Low-Cost Collision Avoidance in Microverse for Unmanned Aerial Vehicle Delivery Networks[1]

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Abstract. Unmanned Aerial Vehicles (UAV) have been widely adopted in many applications, from surveillance to delivery. More UAV delivery businesses are expected to be launched in the foreseeable future to meet food, goods, and medicine needs for residents living in smart cities, remote areas, or places lacking runways. As the density of UAVs operating in a community increases, collision avoidance becomes critical concerning the safety of personnel, property, and UAVs. In the last decade, many solutions have been suggested for collision avoidance scenarios, where typical solutions require integrated sensing, information exchange, and on-board decision-making. However, including these essential components increases the cost and makes it unaffordable for small-size UAVs in terms of payload weight and power consumption. Inspired by the Metaverse-enabled by Digital Twins, Blockchain, Augmented Reality (AR)/Virtual Reality (VR), and the fifth generation (5G) wireless communication technologies; we propose LoCASM, a low-cost collision avoidance scheme in Microverse, a local-scale Metaverse, for UAV delivery networks. LoCASM only requests position (GPS), altitude, velocity, and direction (PAVAD) information from each UAV; relieving the burden of expensive and energy-consuming components. By mirroring UAVs' PAVAD information and the city landscape in the Microverse, the computing-intensive tasks, including UAV tracking, trajectory prediction, and collision avoidance management, are migrated to the Microverse server on the ground. A proof-of-concept prototype of the LoCASM system has been built, and the simulation experimental study has validated the design.

Keywords: Unmanned Aerial Vehicles (UAV) Networks, Collision Avoidance, Microverse, Metaverse.

1 Introduction

The fast development of Unmanned Aerial Vehicles (UAV) technologies and the wide expansion of their applications in various sectors signify a transformative leap toward a more automated and efficient future.[1,2] With UAVs increasingly being deployed for surveillance, delivery, and inspection purposes, their integration into society is becoming more pronounced.[3,4] UAV integration is particularly significant in smart cities, remote areas, and regions where traditional delivery infrastructures, like runways, are non-existent or inadequate.[5] As such, the potential for UAVs to meet critical needs for food, goods, and medicine is vast, promising to bridge gaps in accessibility and convenience for residents in these areas.

Besides security[6,7] and privacy[8,9] concerns inherited from legendary Internet-of-Things (IoT) networks, as the skies become busier with these UAVs, ensuring their safe operation becomes paramount. The density of UAVs operating simultaneously in a community introduces a complex challenge: collision avoidance.[10,11] Collision avoidance is a technical hurdle and a crucial safety concern that impacts the well-being of on-ground personnel, properties, and UAVs themselves. The significance of collision avoidance research, therefore, cannot be overstated. It is essential for the sustainable growth and acceptance of UAV technology in public and commercial spaces.

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Collision avoidance research is foundational in developing systems and protocols enabling UAVs to navigate densely populated airspaces safely.[12] It involves creating sophisticated algorithms and sensor technologies that allow UAVs to detect, communicate, and maneuver around each other and obstacles in real-time.[13] This research is inherently multidisciplinary, incorporating insights from robotics, artificial intelligence, aerospace engineering, and information technology.[14,15]

Moreover, successfully implementing collision avoidance technologies is vital for garnering public trust and regulatory approval.[16] As UAVs become more commonplace, ensuring their safety is essential to prevent accidents that could set back the adoption of this promising technology. Furthermore, effective collision avoidance systems open the door to more complex and varied applications of UAVs, pushing the boundaries of what is possible in delivery services, emergency response, and urban planning.

In the past decade, the challenge of ensuring UAV (Unmanned Aerial Vehicles) safety through effective collision avoidance has garnered significant attention. Three critical components are essential to these avoidance systems: integrated sensing, information exchange, and on-board decision-making. Integrated sensing allows a UAV to perceive its immediate environment through technologies like radar and LiDAR, enabling it to detect potential obstacles. Information exchange involves UAVs communicating with each other and ground control and sharing vital data such as position and intended flight path to maintain safe distances. Lastly, on-board decision-making empowers a UAV to process sensed information in real time and make swift decisions to avoid collisions. Together, these elements form the backbone of advanced collision avoidance strategies widely proposed and explored.

