Leveraging 5G-NR for Finding Mobile Devices with UAVs: Latency vs Accuracy Trade-off

Andra Blaga*‡§, Federico Campolo*§, Filip Lemic*¶, Oriol Sallent‡ and Xavier Costa-Pérez.*†
*i2CAT Foundation, Barcelona, Spain Email:{name.surname}@i2cat.net
†NEC Laboratories Europe, Heidelberg, Germany, and ICREA, Barcelona, Spain
‡Universidad Politècnica de Catalunya, Barcelona, Spain
§Universidad Pompeu Fabra, Barcelona, Spain
¶Faculty of Electrical Engineering and Computing, University of Zagreb, Zagreb, Croatia

***Abstract*—Rapid and accurate localization of individuals during search-and-rescue (SAR) missions is essential for reducing casualties in emergencies. Traditional methods often struggle in disaster scenarios, where obstacles like debris or dense foliage hinder performance, and reliance on user-side actions proves impractical for mission-critical operations. This paper presents a novel approach that leverages a 5G-new radio (NR)-based unmanned aerial vehicle (UAV) localization framework, integrating hybrid techniques with adaptive clustering strategies to localize user equipments (UEs). Unlike traditional methods, our system dynamically adjusts its trajectory to balance latency and accuracy, achieving UEs positioning accuracy within tens of centimeters during simulation tests. By integrating 5G-NR technology into UAV-based localization, our approach provides a robust and scalable solution for mission-critical SAR operations, significantly enhancing the latency and reliability of locating individuals in emergency situations.**

***Index Terms*—, UAVs, 5G-NR, Localization, search-and-rescue.**

I. Introduction

The increasing frequency and intensity of natural disasters, driven by the ongoing effects of climate change, have posed significant challenges to emergency response efforts worldwide. Events such as floods, storms, and typhoons have caused a considerable rise in casualties and economic losses, with a marked increase in both the number and severity of such incidents [1].

Rapid and accurate victim localization is crucial for reducing casualties during emergencies. Traditional approaches often rely on global navigation satellite system (GNSS) for positioning; however, GNSS-based systems face severe limitations in disaster scenarios. These limitations stem from their susceptibility to signal attenuation caused by signal attenuation from obstacles like debris or dense foliage. Moreover, GNSS systems require user-side actions to share location data, which is often impractical, making them unsuitable for mission-critical operations.

In contrast, unmanned aerial vehicles (UAVs), have emerged as a promising tool for search-and-rescue (SAR) missions, providing a flexible and rapidly deployable solution to locate individuals in difficult-to-reach areas [2], [3]. Beyond their common use with computer vision and infrared [4] sensors for *SAR* operations, UAVs are increasingly being utilized also as base station (BS), defined as drone-mounted BS (UxNB) in 3rd generation partnership project (3GPP) terminology [5]. This enables passive localization of UEs even when the ground-based communication infrastructure is compromised [6]. Given that more than 90% of the global population owns a wearable device, this capability represents a powerful tool to track and locate victims when a natural disaster occurs passively [7].

In our previous work [8], [9], we focused on improving the precision of localization using a single-drone methodology to locate individuals using their wearable devices during SAR operations. Although these methods enhanced the individual's position estimation accuracy, they lacked the adaptability required to respond to mission-specific constraints, limiting their effectiveness in dynamic environments.

In the present work, we advance the current state of research by introducing a novel localization approach. This approach integrates various policies that enable the system to dynamically modify its behavior in response to the specific requirements of the mission. The primary contributions of this paper include:

- Design of a single-UAV cellular localization framework that integrates different estimation techniques and an advanced trajectory algorithm that dynamically adjusts the UxNB path to enhance localization accuracy.
- Extension of our work by introducing configurable localization policies that allow for adaptable trade-offs between accuracy and latency in the localization process.
- Development of adaptive clustering-based localization strategies that utilize artificial intelligence (AI), in particular density-based spatial clustering, to prioritize latency or accuracy, depending on the mission conditions.

The remainder of the paper is structured as follows. Section II reviews related work, while Section III introduces our user-plan localization. Then, our localization framework is detailed in Section IV. Section V outlines our evaluation setting, and Section VI presents the outcomes of our performance assessment. Finally, we conclude the paper by summarizing our key findings and conclusions.

