IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 26 April 2025, accepted 12 May 2025, date of publication 14 May 2025, date of current version 23 May 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3570203

RESEARCH ARTICLE

Real-Time FTM-Based Victim Positioning System Using Heterogeneous Robots in Remote and Outdoor Scenarios

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This work was supported in part by the Spanish Ministerio de Ciencia, Innovación y Universidades, Gobierno de España, under Project PID2021-122944OB-I00; and in part by the Maori Project funded by the European Union-NextGenerationEU, and through the University of Malaga through the Open Access Charge: Universidad de Málaga/Consorcio de Bibliotecas Universitarias de Andalucía (CBUA).

ABSTRACT Accurate victim localization in Remote, Outdoor, Unstructured, and Disaster (ROUD) scenarios remains a significant challenge due to limited infrastructure, complex terrains, and time constraints inherent in Search and Rescue (SAR) operations. This article introduces an innovative real-time positioning system that leverages Fine Time Measurement (FTM), a feature of the IEEE 802.11mc amendment, to detect WiFi-enabled devices typically carried by potential victims. The system integrates a Hybrid Wireless Sensor Network (H-WSN) composed of static and mobile anchors mounted on Uncrewed Ground and Aerial Vehicles (UGVs and UAVs), within a Robot Operating System (ROS)-based architecture. A centralized Feedback Information System (FIS) processes real-time RTT data from the field, executes a multilateration algorithm, and provides live geolocation updates to SAR coordinators. The system was validated during a large-scale SAR drill, successfully locating two types of victims—a semi-hidden surface victim and a buried victim—within a $2000\,\mathrm{m}^2$ area in under 7 minutes, without any filtering or post-processing. The maximum positioning error was 22.87 m for the buried victim and 17.14 m for the surface one. The complete system, including source code, dataset, and a containerized environment, is openly available to support reproducibility and further research, highlighting the potential of robotic and wireless technologies to enhance disaster response through accurate, real-time localization in complex environments.

INDEX TERMS Cloud computing, positioning, ROS, search and rescue, uncrewed vehicles, WSN.

I. INTRODUCTION

Remote, Outdoor, Unstructured, and Disaster (ROUD) scenarios impose particularly demanding requirements on victim localization systems. Accurate and real-time positioning of Potential Victims (PVs) within a few meters is a critical capability for Search and Rescue (SAR) missions, especially when access to key areas is challenging or hazardous. The difficulty arises not only in achieving precise localization under these conditions but in doing so swiftly enough to effectively support time-sensitive SAR operations. ROUD environments pose a unique combination of challenges, often rendering traditional localization infrastructures—such as mobile phone base stations—impractical or unavailable. Unlike urban or controlled environments, where reliable coverage and technological support are typically present, the complex topography and unpredictable conditions of ROUD settings significantly hinder the deployment and effectiveness of conventional positioning systems.

The associate editor coordinating the review of this manuscript and approving it for publication was Angelo Trotta.

Global Navigation Satellite System (GNSS)-based positioning technologies are essential for reliable localization and navigation in outdoor SAR operations. Their ubiquity and global accessibility make GNSS the most widely used positioning solution, as it provides coverage without relying on local infrastructure. However, this widespread use does not exempt GNSS from limitations. Its performance can degrade significantly in environments with signal obstructions (e.g., dense vegetation, canyons, collapsed structures), multipath effects, or radio interference. GNSS signals are also inherently vulnerable to spoofing and jamming, which can compromise reliability in critical scenarios (e.g., conflict zones). Additionally, atmospheric conditions—such as dense cloud cover, heavy rain, or ionospheric disturbances—may introduce signal delays and reduce positioning accuracy, especially in dynamic or weather-affected disaster areas.

Table 1 provides a comparative summary of the most commonly used GNSS positioning methods, detailing their underlying principles, typical application domains, and the horizontal/vertical accuracy achievable under ideal or open-sky conditions. The table also highlights the required infrastructure for each solution type, illustrating the trade-offs between positioning precision, system complexity, and cost—factors that must be carefully considered when deploying GNSS-based solutions in challenging or infrastructure-limited environments such as ROUD scenarios.

While drones equipped with cameras, LiDAR, and thermal imaging systems offer valuable capabilities for victim detection and localization, their effectiveness is constrained by strict Line of Sight (LoS) requirements and communication limitations, particularly in cluttered or obstructed environments. Moreover, the data generated by these sensors—especially LiDAR point clouds and high-resolution visual or thermal imagery—are often computationally intensive to process, require significant bandwidth for transmission, and may not always yield reliable results in complex scenarios (e.g., occlusions, poor lighting, or smoke). Due to these limitations, relying solely on onboard sensing can compromise the robustness of SAR operations. As a result, it is increasingly necessary to deploy alternative and redundant sources of positioning and environmental data, such as distributed wireless sensor nodes, to ensure situational awareness in degraded or disconnected environments.

In general, mobile robots can estimate the position of targets relative to their surroundings by using sensors such as LiDAR, thermal cameras, or acoustic devices, and typically employ techniques like Simultaneous Localization and Mapping (SLAM) or visual odometry to build environmental maps and track their own movement. In SAR missions, Uncrewed Ground and Aerial Vehicles (UGVs and UAVs) not only support first responders in victim detection and assistance [6], helping to prevent occupational stress injuries [7], reduce fatigue and stress [8], and increase load-carrying capabilities, but also enhance situational awareness through onboard sensing and processing. Moreover, by integrating mobile robots into Wireless Sensor Networks (WSN) as mobile perception nodes, Hybrid Wireless Sensor Networks (H-WSNs)—comprising both static and mobile nodes—are established. These mobile platforms dynamically extend network coverage, moving through the environment to collect, store, forward, and georeference lightweight sensor data. This capability not only maintains connectivity in areas lacking Internet or GNSS coverage [9], but also provides valuable spatial context for locating and mapping objects within the operational area. Their low power consumption and resilient communication capabilities further enable sustained network operation, a critical advantage in prolonged SAR missions where energy resources are limited.

The primary challenges in ROUD scenarios are locating victims and communicating crucial information to the Command and Control Center (CCC) to ensure swift evacuation and prompt assistance for the victims, who typically remain static. A key difficulty lies in enabling the emergency coordinator—often located in a remote base of operations—to receive this information in real time, in order to make timely decisions and dynamically adjust the progression of SAR tasks based on evolving field conditions.

In such contexts, there is a pressing need for systems that can be rapidly deployed and operate independently of any fixed infrastructure. The so-called golden hours—the first 48 h to 72 h following a disaster—are critical for the successful rescue of victims [10]. Beyond this window, survival rates drop drastically. To accelerate the response, the use of multiple autonomous robots can significantly reduce the time required for exploration and mapping tasks, enabling faster victim detection and more efficient navigation through the affected area [11].

Table 2 summarizes various wireless communication technologies that are widely used in SAR scenarios and that can also be leveraged for positioning purposes. These include Wireless Personal Area Networks (WPAN) such as BLE, Zigbee, and UWB; Wireless Local Area Networks (WLAN) such as WiFi; and Low Power Wide Area Networks (LPWAN) such as LoRa, Sigfox, NB-IoT, and LTE-M.

Bluetooth Low Energy (BLE), particularly from Bluetooth 5.0 onwards, can theoretically reach distances of up to 200 meters under ideal outdoor LoS conditions, utilizing the LE Coded PHY mode, which improves signal robustness and receiver sensitivity at the cost of reduced data rates [20]. By introducing redundancy into transmitted signals, these modes enhance detectability under low Signal-to-Noise Ratio (SNR) conditions—an approach analogous to high Spreading Factors (SF) used in LoRa. However, achieving these theoretical ranges is highly unlikely in realistic SAR operations when relying on Personal Area Networks (PANs), due to signal obstruction, multipath propagation, and electromagnetic interference, which significantly reduce BLE's effective range and reliability. Operating in the crowded 2.4 GHz band, BLE is susceptible to interference from technologies like WiFi and ZigBee, while antenna orientation and physical obstructions (e.g., vegetation, structures, or human

TABLE 1. Comparison of GNSS positioning methods, typical applications, accuracy, and required infrastructure.

Solution Type	Description	Typical Applications	Typical Accuracy (H/V, m)	Required Infrastructure
RTK Fixed	Integer ambiguities fully resolved in carrier-phase RTK [1].	Land surveying, precision robotics navigation	0.02–0.1 / <0.1	GNSS base station or NTRIP caster
RTK Float	Ambiguities not fully resolved in RTK positioning [2].	Precision agriculture, drone-based mapping	0.1–0.5 / 0.2–1	GNSS base station or NTRIP caster
PPP	Precise satellite orbit and clock corrections applied globally [3].	Offshore operations, remote autonomous systems	0.1–1.5 / 0.2–3	GNSS receiver + PPP correction service (e.g., IGS, RTX)
DGPS	GNSS corrections from ground-based reference stations [4].	Maritime navigation, field agriculture	0.3–1 / 1–3	GNSS base station (single-frequency)
Standalone GNSS	GNSS-only solution without correction data [5].	Consumer navigation, smartphones, in-vehicle GPS	3–10 / 10–50	GNSS receiver only

TABLE 2. Comparison of terrestrial positioning technologies and their characteristics for SAR scenarios.

Technology type	Technology	Range	Penetrability	Positioning method	Positioning error	Frequency band	Channel width	Multipath susceptibility
LPWAN	LoRa [12]	2 - 15 km	High (urban/rural)	TDoA	20 - 150 m (outdoor)	868/915 MHz	125–500 kHz	Moderate
	Sigfox [13]	3 - 50 km	Moderate (urban)	RSSI, TDoA	200 - 1500 m (outdoor)	868/902 MHz	100 Hz	High
	NB-IoT [14]	10 - 15 km	High (indoor)	E-CID, OTDOA	50 - 300 m (indoor)	700–2100 MHz	180 kHz	Moderate
	LTE-M [15]	10 - 15 km	High (indoor/outdoor)	Assisted GNSS, OTDOA	5 - 150 m (indoor/outdoor)	700–2100 MHz	1.4 MHz	Moderate
LAN	WiFi (802.11mc) [16]	50 - 100 m	Moderate (walls)	FTM	0.3 - 2 m (indoor/outdoor)	2.4/5 GHz	20–160 MHz	High
PAN	UWB [17], [18]	10 - 20 m	High (walls)	Time of Flight (ToF)	0.1 - 0.5 m (indoor)	3.1–10.6 GHz	≥500 MHz	Low
	BLE [19]	50 - 200 m	Low (walls)	RSSI proximity	1 - 5 m (indoor)	2.4 GHz	2 MHz	High

bodies) further attenuate signals, leading to lower RSSI values, higher Packet Error Rates (PER), and inconsistent localization performance. Due to these practical limitations and the current lack of systematic outdoor evaluations—particularly in dynamic and cluttered SAR conditions—the BLE localization performance metrics reported in Table 2 are based exclusively on controlled indoor experiments.

