International Journal of Networking and Computing – www.ijnc.org, ISSN 2185-2847
Volume 12, Number 1, pages 218–236, January 2022

Location estimation algorithm using UAV for real environments

Masaya Tomiyama
Graduate School of Engineering, Doshisha University
Kyoto, Japan

Yuma Takeda
Faculty of Engineering, Doshisha University
Kyoto, Japan

Takahiro Koita
Graduate School of Engineering, Doshisha University
Kyoto, Japan

Received: February 15, 2021
Revised: May 5, 2021
Revised: June 20, 2021
Accepted: August 27, 2021
Communicated by Takeshi Yokota

Abstract

Unmanned aerial vehicles (UAVs) have demonstrated substantial abilities at disaster sites, as they can be easily moved and are not affected by terrain conditions. The purpose of this study is to search for survivors in the UAV localization system. For this purpose, we explore a localization method using the Received Signal Strength Indicator (RSSI) when aerial photography cannot be used to find victims buried in rubble. We propose a method for estimating the position of disaster survivors using RSSI in an environment surrounded by obstacles. We conducted an experiment in an urban area to evaluate our proposed algorithm. Our proposed algorithm improves the accuracy of position estimation in disaster areas in crowded, obstacle-ridden situations.

Keywords: UAV, RSSI, flight algorithm, position estimation

1 Introduction

This chapter describes the importance of early detection and rescue, the use of unmanned aerial vehicles (UAVs), position estimation methods using RSSI, our research objectives, and the remaining structure of this paper.

1.1 Importance of early detection and rescue

Disasters occur frequently in the world, and earthquakes, tsunamis, typhoons, and abnormal weather have caused great damage to human life and social activity. The effects of abnormal weather around the world are increasing. Japan is considered one of the world's most disaster-prone countries, with earthquakes, tsunamis, volcanic eruptions, typhoons, and heavy rains likely to occur depending on the location, topography, geology, and meteorological conditions.

The number of seismic-designed buildings is increasing due to the frequency of earthquakes and the growing awareness of disaster prevention due to concerns of a Nankai Trough megathrust earthquake. However, many buildings are still not aseismic and large-scale damage due to a Nankai giant earthquake is expected. When an earthquake occurs, it is inevitable that people will become trapped and in need of rescue due to building collapse. If these victims cannot escape on their own, they will need to be found and rescued by others. In addition, many victims may be left behind because of submergence of the city due to the heavy rains that have occurred in recent years. Search and rescue activities begin with requests sent to rescue teams, starting with the Self-Defense Forces, who then begin their search in the disaster area.

The time required to find and rescue victims is critical. Lifesaving is said to be "a game 72 hours after the disaster" , as the limit a human being can survive without drinking and eating is 72 hours. During the Hyogo-ken Nanbu Earthquake (Great Hanshin-Awaji Earthquake) of January 17, 1995, the number of survivors dropped sharply three days after the occurrence. In some cases, despite being alive when found, those rescued after this time ultimately succumbed to their injuries.

As the scale of a disaster increases, it becomes more difficult to detect and recover victims quickly. For example, it is often difficult for search and rescue teams to enter a disaster site due to road and building collapses, and roads are often flooded by heavy rains and divided by earth and sand, thus increasing the time it takes to locate and retrieve victims. In addition, when rescue teams search in areas where roads and buildings have collapsed, they must proceed while removing obstacles to search for more victims. This removal work leads to critical time loss. If the existence of victims can be confirmed more quickly, minimal removal and rescue work can be performed and, as a result, victims can be rescued at earlier.

1.2 Unmanned Aerial Vehicles (UAVs)

The use of unmanned aerial vehicles (UAVs) is increasingly drawing attention in the field of disaster prevention. UAVs are able to fly into areas that are difficult to enter after a disaster. The high mobility of UAVs regardless of terrain is also useful for estimating the location of disaster victims, and for confirming and discovering the existence of victims buried in rubble. Thus, rescue time in the event of a disaster can be shortened.

1.3 Position estimation method using RSSI

Position estimation using RSSI (Received Signal Strength Indicator) is a method for detecting victims using UAVs. Victims are likely to have a terminal (smartphone, etc.), and this terminal sends probe packets. A probe packet is a signal emitted periodically by the terminal that is sent when the terminal performs an active scan to search for nearby access points (APs).

In the event of a disaster, access points often do not function due to infrastructure destruction or building collapse. However, probe packets are sent if the source Wi-Fi function is working and are advantageous in the event of a disaster if the victim's terminal can be used. The probe packet signal is represented by a value called RSSI, which represents the strength of the received signal. RSSI measures the strength of a signal received by a wireless communication device. RSSI increases as the distance between the access point and the terminal increases, making it possible to estimate the location of a victim.

1.4 Purpose

The purpose of this study is to rescue disaster survivors as soon as possible. In Section 1.3, we discussed RSSI. In a real environment, RSSI is affected by obstacles and its surrounding environment, and such problems as unstable values and irregular transmission intervals must be dealt with. These problems significantly reduce the accuracy of location estimation and hinder the quick rescue of survivors. To solve this problem, we propose a method that estimates their positions from the deviation of RSSIs measured at several points for situations where accurately predicting the terminal's position is difficult from an RSSI degraded by obstacles in real environments. Our method is original because it is based on the assumption of position estimation in a real environment. In many conventional RSSI-based position estimation methods, RSSI is measured beforehand without obstacles and enables position estimation in the presence of obstacles [2,3,4]. However, in an actual disaster area, measuring RSSI in advance is almost impossible. Therefore, in this study, instead of measuring the RSSI in advance, we use it (which is unstable due to obstacles) to estimate positions.

