Experimental Evaluation of Data Fusion Techniques and Adaptive Control for Mobile Robot Localization

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***Abstract*—This study presents an approach to improving the localization of mobile robots in a controlled test environment through sensor fusion. Currently, the position of the ground robot (Unmanned Ground Vehicle (UGV) P3DX) can be estimated using an optimization algorithm or another technique based on a previously known map. In contrast, the aerial robot (Unmanned Aerial Vehicle (UAV) Bebop Parrot 2) can determine its relative position by detecting a marker on the ground robot using the Robot Operating System (ROS) WhyCon package. However, ambiguities or disturbances may compromise the accuracy of the robots' localization. To mitigate these limitations, Ultra-WideBand (UWB) sensors were incorporated into the system, enabling a more robust data fusion by integrating information from multiple sensors. Additionally, a filter was applied to reduce the impact of high-frequency noise on position estimation. Accurate localization test data were used to construct a simulated scenario and analyze the performance of the proposed approach. The simulation results demonstrate that sensor fusion, combined with noise filtering, significantly improves localization accuracy, making the approach promising for applications in mobile robot navigation.**

***Index Terms*—Position Estimation, Data Fusion, Adaptive Control, UAV, UGV**

I. Introduction

Accurate target position estimation is a fundamental challenge in robotics, particularly in complex environments where noise, obstacles, and interference can significantly degrade system performance. Reliable position estimation is crucial for applications such as autonomous navigation, human-robot interaction, and adaptive control systems [1]. Ground robots and Unmanned Aerial Vehicles (UAVs) have emerged as powerful tools in these scenarios, offering complementary data acquisition and processing capabilities in dynamic environments.

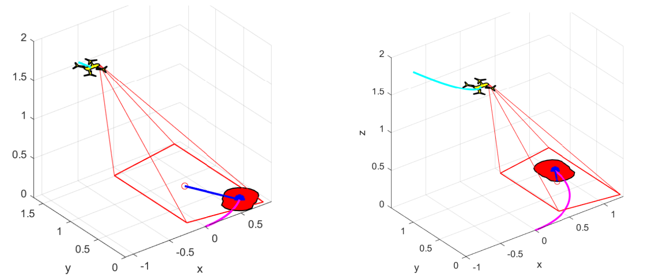
Surface and aerial robots are frequently integrated to leverage their strengths: ground robots excel in stability and continuous operation, while UAVs provide a versatile vantage point for observation and data collection. However, data collected in real-world scenarios is often inherently noisy, compromising the precision required for practical position estimation and control. To address these challenges, advanced filtering techniques and data fusion strategies are needed to enhance the reliability of robotic systems in adverse conditions.

In this work, we propose a robust methodology for target position estimation, combining a ground robot (P3DX) equipped with a bio-inspired global positioning system and a UAV (Bebop Parrot 2) utilizing the Robot Operating System (ROS) WhyCon package for visual target detection. A Wavelet Transform-based filtering approach is employed to mitigate noise by decomposing and isolating the relevant signal components, ensuring accurate and reliable signal conditioning. Moreover, optimized multisensor data fusion integrates information from Ultra-WideBand (UWB), OptiTrack, and visual sensors to inform an adaptive control strategy for real-time adjustments to UAV performance [2].

II. Related Works and Main Contributions

The search for localization methods is a recurring and essential topic for researchers working with mobile robots. Accurate localization is one of the primary requirements to ensure good performance in robotic navigation missions. It is achieved through the probabilistic pose estimation relative to the known position of specific objects of interest (landmarks). In some cases, vertical edges in the environment are used, or features are extracted from a defined and known map, employing correspondences to locate the robot [3]–[6].

The authors thank FAPES (Fundação de Amparo à Pesquisa e Inovação do Espírito Santo) and CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico) for supporting this research. Dr. Araujo-Neto also acknowledges FAPES for his postdoctoral scholarship. This work is also funded by the National Council for Scientific and Technological Development – CNPq, related to project 442696/2023-0.



(a) Ground robot detection (b) Target pursuit

Fig. 1. Simulation of the leader-follower proposal.

Localization using aerial and ground robots is a strategy applicable in both indoor and outdoor scenarios. Collaborative localization is a path explored in the literature, where the approximate relative position between robots is taken as an initial estimate, and information from both robots is combined to obtain a reliable position estimate [7].

