Localization in Unprecedentedly Crowded Airspace for UAVs and SUAVs

MANEL KHELIFI[1] **AND ISMAIL BUTUN**[2,3]**, (Member, IEEE)**

[1]Fortiss GmbH, Research Institute of the Free State of Bavaria associated with Technical University of Munich (TUM), 80805 Munich, Germany
[2]Department of Computer Science, The School of Electrical Engineering and Computer Science, KTH Royal Institute of Technology, 114 28 Stockholm, Sweden
[3]Department of Computer Engineering, Konya Food and Agriculture University, 42080 Konya, Turkey

Corresponding author: Ismail Butun (butun@kth.se)

ABSTRACT The unprecedented proliferation of Unmanned Aerial Vehicles (UAVs), and Swarm Unmanned Aerial Vehicles (SUAVs) have garnered considerable attention from industry and academia owing to their extensive landscape of applications from disaster relief towards smart agriculture. However, flying several UAVs at once poses many challenges to safely and efficiently localizing and monitoring them. Further, they need to maintain their formation distance to avoid collision between team members and any environmental obstacles. Besides, SUAVs are mainly equipped with an on-board Global Positioning System (GPS) receivers to obtain their positions, but they are not accurate enough and suffer from several vulnerabilities that restrict their applications. Thus, in GPS-denied situations, the acquisition of the positions of UAVs can be assisted by alternative technologies and solutions. This paper is one of the foremost in-depth works that present the topic of localization of SUAVs from various perspectives including current research challenges on positioning systems, telecommunication, and path planning, along with future opportunities on automated delivery services such as medicine, remote inspection of industrial sites, and precision agriculture.

INDEX TERMS Swarm UAVs, localization techniques, path planning, communication technologies, survey, SUAV flight coordination.

I. INTRODUCTION

The UAVs revolution forested new opportunities involving different sectors ranging from the aviation industry to public entertainment. According to the study conducted by PWC [1], estimated that the UAV market will be worth approximately $43 billion in 2026. This booming sector is spurred by the rapid progress in UAV technologies and the continued improvements in wireless communication which led to a significant decrease in the unit cost of the UAV. Thereby, they become an attractive way to undertake several challenging missions, in particular when they form a swarm. Thus, considerable research efforts have been devoted to SUAVs, both in industry and academia [2], [3]. Nowadays, SUAVs are being used for countless applications (see Figure 1) such as tracking targets in military missions [4], delivery and load transport [5], smart health, agricultural management, and real-time monitoring in mobile or large scale environments [6], [7], and so on.

The associate editor coordinating the review of this manuscript and approving it for publication was Guillermo Valencia-Palomo.

An increase in the on-air collisions has been reported recently due to the human error. As such, nowadays, collusion possibility of the UAVs is even getting higher, not only due to the sporadic individual hobby flights, but also due to the increased number of professional flock/swarm flights. Unprecedentedly crowded airspace for UAVs and SUAVs is due to this increase in the number of UAVs that exist in per km^3 [8], [9].

Therefore, flying multiple UAVs in a tight collaborative flock improves robustness and safety (Collision avoidance via collaborative action), by delivering many tasks that a single UAV cannot, as well as better decision making to fulfill their missions [3]. The success of UAVs in search and rescue missions executed by Swedish Maritime and Coast Guard has been mentioned in [10] due to installed thermal imaging and reliable navigation systems onboard. Meanwhile, in certain specific circumstances such as assistance in search and rescue missions when a natural disaster occurs, it is essential to know the location of UAVs with the utmost accuracy. However, the process of localization of UAVs and SUAVs depends on the application requirements and has to deal with additional
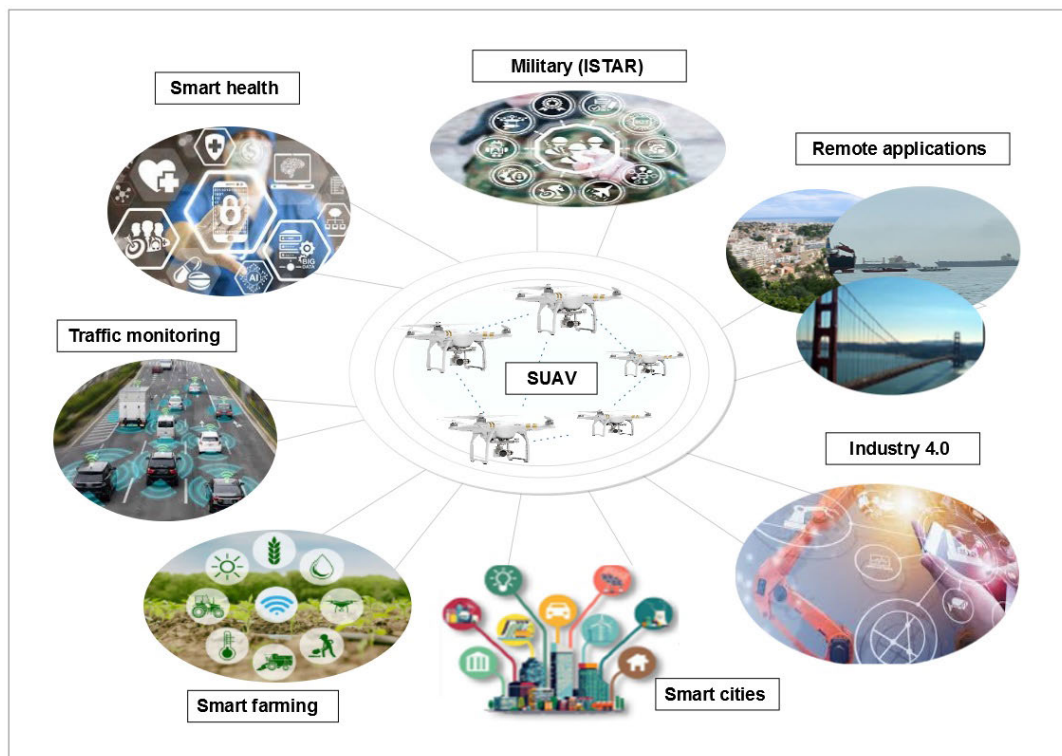
FIGURE 1. Examples of SUAVs applications.

constraints and controversies such as the velocity, height, flight level of the UAV, and the air traffic density, the limited energy autonomy and payload, as well as restricted computational capacity, the stabilization, calibration problems, the weather conditions, and noisy measurements, to name a few.

