# Fast and Precise Neural Network-Based Environment Detection utilizing UWB CSI for Seamless Localization Applications


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***Abstract*—Seamless localization, navigation, and tracking applications can be realized utilizing different sensors and cameras, radio frequency signals such as WiFi, ultra-wideband, and global navigation satellite system, each of which is better suited for different types of environments. As such, awareness of the environment is crucial for the system to efficiently utilize the most relevant resources in each scenario and enable seamless transition between different environments. For example, when vehicles are moving from an open area such as open highway to crowded urban streets, or the opposite, they experience a considerable environment transition, which triggers opportunities for wide-range environment-specific device and algorithm optimization. In this paper, a novel infrastructure-free method utilizing channel state information of ultra-wideband signals and a convolutional neural network is proposed. This method enables a fast detection of the environment type, including crowded urban and open outdoor, reaching a detection latency of only three milliseconds. The experimental data is collected in the real environments of the city of Ghent, Belgium. The test data set, used for numerical performance evaluations, is collected from areas different from those used in the training set. The results show that the proposed method provides an average environment detection accuracy of $90\%$ in the considered test setup.**



***Index Terms*—Channel State Information (CSI), Convolutional Neural Networks (CNN), Environment Detection, Seamless Localization, Signal Processing, Ultra-Wideband (UWB)**


## I. Introduction

Environmental awareness plays a crucial role in seamless localization [1]. In this type of localization, the agent will move in different types of environment and continuous location information is needed in each environment. For example, a pedestrian moving from a park to a city center urban area, or a vehicle which moves from an underground parking to a crowded street and then to a high way, both require a seamless localization method, meaning that the localization is not interrupted when the environment changes and the processing unit of localization switches between the available positioning methods. To elaborate, in each of these areas, the processing unit utilizes the measurements from different types of sensors and specific algorithm to find the location of the moving object. For instance, a vehicle in an open highway can be accurately located using the Global Navigation Satellite Systems (GNSS) signals. In these types of environment, GNSS signals are received with high quality and they are not degraded by multipath effect and signal blockage [2], [3] and the positioning can be done with a trilateration algorithm [2]. However, in a crowded urban area the GNSS signals are poorly received and they are blocked by tall buildings and the crowds. As a result, the vehicle will need other types of available devices such as 5G receivers to find their position using fingerprinting algorithm [4]. In the human eyes, it is easy to detect the change in environment, decide to turn off the GNSS receiver and instead turn on the 5G receiver. However, for a processing unit there should be an artificial intelligence to detect the environment so the vehicle could choose to turn off the GNSS receiver(s) and stop using trilateration algorithm when the vehicle enters crowded urban area. Instead start collecting 5G signals and use fingerprinting algorithm. Otherwise, the GNSS receiver will continue collecting data which results in high power consumption [5], filling memory with unwanted data, and not providing required measurement for an accurate position estimation. The sensors present in a localization scenario are not limited to the 5G or GNSS receivers. There are also other sensors and devices such as LiDAR, Radar, or camera [6]. However, before any of these devices can be used for positioning in scenarios where there is change in environment, there is a need for environment awareness by the processor. This need defines the scope of this research which is environment detection.

Being aware of the type of environment requires a sensing solution and there will be a great demand in sensing methods with the advent of simultaneous communication and sensing functionality in 6G networks [7]. The sensors and devices used in a positioning scenario for position estimation, can be also used for environment recognition and context awareness. One of the devices available in most of the localization scenarios are the Ultra Wide Band (UWB) transceivers [8]–[11]. Considering the scope of this work as environment detection for the goals of seamless localization, we utilize UWB transceiver and present a Convolutional Neural Network (CNN) to classify two types of environment based on signal analysis for fast and accurate detection. The environment types considered in this research are "open outdoor" and "crowded urban" environments. These two types of environments are frequently experienced in seamless localization scenarios [12]. The recognition of the environment is achieved by using the Channel State Information (CSI) of UWB signals which are processed by a deep neural network. The main contributions of this paper are as follows.