WiFi-based positioning using the Fine Time Measurement (FTM) protocol—standardized in IEEE 802.11mc—relies on precise Round Trip Time (RTT) exchanges to estimate distances. Operating in the 5 GHz band with bandwidths ranging from 20 MHz to 160 MHz, WiFi FTM can achieve sub-meter accuracy under favorable conditions, with typical operational ranges between 50 m and 100 m. Unlike BLE, which operates over narrower 2 MHz channels at 2.4 GHz and estimates distances using Received Signal Strength Indicator (RSSI) measurements, WiFi FTM offers superior positioning accuracy compared to BLE, not only due to its higher time resolution but also because its two-way message exchange inherently compensates for clock offset between transmitter and receiver, eliminating the need for precise time synchronization. In contrast, BLE, while energy-efficient and widely supported in consumer devices, suffers from greater susceptibility to environmental variations, often resulting in localization errors exceeding several meters.

Ultra-Wideband (UWB) surpasses both WiFi FTM and BLE in positioning precision by leveraging extremely wide bandwidths (over 500 MHz around 6 GHz to 8 GHz), allowing centimeter-level accuracy and improved resilience to multipath effects. However, despite its accuracy advantages, UWB typically offers shorter communication ranges and faces higher costs and regulatory constraints, limiting its deployment in large-scale outdoor environments.

The positioning errors presented in Table 2 correspond to typical values reported under ideal or near-ideal conditions, often based on controlled environments and post-processed data. Technologies such as UWB and WiFi FTM can achieve sub-meter accuracy indoors with favorable LoS and minimal interference. However, in outdoor or cluttered environments, their performance can degrade significantly, particularly for WiFi FTM, which is more sensitive to multipath and Non-Line-of-Sight (NLoS) conditions unless filtering or compensation methods are applied.

Although technologies such as UWB have demonstrated ranges beyond 100 m under ideal outdoor conditions (e.g., flat open fields with stable antenna alignment and minimal interference), such results are not representative of real-world SAR deployments. In ROUD environments, signal propagation is often hindered by terrain irregularities, vegetation, debris, and dynamic obstacles, further limiting performance. Additionally, most existing studies are restricted to small-scale areas (typically under 600 m^2) and report filtered or post-processed results. Consequently, actual positioning performance during SAR missions—especially in large, obstructed, or dynamic environments—may differ significantly from the values reported.

LPWAN offer long-range communication with minimal energy consumption but rely on low-precision methods like RSSI-based trilateration, making them better suited for coarse-grained localization. In contrast, WPANs and WLANs enable more accurate short- to medium-range positioning, with technologies such as UWB and WiFi FTM using RTT-based measurements rather than RSSI [21]. Although WiFi FTM is primarily intended for indoor use, its broad adoption in commercial devices and greater resilience compared to BLE and ZigBee highlight its potential for victim localization in ROUD scenarios. Given the lack of systematic outdoor studies, further evaluation of WiFi FTM in realistic SAR conditions is needed.

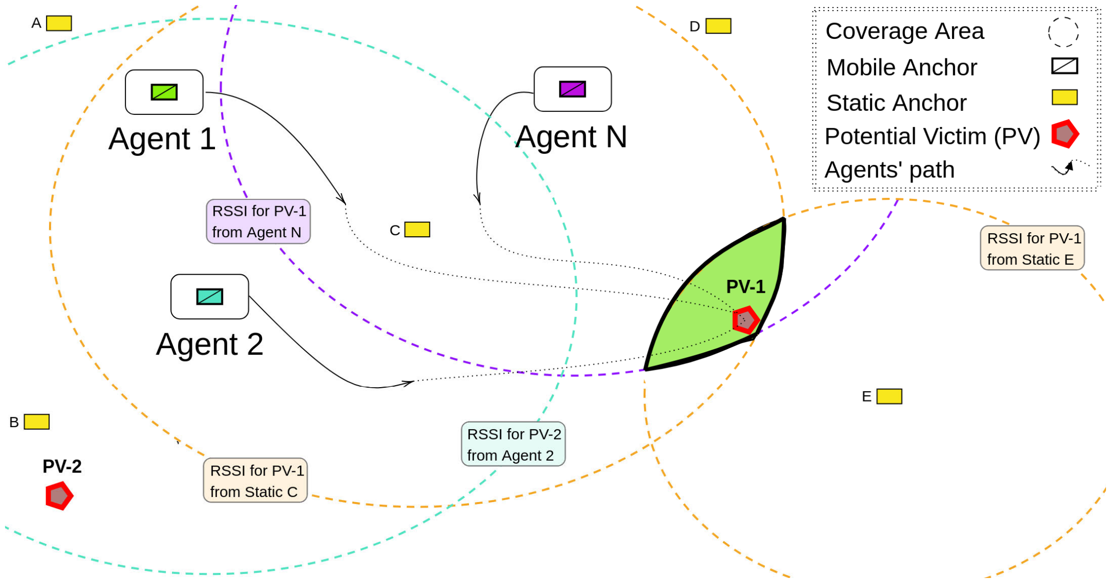

FIGURE 1. FTM-based H-WSN for detecting and geolocating victims in ROUD scenarios.

This work presents a novel real-time victim localization system designed for ROUD scenarios, integrating WiFi FTM technology with a H-WSN composed of static and mobile anchors (see Figure 1). Fully implemented within a ROS-based framework [22] and validated through a realistic SAR drill, our system effectively detected and localized buried or partially obstructed victims in real-time, without relying on extensive filtering or offline post-processing. Importantly, the approach is fully compatible with off-the-shelf smartphones supporting IEEE 802.11mc, enabling immediate deployment without specialized hardware. The proposed solution is reproducible, scalable, and particularly suited to improve early-stage disaster response operations, where infrastructure is limited and timely intervention is critical.

The proposed strategy (illustrated in Figure 1) enables the detection and positioning of PVs—represented as red pentagons—based on RTT measurements exchanged between anchors (acting as FTM responders) and nearby WiFi-enabled devices (acting as FTM initiators). Although RSSI values are also extracted from the captured FTM frames, they are not considered in the positioning algorithm. Instead, RSSI is used primarily for monitoring signal strength, providing additional information to assess link quality, identify potential signal obstructions, and prioritize detections in environments where multiple WiFi-enabled devices are present. The multilateration algorithm implemented for victim localization is based on Iteratively Weighted Least Squares (IWLS), ensuring robust distance estimation even under noisy measurement conditions. The term *potential* reflects that detected WiFi-enabled devices may belong to rescue personnel rather than actual victims.

In this scenario, multiple mobile agents (e.g., UGVs and UAVs) dynamically explore the environment either through teleoperation or preplanned autonomous paths, collecting RTT measurements from FTM bursts along with RSSI values. Static anchors (yellow squares) complement these mobile agents by providing fixed-point observations, improving overall coverage and localization robustness. Dashed contours indicate anchor coverage areas, while curved arrows represent paths followed by mobile agents.

This approach is particularly effective when traditional visual detection methods, such as thermal imaging, are hindered by occlusions, debris, or limited visibility. By integrating signal-based localization into a distributed multi-robot architecture, the system enables real-time victim positioning and supports informed decision-making during early-stage SAR operations.

This work addresses a gap in the current literature by introducing and validating a multi-robot WiFi-based localization framework in realistic SAR conditions. The main contributions are:

- Design, deployment, and evaluation of an H-WSN composed of IEEE 802.11mc-compatible devices, validated in a realistic ROUD scenario involving coordinated operation between a UAV and a UGV. Coordination involved autonomous and teleoperated robotic exploration, complemented by strategic placement of static anchors by human teams, under realistic conditions of electromagnetic interference.
- Integration of an ad-hoc Android application enabling victims' smartphones as FTM initiators to compute and transmit their distance to the H-WSN, demonstrating feasibility with off-the-shelf devices.
- System integration within a distributed ROS-based architecture, enabling real-time acquisition, synchronization, monitoring of network detections, and continuous multilateration-based position updates.

- Open-source release of the complete system implementation, including code, dataset, demonstration video, and a Docker container for reproducibility and ease of use.[1]

The rest of the paper is organized as follows: Section II reviews related works on victim detection and localization using multiple sensors. Section III describes the proposed positioning system architecture for ROUD scenarios, designed to support SAR task coordination remotely in real time. Section IV details the validation experiment performed during a SAR drill. Section V presents the results. Section VI includes the discussion and challenges encountered. And finally, Section VII draws conclusions and outlines future research lines.

II. RELATED WORKS

In ROUD scenarios, various technologies are employed to locate individuals needing SAR assistance, each with distinct advantages and limitations. This section explores the most relevant technologies, such as image recognition methods and signal-based techniques, showcasing various works in the field of SAR that employ different approaches for victim detection and localization.

A. IMAGE RECOGNITION

A commonly used approach for victim detection in SAR operations involves deploying cameras on UAVs or ground robots to identify human bodies through image analysis. Visual recognition can be particularly valuable in early response phases, as it enables rapid scanning of large areas from the air or inaccessible ground zones.

1) RGB-D CAMERAS

Human body recognition plays a pivotal role in enhancing the efficiency and autonomy of SAR efforts. RGB-D cameras, which combine Red, Green, Blue, and Depth information, allow for more robust human detection by integrating spatial structure with color data. This fusion is especially effective under challenging visual conditions, such as variable illumination or low-texture environments. For example, authors in [23] employed RGB-D data within a Visual SLAM framework for 3D reconstruction of disaster environments, enabling the mapping and identification of targets from a mobile ground platform.