Data filtering to improve localization performance is not always limited to maps. When locating objects in images, it is necessary to process the data set efficiently to execute the localization algorithm. Work [8] demonstrated in their work how these techniques can be used to predict and update vehicle positions in surveillance cameras, showcasing the robustness of algorithms such as PF (Particle Filters) applied to vision-based localization.

The use of cameras has supported 3D mapping approaches. Algorithms like PF have been replaced by more complex Gaussian models in grid maps, achieving more accurate results in certain situations [9]. A sparse environment (with dispersed or scarce landmarks), for example, could entail a considerable computational cost for a traditional FastSLAM algorithm, where each particle represents a path sample, and the Extended Kalman Filter (EKF) serves as a characteristic estimator [10].

Work [11] proposed using a bio-inspired algorithm based on the behavior of Leader-Based Bat Algorithm (LBBA) to minimize odometry errors, correcting the localization of a mobile robot during its mission. The Bat Algorithm [12] was compared with other algorithms in the literature due to the need to replace the Particle Filter as a localization algorithm, given its exponential computational complexity. Sensor fusion aims to optimize robot localization, as observed in [13]. In the literature, bio-inspired algorithms have shown promising results for terrestrial robot localization, and this article aims to apply them to UAVs.

III. Methodology

This paper explores a collaborative approach between UAV and Unmanned Ground Vehicle (UGV) in a mapped environment. Equipped with a camera, the UAV autonomously tracks the robot, which performs a positioning task to achieve a target. The camera obtains the distance between the UAV and the ground base, providing a three-dimensional understanding of the environment, as shown in Fig. 1. The integration of these technologies aims to explore the effectiveness of collaboration between UAVs and ground robots to estimate a 3D position from a 2D map:

Research involving multiple robots is conducted with the aim of practical applications in autonomous exploration, search and rescue, warehouse inventory management, agricultural activities, etc. In such applications, accurate localization is crucial to control the robots and ensure the integrity of the equipment [9], [14]. In the context of this paper, the Pioneer 3-DX ground robot (hereinafter referred to as P3-DX) is equipped with a LIght Detection And Ranging (LIDAR) sensor, which will be used to assist in the localization of both robots. This sensor is paramount in robotics and autonomous systems, leading to innovative proposals such as multimodal LIDAR systems. In these systems, LIDAR sensors function similarly to cameras, providing panoramic images that encode depth, reflectivity, or near-infrared light, in addition to point clouds [15].

The 3D localization proposal emerges by combining the 2D localization capability of the P3-DX robot within a previously known map with the knowledge of the UAV's distance (altitude) from the ground robot. Throughout the mission, the UAV tracks the P3-DX ground platform, thereby performing trajectory tracking, as shown in Fig. 1(a), remaining directly above it and maintaining its height relative to a target installed on it (Fig.1(b)) [16].

By integrating LIDAR readings, orientation information (provided by a digital compass, for instance, or another detection device or system), and the UAV's altitude relative to the P3-DX robot, it becomes possible to determine the UAV's position in a familiar 3D environment without relying on a motion capture system such as OptiTrack. However, in this study, the OptiTrack motion capture system is employed, and the fusion of data from UWB sensors is analyzed to provide ground truth for the obtained localization and to supply the orientation of the P3-DX, given that it lacks an onboard digital compass.

Fig. 2 simulates how the camera attached to the UAV detects the target. The trapezoid shown represents the scanning frame of the camera on board the UAV where the target is located. Once the target is identified in the image, the algorithm seeks to keep it in the center of the frame in question, reducing the blue line, which indicates the distance from the frame's center to the target's center, to zero. The UAV is then controlled so that the ground robot can be followed:

The Whycon package from ROS was used for visual marker detection, providing an accurate estimate of the target's position in real-time, essential for controlling the UAV during the experiments. The UAV's height measurements were performed using an onboard camera, whose reliability was evaluated under controlled conditions. Despite the typical instability of these sensors, the vision package ensured adequate accuracy, and the P3DX reference trajectory was defined by a series of target points, interpolated to create a continuous route. Control was based on a trajectory-following algorithm, adjusting the UAV's position to maintain formation with the ground robot.