However, implementing these sophisticated systems poses a significant challenge for small-sized UAVs due to increased costs, payload weight limitations, and heightened power consumption. Integrating advanced sensors, communication systems, and computing capabilities necessary for collision avoidance increases the overall cost, making it economically unfeasible for smaller, budget-constrained UAV operations. Furthermore, these additional components add weight, pushing the UAV beyond its payload capacity, which can hinder the UAV's operational efficiency or ability to carry essential goods. Power consumption is another critical concern; the energy required to run these advanced avionics can drastically reduce the UAV's flight time and operational range, limiting its utility. Thus, while collision avoidance is crucial for the safe operation of UAVs, especially in dense airspaces, finding a balance that allows small-sized UAVs to adopt current technologies without compromising their performance or mission capabilities remains a significant challenge.

Drawing inspiration from the vast potential of the Metaverse, which is powered by Digital Twins, Blockchain, Augmented Reality (AR)/Virtual Reality (VR), and fifth-generation (5G) wireless communication technologies, we introduce a cost-effective collision avoidance strategy named LoCASM (Low-cost Collision Avoidance Scheme in Microverse). LoCASM utilizes Microverse,[17,18] a localized version of the Metaverse tailored for UAV delivery networks. Unlike traditional systems that depend on costly and power-intensive components, LoCASM requires only basic information from each UAV, such as position (GPS), altitude, velocity, and direction (PAVAD), significantly reducing the hardware and energy demands on the UAVs.

The core innovation of LoCASM lies in its use of the Microverse to offload complex computing tasks from individual UAVs to a centralized server on the ground. By replicating the UAVs' PAVAD data and the city's layout within the Microverse, LoCASM can efficiently manage UAV tracking, trajectory forecasting, and collision avoidance without burdening the UAVs themselves. Hence, the LoCASM approach enhances the scalability of UAV delivery networks by minimizing onboard computing requirements and improving safety and efficiency. We have developed a proof-of-concept prototype of the LoCASM system, and our simulation-based experimental studies have confirmed the effectiveness and reliability of the LoCASM design.

The rest of the paper is organized as follows. The background knowledge and related work are presented in Section 2. Section 3 explains the principles of Microverse, a local-scale Metaverse, in detail and introduces LoCASM. Section 4 describes the data set we collected and reports the experimental results. Finally, Section 5 presents our conclusions and discusses ongoing efforts.

2 Background and Related Work

2.1 Digital Twins-enabled Metaverse

The idea of Digital Twins (DTs) was first introduced by Grieves in 2003, which was initially used to describe the procedure of industrial manufacturing.[19] Thanks to the exponential development of enabling technologies such as the Internet of Things (IoT), sensing system, communication, and simulating tools, DTs enjoyed rapid growth during the following decade and were redefined by the National Aeronautical and Space Administration (NASA).[20] Compared to the traditional simulation process, DTs utilize the real-time sensor data and historical data of the physical object (PO) to create a logical replica to realize more accurate simulations. Innovated by this new concept, numerous studies on DT-enabled manufacturing emerged in recent years, covering various industry domains. For instance, the assembling process can benefit from the accurate simulation using a DT-based system, which improves the quality and precision of the workflow[21].[22]

As defined in,[23] Digital Twins can be considered as the first stage of the development of Metaverse, which indicates a hypothetical virtual environment connected to the real physical world—such connection leverages real-time data synchronization as well as other aspect of entanglement. Limited by the capability of current technology, the development of Metaverse is restricted to an early form, for example, in a ”Micro” scale[18] focusing on certain applications or services for a certain domain.

