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BWSAR: A Single-Drone Search-and-Rescue Methodology Leveraging 5G-NR Beam Sweeping Technologies for Victim Localization

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Abstract: Drones integrated with 5G New Radio (NR) base stations have emerged as a promising solution for efficient victim search and localization in emergency zones where cellular networks are disrupted by natural disasters. Traditional approaches relying solely on uplink Sounding Reference Signal (SRS) for localization face limitations due to User Equipment (UE) power constraints. To overcome this, our paper introduces BWSAR, a novel three-stage Search-and-Rescue (SAR) methodology leveraging 5G-NR beam sweeping technologies. BWSAR utilizes downlink Synchronization Signal Block (SSB) for coarse-grained direction estimation, guiding the drone towards potential victim locations. Subsequently, finer-grained beam sweeping with Positioning Reference Signal (PRS) is employed within the identified direction, enabling precise three-dimensional UE coordinate estimation. Furthermore, we propose a trajectory optimization algorithm to expedite the drone's navigation to emergency areas. Simulation results underscore BWSAR's efficacy in reducing positioning errors and completing SAR missions swiftly, within minutes.

Keywords: drone/UAV; 5G NR; positioning; beam sweep; search-and-rescue



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1. Introduction

The occurrence of natural disasters, such as earthquakes, leads to substantial property damage and casualties. In 2017 alone, it is estimated that over 95.6 million people were affected by 335 natural disasters, resulting in an additional loss of 9697 lives and a total cost of USD 335 billion. Promptly searching for and rescuing missing individuals after a disaster strikes is particularly crucial. However, the destruction caused by these calamities often renders cellular networks incapable of providing network services, posing challenges in contacting victims within disaster areas and exacerbating search and rescue efforts. Additionally, the presence of obstacles further hampers Global Navigation Satellite System (GNSS) [1] signal propagation commonly used for positioning purposes in disaster zones, leading to either the inability to locate victims or significantly reduced performance levels. Consequently, GNSS systems encounter difficulties when assisting rapid post-disaster search and rescue missions.

To overcome the challenges mentioned earlier, drones, commonly referred to as Unmanned Aerial Vehicles (UAVs) [2–5], have emerged as a valuable resource in locating missing persons in expansive and challenging terrains. Their inherent portability, coupled with ease of deployment and remarkable adaptability, render them ideally suited for this particular task. Recently, deploying 5G New Radio (NR) base stations on drones [6–8], allows victims' mobile phones to connect to the flying mobile cellular network, facilitating the search and localization of victims. Research efforts predominantly rely on the utilization of the uplink signals for victim localization. Albanese et al. [8] measured the Time of Flight (ToF) of a user uplink signal, thus estimating the distance between the user and the UAV.

Albanese et al. employed a UAV to gather ToF measurement results pertaining to a specific user, and subsequently, devised a pseudo-triangulation algorithm that accurately computes the user's coordinates. This approach efficiently fulfills the objective of victim localization. Blaga et al. [9] proposed a three-dimensional (3D) localization framework with uplink DeModulation Reference Signal (DMRS). Distance estimator and angles estimator are designed for 3D localization, and a 3D UAV prediction trajectory algorithm is proposed for updating the coordinates of the UAV. Sun et al. [10] proposed utilizing 5G uplink physical layer channel Sounding Reference Signals (SRSs) for 3D User Equipment (UE) positioning. They contended that the widespread deployment of large-scale antennas in 5G NR base stations enhances the estimation of uplink Angle of Arrival (AoA) derived from SRSs, thereby enabling precise 3D positioning of UEs. However, ref. [10] did not consider the mobility of 5G NR base stations. Ref. [11] proposed a Lightweight Trustworthy Message Exchange (LTME) scheme for UAV networks by efficiently aggregating the cryptography and trust management technologies. The LTME can provide rich functionality and strong robustness with low computation and communication overheads. Ref. [12] proposed an intelligent clustering routing approach (ICRA) for UAV ad hoc networks. In the routing phase, the ICRA can reduce the end-to-end delay and improve the packet delivery rate by introducing inter-cluster forwarding nodes to forward messages among different clusters.

Upon a thorough analysis of current research findings, we postulate that in disaster-stricken areas, the uplink transmission power of UEs is significantly constrained, leading to severe attenuation of the uplink signal upon reaching the drone. Consequently, the base station may struggle to receive the signal, resulting in diminished positioning accuracy based on the uplink signal. To address this challenge, this paper introduces a novel approach that harnesses 5G NR beam sweeping technologies to aid the UAV in searching and locating victims. This innovative method, termed Beam Sweep-enabled Search and Rescue (BWSAR), offers a promising solution to enhance the precision and efficiency of search and rescue operations.

BWSAR performs a three-stage SAR mission based on downlink Synchronization Signal Blocks (SSBs) and Positioning Reference Signals (PRSs). Initially, the drone flies towards the direction estimated by coarse-grained beam sweeping with SSBs. Afterwards, the drone launches finer-grained beam sweeping process with PRSs within the best direction of the initial process, in which case the three-dimensional coordinate of UEs can be estimated. Moreover, the paper proposes a trajectory updating algorithm to guide the drone to reach emergency areas as quickly as possible. Several simulation experiments are conducted and the results demonstrate that BWSAR performs good in a SAR mission. Our main contributions are highlighted as follows:

- To expedite the SAR operation time, this paper introduces an innovative three-stage SAR methodology that harnesses the potential of 5G NR beams. By deploying an extensive array of antennas within 5G NR base stations, we enable the attainment of precise 3D positioning estimates for UEs, leveraging fine-grained beam sweeping angles.
- An innovative 3D localization approach utilizing downlink PRSs from 5G NR base stations is introduced. To combat the issue of signal attenuation that frequently plagues disaster-affected regions, our method allows for the adaptive adjustment of downlink signal power based on the specific environmental conditions encountered.
- This paper presents a UAV trajectory updating algorithm that meticulously guides UAVs towards disaster-stricken areas. By designing the drone's flight path, the proposed algorithm ensures that communication signals between 5G NR base stations and UEs propagate predominantly within the Line of Sight (LoS), thereby mitigating the detrimental effects of signal obstruction caused by obstacles prevalent in disaster-affected zones.

The remaining sections of this paper are structured as follows. Section 2 summarizes the existing positioning methods based on Radio Access Technology (RAT) and the SAR methods using drones with 5G NR base stations. Section 3 presents the system model and problem formulation of this paper. Section 4 describes the proposed UAV trajectory

progress updating algorithm. Several BWSAR simulation experiments are conducted and results are analyzed in Section 5. Finally, in Section 6, we provide concluding remarks and possible future research tracks.

2. Related Work

2.1. 5G RAT Positioning

In the field of 5G NR positioning technology [13], significant progress has been made in research and standardization in recent years. As a new generation of mobile communication technology, the development of 5G NR's positioning technology is crucial to meet the demand for accurate indoor and outdoor positioning. Ferré et al. [14] provided an in-depth analysis of how 5G-NR can be used for positioning with non-synchronous base stations through the use of PRS to achieve positioning with asynchronous base stations, analyzed in detail the different distribution schemes of the PRS used for positioning in 5G NR systems, and explored the impact of the PRS distribution on the positioning performance with the aim of identifying the optimal PRS distribution scheme to improve the positioning accuracy. In 3GPP Rel-16 and Rel-17, 5G NR localization techniques have been further enhanced and refined, and Keating et al. [15] provided a comprehensive overview of 3GPP's work on localization in 5G NR, focusing on the architectural and physical layer aspects, as well as the multiple localization solutions specified in Rel-16, including Uplink/Downlink-Time Difference of Arrival (UL/DL-TDOA), UL-Angle of Arrival (UL-AoA), DL-Angle of Departure (DL-AoD), and Multi-Round Trip Time (RTT) advanced positioning methods, with the ultimate goal of achieving positioning accuracy of less than 3 m. Wang et al. [16] summarized the latest progress of 3GPP on 5G NR positioning, including the standardized techniques in Release 16 and Release 17, and discusses the research on expanding and improving positioning in Release 18, as well as the future challenges for LOS/NLOS (Non-Line of Sight) identification, the utilization of AoA (Angle of Arrival), and the mitigation of UE/gNB RF (GNodeB Radio Frequency) timing errors. In addition, for algorithms based on single-site 3D localization, Sun et al. [10] explored the feasibility of single-site 3D UE localization using uplink physical layer channel measurement SRSs in 5G NR, and proposed subspace-based joint angular-temporal estimation and statistically based expectation maximization (EM) algorithms. Butt et al. [17] proposed a new algorithm in the integration of Machine Learning (ML) algorithms in 5G radio access networks, discussed the implementation challenges of the solution and the need for architectural changes, and evaluated the performance of the ML-assisted localization approach using deep-learning-assisted UE localization as an example use case.