This paper is one of the foremost comprehensive reviews that focuses on current localization schemes and technologies in the context of SUAVs. It covers the major aspects of this challenging topic by examining existing work on the localization techniques of SUAVs. Open issues and possible directions for future research are also pointed out. In the following, related surveys are reviewed, and the key contributions are outlined.

A. RELEVANT SURVEYS VS. CONTRIBUTIONS OF THIS PAPER

To justify the relevance and contribution of this work, it is worthwhile checking the pertinent work proposed over the last five years in the literature as summarized in Table 1, with their details in the following, which also allows having a broader knowledge in the specific field of UAVs and SUAVs:

Chmaj *et al.* [4] investigated the application of distributed processing for SUAVs. They focused on computer engineering aspects for the implementation of collaboration mechanisms between UAVs, and their used communication and distributed processing principles. Hayat *et al.* [11], discussed the requirements of UAVs for civil applications in terms

of communication and networking. The survey presented in [6], studied the technological and social implications of FANET. Motlagh *et al.* [12], conducted a comprehensive survey of current research progress on UAV-based Internet object services. Wang *et al.* [13] surveyed distributed gateway selection schemes and cloud-based stability control strategies. Kanell *et al.* [14], focused on the current state-of-the-art of computer vision for UAVs. Besides, the authors discussed open challenges and future research directions. Lu *et al.* [15], conducted a comprehensive review of vision-based methods for UAVs across three main aspects: localization and mapping, obstacle avoidance, and trajectory planning. Furthermore, the authors identified the main challenges to be faced and presented future research directions. Chung *et al.* [2] studied modeling, control, planning, sensing, and implementation of SUAVs, with an emphasis on SUAVs flying in a 3-D world. The work in Li *et al.* [16] presented communication technologies used in UAV systems, including 3G/4G/5G, along with recent advances and future trends. The survey presented in [18] investigated the functionality of SUAVs and outlined their possible future research challenges. Mozaffari *et al.* [19], provided a tutorial and a comprehensive guide to harnessing the potential of UAVs for wireless networks. In addition, it introduced UAV three-dimensional deployment, their channel modeling, several validating models with their results, and outstanding challenges and open issues. Alwateer *et al.* [5], addressed the use of UAVs for location-based services while

TABLE 1. Relevant surveys and magazines on SUAVs.

Survey paper	Year	Covered Topics
Ref. [4]	2015	Distributed processing applications for UAVs.
Ref. [11]	2016	Networking of UAVs for Civil Applications.
Ref. [6]	2016	Technological and social implications of FANET.
Ref. [12]	2016	UAVs-Based Internet of Things Services and Future Perspectives.
Ref. [13]	2017	Distributed Gateway Selection.
Ref. [14]	2017	Current state-of-the-art and Trends of Computer Vision for UAVs.
Ref. [15]	2018	Vision-based UAV navigation Geo-spatial information.
Ref. [2]	2018	Trajectory generation, task allocation, adversarial control of Aerial Swarm Robotics.
Ref. [16]	2018	Communication technologies used in UAV systems including 3G/4G/5G.
Ref. [17]	2019	UAV communications for 5G and beyond, Cellular-connected UAVs.
Ref. [18]	2019	functionality, problems and importance of Swarm of UAVs.
Ref. [19]	2019	Opportunities, challenges and open problems of UAVs for wireless networks.
Ref. [5]	2019	Issues in drones for location-based services from human-drone interaction to information processing.
Ref. [20]	2019	Civil applications and key research challenges of UAVs.
Ref. [21]	2019	Machine-Learning Techniques used for UAV-Based Communications.
Ref. [22]	2020	Behaviors of swarm robotic and their current applications.
Ref. [7]	2020	IoT and UAVs in Smart Farming.
Ref. [23]	2020	Applications and future trends in softwarization of UAV networks.
Ref. [3]	2020	Fundamental Challenges and Constraints for Swarming With MAVs.
Ref. [24]	2021	Deep learning models for processing images acquired by UAVs for remote sensing applications.
Ref. [25]	2021	The allocation of resources in UAV-assisted wireless communication.
Ref. [26]	2022	AI-enabled routing protocols for UAV swarm.
Ref. [27]	2022	UAVs use in the monitoring and management of the sugarcane industry.
Ref. [28]	2022	Agricultural practices using UAVs.
Ref. [29]	2022	Research activities and future directions on the localization of SUAVs.
This proposal	2022	Key issues, challenges, and prospects of position-awareness along with state-of-the-art in communication technologies, path and trajectory planning, localization/positioning are investigated for SUAVs.

highlighting issues related to the context of their operations. Zeng *et al.* [17], focused on the applicability of UAVs in 5G mobile networks. The authors provided a discussion centered on UAV-assisted wireless communications and cellular-connected UAVs. Shakhatreh *et al.* [20] analyzed the current civil applications of UAVs and their major challenges. In [21], a detailed review of all relevant research in which ML techniques have been used in UAV-based communications. In particular, a classification of these techniques according to the communication and network aspects in which they are implemented was given. Moreover, various research challenges related to each of the relevant areas were raised. In 2020, Boursianis *et al.* [7], reported the latest research on the application of UAVs and IoT technologies in smart agriculture. It also briefly outlines the key role of UAVs in various scenarios by describing the framework of the *ARAThOU5A* project as a use case. The work presented in [22], provided a review on swarm robotic behaviors and their applications. Current research platforms and industrial applications were described. Oubbati *et al.* [23] surveyed applications and future trends in softwarization of UAV networks (seeks answers to this specific question to be exact: How complicated tasks are handled by advanced software?). Coppola *et al.* [3] discussed the fundamental challenges that must be tackled to successfully develop swarms of micro air vehicles (MAV) for real-world operations. They also reviewed the requirements for conception, localization, and proper functioning of MAV. The work presented in [24] reviewed research conducted on imagery data acquired by UAVs for remote sensing purposes based on Deep

Learning (DL) models. For this, they studied the different types of sensors and their applications, as well as the fundamentals of DL models and their application to solve classification, object detection, and semantic segmentation problems in the field of remote sensing. Shahzadi *et al.* [25] highlighted the concept of 5G and beyond wireless communication, and illustrated recent research that focuses on UAV placement and the allocation of resources in UAV-assisted wireless communication. The work presented in [26] spotted the light on the role of AI methods to improve the performance of UAV networks. It covered the UAV swarm formation methods and presented a detailed overview of AI-enabled routing protocols, as well as the tools, public datasets, and remote experimentation infrastructure used to test these routing protocols. The authors in [27] review the use of UAVs in the sugarcane industry monitoring and management and discuss advantages and drawbacks of their use. Meanwhile, the paper [28] is restricted in presenting UAV use for agricultural purposes. It also examined the application of SLAM methods for precision agriculture practices in the greenhouse. Khelifi and Butun have presented the basic concepts of SUAV localization in [29]. They provide a limited overview of the localization techniques and systems used by SUAVs and their functioning principles. Therefore, this paper comes to complement the survey established in [29] by presenting a wide selection of papers, especially those from the last three years, so that all new developments in the literature are presented, compared, and discussed. In addition, this paper provides preliminaries of localization and path planning, which do not exist in [29]. Furthermore, the communication technologies

used in SUAV are also presented. Additionally, another set of outstanding issues related to new trends and future research directions are highlighted.