Combined with other technologies such as blockchain, a DT-enabled prototype of a university campus was proposed to support social good.[24] Leveraging a 3D modeling engine, virtual avatars of multiple users are created inside the virtual campus, reflecting their real-time status. Another example leverages the DT technique together with Artificial Intelligence to simulate the performance of a UAV system. By introducing a convolutional neural network (CNN) to the UAV autonomous network, the safety performance of different scenarios was evaluated.[25] Moreover, a UAV DTs information forecasting model is proposed to support rapid medical resource delivery.[26] Based on the improved AlexNet neural network, the performance, such as transmission delay and task completion time, outperforms other approaches. However, the above two UAV system studies were both simulated on a software platform, and no physical simulations or tests were performed.

2.2 Collision Avoidance Approaches for UAV Networks

The major algorithms of current research for onboard collision avoidance for UAV systems can be categorized into geometric methods, trajectory optimization methods, and sense-and-avoid methods.[11]

Traditional *geometric approaches* determine the avoidance strategy according to the results of geometric analysis. To prevent the violation of the minimum distance between UAVs or between UAVs and obstacles, these approaches calculate the estimated collision time based on current geometric locations and velocities of the UAVs. Some researchers utilize databases like Automatic Dependent Surveillance-Broadcast (ADS-B) and the Global Positioning System (GPS) to evaluate the worst collision situation by calculating the point of closest approach (PCA)[27].[28] Assuming that all transferred information like positions and velocities are accurate,[27] proposed "Vector Sharing Resolution" to solve possible conflicts. However, most commercial UAVs are not equipped with ADS-B, and the accuracy of GPS is highly related to geographical location.

Trajectory optimization can be further categorized into potential field methods and geo-optimization methods. The difference is that the potential field methods introduce the concept of force-field to determine the behaviours of the UAVs including strategies against collision threats.[29]For instance,[30] proposed an optimized potential field (APF) algorithm to support collision avoidance and trajectory setting in a three-dimensional space. Compared to traditional APF methods, the modified algorithm overcomes the restriction of single UAV trajectory planning and expands to multi-UAV situations. On the other hand, geo-optimization approaches rely on geographical data to generate the best trajectory planning with the help of certain algorithms such as Bayesian optimization, gradient descent, random tree algorithms, etc.[31] is an example of introducing closed-loop rapidly-exploring random tree algorithm and variations for path planning of UAVs. The experiments involved simulations not only in software and hardware but also in real flight tests.

Compared to potential field and optimization methods, *sense-and-avoid* highly relies on the sensors mounted on the UAVs. Instead of setting a strategy for multiple UAVs, sense-and-avoid approaches focus on detecting obstacles and avoiding collision for an individual agent, which simplifies the whole algorithm to evaluate possible conflicts between UAVs and between a certain UAV and environmental obstacles. This collision avoidance scheme can rapidly respond to any possible conflicts by leveraging various types of sensors on board, such as radar and sonar. Gageik et al.[32] presented a lightweight solution based on sensing technologies like low-cost ultrasonic and infrared range finders. Although this may introduce extra noise compared to other expensive sensors, the proposed approach managed to restrain the computation burden and reduce both memory and time costs.

3 Principle and Architecture

The design rationale of LoCASM is to leverage the task-oriented Microverse, a localized Metaverse that creates a DT-based virtual space using real-world information and UAVs' PAVAD data. In the framework of LoCASM, complex computing tasks are migrated from individual UAVs to a centralized server on the ground. This design favors the operational environments in which UAVs are under different administrations. LoCASM does not depend on the collaboration among UAVs. Instead, as long as each UAV communicates the PAVAD data with the ground control, the