2.2. Drone-Based 5G NR Positioning

As the field of UAV technology advances rapidly, its application in SAR solutions for localization purposes has experienced a notable surge. The integration of UAVs into SAR missions offers a compelling solution for precise localization, enhancing the efficiency and effectiveness of search and rescue efforts [8,9,18–21]. Albanese et al. [8] proposed the SARDO system, an automated UAV-based SAR solution that takes advantage of the high penetration of cell phones to locate missing persons. SARDO is designed to locate missing persons by combining pseudo trilateral measurements and machine learning techniques to efficiently localize cell phones in a given area. In addition, Hong et al. [19] introduced the latest progress in the field of 5G converged positioning in terms of both system architecture and key technologies, focusing on analyzing the technical routes of 5G in-band wireless positioning and 5G converged positioning, and looking forward to the architectural evolution and technical challenges of the 6G-oriented space-time service system, discussing the converged positioning technologies based on the 5G mobile communication system. The latter work through the integration of the 5G in-band positioning, satellite positioning, and visual positioning, which significantly improve the positioning accuracy and coverage in complex environments. Blaga et al. [9] proposed a 3DSAR solution that utilizes 5G-NR technology to achieve a single UAV 3D localization SAR solution, which significantly im-

proves the positioning accuracy and coverage in complex environments by means of four main components, i.e., a distance estimator, an angle estimator, 3D localization, and a 3D UAV prediction trajectory algorithm. Ref. [20] proposed a solution for joint 3D positioning and trajectory planning of flying base stations (FBSs) with the objectives of determining the total distance between users and FBSs and minimizing the sum of FBSs flight distance by developing a fuzzy candidate points selection method. Ref. [21] proposed an intelligent solution based on a novel multilayered cellular automata for positioning flying cells and provided a solution for rapid and efficient positioning of multiple UAV base stations to respond in real time to urgent network changes. The scheme considers both backhaul and radio access network constraints, and user requirements in terms of downlink throughput.

3. System Model and Problem Formulation

This section introduces the BWSAR system model architecture and problem formulation in detail. The UAV uses 5G-NR beam sweeping technologies for disaster area search and rescue processes to improve victim location efficiency and accuracy. On this basis, the UAV trajectory progress optimization problem with the shortest search and rescue time is established.

3.1. System Model

In this subsection, we present the search and rescue scenario with single UAV equipped with single 5G NR base station, which is shown in Figure 1. This system consists of one UAV that deploys one 5G NR base station with antennas in a Uniform Rectangular Array (URA) and numbers of UEs. The UEs are denoted as $U = \{ue_i\}$, where i represents the identifier of each UE. We establish the three-dimensional coordinate system with the UAV starting point as the origin $(0, 0, 0)$. Therefore, the position of the UAV and UEs can be denoted as $P_{uav} = (x_{uav}, y_{uav}, z_{uav})$ and $P_{ue_i} = (x_{ue_i}, y_{ue_i}, z_{ue_i})$, respectively. We assume that all UEs are static and UAV is moving with a trajectory $T_{j_{uav}} = \{(x_{uav}^{(j)}, y_{uav}^{(j)}, z_{uav}^{(j)}) | j = 0, 1, \dots, N\}$ where j represents the UAV coordinate at the j th refresh time. In this system, the 5G NR base station on UAV deploys phased antenna array that is URA. With beamforming, AoD estimation process consists of two procedures including initial acquisition based on SSB and beam refinement using DL-PRS.

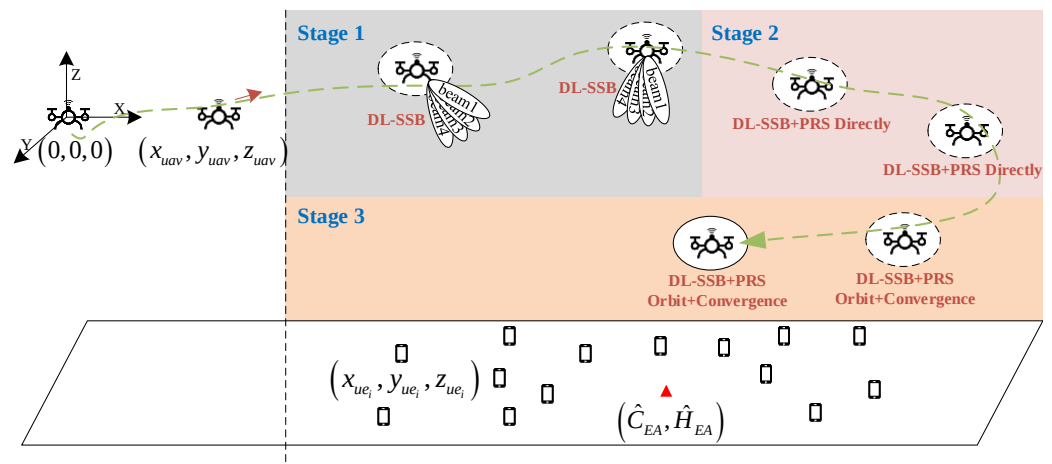


Figure 1. System model: single UAV for search and rescue.

Remark 1. The practical equipping of drones with 5G base stations involves meticulous consideration of various issues, including the weight and power requirements of 5G hardware, the stability and durability of UAVs carrying and operating these base stations, as well as the logistics and costs of on-site maintenance and service of UAVs and their 5G infrastructure. These factors will affect the practical application of the technology proposed in this paper. Consequently, it is imperative to

adaptably select diverse workflows and strategies tailored to the specific requirements of varying scenarios, ensuring optimal performance and efficiency.

During the initial acquisition, beam sweeping takes place at both base station and UEs to select the best beam pair based on the Reference Signal Received Power (RSRP) measurement. Down-link SSBs are a pivotal synchronization mechanism in 5G NR networks, providing a structured and efficient means for time and frequency synchronization, cell search, and channel estimation through periodic transmission of Orthogonal Frequency Division Multiplexing (OFDM) symbols. These SSBs enhance network performance by facilitating rapid cell identification and acquisition, offering robust synchronization even in high-mobility and dense deployment scenarios, and are crucial for achieving the high data rates and low latency that define 5G services.

During the beam refinement, beam sweeping happens at the base station where a set of PRS resources are configured and transmitted over different directions by using finer beams. PRS, or DL-PRS, is designed for multi-Base Station (BS) signal reception by UE, similar to its LTE equivalent. A distinctive feature of PRS is its enhanced audibility, achieved through a muting mechanism that coordinates transmissions from multiple BSs, muting less relevant signals to minimize interference. The PRS Resource Elements (REs) exhibit a staggered pattern that enhances correlation properties, which is instrumental for peak detection. By employing a comb- N pattern with $N \in \{2, 4, 6, 12\}$, it enables the frequency-multiplexing of N distinct Transmission Resource Patterns (TRPs) within a single time slot, each distinguished by a unique frequency offset. Customization of each PRS is facilitated by varying its periodicity ($T_{\text{PRS per}}$), slot offset ($T_{\text{PRS offset}}$), Resource Block (RB) offset ($T_{\text{PRS offset, RB}}$), and RE offset ($T_{\text{PRS offset, RE}}$). This customization caters to diverse service requirements, such as the need for frequent PRS transmissions in latency-sensitive applications, or less frequent transmissions for energy conservation in other devices. As per 3GPP TS 28.211, the periodicity $T_{\text{PRS per}}$ is selected from a set defined by 2μ times a series of values, and the offset $T_{\text{PRS off}}$ is an integer within the range from 0 to one less than the periodicity itself.