1.5 Structure of this paper

The remainder of this paper is structured as follows. Section 2 describes related research and problems. We learned about RSSI, which is the crux of the RSSI-based location estimation method, by conducting a preliminary experiment to investigate its stability and the frequency of its outliers in outdoor conditions. We describe that preliminary experiment in Section 3. Based on the results of preliminary experiments, we explain our proposed method in Section 4. To investigate the practicality of the proposed method, we conducted a location estimation experiment with it in a real environment. In Section 5, we outline our experiment and describe its increased success rate and its decreased search time. In Section 6, we describe our results and discussion and summarize our work in Section 7.

2 Related research and problems

In this section, we describe existing research on location estimation of victims by UAV and consider the issues.

2.1 The UAV flight algorithm in the victim position estimation system

Tatsumi et al. proposed a UAV flight algorithm that determines the flight path based on the signal strength of a probe request as a method of investigating the communication distance, reception strength, and transmission frequency of the probe request to find victims using UAVs[4]. Tatsumi et al.'s proposed method automates the process from the start of the search to the discovery of the victim, making it possible to shorten the flight time by narrowing down the search location and improve the accuracy of probe request reception by making stationary observations. In this victim location estimation system, they used the following flight algorithm. We also adopted this method as a prior method for the experiments conducted in Sections 5 and 6.

2.1.1 Outline of the proposed algorithm

The outline of Tatsumi et al.'s UAV algorithm is shown below.

1) Set a square S_n with the start point as the apex and the measurement interval d as the length of one side. The algorithm initially sets $n = 1$.

2) Measure the probe request at an unmeasured point among the vertices of the set square and record the signal strength.

3) Compare the signal intensities at the four vertices of the set square and set a new square S_{n+1} that is point-symmetrically moved from the set square with the largest point as the point of symmetry.

4) If the signal strength at the measurement point exceeds -50 dBm, it is considered a victim. If not, increase n and return to 2) and try again.

2.2 Experiments for Detection of Handheld Game Console by UAV with Wi-Fi Sensing Function

In real environments, RSSI can be affected by such surrounding factors as obstacles that cause unstable values and erratic transmission intervals. Kashiwara et al. [6] addressed this problem by targeting a portable game terminal, Nintendo 2DS LL, to show that any portable terminal that emits Wi-Fi beacons can be detected. In fact, since some people, including children, won't have smartphones, we show that other devices can also be detected. Then Kashiwara et al. measured the RSSI with mobile gaming devices both indoors and in a car and concluded that the RSSI was reduced by obstacles.

3 Preliminary experiment

We conducted preliminary experiments to measure RSSI in different environments, under various conditions, and with different devices to determine how much RSSI is affected by its surrounding environment, how many meters are needed to create a difference in RSSI when measuring it, and what the maximum RSSI value is that can be measured. In the preliminary experiments, we did not perform any location estimation, only RSSI measurements. This section gives an overview, results, and discussion of our preliminary experiments.

3.1 Experiment outline

In our preliminary experiments, we measured RSSI in different environments and under different conditions with Wireshark as the network analyzer software. The terminals with Wi-Fi capability possessed by the victims were an Android (Nexus 5x), an iPhone (X), and a PC (Mac). The terminals were placed on the ground in each environment at the 0 m(meter) point. The measurement PC was fixed approximately 1.2 m above the ground (Figure 4). The environment consisted of three patterns: a paved road (concrete), grass, and a playground. Figure 1 shows the concrete environment, Figure 2 shows the grass environment, and Figure 3 shows the playground environment. The playground environment was assumed to be obstacle-free, the concrete environment was assumed to have a few obstacles, and the grass environment was assumed to have many obstacles. The weather was sunny; the RSSI was measured four times per minute (about 100 packets) in each environment and at each distance interval. Measurements were taken at 5 m intervals to find out which intervals produced differences in RSSI.

Figure 1: Location where preliminary tests were carried out (concrete)

Figure 2: Location where preliminary tests were carried out (grass)

Figure 3: Location where preliminary tests were carried out (playground)

Figure 4: Holding a notebook PC during experiments

3.2 Differences in environments

Focusing on the differences in the environments, Figures 5, 6, and 7 show the RSSI boxplot when the distance between the terminal and the measurement terminal is 10 m. The vertical axis is the RSSI value (dBm) and, from the left, the concrete, playground, and grass. The RSSI was large in the concrete environment in all models. In addition, since the boxplot of the playground was small in all models, the RSSI swing width was the smallest. The point away from the boxplot that exists in any model and any environment was an outlier. There are many RSSI outliers because the part where the whiskers (lines outside the boxes) are long means that the RSSI swing width is large.

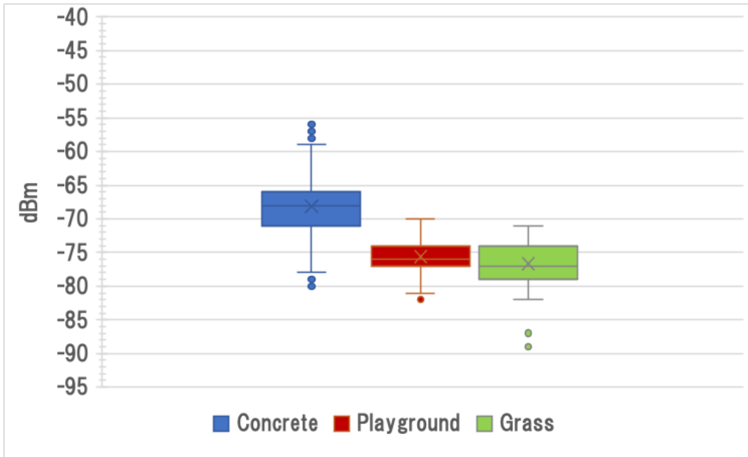

Figure 5: RSSI values measured in each environment with 10m interval using Android