Image-based victim detection methods often leverage deep learning to process RGB-D video streams and identify human shapes and postures. Convolutional Neural Networks (CNNs) have been applied to detect victims in cluttered and unknown urban SAR environments, demonstrating their ability to learn discriminative features for locating individuals under debris or partial occlusions [24]. CNNs are particularly effective due to their hierarchical feature extraction capabilities, which enhance the recognition of human forms even in degraded visual conditions.

[1]https://github.com/Robotics-Mechatronics-UMA/ROUD-PositioningSystem.git

Thermal imaging has also been integrated into victim detection pipelines to complement visible-light cameras. The combination of thermal infrared and visible-spectrum imagery has proven effective for object detection in SAR scenes, improving reliability in low-light or nighttime conditions [25]. More recently, comparative studies have analyzed the performance of different imaging modalities—such as thermal, multispectral, and RGB vision systems—for victim detection in robotic SAR platforms. These analyses highlight the advantages and limitations of each modality depending on environmental conditions and detection objectives [26].

2) INFRARED CAMERAS

Another commonly used approach in SAR operations involves the integration of thermal infrared (TIR) cameras. These sensors capture the infrared radiation naturally emitted by warm bodies, making humans appear as bright silhouettes against cooler backgrounds. This thermal contrast facilitates the identification of individuals, particularly under low-light or nighttime conditions, where visible-spectrum cameras may fail to distinguish targets with sufficient clarity. In comparison to RGB imagery, TIR images are more robust to lighting variations and can enhance detection performance in visually degraded environments [25].

Despite these advantages, TIR systems face several limitations. Their performance can be significantly affected by adverse weather conditions, such as heavy rain or dense fog, which attenuate thermal radiation and reduce image clarity [27]. In addition, environmental noise caused by non-human heat sources—such as engines, fires, or sun-heated surfaces—can result in false positives [28]. Most critically, TIR cameras are less effective when victims are buried, partially covered, or hidden beneath rubble or dense vegetation, as the emitted body heat may be blocked or diffused [29].

To address these challenges, recent efforts have explored multimodal sensor fusion, combining TIR data with visible-spectrum or multispectral imagery. These hybrid systems aim to leverage the complementary strengths of each modality, improving the robustness and reliability of victim detection in complex and unstructured environments.

B. SIGNAL-BASED METHODS

Signal-based methods utilize wireless communication signals to estimate the location of targets, offering an alternative to vision-based approaches, especially in environments where visibility is compromised.

1) LOCALIZATION BY PROXIMITY

Proximity-based localization estimates the position of a Potential Victim (PV) by detecting their device's signal through an Access Point (AP), such as a UAV or ground robot equipped with a BLE scanner. When a PV's device is detected, their location is approximated by the position of the detecting AP. The certainty of this estimation decreases with distance due to signal attenuation and environmental factors. This method is particularly useful in scenarios where high precision is not critical but rapid area coverage is essential.

An experimental evaluation demonstrated the feasibility of using BLE for close-range detection in search and rescue missions with robotic platforms, highlighting its potential for real-world applications where rapid deployment and minimal infrastructure are essential [30]. In addition, a simulation-based study explored outdoor BLE localization using an optimization-driven approach combined with a two-ray ground-reflection propagation model, achieving sub-2-meter accuracy under controlled conditions [31]. However, this method assumes static infrastructure and simplified signal behavior, and it has not been validated in real-world or ROUD environments, where clutter, multipath, and mobility introduce additional challenges.

Overall, experimental validation of signal-based localization methods—including BLE, WiFi, or LPWAN technologies—remains scarce in realistic outdoor or disaster settings. This lack of field testing hinders the ability to generalize performance claims and highlights the need for reproducible studies under operational conditions typical of SAR missions.

2) ANGLE OF ARRIVAL

Angle of Arrival (AoA) is a signal-based localization technique that estimates the direction from which a wireless signal reaches a receiver. These estimations are typically performed using antenna arrays and Multiple Input Multiple Output (MIMO) systems, which measure phase or time differences across spatially separated antennas to infer the incoming signal angle. AoA can be used independently or combined with other metrics, such as RSSI or ToF, to enable triangulation when multiple receivers are available. Modern wireless systems, including advanced WiFi standards and 5G networks, increasingly leverage beamforming techniques and high-density MIMO to improve AoA estimation accuracy and spatial resolution.

However, in disaster scenarios—where victims may be buried, obstructed, or located in complex environments—AoA-based localization faces significant challenges. Multipath propagation caused by reflections from debris, collapsed structures, or uneven terrain can severely distort the estimated angles, particularly under Non-Line-of-Sight (NLoS) conditions. Studies have shown that hybrid localization systems combining RSSI and AoA still suffer from substantial errors in cluttered post-disaster environments, primarily due to multipath effects [32].

To address these limitations, effective AoA-based localization in ROUD scenarios may require complementary strategies, such as advanced multipath mitigation techniques, signal filtering, sensor fusion with additional modalities (e.g., inertial sensors, ToF measurements), or deliberate repositioning of aerial or mobile platforms to improve LoS conditions and angular diversity.

3) MULTILATERATION

Multilateration is a positioning method that estimates the location of a device by using the measured distances to multiple reference points with known coordinates, such as APs or anchors. Each distance defines a region of possible locations: a circle in two dimensions or a sphere in three. The intersection point of at least three circles (in 2D) or four spheres (in 3D) provides the estimated position of the device. The accuracy of multilateration depends not only on the precision of the distance measurements, but also on the spatial distribution of the anchors—captured by the concept of Geometric Dilution of Precision (GDOP), which quantifies how measurement geometry amplifies distance errors in the final position estimate. In [33], the authors address the problem of optimal sensor deployment during robotic exploration in unknown environments. They propose an online strategy that enables a mobile robot to autonomously decide where to place ranging sensors in order to maximize localization accuracy and coverage. By formulating the deployment as an optimization problem solved in real time, their method allows for adaptive sensor placement without prior knowledge of the environment. This approach is particularly relevant for exploration tasks in GPS-denied or infrastructure-less scenarios, such as ROUD environments.

Power-based ranging methods, such as those relying on the RSSI, require the use of propagation models that account for frequency, environmental conditions, and terrain [34]. However, these estimations are particularly sensitive to fast fading and multipath propagation, which introduce significant errors in complex environments [35]. In contrast, Time of Flight (ToF) methods estimate distance by measuring the time a signal takes to travel between the transmitter and receiver. When short, well-defined pulses are used and a clear Line-of-Sight (LoS) is available, ToF becomes more resilient to multipath and fading effects. A major drawback, however, is the requirement for tight time synchronization between APs and the UE, which increases system complexity and cost.

An effective alternative to ToF is the use of RTT measurements, where the same device both sends and receives the signal, effectively cancelling out clock offsets between the transmitter and receiver [36]. Technologies such as UWB and WiFi FTM adopt this approach, enabling centimeter-level ranging accuracy under favorable conditions.

Authors in [37] proposed a passive localization system based on IEEE 802.11mc, where synchronized WiFi access points capture RTT measurements and apply TDoA techniques to estimate the position of target devices without requiring their active participation. Their approach is specifically designed for dense indoor WiFi networks and has not been validated in outdoor or ROUD scenarios, where infrastructure constraints, signal degradation, and environmental variability present additional challenges.

III. SYSTEM ARCHITECTURE

The proposed system architecture consists of three fundamental components, as illustrated in Figure 2: (i) a H-WSN

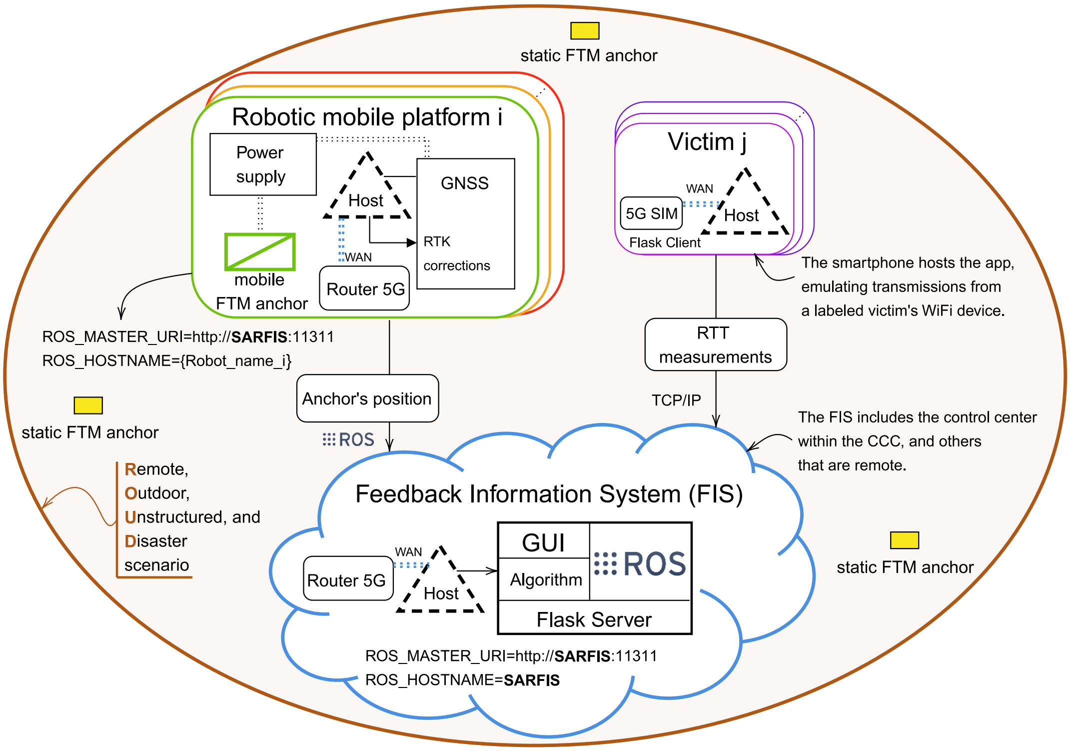

FIGURE 2. **Fundamental components of the localization system.**

composed of FTM-based anchors designed to detect RTT signals from WiFi devices that could be PVs within the operational environment; (ii) a fleet of mobile robotic platforms transporting mobile anchors, each equipped with GNSS receivers for continuous and accurate location tracking; and (iii) a Feedback Information System (FIS) [38] capable of remotely executing a multilateration algorithm using data collected from the agents' operational environment. The FIS provides graphical representations of localization data within the CCC, facilitating informed decision-making by the SAR coordinator.

