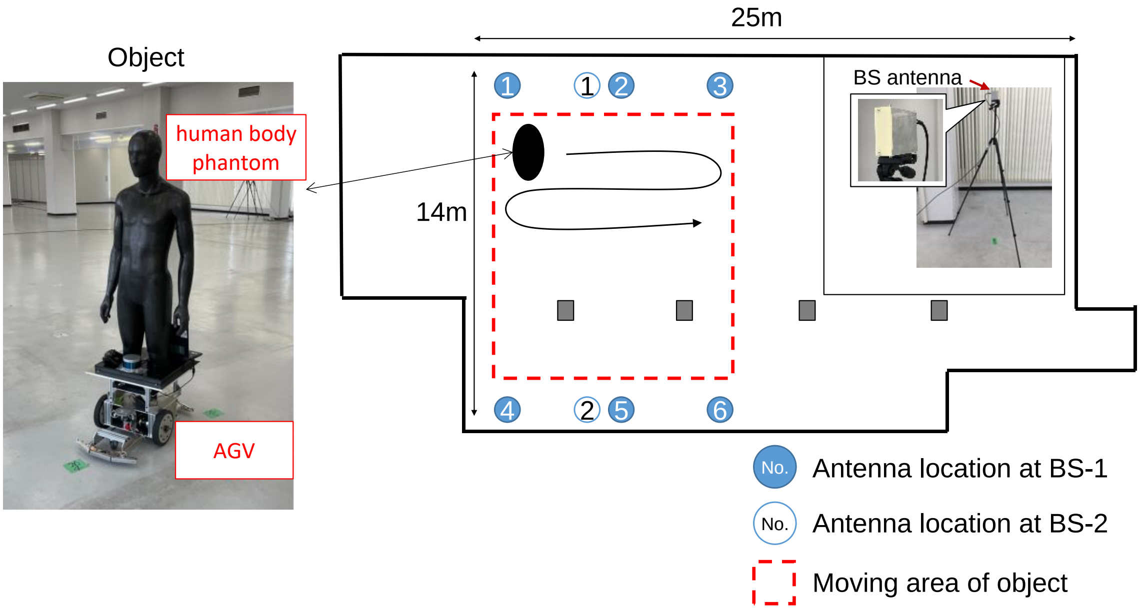

Fig. I-2. Experimental environment.

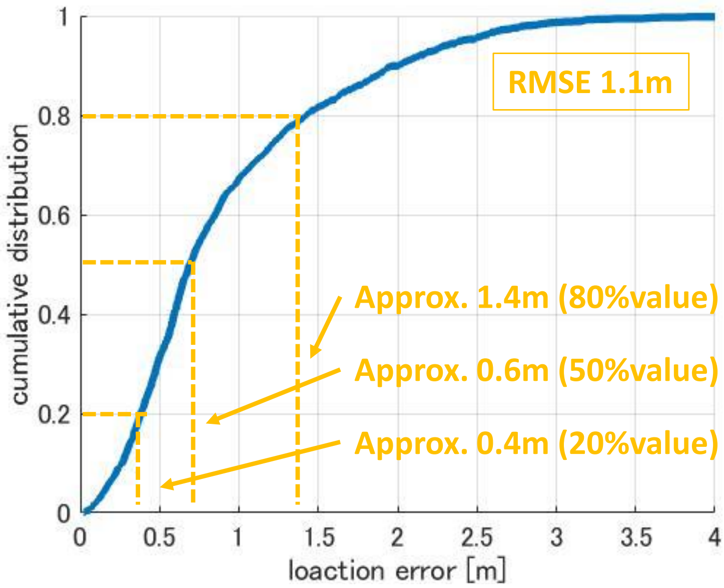

Fig. I-3. Experimental results.

I-4. Conclusion

This paper outlines the CSI-based device-free sensing method for detecting a target object without the need for mobile terminals. Furthermore, we demonstrated the feasibility of achieving 1-meter-class localization through indoor experiments conducted on a radio testbed equipped with the 5G (NR) 28 GHz band. In the future, we intend to validate its application in outdoor scenarios and explore the detection capabilities for multiple objects.

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II. Indoor Experimental Evaluation of Device-free Localization Schemes Using Channel State Information in Distributed Antenna Systems

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***Abstract*—Wireless communication system-based localization techniques that use channel state information (CSI) have attracted much attention. Performance of the CSI-based localization schemes depends strongly on the selected feature information and antenna placement. Herein, we present a real-time CSI-based device-free localization scheme for distributed antenna systems, where CSI feedback frames are collected and used as a dataset for machine learning (ML)-based localization. Experimental results confirmed that the developed localization scheme is effective for detecting a target in an indoor environment. We also discuss how much performance improvement can be expected when antenna placement is given properly.**

II-1. Introduction

Wireless sensing is a key technology supporting the evolution of wireless communication for Beyond-5G and 6G networks [1]. The basic principle of wireless sensing is to characterize the status and behavior of a target object as radio propagation characteristics in wireless channels; a received signal strength indicator (RSSI) and channel state information (CSI) are useful as feature information for wireless sensing. Recently, indoor device-free object detection approaches using radio signals of existing wireless communication infrastructure, have been investigated [2]-[7], where large amounts of CSI in the frequency and spatial domains are acquired simultaneously using multi-input multi-output (MIMO) transmission with orthogonal frequency division multiplexing (OFDM). In [5]-[7], IEEE802.11ac-based wireless local area network (WLAN)-based device-free indoor object detection schemes were proposed, by which CSI feedback frames in WLANs were collected and analyzed to detect a target object and its behavior. However, the performance achieved by the CSI-based approaches depends strongly on the antenna placement and the surrounding propagation environment.

This paper introduces our recent studies of wireless communication system-based indoor device-free localization where feedback beamforming weights are used as effective feature data for machine learning (ML)-based object detection and localization. Experiment results demonstrate that our developed algorithm works well with small datasets in an indoor environment when distributed antenna placement is accomplished properly.

II-2. CSI-based localization approaches

Fig. II-1 presents an illustration of the principles of device-free localization in wireless communication systems where the CSI between the base station (BS) and the terminal is affected by the target presence. Consequently, it is expected to detect the target by learning the relation between the states of the target and of the wireless channel without requiring that the target have wireless devices. However, a challenging hurdle is acquisition of a sufficient amount of CSI from environments. An effective method is to use CSI in existing WLAN systems [5].

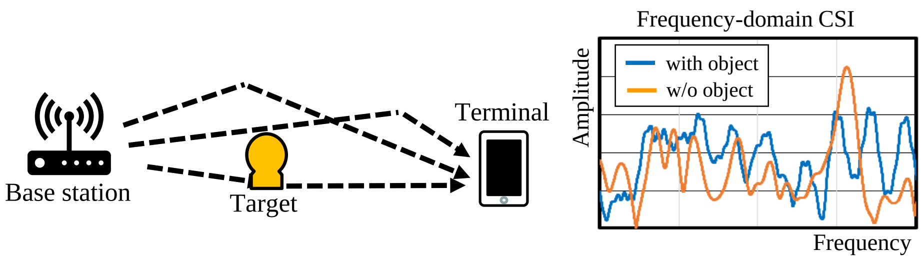


Fig. II-1. Principles of device-free localization using CSI.