1) A novel infrastructure-free approach is proposed to detect the type of environment without the need of any anchor or base station in the environment of interest. This research utilizes the channel information of signals which are transmitted by a first UWB device mounted on one arm of the pedestrian, travelled in the environment, and then received by a second UWB device mounted on the other arm of the pedestrian. This method mimics 6G sensing functionality by using Joint Radar and Communication (JRC) system [13]. Therefore, the results of this research provides future opportunities of utilizing 6G in environment detection.
2) Experimental data has been collected in $4$ real-world environments of 2 types utilizing specific UWB devices [14] and an accurate and fast detection is done for the two types of environment including crowded urban and open outdoor. Detection of these two types is quite challenging, as both environments comprise outdoor built-up areas. Our proposed detection method is novel considering that a precise and fast method of detection is still not considered in the literature.

Detailed comparison between state-of-the-art methods and our method is presented in Section II. Our proposed CNN-based environment detection utilizing UWB CSI is presented in Section III, the experimental evaluation is provided in Section IV, followed by conclusion and future work in Section V.

## II. Related Works

Environment detection is an emerging topic in the field of positioning addressing the problems in seamless localization. Different methods have been introduced in recent years to provide the detection of type of the environment as indoor or outdoor for positioning purposes. These methods are whether GNSS-based or multisensor-based methods.

### A. GNSS-based Methods

One of the frequently used methods is the analysis of GNSS signals and available number of satellites utilizing machine learning algorithms [15]. However, the GNSS-based methods are generally considered to be power-hungry [16], which in many cases have uncertainties due to the reflections of the signals. Furthermore, the efficiency of the GNSS-based methods are highly dependent on the available satellites. However, we present a method which consumes relatively low amount of energy with high accuracy and without the need of pre-installed satellites, base stations or anchors in the environment of interest.

### B. Multisensor-based Methods

In multisensor-based methods, several sensors are utilized to enable the environment detection for the user. Authors in [17], have utilized barometer, magnetometer, GNSS receiver, light, and pressure to detect the type of environment between indoor and outdoor. Authors have considered urban area and open outdoor area both with the class of "outdoor", and the average required time to detect the type of environment is $5s$. Nevertheless, in this work we present a fast method to detect between crowded urban and open outdoor.

WiFiBoost [18] takes advantage of the WiFi Access Points (APs) installed in the environment to collect the Received Signal Strength Indicator (RSSI) of WiFi signals and train an AdaBoost-based machine learning method using the training data set. This infrastructure-based method requires different classifiers for each building in the test scenario and it is essential for this method to have more than a hundred APs in the environments of interest to get a good accuracy in environment detection. In this article, we introduce a method which utilizes only UWB devices and does not require an amount of time for sensor fusion. Our method is also not dependent on the available base stations in the environment.

Authors in [16] utilize the Inertial Measurement Unit (IMU) inside a smart phone to detect the physical activities of the user and then make a decision about the environment type based on the user's activity. However, the investigation of open outdoor and crowded urban are excluded because of the unavailability of data and there is not available. In this article, we introduce a novel method to classify the crowded urban and open outdoor area. To test the proposed method based on the real-world data, the data collection with RF devices had to be done in the different areas of the city. The data collection by the data collector carrying the devices required permissions from the city organizations. Different permissions have been collected for the days of measurement campaigns in the city of Ghent. We have collected and analyzed the real-world data utilizing specific UWB devices to detect the environment.

Ali et al. [5] have presented SenseIO for indoor/outdoor detection. SenseIO is a multi-model method which utilizes four different methods for environment detection. It takes advantage of the Global Positioning System (GPS) cell tower, WiFi APs, light intensity, and human activity recognition. In spite of different technologies and sensors utilized in SenseIO, the environment detection accuracy for outdoor areas stays below 90%. However, in the critical scenarios of seamless localization for autonomous vehicles and drones, a precise and fast detection of the environment type is necessary. In our method, we introduce an approach which is totally independent of GNSS signals. In none of the investigated recent methods, visual sensors such as camera or LiDAR have been used. The reason could be that keeping a camera on for the whole scenario of a seamless localization for the purpose of environment detection can be power-hungry, fill the memory fast, and result in long computations by the processing unit. As discussed above, fast and accurate recognition of crowded urban and open outdoor areas has remained unaccomplished in previous works. In this work, we utilize UWB Channel State Information (CSI) to introduce an infrastructure-free method to recognize between open outdoor and crowded urban areas in a few milliseconds. In a seamless localization scenario, there might be other devices available to localize the user. However, not all of the available devices are suitable for environment detection. UWB is a low-power and cheap technology in comparison with many other devices such as camera or GNSS receivers. Furthermore, the CSI of the signals provides a good source of information for fast detection of the type of the environment [4].