B. MAIN CONTRIBUTIONS OF THIS PAPER AND STRUCTURE

By no means, researchers in the UAV field lack a body of literature as a quite good number of survey articles have been presented in this area, but without covering deeply the state of the art of SUAVs for localization purposes. However, there is a clear need for a good summary with a current state of the art of SUAVs that surround the major localization aspects which are of prime importance in realizing real-world scenarios. This paper can help researchers and newcomers to enhance and broaden their overview of the field.

The contributions treated in this work are summarized as follows:

- Localization technologies, navigation and path planning systems for UAVs and SUAVs are briefly reviewed.
- State-of-the-art of localization/positioning SUAVs is presented.
- The challenges faced by SUAVs and future research directions are described.

1) ARTICLE ORGANIZATION

The rest of this paper is organized as follows: Section II presents a brief introduction of the principles of localization in UAV/SUAV. It further provides an overview of localization technologies of SUAVs and the existing path planning methods. Section III reviews the state-of-the-art localization systems and their potential for SUAVs. Future research directions are outlined in Section IV. Finally, the paper is concluded in Section V.

II. BACKGROUND

Before analyzing different localization systems used in SUAVs, it is important to first understand the basic concepts and conventional techniques of localization as well as the most popular wireless technologies used in the localization process. Also, when talking about localization it is very relevant to differentiate it from navigation and path planning methods, which will also be explained briefly in the following.

A. PRELIMINARIES OF LOCALIZATION

Localization specifies the system for calculating the position of an object. Any position is systematically associated with a reference system [30]. The process of obtaining the position or location is called positioning and/or geo-referencing [31]. However, a distinction is sometimes made between positioning and localization. Positioning refers to the process of determining the position of the object. Therefore, localization relates to the estimation of the position of this object by the reference system such as the infrastructure [11], [32]. In the context of SUAVs, the process of estimation of the position is used to localize a target or another UAV [19], [3].

In general, the estimation is based on the analysis of a measurable quantity with a corresponding model of the system, that describes the relation of this quantity compared to the desired one [32]. Various approaches are proposed in the literature to formulate the estimation problem and the observation model. All these approaches aim to extract as much information as possible from the available observations to raise the localization accuracy [3], [11], [19]. This latter refers to the accuracy of the position estimate concerning the actual position by describing the consistency of the estimate. It depends on the range measurement errors, the calibration of the UAV noise, its position in the network, the effects of random actions, imprecise models, and environmental conditions [29], [32]. Thereby, to measure the distance between the target and the receiver different methods have been proposed in the literature [30], [32]. For instance, Received Signal Strength (RSS) [30], Time Difference of Arrival (TDoA) [30], Time of arrival (ToA) [33], Time of Flight (ToF) [34], Angle of Arrival (AoA) [35], antenna array systems [36], [37], trilateration [35], triangulation [35], hyperbolic [32], hybrid [32], etc. Several previous articles already contain detailed descriptions of these methods and their characteristics; please refer to these articles for more details [30], [32], [35].

B. LOCALIZATION TECHNOLOGIES

To understand how the localization systems work, it is very valuable to firstly describe the mainly used technologies in this process. Currently, there are numerous wireless localization technologies used by the UAVs/SUAVs, depending on their environment type:

Inertial Navigation System (INS) [38] is an earlier navigation system that operates offline and has a triggered initial precise position; the following positions are calculated from that initial position by using a 3-axis accelerometer [39]. INS was followed by Global Navigation Satellite System (GNSS) later on [40], [41]. As mentioned in [41], GNSS is the most accurate positioning system that is used on earth today. It is not only utilized for the navigation and positioning of the UAVs but also by almost any kind of moving vehicle for the same purposes. There are various types as it is contributed and used by various countries from all over the world, such as the Global Positioning System (GPS) [41]. GPS is a satellite-based navigation system that is employed in a wide range of applications from mapping and vehicle navigation to surveying. It is the most popular and worldwide known system [41].

Before GPS systems were out there, cellular systems were being used for localization purposes [39]. Especially, cellular systems of all generations 2G, 3G, 4G, 5G because they provide higher data rates, more connectivity, better coverage and a wider range of services [5], [41]. In addition, they are very well suited with the triangulation method, as cellular towers can serve as fixed positioned beacons for the target location to be calculated [39].

Usage of gravitational fields in the localization and navigation purposes has been successfully used in the past. In [42], the feasibility of using prior gravity anomaly measurements

that are nautical mile apart for underwater simultaneous localization and mapping are shown. According to authors' finding, the prior gravity anomaly measurements, coupled with the developed tools (such as using particle filters), provided guidance to select optimal areas and missions for the AUV (autonomous underwater vehicles) could transit through towards minimal localization error at the goal location.

In the recent past, aerial navigation by magnetic map matching has been demonstrated as a viable GNSS-alternative navigation technique. Real-world demonstrations have shown the accuracy of 10s of meters over hour-long flights, but these flights required accurate magnetic maps which are not always available. Magnetic map availability and resolution varies all around the globe. Removing the dependency on prior survey maps is really important as it extends the benefits of aerial magnetic navigation to small unmanned aerial vehicles (sUAV) at lower altitudes where magnetic maps are especially under sampled or unavailable. For instance, in [43], a simultaneous localization and mapping (SLAM) algorithm is introduced which uses scalar magnetic measurements to constrain a drifting INS. The algorithm was then demonstrated on real magnetic navigation flight test data with a successful demonstration accuracy ($\tilde{1}$0s of meters) during a 100-minute flight without the use of a prior magnetic map.