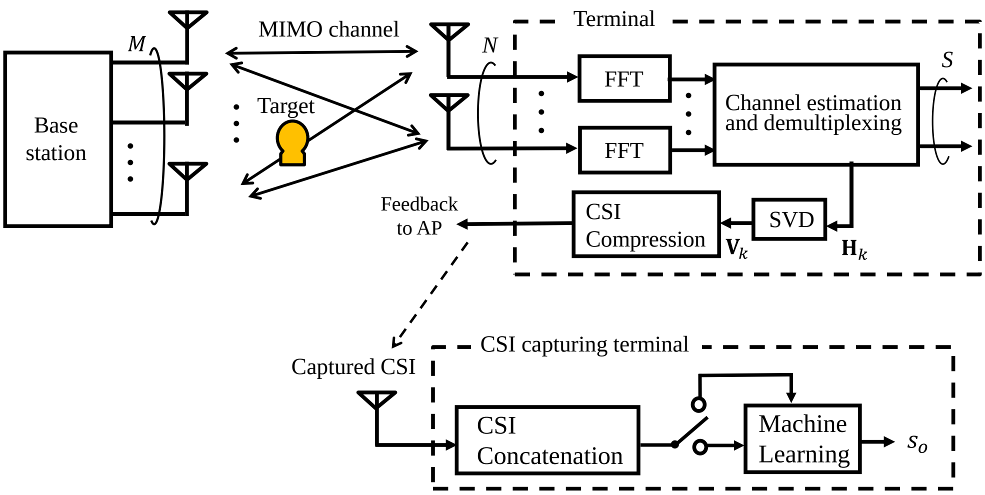
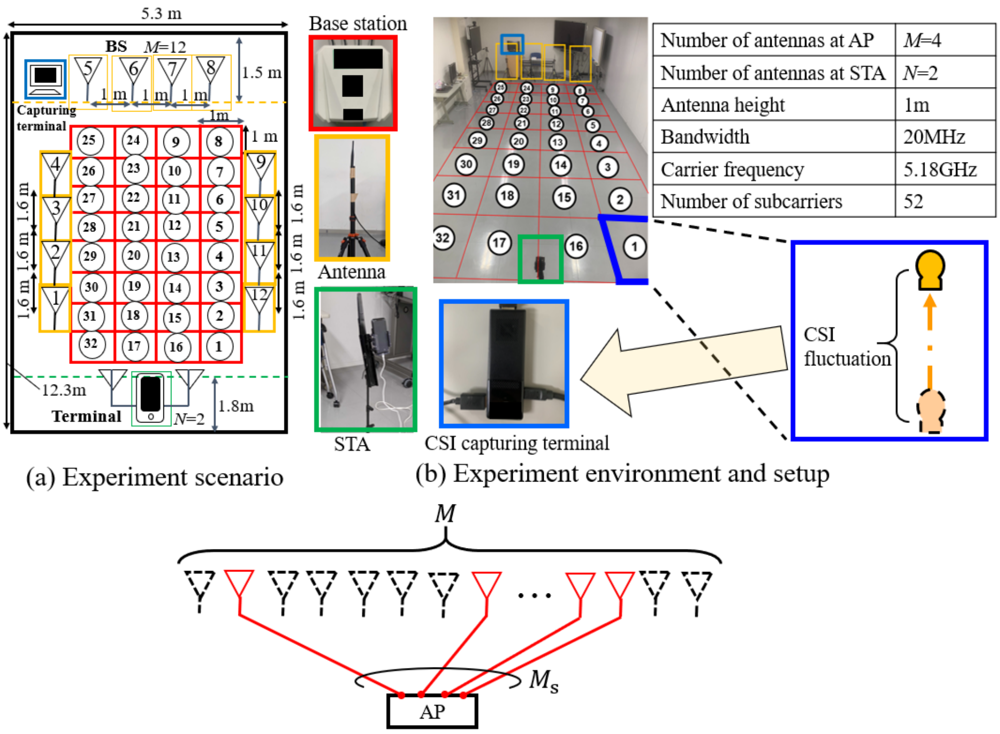


Fig. II-2. Block diagram of the device-free object detection system.

Fig. II-2 portrays a block diagram of the object detection and localization system consisting of an BS, a terminal, and a CSI-capturing terminal, where M, N, and S respectively denote the numbers of transmit antennas, received antennas, and streams. On the terminal side, after channel estimation, a compressed version of a right-singular matrix obtained by singular value decomposition of the channel matrix is fed back to the BS side as beam-forming weights (BFWs). After the CSI-capturing terminal collects feedback frames sent by the terminal, it extracts the compressed CSI samples and uses them for ML-based localization [5]-[7]. To improve the localization performance, we developed an effective lightweight algorithm with a small dataset [6], where current and past BFWs are concatenated as single data to build more accurate feature data. In addition, a frequency-domain sampling-based CSI compression [6] is adopted to minimize the dataset and the required complexity. After applying frequency-domain sampling and concatenating multiple BFWs as single feature data, they are used for both off-line training and for on-line detection.



(a) Experiment scenario (b) Experiment environment and setup

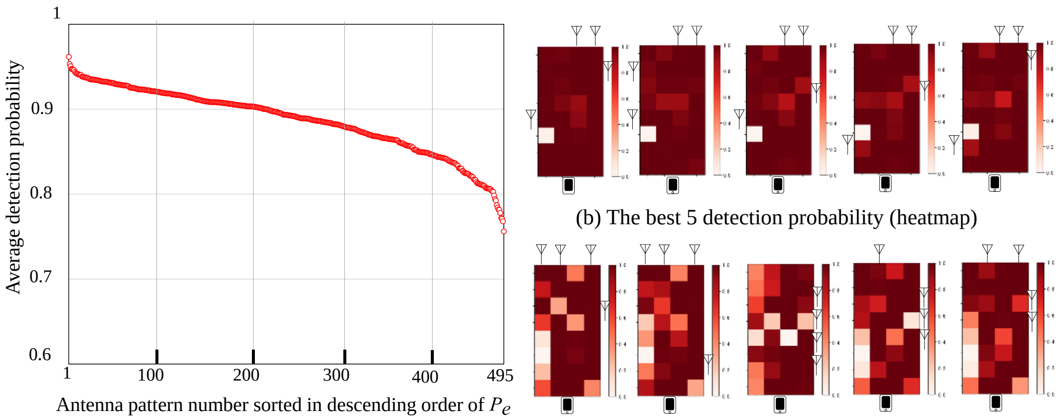
(c) Distributed antenna selection for wireless localization

Fig. II-3. Experiment scenario and setup.

II-3. Experiment scenario and results

To clarify the effectiveness of the developed algorithm in a real environment, we conducted experimental evaluations of indoor localization with the developed algorithm. The experiment scenario and setup using IEEE802.11ac-based WLAN [8] are depicted in Fig. II-3. Details of the experiments are presented in an earlier report of the relevant literature [7]. The detection area is divided into R regions labeled as 1, …, R=32. For this experiment, we consider a multi-class classification problem to detect the location (label) of a single target object. Random Forest model is used and built by off-line training with measured CSI. We evaluate the detection probability, which is defined as a conditional probability that the ML result is the same as the actual label number where a target person is located in one of the R=32 labeled areas. In this scenario, the detection probability is evaluated when a few (M_s=4) antennas are selected among numerous distributed antennas (M=12) to elucidate the relation between antenna placement and the detection probability.

Fig. II-4 (a) presents the detection probabilities for all possible antenna patterns where M_s=4 antennas are selected among M=12. The total number of antenna combinations is 495. The horizontal axis index shows the antenna pattern numbers sorted from left to right in descending order of the average detection probability. The result indicates that about 20-point performance improvement can be confirmed for the antenna patterns with the maximum (best) and minimum (worst) detection probabilities. Heatmaps of the best 5 and the worst 5 area-wise detection probabilities are also shown respectively in Fig. II-4 (b) and Fig. II-4 (c). Results imply that a lower detection probability (better performance) tends to be obtained when the AP antenna positions are distributed.

