An empirical study on radio propagation estimation for UAVs flying at low-altitude with machine learning

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Abstract—This paper presents a hybrid approach with machine learning and light-weight radio propagation model to estimate wireless communication range between Unmanned Aerial Vehicles (UAVs) flying at low altitude and their operators for crop-spraying in orchards. Additionally, it clarifies key factors to realize the approach by comparing measured data in a real field and simulation results. Simulation and measurement results shown in this paper reveals significant discrepancies between Irregular Terrain Model (ITM) and ray-tracing simulation results and some different patterns of signal attenuation due to vegetation and artificial obstacles such as trees and buildings between UAVs and their operators. The authors show that 3D special information, which is voxelized point cloud data measured in a real field, can improve the accuracy of results of the light-weight radio propagation model and discuss on detailed design of our approach with consideration of radio propagation characteristics.

Index Terms—UAV, BVLOS, low-altitude flight, radio propagation, machine learning

Fig. 1. Crop-spaying with UAV in an orange orchard in Japan

I. Introduction

Crop-spraying by man-hand is grueling work for farmers because it makes them walk around their farmlands with a few gallons of liquid agricultural chemicals. Crop-sprayers, Unmanned Aerial Vehicles (UAVs) with a sprayer and a tank filled with liquid agricultural chemicals, can be a solution to help farmers.

There are some issues on flying crop-sprayers in farmlands in Japan. There are normally farmlands in mountainous areas or residential areas due to a few of flat lands in Japan. Especially, orchards are often located in river valleys because land with good drainage, that is suitable for orchards, are located in such mountainous areas. Fig. 1 shows a crop-sprayer that is actually operated in an orchard in Japan. Crop-spraying by UAVs must always fly at low altitudes to ensure that agricultural chemicals are sprayed onto crops while preventing the agricultural chemicals from drifting onto other nearby objects. Additionally, houses, power lines, and other obstacles surround the orchard and make it difficult to fly the crop-sprayer with line-of-sight. For this reason, it is necessary not only to be careful when flying UAVs, but also to operate UAVs in BVLOS (Beyond Visual Line of Sight) environment.

Current crop-sprayers are often operated in VLOS (Visual Line of Sight) areas due to strict regulations for BVLOS [1], [2]. The regulations claim operators to always monitor UAVs by video real-time streamed from cameras installed on UAVs. The BVLOS regulations require UAVs and operators to keep stable wireless communication enough to transmit and receive control commands, telemetry data, and video streams simultaneously.

There are some radio systems that can be used for UAVs in Japan: U169, U2.4, U5.7, [3] and DR-IoT [4]. U169, U2.4 and U5.7 are wireless communication systems operating for UAVs in the licensed 169 MHz, 2.4 GHz and 5.7 GHz bands, respectively, and widely used for UAV operation in Japan. The maximum transmission power of U2.4 and

U5.7 is 1 W, while the maximum power of U169 is limited up to 10mW due to domestic regulations. The modulation schemes are not regulated in the bands. U169 and U2.4 are majorly used for transferring commands and telemetry data. U5.7 are used for video transmission. Since frequency is higher, communication range is narrower, U5.7 has less coverage than U2.4. The narrow communication range of U5.7 limits UAV flight area in BVLOS environment.

DR-IoT (Diversified-Range/Disaster Response IoT) is a VHF-band wireless and is being regulated in Japan. Its modulation scheme is GMSK. Its maximum transmission power is 5 W on the ground and 1 W in the air so that it has higher transmit power than the U169 system, which uses the same VHF band, enabling DR-IoT to achieve a wider communication range. DR-IoT has multiple channels with different bitrates and allows users to change more adaptive channel for their use. For this reason, DR-IoT have potential to transmit commands, telemetry data, and video streams simultaneously.

Therefore, we propose a method that accurately estimates communication range of UAVs by combining a lightweight propagation simulation with a machine learning model. The proposed method improves the simulation results of light-weight radio propagation models such as Irregular Terrain Model (ITM) by inputting the results and 3D spatial information captured by sensor devices installed on UAVs such as 3D LiDAR devices to machine-learning. In this paper, we evaluate the differences between ITM and ray tracing simulation results targeted in an actual orchard for detailed design of the proposed system.