In another work [44], authors have shown another usage of magnetic anomalies for indoor positioning algorithms, by presenting a publicly available dataset for the evaluations. The dataset includes Inertial Measurement Unit (IMU) and magnetometer measurements along with ground truth position measurements with an accuracy of cms.

Another interesting communication technology is Optical wireless communications (OWC) [39]. It used the spectrum of the light which requires direct Line-of-Sight (LoS) for communication. Hence, limited by the physical (terrain, landscape, etc.) and natural (fog, rain, etc.) obstacles. For instance, Infra-Red (IR) [45], Laser scanner or LIght Detection And Ranging (LIDAR) [45] which is mostly used in automated collision avoidance systems. It allows measuring distances by illuminating the target with laser light and then measuring the reflection with a sensor. Some other technologies used Radio Frequency (RF) [39], [45] such as Ultra-Wide Band (UWB), Radio Frequency Identification (RFID), Bluetooth, Wireless Fidelity (Wi-Fi), ZigBee/Z-Wave, and Low Power Wide Area Network (LPWAN). UWB is a radio technology that exploits a very low energy level for short-range, high-bandwidth communications over a large portion of the radio spectrum. It has traditional applications in non-cooperative radar imaging, as well as most recent applications, span target sensor data collection, and precision locating towards tracking applications. Owing to its very short pulse duration, UWB is a promising technology for ultra low power, precise ranging, and positioning applications. Since GNSS signals are mostly blocked and useless indoors, RFID has been offered to solve indoor localization [39] while
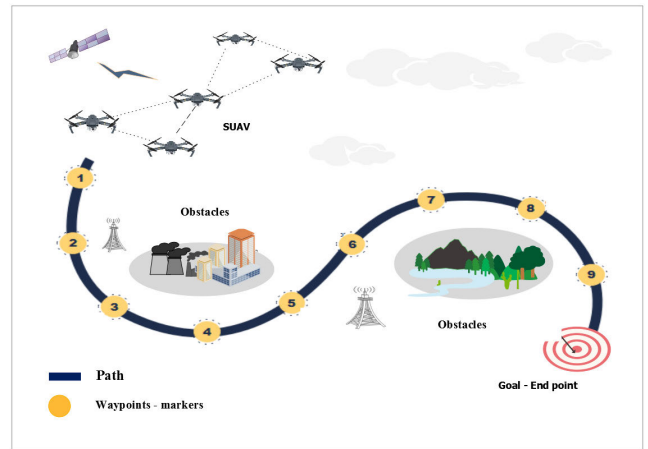

FIGURE 2. An example of simple path planing.

Bluetooth uses a 2.4 GHz radio frequency band and various applications of it can be found in the smart home, health, and sports industry.

As mentioned in [46], Bluetooth technology is employed by a UAV system to operate in short-range wireless for executing some tasks it is developed. The goal was to achieve an autonomous flight that is capable of carrying on different flight missions. Wi-Fi is an IEEE 802.11 based wireless network technology [39] used in-flight control of UAVs and real-time data transmission (such as photo, video, GPS data, etc.) between UAVs and devices on the ground. ZigBee/Z-Wave is a low-energy wireless protocol based on IEEE 802.15.4 standard commonly used in home/office automation, medical, and industrial applications that have low data rate transmission, require long battery life, and need secure networking [39].

Meanwhile, to further increase the positioning accuracy of UAVs, alternative solutions that exploit existing radio transmissions such as WiFi, ultra-wideband (UWB), or cellular networks for trilateration or triangulation with antenna arrays should be considered [37]. These advanced solutions significantly improve the accuracy of the localization system and reduce the required infrastructure [47].

In general, existing technologies yield advantages and restrictions. Thus, it is difficult to create cost-effective yet efficient localization solutions using a standalone technology [32]. Given the complementary characteristics of these various technologies, the integration of multiple technologies at once is becoming a trend to achieve reliable, continuous, accurate, and fault-free localization.

C. NAVIGATION AND PATH PLANNING METHODS

Navigation is defined as the process of guiding a user or an object to a target, usually by following a predefined path. For this, it is necessary to continuously repeat the process of localization and provide directions to follow a path or reach the target. Therefore, path planning in the context of UAVs is considered as following a trajectory (markers) in the air by flying from one position to another (see Figure 2).

Most methods of path planning use algorithms created for the decomposition of an area of interest to assess the one that should be used to give the optimal solution to determine the actual position. In particular, in applications of monitoring hazardous environments, distributed tracking and detection are mainly typical SUAV tasks. However, to ensure safe mission accomplishment, SUAVs need to plan their paths properly. They have to avoid collisions with surrounding obstacles by maintaining a formation distance between each UAV of the team. Additionally, they compute their positions and orientations relative to each other according to global or local information and/or throughout a reference map. Besides, navigation depends on the availability of the environment map and it only starts once the map is built. Hence, it is necessary to use the location information correctly to assess the positions of UAVs while following a safe and quick free-collision flight path to reach the target positions.

Some pioneering methods such as RRT [48] and *RRT* ∗ [49] use re-planning algorithms to avoid obstacle-filled and complex environments. While these methods can achieve safe and fast planning paths, they are too slow and very time-consuming. Hence, UAV flight path delay is a major constraint that requires real-time planning. Furthermore, planning paths for a large team of UAVs is highly computational and time-demanding. If the path planning is based on local information and an estimation of the status of UAVs to dynamically plan the trajectory, this is a local path planning [15]. In contrast, planning a global path implies the localization of the source and destination of the target in a built-up map to calculate an initial path. Consequently, global path planning involves the use of a static map while for local path planning a dynamic real-time map is constructed. This local dynamic map (LDM) contains several layers of information that can be used to auto-adapt the location and improve the efficiency of maintaining this specific dynamic flight path. Therefore, some works rely on estimating the motion of UAVs to build the map by using only data from onboard visual sensors such as cameras, LiDAR sensors, 3D sensors, and so on [15]. While others opt for the Simultaneous Localization and Mapping (SLAM) approach [50]. The latter, allows a UAV to localize itself in an unknown environment by merging different sources of information while moving and at the same time building a map without any prior information.

Recently, machine learning (ML)/artificial intelligence (AI) based approaches have been an attractive tool for UAVs path planning [51]. They have a great ability to handle the uncertainty present in the environment with low computational complexity [52]. In addition, ML/AI methods provide an adaptive structure that is easy to implement and which is suitable for SUAVs collision-free paths to safely reach their mission goals as they efficiently model this complex optimization problem.

