Opportunities for autonomous UAV in harsh environments

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Abstract—**This paper describes the challenges raised from the use of Unmanned Aerial Vehicles (UAVs) on the exploration of inhospitable places that present limitations and risks to humans; for instance, we describe the case of cave exploration. UAVs have emerged as an attractive alternative for performing this task in a safety and reliable manner. However, challenges regarding control management, accurate positioning and navigation, and reliable wireless connectivity need to be addressed in order to achieve effective solutions. Herein, we address those challenges and present possible solutions for enabling the use of UAVs in harsh environments.**

Index Terms—**harsh environment, location and positioning, multipath channels, Unmanned Aerial Vehicles.**

I. INTRODUCTION

An Unmanned Aerial Vehicle (UAV) is an aircraft that can fly without any human input or supervision. Usually, they are part of an Unmanned Aerial System (UAS) together with a Ground Control Station (GCS) and the communication links [1]. Historically, they were mostly employed in military applications, but have been gaining ground in civilian applications such as precision agriculture, track monitoring, surveillance, logistics, search-rescue missions, among others [2]. UAVs are usually very resource-constrained, greatly impacting aspects such as maximum flight time, communication efficiency and data processing and storage. Energy-efficiency must be taken into account in any UAV-based solution to maximize battery life and flight time.

There is a growing interest on using UAVs as a low-cost technology for providing connectivity in indoors environments, specially for industry applications. UAVs can also be used to reach dangerous places where humans cannot access in safety conditions [3]. However, missions over confined spaces, where absolute positioning signals and remote control are not available or sufficiently precise represent a very challenging task. Particularly, UAV systems in confined environments would need robust wireless communications, three-dimensional trajectory data, precise control, and scheduling (UAV's control commands).

Regardless of their size or autonomy level, the state of UAVs is required to be known by its controller or its automatic pilot. Based on the acquired data, the UAV control system can command the actuators so the desired trajectory is met [4]. UAV state comprise its position, velocity, altitude, airspeed, angle-of-attack, sideslip angle, and rotation (pitch, roll, and yaw) rates, which are acquired by an Inertial Measurement Unit (IMU) and Global Positioning System (GPS) receiver. IMU measurements present accumulated error over time, which is compensated by the GPS location information [5].

When considering a harsh and confined environment, the navigation and therefore UAV control can be seriously compromised. High-frequency waves cannot penetrate dense obstacles, and in general the GPS system is not available. Therefore, the UAV must either operate remotely within a Line of Sight (LoS) or employ another navigation strategy for a GPS-denied environment [6]. One of the strategies to compensate the lack of GPS signals are fusing IMU and camera data, resulting in a vision-based navigation strategy. Popular strategies for vision-based navigation are the Simultaneous Localization and Mapping (SLAM), which builds an environment map and estimate the UAV position based on the acquired image, and Visual Odometry (VO), which estimates the vehicle's position and orientation based on the sequence of images acquired [5]. However, some environments may have no light to apply a vision-based approach in UAV localization. The use of a lightning source at all times would demand UAV power and decrease its autonomy. Therefore, other localization techniques are required that do not rely on computer vision.

In UAV applications, there is a predominance of decentralized localization strategies based on distance, such as the Received Signal Strength Indication (RSSI) and Time Difference of Arrival (TDOA). RSSI is a technique in which the distance between nodes is estimated using the signal strength and used to calculate the position [7]. This technique was applied for UAVs in GPS-denied environments in [8]. TDOA

bases its measurement on the difference in the arrival times of a signal coming from multiple sources. This technique, applied in [9] is cost effective and less affected by radio reflection [7]. Ultra-wideband (UWB) technology has attracted interest as a promising solution for accurate location and tracking due to its ability on resolving multipath and penetrating obstacles [10].

In this paper, we discuss the challenges and potentials technologies to address the use of UAVs in harsh environments by considering the special case of cave exploration. Section II describes our case study. Section III presents the main challenges regarding communication, control, and positioning issues. Finally, Section IV presents some final remarks.

II. CASE STUDY: CAVE EXPLORATION

Caves have been present in mankind History since the prehistoric period, being used for shelter, economic activities, storage and ritual purposes [11]. As an example, in Brazil, there are around 6000 identified caves, many of them without speleological studies. Cave surveying (or cave mapping) is an attempt to accurately record the cave and its characteristics [12]. Those maps detail the cave extension, layout and passages, and are useful not only for cave research, but for other knowledge areas such as archaeology, biology, geology, and others [13]. Traditionally, cave mapping has been done in a rudimentary manner, using tools such as compasses or clinometers and taking notes that were used to draw the cave maps [12]. The improvement of available tools such as 3D sensors allowed speleologists to provide better mapping and cave information [14]–[16]. All these strategies, however, still depend on a person entering the cave, which can be hazardous for the speleologist depending on the environment or even impossible if the area to be mapped is unreachable by humans.