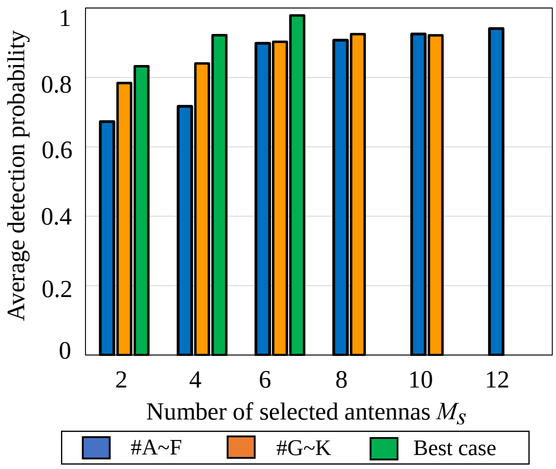


(a) Average detection probability for different antenna positions

(b) The best 5 detection probability (heatmap)

(c) The worst 5 detection probability (heatmap)

Fig. II-4. Average detection probability for selected antenna positions.



	Selected antenna numbers in Fig.3
A	(5, 6)
B	(5, 6, 7, 8)
C	(1, 2, 5, 6, 7, 8)
D	(1, 2, 3, 4, 5, 6, 7, 8)
E	(1, 2, 3, 4, 5, 6, 7, 8, 11, 12)
F	(1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12)
G	(3, 5)
H	(3, 5, 6, 12)
I	(1, 3, 5, 7, 10, 12)
J	(1, 3, 4, 5, 6, 7, 10, 12)
K	(1, 3, 4, 5, 6, 7, 8, 10, 11, 12)

Fig. II-5 Average detection probability in case of Ms = 2, 4, 6, 8, 10, and 12.

Fig. II-5 portrays the detection probability for a particular antenna placement in terms of the number of selected antennas. The table in the figure presents the selected antenna elements for each case, which corresponds to the antenna numbers in Fig. II-3 (a). This figure shows that distributing the antenna placement improves the localization performance, which consequently maximizes the average detection probability. Results indicate that the overall detection probability improves as M_s increases because M_s becomes greater, and because more features are used for ML-based localization. This finding implies that, if using the optimal antenna pattern for M_s=4 is possible, then average detection probability comparable to the case of M_s=12 can be achieved.

II-4. Conclusion

As described herein, we introduced a device-free localization scheme using concatenated CSI in wireless communication systems with distributed antennas. Experiment results demonstrate that the developed scheme works well with small datasets in an indoor environment scenario. Moreover, we have demonstrated that the antenna placement strongly affects the achievable localization performance in an indoor environment. Developing object detection algorithms with a more powerful ML model is left as a subject for our future work.

Acknowledgments

We thank Mr. Junsuke Izumi and Mr. Shunsuke Shimizu, master course students at Kyushu University, for their contributions to this research.

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III. CSI2Image: CSI-to-Image Conversion using a Generative Model

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***Abstract*—Wireless sensing studies based on channel state information (CSI) continue to be successful in various sensing tasks. However, we still have no clear answer to what extent we can extract the environmental parameters of physical space from CSI. We proposed CSI2Image to address such a challenging issue. It converts CSI observations into RGB images corresponding to the physical space using generative adversarial network (GAN) architecture. The generated RGB images intuitively show the relationship between the CSI observations and the physical space, and potentially help us to extract many environmental parameters for multi-purpose sensing system.**

III-1. Introduction

Wireless sensing is becoming an increasingly attractive sensing technique in Beyond 5G and 6G networks due to its potential to solve issues associated with conventional sensor-based sensing and its ability to provide extensive, precise, and non-invasive sensing. CSI based sensing is crucial for integrating communication and radar sensing. Many studies have shown its adaptability for various sensing tasks, including activity recognition [1], [2], vital signal sensing [3], [4], and localization [5], [6]. However, CSI based sensing faces an open issue: how information in physical space is reflected in CSI observations. To address this, further research is needed to better understand the relationship between physical space and CSI observations.

To tackle the challenging issue, this paper introduces CSI2Image [7]. It converts CSI observations in a more intuitive format, RGB images, allowing us to comprehensively understand how CSI reflects the physical space. CSI2Image generates images of the physical space from CSI observations using GAN architecture in an end-to-end manner. Experiments demonstrated that the well-trained CSI2Image can generate the snapshots of the physical space from the CSI observations by extracting rich information from them. In addition, thanks to the advancement of sophisticated image recognition techniques, we can extract the various properties of the physical space using the generated images and image recognition techniques.

III-2. CSI2Image

Fig. III-1 shows the overview of the proposed CSI2Image. The basic architecture is based on DCGAN [8], thus the models are trained in an adversarial manner: the generator aims to generate realistic images, while the discriminator tries to distinguish between real and generated images. The generator takes both CSI observations and latent variables from a standard normal distribution as input. In addition, it is assumed that we have a pair of time-synchronized CSI observations and images of the targeted physical space.

We experimentally confirmed that simply introducing DCGAN does not lead to satisfactory results. We proposed a unique training loop called "Hybrid Learning", which aims to ensure the generalizability of the networks for both image generation and real/fake determination, as well as obtaining the precise mapping from CSIs to the images. Fig. III-2 shows the three different training steps included in the Hybrid Learning. The first step is CSI2Image Learning, where the generator is supervised trained using CSI observation and their corresponding images, followed by Discriminator Learning, where the discriminator is trained with real images and generated images, but this time the generator generates images from random latent variables. Finally, after every K iteration, Generality Learning is triggered to update the parameters of networks and deceive the discriminator with the images generated by CSI observations. The generator acquires the mapping from the probability field of CSI to that of the image domain while avoiding overfitting to the training dataset through the combination of direct supervision and adversarial training. The training loop successfully displays the surrounding environment in the physical space containing in CSI observations in RGB images. To extract the properties of the physical space from the images, we can employ existing vision-based object detection techniques like YOLO [9] according to the task specification.

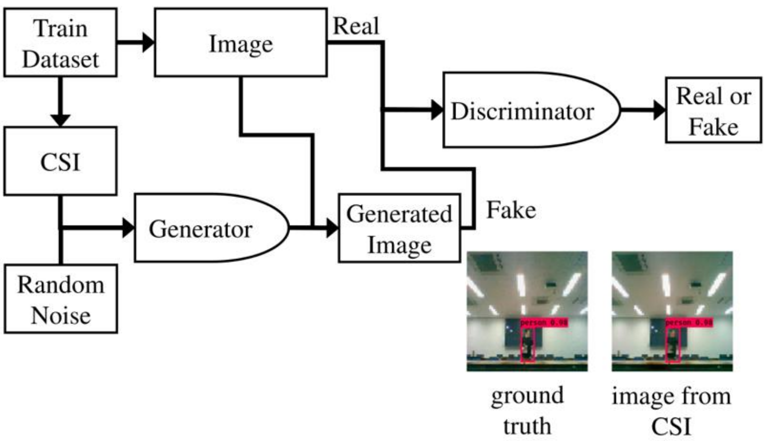
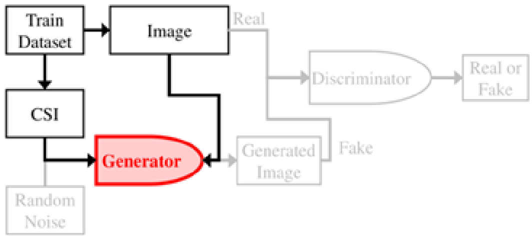
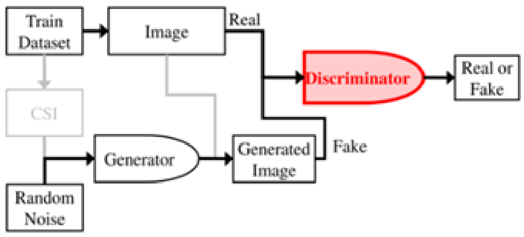


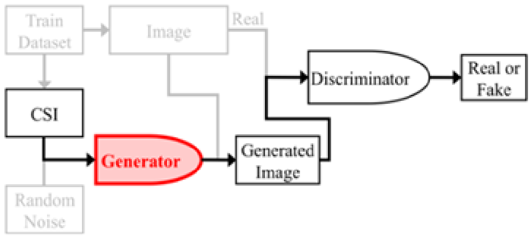
Fig. III-1. The overview of CSI2Image.