II. Related Work

Precise, low-latency location data is crucial for the success of SAR missions in emergency situations and police investigations. Prior work has explored various sensor-based and wireless technologies for localization. For example, [10], [11] investigate the use of thermal cameras and infrared sensors mounted on UAVs to enhance target detection, while [12]

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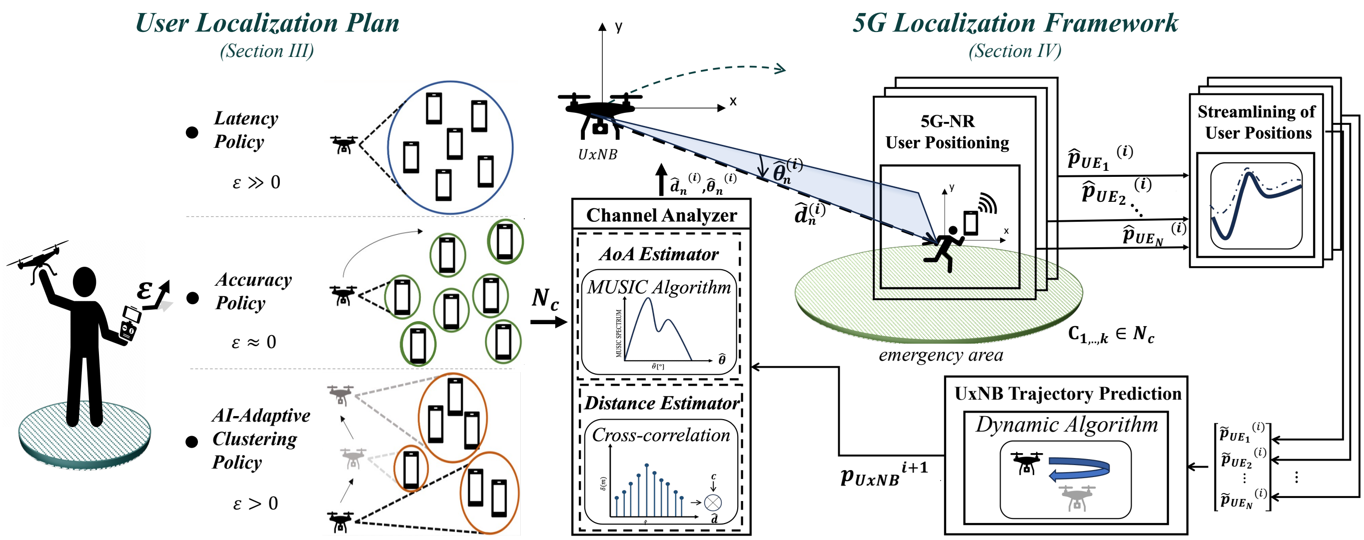

Figure 1: Illustration of the proposed search and rescue solution. The *User Localization Plan* (left) involves selecting the desired policy by setting the distance parameter ε between data points, which determines the number of clusters N_c. This clustering information is then fed into the proposed localization framework (right).

presents a Wi-Fi-based method using received signal strength indicator (RSSI) measurements for device positioning when satellite-based systems are unavailable. In addition, in [13] an experimental work is developed based on the location of multiple targets that combines the measurements RSSI and angle of arrival (AoA). In ultra wide band (UWB) technology, [14] discusses the use of transceivers mounted on UAVs for high-precision localization in SAR scenarios. Experimental cellular technology solutions, as described in [7], employ pseudo-trilateration using a single UAV-based flying BS to estimate user locations with an accuracy of a few tens of meters. Additionally, [15], [16] review 5G-NR positioning techniques, emphasizing the enhanced accuracy from increased line-of-sight (LOS) opportunities provided by UxNB. Integrating 5G-NR with UAVs improves localization precision and responsiveness, making it a valuable tool for emergency response.

Building on these developments, our work integrates 5G-NR technology with UxNB and introduces a novel set of policies designed to optimize the localization process. These policies—prioritizing latency, accuracy, and AI-based adaptive clustering—enable dynamic adjustments to the framework based on mission requirements, enhancing the flexibility and effectiveness of SAR operations in rapidly evolving scenarios.

III. Users Localization Plan

Unexpected emergencies present unpredictable challenges that require adaptable and context-specific responses. To effectively address these situations, it is crucial to employ strategies tailored to the unique conditions of each disaster. To support this need, we propose a flexible localization framework that empowers decision-makers to adjust their approach based on the specific requirements of the emergency at hand.

