Simplified Experimental Evaluation of Radio Emitter Localization Using UAV-based Sensors

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***Abstract*—Recently, various efforts have been made to utilize Unmanned Aerial Vehicles (UAVs), even for application technologies expected in the future including positioning/localization. For examples, UAVs can be used to detect the location of victims in disaster areas to facilitate the rescue support. They can be also used to estimate the position of illegally emitted radio wave sources for monitoring proper radio wave usage. In conventional studies, the positioning/localization of ground-based radio wave sources were conducted using the positional fingerprinting method by placing multiple radio-frequency (RF) sensors at predetermined locations in an urban environment. In this paper, time-series based fingerprinting method is furthermore proposed using aerial RF sensors. Specifically, the proposed low-cost and high-accuracy location estimation method is realized by flying a single UAV as a receiving sensor on a predetermined trajectory and expanding the data used in the original location fingerprinting method with respect to the time axis to achieve a time-series data. Simplified validation experiments are conducted to show the effectiveness of the proposed method in this paper.**

I. Introduction

In recent years, communication devices such as smartphones have become widespread, and the Internet-of-Things (IoT), in which various things are connected to the Internet, has been proliferated. In conjunction with this trend, wireless communication technology has been advancing with the launch of 5G (5th generation mobile communication system) services and the practical application of LPWA (Low Power Wide Area), a wireless communication technology featuring power-saving long-distance communication that is expected to be used in the IoT. Among the advances in wireless communication technology, services using location information of objects and people have been attracting attention, and familiar examples of GPS-based services are map applications and smartphone games such as Pokemon GO. There are also attempts to use location information as big data. In the Great East Japan Earthquake, the situation of the inundation area was unclear at the time of the tsunami, but the location information of a car navigation system was analyzed and found to be congested due to the gridlock phenomenon. [1] provides another example of monitoring locations of communication devices at factories to predict operating conditions and use this information to make investment decisions. In addition, location information is indispensable for the realization of more advanced AR/VR technology and automatic driving technology, which are currently being actively researched.

GPS is the most common method for estimating location information, which is based on the difference of time arrival sent from four or more GPS satellites. Although GPS can provide accurate location estimation in open outdoor environments with Line-of-Sight (LoS), the accuracy of location estimation deteriorates significantly in urban environments such as tunnels, underground, inside buildings, and urban areas with many buildings due to the incurred NLoS (non-Line-of-sight) environment between GPS sattelites and the receivers [2]. There were also other geometric approaches to estimate the location using information angle of arrival (AOA) etc., but the estimation accuracy is similarly degraded in NLoS environments [3]. To improve the estimation accuracy even in NLoS environments, a statistical estimation method called the location fingerprint method using Unmanned Aerial Vehicles (UAVs) had been proposed to increase the probability of LoS in urban environments [4]. This conventional work proposed to use UAVs as Rx sensors for outdoor location estimation in which multiple UAV sensors are hovered at predetermined positions. The advantage of this method is that it can improve localization estimation accuracy compared to such conventional cases where sensors are placed on the ground owing to the improved LoS condition. On the other hand, there are some drawbacks including the computational cost required to optimize the placement of UAV sensors and the fact that the mobility of UAVs were not fully exploited since the UAVs just hover at fixed points.

In this study, we propose a time-series position fingerprinting method that extends position fingerprint data to the time axis by using UAV sensors orbiting on a predetermined trajectory, aiming to improve the accuracy of position estimation. For the position estimation algorithm, several machine learning methods of different regression models are used to improve the position estimation accuracy. Especially, simplified small-scale experiments were conducted to validate the proposed method.

This paper is organized as follows. In Section 2, after summarizing existing localization techniques, our proposed method is presented. In Section 3, the proposed method is evaluated by simplified small-scale experiments. Finally, Section 4 concludes our findings.