3.2. Problem Formulation

The main objective of UAVs in conducting search and rescue missions is to swiftly locate and approach the victim UEs to provide assistance. Therefore, there are two primary challenges: firstly, locating all UEs to determine the end point for the UAV, and secondly, finding an optimal trajectory to reach the UEs rapidly.

With 5G NR positioning techniques, the estimated coordinates of UEs can be denoted as $\hat{P}_{ue_i} = (\hat{x}_{ue_i}, \hat{y}_{ue_i}, \hat{z}_{ue_i})$, where $i = 0, 1, \dots, M$. M is less than the total number of UEs $|U|$. The reason is that some UEs may not be located because of the bad downlink or uplink reference signals when transmitting over disaster environment. Here, we define the estimated Emergency Area (EA) as a two-dimensional circle of center $\hat{C}_{EA}$ and radius $\hat{\rho}_{EA}$, calculated as follows:

$$\begin{aligned} \hat{C}_{EA} = (\hat{x}_{EA}, \hat{y}_{EA}) &= \left(\sum_{i=1}^M \frac{\hat{x}_{ue_i}}{M}, \sum_{i=1}^M \frac{\hat{y}_{ue_i}}{M} \right) \\ \hat{\rho}_{EA} &= \max_{i=1}^M \{ \|\hat{P}_{ue_i} - \hat{C}_{EA}\| \} = \max_{i=1}^M \left\{ \sqrt{(\hat{x}_{ue_i} - \hat{x}_{EA})^2 + (\hat{y}_{ue_i} - \hat{y}_{EA})^2} \right\} \end{aligned} \quad (1)$$

In the three-dimensional space, the altitude of the EA is denoted as $\hat{H}_{EA} = \max_{i=1}^M \{ \hat{z}_{ue_i} + H_0 \}$, where H_0 is a constant value. H_0 means that the UAV should maintain a certain flight altitude to ensure LoS connectivity with most UEs. At each time, the UAV always flies towards the estimated EA until it arrives. The trajectory of the UAV from the start point $(0, 0, 0)$ to the final point $P_{uav}^{(N)} = (x_{uav}^{(N)}, y_{uav}^{(N)}, z_{uav}^{(N)})$ can be denoted as $T_{juav} = \{(x_{uav}^{(j)}, y_{uav}^{(j)}, z_{uav}^{(j)}) | j = 0, 1, \dots, N\}$, where T_{juav} represents the j th coordinate

of UAV and $(x_{uav}^{(0)}, y_{uav}^{(0)}, z_{uav}^{(0)}) = (0, 0, 0)$. Therefore, the problem formulation can be described as:

$$\begin{aligned} \pi^* &= \arg \min \sum Tj_{uav} \\ \text{s.t. } &\left\| P_{uav}^{(N)} - (\hat{C}_{EA}, \hat{H}_{EA}) \right\| < \epsilon \end{aligned} \quad (2)$$

where

$$\sum Tj_{uav} = \sum_{j=0}^{N-1} \| P_{uav}^{(j+1)} - P_{uav}^{(j)} \|, \quad (3)$$

where π represents the distance the UAV needs to fly and the strategies for generating such a flying trajectory, respectively, and the constraint $\| P_{uav}^{(N)} - (\hat{C}_{EA}, \hat{H}_{EA}) \| < \epsilon$ serves to confine the ultimate convergence location of the UAV within a specific proximity of the equivalent center of the UEs. This is imperative due to the inherent limitation on the communication radius of the 5G base station mounted on the UAV, necessitating the UEs to maintain a position within the effective communication sphere to ensure seamless connectivity. Moreover, ϵ usually represents a preset experience value determined by the performance of the 5G base station on the UAV. The formulation (2) indicates that the UAV should find an optimal strategy π^* to guide its flight within a three-dimensional range with $(\hat{C}_{EA}, \hat{H}_{EA})$ as the center and a radius of ϵ before it can stop.

Remark 2. During the execution of long-duration missions, the energy consumption of drones and 5G base stations emerges as a primary concern. As aerial platforms, drones possess inherent limitations in terms of fuel capacity or battery life, which directly impacts their operational endurance and ability to sustain missions over extended periods. On the other hand, 5G base stations require substantial amounts of power to transmit and receive high-speed data, thereby augmenting the overall energy demand. Consequently, it becomes imperative to explore strategies aimed at optimizing energy consumption, such as implementing dynamic power management algorithms for the 5G base stations and adopting energy-efficient flight profiles for the drones.

4. UAV-TPUA: UAV Trajectory Progress Updating Algorithm

Taking into account the challenging wireless conditions in the disaster area, relying solely on terminal uplink reference signals (e.g., SRS) for continuous positioning may face issues with insufficient uplink power, ultimately resulting in an inability to accurately determine the location. In this context, this section proposes to leverage DL-SSB carried within beams for coarse positioning and DL-SSB+PRS for finer positioning.

4.1. Angle Measurement of URA

When using URA, array elements are distributed in the yz -plane in a rectangular lattice while the array bore sight is along the x -axis. For a wave propagation in a direction described by azimuth ϕ and elevation θ , the wave-vector $\mathbf{k}$ is given by:

$$\mathbf{k}(\phi, \theta) = (k_x, k_y, k_z) = \frac{2\pi}{\lambda} (\sin \theta \cos \phi, \sin \theta \sin \phi, \cos \theta) \quad (4)$$

The steering vector represents the set of phase delays for an incoming wave at each sensor element. For a plane wave that is described by a wave vector $\mathbf{k}$, with N elements in an antenna array, steering vector $\mathbf{w}(k)$ is an $N \times 1$ complex vector representing the relative phases at each antenna and is given by:

$$\mathbf{w}(\theta, \phi) = [e^{-j\mathbf{k} \cdot \mathbf{r}_1}, e^{-j\mathbf{k} \cdot \mathbf{r}_2}, \dots, e^{-j\mathbf{k} \cdot \mathbf{r}_M}]^T \quad (5)$$

where $\mathbf{r}_i = (x_i, y_i, z_i)$ is the location of the i th antenna element. To estimate the AoD, the base station goes through a beam training process with a code book containing a set of code

words $C^P = \{\mathbf{w}^1, \dots, \mathbf{w}^P\}$. Therefore, a coarse estimation for the AoD of the propagation path is described as:

$$p^* = \arg \max_{p \in \mathcal{P}} A^p \quad (6)$$

where the beam with code word $\mathbf{w}^p(\theta, \phi)$ maximizes the received power A^p on the UE. Without considering the noise, the ideal received signal strength is given by:

$$A^p = \sqrt{(\mathbf{h}\mathbf{w}^p(\theta, \phi))^H (\mathbf{h}\mathbf{w}^p(\theta, \phi))} \quad (7)$$

Thus, using the beam index p , the UE can derive the azimuth (θ) and elevation (ϕ) from the positioning assistance data sent to the UE.

4.2. Updating Trajectory Progress

The specific three-stages BWSAR framework will be described in detail below. In the initial stage, firstly, the UAV autonomously scans the entire emergency area using configurable beams and transmitting power. Secondly, the UAV can estimate the directions of all UEs with higher Signal-to-Noise Ratios (SNRs). During the second stage, the UAV can further optimize the angles of transmitting signals within the initially estimated directions. In the third stage, when the UAV approaches the emergency area, it can conduct three-dimensional positioning of the UEs (including AoA and ToA).