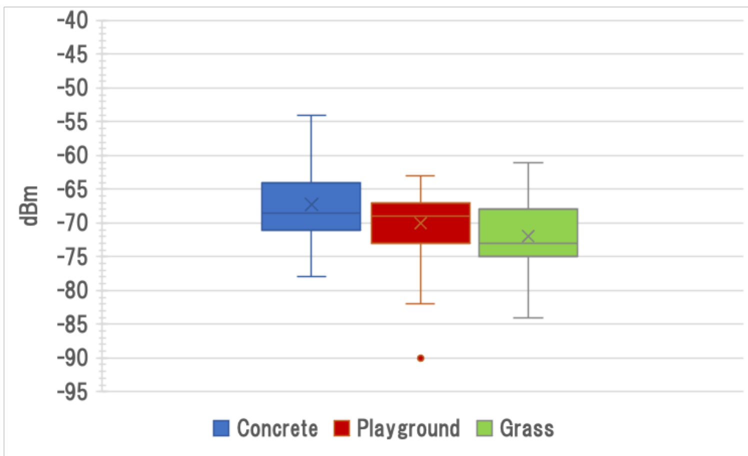

Figure 6: RSSI values measured in each environment with 10m interval using iPhone

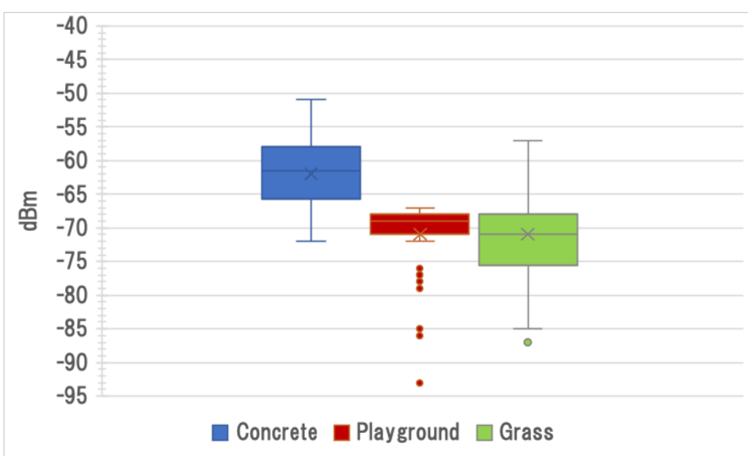

Figure 7: RSSI values measured in each environment with 10m interval using PC

3.3 Differences in terminals

Focusing on the difference between the terminals, Figures 8, 9, and 10 show the RSSI boxplots when the distance between the terminal and the measurement terminal is 5 m, 10 m, and 15 m in a concrete environment. The vertical axis is the RSSI value (dBm) and, from the left, the distance is 5 m, 10 m, and 15 m.

On the Android and iPhone, the closer the distance, the larger the RSSI. Since the average RSSIs of 5 m, 10 m, and 15 m are different, the RSSI can be compared. Since the average RSSI of the PC is almost the same at 5 m and 10 m, an RSSI comparison is clearly difficult. The point away from the boxplot that exists in any terminal and any environment is an outlier. In addition, since there are many parts with long whiskers, there are many RSSI outliers, even in concrete.

Figures 11, 12, and 13 show the RSSI boxplots when the distance between the terminal and the measurement terminal is 5 m, 10 m, and 15 m in the playground environment. The vertical axis is the RSSI value (dBm) and, from the left, the distance is 5 m, 10 m, and 15 m.

We can see that the RSSI can be compared because the RSSI becomes larger as the distance becomes shorter in any terminal. Compared to concrete and grass, the boxplot is much smaller in the playground, indicating that the RSSI is stable. Therefore, the outliers, which are the outliers of RSSI, are more noticeable, which means that outliers exist even in the relatively stable playground.

Figures 14, 15, and 16 show boxplots of RSSI values when the distance between the terminal and the measuring terminal is 5 m, 10 m, and 15 m in the grass environment. The vertical axis is the RSSI value (dBm) and, from the left, the distance is 5 m, 10 m, and 15 m.

On the iPhone and PC, the whiskers of the boxplot are longer than those of concrete and playgrounds, indicating that the RSSI swing width is large. This is quite a bit affected by the grass and fallen leaves between the terminal and the measurement terminal.

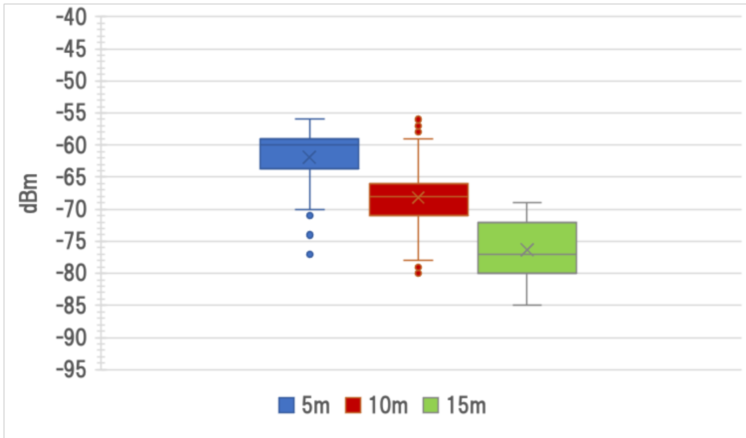

Figure 8: RSSI values measured on concrete at each distance interval using Android