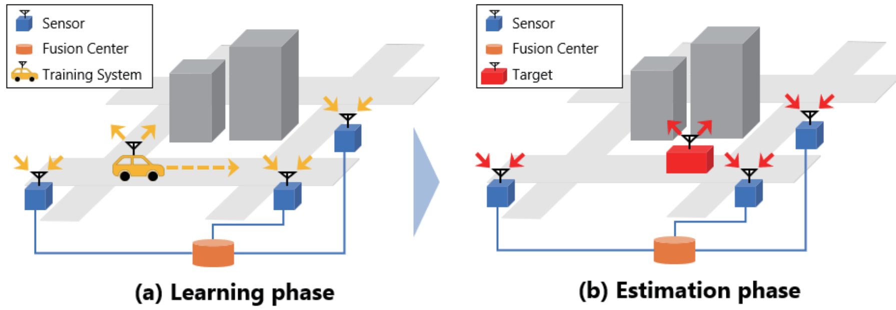

Fig. 1. Two phases of fingerprint-based localization method [8], [9].

II. Localization Methods

A. Localization Methods of Unknown Emitters

There are two main types of methods for estimating the location of a radio transmission source: an active method in which the target terminal receives radio waves emitted by a beacon whose absolute location is known and estimates its own location and a passive method in which a sensor receives radio waves transmitted by the target terminal and the system estimates the terminal's location. A well-known example of the former is the Global Positioning System (GPS), but it is not suitable for estimating the location of illegal radio wave sources because of the hardware limitation of a GPS chip non-necessarily equipped in the target terminal and the need for cooperation between the localization system and the terminal to be estimated. For this reason, the monitoring of illegal radio waves often employs the latter method in which the location is estimated by the system using information on radio waves emitted by the target terminals.

The radio wave information used for location estimation includes the received signal strength indicator (RSSI), time difference of arrival (TDOA), and angle of arrival (AOA). Localization using the AOA is called triangulation, which is also used in DEURAS-D, one of the above-mentioned DEURAS [5] programs. However, such a geometric method assumes that the distance between the terminal and the sensor is in an LoS condition, but in environments with many scattering objects, e.g., urban areas, it is easy to become NLoS and the accuracy of localization is greatly degraded [6].

Therefore, this paper uses the location fingerprinting method, i.e., a statistical location estimation method, to enable location estimation even in NLoS environments. The next section provides an overview of the fingerprint localization.

B. Fingerprint Localization

Fingerprint localization is a method that collects position-dependent information as fingerprints and statistically estimates the position by pattern matching [7]. As shown in Figure 1, fingerprint-based localization is largely divided into a learning phase and an estimation phase. In the learning phase, a location fingerprint database is constructed from the propagation characteristics of a radio wave source whose location and parameters are known in advance, which is observed by a sensor while moving. In the estimation phase, radio waves from an unknown target are observed and their positions are estimated by pattern matching with the positional fingerprint database constructed in the learning phase. This method is expected to further improve the accuracy of localization due to recent advances in statistics such as machine learning [10].

In outdoor location estimation, in addition to location fingerprinting based on RF signals, there are also methods using visual fingerprinting based on images captured by mobile terminals or motion fingerprinting based on motion sensors such as acceleration, electronic compass, and gyroscope [11]. These methods have significant drawbacks e.g. the performance is easily affected by surrounding environments and weather conditions and also the applicable distance range is limited.

In this study, an RF fingerprint called RSSI (Received Signal Strength Indicator) is used as location fingerprint because it is easy to implement in hardware and does not require time synchronization. When the position coordinate of the k-th emitter is $\mathbf{u}_k$ and the RSSI observed at the n-th sensor is $P_n(\mathbf{u}_k)$ [dB], the fingerprint vector $\mathbf{F}_k^{\mathrm{DB}}$ is expressed as follows where N denotes the total number of deployed sensors.

$$\mathbf{F}_k^{\mathrm{DB}} = [P_1(\mathbf{u}_k), \ldots, P_N(\mathbf{u}_k)]. \tag{1}$$

A regression process will be applied over the fingerprint database $\mathbf{F}_k^{\mathrm{DB}}$. In the estimation process, the RSSI fingerprints i.e. $P_{\forall n}^{\mathrm{target}}$ [dB] observed by the n-th sensor will be compared to the regression function to predict the location of the unknown emitter.