(a) CSI2Image Learning



(b) Discriminator Learning



(c) Generality Learning

Fig. III-2. The proposed hybrid learning.

III-3. Evaluation

To demonstrate the performance of CSI2Image to accurately generate RGB images of an indoor space from CSI observations and its performance in different sensing tasks, we conducted two experiments: object classification and human location classification. As shown in Fig. III-3, CSI2Image successfully generated the RGB images and achieved over 90% accuracy for both tasks. Especially for human location classification task, we compared the efficiency of our proposed Hybrid Learning compared to supervised learning only with the generator (gonly) and original DCGAN training scheme (gan). Experimental results show that Hybrid Learning outperforms the other two methods in terms of detection rate, similarity score between generated images and ground truth, bounding box confidence scores, and classification accuracy. This advantage is even more pronounced in more complex scenarios involving two people.

Fig. III-3. Qualitative and quantitative evaluation for different sensing tasks. (top) Object classification, (bottom) Human location classification.

III-4. Conclusion

This paper introduced the overview of CSI2Image, a GAN-based CSI-to-image conversion method. We demonstrated that the combination of direct supervision and adversarial training successfully achieves the conversion. The conversion not only helps us to represent physical information CSI has in a more explicable format but also helps us to construct multi-purpose sensing system with the vision-based detection techniques.

Acknowledgements

This work was supported in part by the Japan Society for the Promotion of Science (JSPS) KAKENHI under Grant JP19H01101 and Grant JP17KT0042, and in part by the JST PRESTO, Japan, under Grant JPMJPR2032.

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IV. Use Cases for CSI Sensing with an Example of Pedestrian Movement Direction Identification

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***Abstract*—The original purpose of communication is to convey information. Channel state information (CSI) is used for high-speed transmission and can also function as a sensor. Adding sensing ability to the communication function is expected to open up new services and applications. This paper describes use cases for CSI sensing from the perspectives of commercial products and my research, specifically pedestrian movement direction identification.**

IV-1. Introduction

Wireless communication has traditionally been used to carry information through space as a medium. Most wireless communication systems currently use MIMO-OFDM transmission to achieve high-speed transmission rates. This method uses channel state information (CSI) that indicates the radio propagation condition between the transmitter and receiver. CSI can also be used as a sensor since it indicates the spatial information between a transmitter and receiver. The sensing using this information corresponds to incorporating sensing into communication, which has been discussed in "Beyond 5G and 6G" and "IEEE802.11 wireless LAN". The technical terms for this are integrated sensing and communication (ISAC) and joint sensing and communication (JSAC). However, most current wireless communication chipsets do not provide an interface for users to obtain CSI.

While research activity for CSI sensing is currently high, the number of commercial products for Wi-Fi sensing is rare. In my opinion, the reason is that the service requirements of use cases are strict, and the requirements are not entirely satisfied due to the uncertainty of radio propagation. Compared with RSSI, which also indicates the radio propagation condition, CSI has a higher reproducibility; thus, the use of CSI is suitable for sensing. The disadvantage of CSI is that it depends on the transmitter's and receiver's location. When the location changes, the CSI also differs from the change before its location.

IEEE802.11bf discusses use cases for sensing [1] but does not confirm the feasibility. The paper describes use cases of CSI sensing applications from commercial products and my research, including advantages and disadvantages from the feasibility viewpoint.

IV-2. Use cases in IEEE802.11bf and commercial products

The difference between mobile communication and wireless LAN is the coverage area. The use cases differ depending on whether the sensing target exists in an outdoor public space or an indoor room. CSI indicates the radio propagation condition between the transmitter and receiver. Therefore, detecting a specific sensing target is difficult in an outdoor public space because of the wide area.

IEEE802.11bf discusses use cases for existing wireless LAN standards, which operate at 2.4GHz, 5GHz, 6GHz, and 60GHz [1]. The range resolution relates to the signal bandwidth, i.e., the frequency band. The specific use case for the high-frequency band, i.e., 60GHz, is high-resolution sensing, e.g., gesture recognition (hand or figure movement), and for the low-frequency band, is low-resolution sensing, e.g., human presence and motion detection [2]. Among them, CSI sensing mainly corresponds to low-resolution sensing. The use cases discussed in IEEE802.11bf are as follows: Room sensing, Gesture recognition for full-body movement, Health care, and Car sensing.

I found some information about the feasibility of the above use cases. Hex Home by Origin Wireless is a commercial product for room sensing and healthcare [3]. Specifically, room sensing is used for home security by detecting intruders and is also for home monitoring of older people and/or children. The CSI variation is used to detect human movement. Healthcare is used for measuring breathing rate using the CSI periodicity. Wiz product named SpaceSense by Signify is another commercial product that corresponds to room sensing, i.e., a smart light [4]. This light control uses the CSI variation relating to the detection of human movement. Although I could not confirm whether car sensing by Murata Manufacturing has been commercialized, CSI sensing is used to detect the presence of a child in the car by measuring movement detection and breathing rate [5]. Note that the accuracy of breathing rate measurement depends on the location of the transmitter and receiver.

Fig. IV-1 shows the relationship between use cases and the purpose of the product. CSI variation is used for presence detection, and there are many examples of its application. Combining presence detection and breathing rate measurement for intruder detection is possible, but I could not find such a product.

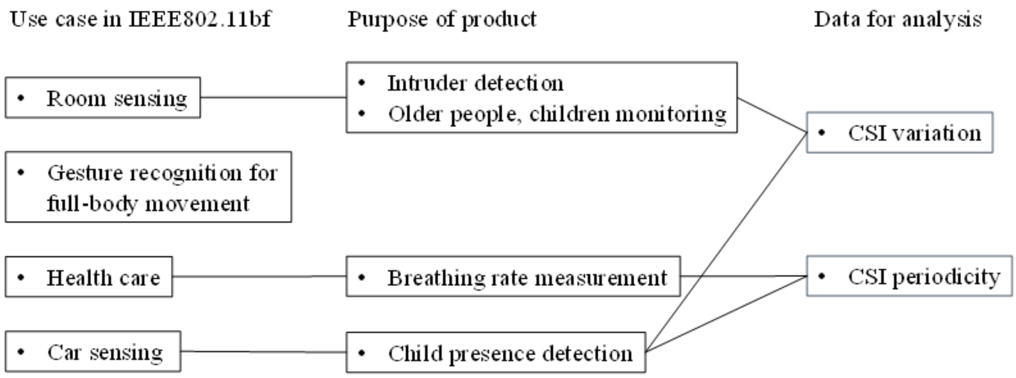

Fig. IV-1. Relationship between use cases and the purpose of products.

IV-3. Use cases in my research

My research aims to investigate the potential of CSI sensing without considering the user's needs. Basically, the commercial products mentioned above do not require machine learning. Based on my experience with Wi-Fi, use cases for CSI sensing can be categorized into those that require machine learning and those that do not.

CSI sensing can be used for various applications without machine learning. Here are some examples of CSI sensing use cases that do not require machine learning: breathing rate measurement [6], people counting using breathing rate measurement [6], and propeller rotation speed measurement [7].

CSI sensing can also be used with machine learning for more advanced applications such as human activity recognition [8], material identification [9], pedestrian movement direction identification [10], human location estimation [11], water height estimation in a bottle [12], pose estimation [13], and laundry dryness estimation [14].