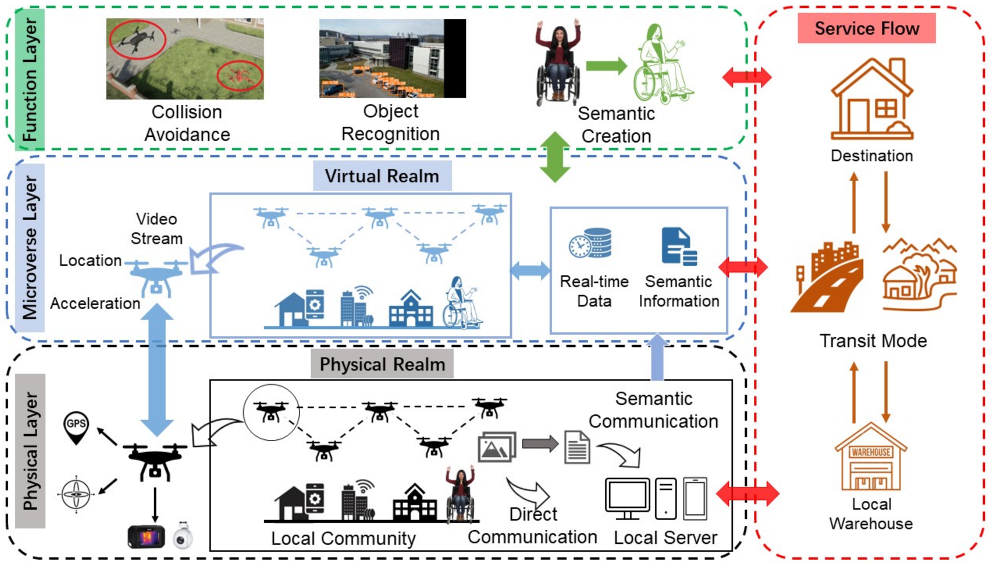


Fig 1 LoCASM Architecture.

Microverse-based collision avoidance system would take over all the computing-intensive tasks, including UAV tracking, trajectory forecasting, and collision avoidance. We envision the LoCASM scheme, shown in Fig. 1, will enhance the scalability of UAV delivery networks by minimizing on-board computing requirements and improving safety and efficiency.

3.1 System Architecture

Figure 1 shows a hierarchical architectural view of the envisioned LoCASM framework. Following the design principle of Microverse systems, LoCASM categorizes the diverse components of the Metaverse into specific levels, each serving distinct roles.

Since LoCASM is designed for a Microverse covering a smart community or smart city, the physical environment is initiated in the digital space by creating the digital twins of main objects, such as buildings, trees, roads, towers, and other objects that potentially may obstacle the flight path of UAVs. Then, UAVs and other mobile objects will be created in real-time when the system is operating.

The *physical layer* contains a variety of UAVs performing delivery tasks over the local community. Each of the UAVs is equipped with sensors transferring real-time information such as PAVAD data to the local server. Besides the directly communicated data, simple semantic information is also generated by lightweight onboard AI algorithms such as low-cost object recognition and further transmitted to the server instantaneously. After certain processing by the server, this information is subsequently stored in a structured database, ensuring the creation of a comprehensive repository.

In LoCASM, we adopt semantic communication to reduce the workload for the communication system. Each UAV does not transmit raw data to the LoCASM server but the meaning or intent of the information. It offers a transformative approach to reducing data size in UAV network communications.[33] By prioritizing the transmission of semantically significant information, unnecessary data that does not contribute to the intended message's understanding can be filtered out, leading to more efficient use of the limited bandwidth available in UAV networks. The semantic filtering ensures that only the most relevant, meaning-laden data is transmitted, significantly reducing the volume of data that needs to be sent. Consequently, semantic communication not only alleviates the burden on the network's capacity but also enhances the operational efficiency of UAVs by enabling faster and more reliable communication, which is particularly crucial in scenarios requiring real-time data exchange and decision-making, where the rapid dissemination of critical information can be lifesaving or mission-critical.

Leveraging the pre-constructed virtual community environment, the *Microverse layer* reconstructs a virtual replica of mobile units, including UAVs, using dynamic semantic information provided by them. Consequently, any observed occurrences or deviations inside the tangible realm are promptly reflected within the digital domain.

The synchronization of various elements not only provides a visible monitoring of the whole delivery process but also serves to enable various functionalities of the framework. Based on the various information collected from the physical realm, the local server would have a clear observation of the delivery system as well as any new elements compared to the original virtual environment. For instance, with the help of lightweight onboard object detection deployed on UAVs, the local server is informed of unexpected obstacles such as new infrastructures, parking vehicles, and pedestrians. Utilizing semantic communication as an alternate approach, it is no longer necessary for UAVs to transfer enormous video frames or even stream them to the server. Instead, the local server only needs to collect key features of the objects that can describe interesting characteristics for creating a virtual replica inside the Microverse. Compared to the traditional way of sending raw data, semantic communication offloads computation pressure and reduces network overheads, especially for large UAV swarms.