A. Assumptions

Our proposed user localization framework is built on the following key assumptions:

- The UxNB performs a reconnaissance flight over the disaster area to evaluate the presence and distribution of potential victims. For this analysis, it is assumed that the coverage area is sufficiently wide to encompass all missing individuals.
- The victim location is performed on the horizontal plane. The energy-efficient framework enables the UxNB to complete its mission on a single battery charge, as demonstrated by existing research [7], which reports a low battery consumption cost of 5%. The different policies adjust the sampling frequency R_{UxNB} by determining how often the UxNB processes reference signals transmitted by the UEs in the uplink (UL) within the 5G-NR frame [17].

B. Policy Selection Framework

We introduce a policy selection framework that dynamically balances tracking time and localization accuracy based on mission requirements. Once selected, the UxNB groups the total N_{Tot} UEs into N_c clusters, enabling efficient localization within a predefined time T_w. The policies are shown in Fig. 1 and described below:

1) **Latency Policy**: Ideal for time-critical scenarios requiring rapid user localization, this policy groups all users into a single cluster ($N_c = 1$) to enable continuous monitoring of their positions throughout the entire duration of T_w s. The UxNB estimates each UE position at a frequency of $R_{\text{UxNB}} = F_{\text{5G-NR}}/N_{\text{Tot}}$ Hz, with $F_{\text{5G-NR}}$ representing the number of 5G-NR frames per second, typically $F_{\text{5G-NR}} =$ 100 Hz, and N_{Tot} the total number of the UEs.
2) **Accuracy Policy**: Designed for scenarios where pinpoint precision is essential, this approach assigns each user to its own cluster ($N_c = N_{\text{Tot}}$), allowing the UxNB to focus

individually on each user for a duration of $t_{w_c} = T_w/N_{\text{Tot}}$ s to maximize precision. During this time, the sampling frequency for each UE is set to $R_{\text{UxNB}} = F_{\text{5G-NR}}$ Hz.

3) **AI-Adaptive Clustering Policy**: Designed for missions that require a balance between tracking latency and accuracy, this policy employs an adaptive clustering algorithm to determine the optimal number of clusters N_c dynamically. Each cluster C_k contains a subset of UEs, represented as $N_{\text{UE}}^{(k)}$, where $k = 1, \ldots, N_c$. The UxNB monitors each cluster for a time $t_{w_c} = T_w/N_c$ s with a sampling frequency of $R_{\text{UxNB}} = F_{\text{5G-NR}}/N_{\text{UE}}^{(k)}$ Hz, optimizing both latency and accuracy in real-time.

C. Clustering Algorithm Selection

Clustering algorithms classify data points based on similarity, grouping similar data points, and separating dissimilar ones into clusters. Typically, similarity is measured using the distance between data values. For instance, K-means employs the Euclidean distance to form clusters, while Gaussian Mixture Models estimate the probability of each data point belonging to a particular cluster. However, both methods require a predefined number of clusters N_c, limiting their flexibility. To address this, we employ the density-based spatial clustering of applications with noise (DBSCAN) algorithm, which begins by selecting a random data point as the center of a cluster and searches for all data points within a distance ε. The reference point is marked as noise if no additional points are found within this range. Otherwise, the algorithm continues to expand the cluster by including all reachable points within distance ε, repeating this process until no further points can be added. This iterative approach allows for the definition of clusters without specifying their number in advance. The key advantage of the DBSCAN algorithm is its ability to estimate the number of clusters N_c based solely on the chosen distance parameter ε [18].

In Fig. 1, left part, the selection of ε values is illustrated for the three proposed policies. For the *Latency* policy, setting a large ε results in a single cluster, reflecting the requirement for broader data aggregation. Conversely, for scenarios where the UxNB needs to focus on individual users, such as in the *Accuracy* policy, a smaller ε is used to minimize the distance between points, effectively isolating each user.

For *AI-based adaptive clustering* policy, we optimize the ε value to balance cluster density and separation by analyzing distances between data points and their nearest neighbors using the Nearest Neighbors algorithm [19]. The optimal ε is chosen to ensure that 90-95% of the data points have at least one neighbor within this range. This adjustment enhances clustering quality, allowing the UxNB to effectively target specific user groups while balancing localization latency and accuracy. Nearby users are grouped into a single cluster, achieving the optimal trade-off between precision and efficiency. A detailed example of this ε setting is presented in Sec. VI.