In summary, as SUAVs become more autonomous, they have to figure out feasible paths for the whole swarm to operate at high levels of autonomy and without any human interaction.

III. STATE OF THE ART LOCALIZATION SYSTEMS AND THEIR POTENTIAL FOR SUAVS

Many excellent studies and papers have been published to tackle the localization of SUAVs issues. In this section, state-of-the-art research efforts in this field are presented. Existing approaches and the most popular localization techniques are reviewed according to two main categories namely: the positioning techniques, and the communication architectures. Further, scalability is the key milestone towards the application of SUAVs in large-scale networks. As such, this paper elaborated aforementioned important aspects in each category that is presented.

A. THE POSITIONING TECHNIQUES

Flying a swarm of UAVs simultaneously implies the strict requirement to maintain a safe and controlled formation distance between them during their missions. For this, they must continuously adapt and estimate their positions according to the flight conditions and the surrounding environment [4], [11]. Therefore, such constraints introduce significant challenges that complicate their localization process and that of the targets as well [3], [19]. Also, a distinction must be made between absolute localization (i.e., relative to a map) and relative localization (i.e., relative to other drones in the swarm) during the position calculation process. In what follows, several prospective techniques used in the literature on UAV swarm localization are briefly outlined while the state of the art related to the use of these techniques to compute their positions are highlighted. Additionally, five classes are identified: Computer vision, measurement requirements, Cooperative localization, Intelligent localization, and Place-based localization techniques.

1) COMPUTER VISION TECHNIQUES

Computer vision techniques remain one of the most important and challenging methods in the literature; Please refer to [14], [15], which are useful surveys on computer vision-based systems for mobile robotics and UAVs.

Meanwhile, the fast growth and the proliferation of external cameras, all types of sensors, and other embedded UAV systems have led to greater volumes of real-time aerial images and information under different environmental conditions (see Figure 3). Consequently, a significant enhancement in the estimation of the UAVs' positions and mapping has been demonstrated.

Further, according to the purposes of UAVs swarm tasks, two main classes of computer vision can be distinguished depending on their environment. The first is where the environment is to be explored such as target recognition, navigation, coverage, and mapping. The second is only to be traversed or exploited. For example, crossing an obstacle field with a prescribed goal or desired formation [2].

However, the scalability of methods in these categories is limited by the computational power, the quality of the onboard sensors and cameras, as well as the energy
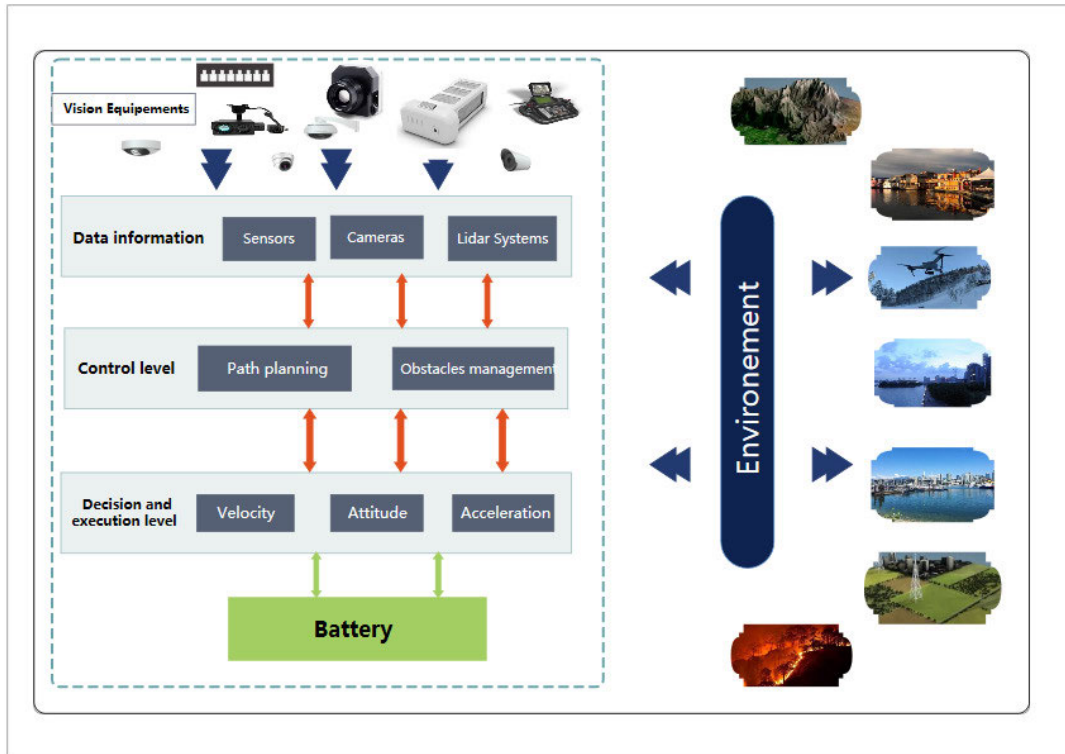
FIGURE 3. Computer vision system bricks.

consumption of the UAVs. Thus, such vision-based techniques pose a high computational complexity to communicate and collect information and measurements needed to perform their assigned tasks.

Tang *et al.* in [53] proposed a vision-aided flocking system for multiple UAVs which is based on LiDAR sensors and installed onboard cameras. It is one of the recent works that addressed the issue of the GPS-denied environment. This system tracks and collects the information and, through the SLAM techniques, it can learn and explore the environment. Using a UAV platform, Zhao *et al.* in [54] presented a real-time vision system for autonomous cargo transfer. They employ robust algorithms for ellipse detection and tracking and single-circle-based position estimation. However, one limitation of this approach is that it relies on some standard shapes as backup reference points for detecting targets, which makes it difficult to be extended to large uncontrolled environments, and thus limits its scalability. So far, modeling the visual world and performing its three-dimensional reconstruction in all its rich complexity is far from being an easy task. Consequently, this subject has been a hot spot for research and continues to attract attention.

2) MEASUREMENT REQUIREMENTS

Most of the current and ongoing techniques emerging from the UAV swarm localization literature can be classified according to their data measurement requirements into two main categories, namely range-based and range-free.