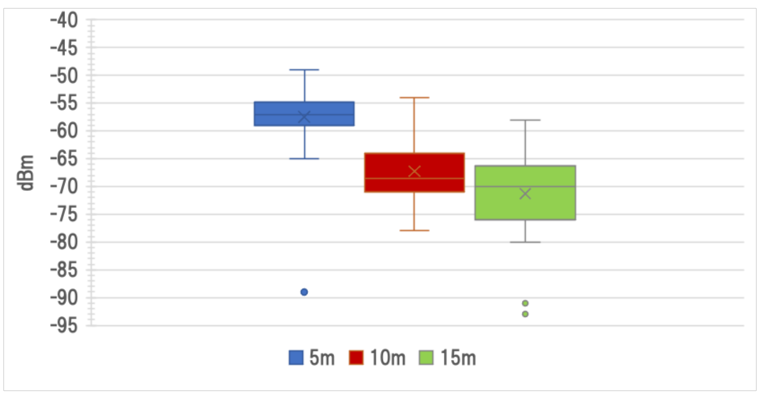

Figure 9: RSSI values measured on concrete at each distance interval using iPhone

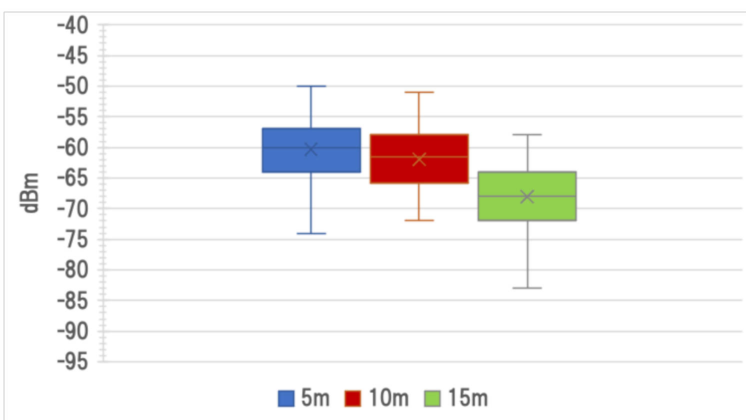

Figure 10: RSSI values measured on concrete at each distance interval using PC

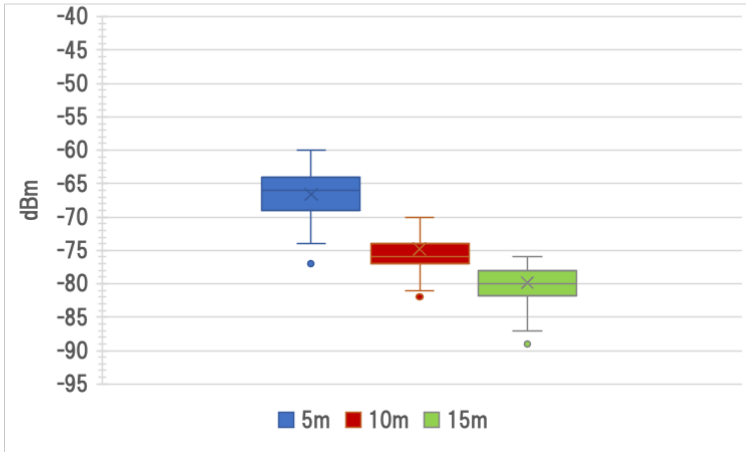

Figure 11: RSSI values measured in playground at each distance interval using Android

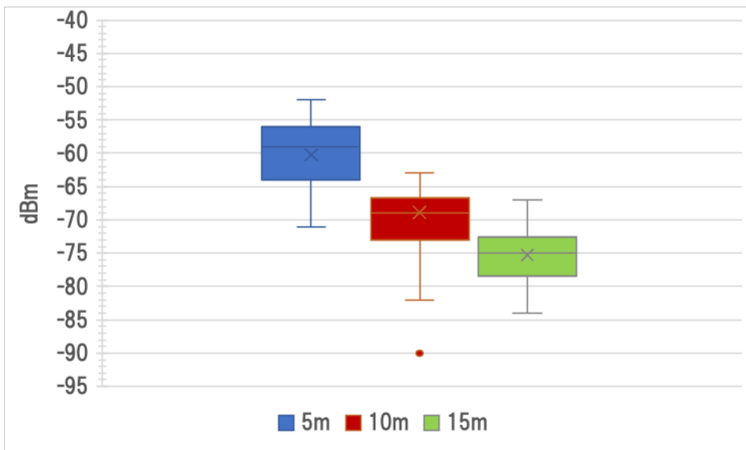

Figure 12: RSSI values measured in playground at each distance interval using iPhone