In [16], a mobile cave mapping with LiDAR is presented, and in that work is suggested the use of an Unmanned Aerial Vehicle (UAV) integrated to a LiDAR sensor for cave mapping. Digital photogrammetry can also be deployed in UAVs to help speleologists, as demonstrated in [17]. Even though UAVs can bring many benefits to cave surveying due to its access to dangerous and inaccessible sites, there are some factors that hinder the use of those vehicles in these environments. Indeed, non-maintained or natural subterranean environments can be considered one of the most challenging for robotic operations [6], since they can present limited access, have water, gases and wildlife inside them, have no illumination and greatly affected communication. Therefore, robots or Unmanned Vehicles employed in such environments must present higher reliability and robustness.

In general, inhospitable scenarios as those of caves present different rock formations and environments and passages of variable dimensions. In its interior can occur the total absence of light, irregular ground and different kinds and sizes of obstacles such as speleothems, besides the possibility of containing bodies, water and cave fauna, especially bats. Those characteristics represent a very difficult challenge for UAV navigation and manoeuvres. Also, the irregular environment influences the communication signals through reflection, diffraction and scattering, making UAV operation very challenging in these environments. Fig. II shows an example of a cave.
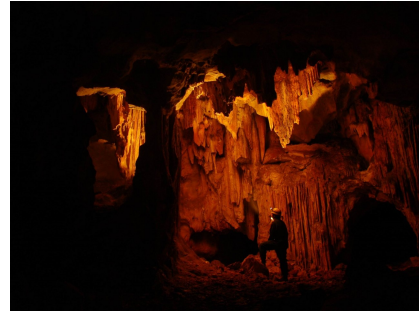

Fig. 1. Interior of the Pinheiro Seco cave, located in the municipality of Castro, in the state of Paraná, Brazil.

III. CHALLENGES AND POTENTIAL DIRECTIONS

In this section, we describe the main challenges regarding the control of UAVs inside the described environments, the communications and positioning issues as well as the corresponding possible solutions.

A. Challenges in Control

1) **Communication Maintenance:** Regardless of whether the drone is autonomous or remotely controlled, the flight control will depend heavily on the communication link maintenance to keep the aircraft stable during flight [18]. Communication disruption in remotely operated UAVs can cause the operator to lose control of the aircraft, which can become unstable and crash. In autonomous UAVs, the autopilot is a key component of the aircraft control system, receiving GPS positioning data and controlling the UAV to follow reference paths, avoid obstacles or navigate through waypoints. In GPS-denied environments (cave scenarios) or if GPS signals outages happens, the navigation system can deteriorate rapidly due to the large sensor errors presented by the low cost microelectromechanical sensors used in most off-the-shelf autopilot systems [19].

2) **Delay:** In embedded systems, the network represents the interconnections among components (sensors, actuators, controller and ground station) [20]–[22]. Delays on the network can greatly prejudice robust networked control systems, which need reliable real-time information to provide fast, accurate responses. An example can be seen in [23], where network issues such as transmission delay and packet loss can result in a significant threat to the train stability and operation safety. Likewise, delayed UAV information fed to the control system can cause instability and the inability of returning to the initial navigation point or avoiding obstacles inside the environment. Therefore, reducing the delay is a big challenge when working with critical embedded real-time systems.

3) **Noise, Bit Errors, and the Risk of Instability:** In control systems with quantized feedback control values being transmitted from a controller to the sensor/actuators over a noisy feedback channel, randomly occurring bit errors will degrade the performance of the system. This degradation will depend on a number of factors, including the channel noise and whether the control levels have been coded to deal with more than a single bit error. With a noisy channel and frequent bit errors, the performance in the close loop system can evolve to the point of instability [24], [25]. When using UAVs inside a cave, a control system instability could represent the lost of the UAV or a possible damage to the cave So it is important to reduce the channel noise and prevent a system instability in order to reap the best benefits from UAV usage.