The dynamics of the experiment in which a UAV follows a

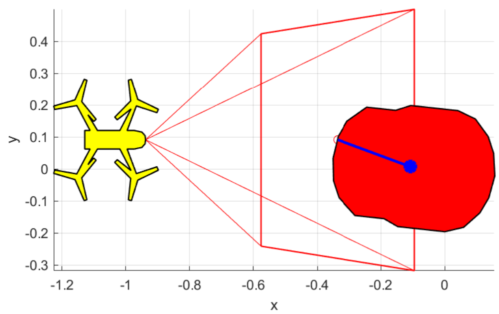


Fig. 2. Top view of VTNT detection by the UAV.

ground robot can be directly associated with implementing an adaptive control algorithm for trajectory tracking [17]. In the experiment, the UAV must continuously adjust its position in response to variations in the ground robot's trajectory, compensating for changes in speed, external disturbances, and possible uncertainties in estimating the relative position. Similarly, an adaptive controller adjusts its parameters in real time to minimize errors and ensure that a controlled robot follows a predefined trajectory with high precision. The UAV control system uses measurements of the ground robot's position, speed, and orientation to recalibrate its navigation commands, just as an adaptive algorithm processes sensory information and updates its gains to optimize control performance. Thus, the experiment illustrates in practice the fundamental principles of adaptive control, evidencing its applicability in dynamic systems subject to variations in operational conditions.

A. The Experimental Arena

The following describes the arena configuration used to experiment and validate the proposed algorithm. The arena involves four main items, namely, the ground robot, the Pioneer 3-DX differential platform, the adopted UAV, the four-engine Parrot Bebop 2, the OptiTrack motion capture system, in this case adopting the OptiTrack Prime 13 cameras, and the ROS, used to provide communication between the control computer and the robots, carried out via a Wi-Fi channel.

The OptiTrack Prime 13 cameras are high-precision (*full* HD), configured to obtain images at a rate of 180 frames per second (they can capture up to 240 frames per second). They were used to compare the robot's actual position (*ground truth*) with the position calculated by the algorithm and also to obtain the orientation of the ground robot. They have lenses that allow high-fidelity motion capture, making them ideal for controlled environments requiring detailed movement recording. Twelve of them are arranged around the test environment to capture position and orientation data from the robots.

The Parrot Bebop 2 quad-engine UAV is a small, lightweight, rugged UAV equipped with a front-facing fisheye camera that allows it to capture high-quality images and videos (*full HD*). It has stable flight capabilities and is easily controlled, making it an excellent candidate for aerial filming and data collection in experiments. The Pioneer 3-DX differential mobile robot is a well-known differential platform equipped with a Slamtec RPLIDAR-A2M12 LIDAR sensor with 360-degree detection of the surrounding environment, essential for mapping and accurate distance measurements. The point cloud collected by such a sensor has 1600 points per 360° scan, each corresponding to a distance in the range of $0.2\,\mathrm{m}$ and $12\,\mathrm{m}$, for white objects, and between $0.2\,\mathrm{m}$ and $10\,\mathrm{m}$, for black objects. In this work, however, only the frontal scan, corresponding to 180°, is considered, which corresponds to a cloud of 800 points. However, since the experimental arena does not have distances greater than $10\,\mathrm{m}$, the color of the objects is not significant. As for the scan, the update is performed at a rate of $10\,\mathrm{Hz}$.

The experimental arena also has two computers, one WINDOWS 10 and the other LINUX Ubuntu 20.04. The first is used to run the Motive software, part of the OptiTrack motion capture system, which processes the collected images and provides the position and orientation of the object being monitored, in addition to running the *script* MATLAB® corresponding to the proposed system. As for the LINUX computer, it establishes a ROS network that allows communication between the control computer and the vehicles, which is based on an ad-hoc Wi-Fi channel created by a router included in the experimental arena, which does not have access to the web (see Fig.3):

IV. Results

This section presents simulated and experimental results to validate the previous proposal. In all scenarios, the P3-DX robot moves through the test arena while the UAV flies above it, maintaining a position directly above the mobile base throughout the mission. Therefore, the two vehicles navigate as a leader-follower multi-robot system, with the leader robot, the P3-DX, searching for a specific target point [18]. Thus, the follower tracks the leader, maintaining a position relative to it, defined as $x_f = x_l, y_f = y_l$, and $z_f = z_l + h$, where h is a specified distance and the subscripts f and l represent the follower and the leader, respectively. To ensure that the quadcopter maintains the correct position relative to the leader, a visual marker (a target) is installed on top of the leader (see Fig.4), which can be visually perceived by the UAV, and whose center of gravity in the images defines the position of the leader, a reference for the UAV. The objective is to estimate the position of the UAV in space, using only the proprioceptive and exteroceptive sensors of the robots.