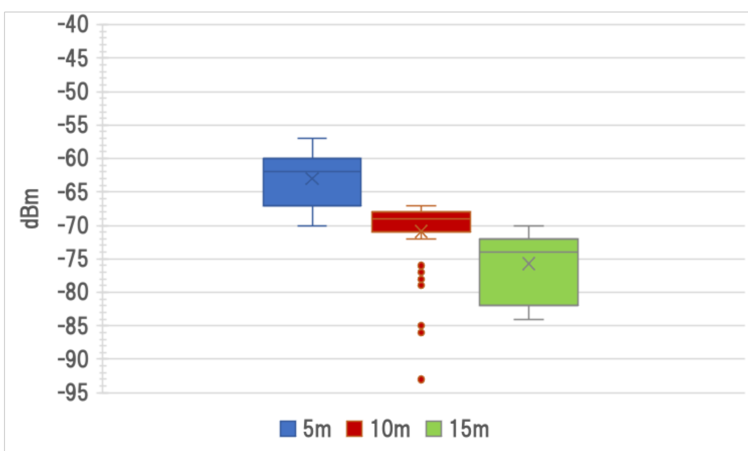

Figure 13: RSSI values measured in playground at each distance interval using PC

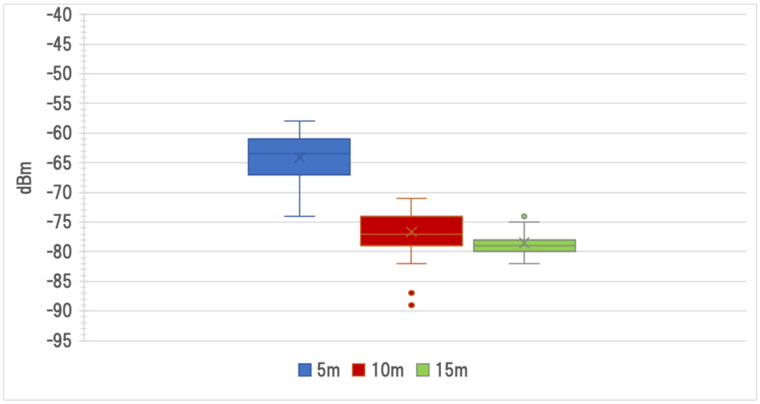

Figure 14: RSSI values measured in grass at each distance interval using Android

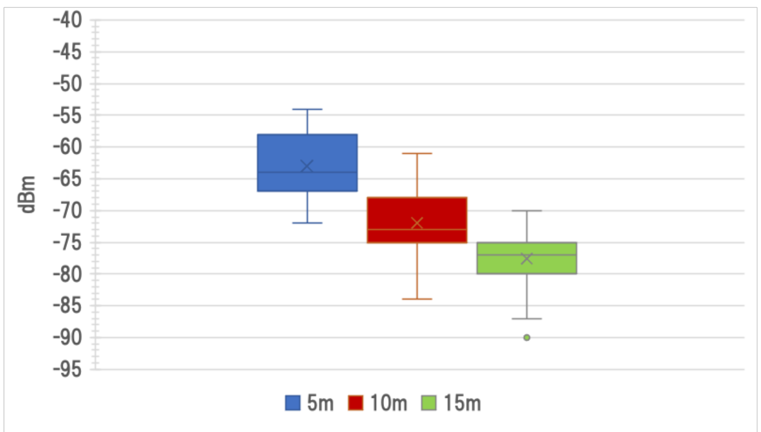

Figure 15: RSSI values measured in grass at each distance interval using iPhone

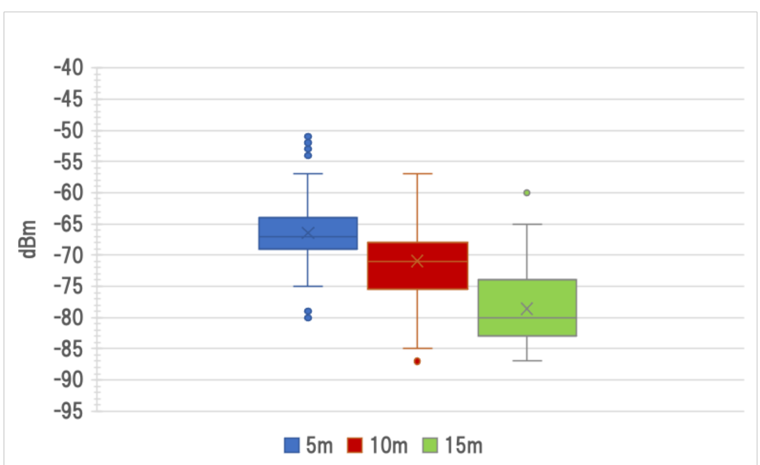

Figure 16: RSSI values measured in grass at each distance interval using PC

Table 1: Number of RSSI outliers and total number of RSSI

	Concrete	Playground	Grass	Total
Number of RSSI outliers	36	25	55	116
Total number of RSSI	259	255	258	772

3.4 Discussion

As can be seen from the boxplots of each result, there are many RSSI outliers. In every environment and every terminal, there are whiskers and detached points. In the position estimation, not only the outliers but also the RSSI corresponding to the whiskers should be regarded as outliers. The best way to improve the accuracy of position estimation is to measure RSSI in advance at the place where you want to estimate the position and acquire information on the average value and outliers. However, when estimating the position in the event of an actual disaster, it is not possible to plan RSSI at that location in advance, depending on the situation, and therefore it is difficult to determine whether the RSSI measured at the time of position estimation is an outlier[6]. Thus, in this study we use the RSSI deviation to check whether outliers are included in the measurement.

The boxplots of each result show many RSSI outliers. In every environment and every terminal, there are whiskers and detached points. In the position estimation, both the outliers and the RSSI corresponding to the whiskers should be regarded as outliers. The best way to improve the accuracy of the position estimation is to measure the RSSI in advance where you want to estimate the position and acquire information on the average values and outliers. However, since estimating the position of actual disasters is obviously impossible before they occur, RSSI can't be planned at that location in advance. Therefore, it is difficult to determine whether the RSSI measured at the time of the position estimation is an outlier. Thus, we use RSSI deviation to determine whether outliers are included in the measurement.

Table 1 shows the number of RSSI outliers in each environment. In the environment on concrete, there were 36 outliers out of a total of 259 RSSI. In the playground environment, there were 25 outliers out of a total of 255 RSSI. In the grass environment, there were 55 outliers out of a total of 258 RSSIs. Out of a total of 772, there were 116 outliers. During a certain period of time, outliers occur in clusters. Therefore, not all outliers have a negative impact on location estimation, but the number is not negligible. In the playground with few obstacles, outliers were few, while in the grass with many obstacles, outliers were more than twice as many as in a playground. Therefore, the presence or absence of obstacles may also have effects on the occurrence of outliers.