II. Related Work

Radio propagation models such as two-lay ground and irregular terrain model are widely used for modeling and estimating wireless communication range in various scenarios. Machine learning has emerged as the dominant paradigm to overcome the computational complexity and limited accuracy of traditional model-driven (e.g., ray tracing) and interpolation-based techniques. The existing wireless communication range estimation methods can be categorized as the following:

- Model-Driven Methods: These are traditional methods based on physics and empirical models (e.g., Friis, log-distance). While the methods are computationally efficient, their accuracy degrades significantly in complex, actual propagation conditions.
- Data-Driven Methods: These methods solely rely on measured or simulated data to train machine learning models to estimate RF parameters at unmeasured locations. They are highly flexible and excel in complex environments, however; it requires users to collect large amount of measurements in the real world.
- Hybrid Model-Data Driven Methods: These approaches strategically integrate domain knowledge (the physics of radio propagation) into the data-driven model structure or loss function. This fusion aims to achieve high accuracy with greater generalization and robustness,

Model-driven methods are relatively computationally light and lightweight, making it easy to calculate simulation results. They are well-suited for estimating UAV communication range on site, as calculations can be easily performed by bringing computational resources like a laptop to the actual location where the drone will fly.

Meanwhile, many methods employ abstract models that cannot account for signal attenuation caused by obstacles on the ground. Irregular Terrain Model calculates signal level attenuation with consideration of height difference due to terrain, but that model does not consider the effect of obstacles. Ray tracing simulation can include signal level attenuation and multi-path effect due to obstacles such as buildings and trees. However, current ray-tracing models requires a long time to calculate results and much computational resources for its execution [5]. These models are often limited to calculate the behavior of radio propagation due to specific geographical conditions, such as attenuation and fading by building and other obstacles on the ground. Consequently, they are insufficient for estimating UAVs communication range, where these conditions vary depending on the flight path.

Data-driven methods can achieve the most realistic estimation accuracy by basing their estimates on data measured within the flight range. However, collecting measurement data by flying a UAV remains practically impossible in BVLOS environments. Furthermore, Raju, et al. reported in [6] that the existing radio map estimation systems were designed with less empirical validation and machine-learning-based radio map estimation requires a large amount of training data. Collecting such measurement data is not easily implemented.

Hybrid model-data driven methods are suitable to estimate communication range for UAV operation in BVLOS environment. They roughly estimate a communication range using a light-weight radio propagation model, then corrects the estimation results of that light-weight model using other methods. Therefore, depending on the combined technique, it has the potential to improve accuracy or reduce computation time.

Nagao et al. [7] and Imai et al. [8] proposed a method that takes aerial photographs of the target area as input and outputs estimated received signal strength values that account for the influence of artificial structures such as buildings captured in the aerial photographs. However, in the farmland targeted by this paper, while it is naturally necessary to consider the presence of buildings, there is the challenge that aerial photographs struggle to represent terrain undulations, building heights, and visibility between drones flying low near the ground and their operators—making it difficult to provide information related to the vertical dimension.

Current hybrid-driven methods focus on supplementing measurements in specific conditions to other geographical conditions. However, as far as we know, there is not a light-weight wireless communication range estimation method that can incorporate factors such as obstacle-induced shielding and fading into its estimation results in a manner comparable to ray tracing simulation, yet simultaneously achieve results with minimal computational resources during estimation, similar to model-driven methods.

Since crop-sprayers fly at low altitudes, they are closer to obstacles like trees, utility poles, buildings and the ground during flying. This makes it hard for UAVs and their operators to secure Fresnel zones, which are elliptic spaces between a sender and receiver and are necessary to propagate radio waves effectively. Therefore, it is important to consider not only obstacles like buildings but also the effects of vegetation. Additionaly, radio propagation in lower frequencies bands such as VHF-band easily changes by vegetation because the behavior of diffraction is affected by the amount and density of leafs and trees, it is also significant to consider the changes of vegeation in the four seasons.

Radio propagation models such as ray tracing simulation models include the signal attenuation by multi-path and fading effect by buildings, trees, and other obstructions and has potential to estimate more accurate received signal strength than other models. There are imaging method and launcing method for ray tracing simulation. The computational effort of both methods are $O(M^N)$ and $O(L \times S)$. M is the number of surfaces and N is the number of reflections. L and S are the number of rays and steps to follow a ray, respectively. The enormous amount of computational effort shows that ray tracing models requires high-performance computation servers to be performed. Therefore, the proposed system uses machine learning to rapidly obtain estimation results equivalent to ray tracing.