IV. 5G Localization Framework

Fig. 1 illustrates our proposed localization solution. The left side presents the *user localization plan*, discussed in detail in Sec. III, while the right side shows the *5G-based localization framework*. The introduction of the 5G-NR standard brings a flexible waveform and frame structure, controlled by the numerology parameter (μ). From a localization standpoint, this flexibility enables the use of wider bandwidths and larger antenna arrays, allowing more precise time of flight (ToF) and AoA measurements. For these purposes, five different reference signals have been introduced: demodulation reference signal (DMRS), positioning reference signal (PRS), phase tracking reference signal (PTRS), sounding reference signal (SRS), and channel state information reference signal (CSI-RS) [20]. Our localization framework uses the SRS, as it is specifically tailored for positioning, as highlighted in [21]. The UE transmits the SRS in the UL at every slot, utilizing the full bandwidth to maximize accuracy [21].

A. Channel Analyzer

The first block of the 5G-based localization framework is the *Channel Analyzer*, which estimates both ToF and AoA through its two sub-systems: the *Distance Estimator* and *AoA Estimator*.

The *Distance Estimator* determines the ToF, denoted as τ by performing a cross-correlation between the transmitted and received SRS sequences. This method leverages the fact that the SRS belongs to the family of constant amplitude zero auto correlation (CAZAC) sequences, which exhibit a correlation peak when aligned with a delayed version of themselves. The position of this peak corresponds to the delay τ, allowing the ToF-based distance to be calculated as $\hat{d} = \tau c$, where c is the speed of light.

The *AoA Estimator* constructs the channel state information (CSI) matrix using the transmitted and received SRS sequences and applies the multiple signal classification (MUSIC) algorithm to estimate the angle of arrival $\hat{\theta}$. By exploiting the orthogonality between the signal and noise subspaces, the MUSIC algorithm identifies the signal AoA by finding the angle $\hat{\theta}$ that minimizes the expression $\beta^H(\theta)Q_N Q_N^H \beta(\theta)$, where β is the steering vector and Q_N represents the noise subspace [22].

B. 5G-NR User Positioning

Let $\boldsymbol{P}_{\text{UxNB}} = [\boldsymbol{x}_{\text{UxNB}}, \boldsymbol{y}_{\text{UxNB}}]^\top$ and $\boldsymbol{P}_{\text{UE}_n} = [\boldsymbol{x}_{\text{UE}_n}, \boldsymbol{y}_{\text{UE}_n}]^\top$ represent the matrices of the x and y coordinates of the UxNB and the n-th UE, $n = 1, \ldots, N_{\text{ToT}}$, respectively, along their trajectories during the entire inference period of length $\mathcal{I}$. To estimate the n-th UE position using the measurements provided by the *Channel Analyzer* block, as shown in Fig. 1. Two techniques can be employed for this purpose: multilateration and hybrid localization.

In the *multilateration* approach, the n-th UE position is estimated using only the ToF-based distance estimates $\hat{d}_n^{(i)}$, and the known positions of the UxNB. The UxNB collects multiple distance measurements along its trajectory. Once at least four measurements from distinct locations are available, the UxNB estimates the i-th position of the n-th UE by solving the non-linear least squares (NLS) problem:

$$\hat{\boldsymbol{p}}_{\text{UE},n}^{(i)} = \arg\min |\boldsymbol{d}_n - \hat{\boldsymbol{d}}_n|^2. \tag{1}$$

Here, $\boldsymbol{d}_n$ and $\hat{\boldsymbol{d}}_n$ represent the actual and estimated distances up to time-step i, with $\boldsymbol{d}_n = |\boldsymbol{P}'_{\text{UE},n} - \boldsymbol{P}'_{\text{UxNB}}|^2$, where $\boldsymbol{P}'_{\text{UE},n}$ and $\boldsymbol{P}'_{\text{UxNB}}$ are the subsets of the n-th UE and the UxNB coordinates up to time-step i.