The P3-DX, equipped with a LIDAR sensor, collects distance measurements on a predefined map. Using the proposed algorithm, its 2D position is estimated. After getting the target installed on the P3-DX, the UAV calculates its distance (in the Z direction) to it (and therefore to the ground), allowing it to follow the robot consistently during the completion of the mission. This mission consists of moving safely and autonomously around the laboratory to preserve the equipment's integrity. To this end, EVA (Ethylene Vinyl Acetate) sheets are used as obstacles, a soft material that can be assembled in

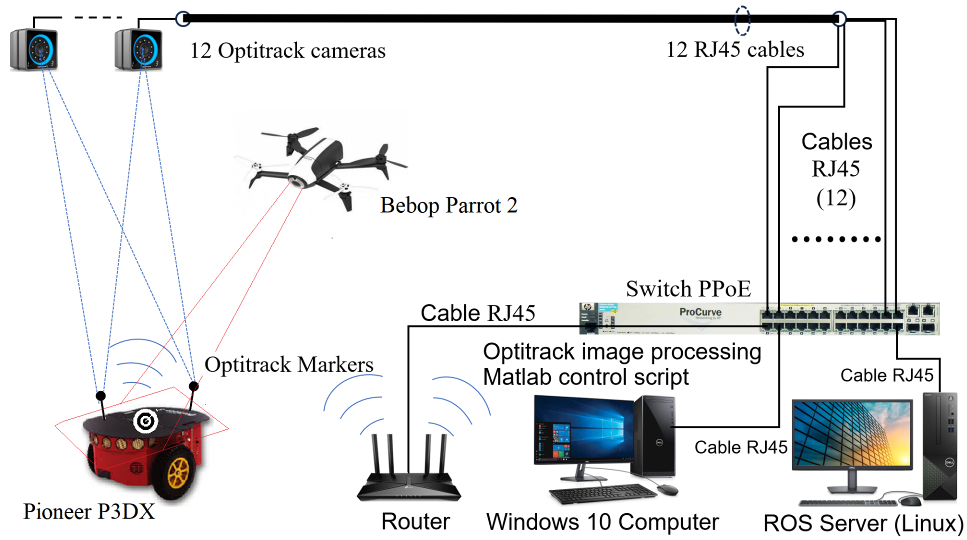


Fig. 3. Block diagram showing the system architecture.

different shapes, and protective nets are installed on the sides for the safety of the personnel present in the laboratory.

The UAV needs to take off and identify, through the image provided by its camera, the P3-DX platform, which has the target on top. Upon successfully locating the target, it must move to align itself with the mobile base, initiating the mission throughout the laboratory. To visually identify the target, the Whycon package, available for ROS, was used [19]. This provides the distance values on the XYZ axes, and only after obtaining these values is it possible to control the UAV to stay just above the ground robot.

Fig. 4 presents a partial snapshot of the test arena, showing the Optitrack cameras, the safety nets, the P3-DX robot, the Bebop 2 quad-engine aircraft, and the image obtained by the Whycon package. The Linux computer window shows the visual space in which it is possible to locate the target at approximately one and a half meters vertical distance. The values in red represent the calculated distances used to control the leader-follower formation [16], [18], [20]:

The mission can begin after identifying the relative position of the UAV about the target. First, the UAV is located globally on the environmental map using the LBBA optimization algorithm. This strategy consists of finding it in the real world using sensory information (range measurements from the LIDAR sensor) and comparing them with estimated measurements obtained through a known map and as close as possible to the real environment. In addition, the use of UWB sensors can complement the localization process by providing additional distance measurements and contributing to the robustness of the position estimate. Having the XY position is crucial for the mission's success since the P3-DX will act as a guide along the previously defined path. It is up to the UAV to follow the leader and locate itself in Cartesian space (XYZ coordinates), merging the information from its sensors (digital compass, camera, UWB sensors) with the information calculated by the localization algorithm. It is observed that the P3-DX robot used does not have a compass, but its orientation is available, given by the OptiTrack system, which emulates the compass.