III. Radio propagation estimation with machine learning with 3D spatial information

The proposed method involves a UAV with sensors to capture 3D spatial information and a ground control station (GCS) to control the UAV. The proposed method estimates received signal strength values in the field by improving light-weight simulation results using machine-learning.

The UAV has some sensor devices such as 3D LiDAR devices and cameras. The sensor devices collect 3D special information, for example, point cloud data captured by the 3D LiDAR devices, or images by the cameras. Since the terrain characteristics are unlikely to change significantly in the short term, the 3D special information can be collected by a UAV with the sensor devices different from crop-sprayers. GCS builds detailed terrain characteristics with the sensor data and calculates received signal strength values in the flight area.

The calculation of received signal strength estimates are performed by the following two steps. GCS calculates the estimates of received signal strength in the flight area using a light-weight radio propagation model. GCS executes a machine-learning model with the simulation results and the 3D special information as input and obtains correction values of the simulation results or more accurate received signal strength values from the machine-learning model.

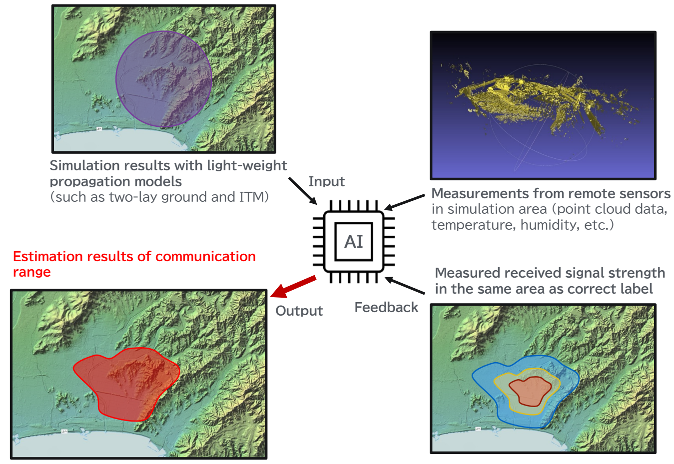

Fig. 2. Basic concept of the proposed method

The measurement data using the sensor devices are stored as 3D point cloud data. They are transferred to GCS during the UAV is flying in the target field when the UAV have a wide-band communication link or after the UAV lands on the ground.

The proposed system uses ITM as a light-weight simulation model because the results of ITM simulation include the signal level attenuation due to terrain elevation, instead of radio propagation models such as ray tracing models. The altitude data can be imported from public geographical database such as the Geospatial Information Authority of Japan (GSI) map.

GCS executes a reinforcement learning to obtain correction values to the simulation results or directly obtain more accurate received signal strength values. It inputs the 3D spacial data and light-weight simulation results to the model after voxelizing the original point cloud data to reduce data size. Unsupervisored learning using actual received signal strength values is idealy suitable to obtain accurate estimation results, however, it is not realistic to measure the values due to enormous patterns of crop-sprayers operation conditions. Therefore, reinforcement learning with the 3D special information can be better than other learning methods.

IV. Comparison of simulation and measurement results

This section shows the simulation results and measured values we measured by flying an UAV with multiple sensors in an actual orchard and evaluates the results.

TABLE I
Simulation parameters

Frequency	2480 [MHz] (U2.4) 220 [MHz] (DR-IoT)
TX power	250 [mW] (24 [dBm])
TX antenna height	1.0 [m]
RX antenna height	1.5 [m]
TX/RX antenna gain	2.15 [dB]
TX/RX cable loss	0.9 [dB]
Mesh size	1 [m]
Propagation model	ITM and Ray tracing
Ray tracing algorithm	Imaging
Ray tracing reflection	1

TABLE II
Field measurement configurations

Frequency	220 [MHz] (DR-IoT)
TX power	250 [mW] (24 [dBm]) [m]
TX antenna height	1.0 [m]
RX antenna height	1.5 [m]
TX/RX antenna gain	2.15 [dBi]
TX/RX cable loss	1.2 [dBi]

A. Scenario

We measured actual signal strength values when an UAV with sensor devices flying in an actual mandarin orange orchard. The orange orchard is located in Konan city, Kochi prefecture, Japan. Additionaly we performed radio propagation simulation using ITM and ray tracing model in the same field.