In ROS 1, nodes must communicate directly with each other using TCP connections for topics, not just through the Master. Each node runs an XML-RPC server on a TCP port to handle registration and setup. To exchange messages across different networks (e.g., behind different routers), nodes must have direct IP reachability, the correct `ROS_MASTER_URI` configuration, and properly set `ROS_IP` or `ROS_HOSTNAME` to advertise accessible addresses. Without this, even if nodes can register with the Master, they won't be able to establish peer-to-peer connections for topics. Common solutions include using a VPN to create a virtual LAN, setting up port forwarding on routers, or requesting static public IP addresses from the ISP to allow direct access.

Virtual Private Networks (VPNs) provide an effective way to connect distributed ROS 1 nodes across different physical networks by creating a secure, private IP-level communication environment. This allows nodes to establish the necessary peer-to-peer connections required by ROS 1 for topic and service exchange. However, using a VPN can introduce additional latency compared to a direct LAN connection, and packet encapsulation overhead may lead to Maximum Transmission Unit (MTU) issues, potentially causing message fragmentation or connection instability if not properly addressed. Despite these challenges, VPNs remain a reliable solution to enable robust and flexible ROS 1 deployments over heterogeneous network infrastructures.

Among available VPN solutions, ZeroTier stands out for its simplicity, automatic network management, and its ability to optimize direct peer-to-peer connections whenever possible. It offers encrypted communication with minimal configuration effort, making it particularly attractive for ROS 1 systems that require rapid and stable network setups across diverse and dynamic environments.

Thus, all PCs onboard the robotic platforms and those within the FIS are interconnected through a VPN, which also enables communication with the victims' smartphones. The system uses ZeroTier, a peer-to-peer VPN that includes end-to-end encryption and is specifically suitable for robotic applications with ROS due to its low-latency architecture that does not route traffic through central servers. We opted for ZeroTier over similar solutions such as Husarnet—which is also based on ZeroTier—because of our prior experience and the simpler, more scalable network management it offers. Each agent is assigned a unique hostname and a virtual IP within the private VPN, which is centrally configured and monitored from the CCC center.

The main challenge lies in managing and processing WiFi signals from lost UEs, such as smartphones, within the deployed H-WSN. To enable efficient experimentation, we use an Android application [39] installed on the victims' smartphones. While deploying a mobile application on victims' devices may seem unrealistic in real-world scenarios, this approach allows us to: (i) facilitate communication between the operational environment and the CCC; (ii) support testing of localization algorithms in ROUD scenarios while reducing costs; and (iii) minimize system latency. This strategy enables testing different multilateration algorithms in real time without relying on local configurations, effectively demonstrating the practical functionality of our system.

Our purpose is to demonstrate the implementation of the proposed real-time localization system using the Iterative Weighted Least Squares (IWLS) algorithm, which generalizes Ordinary Least Squares (OLS) by incorporating dynamic weighting schemes to handle noisy data or outliers [40]. Additionally, we provide, along with a raw dataset, detailed guidance on applying other algorithms and/or filters.

The localization procedure begins by receiving WiFi RTT distance measurements and extracting the known positions of the anchors. These GPS positions are transformed into Earth-Centered, Earth-Fixed (ECEF) Cartesian coordinates to operate within a uniform metric space. An initial position estimate is selected near the anchor reporting the shortest measured distance to the device, and an iterative refinement process is applied. In each iteration, estimated distances are computed, the Jacobian matrix is built, and the position is updated using weighted least squares. The key aspect of IWLS is that observation weights are dynamically updated based on residual errors, following the selected strategy (OLS, Huber, Trimmed, or Tukey). Once convergence is reached, the estimated position is converted back from ECEF to GPS coordinates to provide a geodetically meaningful output.

The mobile application sends RTT information in real time to the remote FIS, indicating which anchors (identified by their MAC addresses) have detected the smartphone and their respective distances, as shown in Figure 3. We assume smartphones have an active SIM card; however, in ROUD scenarios, coverage loss or degradation is common. The proposed system only requires an Internet connection to join the VPN; functionality is automatically restored when the connection is reestablished. RTT packet readings are associated with the GNSS positions of the anchors, whose measurements achieve RTK-level accuracy depending on the available differential corrections, thus impacting overall system accuracy. The H-WSN nodes (FTM anchors) are based on Google WiFi Mesh devices [41].

Two hardware versions have been employed: model GL0102, operating at 5 V and 3 A (15 W) via USB-C, and model GJ2CQ, operating at 14 V and 1.1 A (15.4 W) via a barrel connector. Each anchor is powered by a 20 000 mA h external DC battery. The GL0102 model achieves up to 6.7 h

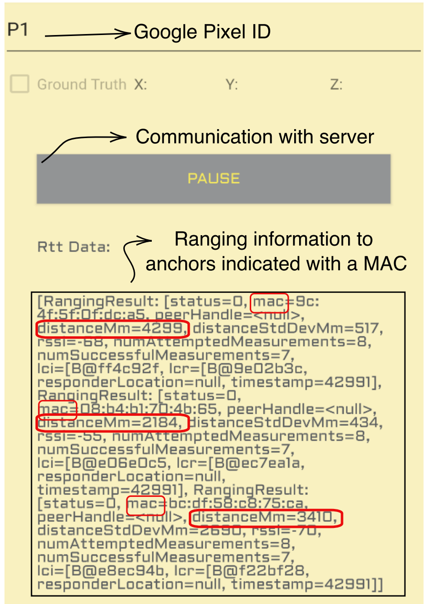

FIGURE 3. Android application interface.

of continuous operation, whereas the GJ2CQ model reaches approximately 5.5 h due to conversion losses. GL0102 units are preferred for static anchors and UAV-mounted nodes, where autonomy is critical, while GJ2CQ units are deployed mainly on UGVs, which can supply continuous power. The combined weight of a static anchor and its power source is approximately 500 g, facilitating rapid deployment without hindering SAR operations.

Smartphones emit probe requests over both 2.4 GHz and 5 GHz bands when WiFi is enabled, even if not connected, provided the device supports dual-band operation. While Google WiFi can detect beacons in both bands, FTM sessions—and thus effective localization—occur only if the smartphone operates in the 5 GHz band, due to hardware limitations favoring this less congested frequency with better temporal resolution.

Mobile anchors are integrated into autonomous robotic platforms. UGVs can operate for several days without recharging, while UAVs are deployed for flight sessions of approximately 25 min, with their onboard anchors independently powered. This setup ensures that the system meets the energy and operational demands of time-sensitive SAR scenarios while maintaining deployment flexibility.

The Google WiFi device uses only the non-DFS (Dynamic Frequency Selection) 5 GHz channels (36 , 40 , 44 , 48) for WiFi FTM, as it avoids DFS channels (52 to 144) to ensure quick startup and stable operation without radar scanning delays. This restriction limits the available spectrum for wide channels (e.g., 80 MHz), which are essential for higher temporal resolution in FTM-based ranging. While using these lower channels reduces complexity and improves compatibility, it can also lead to increased multipath interference in dense indoor environments, as the limited frequency diversity may cause reflected signals to be indistinguishable from direct paths. This can degrade positioning accuracy. However, in low-interference or open environments, the use of clean 80 MHz non-DFS channels can still provide reliable sub-meter accuracy.

The victim's smartphone forwards RTT measurements to a Flask server [42] connected to the multilateration algorithm, which is integrated within the ROS 1 architecture. The mobile application allows the selection of the socket (IP and port) for RTT data transmission, enabling a direct connection to the server in the FIS, where the ROS master is hosted.

The RTT information is then integrated into ROS and processed remotely together with the GNSS position of the anchors, which is published by the PCs on board the robots in ROS topics. Once the FIS collects all the necessary information, two dedicated computers evaluate the effectiveness of the positioning system in real time. Two different PCs are used to distribute the computational load, as each has to process other information from the application scenario. However, the whole system can run on one PC and even in a virtual container (as presented in the open repository) to launch via a portable image. Using more than one PC, they can be in a different physical location if they operate on the same VPN, which is useful for providing visual information to SAR team coordinators at different locations.

The FIS is composed of three running processes:

- The Flask server, which receives the RTT and RSSI information through the smartphones carried by the victims, including their labels to register them.
- The multilateration algorithm, in which different ROS nodes subscribe and publish information of interest. For instance, the algorithm must be able to get the RTK GNSS measurements via ROS subscription, while it has to publish the estimated coordinates for the PVs, including those WiFi devices in the operational environment that are not true victims.
- The Graphical User Interface (GUI), integrated in the SARFIS tool, displays, in real time, the positions of mobile and static anchors, as well as other visual information of interest.

On the one hand, one PC hosts the Flask server, the ROS master node, and runs the multilateration algorithm, producing the results it publishes in different ROS topics. This information is available on any PC with the proper configuration in the ROS network.

As it is operating with ROS 1 , all the hosts on the network must know the master's virtual IP or, failing that, its hostname (registered in the */etc/hosts* file of the equipment). Figure 2 shows how to set environment variables, but the shared public repository provides more details on implementation. Finally, the Flask server has to run in a separate thread to synchronize the reception of WiFi data (coming from the Flask clients hosted on the victims' smartphones) and the ROS nodes that must distribute all the information in the system. The Flask server does not run on ROS, but opens a port (5001) to give access to the clients. In parallel, ROS nodes use the ephemeral ports of each PC (running on Ubuntu 20.04).

On the other hand, another PC runs the SARFIS tool. Whenever an anchor detection is generated, a circumference with a radius equal to the distance estimated by RTT will be displayed in real time. In this way, the CCC is alerted that a PV may have been detected in the vicinity of the anchor, whose position is the center of the circumference. In addition, the detected RSSI value is located at the edge of the circumference, which relates to the proximity to the transmitting device concerning the pose of the mobile robot carrying the anchor.

IV. EXPERIMENTAL SETUP

A realistic experiment was conducted in JEMERG XVII (a multidisciplinary exercise with actual first responders organized by the University of Malaga) [43]. This event was characterized by a highly complex communication environment with approximately 200 participants. Each entity involved, including the Army (both land and air forces), Provincial Firefighters Consortium, Malaga's local fire brigade, National Police, and Emergency Coordination Center, operated independent communication systems, creating a realistic, interference-rich scenario. The trial was carried out in a realistic outdoor disaster scenario, under the fixed scheduling and logistical constraints of the exercise, which could not be modified to artificially introduce additional environmental variables.