In the *hybrid localization* approach, both ToF-based and AoA estimations, $\hat{d}_n^{(i)}$ and $\hat{\theta}_n^{(i)}$, are integrated. This method enables the UxNB to generate multiple position estimates of the n-th UE along its trajectory, without needing to wait for at least four distance measurements to obtain an estimation. Combining these measurements can also enhance accuracy by leveraging both distance and angle data. As a result, at each time-step i, the position of the n-th UE is estimated as:

$$\hat{\boldsymbol{p}}_{\text{UE},n}^{(i)} = \Big[x_{\text{UxNB}}^{(i)} + \hat{d}_n^{(i)} \cdot \cos\hat{\theta}_n^{(i)}, \\ y_{\text{UxNB}}^{(i)} + \hat{d}_n^{(i)} \cdot \sin\hat{\theta}_n^{(i)}\Big]^\top, \quad \forall i \in \mathcal{I}. \quad (2)$$

C. Streamlining of User Positions

For mobile device tracking, we apply an exponentially weighted moving average (EWMA) filter to the position estimates, expressed as:

$$\tilde{\boldsymbol{p}}_{\text{UE},n}^{(i)} = (1-\alpha)\hat{\boldsymbol{p}}_{\text{UE},n}^{(i-1)} + \alpha\hat{\boldsymbol{p}}_{\text{UE},n}^{(i)}, \quad (3)$$

where $\tilde{\boldsymbol{p}}_{\text{UE},n}^{(i)}$ denotes the smoothed position estimate, and α represents the filter weight. The EWMA filter adaptively balances the impact of historical data and current measurements, with the choice of α, tailored to the mobility characteristics of the mobility of the UE target devices. Further details on the optimization and selection of α are provided in Sec.V.

D. UxNB Trajectory Prediction

The UxNB Trajectory Prediction block, depicted in Fig. 1, builds upon the methodology developed in our previous work on the UxNB trajectory framework [8], [9]. In this work, we further refine and apply the spiral trajectory strategy to optimize the UxNB approach toward the UEs within the emergency area, ensuring efficient coverage and localization. The algorithm determines the next position of the UxNB, denoted as $\boldsymbol{p}_{\text{UxNB}+1}^{(i)}$, by first calculating the weighted center of the UE positions in the defined emergency area and then identifying the maximum distance to the farthest UE to establish a coverage radius. The UxNB then follows a spiral-like trajectory within this area, ensuring optimal positioning relative to the UEs. The new position is iteratively updated to keep the UxNB near the center of the emergency area while effectively covering all UEs. This approach dynamically adapts the UxNB path to maximize coverage.

V. Evaluation Environment

In this section, we outline the simulated environment used to evaluate the proposed localization solution. The scenario, simulated using MATLAB R2024a, includes an UxNB and $N_{\text{Tot}} = 10$ UEs positioned within the SAR area. The UxNB is equipped with a 2x2 uniform rectangular array (URA), chosen to minimize the array size and reduce the overall payload weight, while still supporting AoA estimation and the total inference time is set to $T_w = 10$ minutes.

Table I: Cellular simulation parameters.

Settings	**4G-LTE**	**5G-NR**
Carrier frequency (f_c) [GHz]	2.515	2.515
Reference signal	SRS	SRS
Bandwidth (BW) [MHz]	20	100
Numerology	$\mu = 0$	$\mu = 2$
Δ_f [kHz]	15	60
Resource blocks (RBs)	100	135
Sampling frequency (f_s) [MHz]	30.72	245.76
N_{FFT}	2048	4096
Δ_s [m]	~4.9	~2.4

The communication channel between the UxNB and the UE is modeled as an air-to-ground (A2G) channel following the 3GPP standard TR 38.901 [23]. This setup employs a geometry-based stochastic channel clustered delay line (CDL) to replicate the A2G propagation environment, creating a realistic UxNB-enabled cellular network. The CDL model is further customized to accurately represent the characteristics of A2G propagation [24].

The UxNB moves at a constant speed of 5 m/s, following the trajectory defined by the algorithm in [8], [9], at an altitude of 100 m. The UEs are either static or move randomly at speeds of 0 to 2 m/s. We simulate realistic paths using the self-similar least action walk (SLAW) model, generating two-dimensional coordinates based on real GPS data [25]. The Hurst and Lévy exponents, set to 0.6 and 1, respectively, control waypoint self-similarity and pause times over T_w. The filter weight α in the EWMA is set to 0.02, aligning with typical walking speeds of users. Finally, Table I outlines the cellular simulation parameters based on the 3GPP standard [26]. Both systems use the same carrier frequency (2.515 GHz) and utilize the SRS for ToF and AoA estimations as described in Sec. IV-A.