4 Proposed algorithm

This section reviews the challenges of a UAV path planning algorithm and the proposed method. We focus on the RSSI increase or decrease due to obstacles. RSSI increases as the distance between the access point and the device decreases. However, RSSI is unstable because outliers occur due to the influence of surrounding objects, radio waves, and the terminal itself. Previous studies have proposed methods with measures against outliers. However, these methods determine position only by determining the RSSI value. If the victim is covered with obstacles, the RSSI value will be lower. Therefore, it is difficult to judge based on the RSSI value alone. Our proposed method uses the deviation of RSSI.

4.1 Outline of the proposed algorithm

The outline of the proposed method is shown below.

1) Set a square S_n, which includes the starting point of the vertex, and measurement interval d is the length of one side. The algorithm initially sets $n = 1$.

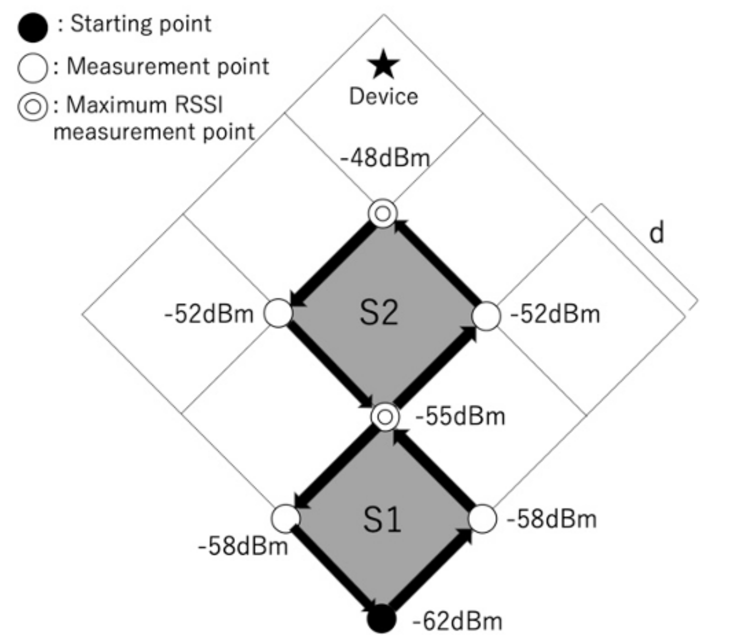

Figure 17: Proposed algorithm

2) Measure the RSSI at the unmeasured points of the set square vertices.

3) Compare the RSSI at the four vertices of the set square and newly set the square S_{n+1}, which is the point symmetric movement of the set square with the maximum point as the symmetry point.

4) Calculate the deviations of the four RSSIs measured in 3) and compare the deviations of S_n and S_{n-1}. Change d if significantly different.

5) When the RSSI of the measurement point exceeds -50 dBm, it is assumed that the victim's position is specified. If not, increase n and return to 2) and try again.

The originality of our proposed method lies mainly in 4), where the deviations of the four RSSIs measured in 3) are calculated and compared with the deviations of S_n and S_{n-1}. If their deviations are significantly different, d is changed to prevent the RSSI from going in the wrong direction if an outlier occurs. If the RSSI values of the four points of the square are almost the same and they cannot be orientated, changing d can improve the situation.

4.2 Explanation with examples

Figure 17 shows an example operation when the measurement interval is d. We first set a square S_1 that includes the start point at the vertex. RSSI measurements at the four vertices of S_1 recorded -58 dBm, -62 dBm, -58 dBm, and -55 dBm, respectively. Then, we set a square S_2 by moving S_2 to the point where the maximum RSSI of -55 dBm was recorded. Next, we measured RSSI at the remaining three vertices of S_2, and recorded -48 dBm, -52 dBm, and -52 dBm, respectively. Victims were found where we recorded signal strengths exceeding -50 dBm and -48 dBm. Here, the difference between the minimum RSSI and the maximum RSSI in S_1 is 7 dBm, and the difference between the minimum RSSI and the maximum RSSI in S_2 is 7 dBm. In this case, we encountered no problems. However, if the difference between the minimum RSSI of S_2 and the maximum RSSI of S_2 becomes a very small value, such as 2 to 3 dBm, the measurement interval d changes. In our research experiment, measurement is performed by changing d to $2d$ and changing d to $1/2d$.

Figure 18 shows an example of the actual flow. In this way, the position of the victim is estimated while forming the square S_n.