Stage 1: DL-SSB only. In the initial phase, which is when the UAV is in the far part of the emergency zone, the altitude of the UAV is relatively high. Specifically, let $z_{uav} > \gamma_1$ be the remote area judgment condition, where γ_1 is the preset height value, which can be set according to the performance and experience of the UAV 5G base station. In this phase, the strategy is to quickly fly the UAV to the target area, while the UE positioning accuracy is not high. Therefore, during this phase, the UAV uses the DL-SSB to quickly search the entire airspace and obtain all UE Angle information $(\theta_{i,j}^{ssb}, \phi_{i,j}^{ssb})$, $i = 1, 2, \dots, U$, $j = 0, 1, \dots, N$, where $\theta_{i,j}^{ssb}$ and $\phi_{i,j}^{ssb}$ represent the pitch angle and azimuth angle of the i th UE in frame j , respectively. Next, within this refresh interval ΔT , the UAV selects the direction with the largest RSRP among all UEs and flies in that direction at the preset flight speed. Let $(\theta_{i_{cho},j}^{ssb}, \phi_{i_{cho},j}^{ssb})$ be the chosen target direction information, then after j th refresh interval, the position of the UAV can be expressed as:

$$\begin{aligned} P_{uav}^{(j+1)} &= (x_{uav}^{(j+1)}, y_{uav}^{(j+1)}, z_{uav}^{(j+1)}) = f(x_{uav}^{(j)}, y_{uav}^{(j)}, z_{uav}^{(j)}, \theta_{i_{cho},j}^{ssb}, \phi_{i_{cho},j}^{ssb}, \Delta s) \\ &= \begin{pmatrix} \Delta s \sin \theta_{i_{cho},j}^{ssb} \cos \phi_{i_{cho},j}^{ssb} + x_{uav}^{(j)} \\ \Delta s \sin \theta_{i_{cho},j}^{ssb} \sin \phi_{i_{cho},j}^{ssb} + y_{uav}^{(j)} \\ \Delta s \cos \theta_{i_{cho},j}^{ssb} + z_{uav}^{(j)} \end{pmatrix} \end{aligned} \quad (8)$$

Stage 2: DL-SSB+PRS Directly. In this stage, given the proximity of the UAV base station to the approximate center of the UEs, we employ the DL-SSB+PRS technology for precise UEs localization and direct flight of the UAV towards the destination location. Initially, we continue to utilize the SSB coarse angle measurement technique from the **Stage 1** to identify the potential target area. Subsequently, the UAV re-configures DL-PRS with finer beams within the direction chosen by UEs in **Stage 1**. UEs select the best beam and report beam identifier and RSRP, which can be used to estimate $[\theta_{i,j}^{prs}, \phi_{i,j}^{prs}, \tau_{i,j}^{prs}]$. Thus, the UEs' location can be estimated as shown in Equation (9):

$$\begin{aligned} \hat{P}_{ue_{i,j+1}} &= (\hat{x}_{ue_{i,j+1}}, \hat{y}_{ue_{i,j+1}}, \hat{z}_{ue_{i,j+1}}) \\ &= \begin{pmatrix} x_{uav}^{(j)} + \tau_{i,j+1}^{prs} c \frac{\sin \theta_{i,j+1}^{prs} \cos \theta_{i,j+1}^{prs} \cos \phi_{i,j+1}^{prs}}{\sin^2 \theta_{i,j+1}^{prs} + \cos^2 \phi_{i,j+1}^{prs} \cos \theta_{i,j+1}^{prs}}, \\ y_{uav}^{(j)} + \tau_{i,j+1}^{prs} c \frac{\sin^2 \theta_{i,j+1}^{prs} \cos \phi_{i,j+1}^{prs}}{\sin^2 \theta_{i,j+1}^{prs} + \cos^2 \phi_{i,j+1}^{prs} \cos \theta_{i,j+1}^{prs}}, \\ z_{uav}^{(j)} + \tau_{i,j+1}^{prs} c \frac{\sin^2 \theta_{i,j+1}^{prs} \sin \phi_{i,j+1}^{prs}}{\sin^2 \theta_{i,j+1}^{prs} + \cos^2 \phi_{i,j+1}^{prs} \cos \theta_{i,j+1}^{prs}} \end{pmatrix} \end{aligned} \quad (9)$$

where $\theta_{i,j+1}^{prs}$, $\phi_{i,j+1}^{prs}$ and $\tau_{i,j+1}^{prs}$ represent the elevation and azimuth, respectively. On this basis, according to Equation (1), we can easily get all UEs corresponding EA regions as follows:

$$\begin{aligned}\hat{C}_{EA}^{j+1} &= (\hat{x}_{EA}^{j+1}, \hat{y}_{EA}^{j+1}) = \left(\sum_{i=1}^M \frac{\hat{x}_{ue_{i,j+1}}}{M}, \sum_{i=1}^M \frac{\hat{y}_{ue_{i,j+1}}}{M} \right) \\ \hat{H}_{EA}^{j+1} &= \max_{i=1}^M \{ \hat{z}_{ue_{i,j+1}} + H_0 \} \\ \hat{\rho}_{EA}^{j+1} &= \max_{i=1}^M \left\{ \left\| \hat{P}_{ue_{i,j+1}} - \hat{C}_{EA}^{j+1} \right\| \right\} = \max_{i=1}^M \left\{ \sqrt{(\hat{x}_{ue_{i,j+1}} - \hat{x}_{EA}^{j+1})^2 + (\hat{y}_{ue_{i,j+1}} - \hat{y}_{EA}^{j+1})^2} \right\}\end{aligned}\quad (10)$$

After estimating $\hat{C}_{EA}^{j+1}$, $\hat{H}_{EA}^{j+1}$ and $\hat{\rho}_{EA}^{j+1}$, the next coordinate of the UAV can be predicted by the following formula:

$$\begin{aligned}P_{uav}^{next} &= (x_{uav}^{(j+1)}, y_{uav}^{(j+1)}, z_{uav}^{(j+1)}) = f(x_{uav}^{(j)}, y_{uav}^{(j)}, z_{uav}^{(j)}, \hat{x}_{EA}, \hat{y}_{EA}, \Delta s) \\ &= \begin{pmatrix} \frac{\Delta s (\hat{x}_{EA} - x_{uav}^{(j)})}{\sqrt{(\hat{x}_{EA} - x_{uav}^{(j)})^2 + (\hat{y}_{EA} - y_{uav}^{(j)})^2 + (\hat{H}_{EA}^{(j)} - z_{uav}^{(j)})^2}} + x_{uav}^{(j)}, \\ \frac{\Delta s (\hat{y}_{EA} - y_{uav}^{(j)})}{\sqrt{(\hat{x}_{EA} - x_{uav}^{(j)})^2 + (\hat{y}_{EA} - y_{uav}^{(j)})^2 + (\hat{H}_{EA}^{(j)} - z_{uav}^{(j)})^2}} + y_{uav}^{(j)}, \\ \frac{\Delta s (\hat{H}_{EA}^{(j)} - z_{uav}^{(j)})}{\sqrt{(\hat{x}_{EA} - x_{uav}^{(j)})^2 + (\hat{y}_{EA} - y_{uav}^{(j)})^2 + (\hat{H}_{EA}^{(j)} - z_{uav}^{(j)})^2}} + z_{uav}^{(j)} \end{pmatrix}\end{aligned}\quad (11)$$

where v and ΔT represents the flight speed and decision time of the UAV.