VI. Performance Evaluation

In this section, we first evaluate the localization accuracy of the proposed system by comparing the two methods considered: multilateration and hybrid. We also highlight the improvements enabled by 5G-NR using 4G-LTE as a baseline. Finally, we assess the accuracy and latency of the 5G-NR-based hybrid approach across three localization policies of Sec. III, focusing on their impact on positioning error and system responsiveness.

A. Localization Performance

To evaluate the localization performance in 4G-LTE and 5G-NR, we analyzed the cumulative distribution function (CDF) of positioning error, depicted in Fig.2, comparing multilateration and hybrid localization methods. The results were obtained through multiple Monte Carlo simulations to ensure a 95% confidence interval.

The *multilateration* technique, indicated by dashed lines, relies solely on ToF-based measurements to estimate the UE position. In 4G-LTE, this method exhibits notable limitations, with the CDF revealing that positioning errors exceed 5 meters in over 20% of the cases. Although multilateration improves in 5G-NR, it still shows errors up to 2.5 m at the 90th

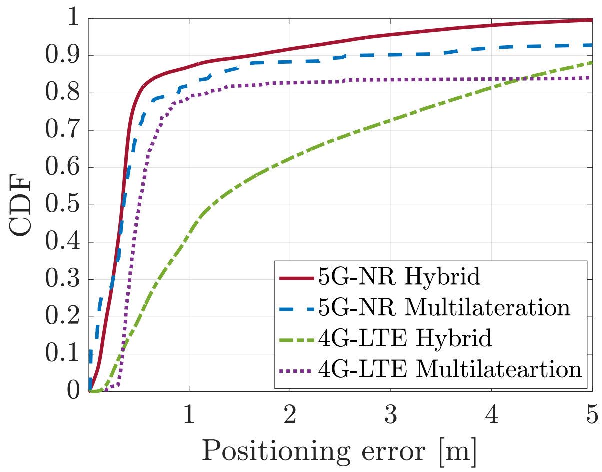

Figure 2: Comparison of the positioning error CDF m for UE_1 using multilateration and hybrid localization techniques with both 4G-LTE and 5G-NR standards.

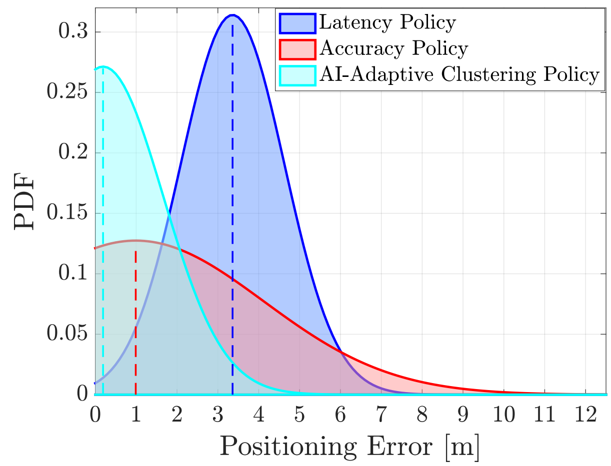

Figure 3: Positioning error PDF [m] comparison for the three localization policies.

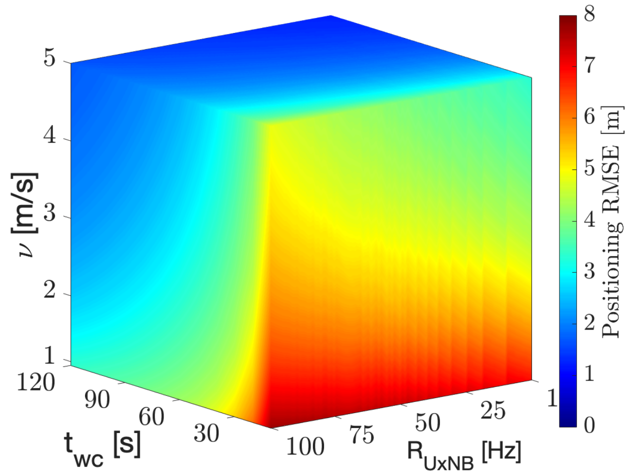

Figure 4: UE positioning RMSE [m] for varying UxNB speeds (ν) [m/s], sampling frequencies (R_{UxNB}) [Hz], and cluster observation times (t_{w_c}) [s].

percentile, highlighting that ToF alone is insufficient for sub-meter accuracy under the tested conditions.