C. UAV Sensor Enabled Time-Series Fingerprint Localization

To further improve the estimation accuracy even in NLoS environments, [4] proposed to use UAVs working as RF sensors to increase the probability of LoS in urban environments. In other words, multiple UAV sensors are hovered at predetermined positions to measure the RF fingerprints in the training phase and also in the estimation phase. Owing to the enhancement of LoS condition, this method is expected to improve localization estimation accuracy compared to conventional case where sensors are fixed on the ground. However, there are still some drawbacks including the computational cost required to optimize the placement of UAV sensors, the

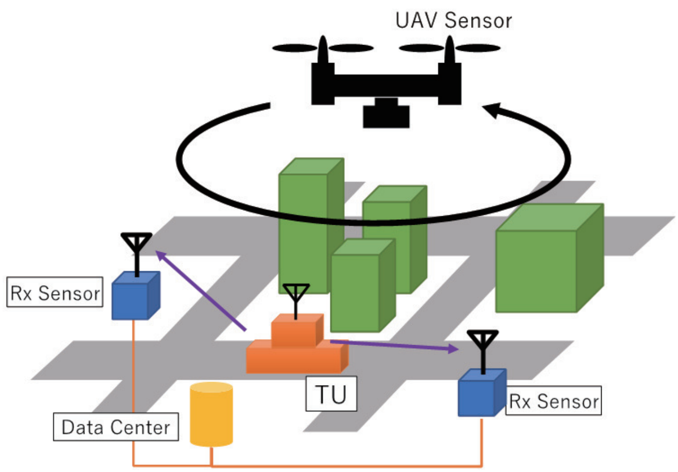

Fig. 2. The proposed UAV sensor.

cost of deploying more sensors for higher estimation accuracy and the fact that the mobility of UAVs were not fully exploited since the UAVs just hover at fixed points. To solve this issue, this paper proposes a time-series location fingerprinting method that a single UAV sensor flies over a predefined orbit to collect many RF fingerprint time-series samples on its trajectory as shown in Fig. 2. This proposed method aims to achieve higher accuracy at a lower cost than existing methods.

When the position coordinate of the k-th emitter is $\mathbf{u}_k$ and the RSSI observed at the t-th time of the UAV sensor is $P_t(\mathbf{u}_k)$ [dB], the fingerprint vector $\tilde{\mathbf{F}}_k^{\mathrm{DB}}$ is expressed as follows where T denotes the total number of fingerprint samples measured on the UAV's orbit.

$$\tilde{\mathbf{F}}_k^{\mathrm{DB}} = [P_1(\mathbf{u}_k), \ldots, P_T(\mathbf{u}_k)]. \tag{2}$$

Compared to Eq. (1), the proposed method can virtually increase the number of RF sensors by arbitrarily selecting a large enough samples T when the UAV patrols over its trajectory. Also, since only a single UAV is employed, lower facility cost can also be expected.

A regression process will be applied over the fingerprint database $\tilde{\mathbf{F}}_k^{\mathrm{DB}}$ where $\mathbf{R}$ denotes a specific regression function e.g. Gaussian process.

$$\mathbf{M}^{\mathrm{DB}}\left(\tilde{\mathbf{F}}^{\mathrm{EST}}, \mathbf{u}\right) = \mathbf{R}\left(\tilde{\mathbf{F}}_{\forall k}^{\mathrm{DB}}, \mathbf{u}_{\forall k}\right). \tag{3}$$

In the estimation process, the RSSI fingerprints i.e. $P_{\forall t}^{\mathrm{target}}$ [dB] observed at the t-th sampling time will be compared to the regression database to predict the location of the unknown emitter.

$$\hat{\mathbf{u}} = \arg\min_{\mathbf{u}} \mathbf{M}^{\mathrm{DB}}\left(\tilde{\mathbf{F}}^{\mathrm{target}}, \mathbf{u}\right). \tag{4}$$