3.2 LoCASM algorithm

A collision scenario is determined by the distance relationship between an UAV and any other obstacles including other UAVs or environmental objects. As shown in Figure 2, a collision may happen between UAV A and obstacle Y when the distance D_{AY} is less than Safe Distance D_{safe}. The distance situation can be mathematically expressed as:

$$D_{AY} = ||r_A - r_Y|| < D_{safe} \tag{1}$$

where r_A and r_Y are the position vectors of UAV A and obstacle Y. Similarly, the real-time distance between UAV A and obstacle X is safe at the moment. Unlike traditional approaches, LoCASM does not require onboard sensors to generate a detection range[11] to determine the risk of collision. Equation (1) is evaluated according to the collected PAVAD data and the static database of the environmental objects. For example, the position vectors are calculated by GPS information while the Safe Distance D_{safe} is determined by real-time velocities, GPS deviations, network latency, etc.

Similar to traditional delivery networks, UAV delivery tasks are assigned to local warehouses to ship items to certain targets. As shown in Figure 3, a screenshot of a delivery network in Rwanda established by Zipline,[34] where the delivery routine is predetermined according to the destination. In such case, the low-cost collision avoidance strategy for UAV A and Obstacle Y can

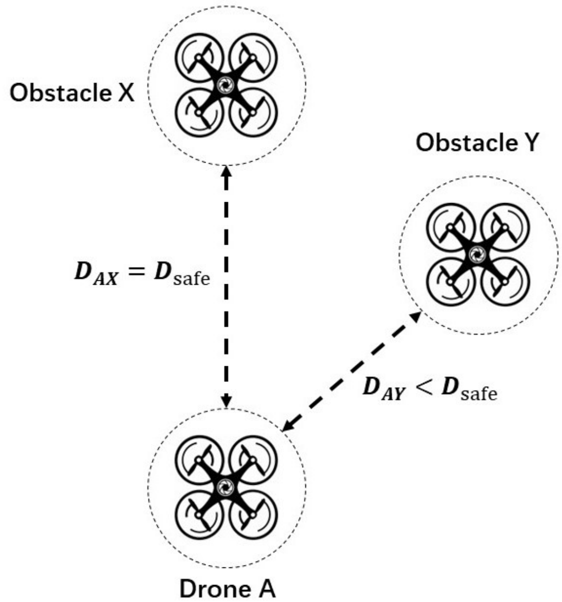


Fig 2 Collision distance.

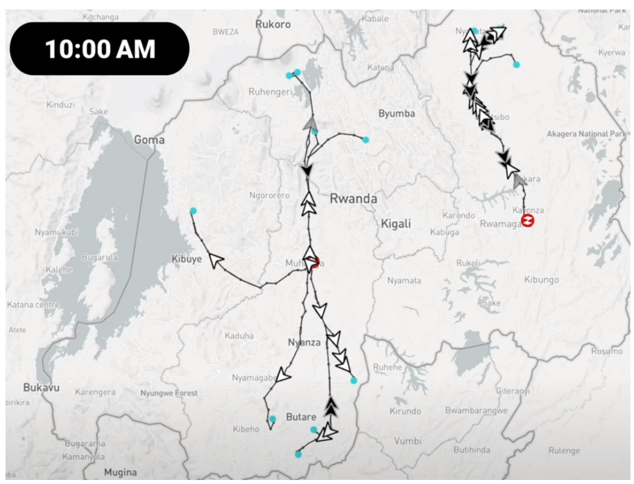
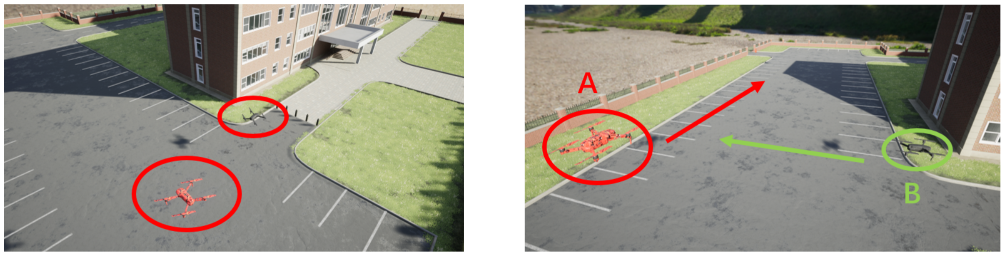