On the day of the test, weather conditions were typical of summer in southern Spain (Málaga), with temperatures exceeding 30 °C, sunny skies, and light cloud coverage. Although no heavy smoke or dust was present, the high ambient temperature imposed physiological constraints on human activity and highlighted the system's benefit in reducing human exposure during the hottest hours, which is a key advantage in search-and-rescue operations. While GNSS signals were unaffected due to the mild atmospheric conditions, the test environment still provided realistic multipath challenges due to terrain, vegetation, and partial burial of devices.

The explored terrain has a perimeter of 180 m and an area of 2000 m^2. Two fake victims were located on the ground, each with a smartphone in their pockets. Both were hidden, although one of them was above ground (X3) and the other (P1) was covered with scrap metal. The actual distance between them is 3.5 m. Table 3 presents the open-source dataset, including input and output information to the FIS, useful for offline reproduction experiments.

Human SAR agents initially deployed four static FTM-based anchors, identified as 1F, AB, A5, and AA, in tactical positions considered safe zones with Line-of-Sight (LoS) to the catastrophic scenario. These anchors were equipped with portable external power supplies and strategically placed to cover a broad area for subsequent exploration by robotic agents.

TABLE 3. Number of ROS messages during the experiment.

ROS topic	Nº of messages
FTM anchors' positions (*sensor_msgs/NavSatFix*)	
/Anchor{*label*}/position	5
/FV8/mavros/global_position/raw/fix	885
/RoverJ8/gps0/fix	3539
Victims' detections from the H-WSN (*std_msgs/String*)	
/Anchor1F/wifi_rtt_estimation	687
/AnchorAA/wifi_rtt_estimation	6
/FV8/wifi_rtt_estimation	1427
/RoverJ8/wifi_rtt_estimation	1414
Algorithm outputs (*std_msgs/String*)	
/geo_multilateration	529
Offline reproducible data (*std_msgs/String*)	
/infoServer	1692
/inputServer	1682

To accurately register the positions of the static anchors, human agents used smartphones connected to RTK GNSS modules. When placing an anchor, the operator positioned the smartphone statically on it and waited to send five fixed positions via ROS [44], ensuring that the decimal values remained constant to guarantee a fixed position with an error margin of 2 cm to 10 cm. The geolocation of each anchor was transmitted on the ROS topic `/Anchor{label}/position` and stored in the FIS, where positions were displayed on the GUI with corresponding labels.

In addition to the static anchors, two mobile robots—a UGV named Rover J8 and a UAV named FV8—explored the area within the ROUD scenario, introducing two additional FTM-based anchors in the area of interest. Their detections were published on the topics `/{robot_name}/wifi_rtt_estimations`.

The UGV and UAV were equipped with the necessary sensors and communication systems to detect WiFi RTT signals from PVs. The UAV was teleoperated and took off from a point of interest, while the UGV followed a human agent using a LiDAR-based *follow me* mode and maintained its position upon reaching a designated point. Both mobile robots explored the area for 7 min and 22 s. The UAV's pilot conducted the scan by performing circular traverses at different altitudes to capture possible victims with the UAV camera.

PVs were emulated using smartphones: P1, a Google Pixel 3, was buried and hidden, while X3, a Xiaomi Mi10T Lite, was placed semi-buried on the surface. Their true positions were recorded before the exercise as ground truth.

V. RESULTS

During the experiment, various results were obtained with respect to the detection and localization of PVs. Two static

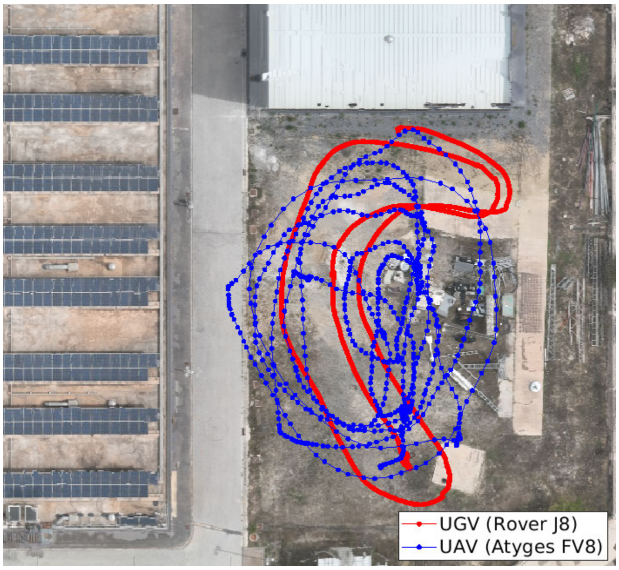

FIGURE 4. Trajectories followed by the mobile anchors on UGV (red) and UAV (blue).

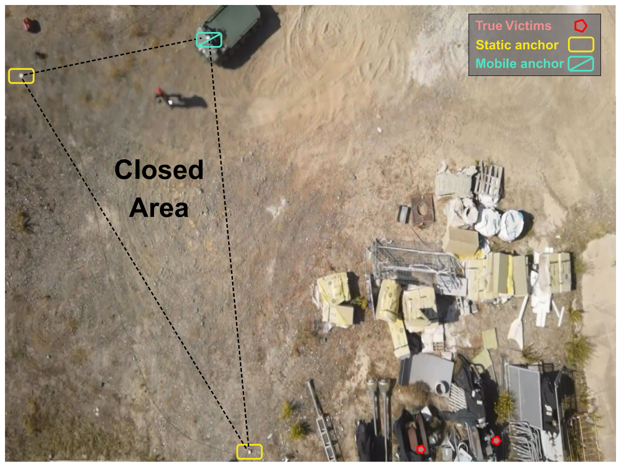

FIGURE 5. Field of view of the UAV when hovering 21 m above the UGV, while searching victims.

anchors (AB and A5) did not detect any RTT signals from the victims due to suboptimal positioning. However, this was not considered an error but a probabilistic outcome, as the human agents could not know the victims' locations beforehand.

The trajectories of the UGV (red) and UAV (blue) are illustrated in Figure 4. Upon detecting the two victims (P1 and X3), already being detected by the static anchors, the CCC instructed the UGV to scan the area, resulting in two mobile anchors operating during the final five minutes of the exercise. Figure 5 shows the UAV's camera view at 21 m altitude, displaying the UGV following a human agent at approximately 1 m/s. Since each H-WSN anchor can cover medium distances (greater than 100 m with LoS), mobile agents must integrate situational awareness so that areas enclosed by three or more anchors are known to be scanned by the system.

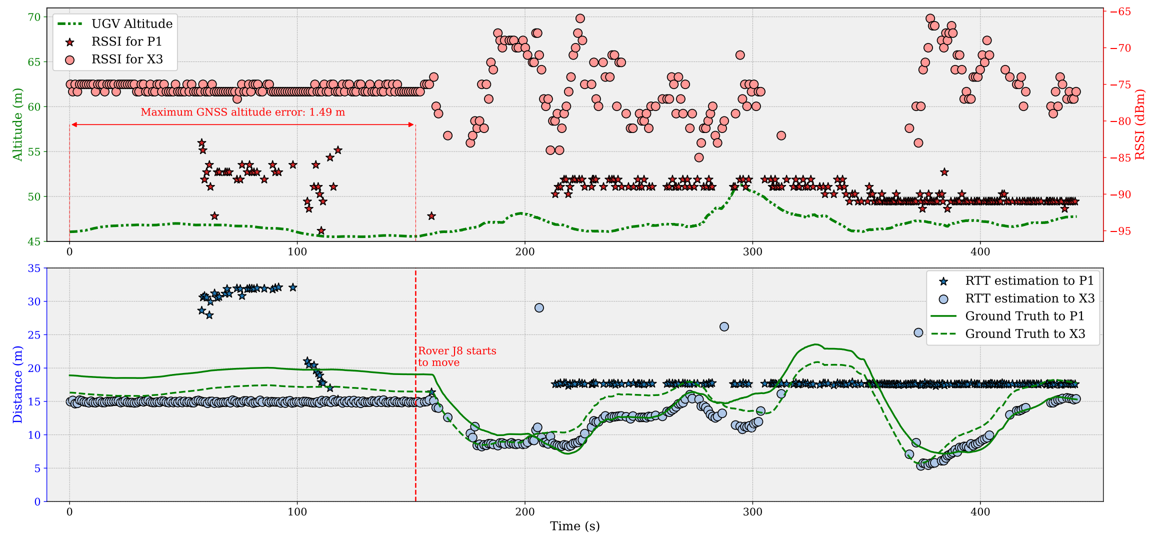

FIGURE 6. Victim detections and RTT distance estimated from the UGV's anchor.

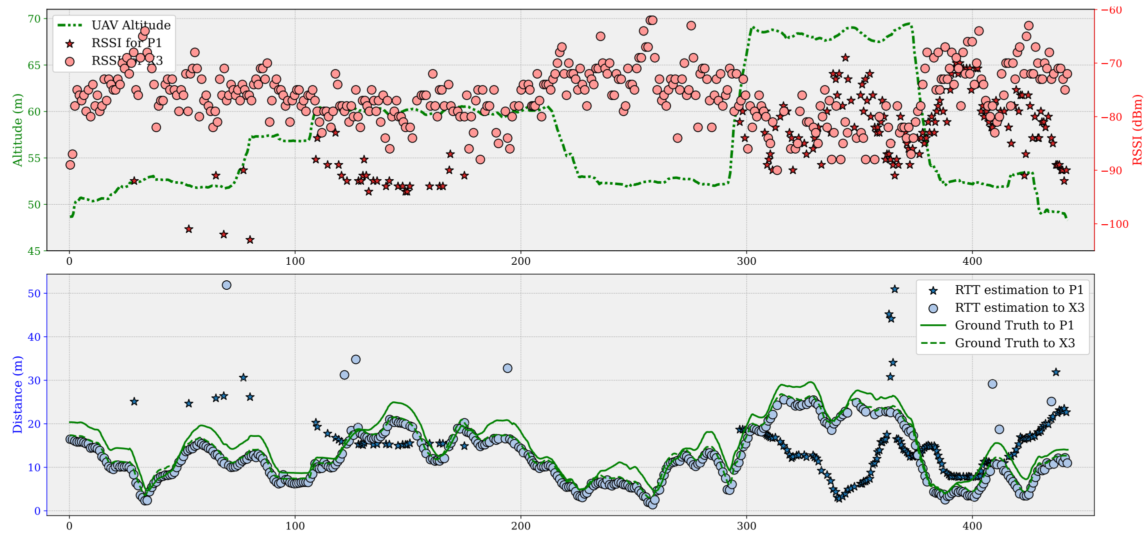

FIGURE 7. Victim detections and RTT distance estimated from the UAV's anchor.