Fig. 3 shows the bird-eye view of the orange orchard. White lines in that figure are boundaries of the orchard and other farms. The area surrounded by white dotted lines is a simulation area we configured for this evaluation. The simulation area is approximately a 120 x 80 m rectangle. We installed a DR-IoT fixed station next to a work shed located on the northen side of the orange orchard because we heard from the crop-sprayer's operators that they usually stand and manupulate their UAVs around that point in current operation.

Fig. 5 shows a heat map of altitude in the same field. The orange farm is terraced with its elevation decreasing as it slopes southward. The south side of the orage farm is out of line of sight from the work shed because of the terraced farm and mandarin orange trees between the work shed and the southen area of the farm.

We implemented an UAV for 3D special infomration collection and received signal strength measurement. Fig. 5 shows the overview of the UAV. The UAV has a Avia 3D LiDAR sensor, a high-resolution camera, a DR-IoT radio and a Jetson Orin Nano. The Jetson Orin nano collects point cloud data and videos during flying over the orchard with 3D LiDAR sensor and high-resolution camera. The DR-IoT radio periodically transmits a 100-byte packet to the DR-IoT fixed station installed next to the work sched for the station to record received signal strength values.

Table I shows parameters of ITM and ray tracing simulation. We performed the simulations for U2.4 and DR-IoT. We used point cloud data measured by AViA LiDAR (Avia) [9] to consider obstacles obstructing line of sight between the work shed and UAV. The point cloud data we collected exceeded 100,000 points.

Since ray tracing simulation with the enormous amount of point cloud data takes a long time to calculate results, we voxelized the point cloud data to shrink the size of that data as shown in Fig. 6. We divided the simulation field with 1m x 1m squre meshes and defined a box in meshes as an abstracted obstracle. The height of the abstracted obstracle is the same as the highest height values of point cloud data in the mesh. The base height of the abstracted obstracle was referred to the altitude data of public maps published by Geospatial Information Authority of Japan. We used Scenargie RF Planner [10] to calculate ITM and ray-tracing simulation results.

Table II shows the field measurement configurations. We measured actual received signal strength values in a part of the orange orchard by walking with a DR-IoT radio the same as one installed on the UAV and an antenna because bad weather made the UAV hard to fly. We performed a field experiment to collect the data in October, 2025. In this field experiment, we did not measure actual received signal strength values of U2.4 system because the UAV we used for measurement were operated by U2.4 system and could interfere signals for measurement. Although the maximum transmission power of DR-IoT is 1 W, the transmission power was configured to 250 mW to avoid errors of measurement values due to saturation by strong received signal level. Depending on RF circuit implementation, strong received signals generally saturate a power ampilifier on RF circuits and makes it difficult to identify the accurate received signal strength. Therefore, we restricted the transmission power of the fixed station to 250 mW and collected actual received signal strength values in points far from the fixed station.

B. Results

Fig. 9 and Fig. 10 show the results of ITM and ray-tracing simulation in DR-IoT. The maps shown in the figures are oriented with north at the top. The areas or points filled in red indicate received signal strength is between -40 dBm to -50 dBm. The orange areas or points indicate the signal strength is 10 dB lower than the red ones. The signal strength decrease by 10 dB as the colors change from yellow to green, light blue, blue, and purple.

The ITM simulation results show signal attenuation following altitudes at any points of the simulation field. The ray tracing simulation results show signal attenuation level significantly different from the ITM simulation and many blind zones. Comparing the two results, the ray tracing simulation results could contain the effect of that the work shed blocks line-of-sight to the UAV. This is likely due to signal attenuation from structures and orange trees, which