B. Challenges in Communications

1) **Channel Characterization**: Appropriate characterization of channel propagation effects is of paramount importance for the design and analysis of UAV assisted wireless communication networks. There has been a great interest in the research community in measuring and modelling air-to-ground and air-to-air wireless channels – the survey in [26] summarizes the main findings in this area. For instance, fading, path loss, shadowing and Doppler effect have been measured or modelled considering different types of UAVs, carrier frequency and communication technology [27]–[34]. Common to these works is the conclusion that line-of-sight (LOS) plays a great role and that the UAV altitude has a direct relation to the amount of LOS, especially in air-to-ground channels. Moreover, these works focus basically on aerial or over the ground communications, not in underground channels. Although not including UAVs, there is a rich literature devoted to the wireless characterization of tunnels and mines [35]–[38], but the same cannot be said for the case of natural caves. A recent exception is the experimental work reported in [39], which characterizes the wireless channel inside a touristic cave in Malaysia. Although a natural cave differs in many ways from an underground mine, such as depth, width of the paths, type of rocks, among other points, the authors in [39] also report the severe impact of non-line-of-sight (NLOS) conditions induced by the irregular trajectory inside the cave, with several corners. Despite the differences, localization and tracking schemes designed and deployed to work in underground mines (*e.g.* [40]), should be adaptable to the particular characteristics of wireless propagation inside caves.

2) **Diversity and reliability enhancements**: In harsh environments, the radio signal can be dramatically degradedby diffraction, reflection and scattering due to obstacles, resulting in several replicas with different amplitudes, delay and Doppler components. This leads to destructive and constructive interference of the different signal versions arriving at the receiver, which make its detection extremely difficult. Diversity techniques such as frequency or time diversity, spatial diversity with the use of multiple antennas in multiple-input multiple output (MIMO) schemes, and cooperative diversity can be applied to improve the reliability of the signal in multipath channels. For instance, cooperative relaying, even with a single relay, can significantly improve the performance of the system; however, harsh environments would require the employment of numerous relays, and their placements could drastically affect the system performance, thus becoming a very challenging task [41]. Moreover, UAV relaying would present more complexities in the sense that the air-to-air link and the air-to-ground link are asymmetric and relaying happens in a 3D space. In [42], the use of multiple UAVs in relaying is tackled by studying the optimum positions of UAVs in relaying systems, equations for the best altitudes and distances are derived by maximizing the end-to-end SNR. However, the coordination of multiple UAVs is also an intricate task. In [43], it was demonstrated that multiple antennas on the UAV provide a more robust radio channel in front of the antenna changes of orientation when the UAV is maneuvering. On the other hand, unlike narrowband channels, the UWB channel does not suffer from dense multipath propagation due to the inherent frequency diversity. However, a severe penalty in throughput and quality of service is experimented beyond short distances, then high data-rate UWB communications systems are range restricted. Therefore, spatial diversity joint with UWB in UWB-MIMO systems can lead to an increase signal-to-noise ratio (SNR), which can help to extend the range, reduce spatial power variations, and enable the use of high-level modulation for higher data rates [44]. Indeed, UWB-MIMO systems have the potential to deliver extremely high data rates over short distances. However, even though multiple antennas on UAVs can bring improvements on coverage and diversity gains, it comes at the expense of increased computational capabilities, space, and power requirements.

3) **Resource allocation and networking** Maintaining connectivity of autonomous objects is crucial for suitable performance of the targeted tasks. Therefore, the communication between UAVs and between UAV and the infrastructure needs to be reliable in order to support the exchange of control messages, data offloading form sensors to UAVs, then among UAVs, and finally to the infrastructure [45]–[47]. Authors in [46] have evaluated a deployment composed of several UAVs, from which one is elected leader, and then aggregates the traffic from remaining UAVs and relays to the infrastructure or control center, while clusters members only connect to each other. Authors propose an resource subchannel allocation scheme which is shown to be NP-hard in urban environments. In a similar setting, [45] propose a

solution in which spectrum sharing between UAV transmissions is allowed thus enhancing spectral efficiency (e.g. high data rates). In both works urban scenarios are assumed, hence we expect that under harsh conditions such allocation schemes might not be feasible, thus demanding dedicated resources form the network, or even dedicated architecture.

C. Challenges in Sensor Fusion and Positioning

As aforesaid, the proposed solution aims at autonomously flying UAVs, while still maintaining reliable wireless connection to edge servers to forward sensory data and offload computation. The target deployment scenario (caves) imposes difficult technological challenges due to its radio propagation features and harsh (inaccessible) environment for humans. In such situations, cyber physical systems which perform intended tasks autonomously based on current state and sensing with limited or even without human intervention are favored [48], [49]. To achieve that, the autonomous systems under investigation rely on information about network dynamics and environment features. Actually, it is necessary to simultaneously acquire, combine, and process large data base from various heterogeneous sources and then infer meaningful events and patterns to assist in the drone flight control and operation. It is also important to develop new positioning techniques for accurate 3D localization and reliable navigation of such unmanned vehicles.