Fig 3 Zipline delivery network in Rwanda.

be straightforward: If Y is another UAV, the local server would ask the higher UAV to increase the elevation while the lower UAV to decrease until the altitude deviation is larger than D_{safe}. Similarly, if Y is a static obstacle, such as an environmental object inside the virtual Microverse space, the server would send instructions for A to fly higher until D_{safe} is satisfied. Compared to a traditional geometric method, which relies on the computation of PCA,[27] LoCASM not only maintains the original delivery routine in longitude and latitude but also reduces the computation requirements.



a b

Fig 4 (a) Screen shot of UE5-based LoCASM prototype. (b) Original trajectories of two UAVs

4 Experimental Results and Analysis

4.1 Experiment Setup

The experiments employ several mini 3 UAVs in the parking lot of the engineering building from our testbed premises, utilizing the same Wireless Local Area Network (WLAN) that connects to the local server inside the building. A Pixel 7 smart phone installed with specially developed Android application collects data from various sensors to the Digital Twin (DT) in the virtual environment. The vital parameters such as position (GPS), altitude, velocity, and direction (PAVAD) are transmitted as JavaScript Object Notation (JSON) packets, ensuring the Virtual Replica's location in the Microverse is synchronized.

To validate the feasibility of our proposed LoCASM framework, we develop a prototype using Unreal Engine, accurately modeling the actual engineering building. The LoCASM prototype includes virtual replicas of the UAVs, as shown in the red circle in Figure 4 (a), which reflect their real-world position in real time.

As illustrated in Figure 2, one of the key points is to determine the safe distance D_{safe} for the collision avoidance model. The choice of D_{safe} can be affected by many factors, such as the size of UAVs, network latency, and the accuracy of the positioning sensors, etc. In our case study, two UAVs are allocated near our engineering building finishing delivery tasks according to their separate routines. The virtual representation of the scenario is shown in Figure 4 (b), where UAV A is flying following the red trajectory while UAV B is approaching following the green arrow.

The approximate calculation of D_{safe} can be mathematically expressed as:

$$D_{safe} = Size_A + Size_B + GPS_A + GPS_B + V_A \times RTD_A + V_B \times RTD_B \tag{2}$$

where the UAVs are considered spherical objects with a radius of $Size$ and GPS stands for the deviation of GPS position. RTD and V represent round-trip delay (RTD) caused by network latency and the maximum velocity of the UAVs, respectively.

Considering the UAVs used in the experimental case study are identical, Eq.(2) can be simplified into:

$$D_{safe} = Size \times 2 + GPS \times 2 + (V_A + V_B) \times RTD \tag{3}$$

assuming the UAVs' size, GPS deviation, and RTD are the same.