Stage 3: DL-SSB+PRS Orbit+Convergence. In the final phase of our approach, we aim to maximize the observation of the victim's environment and minimize the positioning inaccuracies that arise due to the UAV's current location and the presence of UEs in NLOS conditions. To achieve this, we alter the UAV's flight strategy to involve hovering and descending towards the target destination, thereby enhancing the precision of the localization process. Furthermore, the targeted angle measurement and positioning methodology remains consistent with the previous stage, leveraging the DL-SSB+PRS framework. To mitigate the adverse effects of NLOS conditions on the base station's location determination, the UAV and UEs maintain a pitch angle of approximately 45 degrees during the descent trajectory of the UAV's hovering phase, as it converges towards the destination. This strategic positioning aids in reducing interference and ensuring accurate location updates. The specific steps involved in the location updating process are outlined in detail as shown in Algorithm 1.

Algorithm 1: Stage 3: DL-SSB+PRS Orbit+Convergence.

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1 Perform the same precise positioning technique using DL-SSB+PRS as in Stage 2;
2 Calculate  $d_{xy} = \sqrt{(x_{uav} - x_j)^2 + (y_{uav} - y_j)^2}$ ,  $d_z = z_{uav} - z_j$ ;
3 if  $d_z - d_{xy} < \Delta s$  then
4   if  $d_z - d_{xy} > 0$  then
5      $s_{xy} = \sqrt{\Delta s^2 - (d_z - d_{xy})^2}$ ,  $tmp = 1$ ;
6   end
7   else
8      $s_{xy} = \Delta s$ ,  $tmp = 0$ ;
9   end
10   $x_{uav}^{next} = x_{uav} - s_{xy} f_1(\theta)$  where  $\theta$  is the rotation angle of the UAV;
11   $y_{uav}^{next} = y_{uav} - s_{xy} f_2(\theta)$ ;
12   $z_{uav}^{next} = z_{uav} - (d_z - d_{xy}) \times tmp$ ;
13 end
14 else
15    $x_{uav}^{next} = x_{uav}$ ,  $y_{uav}^{next} = y_{uav}$ ,  $z_{uav}^{next} = z_{uav} - \frac{\Delta s}{10}$ ;
16 end

```

This paper encapsulates the aforementioned strategy into the Algorithm 2, facilitating its deployment onto UAVs for prediction of search and rescue trajectories.

Algorithm 2: UAV-TPUA