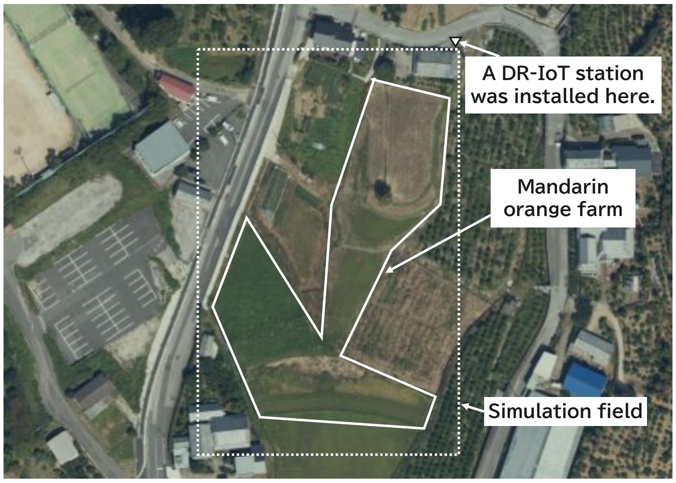

Fig. 3. Bird-eye view of a target mandarin orange orchard

Fig. 4. Altitude of the target orchard

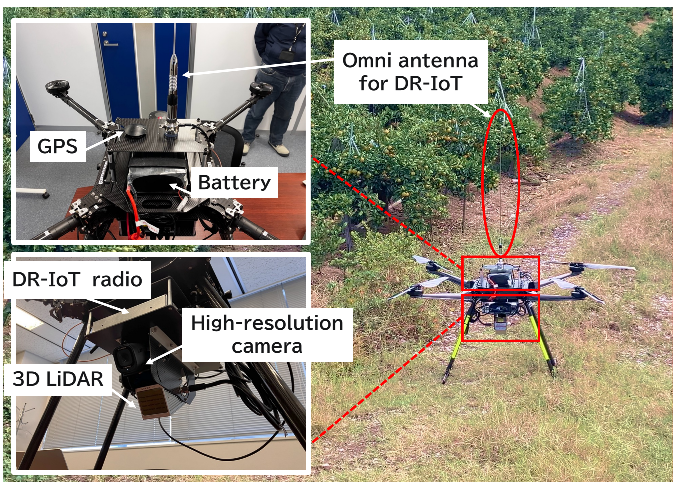

Fig. 5. UAV for measurement 3D special information and RSSI

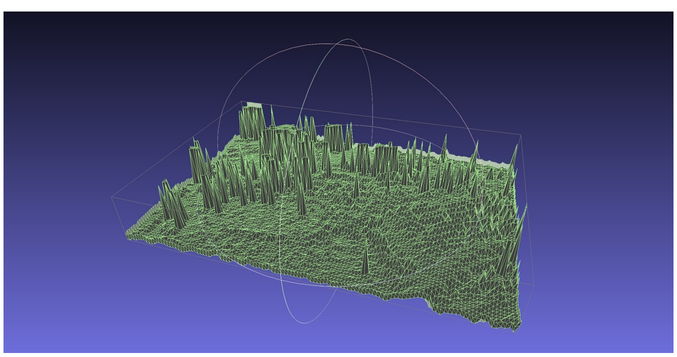

Fig. 6. Mesh data after voxelization (Each square is 1 x 1m).

are not included in the ITM results. It is noted that the ray tracing simulation results consider only reflection and do not consider the effect of diffraction. Since radio wave with lower frequency has better diffraction, ray tracing simulation considering both of reflection and diffraction can show results with fewer blind zones than the current ones.

Fig. 7 and Fig. 8 show the results of ITM and ray-tracing simulation in U2.4 system. As shown in the simulation results of DR-IoT system, the figures show the ray tracing simulation results show blind zones in the simulation field. Since radio wave with higher frequency has poor diffraction, the simulation results of U2.4 system show lower signal level than DR-IoT system. Comparing the results for U2.4 and DR-IoT, DR-IoT, which has a lower frequency and better propagation characteristics, could be better for UAV operators. Comparing the two ray tracing results between DR-IoT and U2.4, the locations of blind zones are slightly different.

Fig. 11 shows measured received signal values. Comparing the measured values with the ray tracing simulation results of DR-IoT system, The ray tracing simulation results follow the measured values. On the other hand, the ITM simulation results are significantly different from the measured values. There are up to 20 dB difference between them.

Consequently, the ray tracing simulation results closely follow the measured received signal strength values between a UAV and its operator, while the ITM model results show significant differences from the measured ones. The simulation and measured data show that vegetation and artificial obstacles like buildings have significant impact on signal attenuation for UAVs at low altitude.