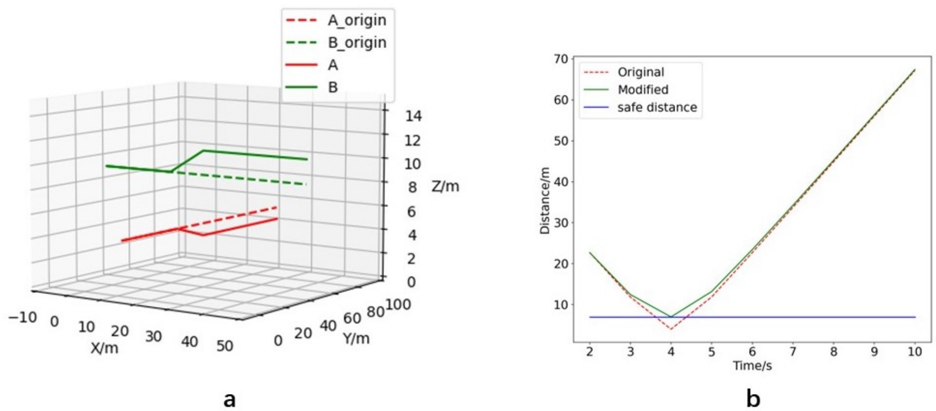


Fig 5 (a) 3D trajectories of both UAVs. (b) Relative distance compared to D_{safe}

4.2 Results

To measure the approximate GPS deviation, the UAVs are operated near the building's parking lot. The Return to Home(RTH) function is utilized to measure the accuracy of GPS signals. To get the best results, we chose an open parking lot area without nearby obstacles blocking the GPS satellites. The tests are run on both UAVs for ten rounds in various flying routines. The worst case shows 1.86 meters in deviation.

Meanwhile, real-time data like GPS and velocity are transmitted from the UAVs to cellphones and further to the local server inside the building in the form of JSON packets with time stamps. Thus, the RTD can be calculated by: $RTD = RTD_{dc} + RTD_{cs}$, where RTD_{dc} stands for UAV-to-controller RTD and RTD_{cs} stands for controller-to-server RTD. After ten field test sessions, the maximum RTD_{dc} adds up to 48 ms when the UAV is flying in high-quality mode. On the other hand, based on the Wireless Local Area Network (WLAN), the worst delay for controller-sever is 31 ms in total.

Limited by the UAVs we possess and the flying restrictions, the LoCASM simulation is operated inside the UE5-enabled virtual system. The original trajectories of the two UAVs are illustrated in Figure 4 (b), where UAV A is flying at a fixed velocity of 10 m/s and B at 5 m/s. If we set the size of UAVs as 0.5 m, maximum GPS deviation as 2 m, and RTD as 80 ms, D_{safe} can be approximated by Equation 3 as 6.2 m. Considering other possible factors, we adopt $D_{safe} = 7m$ for simulation of the collision avoidance. As shown in Figure 5, the original trajectories will reach the closest point where $D = 4m$ at $Time = 4s$, when the two UAVs are flying along two perpendicular roads at different horizontal levels, and their locations are updated for every one second. We can notice that both UAVs change their flying altitude at the third second according to the LoCASM scheme, where the higher UAV rises and the lower UAV dives so that the horizontal deviation satisfies the safe distance. The relative distances of the original and modified routine are calculated in Fig. 5 (b).

4.3 Discussion

A more accurate way to measure the deviation of positioning sensors is using the Real-Time Kinematic (RTK) positioning[35] technique, which can correct the errors of current satellite navigation

(GNSS) systems such as GPS. With the help of RTK receivers or RTK UAVs, we can acquire high positional accuracy of the UAV itself within 10 cm. The corresponding safe distance can be much smaller then using traditional GPS signals.

5 Conclusions

This paper introduces *LoCASM*, a lightweight collision avoidance system for UAV-enabled delivery based on a task-oriented, edge-scale Microverse system, and validates it through a case study. The prototype of a smart local delivery Microverse for smart communities demonstrated that the task-oriented Microverse is promising to significantly alter the traditional ways of managing local delivery systems.

In proposing the current prototype LoCASM based on the Microverse, our future work will focus on several aspects. First of all, a complete vision of the Microverse Platform that reflects not only the elements in the case study but also other infrastructures in the local community will be recreated to enable a full experiment for framework test. Moreover, the current study is constrained by limited equipment, such as the selection of UAVs and sensors. A more comprehensive evaluation of the delivery procedure, which is closer to real life, will be conducted to test more benchmark analyses in various UAV delivery scenarios. Finally, according to the various capabilities of different UAVs, more complicated algorithms, including path forecasting and trajectory planning, will be adopted.

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