```

1 Initialize  $v, \Delta T, H_0, t \leftarrow 0, P_{uav}^{(0)} \leftarrow (0, 0, 0), \epsilon \leftarrow \epsilon_0, \hat{C}_{EA} \leftarrow (+\infty, +\infty),$ 
    $\hat{H}_{EA} \leftarrow +\infty, \text{URA} \leftarrow M \times N$  antennas;
2 Initialize UEs' location as  $\{P_{ue_i} | i = 0, 1, 2, \dots, |U|\}$  randomly in an emergency
   area;
3 while convergence condition  $cc$  do
4   if  $z_{uav} > \gamma_1$  then
5     Perform DL-SSB rough angle measurement operation;
6     Get SSB measurements information  $rsrp_{i,j}^{ssb}$  from all UEs;
7     The UAV flies towards  $(\theta_{i_{cho},j}^{ssb}, \phi_{i_{cho},j}^{ssb})$  and the position coordinate is updated
       according to Equation (8);
8   end
9   else if  $\gamma_1 > z_{uav} > \gamma_2$  then
10    Perform DL-SSB+PRS fine angle measurement operation;
11    Get PRS measurements information  $rsrp_{i,j}^{prs}$  from all UEs;
12    Estimate  $[\theta_{i,j}^{prs}, \phi_{i,j}^{prs}, \tau_{i,j}^{prs}]$  and obtain the corresponding position coordinates
        $\hat{P}_{ue_{i,j+1}}$  according to Equation (9);
13    Calculate  $\hat{C}_{EA}^{j+1}, \hat{H}_{EA}^{j+1}$  and  $\hat{\rho}_{EA}^{j+1}$  according to Equation (10);
14    Update the UAV's position coordinates according to Equation (11);
15  end
16  else
17    Perform the Algorithm 1;
18  end
19   $t \leftarrow t + \Delta T, P_{uav}^{(t)} \leftarrow P_{uav}^{next};$ 
20 end

```

5. BWSAR Simulation

In this section, we simulate the entire process of the drone flying from outside the disaster area to the victim, and analyze the relationship between localization accuracy and distance, the differences in trajectory caused by flight strategies, and the circling method after approaching the victim. We present the variation of positioning error over time.

5.1. PRS Setting

In the process of beam refinement, the PRS is propagated through beamforming technology, with each PRS beam corresponding to a PRS resource. In this example, the PRS slot offset ($T_{PRS \text{ offset}}$) is configured as a 1×12 array, with incremental values ranging from 0 to 11, assigning a unique timeslot offset to each beam and thus avoiding temporal overlap of PRS signals from different beams. The RE offset ($T_{PRS \text{ offset, RE}}$) is also a 1×12 array, with values incrementing from 0 to 11, ensuring a unique RE offset for each beam, which enhances the channel estimation capability of the signals.

Experimentation employs 12 PRS beams for fine-grained beam scanning, which improves the accuracy of positioning, especially in the precise location determination of UE within complex wireless environments. This meticulous allocation and strategic beam management are pivotal for optimizing the performance of positioning services in 5G networks, ensuring reliable and high-precision positioning outcomes.

5.2. Channel Propagation Model

The channel is modeled according to the standard using the Clustered Delay Line (CDL) impulse response, which can be defined up to a maximum bandwidth of 2 GHz. Additionally, the simulations employ the Shooting and Bouncing Rays (SBR) method to analyze the characteristics of the wireless channel. Noise power spectral density can be modeled by the following formula:

$$N_0 = k_B \cdot BW \cdot T_e \quad (12)$$

where k_B denotes the Boltzmann constant [JK^{-1}]. BW is the bandwidth [Hz]. $T_e = T_{ant} + 290(NF - 1)$ represents the noise temperature [K]. NF is the linearized noise figure, both referring to the receive antenna. For DL measurement, $NF = 10$ dB and we set $T_{ant} = 298$ K (25°C).

5.3. SAR Setting

The UAV is configured with a flight speed of 100 km/h, with the UE position remaining stationary. The positioning update intervals for the first, second, and third phases are set to 90 ms, 30 ms, and 10 ms, respectively. When the UAV's flight altitude is less than 200 m, the second phase of dual-beam downlink positioning strategy using SSB and PRS is initiated. Upon reaching an altitude below 50 m, the third phase of hovering positioning strategy is activated. The positioning process is concluded and converged when the distance of the UE's positioning results for five consecutive instances is less than 1 m from the mean value.

5.4. Simulation Result

As illustrated in Figure 2, lowering the UAV's altitude and reducing the distance between the UAV and the victim result in a decreased overall localization error. Building upon this finding, we introduce a two-stage trajectory updating algorithm designed to progressively guide the UAV towards the victim over time.

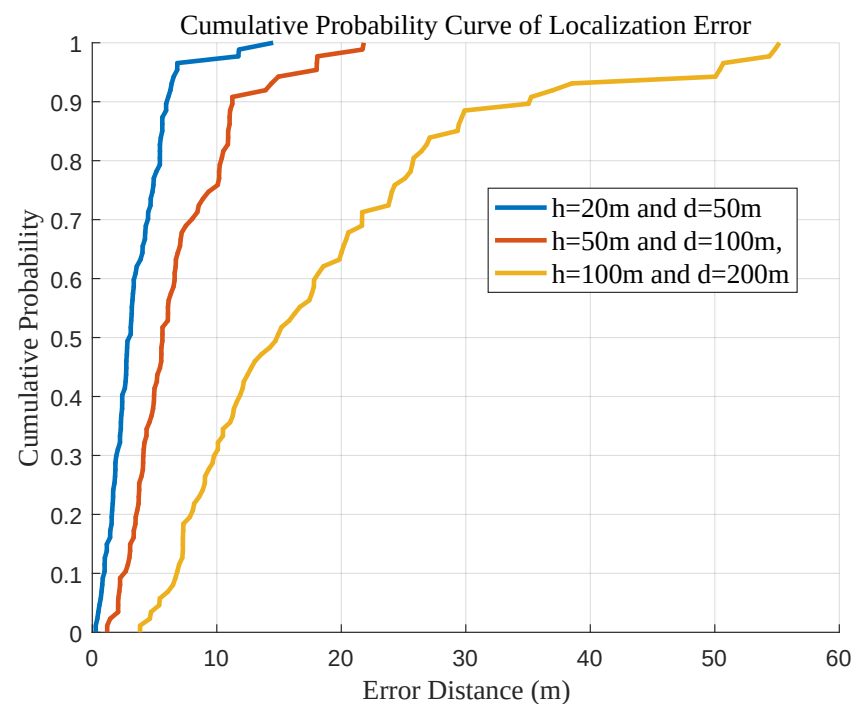


Figure 2. Localization error vs. distance between the UAV and the victim.

Figure 3 depicts the UAV's trajectory with two different flight strategies, which are "SSB only" and "SSB+PRS", respectively. The red triangle represents the destination position of the victim (or target) in the simulated scenarios. It can be observed that using PRS can

enhance the trajectory accuracy. However, the improvement of the “SSB+PRS” flight strategy compared to “SSB only” is not very significant. In light of this scenario, we have included the PRS beam sweeping time in the simulation analysis to assess the merits and demerits of these two strategies, whose results are shown in Figure 4.

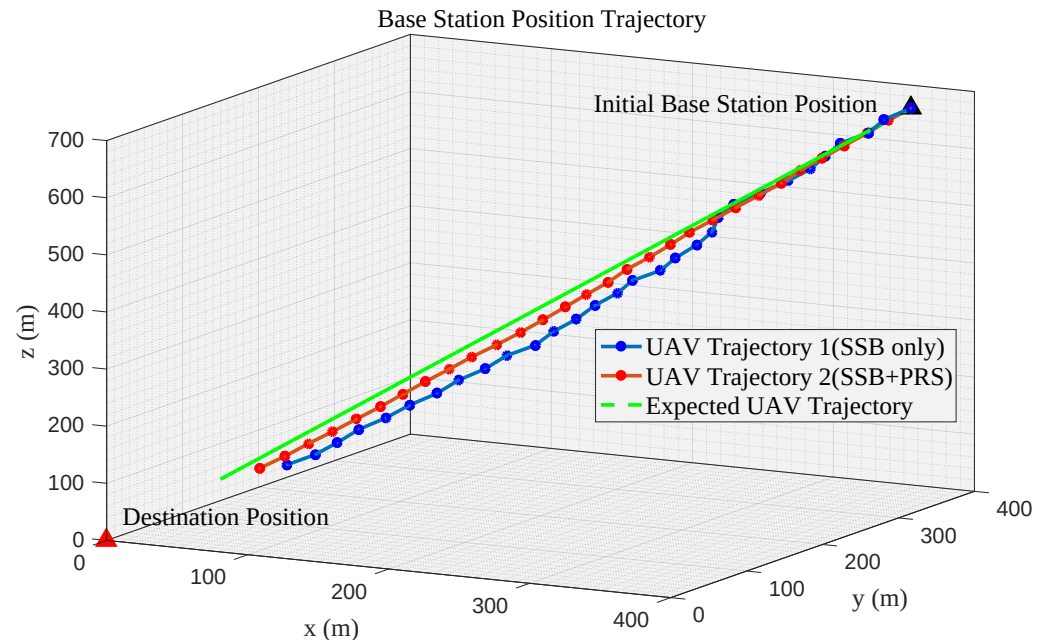


Figure 3. The UAV trajectory with two different flight strategies.

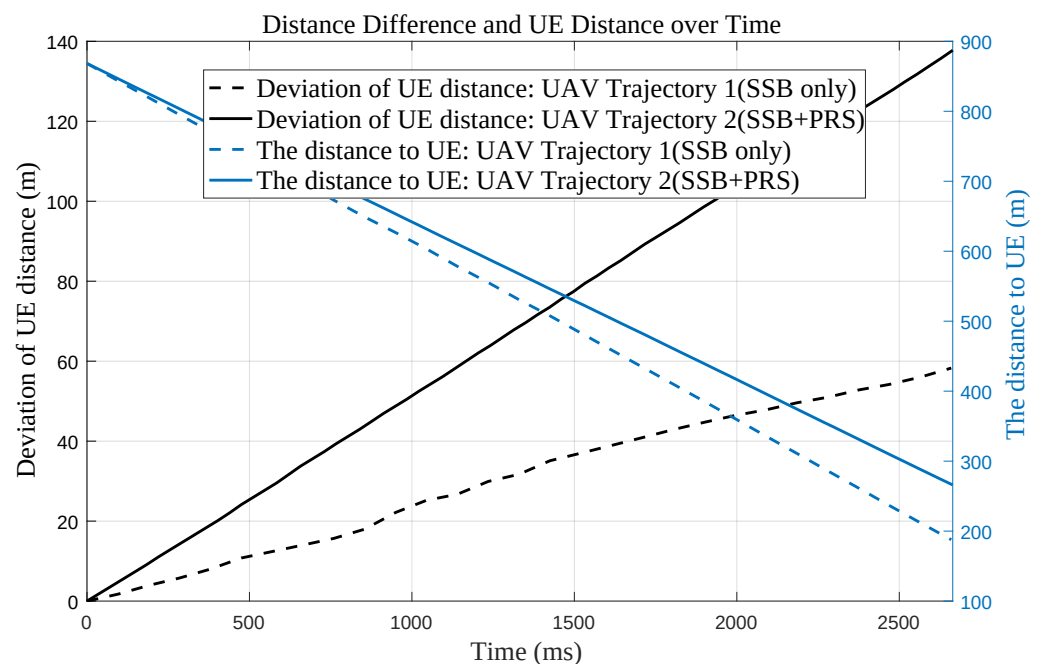


Figure 4. The distance to UE over time with two different flight strategies.