IV-4. Pedestrian movement direction identification

Pedestrian movement direction identification is one of the use cases for CSI sensing. Nowadays, access points are often installed on the ceilings of offices and are connected to Ethernet or wireless mesh networks. In the future, if it becomes possible to measure CSI from communication between access points, it will be possible to estimate human flow.

Suppose consider a crossroads in a hallway. As shown in Fig. IV-2, one transmitter and three receivers are installed. Due to cost constraints, it is necessary to reduce the number of receivers as much as possible. There are 13 types of movement directions: four entrances to the crossroads and three exits from the crossroads per entrance. In addition to the twelve conditions, there is the condition that no humans are at the crossroads. Three people walked ten times for CSI measurements for each direction, resulting in 30 samples per direction. Including the case where no humans are at the crossroads, the total number of samples is 390. If the CSI differs in every direction, it is necessary to pay attention to the time series of CSI. Therefore, LSTM is used as a machine learning algorithm to classify the 13 types of movement directions, and accuracy is evaluated by leave-one-out cross-validation.

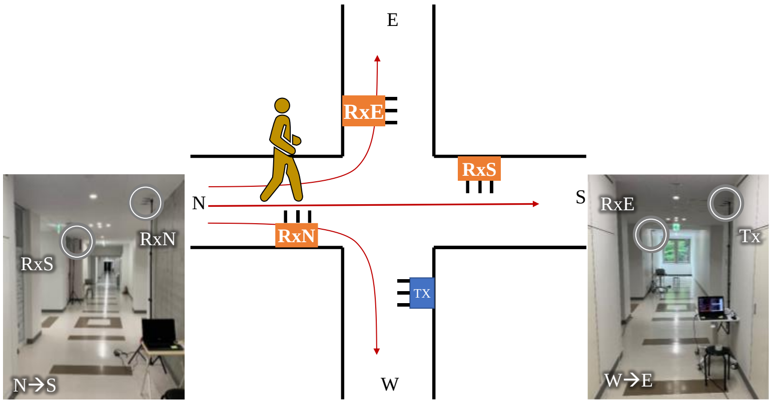

Fig. IV-2. Experimental environment.

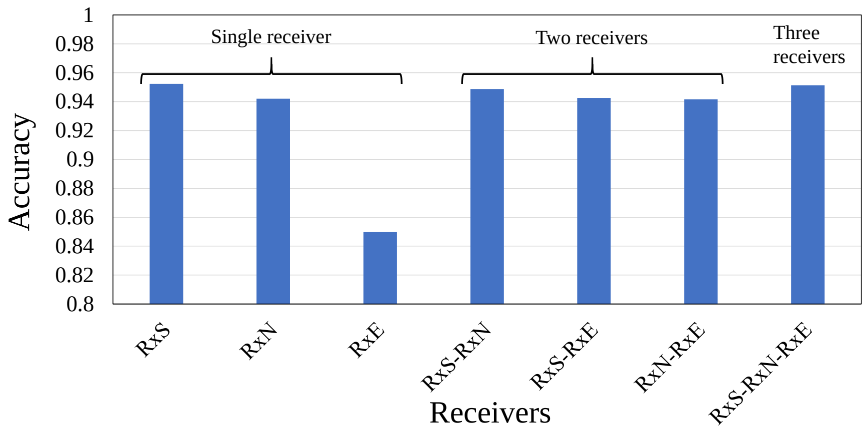

Fig. IV-3. Experimental result.

The accuracy of the difference in the number of receivers is shown in Fig. IV-3. The accuracy improves with the number of receivers and is over 90% when the number of receivers is two or three. When the receiver is only RxE, the accuracy is less than 90%. Fig. IV-4 shows the time-series CSI in three receives. When a human walks from N to S, the CSI fluctuation at only RxE is short. Because of the short time of the CSI fluctuation, it isn't easy to distinguish when a human walks from N to S and when a human walks from S to N. The confusion matrix using only RxE is shown in Fig. IV-5, where the label indicates direction and "nothing" indicates no human exists. I found that the estimation error occurs between StoN and NtoS. Therefore, the receiver at a non-line-of-sight location from the transmitter needs to be set to achieve higher accuracy.

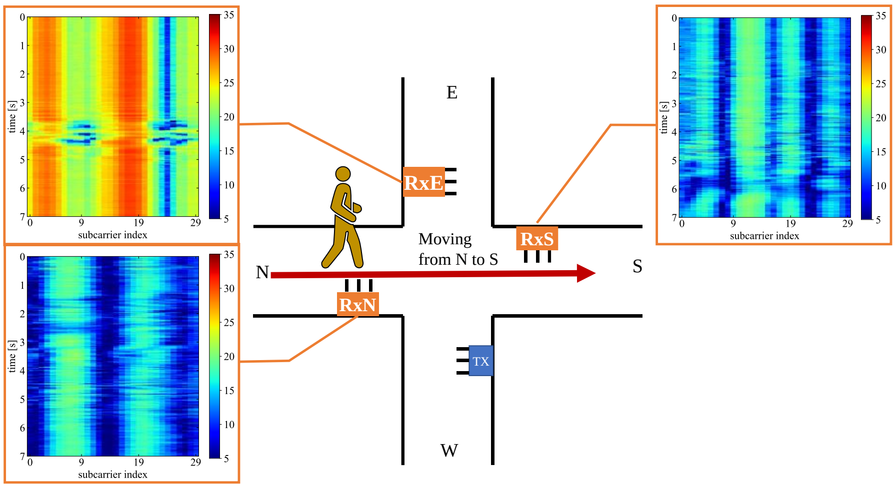

Fig. IV-4. CSI at each receiver.

True label \ Predicted label	Nothing	EtoN	EtoW	EtoS	NtoW	NtoS	NtoE	WtoS	WtoE	WtoN	StoE	StoN	StoW
Nothing	0.82	0.00	0.02	0.01	0.05	0.02	0.00	0.00	0.02	0.01	0.01	0.04	0.00
EtoN	0.00	0.90	0.04	0.04	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00
EtoW	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EtoS	0.00	0.01	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NtoW	0.03	0.00	0.00	0.00	0.96	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
NtoS	0.00	0.00	0.00	0.00	0.00	0.49	0.00	0.01	0.00	0.00	0.00	0.50	0.00
NtoE	0.00	0.00	0.00	0.00	0.00	0.00	0.84	0.00	0.06	0.00	0.10	0.00	0.00
WtoS	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.94	0.00	0.01	0.00	0.00	0.03
WtoE	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.02	0.92	0.03	0.00	0.00	0.00
WtoN	0.03	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.97	0.00	0.00	0.00
StoE	0.00	0.00	0.00	0.00	0.00	0.01	0.07	0.00	0.00	0.00	0.93	0.00	0.00
StoN	0.04	0.00	0.00	0.00	0.01	0.55	0.00	0.00	0.00	0.00	0.00	0.37	0.02
StoW	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.02	0.01	0.00	0.00	0.03	0.92

Fig. IV-5. Confusion matrix at RxE.

IV-5. Conclusion

The paper describes use cases for CSI sensing from commercial products and my research, specifically pedestrian movement direction identification. Although only some commercial products utilize CSI sensing, various services are expected to be created in the future by utilizing this technology.

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V. Integrated Sensing and Communication (ISAC)

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Abstract—6G will serve as a distributed neural network for the future Intelligence of Everything. Network Sensing and Native AI will become two new usage scenarios in the era of connected intelligence. 6G will integrate sensing with communication in a single system. Radio waves can be exploited to "see" the physical world and make a digital twin in the cyber world. This paper introduces the concept of integrated sensing and communication (ISAC) and typical use cases, and provides two case studies of how to use 6G ISAC to improve localization accuracy and perform millimeter level imaging using future portable devices. The research challenges to implementing ISAC in practice are discussed.