V. Conclution

This paper presented a hybrid approach with machine learning and light-weight radio propagation model for wireless communication range estimation for UAVs at low altitude and their operators for crop-spraying in orchards and clarified vegetation and obstacles on the ground has significant impact on the accuracy of the esimation results. Since vegetation changes due to the changing of seasons, we will collect measurements and 3D geographical data in

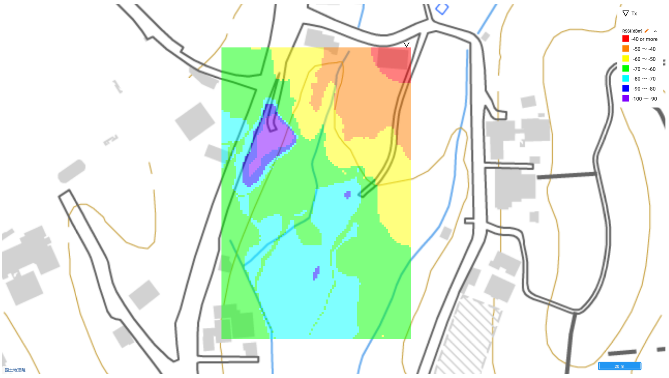

Fig. 7. ITM simulation results in U2.4 system

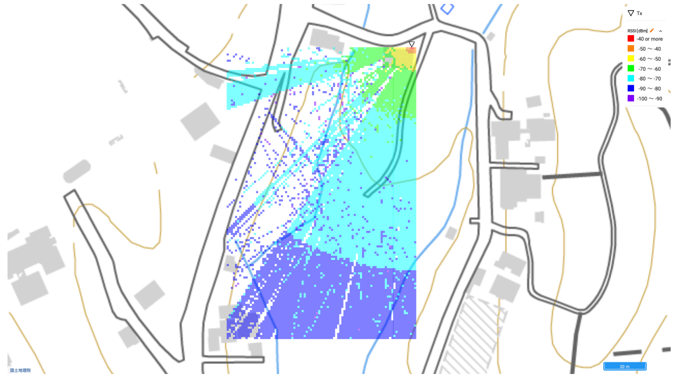

Fig. 8. Ray-Tracing simulation results in U2.4 system

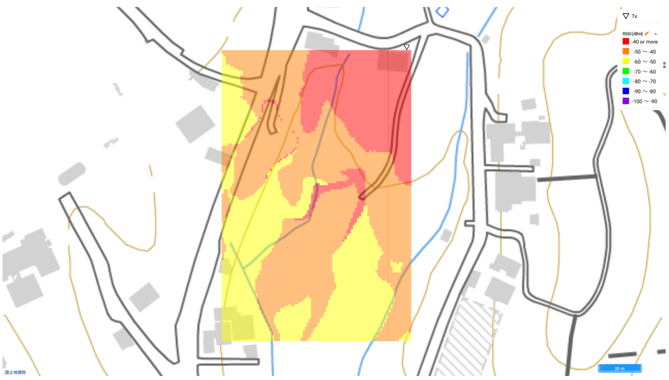

Fig. 9. ITM simulation results in DR-IoT

Fig. 10. Ray-tracing simulation results in DR-IoT

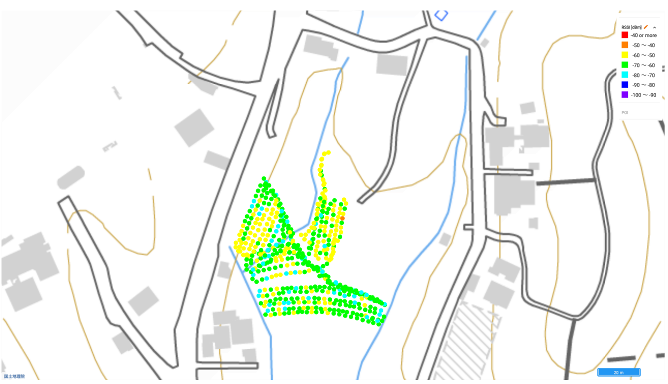

Fig. 11. Measured values of DR-IoT with 24 dBm of TX power

different seasons and estimates a machine learning model built with the simulation and measured data.

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