III. Simplified Validation Experiment

A. Experiment Setup

Regardless of a proposal of a localization method for outdoor environment, it is difficult to conduct evaluation experiments in a real environment since it is currently hard to make a UAV patrolling a wide urban area e.g. our university's campus due to legal restrictions in Japan etc. Therefore, we conducted small-scale experiments in our university's gymnasium using a line tracer equipped with a WiFi module imitating a UAV to evaluate the proposed method. In an urban environment, the UAV is considered to be flying and the Tx is on the ground, but in our experiments, the line tracer runs on the floor while the Tx is located at a high position instead. Therefore, although the line tracer is not flying, it is considered to be a UAV and will be referred to as a UAV in this section.

Fig. 3. Line tracer's route.

Fig. 4. Tx used in the experiment.

TABLE I
Experiment Specification

Wireless device	Raspberry Pi 4 Model B
Line tracer model	Picar-4WD
Antenna model	WN-G300UA
Central frequency	2.412 GHz
Specification	IEEE 802.11n
Emitter height	1.6 m
UAV antenna height from ground	0.1 m
UAV trajectory's radius	3 m
Gymnasium area	$43.4 \times 34.6\mathrm{m}^2$

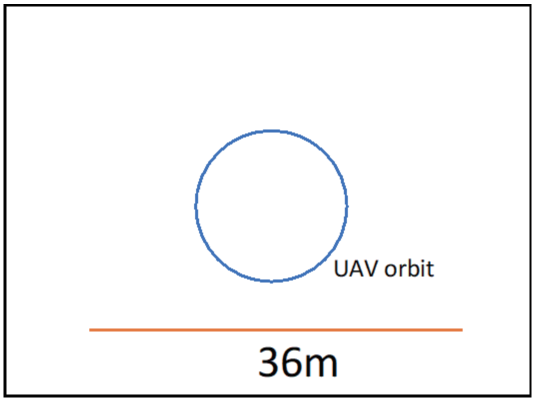

Fig. 5. Experiment without obstacles.

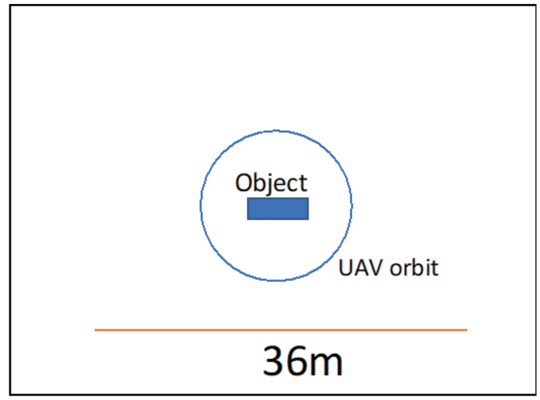

Fig. 7. Experiment with obstacles.

Table I shows the equipment used in this experiment. The Picar-4WD is a robot kit equipped with gray-scale sensors, ultrasonic sensors etc. and can be controlled using a Raspberry Pi. Figure 3 shows how the UAV runs.

The UAV was equipped with a Raspberry Pi 4 and communicated using an external WiFi antenna connected to the Raspberry Pi 4. RSSI was measured as the fingerprint information. The RSSI measurement frequency was about 1000 points/circle. These RSSI measurements were not synchronized with each revolution of the UAV, and varied slightly.

As with the UAV, another Raspberry Pi 4 was used as the radio wave source (Tx), and an external WiFi antenna was used for communication. The Tx was fixed at a height of 1.6 m using a tripod to imitate the height difference between the UAV and the radio wave source in an urban environment. Figure 4 shows the Tx used in the experiment.

B. Performance Analysis

1) Experiment Results in Environments w/o Obstacles: We measured time-series position fingerprint information in a simple environment without any obstacles in a gymnasium and estimated the position using the proposed method.