V-1. Introduction

In 6G mobile communication systems, the use of higher frequency bands (from mmWave up to THz), wider bandwidth, and massive antenna arrays will enable high accuracy and high-resolution sensing, which can help implement the integration of wireless signal sensing and communication (ISAC)[1] in a single system for their mutual benefit. On the one hand, the entire communications network can serve as a sensor. The radio signals transmitted and received by network elements and the radio wave transmissions, reflections, and scattering can be used to sense and better understand the physical world. The capabilities to obtain range, velocity, and angle information from the radio signals can provide a broad range of new services, such as high accuracy localization, gesture capturing and activity recognition, passive object detection and tracking, as well as imaging and environment reconstruction [2]. This is called "network as a sensor". On the other hand, the capabilities of high-accuracy localization, imaging, and environment reconstruction obtained from sensing can improve communication performance.

V-2. ISAC use case overview

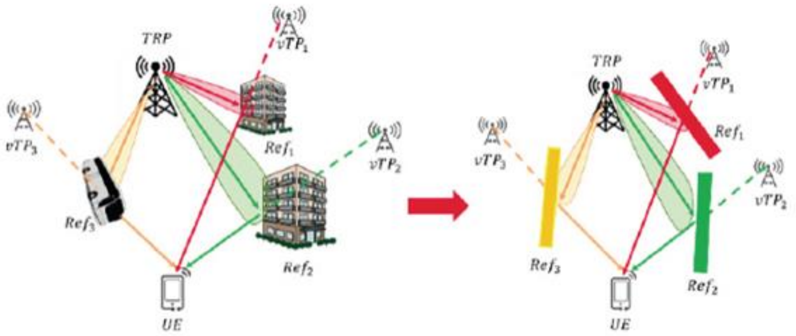
Wireless sensing has long been a separate technology developed in parallel with the mobile communication systems. Positioning is the only sensing service that mobile communication systems (until 5G) could offer. General sensing rather than positioning will become a new function integrated into the 6G mobile communication system. This capability will open up brand new services for 6G. These services are currently provided by various dedicated sensing equipment, such as radar, light detection and ranging (LIDAR), and professional CT and MRI equipment. The ISAC capability will thus enable many new services that mobile communication system operators can offer. These include very high accuracy positioning, localization and tracking, imaging for biomedical and security applications, simultaneous localization and mapping to automatically construct maps of complex indoor or outdoor environments, pollution or natural disaster monitoring, gesture and activity recognition, flaw and material detection and many other services. These services will in turn enable application scenarios in all kinds of business for future consumers and vertical industries. The potential new services that could be supported by future ISAC systems are listed in Table 1. In the table, the use cases are categorized into four functional categories across different applications/industries (vertical industry, consumer and public services):

- High-accuracy localization and tracking
- Simultaneous imaging, mapping and localization
- Augmented human sensing
- Gesture and activity recognition

V-3. ISAC for centimeter-level positioning

V-3.1. Background, motivation, and high-level scheme

The integration of sensing and communication functions can happen at three different levels, from loosely coupled to fully integrated. At the lowest integration level, sensing and communication capabilities can co-exist on hardware by sharing the spectrum, which is more efficient than dedicated spectrum usage. Sensing can benefit from the economies of scale in the mobile communication network, where shared hardware will be cost effective and eases deployment and 6G requires solutions for sub-centimeter level positioning techniques for various future applications and use cases. This level of accuracy for positioning requires much more detailed knowledge of the radio signal propagation environment where sensing comes into play. By learning the environment RF map and the way the transmitted waveform is manipulated by it, the UE position can be obtained as a function of the measurement parameters. This way, the multipath nature of the propagation channel will be helpful. Moving to higher frequencies can further facilitate such sensing-assisted positioning because the channel becomes sparser, and hence, characterizing the mapping between UE position and its propagation channel takes less effort. In a reflection-dominant environment (which is the case in higher frequencies), one such mapping can be obtained by decomposing the multipath channel as multiple LOS channels coming from multiple anchors. Those anchors are obtained by mirroring the transmission point (TP) over the surface of the corresponding reflector for each path. Those virtual anchors are referred to as virtual TPs or vTPs.



(a) the real reflectors map (b) the extracted geometrical representation to the visible reflectors

Fig. V-1. Mapping the objects/reflectors of the environment to virtual anchors, i.e., mapping multipath components to vTPs.

V-4. ISAC for mm-level imaging at the THz band

THz lies between the mm-Wave and infrared frequencies, and thus has millimeter-level and even sub-mm level wavelength, making the ISAC system at the THz band (ISAC-THz) particularly suitable for high resolution sensing applications such as millimeter-level resolution 3D imaging. Like the other lower frequency radio waves, THz can penetrate some obstacles, achieving high-precision sensing in all weather and lighting conditions. Recent developments in semiconductor technology have bridged the "THz band gap" and made the hardware feasible at the terminal side. ISAC-THz based portable devices will thus open the door for numerous new sensing applications such as augmented human sensing with very high resolution.

V-4.1. Compressed sensing-based tomography imaging

A major challenge for the virtual aperture imaging technique is the irregular scanning trajectory caused by the user moving the ISAC imaging module to perform THz scanning on an object. Assume a zigzag scanning routine is used to image an object, as shown in A major challenge for the virtual aperture imaging technique is the irregular scanning trajectory caused by the user moving the ISAC imaging module to perform THz scanning on an object. Assume a zigzag scanning routine is used to image an object, as shown in Fig. V-2. The echo samplings in the horizontal direction are continuous, i.e., the spatial spacing between sampling points is comparable to the wavelength of the echo signal. However, continuous sampling cannot be maintained in the vertical direction. As a result, the echo samplings in the vertical direction are sparse, which will cause high and non-uniform sidelobe effects, giving rise to false artifacts, which may lead to imaging failure. To solve this challenge, we consider decomposing the scanning trajectory on a two-dimensional (2D) plane into several sets of linear scanning tracks along the horizontal direction, where the sparseness of the sampling signals in the vertical domain is then equivalent to the sparseness between horizontal tracks, as illustrated in Fig. V-2. In this case, the reflected/echo information from the object can be retrieved from these vertically sparse samplings via compressed sensing techniques [3]. As depicted in Fig. V-3 (a), the robotic arm scans at a speed of 1 m/s with the scanning area set as 10 cm by 12 cm in the prototype.