In **range-based** localization schemes, SUAVs use the connectivity information from the UAVs and/or anchor-related data to estimate their positions. They have very accurate position determination because they require complex equipment to obtain angle and/or distance measurements [55]. Unlike range-based schemes, **range-free** approaches consume less energy and computing capacity. They are less complex to implement. Hence, they are more attractive but less accurate as they provide relative positions. In addition, they are more robust and scalable as they do not require a high computation load.

So far, the positions of the UAVs are considered known and it might be thought that it is unnecessary to calculate them since they can be measured directly using onboard INS devices and Global Positioning Systems (GPS) [56]. The integration of INS measurements with the utmost localization technique GPS as well as updated velocity measurements, allows accurate positions. These positions can not be acquired in areas where the GPS signal is obscured [57]. Therefore, alternative solutions can be considered. For example, the use of visual localization based on optical flow technologies or visual recognition pastern [58]. These solutions eliminate the requirement of using any external localization system. Saska *et al.* in [59] investigate the self-stabilization of SUAVs by using a visual system in an indoor and outdoor environment, and without recourse to a GPS. Rubenstein *et al.* in [60] employed anchors in a large swarm of autonomous robots to infer their locations. They selected four robots

as anchors (robots that know their locations) to which the others are relatively localized by using the trilateration of infrared signals. In [61], Ledergerber *et al.* study the use of a UWB localization system by a set of anchors that periodically send signals to UAVs. The latter are localized to the signals received from the anchors through TOA (Time Of Arrival) or TDOA (Time Difference Of Arrival). In [62], a distributed collaborative autonomous generation (DCAG) technique based on the deep neural network (DNN) is proposed to localize the target by using the UAV swarms. Thanks to AOA (angle of arrival) measurements that depend on the target-receiver distance, they adjust heading angles for optimal swarm deployment. Moreover, this sophisticated mechanism increases the network complexity and leads to a high computational cost. Among many range-based techniques, received signal strength RSS is one of the cheapest ways to measure the distance. In addition, several alternatives based on antenna arrays to traditional positioning techniques have recently been explored [37], [63], [64]. For instance, the work presented in [63] used the target guiding technology based on region division for search and rescue purposes. It used wireless sniffers to collect RSSI and AOA from a target, while the AOA data is obtained through an antenna array method. Stojkoska *et al.* in [65] combine Multi-dimensional Scaling (MDS) method and Weighted Centroid Localization (WCL) to convert the RSS signals between the-mini UAV into distances. The localization accuracy claimed in this work is less than 5% of the radio range in a non-complex environment. In [66], the authors explored the use of Wi-Fi RSS to estimate the distance between UAVs by using a Boid-based flocking model.

3) COOPERATIVE LOCALIZATION METHODS

The use of cooperative localization (CL) in mobile robotics has attracted considerable interest over the last decade [67]. They have been widely studied in UAV networks as the basic concept behind CL is to employ multiple UAVs as a team to help them find their positions and orientations relative to each other [68]. This team collaboration improves the accuracy of localization by combining different measurements derived from various estimations of positions. However, the methods by which the measurements are combined, collected and shared between UAVs vary based on the controller processing [69]. Therefore, these promising techniques can be classified into centralized where a single unit controls all the swarm as one system [3] and distributed in which each UAV independently computes its location, as shown in Figure 4.

Several localization approaches are presented in the literature for SUAVs that apply CL. One of the relevant works was proposed for a team of cooperative robots in [70]. The authors used a combination of the Maximum Likelihood Estimation (MLE) method and numerical optimization to improve robot localization using information from relative observations among the team. In [71], [72] methods based on Extended Kalman Filter (EKF) were introduced. The approach in [71] fuses proprioceptive and exteroceptive
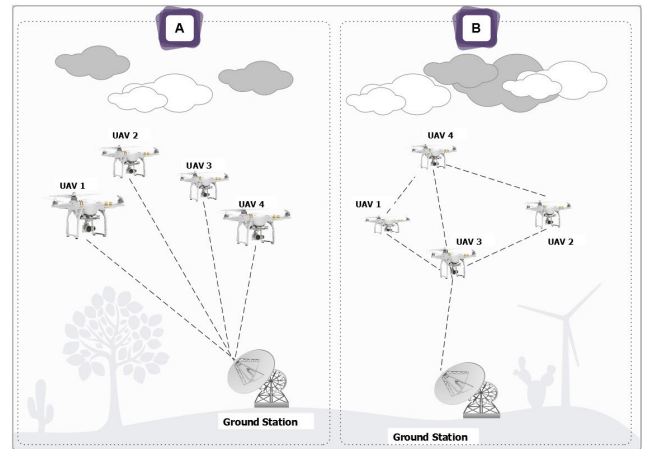

FIGURE 4. The cooperative localization architecture. A: Centralized method; B: Distributed method.

measurements contained in the relative observations between robots. In [72], the authors employ a distributed Consensus Extended KFs (CEKF) for position and velocity state estimation of SUAV. The approach was tested on a swarm of five aircraft equipped with heterogeneous onboard sensors. Nerurkar *et al.* [73] proposed an algorithm that distributes the computations among the team of robots and constructs a distributed MAP-based CL. However this approach requires synchronous communication among the robot team whereas, this may not be possible in harsh environments where they must tolerate communication failures. The consensus theory, according to which a team of UAVs controls the processing system in a distributed way to converge towards a common agreement and value, was introduced in [74]. In [74], decentralized sliding mode controllers (SMCs) which allow the members of SUAVs to reach a consensus in altitude, handing, and angles were designed. The work proposed in [75] tackled the problem of formation keeping by applying the backstepping and graph theory methods in cooperative control between UAVs. Although this approach allows rapid dynamic response and low tracking error when tracking the virtual leader, it only takes into account the formation system of the UAVs from their take-off to their assembly process, without addressing the formation vortex effect, the desired mission goal, the shape and the quality of each UAV.

As stressed in [76], when it comes to the large-scale networks with limited centralization ability, it is not possible to employ a centralized entity to perform joint real-time decision making for the entire network. This introduces the scalability challenges, while multi-agent reinforcement shows the opportunity to cope with theses challenges and extend the intelligent algorithm to cooperative large-scale network.

4) INTELLIGENT LOCALIZATION STRATEGIES

Artificial intelligence (AI)-based localization techniques using machine learning (ML) are key enabler approaches for providing SUAVs and target positions. Such methods are able

of learning environmental properties and quickly adjusting the behavior of SUAVs. Although, their high mobility, they can autonomously enhance their performances with AI/ML methods to provide more accurate estimates of their positions. Yet, even though they provide huge benefits, a critical constraint of these techniques is the arduous adaptation process to dynamic conditions, as they have to handle the growing amount of all training data which highly affects their scalability. Added to that, these methods increase the computational complexity and cannot be executed on board due to the limited computational capacity to learn the model and decide the appropriate policy actions.