Multidimensional sensor fusion combines sensory data from various heterogeneous sources so that the aggregated information offers more certainty than each component separately would [50]. This module has pivotal role for the overall solution as it acquires and processes information of many heterogeneous sources from non- and communication domains (*e.g.*, laser technologies, video cameras, inertial measurement units and available transducers). For instance, UWB communication systems provide centimeter accuracy, strong multipath resistance and a good material penetration capability, which can be useful under Non-Line-of-Sight (NLoS) conditions due to its very large bandwidth. However, the transmission of information can be severely degraded under strong scattering conditions. Alternatively, radar systems implementing pulse compression techniques can significantly improve the range measurement precision if the effective bandwidth of the received signal is increased while keeping its energy constant [51], [52]. For combining such large and multidimensional data inside the sensor fusion component, the recursive Bayesian estimation approach (also known as Bayesian filtering) has been receiving a lot of attention lately [53], [54] as a viable solution to combine multidimensional data and enable positioning and tracking tasks, for example, Authors in [55]–[60] successfully applied these techniques in various deployment scenarios. A particularly useful approach is to combine Bayesian filtering with other machine learning models such as Gaussian processes [61], [62].

Equally important, modern radio access technologies such as 5G New Radio with large bandwidth, high carrier frequency, densely deployed base stations, and antenna arrays enable machine type communication in such a way that accurate positioning is provided by the radio network itself [63]–[65]. Hybrid strategies using heterogeneous sources of information and exploiting various metrics (such as time of flight, received signal strength, direction of arrival and combinations thereof) are of interest. As previously mentioned, the envisaged mechanisms rely on modern network architecture wherein communicating nodes offload not only sensory data, but also high demanding computational tasks to more capable edge servers that then estimate the target node position after gathering measurements and prior history [65], [66].

In the same way [67] addressed the prospects and key enabling technologies for highly efficient and accurate device positioning and tracking in 5G radio access networks. Building on the premises of ultra-dense networks as well as on the adoption of multicarrier waveforms and antenna arrays in the access nodes (ANs), the authors formulate extended Kalman filter (EKF)-based solutions for computationally efficient joint estimation and tracking of the time of arrival (ToA) and direction of arrival (DoA) of the user nodes (UNs) using uplink reference signals. Then, a second EKF stage was proposed in order to fuse the individual DoA and ToA estimates from one or several ANs into a UN position estimate. The computing complexity and energy consumption at the UN side were kept to a minimum. In results they demonstrated that by using their methods, sub-meter scale positioning and tracking accuracy of moving devices is indeed technically feasible in future 5G. Positioning is a key enabler for new services in the upcoming wireless communication systems, for example, transportation, logistics, healthy care, animal husbandry, environmental monitoring and even wearables [58], [66], [68]. In the scenarios under consideration, access points, supporting localization units and low computation power terminals may also offload their computation to nearby edge server that actually estimate the target node position based on heterogeneous metrics and achieve better accuracy. Bayesian networks are employed here to capture the qualitative relationships between the random quantities aiming at obtaining valid posterior estimates for the unknown varieties of interest. The Markov Chain Monte Carlo (MCMC) method (a powerful generic computational approach) can be employed to approximately sample from arbitrary distributions [69]. Thus, we also resort to Bayesian probabilistic models to develop our collaborative localization procedure [70], [71]. In particular, the Hamiltonian Monte Carlo approach may be employed to carry out the MCMC method in a computationally efficient manner [54], [72].

IV. Concluding Remarks

UAVs are becoming an attractive technology for various civil and military applications. However, indoor environments usually comprise passive objects that cause performance degradation, anomalous scattering, path loss, multipath fading, and interference effects. In this paper we present challenges and possible solutions for the use of UAVs in inhospitable environments by exemplifying the case of cave exploration.

Although UAVs offer great opportunities for several sectors of our society through civil, commercial and military applications, their widespread adoption and seamless operation are still hindered by daunting technological challenges. As addressed in Section III-B, the target (indoor) deployment scenario imposes strong scattering conditions rendering an aggressive radio channel which limits the set of wireless radio access technologies capable of operating in such harsh circumstances. Therefore, further development is still needed to identify valid metrics (even non-communication based) to allow localization, mapping and navigation tasks. Typically, autonomous systems have limited computational and hardware capabilities, as well as limited power resources. Therefore, energy-efficient routing algorithms and network structure for sensory data an computation offloading in order to save battery time are needed, as well as effective charging techniques. In such applications, sensory data is crucial for proper autonomous system operation, so both real-time and stored data (from previous events and already discovered patterns) need to be properly combined to achieve accurate positioning and decision making, mainly in mission-critical applications. Moreover, the UAV popularization is still limited by the adoption of affordable materials and efficient technologies so as to reduce overall costs. Finally, UAV regulation by national aviation authorities may limit applications and deployment scenarios owing to mainly safety issues.

The addressed challenges provide unique guidelines that allow future researches in this field to continue looking for effective solutions, once UAVs are expected to be an important tool to improve the human quality of life.

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