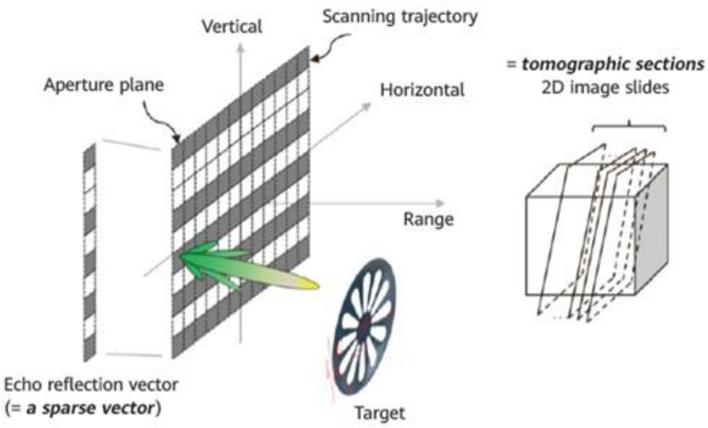
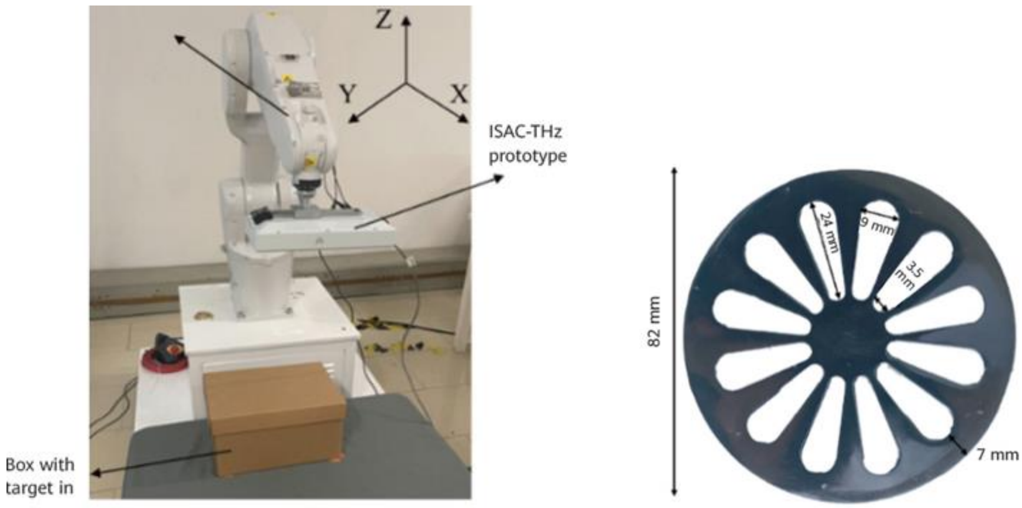


Fig. V-2. Illustration of the sparse scanning approach and the tomographic imaging techniques.

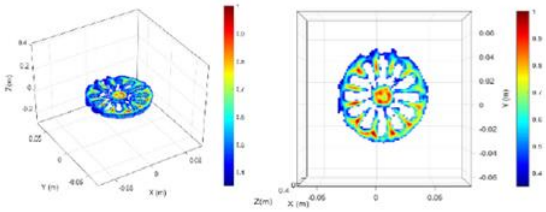


(a) Prototype setup for THz sensing where the ISAC-THz module is held by a robot arm representing a human arm

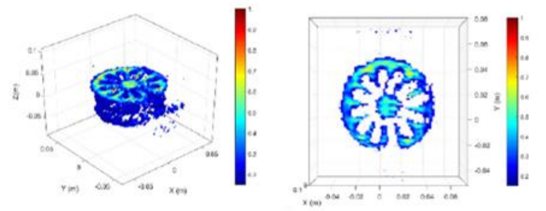
(b) Target object in the box

Fig. V-3. Setup of the ISAC-THz prototype.

The longitudinal spacings of the scan trajectories are controlled to simulate the sparsity in the trajectories of the user's hand-held scanning behavior. The target object to be imaged, as shown in Fig. V-3 (b), is put in a box with a cap on top of it. As we can see from Fig. V-3 (b), the smallest distance in the hallowed pattern is 3.5 mm, so the highest resolution of the imaging results can be 3.5 mm. The proof-of-concept THz imaging performances with different sparsity configurations in the scanning patterns are presented and compared in Fig. V-4. In each of the figures, the 3D imaging results are shown on the left and the cross-range profile perceived from top down is shown on the right. The non-sparse full aperture scanning in Fig. V-4 (a) is an ideal case, in which the vertical sampling is half wavelength adjacent. This achieves the best PSLR and ISLR performance, which is set as an upper bound performance reference. Then, in order to simulate the sparsity in real free hand scanning, we assume different sparsity configurations in tests, from 50% (medium sparsity) to 25% (most sparsity), where X% sparsity means that there are X % of the full samplings remaining in the vertical direction. With the collection of fewer samplings, stronger sidelobe interference occurs at the resulted aperture, resulting in worse imaging performance. From the comparison of Fig. V-4 (c) and Fig. V-4 (d), we see that when the sparsity is too high, the traditional tomography algorithm is not enough to recover the images. In this case, the compressed-sensing based tomography approach showed its superior performance.



(a) Non-sparse full aperture scanning (ideal case)



(b) Sparse scanning with 50% sparsity (medium sparsity)

Fig. V-4. Imaging results at different sparsity configurations.

V-5. Conclusion

With the concept of ISAC being commonly accepted as one of the key technology trends for 6G, this paper takes a step forward and elaborates two case studies on how 6G ISAC technologies can be applied to improve localization and to perform high resolution imaging. In particular, the proposed SAPE scheme utilizes the joint benefit of device free and device-based sensing and greatly improves the positioning accuracy compared with the current NR scheme. The prototype of the THz camera justifies the feasibility of mm-level imaging resolution on portable devices for both 2D and 3D objects placed in a box.

Joint efforts from both academia and industry are needed to address further challenges in the system level evaluation of ISAC, new channel modeling methodology, new waveform design, low complexity algorithm design, and low-cost hardware design.

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VI. Space-Time Synchronization

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NICT

***Abstract*—For mobile communication technology to transform from a means of man-to-man communication to an infrastructure for various vertical sectors in society, the method of the time synchronization should shift from the traditional leader-follower structure to autonomous distributed synchronization. Furthermore, synchronization must not only be limited to time but also extend to space, entailing the sharing (synchronization) of spatial coordinate axes. This would be realized by three basic technologies, namely compact atomic clocks, wireless time synchronization, and cluster clock systems. The combination will eventually acquire sensing capabilities like distance measurement through radio wave propagation time.**

VI-1. Introduction

Networks have so far operated under the assumption that participant clocks are not synchronized, establishing a kind of pseudo-synchronization on a one-to-one basis when necessary, where signal transmission time was not taken into account. On the other hand, GNSS has vividly demonstrated its high value by having participants (in this case, many GNSS satellites) with perfectly synchronized clocks, where signal transmission time was taken into account. A prime example is the ability of positioning through radio wave propagation time. Currently, mobile network base stations obtain time from GNSS, but synchronization to GNSS time requires a certain duration, during which the local clock frequency drifts, making it not easy to maintain a consistently synchronized clock in ns level. Additionally, synchronization through GNSS has limitations, such as being unusable indoors and vulnerability due to weak satellite signal strength. Furthermore, we should note that the heavy societal dependence on GNSS has led to considerations for timekeeping methods independent of GNSS, as indicated by executive orders from the United States [1].

Beyond 5G networks are expected to transcend mere human communication and become a social infrastructure for various economic activities. Space-time synchronization proposed here will demonstrate solutions to the concern about the resiliency while enjoying the benefits of a synchronized network. This is based on:

(1) Enhancing the basic strength of synchronized systems by implementing inexpensive, miniaturized atomic clocks in base stations, autonomous vehicles, and even mobile devices in future.

(2) Measuring time differences between clocks at nodes and achieving high-precision synchronization when necessary. Wireless time difference measurement or time synchronization also enables distance measurement based on the signal propagation time.

(3) Creating a virtual clock through the weighted average of local clocks at individual nodes and sharing it across the network, thus generating a standard network clock with high resiliency.

VI-2. Three technologies comprising space-time synchronization

Toward 6G, ITU-R WP5D composed a document of technology aspects, "Future technology trend for IMT-2030" [2]. This document clearly mentions that the three technologies are key for real-time communications/services. Here, we briefly describe what they are, as follows.

VI-2.1. Chip-level integrated frequency standard (CLIFS)

Atomic clocks, with its ticking rate determined by atomic transition frequencies and known for their extremely high frequency stability, became commercially available with the size of a matchbox in 2010. However, mass production was not feasible, limiting their widespread use in consumer products. Recent advances in MEMS technology are about making it possible to mass-produce atomic cells and GHz band oscillators with low phase noise, leading to reduced costs. For instance, Fig. VI-1 shows mass-produced atomic cells using silicon process technology. As a source oscillator, 3.4 GHz oscillator using a solid-state thin-film element (FBAR) recently achieves low phase noise below -124 dBc/Hz at the power consumption of 3mW. The size projected currently ongoing is not yet suitable for handsets but is sufficient for base stations, autonomous vehicles, and drones.