The localization problem is formulated as a multidimensional optimization problem that can be solved using numerous ML techniques [3], [30]. To date, evolutionary and bio-inspired AI methods are the most studied techniques in the literature [21], as illustrated in Figure 5 (the plotted data is collected from [77]).
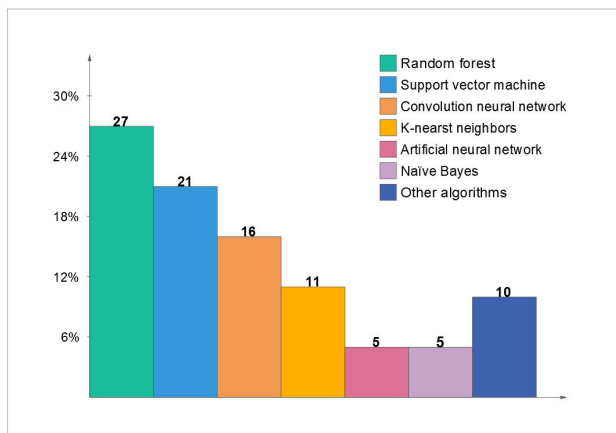

FIGURE 5. AI/ML algorithms used in UAV research.

Furthermore, the localization of UAVs is generally related to the target tracking with a predefined deployment and/or the optimal one by a designed path planning. Thus, many works have investigated the use of AI/ML in path planning. In the following, some relevant AI/ML-based UAV swarm contributions are described. In [78], the authors analyze how UAVs perform their task by combining PSO with the Hungarian algorithm. The latter is used to quickly solve the assignment problem, while PSO is adopted to iteratively compute the optimal relative position relationship, whereby each target position is assigned to a UAV. In [79], the authors merged direct and indirect Reinforcement Learning (RL) estimates by applying a consensus-based fusion method to generate the relative positions in two dimensions. Their proposed RL estimation was applied to propose a distributed formation control. The work presented in [80] focused on the vision-based collision avoidance for UAVs. The proposed system distributed calculations among multiple UAVs to perform object tracking, detection and collision avoidance. It uses deep CNNs to fuse the images from the UAVs' cameras.

Then, it built a recurrent neural network (RNN) to obtain high-level image features for object tracking and to extract low-level image features for noise. Opromolla *et al.* in [58], used a machine learning framework that exploited SUAVs in mission-critical scenarios. This framework is based on the You Only Look Once (YOLO) object detection system [81], which is a DL-and visual-based detection/tracking system. It used training knowledge to predict the expected position of a nearby UAV and allows vision-based detection to focus on the expected region, which simplifies the task. Please refer to this survey [82] for more other optimization algorithms based on AI/machine learning techniques.

5) PLACE-BASED LOCALIZATION TECHNIQUES

Localization techniques can also be grouped into two major categories due to where the localization takes place; indoor vs. outdoor. The most distinguished among these is the usage of GNSS aid during the localization of the outdoors for precise estimation. However, GNSS connectivity in congested urban areas with a dense distribution of skyscrapers might be challenging even for outdoor navigation. In the same manner, localization is a real challenge for indoor environments. Hence GNSS signals are blocked by the thick walls, concrete, and steel, some other methods are used for indoor localization. For **outdoor localization**, other than very well-known techniques/technologies, some other methodologies are also being proposed. For instance, Hoshiba *et al.* authors designed and implemented a UAV-embedded microphone array system for sound source localization in outdoor environments. The concept is based on exploiting sound information as an aid for localization of the UAVs in search and rescue activities to compensate for poor visual information [83].

Indoor localization and navigation of UAVs constitute a critical part of autonomous flight and automated visual inspection of elements in continuously changing environments such as construction sites. In [84], Kayhani *et al.* discussed the implementation and performance assessment of an Extended Kalman Filter (EKF) for improving the estimation process of a previously developed indoor localization framework that has used visual markers.

To enhance the precision for indoor/outdoor localization and navigation, usage of SUAVs in which UAVs share useful information collaboratively, is a good candidate solution and that offers flexible scalability. For instance, Misra *et al.* discussed a scheme in which the swarm of UAVs forms an aerial IoT network [85]. In the proposal, UAVs opportunistically share information whenever they are in the communication range with each other to enhance overall consensus-ed data.

B. THE COMMUNICATION ARCHITECTURES

The use of SUAVs has spread to many applications and use-cases such as in environmental monitoring (both for civilian or military purposes), target tracking, medical applications, disaster management [18], [20], [22]. Consequently, a variety of localization approaches using different communication architecture have been proposed to achieve different goals
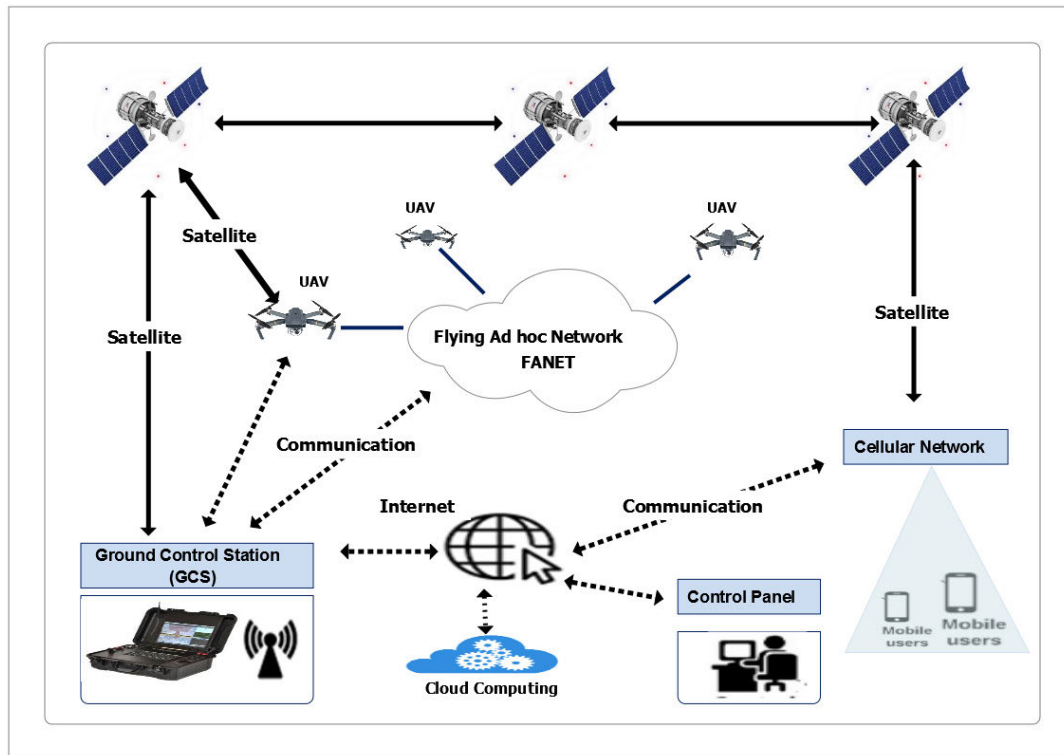
FIGURE 6. SUAV communication architecture.