## III. System Description and Methodology

We utilize a neural network-based method. There are two phases in estimating the type of the environment. The first phase is training the network. In this phase, the CNN is trained utilizing the CSI data computed from Channel Impulse Response (CIR) of the signals. In the test phase, the data, which was not previously seen by the network, will be fed to the CNN to get an estimate on the type of the environment.

The collected data which are the CIR of UWB signals, are recorded utilizing Wi-PoS devices [14]. The UWB signal travels from the UWB transceiver on one arm of the pedestrian, travels in the area and returns to the UWB transceiver on the other arm. During the time of the travel, the signal experiences multipath radio propagation with various environment interactions, such as reflections, diffraction and scattering, which are influenced by the features of the environment. For instance, a crowded urban environment with narrow street or sidewalks, tall walls, group of people, or moving vehicles result in effects to the signals which are different than those effects of open environments free from multipath effects [19]. Consequently, the CIR of the signal will be affected by these channel effects [20]. Thus, the patterns in environments generate the patterns in the signal data and these patterns can be learned by the neural networks [21]. To get the frequency spectrum of the received signals and provide meaningful data for the CNN, the CSI is computed from CIR by calculating the Fast Fourier Transform (FFT) of the signals [22]. Thus, CSI is a frequency domain signal feature which describes how a signal propagates from the transmitter to the receiver. In this way, CSI is able to characterize the environment [4] and is a good candidate for environment recognition utilizing the power of Artificial Intelligence (AI).

For deeper understanding of the CIR and CSI, and especially how they are affected by the environment, it is beneficial to consider a related multipath radio propagation channel model. Assuming use of omnidirectional antennas, the received signal at the receiver can be represented as [23]

$$r(t) = \sum_{k=0}^{K-1} b_k s(t - \tau_k) e^{j2\pi f_{\mathrm{D},k} t} + w(t) \tag{1}$$

where $s(t)$ is the transmitted signal as a function of time $t$ with $K$ number of multipath components. Furthermore, $b_k$ is a complex path coefficient for the $k^{\text{th}}$ multipath component, $\tau_k$ and $f_{\mathrm{D},k}$ denote the path delay and Doppler shift in respective order. Finally, $w(t)$ is additive white Gaussian noise. The environment affects the parameters of the above signal model in various ways. For example, the path delays $\tau_k$ are related to path propagation time and consequently the distances, and reveal some information on proximity and density of surrounding objects. Moreover, path coefficients $b_k$ are affected by attenuation along the path and different channel interactions, such as reflections, scattering and diffraction, which depend, for example, on used materials in surrounding objects. In addition, moving objects in the environment induce Doppler shifts $f_{\mathrm{D},k}$ to each multipath, which causes time-depended phase rotation of the received signal. From (1), the CIR, and consequently the CSI via the Fourier transform, can be estimated by assuming the signal $s(t)$ known at the receiver.

To feed the CSI data to the neural network, the real and imaginary part of the data are added to two separate consecutive columns. The prepared CSI matrices are then fed to the neural network. Extracting features from radio frequency signals can be challenging. CNN has the capability to extract the patterns from input data, while other machine learning solutions such as k-nearest neighbor (KNN) relies heavily on the quality of the features that are used for classification. In the training phase, the training data set is utilized to train the network and optimize the weights and the biases of the neurons. Once trained, a test data set is fed to the network to evaluate its performance on unseen data collected in different areas. The network will then estimate the type of environment based on the input test CSI. Our proposed neural network is made of the following main layers with sub-layers:

- Input layer with 3000 inputs for 300 $\times$ 2 real and imaginary parts of CSI data.
- Convolution 2D layer with 1 input channel and 4 output channels, Rectified Linear Unit (ReLU) activation function, Batch Normalization with 4 number of features and a max pooling layer.
- Convolution 2D layer with 4 input channel input and 8 output channels, ReLU activation function, Batch Normalization with 8 number of features and a max pooling layer.
- Convolution 2D layer with 8 input channel and 16 output channels, ReLU activation function, Batch Normalization

with 16 number of features and a flattening.