The `geo_multilateration` topic contained all positions estimated by the multilateration algorithm, including any WiFi devices within H-WSN coverage. The smartphones emulating the victims transmitted RTT measurements with identification tags. Victim P1 was geolocated only four times due to being buried, whereas X3 was localized 289 times. The algorithm computed 236 geolocations for potential victims, intentionally including additional detections to verify the system's ability to identify wearable devices with WiFi in the environment.

RTT messages for P1 included 227 detections from the UGV and 179 from the UAV. For X3, there were 316 messages from the UGV and 406 from the UAV, indicating that the semi-buried victim (P1) was less frequently detected than the semi-exposed victim (X3) despite their proximity.

Figures 6 and 7 show the RSSI values of the detections made by the anchors onboard the robotic agents, along with their altitudes during the scans. In addition, these figures include a comparison between the RTT-estimated distances to the victims and the real distances, taking as ground truth the GNSS receiver positions of each robot, corrected differentially. Each point represents a single detection by each mobile anchor, significantly outperforming the detection capability of the static H-WSN. For example, node AA detected a WiFi device only six times, nodes AB and A5 detected none, and node 1F contributed 687 detections to the algorithm.

Furthermore, the UGV remained stationary at the designated point, during which the RSSI of its detections stayed stable around −75 dBm. Two minutes and 32 seconds (152 s) after the UAV's takeoff, the UGV began moving, allowing an analysis of the GNSS receiver error. The UGV's reported altitude fluctuated by up to 1.49 m despite the application of differential corrections (Figure 6). This behavior indicates

TABLE 4. Results for P1 (semi-buried) and X3 (hidden).

Error	80% Percentile [m]	95% Percentile [m]	Nº of detections
RTT (Round Trip Time)			
X3 from UGV	6.96	8.80	316
X3 from UAV	9.28	14.05	406
X3 from 1F	2.03	2.25	426
P1 from UGV	1.10	12.95	227
P1 from UAV	7.13	10.91	179
P1 from AA	1.72	1.81	6
Multilateration			
X3	17.98	22.87	289
P1	16.75	17.14	4

that the GNSS measurements had differential GPS (DGPS) accuracy but were still affected by multipath and shadowing effects from surrounding structures, typical of ROUD environments. These inherent GNSS errors suggest a degradation of multilateration accuracy due to unstable communications. Nevertheless, the RTT-based distance estimations remained quite close to the ground truth, particularly for the transmitter located on the surface (X3).

Table 4 presents the results of the multilateration process. The localization system achieved a median estimated distance error of 12.97 m for X3 and 13.98 m for P1 with respect to their absolute positions. Additionally, the table shows the 80% and 95% sorted horizontal errors compared with the ground truth. It can be observed that three anchors viewed the X3 victim more than 300 times, resulting in 289 multilateration geolocations. In contrast, the most hidden victim (P1) could only be geolocated four times, despite the mobile agents detecting its signal approximately 200 times each. However, the only static anchor that could have contributed to the trilateration (AA) detected this victim only six times and never detected X3.

Figure 8 illustrates the empirical cumulative distribution function (ECDF) of distance and horizontal positioning errors for both victims. Since victim P1 was only geolocated four times, it is insufficient to validate accuracy for buried victims. The algorithm converged 289 times for the semi-hidden victim, confirming the system's utility for SAR teams as it allows quick localization of wireless devices at disaster scenes, even if semi-hidden or partially buried.

Percentiles have been superimposed for all graphs. The black squares represent the 80% percentile, while the black circles indicate the 95% percentile. These values are also shown in Table 4.

Through the ROS 1 architecture, subscriptions have been enabled using checkboxes that allow the information of interest to be visualized in real time (Figure 9). Static anchors, as well as the circles associated with their detections, are shown in yellow. These circles have a radius equal to the estimated RTT distance of each anchor.

In the case of the UGV, its onboard anchor and detections are shown in red, while the UAV's detections and GNSS RTK positions appear in blue. Anchor altitudes are displayed in black (referenced to WGS84), and RSSI values are indicated at the circles' edges. When the algorithm converges, the estimated position is marked with a blue circle and the corresponding device label.

Other WiFi devices may also be detected, such as X2 (intentionally placed and moving in the scenario), identified by the UAV and labeled accordingly. Additional detections, including unknown devices, appear near the UAV's position. To reduce false positives, all smartphones carried by rescuers and victims were pre-registered using a mobile application that acts as a WiFi-FTM initiator, transmitting a unique identifier. This allows the system to link each detection to a known device (e.g., X3, P1) or flag it as unknown, improving victim identification and filtering unrelated sources.

VI. DISCUSSION

The proposed system was implemented in a simulated yet realistic environment reflecting ROUD characteristics, exposing several technical and operational challenges relevant to real-world deployment.

A. TOWARDS AN OPTIMAL DEPLOYMENT

A primary challenge lies in the system's complexity, which could suggest a slower deployment process due to the involvement of multiple static and mobile anchors, as well as several cooperative mobile robots.

Nevertheless, field experiments demonstrated that agile deployment is achievable under realistic constraints. During testing with professional first responders in JEMERG, the system was allocated a 45-minute setup window, which coincided with ongoing operations. Within this timeframe, exploration and victim detection were completed in just 7 minutes. The deployed H-WSN successfully detected the surface victim 1,148 times and the buried victim 412 times, transmitting data in real time.

It is important to emphasize that the system does not require all elements to converge simultaneously at the disaster scene. The use of an H-WSN inherently enables progressive system expansion, allowing new anchors to be incrementally deployed and immediately incorporated into the multilateration process. Moreover, decisions regarding the addition of new nodes can be made remotely by the emergency coordinator, thanks to the real-time reporting capabilities of the proposed system. Specifically, the system continuously provides information on the number of detections for each tag, whether the device has been identified, the received signal strength, and the number of successful localizations performed by each anchor. This operational flexibility allows for continuous improvements in localization accuracy and robustness as additional measurements become available.

Although static anchor placement was the most time-consuming phase, the proposed strategy leverages human mobility: agents en route to the area of interest can opportunistically deploy lightweight, battery-powered anchors, thereby contributing to environmental sensing without

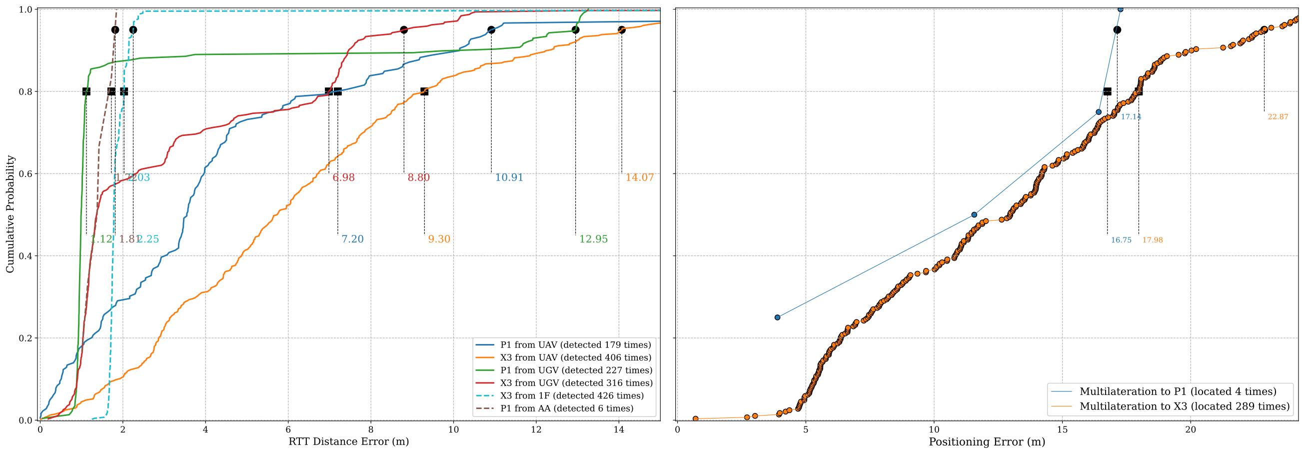

FIGURE 8. ECDF of distance and horizontal positioning error for both victims.