The curve on the left vertical axis represents the deviation in distance to the UE compared to the ideal trajectory at different time points under the two updating strategies. Although PRS can improve trajectory accuracy, the red curve gradually deviates more over time due to the fact that during the time required for PRS sweeping, the UAV is actually able to continue moving in the SSB only scheme. The curve on the right represents the distance from the base station to the UE starting from the same initial point at different time points.

It can be observed that the SSB scheme is closer to the UE in the same amount of time spent. Therefore, based on the above observations, SSB only is chosen as the first-stage strategy.

According to the resource high-frequency band base station's maximum coverage range of 1 km–2 km, following the principle of a 45° elevation angle, the drone flies at a height of 700 m to a specific location to access the UE in need of search and rescue. After access, the drone flight is divided into three stages, whose trajectory is shown in Figures 5 and 6:

- Stage 1: SSB only (ending at approximately 200 m altitude) for the drone to quickly approach the search and rescue area;
- Stage 2: SSB+PRS (straight flight, ending at approximately 50 m), for drone position adjustment;
- Stage 3: SSB+PRS (circular flight until positioning convergence is achieved), for the drone to complete the final positioning stage.

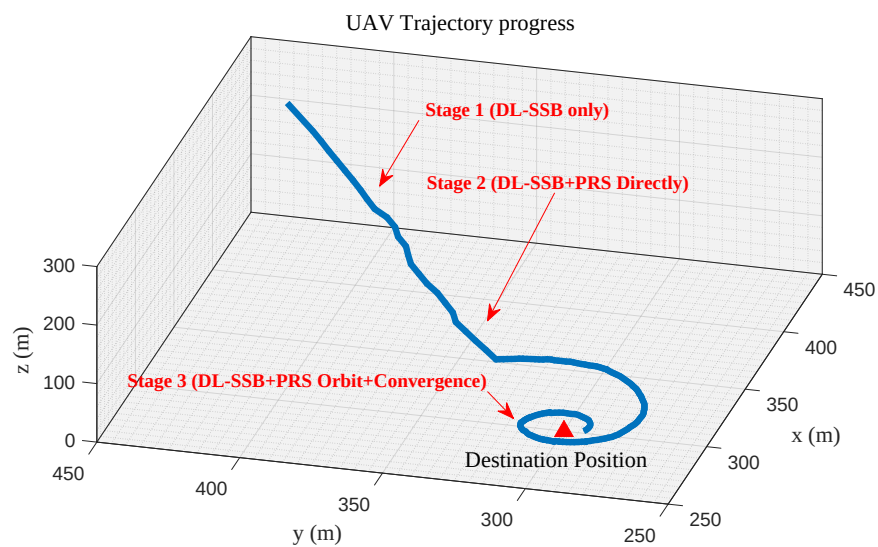


Figure 5. The complete flight trajectory of the UAV.

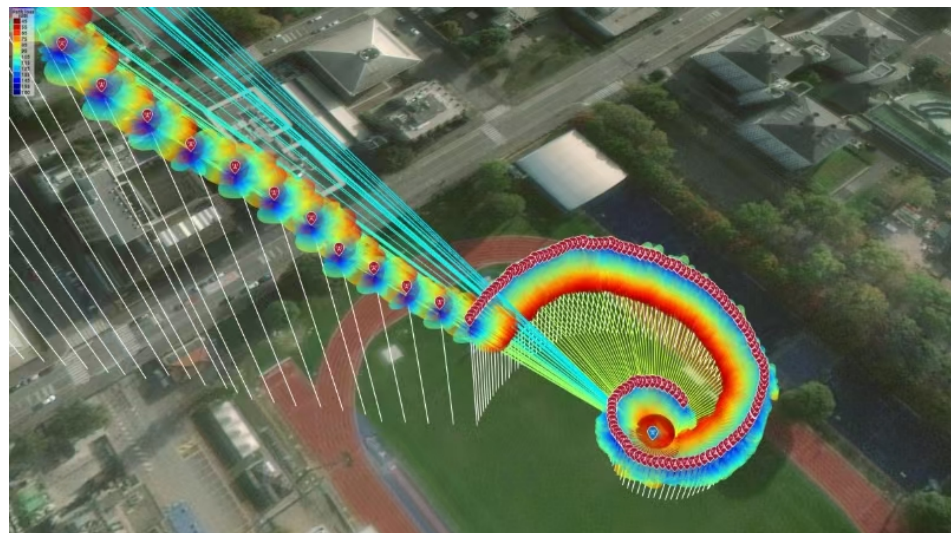


Figure 6. Schematic diagram of the actual UAV flight trajectory.

After the drone approaches the search and rescue area, it enters the Stage 3. According to the previous experiments, in line-of-sight conditions, the measurement error is further reduced compared to the initial positioning results. Therefore, to ensure the final positioning result is generated in line-of-sight conditions as much as possible, the drone should

not only lower its altitude to approach the UE but also consider flying around the vicinity of the search and rescue personnel to ensure that most of the line-of-sight remains within the visual range. Additionally, based on the beam situation, when the drone's position is at a 45° elevation angle towards the terminal position, it is more advantageous for beam sweeping and measuring to obtain more accurate beam measurement results. Therefore, during the circular flight, the drone's trajectory should always aim to be at a 45° elevation angle towards the terminal position, while gradually approaching the UE in the xy plane with a very small angle θ , forming the trajectory shown in Figure 7.

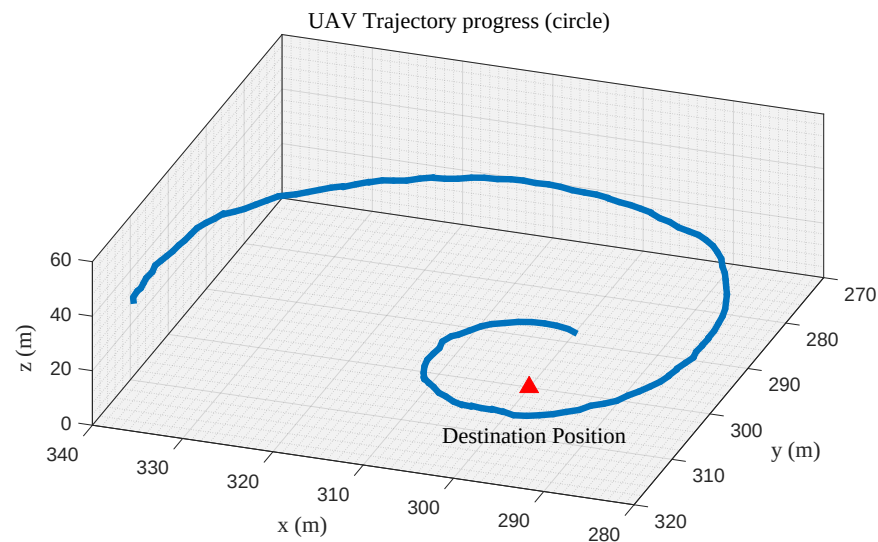


Figure 7. The UAV in stage 3 flies around the victim in a circular trajectory.

Figure 8 shows the variation of distance error over time between the UAV and the victim throughout the entire trajectory. In our approach, after entering Stage 2, utilizing “SSB+PRS” allows for positioning of the UE. To illustrate the assistance provided by this approach in positioning, we simulated the positioning accuracy at different time points starting from Stage 2. The simulation results are shown in the following figure. It can be observed that at the beginning of Stage 2, the positioning error is relatively large. As time progresses and the airborne base station approaches the UE, the positioning accuracy significantly improves upon entering Stage 3. Based on the convergence and setting conditions, the positioning accuracy of our approach can reach 1 m within 1 min.

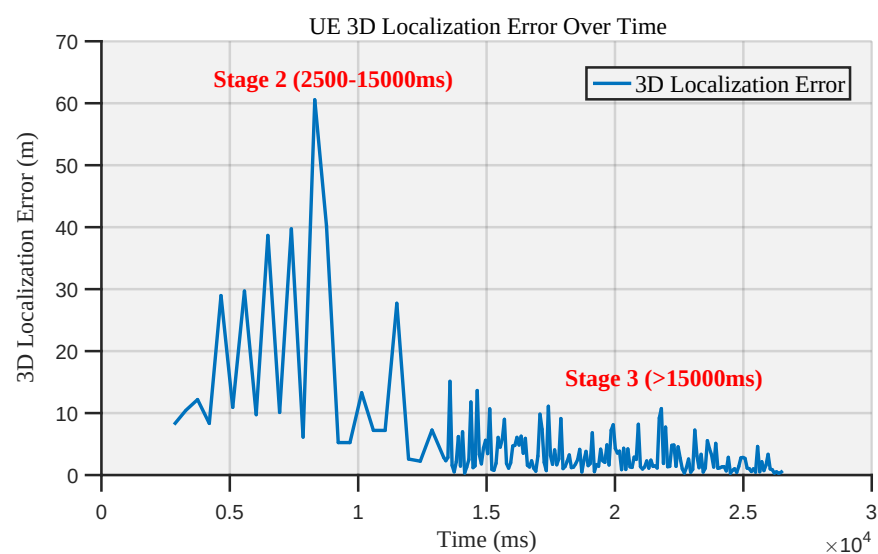


Figure 8. The localization error over time.

6. Conclusions

This paper proposes the use of drones equipped with 5G NR base stations to search and rescue victims carrying 5G mobile phones in disaster areas. In response to the issue of limited positioning accuracy and long search and rescue time in existing research results using uplink reference signals for victim localization, this paper suggests utilizing 5G NR downlink beam sweeping technology to assist drones in conducting search and rescue missions. To this end, this paper presents a three-stage search and rescue process. In the initial stage, drones emit SSB bursts within the coarse-grained beam sweeping range to determine the approximate direction of victims in the disaster area. In the subsequent stage, drones refine the narrow beam within the selected SSB burst set beam range, emit PRS, and take full advantage of the high beam resolution brought by the massive antennas carried by 5G NR base stations to achieve precise 3D positioning of victims in the disaster area. Based on this two-stage search and rescue approach, this paper proposes a drone trajectory update algorithm to guide drones to quickly fly from outside the disaster area to the vicinity of the victims in the disaster area, completing fast search and rescue tasks. Simulation results show that as the algorithm converges, the final accuracy error of the drone to the victims is around 1 m, demonstrating the feasibility and advantages of the proposed BWSAR in this paper.

Possible future research directions may focus on multi-modal fusion positioning technology and intelligent search and rescue algorithms [22]. Combine 5G NR beam scanning technology with other sensor data, such as visual, infrared or acoustic sensors, to improve positioning accuracy and robustness. This multi-modal fusion can reduce the dependence on a single technology and improve the efficiency of search and rescue in complex environments. In addition, more advanced algorithms, such as intelligent decision systems based on machine learning or deep learning, are developed to optimize search and rescue paths and strategies for drones. These algorithms can adapt to different environments and conditions, enabling more efficient and automated search and rescue missions.