- Fully connected layer with 128 neurons, ReLU activation function, Batch Normalization with 32 number of features and a Dropout with 0.3 dropout rate.
- Fully connected layer with 32 neurons and a Softmax classifier.

The optimizer utilized in this method is AdamW to optimize the learning rate, weights and biases of the network. The regularization methods utilized are dropout and early stopping to prevent the network from learning the details and noise in the training set. Furthermore, L2 regularization method is considered to reduce the chance of model over-fitting. The computational resources required for training a neural network depend on its parameters and hyperparameters. For the network used in this study, there are about 7 billion operations required for the forward and backward pass over 3000 input matrices for 250 epochs. Due to the high computational requirements, specialized hardware like GPUs are necessary. In this research, an NVIDIA GeForce RTX 3060 GPU is utilized, and training of the network took less than one hour.

## IV. Experimental Evaluation

To implement the presented idea, a pedestrian has collected the data in different areas of Ghent city, Belgium. The pedestrian as shown in Figure 1 walks in the defined areas carrying the sensors, power banks, and the laptop for data collection. Two Wi-PoS devices are placed on the arms of the pedestrian. The reason that the devices are installed on the arms of pedestrian (but not in the pocket or backpack) is that Wi-PoS devices have an antenna which must not be blocked by any object. These devices have a Decawave DW1000 UWB transceiver [14]. As the pedestrian walks in the environment, the signal is transmitted with one of the transceivers on one arm and then received back by the transceiver on the other arm.

### A. Data Collection

The pedestrian walks on a pre-defined route for 10 minutes with a sampling rate of 6 samples per second. The CIR data is collected using a Python script and the data is stored on the laptop. The areas, where the pedestrian collects the data, are illustrated in Figure 2. For the training data collection with a label of "Open Outdoor" the pedestrian walks inside the Citadel Park. The reason that we have labeled this area as "Open Outdoor" is that there are very few short walls, few people far from the pedestrian and most parts of the area are open and low in multipath effect. The training data collection for the label of "crowded urban" is done in the Graffiti Alley. The reason for this label is that in this alley there are tall walls, some parts of the alley are covered by roof, people and some bikes moved near the pedestrian on the day of data collection. The test set data collection with label of "open outdoor" is done in Portus Ganda. It is a port area where the apartments are far from the pedestrian, the area is not blocked for receiving satellite signals and there are few people walking around. The test set data collection with label of "crowded urban" is done

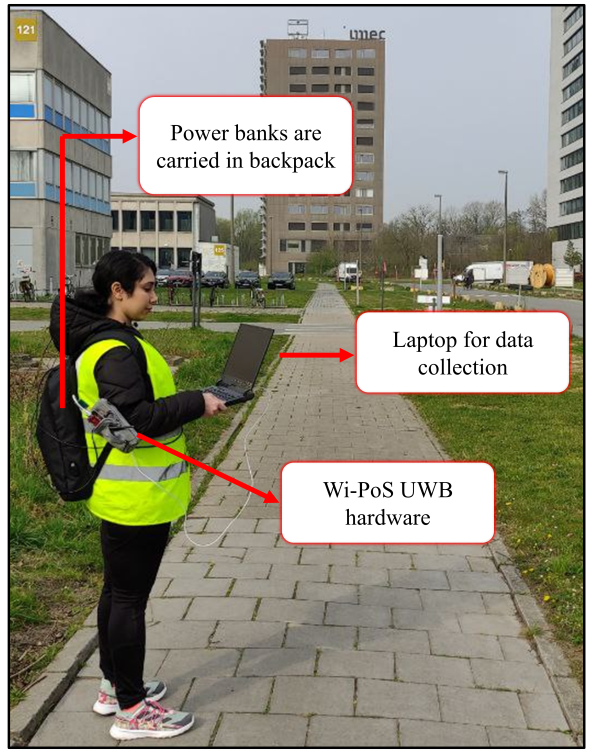


Fig. 1. The pedestrian carrying the setup in an open outdoor environment. She walks on a predefined route for 10 minutes with speed of $6km/h$ in each environment.

in Sint Pieters railway station; where some parts are covered by roof, there are many people and some trains passing near the pedestrian, and there are tunnels on the path of pedestrian to get to the platform. To summarize, the park and port area are labeled as "open outdoor", the alley and the railway station are labeled as "crowded urban".