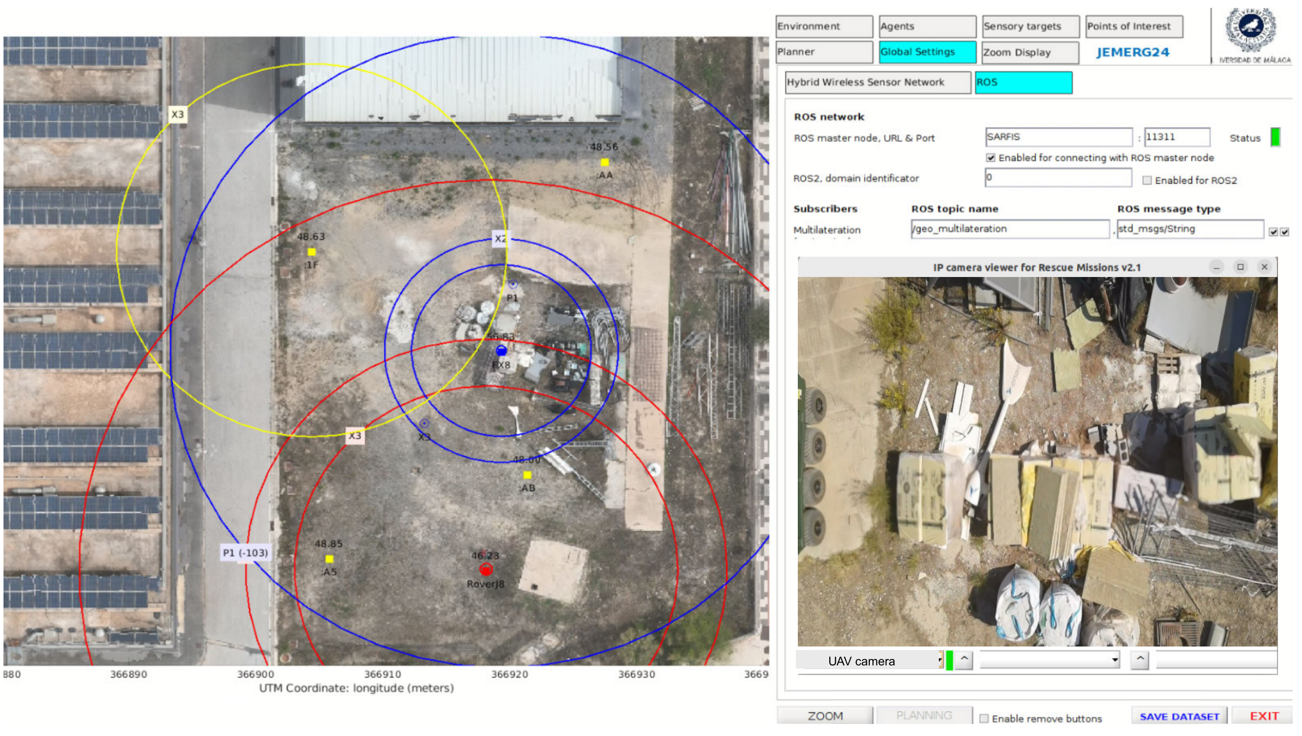

FIGURE 9. The SARFIS tool showing RTT and multilateration estimations in the CCC.

disrupting their primary missions. Moreover, the system eliminates the need for multiple PCs or base stations—detection events can be transmitted directly from a victim's smartphone. While this assumption is not yet fully realistic, it serves as a proof of concept for a lightweight and flexible localization strategy.

This human-assisted deployment is particularly useful for enriching the multilateration algorithm. Notably, even if mobile robots reach the target area first—potentially with three or more anchors—the subsequent arrival of SAR personnel allows for easy expansion of the H-WSN. Agents simply need to power on the devices and place them at a fixed location, whose coordinates can be recorded using the agent's GPS. In this context, several approaches were explored; in the conducted experiments, the agent carried a smartphone running an application [44] that transmitted their location to the system via ROS, including its identity label via ROS. This was the case for X2, which was also detected, as the application included an FTM initiator, similar to the victims' devices. However, prior registration of X2 allowed it to be discarded as a victim to be searched for.

Notably, the WiFi nodes in the network—both mobile and static anchors—are not required to form a mesh or communicate with each other. Instead, they operate independently and interact only with the mobile devices carried by potential victims or other FTM-based tags. This architectural simplification reduces network overhead and setup complexity, while still enabling effective data collection for multilateration-based positioning.

Although the current architecture relies on centralized coordination and static infrastructure, efforts are already underway to reduce system complexity by introducing greater edge-based computation and autonomy. This shift is expected to minimize deployment overhead and enhance scalability without compromising robustness. The positive feedback received from SAR personnel during field tests further supports the relevance and applicability of this direction, reinforcing the system's potential for real-world adoption in complex emergency scenarios.

Another important issue is the need to develop simulation environments that faithfully replicate the conditions observed in real ROUD scenarios. Ensuring high-fidelity representations of environmental factors such as signal propagation, obstacles, debris, and structural elements is essential for accurately predicting system behavior and validating localization strategies prior to field deployment.

Although the system was not tested under extreme weather conditions such as heavy smoke, dust, or rain, it was validated during a large-scale emergency response exercise (JEMERG) involving over 200 participants and multiple independent communication systems, creating a realistic interference-rich environment. While weather conditions were typical of summer in southern Spain—hot and dry—the high temperatures emphasized the value of minimizing human exposure during peak heat hours. The test environment also posed real-world challenges, including multipath effects caused by terrain irregularities, dense vegetation, debris, and nearby buildings.

In this regard, JEMERG has served as a valuable testbed, where we continuously introduce improvements and increasingly realistic conditions to our experimental setups, allowing for progressive refinement and validation of the proposed system.

While the current evaluation demonstrated the system's feasibility under realistic conditions, further testing under more extreme environmental scenarios is necessary to better understand its robustness and limitations. Assessing performance in harsher settings—such as environments with high signal attenuation, greater structural complexity, or extreme weather—would provide valuable insights into the system's reliability and adaptability in diverse SAR operations.

During the experimental deployments, additional observations were made regarding the operational dynamics between UGVs and UAVs in the context of ROUD environments. While UGVs offer stability and payload capacity—making them suitable platforms for tasks such as casualty evacuation—their mobility is often limited when navigating debris-filled or uneven terrain. Moreover, being in constant contact with the ground makes UGVs particularly susceptible to multipath effects, which can degrade the quality of wireless measurements.

Nonetheless, UGVs offer important operational advantages. Even when they are unable to approach debris piles directly—due to potential risks to hidden victims, GNSS signal degradation, or communication coverage gaps—they can still navigate around the perimeter, maintaining both GNSS coverage and network connectivity while continuously testing new LoS paths as updated observations are reported to the FIS. This capability allows them to act as persistent ground-level probes. Additionally, their extended energy autonomy enables them to operate continuously throughout the golden hours of a SAR mission without the need for recharging or refueling, ensuring persistent support during the most critical phase of response.

UAVs, on the other hand, provide aerial reach for detecting and localizing victims in inaccessible areas, yet are constrained by short battery life. This trade-off highlights the need for robust coordination strategies and energy-efficient flight planning to ensure continuous mission coverage.

A specific behavior observed during field trials suggests that stationary UGVs may serve not only as mobile platforms but also as effective signal observation posts. When a UGV remained static near a point of interest, it continued to detect signals from PVs with different characteristics depending on the victim's condition or position. For instance, as shown in Figure 6, the surface victim (X3) produced a relatively stable RSSI, while the semi-buried victim (P1) exhibited more variable signal values. Interestingly, this pattern inverted when the UGV was in motion, likely due to changes in relative geometry or temporary occlusions.

These findings suggest that analyzing RSSI stability and fluctuation patterns—while the UGV is both stationary and in motion—may offer insights into the level of obstruction between the node and the PV. This could enable a lightweight heuristic to distinguish whether a detected signal source corresponds to a victim on the surface, hidden under light debris, or partially buried, which would greatly aid prioritization and decision-making during SAR operations.

In light of these results, it becomes evident that the proposed localization system not only estimates the geographic coordinates of a detected victim, but also provides contextual information that can support real-time decision-making in complex environments. However, to improve the reliability of these detections, it is necessary to incorporate a real-time filtering mechanism—such as a moving median or an Extended Kalman Filter (EKF)—to refine the output of the multilateration algorithm and deliver more precise and stable positioning data.

Although delivering a commercially mature product is not the aim of this article, we provide a first functional prototype, along with access to the experimental dataset and visual documentation of the field trials. This data is openly available to the research community and can be analyzed or filtered offline for further development. Nevertheless, the system's architecture requires an online filtering approach, since the multilateration algorithm operates in the cloud by merging two asynchronous data sources: a Flask-based server that collects RTT estimations, and a ROS topic that streams GNSS positions from the mobile agents. Ensuring temporal consistency between these streams in real time remains a key challenge for future work.

B. COMMUNICATION ARCHITECTURE

ROS 1 operates on a peer-to-peer architecture, where nodes establish communication using dynamically assigned ephemeral Transmission Control Protocol (TCP) ports. These connections are negotiated through eXtensible Markup Language (XML) messages using the XML Remote Procedure Call (XML-RPC) protocol, coordinated by the ROS Master. On Ubuntu systems, these ports typically fall within the range 32768 to 60999, which are often restricted by firewalls or Virtual Private Network (VPN) configurations in secure or controlled environments. As a result, direct connections between nodes may fail—especially when Network Address Translation (NAT) traversal or port filtering prevents successful negotiation—leading to communication issues within the system.

To overcome these limitations, our system leverages ZeroTier, a software-defined virtual LAN that facilitates encrypted, peer-to-peer communication across NAT boundaries without requiring static public IPs. While some VPNs may relay traffic or impose restrictions, ZeroTier supports direct communication between peers, provided local firewall rules permit it. In our deployment, the Command and Control Center (CCC) maintains full control over the firewall configurations of the VPN interfaces, ensuring that no local policies block the necessary ephemeral ports.

By assigning static virtual IPs and enabling direct socket-level access between all agents, ZeroTier ensures that all ROS components—including publishers, subscribers, and service clients—can communicate reliably across the distributed system. This approach effectively mitigates common connectivity issues in ROS 1 and provides a scalable networking solution for multi-agent coordination over wide-area or cellular networks.

Although the system demonstrates reliable performance under normal VPN-based communication, resilience to network failures remains a critical challenge for real-world deployments. The current implementation depends on continuous VPN connectivity for real-time operation and may experience degraded functionality or data loss during prolonged communication outages.

To address this, future versions of the system will incorporate redundant communication channels, such as LoRa and Non-Terrestrial Networks (NTN), which offer low-bandwidth but resilient alternatives for transmitting essential data or alerts when primary links fail. Additionally, local buffering mechanisms will be explored to temporarily store sensor and localization data, allowing delayed synchronization upon reconnection. Mobile agents acting as data MULEs (Mobile Ubiquitous LAN Extensions) are also being considered to collect and relay information from disconnected nodes, extending the operational capabilities of the system in highly degraded or infrastructure-less environments. These strategies aim to preserve minimal situational awareness and data integrity even in the presence of severe communication disruptions.

An additional aspect under consideration is the gradual migration of the system's architecture toward the Edge, aiming to reduce central dependencies and improve real-time responsiveness in dynamic environments.

Currently, RTT estimation relies on measurements taken by the UE (the victim's smartphone) rather than the AP (anchor), due to privacy concerns. A potential improvement would be to determine distance through the AP while anonymizing the UE's identity, thus preventing exposure of personal information. This approach requires further research into secure, privacy-preserving methodologies for distance estimation in public safety applications.