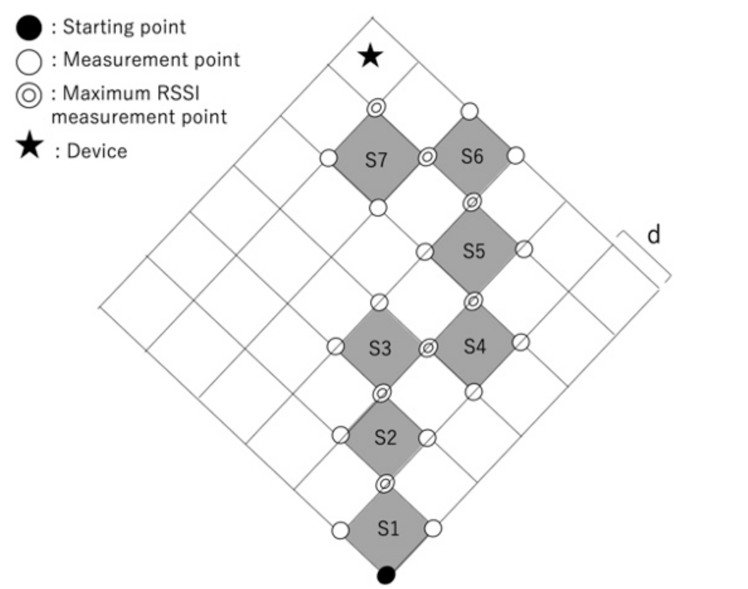

Figure 18: Overall flow of the proposed method

5 Evaluation

To evaluate the algorithm, we changed the length of measurement interval d and examined the results in a real environment with two methods: the previous [4] and our proposed. The RSSI was measured on a PC using network analyzer software called Wireshark. An iPhone (X) was used as a survivor's device. From our previous study [7], we confirmed that altitudes between from 1 to 5 meters do not affect the result much. However, in this previous study [7], the flight was unstable when the UAV equipped with the special device used in the previous study was used (shown in Figure 19). Thus this experiment was carried out without using UAV, where an experimenter moved instead of it. After the calculation process, the UAV moved, and we used PC and Wireshark for this experiment. We ensured the experiment's validity and practicality without the UAV by moving at the identical speed and identical latency as when the UAV was actually used. The altitude was fixed at a constant level. As in the preliminary experiments, the measuring PC was fixed about 1.2 m above the ground. The RSSI measurement time for one block was 15 seconds. The environments were a city park and a parking lot. The park is located in an open urban area. There are many buildings and obstacles around the parking lot. The weather was sunny. Length d of one side of the square, which is the measurement interval, starts at 5 m. For the previous method, we used the method described in Section 2.1.1.In the previous method, the search was always done at $d = 5$ m. The altitude of the measurements was also fixed because an excessively short interval would not show any difference in RSSI. From the preliminary experiments, we decided on a minimum distance of 5 m to measure the RSSI difference. In the proposed method, we used two approaches: changing $d = 5$ m to $d = 2.5$ m at the time of the change and changing $d = 5$ m to $d = 10$ m at the time of the change. The position estimation was defined as complete when RSSI exceeded -50 dBm. From related research [8], since we know that the maximum distance at which RSSI can be measured is about 50 m, we placed the phone at a distance of about 50 m and started the experiment from the place where the first RSSI was measured. As in the preliminary experiments, the terminals were set on the ground in their respective environments at 0 m. We set the end time of each search to 30 minutes, taking into account the maximum flight time of one UAV, which is suitable for estimating the location of the survivors.

The previous method, the proposed method ($d = 2.5$ m), and the proposed method ($d = 10$ m) searched twenty times in each environment. Figure 20 shows the park where the experiment was

Figure 19: UAV equipped with the special device used in the previous study [7]

conducted, and Figure 21 shows the parking lot.

6 Results and Discussion

6.1 Results

Figure 22 shows the results for the park. Figure 23 shows the parking lot results. Each shows a total of three search times and success rates for the previous method and the proposed method.

Turning our attention to the results for the park in Figure 22, with the previous method, the average search time to success was 21.4 minutes, the overall average time including failures was 23.6 minutes, and the success rate was 80%. With the proposed method changing the measurement interval from 5 m to 2.5 m, the average search time to success was 22.2 minutes, the overall average time including failures was 24.4 minutes, and the success rate was 90%. With the proposed method changing the measurement interval from 5 m to 10 m, the average search time to success was 23.4 minutes, the overall average time including failures was 25.7 minutes, and the success rate was 80%. We found no large difference when comparing each search time, probably because the park was an open area and the influence of obstacles such as surrounding buildings on the RSSI was small.

Figure 23 shows the parking lot results for a total of three search times and the success rates for the previous method and proposed methods. First, with the previous method, the average search time to success was 24.4 minutes, the overall average time including failures was 28.7 minutes, and the success rate was 40%. With the proposed method changing the measurement interval from 5 m to 2.5 m, the average search time to success was 19.2 minutes, the overall average time including failures was 21.5 minutes, and the success rate was 75%. With the proposed method changing the measurement interval from 5 m to 10 m, the average search time to success was 17.4 minutes, the overall average time including failures was 24.2 minutes, and the success rate was 70%.

Comparing the respective search times, the proposed method takes less time than the previous method. Comparing the two proposed methods, proposed method (d = 10 m) had good success search times while proposed method (d = 2.5 m) had a good average search time including failures. It can be said from the results that the proposed method (d = 2.5 m) is a balanced method.

When comparing the success rates, the proposed method showed better results than the previous method. There was no significant change in the success rate between 2.5 m and 10 m, but in some