In this experiment, Tx was placed on a 36-m line in a gymnasium with no obstacles, and moved every 0.5 m step each time the UAV completes a circle orbit in the gymnasium, acquiring time-series fingerprint information for training purposes and creating a regression model for localization. In the same way, we randomly measured at 10 positions of unknown Tx on the line to collect time-series fingerprints for location estimation of the unknown Tx.

Figure 6 shows the processed measurement data. A position estimation regression model was created using the measurement data. The regression model takes as input values the time-series position fingerprint information (100 dimensions) for one UAV orbit and outputs the estimated coordinates of Tx. There are various possible machine learning algorithms for creating a regression model for position estimation, including regression tree models, neural network regression, Gaussian process regression, SVR etc. and the algorithm suitable for position estimation may vary depending on the type of fingerprint information used and the environment in which the position fingerprint is measured.

In this experiment, Gaussian process regression, regression

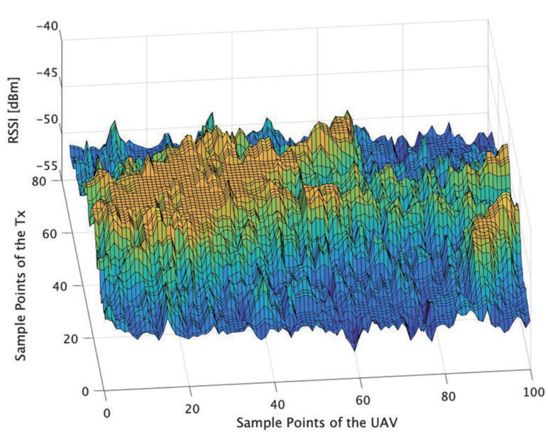

Fig. 6. Measurement results without obstacles.

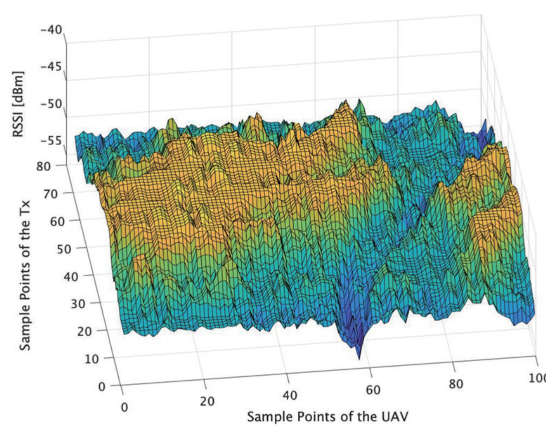

Fig. 8. Measurement results without obstacles.

TABLE II
LOCALIZATION RESULTS IN ENVIRONMENT WITHOUT OBSTACLES.

Regression model	Training RMSE	Estimation RMSE
Gaussian process regression	1.47 m	2.44 m
Regression tree model	1.96 m	4.31 m
Neural network regression	2.26 m	7×10^7 m

TABLE III
LOCALIZATION RESULTS IN ENVIRONMENT WITH OBSTACLES.

Regression model	Training RMSE	Estimation RMSE
Gaussian process regression	1.11 m	2.08 m
Regression tree model	1.78 m	3.87 m
Neural network regression	2.31 m	3.01 m

tree model, and neural network regression were trained and the location estimation accuracy of each model was compared. Table II shows the location estimation performance of each model.

The table shows that the Gaussian process regression has the best estimation accuracy, with an estimation error of 2.44 m, or 6.8% for a measurement range of 36 m. The neural network regression has a much lower estimation accuracy than the Gaussian process regression. The accuracy of the unknown location estimation for the neural network regression was significantly lower. This indicates that the model was over-training with respect to the training data.

2) Experiment Results in Environments w. Obstacles: In this section, we evaluate the proposed method by performing the same RSSI-based position estimation in an environment where obstacles are placed in the center of the UAV's orbit.