For the training, 3000 CIR data observations have been utilized from the collected data set in each environment. A random splitting is done to separate the training and validation data, where 70% is used for training. For testing the proposed method, the CIR data collected from different urban and open outdoor areas are considered. 600 randomly selected CIR measurements in each test area are used for testing the method.

### B. Results

The training and validation accuracy are presented in Figure 3. The training accuracy reaches 98% showing that the network is able to learn the patterns in CSI data and estimate the type of environment. Considering the validation accuracy increasing up to 95%, the network generalizes well utilizing the regularization methods. Furthermore, the network behaves robustly against unseen validation data.

The training and validation loss are presented in Figure 4. The downward trend of loss values for the training data set illustrates that the model fits well to the data. The decreasing loss values for the validation set shows that the model is performing well since the validation loss is not increasing

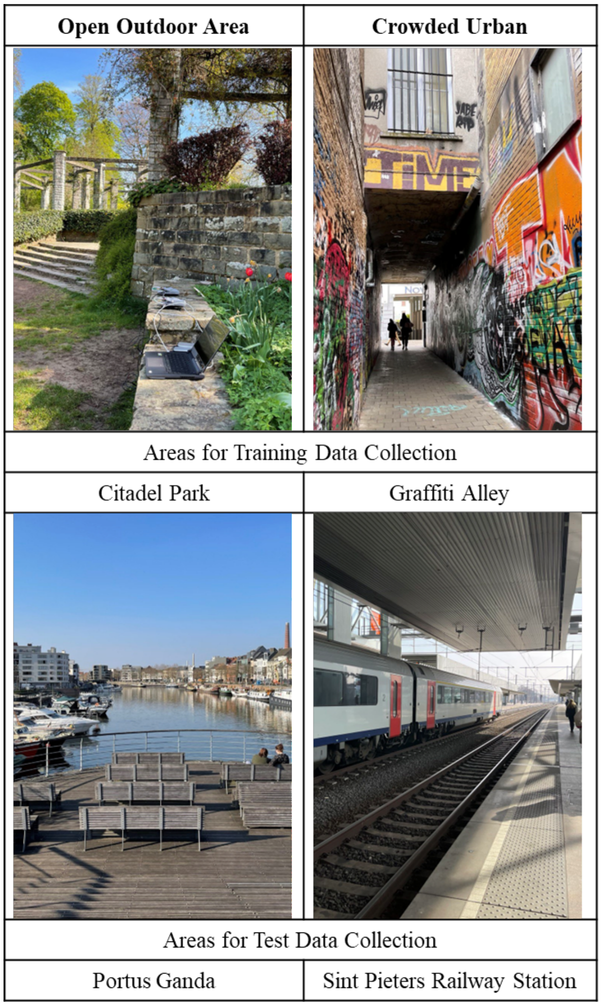


Fig. 2. The areas where training and test data sets are collected. Areas considered for training data collection are a park and an alley. Areas for test data collection are a port area and railway station.

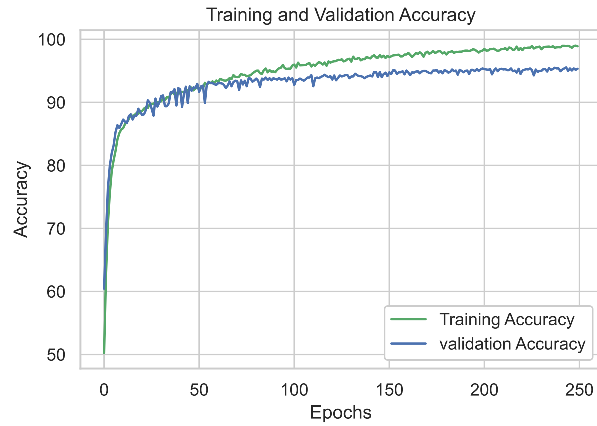


Fig. 3. Training and validation accuracy.