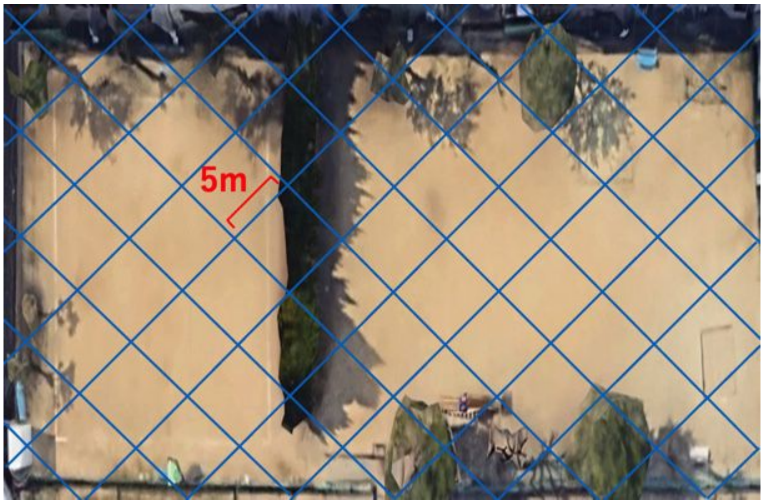

Figure 20: Park where the experiment was conducted

Figure 21: Parking lot where the experiment was conducted

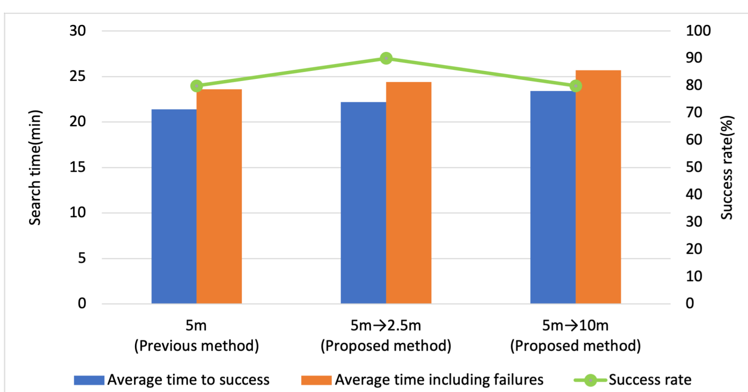

Figure 22: The park where the experiment was conducted

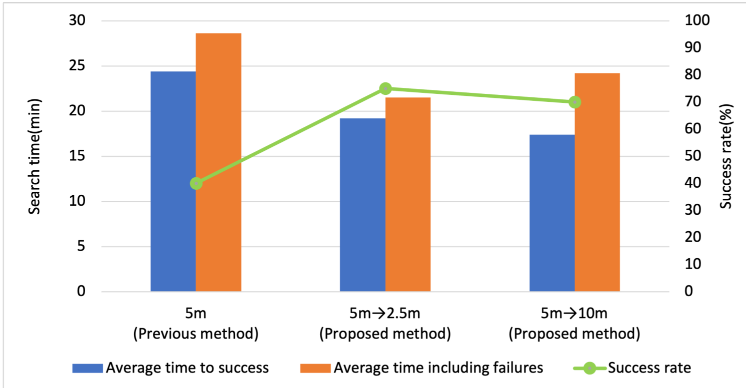

Figure 23: Parking lot where the experiment was conducted

cases it failed.

In the previous method, when an RSSI outlier occurs, orientation is not possible after the measurement, the movement often stagnates, the time passes, and the search ends. However, the proposed method sometimes breaks the deadlock and raises its success rate because the distance and the environment where the RSSI is measured change at both 2.5 and 10 m.

When comparing the proposed method at 2.5 and 10 m, the proposed method ($d = 10$ m) more successfully broke the stalemate. However, the success rate of the proposed method ($d = 10$ m) was lower than that of the proposed method ($d = 2.5$ m) because the search time became longer when the 10 m measurement was performed many times.

6.2 Discussion

We proposed a method that considers the decrease in RSSI due to obstacles when searching for victims. The results indicate that the proposed method ($d = 2.5$ m) is a well-balanced method, but proposed method ($d = 10$ m)'s successful search time result is better. Thus, it is advisable to use a well-balanced combination of $d = 2.5$ m and $d = 10$ m. In addition, other conditions such as the measurement period and UAV side restrictions must be taken into consideration. When the distance to the terminal is within 5 m, -50 dBm or more is measured, so the goal of discovery of the victims is -50 dBm. However, in reality, it is conceivable that the RSSI will be significantly reduced due to obstacles such as rubble and the distance to the terminal will be -50 dBm or less even within 5 m. Therefore, we must consider the search end condition.

Moreover, this time, we used the deviation of the RSSI of the four vertices of the square; however, during the experiment, there were cases where the RSSI was the same for all four vertices. These are issues we will explore in the future.

7 Conclusion

The purpose of this research was to propose a location estimation algorithm using UAVs specialized for the real environment. To achieve this goal, we proposed an algorithm that changes the length of d, which is the edge of a square search grid, using RSSI deviation. In order to evaluate the algorithm in the actual environment, we performed a location estimation experiment with the proposed method and the existing method in the open area of a park and the dense area of a parking lot. As a result, differences in d length and deviations in d affected detection rates and search times for wireless devices. Other conditions such as measurement time and UAV side constraints also affect the detection rate and search time of wireless devices and should be taken into account. This challenge is one of the key issues for us to clarify.

References

[1] W. Nakai and R. Katsuma, “Indoor Position Estimation Method Resistant to RSSI Distance Measurement Error Due to a Small Number of Obstacles,” Proceedings of the 27th Multimedia Communication and Distributed Processing Workshop, pp.39-47, 2019.

[2] H. Osaka, T. Abe, and T. Suganuma, “A Basic Design to Improve Estimation Accuracy of Outdoor Sensor Positions Using UAV,” IEICE Technical Report IN2016-77, pp.63-68, 2016.

[3] T. Hurudate, M. Horikawa, and M. Sugawara, “Proposal of Indoor Positioning Method using Received Signal Strength,” IPSJ SIG Technical Report, vol.2014-ITS-59, no.21, pp.1-4, 2014.

[4] Y. Tatsumi, H. Kawanaka, and T. Koita, ”A Path-Planning Algorithm for UAV Position-Estimation Systems at Disaster Sites,” 2018 IEEE 24th International Conference on Embedded and Real-Time Computing Systems and Applications (RTCSA), Hakodate, pp.248-249, doi: 10.1109/RTCSA.2018.00044, 2018.

[5] S. Kashihara, A. Yamamoto, K. Matsuzaki, K. Miyazaki, T. Seki, G. Urakawa, M. Fukumoto, and C. Ohta, “Experiments for Detection of Handheld Game Console by UAV with Wi-Fi Sensing Function,” IEICE Technical Report, vol.119, no.53, SeMI2019-1, pp.1-6, 2019.

[6] M. Tomiyama, “Proposal of Position Estimation Method using RSSI,” Doshisha University Graduation Thesis, 2020.

[7] M. Yoneda, “Considerations for Moving Message Ferries in Delay Tolerant Networks,” Doshisha University Graduation Thesis, 2018.

[8] Y. Takeda, “Proposal of an algorithm for estimation in obstacle assumption state using RSSI,” Doshisha University Graduation Thesis, 2021.