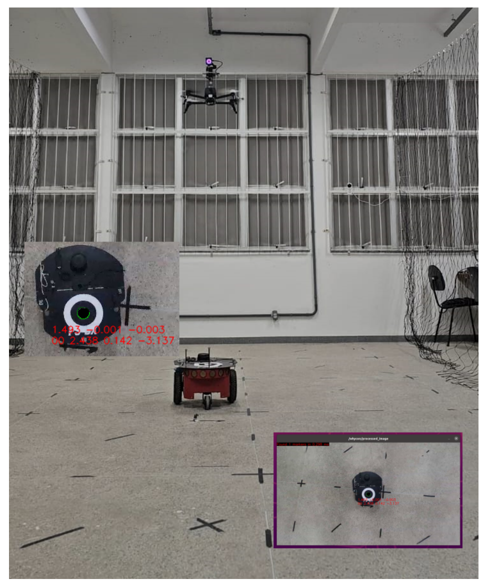


Fig. 4. Capturing the distance from the UAV to the UGV.

Controlling multiple robots is a challenging scenario widely applicable in the industry. The scenario presented in this article could be two robots performing internal or external security functions, an inspection of industrial facilities, such as warehouses or large factories, and even in scenarios where visual inspection is required in conditions that may compromise human health, such as in facilities with radioactive materials or substances that are harmful to human health and well-being, such as pandemic scenarios. Three obstacle towers are identified in the proposed mission to test autonomous localization and control, which can simulate warehouse shelves. The robots must follow a path around these obstacles to make open and closed turns, maintaining the leader-follower formation. The graphical representation of this experiment can be seen in Fig. 5, in which the route taken by the UAV is represented by the blue line. In contrast, the gray columns represent the obstacles present in the navigation environment:

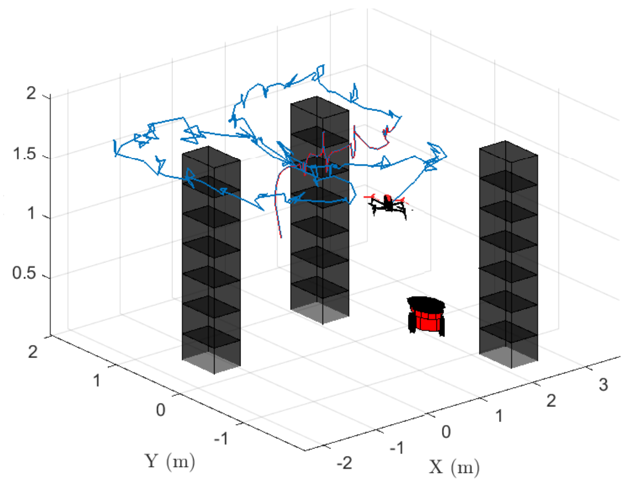


Fig. 5. Graphical representation of the mission by the UAV.

Fig. 6 shows the planned routes followed by the UAV and the ground robot. The planned route for the P3-DX is defined by interpolating line segments between reference points defined on the previously known 2D map. As for the Bebop 2, its planned route is followed by the ground platform, the leader it tracks. As can be seen, the two vehicles share similar paths at several points (starting their mission at the positions indicated by the arrows). This suggests that the leader-follower formation followed the planned route accurately at many points. However, there are also areas where the blue line diverges significantly from the red line, indicating that, at certain moments, especially on sharp curves, the UAV deviated from the planned route. However, such deviation did not compromise the vehicles' integrity or the mission's accomplishment.

The oscillatory movement of the UAV, noticeable in its path as illustrated in Fig. 7, occurs due to the control technique used in this experiment. Since the UAV reacts to the movement of the UGV, the control aims to stabilize the relative position of the aerial robot concerning the ground robot based on the target present in the latter. More significant difficulties are observed in very narrow curves, as seen in the results presented. Although it does not compromise the integrity of the equipment, it is necessary to use adaptive control capable of guaranteeing stability in experiments carried out in less controlled environments [21].

In case of significant oscillation or loss of target, the UAV is placed in *standby* mode and stabilized in the air, returning to the mission only when it can see the UAV again. This approach ensures the safety of the equipment and allows the mission to continue, even in a scenario where the robot could be hijacked,

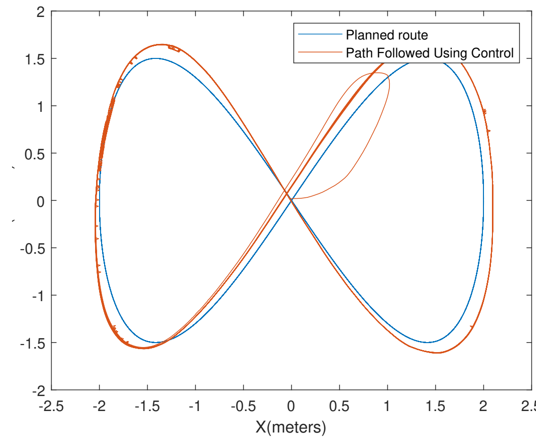


Fig. 6. Comparing planned and actual vehicle routes.