In contrast, the *hybrid localization* approach, represented by solid lines, integrates ToF and AoA measurements, effectively combining distance and angular data for more precise UE positioning. The 5G-NR hybrid method significantly outperforms other techniques, with over 90% of positioning errors falling below 1.5 m, thanks to its wider bandwidth and higher resolution, enabling more accurate AoA estimations and improved multipath handling. The 4G-LTE hybrid approach, while showing modest gains over its ToF counterpart, still struggles with greater inaccuracies due to its narrower bandwidth and lower spatial resolution.

B. Policy Performance Evaluation

The performance of the 5G-NR-based hybrid localization system was analyzed using three strategies: Latency Policy, Accuracy Policy, and AI-based Adaptive Clustering Policy. Fig. 3 illustrates the probability density function (PDF) of the positioning error for each policy, with Latency Policy depicted in blue, the Accuracy Policy in red, and the AI-Adaptive Clustering policy in cyan.

Latency policy showed the highest positioning error, with a median error of 3.36 m and a standard deviation of 1.27 m. This outcome is due to the fixed trajectory of the UAV, which does not adjust its path dynamically to focus on each UE. Nevertheless, this approach offers a crucial advantage in terms of latency, enabling a quick estimation of all UEs positions within the first 10 ms, as the UxNB receives the SRS from each UE at every slot defined by μ in the 5G-NR frame.

In contrast, Accuracy Policy achieved improved results, with a median error of 0.99 m and a standard deviation of 3.13 m. By setting a smaller ε value in the clustering algorithm, this approach focuses on each UE individually, resulting in $N_c = N_{\text{Tot}}$ single-user clusters. This method prioritizes accuracy over latency, dedicating approximately 1 minute per UE cluster, achieving a positioning RMSE of about 2.8 m per UE.

AI-Adaptive Clustering policy strikes the best balance between accuracy and latency, yielding a median error of 0.19 m and a standard deviation of 1.47 m. Setting ε to around 4 formed $N_c = 5$ clusters, improving upon the latency obtained by Accuracy Policy. This adaptive strategy enabled the UxNB to localize all UEs within 9 minutes, with an average observation time of roughly 2 minutes per cluster. By dynamically adjusting the balance between latency and accuracy, this policy allowed real-time adaptation of the UxNB trajectory, providing a versatile solution with high accuracy and reduced latency.

C. UxNB Behavior Influence Evaluation

To delve deeper into AI-Adaptive Clustering Policy, Fig. 4 presents the root mean square error (RMSE) of the UE positioning error as influenced by the UxNB speed ν, sampling frequency R_{UxNB}, and observation time t_{w_c}. The heatmap indicates the error levels, with red representing the highest errors and blue the lowest. Analysis reveals that the maximum error, approximately 8 m, occurs when the UxNB moves at 1 m/s with a high sampling frequency of 100 Hz (one sample every 10 ms). Conversely, the minimum error, around 25 cm, is achieved at a UxNB speed of 5 m/s and a positioning frequency of 1 Hz, using an observation time of 2 minutes per cluster. These findings underscore the significance of fine-tuning UxNB speed and sampling frequency to optimize precision and responsiveness, thus improving the overall effectiveness of AI-adaptive clustering Policy.

VII. Summary and Conclusion

Natural disasters, exacerbated by climate change, often result in a higher number of individuals lost or trapped, making efficient SAR operations essential. To address this, we present a localization strategy module that balances tracking speed and localization accuracy through three distinct target policies. By employing AI-Adaptive Clustering Policy, our approach dynamically balances latency and precision, achieving sub-meter accuracy with a median error of tens of centimeters. Integrating the hybrid localization technique consistently outperforms traditional methods, especially in complex environments. Notably, the hybrid approach, combined with an intelligent and dynamic UxNB trajectory, significantly reduces positioning error—improving accuracy by an order of magnitude ($\sim$5.5 m vs 1.5 m at $\sim$0.90 CDF), compared to 4G-LTE systems.

Future work will focus on implementing this framework in real-world scenarios, addressing challenges like power consumption, UxNB battery life, and system reliability. Integrating edge computing for real-time data processing and addressing communication latency and scalability limitations will also be key areas for enhancing UxNB technology.

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