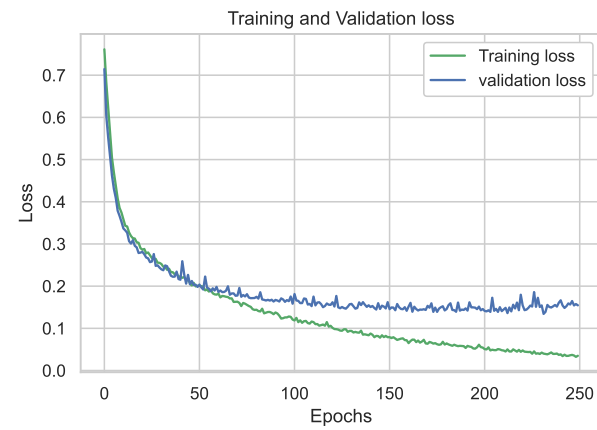


Fig. 4. Training and validation loss.

after a number of epochs due to overfitting on the unseen data collected at the same area. To visualize the classification algorithm performance and compare the ground truth with the estimated environment type for test UWB CIR data, the confusion matrix is extracted. This way, we assess the neural network based on the data collected on areas totally different than those used for validation but within the classes of “crowded urban” and “open outdoor”. The confusion matrix is illustrated in Figure 5.

600 CIR samples, collected in two different test environments, have been utilized for testing the presented method. As illustrated in Figure 5, the number of True-Open Area equals 571 out of 600; meaning that the estimation of open outdoor environment has been correct for 571 CIR samples out of 600 samples. The number of the True-Crowded Urban equals 509 out of 600 CIR samples; meaning that the estimation of crowded urban environment has been correct for 509 out of 600 CIR samples. These values result in a test accuracy of $90\%$, a precision of $85\%$ for the crowded urban environment type, and a precision of $95\%$ for the open outdoor environment type. These values prove that the model is working better for open outdoor environment detection. This can be explained by the fact that some samples colleted in crowded urban area might be closer to those collected in open outdoor area regarding the environment features. Thus, it is more straightforward for the network to detect the open outdoor rather than crowded urban based on the training data. The trained network can estimate the environment type for each CSI measurement in just 3 milliseconds using high-end GPUs and PyTorch software on laptop. This approach is faster than previous methods in the literature. When comparing the required time for a laptop to a smartphone, running the Python code on an iPhone 12 Pro Max increases the time to 10 milliseconds.

## V. Conclusion

A fast infrastructure-free method for environment detection is proposed in this work utilizing CSI based processing with neural networks for seamless localization applications, enabling seamless transition between crowded urban and open outdoor environment. The detection of the type of environment

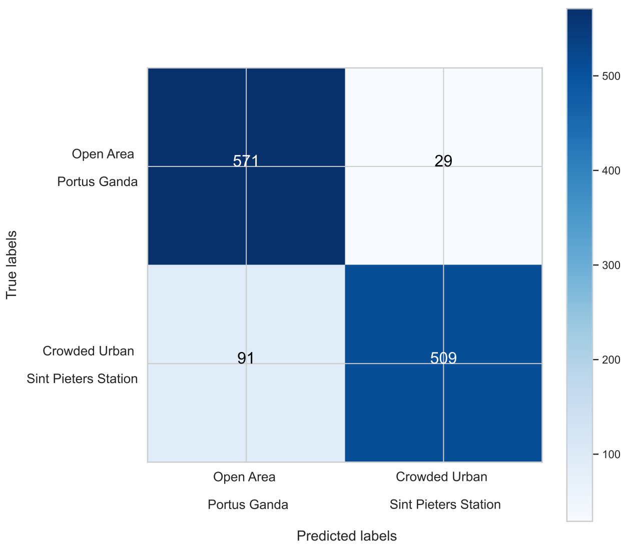


Fig. 5. Confusion matrix for the test set made of 600 number of CIR samples collected in open outdoor environment and 600 samples collected in crowded urban environment.

is done in less than 3 msec and without any required beacons in the environment of interest, in contrast to other state-of-the-art approaches. Real-world data of UWB signals CIR is collected utilizing Wi-PoS devices developed by Imec research organization. CNNs are used to recognize the pattern in the collected data and classify the type of environment. The results show that the proposed method has a test accuracy of 90% and provides an estimate for each single measurement of CSI within a few milliseconds. In the next steps of this research, we will investigate other types of environment and investigate the effect of time correlation between the measurements. Considering that recent UWB radio chips already have two antennas, in the near future it is likely that the whole process be realized using only a single UWB transceiver, as in later generations there might be a possibility of simultaneously transmitting and receiving a signal. Furthermore, the 6G sensing functionality utilizing the joint radar and communication system can completely replace the UWB system for environment detection.

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