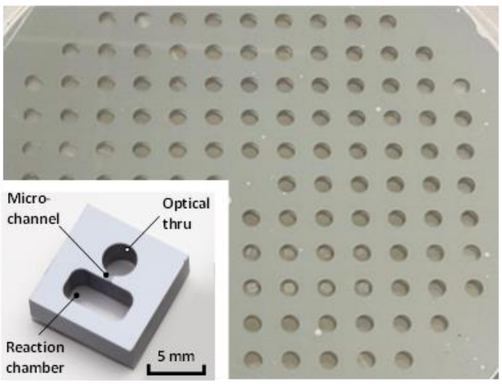

Fig. VI-1. Attempt for mass production of alkali-atom cells using MEMS technology.

VI-2.2. Wireless Two-way Interferometry (Wi-Wi)

To achieve high precision in comparing local clock times, signals are sent bidirectionally between nodes, enabling the measurement of both clock difference and signal propagation time. Wireless Two-way Interferometry (Wi-Wi) achieves both syntonization (=identical frequency) and synchronization through the carrier wave of wireless communication. Wi-Wi first compares the carrier phase difference between the local clocks of leader and follower modules. Phase locking (precise syntonization) is accomplished as the follower module stabilizes its local clock to the leader clock. After clock drift is corrected by phase stabilization, the clock is compared through packet transmission and arrival timings. The follower module can then adjust its clock to the leader clock for synchronization.

We have developed a module incorporating a commercial off-the-shelf 920MHz RF chip, fully aligned with the IEEE 802.15.4g standard. It can stabilize the phase with a jitter of ~20 ps and then synchronize the clock to 30 ns. Fig. VI-2 shows the latest version of our Wi-Wi module, where the board size is 67.25mm x 31.75mm.

Two-way measurement provides the significant byproduct of ranging, stemming from the propagation time measurement. Phase measurement allows us to measure distance variation at the sub-cm level. While there is room for improvement in synchronization error, combining it with wide-bandwidth signals can feasibly suppress it to the sub-ns level.

Fig. VI-2. Wi-Wi module.

VI-2.3. Cluster clock system

With local clocks having high frequency stability, it may not be the best way to synchronize with an external master clock with a wide servo bandwidth. Rather, making slight frequency adjustments to the atomic clock within a low bandwidth might yield a more stable and reliable clock. Also, creating a virtual clock by locally sharing a weighted mean of the many clocks within the network enhances frequency stability and reduces the risk that specific clock failures affect whole network. Fig. VI-3 shows a POC setup where ten nodes, each equipped with compact atomic clocks, are installed within the same rack and interconnected by optical fiber, realizing a wired cluster clock architecture. A virtual clock is generated through numerical processing from the time difference between the neighbor clocks. Adding frequency and phase offset to the signal of local free-running atomic clocks, each node can generate the ensemble clock as real signals.

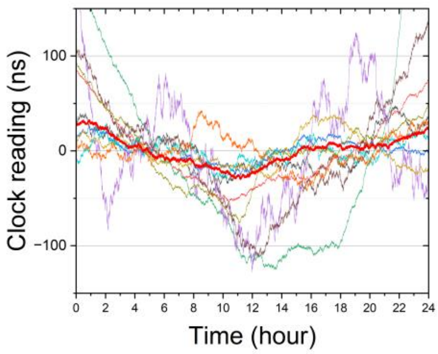

Fig. VI-3. Demonstration of a cluster clock.
Left: Ten nodes equipped with compact atomic clock are connected in a star topology.
Right: Records of clock reading in one day. Cluster clock (red curve) shows an enhanced stability, whereas ten thin curves are those of each clock.

VI-3. Space-Time Synchronization

Traditionally, synchronization often has involved a leader-follower model where the leader's signal is followed by the followers, including delay as well as noise within the propagation delay, signifying that the time coordinate axis between the leader and follower are not shared. This indicates that synchronization is about sharing the time coordinate axis. Extending this concept to space constitutes the idea of space-time synchronization. Wi-Wi, by measuring propagation delays, enables distance measurements. Furthermore, combining multiple units allows for positioning. This implies that the spatial coordinate axes are shared among network participants, leading to applications like multiple machines coordinating work based on the information of mutual positioning, or multiple vehicles and pedestrians on roads moving coherently to avoid collisions.

VI-4. Conclusion

The concepts of space-time synchronization and three key technology that realizes space-time synchronization are briefly described. This idea will make the mobile communication system more robust, resilient, and could make energy efficient.

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Abbreviation List

Abbreviation	Explanation
ABG	Alpha-Beta-Gamma
AI	Artificial Intelligence
ALD	Atomic Layer Deposited
AMC	Adaptive Modulation and Coding
AoA	Angle of Arrival
AR	Augmented Reality
ASIC	Application Specific Integrated Circuit
AWG	Arbitrary Waveform Generator
BAN	Body Area Network
BCB	Benzo cyclobutene
BER	Bit Error Rate
BF	BeamForming
BS	Base Station
CC	Component Carrier
CI	Close-in
CMOS	Complementary Metal Oxide Semiconductor
CPS	Cyber Physical System
CSI	Channel State Information
DC	Direct Current
DFT	Discrete Fourier Transform
DL	Down Link
DNN	Deep Neural Network
DOA	Direction of Arrival
DSP	Digital Signal Processing
EIRP	
EVM	Error Vector Magnitude
eWLB	embedded Wafer Level Ball grid array
FDD	Frequency Division Duplex
FDE	Frequency Domain Equalize

Abbreviation	Explanation
FSPL	Free Space Path Loss
HARQ	Hybrid Automatic Repeat Request
HPBW	Half Power Beam Width
IBO	Input Back Off
IFFT	Inverse Fast Fourier Transform
InH	Indoor hotspot cell
ISAC	Integrated Sensing and Communication
ITU-R	International Telecommunication Union Radiocommunication Sector
KPI	Key Performance Indicator
LAN	Local Area Network
LNA	Low-Noise Amplifier
LOS	Light of Sight
LTE	Long Tern Evolution
MCM	Multichip Module
MIMO	Multiple-Input and Multiple-Output
MMIC	Monolithic Microwave IC
MS	Mobile Station
MOS	Metal Oxide Semiconductor
MOS-HEMT	Metal-Oxide-Semiconductor Eigh-Electron-Mobility Transistor
MSL	Microstrip Line
NLOS	Non-Line of Sight
NR	New Radio
NRNT	New Radio Network Topology
OAM	Orbital Angular Momentum
OFDM	Orthogonal Frequency Division Multiplexing
PA	Power Amplifier
PAE	
PCB	Printed Circuit Board
PLE	Path Loss Exponent
QMH	Qualitative Microwave Holography
RAN	Radio Access Network

Abbreviation	Explanation
RAT	Radio Access Technology
RD	Relay Device
RF	Radio Frequency
RIS	Reconfigurable Intelligent Surface
RMSE	Root Mean Square Error
RS	Relay Station
Rx	Receiver
SAG	Selective-Area Growth
SC	Single Carrier
SiP	System-in-Package
SISO	Single-Input Single-Output
SIW	Substrate-Integrated Waveguide
SNR	Signal to Noise power Ratio
TDD	Time Division Duplex
TDS	Time Domain Spectroscopy
THz	Tera Hertz
TMA	Trimethylaluminum
TSV	Through-silicon Via
Tx	Transmitter
UCA	Uniform Circular Array
UE	User Equipment
UL	Up Link
VR	Virtual Reality