Processing localization data onboard UGVs and UAVs would significantly improve computation times and enable real-time localization. Thus, developing hybrid platforms that prioritize Edge computing—specifically, processing data on the mobile robots themselves—is crucial. Moving multilateration algorithms, RTT signal processing, and GNSS-based positioning onboard, while reserving the Cloud only for monitoring and high-level coordination, could offer a more robust and autonomous solution. However, this would require the development of ad-hoc FTM anchors capable of acting as Internet of Robotic Things (IoRT) nodes. Such advancements could help reduce processing bottlenecks and communication latencies, providing faster and more accurate updates of estimated victim locations. This evolution could enable a fully decentralized localization strategy, where each mobile robot independently detects and localizes victims based on its own movement and sensing, without relying on external infrastructure.

Currently, the system operates using ROS 1, which presents limitations in scalability and communication robustness for distributed real-time applications. ROS 1 was initially chosen because certain required ROS packages and drivers were not yet fully operational in ROS 2, and protecting information transmission was critical. Consequently, bridging between ROS 1 and ROS 2 was avoided, centralizing all communications through the FIS to meet the realistic emergency conditions set in JEMERG XVII. Transitioning to ROS 2 would enhance system capabilities by leveraging improved middleware and real-time features, providing a more robust, scalable framework better suited for future SAR operations in ROUD scenarios. Migrating to ROS 2 would also improve compatibility with advanced robotic technologies, increasingly becoming the standard in the field.

To further improve system robustness, the integration of Ultra-Wideband (UWB) technology is being considered as a complementary solution. UWB offers much finer time resolution thanks to its large bandwidth (typically greater than 500 MHz), allowing it to resolve multipath components and isolate the true line-of-sight path even in complex environments. This makes UWB highly suitable for short-range, high-accuracy localization (e.g., <30 cm). However, UWB has a limited effective range—typically around 30–50 meters indoors—due to regulatory power constraints (e.g., –41.3 dBm/MHz) and heavy dependence on the signal-to-noise ratio (SNR) at the receiver. In outdoor environments, where SNR is often higher, UWB can achieve ranges of up to 100–150 meters under line-of-sight conditions. Conversely, in indoor or cluttered environments, walls, obstacles, and interference can degrade SNR and reduce the reliable range to 10–30 meters, affecting positioning accuracy. Thus, while UWB is a powerful tool for precision tracking, its integration must consider environmental factors and range trade-offs, making it particularly effective for enhancing positioning performance in the close-range segment of hybrid localization systems.

In contrast, WiFi FTM's ability to resolve multipath is fundamentally limited by the channel bandwidth available. With Google WiFi restricted to non-DFS channels, the device typically operates with a maximum bandwidth of 80 MHz, resulting in a time resolution of approximately 12.5 nanoseconds—equivalent to a spatial resolution of about 3.75 meters. Consequently, if a reflected signal arrives within 3.75 meters of the direct path (in terms of propagation delay), the device cannot distinguish between them. As a result, FTM-based distance estimations may exhibit positive bias when the receiver locks onto a reflected path, particularly in cluttered indoor environments. Google WiFi devices mitigate this issue through repeated measurements, statistical filtering, and by leveraging cleaner spectrum in the lower 5 GHz range. However, their inability to operate on DFS channels limits their flexibility in crowded radio environments, potentially exacerbating multipath-induced errors. To achieve higher positioning reliability, systems must either incorporate sensor fusion (e.g., IMUs, environmental maps) or complement FTM with technologies such as UWB, which inherently resolve multipath effects thanks to their sub-nanosecond time resolution.

Another important research direction is the differentiation between signals emitted by non-victim devices and those originating from actual victims, since the current system detects all WiFi-enabled devices indiscriminately. Developing algorithms capable of filtering irrelevant signals would significantly enhance detection accuracy and operational reliability.

In our implementation, devices such as X2 were explicitly pre-registered as part of the SAR team's equipment within the system. Each registered device was assigned a unique identifier, enabling the system to recognize and categorize their signals accordingly, thereby preventing them from being misinterpreted as potential victims. This pre-registration strategy effectively mitigated false positives and operator misjudgments during the field exercise.

We acknowledge that, although this manual registration process proved effective under controlled conditions, scalability and operational robustness could be further improved through the development of automated filtering or device-tagging mechanisms. Enhancements such as standardized unique victim identifiers or cryptographic device tags have been identified as promising lines for future research and are discussed in the corresponding section of the manuscript.

VII. CONCLUSION

This work has presented a comprehensive approach to real-time detection and localization of victims in ROUD scenarios using an FTM-based H-WSN, whose mobile nodes are mounted on robotic platforms. The proposed localization system enables the detection of WiFi-enabled devices carried by Potential Victims (PVs), distinguishing between partially buried and exposed devices, thus providing invaluable assistance to Search and Rescue (SAR) operations in environments where traditional localization methods are impractical.

Experimental results demonstrated that the system can geolocate PVs with an error below 20 meters, without applying any filtering, within a short search time. Four static anchors were strategically deployed on the ground near the simulated disaster site, aiming to achieve diverse line-of-sight (LoS) coverage from four distinct points surrounding the area. Additionally, two mobile robots—a UGV and a UAV—each carried an anchor to contribute to the detection of FTM initiators (potential victims). This deployment strategy enables the rapid and flexible distribution of H-WSN nodes across the area of interest. The system allows for swift narrowing of search areas, which is crucial given that victims may be obscured not only by debris but also by environmental factors such as fog, smoke, dust, rain, or dense vegetation. Consequently, deploying an H-WSN through both human and robotic agents proves highly effective in reducing response times and enhancing the overall efficiency of SAR missions. Moreover, positive feedback from the SAR coordinator—who served as the chief firefighter and was responsible for organizing resources across various emergency scenarios, including the one presented in this paper—further validated the system's practicality and effectiveness in supporting real-world operations.

Leveraging the ROS framework, the FTM-based system integrates independent communication systems within heterogeneous robot architectures. In the proposed configuration, two uncrewed vehicles explore an area augmented with pre-arranged static anchors, enabling multilateration whenever three or more nodes receive signals from PVs. The integration of UGVs and UAVs exploits their complementary strengths: UGVs offer stability and payload capacity, while UAVs provide access to hard-to-reach areas. Additionally, the system delivers real-time visualization of detections and multilateration-based position estimates, processed remotely in the Cloud, enabling the SAR coordinator to make immediate operational decisions.

The system presented is an initial prototype, the result of research and development efforts, aimed at testing the feasibility of operating in emergency scenarios using an H-WSN based on FTM technology. The primary objective was to provide real-time information to the emergency coordinator to support SAR operations. The prototype successfully demonstrated the efficiency and potential of FTM-based localization in disaster environments. Moving forward, it will be important to focus on the development of a dedicated, ad-hoc system designed to overcome the practical limitations identified during testing and to enhance performance under real-world operational conditions.

The open repository associated with this work provides a realistic dataset along with the code for data generation and testing. It includes recordings of two ROS topics that capture the system's raw inputs and outputs, allowing the experimental scenario to be replayed within the 2000-square-meter environment without latency-related issues. Researchers can experiment with varying numbers of anchors to assess their impact on localization performance and search efficiency. Furthermore, the repository offers an instance of the SARFIS tool, enabling flexible evaluation of the ILS-based multilateration algorithm. Users can select from different estimation modes—such as Huber for moderate outliers or Trimmed for severe outlier rejection [45]—facilitating comprehensive testing through ROS bag replays.

The system has been tested experimentally with six anchors (four static and two mobile) without observing latency issues or degradation in detection rates. Given the low bandwidth requirements of the transmitted data (primarily distance estimations and metadata), scaling to tens of anchors is feasible, provided that communication channels remain stable. This aspect is remotely managed by the mission coordinator, as both data generation and network traffic are monitored and controlled from the CCC center.

Moreover, the modularity of the ROS-based infrastructure allows multiple robots to be integrated flexibly, each contributing to data collection and exploration without central coordination bottlenecks. Nevertheless, in very large deployments, factors such as wireless network congestion and real-time processing limits should be considered. As part of future work, stress-testing scenarios with higher numbers of nodes are planned to systematically assess scalability under more demanding conditions.

Future research will address the identified challenges to further enhance system efficiency and operational practicality. Key directions include simplifying the system architecture to reduce setup time, extending UAV autonomy for continuous mission coverage, and developing algorithms to distinguish signals from non-victim devices to improve detection reliability. Migrating the current system to ROS 2 over ZeroTier will bolster scalability, enhance network resilience, and improve communication flexibility. Unlike ROS 1, which relies on a centralized Master and static node registration, ROS 2 leverages a decentralized DDS-based architecture that enables dynamic node discovery, more robust peer-to-peer communication, and better handling of MTU variations and reconnections without manual intervention. Additionally, exploring secure, privacy-preserving distance estimation methods will address critical privacy concerns.

Another promising avenue involves applying the system as a backup positioning solution for tracking human and robotic SAR agents operating in GNSS-denied disaster environments. Evaluating its effectiveness in larger, more realistic ROUD scenarios will be essential to validate and refine system performance.

Additionally, we propose inverting the current architecture so that mobile robots carry the FTM initiator instead of the responder, with the localization algorithm executed at the Edge on the robot's onboard PC. This modification would help mitigate privacy and cybersecurity risks associated with the identification of victims. Advancing this concept will require the design and development of ad-hoc responder devices capable of being attached to clothing, integrated into smartphones, or embedded into wearable formats such as bracelets or watches. Such a solution would enable the deployment of localization applications where the target individual remains completely passive, while maintaining high accuracy and operational flexibility.

ACKNOWLEDGMENT

The authors would like to thank the Chair for Safety, Emergencies, and Disasters of the University of Málaga, led by Prof. Jesús Miranda-Páez, for organizing the exercises. They also express their sincere gratitude to Juan Manuel Ravina Vergara, firefighter and coordinator of Scenario and Intervention Teams, for his invaluable support and collaboration during the field deployments. Finally, they acknowledge the continuous support of their colleagues from the UMA Robotics and Mechatronics Group.

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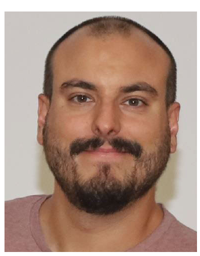

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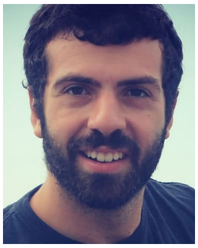

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