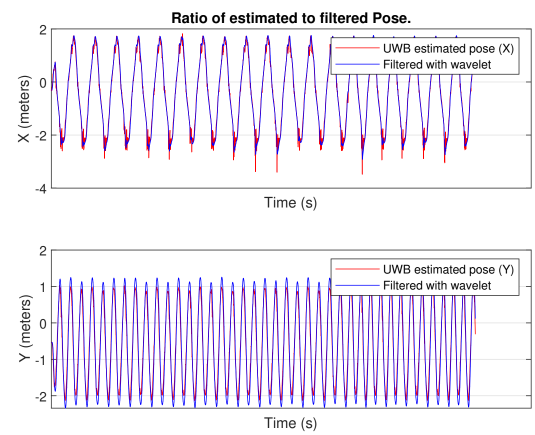


Fig. 7. Position analysis after data filtering.

for example. The fact that both robots work together helps in situations of unsuccessful locations in ambiguous scenarios by the LBBA localization algorithm, providing localization strategies and reinforcing position confirmation. This makes it possible to identify whether there was a failure in the localization of the algorithms or some external interference, such as wheel slippage, floor inclination, robot hijacking, and strong winds, among others.

The mission begins only after executing the global localization procedure using the LBBA algorithm to obtain the initial position estimate of the ground robot. After that, the local localization strategy is adopted throughout the experiment. As shown in Table I, the scenario with filtering exhibits a lower error than the one without it. It is concluded that using filtered data provides better conditions for control. This behavior can be justified by the filters' ability to smooth sensory data, removing rapid oscillations and noise that could induce undesirable behaviors in the controller. Although data smoothing allows the controller to generate more consistent and stable movement commands, there is still a slight delay when applied in real tests. It may be detrimental if the mission requires higher speeds from the robots during their movement across the map.

TABLE I
ROOT MEAN SQUARE ERROR (RMSE) COMPARISON BETWEEN LBBA AND FILTERED LBBA IN UAV TRACKING UGV POSITION SIMULATION.

Metric (Estimate)	RMSE X (m)	RMSE Y (m)	RMSE Z (m)
Pose	0.045	0.022	0.092
Filtered Pose	0.012	0.014	0.074

The UGV is capable of locating itself in the two-dimensional (XY) environment through LIDAR readings, which are compared with the LBBA's position estimates on a known map. On the other hand, the UAV obtains its position in the three-dimensional (XYZ) space through sensor fusion. It is essential to highlight that, in this study, the Bebop 2 is controlled in such a way as to keep the target in the center of its camera image and follow the orientation of the P3-DX robot throughout the mission. Therefore, in some moments of high acceleration and sharp turns, it is expected that the UAV's localization performance will worsen, which explains the degradation of the hit rate.

The number of bats used for initial global localization was $3,000$ particles, showing high 2D localization accuracy of the P3-DX. Ensuring that the VTNT is globally localized and that the UAV is observing the target, the mission begins along the laboratory and the number of particles for local localization. At the same time, the robot move was reduced to 50 particles (1.6% of the initial particle amount), seeking to maintain the frequency of good localizations throughout the experiment and reduce the number of algorithm calculations.

V. CONCLUSIONS

A method is proposed to localize a UAV in 3D space using sensory data from a 2D LIDAR sensor onboard a ground robot in formation with the UAV and altitude information provided by a camera on the UAV, relative to a marker on the ground robot. The proposal, based on the LBBA algorithm, allows the localization of the ground vehicle on a known 2D map and, by merging these data with the altitude information of the UAV, to obtain the 3D location of the latter. Experimental results indicate that the methodology is efficient and does not interfere with the cooperative task of the robots. Therefore, when navigating in formation, it is possible to merge sensory data from the vehicles to improve their localization in the environment, which is crucial for adequate control. Initially, a known environment is considered to validate the algorithm; future work should explore adaptations for unknown environments, including map construction and uncertainty management.

ACKNOWLEDGMENT

The authors gratefully acknowledge the support of UFES, CEFET-MG, and Leuphana Universität Lüneburg for their collaboration.

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