In this experiment, we measured training data in the same environment as mentioned in previous section, with an obstacle (ping-pong table) placed in the center of the UAV's circular trajectory as shown in Figure 7, and randomly measured at 10 positions of unknown Tx on the line to collect time-series fingerprints for location estimation of the unknown Tx. Next, we used the data shown in Figure 8 to train regression models for location estimation. The location estimation errors for each regression model are summarized in Table III.

Table III shows that the Gaussian process regression model provides the most accurate location estimation, even in the presence of obstacles. The neural network regression did not over-learn like in the case without obstacles and was more accurate than the regression tree model. When comparing the RMSE of the Gaussian process regression in both scenarios, it is interesting to find out that the performance in an environment with obstacles is better than that in the same environment with no obstacle. It indicates that the proposed method in this paper may be a good solution for localization in NLoS environments, which had long been an issue of existing localization methods like triangulation.

IV. CONCLUSION

In this paper, we propose a time-series location fingerprinting method to improve the accuracy of outdoor location estimation of radio sources. Existing location estimation methods based on the location fingerprinting method using hovering UAVs have problems with degraded location estimation accuracy in NLoS environments and difficulty in optimizing the positioning of the UAVs. The proposed method in this paper extends the position fingerprinting method to the time axis by using UAVs to patrol, thereby simplifying the UAV deployment and improving the accuracy of obtaining position fingerprint information in the LoS environment.

Simulations of the proposed method in an urban area showed an improvement in location estimation accuracy compared to existing methods. In a simplified small-scale experiment conducted at a gymnasium, we confirmed that the proposed method can achieve an estimation accuracy within 7% of the measurement range. Comparative evaluation with and without obstructions showed that the proposed method improved position estimation accuracy in the presence of obstacles (an NLoS environment) compared to the absence of such obstructions (a LoS environment), confirming the possibility that the proposed method is suitable for outdoor position estimation in urban areas where LoS condition is hard to be attained.

REFERENCES

[1] "KDDI Location Data". https://k-locationdata.kddi.com/alternative/
[2] A. LaMarca et al. "Place Lab: Device Positioning Using Radio Beacons in the Wild", Lecture Notes in Computer Science, vol. 3468, Springer, Berlin, Heidelberg, 2005.
[3] I. Guvenc and C.C. Chong, "A Survey on TOA Based Wireless Localization and NLOS Mitigation Techniques," in IEEE Communications Surveys & Tutorials, vol. 11, no. 3, pp. 107-124, 3rd Quarter 2009.
[4] S. Tanaka, G.K. Tran, K. Sakaguchi, "Outdoor Localization of RF Emitter Using UAV-based Sensors," SmartCom2019, Nov. 2019.
[5] Ministry of Internal Affairs and Communications Japan DEURAS Direction Finder (DEURAS-D). Available online: https://www.tele.soumu.go.jp/e/adm/monitoring/moni/type/deurasys/deuras_d.htm (accessed on 21 Dec. 2023).
[6] Q.D. Vo, P. De, "A Survey of Fingerprint based Outdoor Localization," *IEEE Commun. Surv. Tutor.* **2015**, *18*, 491–506.
[7] T. Yu et al., "A guide of fingerprint based radio emitter localization using multiple sensors," *IEICE Trans. Commun.* **2018**, *101*, 2104–2119.
[8] G. K. Tran, T. Kamei, S. Tanaka, "Route Optimization of Unmanned Aerial Vehicle Sensors for Localization of Wireless Emitters in Outdoor Environments," Network 2023, 3, 326-342.
[9] T. Kamei, S. Tanaka, G.K. Tran, "Study on the Optimization of Flight Paths for Fingerprint-Based Outdoor Localization Using UAV," IEEE PIMRC2022, Sept. 2022.
[10] M.A. Alsheikh, S. Lin, D. Niyato, H.P. Tan, "Machine Learning in Wireless Sensor Networks: Algorithms, Strategies, and Applications," *IEEE Commun. Surv. Tutor.* **2014**, *16*, 1996–2018.
[11] G. Schroth et al., "Mobile visual location recognition", IEEE Signal Process. Mag., vol. 28, no. 4, pp. 77-89, Jul. 2011.