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Conflicts of Interest: Author Ming He, Keliang Du, Haoran Huang, Qi Song and Xunyu Liu were employed by the company China Mobile (Chengdu) Information and Telecommunication Technology Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Specht, C.; Dabrowski, P.; Pawelski, J.; Specht, M.; Szot, T. Comparative Analysis of Positioning Accuracy of GNSS Receivers of Samsung Galaxy Smartphones in Marine Dynamic Measurements. *Adv. Space Res.* **2019**, *63*, 3018–3028. [CrossRef]
2. Shakhathreh, H.; Sawalmeh, A.; Al-Fuqaha, A.; Dou, Z.; Almaita, E.; Khalil, I.; Othman, N.; Khreishah, A.; Guizani, M. Unmanned Aerial Vehicles (UAVs): A Survey on Civil Applications and Key Research Challenges. *IEEE Access* **2019**, *7*, 48572–48634. [CrossRef]
3. Panda, K.G.; Das, S.; Sen, D.; Arif, W. Design and Deployment of UAV-Aided Post-Disaster Emergency Network. *IEEE Access* **2019**, *7*, 102985–102999. [CrossRef]
4. Xiao, Q.; Gao, J. The Multi-Visit Vehicle Routing Problem with Drones under Carbon Trading Mechanism. *Sustainability* **2024**, *16*, 6145. [CrossRef]
5. Baniyadi, P.; Foumani, M.; Smith-Miles, K.; Ejov, V. A transformation technique for the clustered generalized traveling salesman problem with applications to logistics. *Eur. J. Oper. Res.* **2020**, *285*, 444–457. [CrossRef]
6. Namuduri, K. Flying cell towers to the rescue. *IEEE Spectr.* **2017**, *54*, 38–43. [CrossRef]

7. Zhao, N.; Lu, W.; Sheng, M.; Chen, Y.; Tang, J.; Yu, F.R.; Wong, K.K. UAV-Assisted Emergency Networks in Disasters. *IEEE Wirel. Commun.* **2019**, *26*, 45–51. [\[CrossRef\]](#)
8. Albanese, A.; Sciancalepore, V.; Costa-Pérez, X. SARDO: An automated search-and-rescue drone-based solution for victims localization. *IEEE Trans. Mob. Comput.* **2021**, *21*, 3312–3325. [\[CrossRef\]](#)
9. Blaga, A.; Campolo, F.; Rea, M.; Costa-Pérez, X. 3DSAR: A Single-Drone 3D Cellular Search and Rescue Solution Leveraging 5G-NR. In Proceedings of the GLOBECOM 2023—2023 IEEE Global Communications Conference, Kuala Lumpur, Malaysia, 4–8 December 2023; pp. 6183–6188.
10. Sun, B.; Tan, B.; Wang, W.; Lohan, E.S. A comparative study of 3D UE positioning in 5G new radio with a single station. *Sensors* **2021**, *21*, 1178. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Liu, Z.; Guo, J.; Huang, F.; Cai, D.; Wu, Y.; Chen, X.; Igorevich, K.K. Lightweight Trustworthy Message Exchange in Unmanned Aerial Vehicle Networks. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 2144–2157. [\[CrossRef\]](#)
12. Guo, J.; Gao, H.; Liu, Z.; Huang, F.; Zhang, J.; Li, X.; Ma, J. ICRA: An Intelligent Clustering Routing Approach for UAV Ad Hoc Networks. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 2447–2460. [\[CrossRef\]](#)
13. Italiano, L.; Tedeschini, B.; Brambilla, M.; Huang, H.; Nicoli, M.; Wymeersch, H. A Tutorial on 5G Positioning. *IEEE Commun. Surv. Tutor.* **2024**. [\[CrossRef\]](#)
14. Ferre, R.M.; Seco-Granados, G.; Lohan, E.S. Positioning Reference Signal design for positioning via 5G. In Proceedings of the Finnish URSI Convention on Radio Science, URSI, Tampere, Finland, 18 October 2019.
15. Keating, R.; Säily, M.; Hultkonen, J.; Karjalainen, J. Overview of positioning in 5G new radio. In Proceedings of the 2019 16th International Symposium on Wireless Communication Systems (ISWCS), Oulu, Finland, 27–30 August 2019; pp. 320–324.
16. Wang, Y.; Huang, S.; Yu, Y.; Li, C.; Hoeher, P.A.; Soong, A.C. Recent Progress on 3GPP 5G Positioning. In Proceedings of the 2023 IEEE 97th Vehicular Technology Conference (VTC2023-Spring), Florence, Italy, 20–23 June 2023; pp. 1–6.
17. Butt, M.M.; Pantelidou, A.; Kovács, I.Z. ML-assisted UE positioning: Performance analysis and 5G architecture enhancements. *IEEE Open J. Veh. Technol.* **2021**, *2*, 377–388. [\[CrossRef\]](#)
18. Sotirioudis, S.P.; Athanasiadou, G.; Tsoulos, G.; Sarigiannidis, P.; Christodoulou, C.G.; Goudos, S.K. Evolutionary Ensemble Learning Pathloss Prediction for 4G and 5G Flying Base Stations With UAVs. *IEEE Trans. Antennas Propag.* **2023**, *71*, 5994–6005. [\[CrossRef\]](#)
19. Hong, X.; Hong, X.; Peng, A.; Sun, T.; Tang, G.; Yang, Q.; Zhen, L.; Shi, J. Evolution of key technologies and system architecture based on 5G mobile communication system convergence positioning. *J. Xiamen Univ.* **2021**, *60*, 571–585.
20. Sobouti, M.J.; Adarbah, H.Y.; Alagheband, A.; Chitsaz, H.; Mohajerzadeh, A.; Sookhak, M.; Seno, S.A.H.; Vahedian, A.; Afghah, F. Efficient Fuzzy-Based 3-D Flying Base Station Positioning and Trajectory for Emergency Management in 5G and Beyond Cellular Networks. *IEEE Syst. J.* **2024**, *18*, 814–825. [\[CrossRef\]](#)
21. Cardoso, E.H.S.; De Araújo, J.P.L.; De Carvalho, S.V.; Vijaykumar, N.; Francês, C.R.L. Novel Multilayered Cellular Automata for Flying Cells Positioning on 5G Cellular Self-Organising Networks. *IEEE Access* **2020**, *8*, 227076–227099. [\[CrossRef\]](#)
22. Del Peral-Rosado, J.A.; Nolle, P.; Razavi, S.M.; Lindmark, G.; Shrestha, D.; Gunnarsson, F.; Kaltenberger, F.; Sirola, N.; Särkkä, O.; Roström, J.; et al. Design Considerations of Dedicated and Aerial 5G Networks for Enhanced Positioning Services. In Proceedings of the 2022 10th Workshop on Satellite Navigation Technology (NAVITEC), Virtual, 5–7 April 2022; pp. 1–12.

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