(see Figure 6). In the following subsections, the major contributions proposed in the literature related to this subject are investigated.

1) INFRASTRUCTURE BASED SWARM

A flying ad hoc network (FANET) is a group of UAVs communicating with each other with no need for an access point. At least one of the UAVs in FANET is connected to a ground station or satellite for acting as a central authority to carry out data offloading missions. UAVs in a FANET carry out their missions without human help, just like an auto-piloted vehicle. In recent years, many researchers have focused on FANETs due to low-cost circuitry and lighter payload owing to the ad-hoc networking. FANETs are being used in various applications, such as military and civil applications, and disaster monitoring (such as avalanches and wildfires) [86].

A WANET is a wireless ad-hoc network that doesn't depend on existing infrastructure to constitute the network. As such, switches, routers, and access points are not needed for the operation of an ad-hoc network. On contrary, nodes establish connections dynamically due to dynamic routing algorithms.

A FANET, is a flying WANET in which all UAVs are part of a network of communications that is established between the UAVs such as the wireless nodes in a WANET.

The utmost advantage of FANET is its autonomy which is based upon distributed-decision making. Direct (one-to-one) communication in between the UAVs allows

distributed-decision making. This also enables built-in autonomy as the entire swarm will not be dependent on a central infrastructure-based decision engine to execute the preassigned tasks. Some disadvantages of FANET are size, weight, and power-related implications.

Scalability of the FANETs can be managed automatically and seamlessly due to ad-hoc nature of the network configuration.

To establish a FANET, network hardware along with the software is required to onboard each UAV. The distance over which UAVs can reliably communicate with each other in a FANET limits the networking-related implementation. The re-configuration of the SUAV routing algorithms dynamically is a challenging task as it might cause packet losses. Therefore, finding ways of reliable FANET communication is needed, especially for the critical SUAV applications in which accuracy of the UAV telemetry data is important. In this regard, Kim *et al.* [87] proposed a hybrid architecture of an infrastructure-based network making use of cellular wireless communications infrastructure and establishing network protocol between drones without the intervention of a GCS.

Owing to the versatility of the UAVs, FANET is a promising technology for future networked systems. One example of the versatility of the UAVs is the high mobility, which will enable fast and frequent topological variations of the FANET (this is one of the most distinguishing features of FANETs). Henceforth, the topology management (suiting the path and

TABLE 2. Qualitative comparison of SUAVs localization techniques.

Reference	Category	Features	Highlights
Ref. [53]	computer vision	LiDAR sensors & SLAM technique	vision-aided flocking system in GPS-denied environments
Ref. [54]	computer vision	Anchors & ellipse detection	real-time vision system for autonomous cargo transfer
Ref. [59]	measurement-based	self-stabilization	the self-stabilization of SUAVs is achieved by using a visual system in an indoor and outdoor environment without the recourse to a GPS system.
Ref. [60]	measurement-based	trilateration with anchors	employed anchors in a large swarm of autonomous robots to which the others are relatively localized by using the trilateration of infrared signals.
Ref. [62]	measurement-based	angle of arrival (AoA)	a DCAG technique based on the DNN is proposed to localize target by using the UAV swarms; owing to the AOA measurements that depend on the target-receiver distance, they adjust heading angles for optimal swarm deployment.
Ref. [65]	measurement-based	MCL & WCL	conversion of the RSS signals between the-mini UAV into distances.
Ref. [66]	measurement-based	RSS	the use of Wi-Fi RSS to estimate the distance between UAVs by using a Boid-based flocking model.
Ref. [70]	cooperative	MLE & numerical optimization	localization of the cooperative robots
Ref. [71]	cooperative	EKF	fusing proprioceptive and exteroceptive measurements
Ref. [72]	cooperative	CEKF	position and velocity state estimation of SUAVs
Ref. [73]	cooperative	MAP-based CL	requires synchronous communication among the robot team
Ref. [74]	cooperative	decentralized-SMC	SUAV reach a consensus in altitude, handing, and angles
Ref. [75]	cooperative	back-stepping & graph-theory	rapid dynamic response and low tracking error
Ref. [58]	intelligent	ML	is based on YOLO object detection system
Ref. [78]	intelligent	PSO	optimal relative position
Ref. [83]	outdoor	UAV-embedded microphone array system	exploiting sound information as an aid for localization of the UAVs in search and rescue activities to compensate for poor visual information
Ref. [84]	indoor	EKF	improving the estimation process of a previously developed indoor localization framework that have used visual markers
Ref. [85]	indoor/outdoor	collaborative	UAVs opportunistically share information whenever they are in communication range of each other to enhance overall consensus-ed data
Ref. [86]	infrastructure	semi-autonomous	GCS is equipped with a transmitter/receiver that transmits command messages and collects telemetry data to/from the managed UAVs.
Ref. [87]	FANET	cellular communication	a hybrid architecture of an infrastructure-based network making use of cellular wireless communications infrastructure and establishing network protocol between drones without intervention of a GCS.

on-wards movements of the UAVs) constitutes one of the most critical issues in FANET [87].

C. SUMMARY
Table 2 summarizes the reviewed systems in the previous section. It shows some of the key outstanding features possessed by the localization techniques of SUAVs. The latter is comprehensively compared with respect to their features.

IV. FUTURE RESEARCH DIRECTIONS
Even though the fast emergence of SUAVs in the military, industrial and civilian applications and in many emerging areas, their proficient use poses several challenges, especially in their localization process. Although these emerging technologies bring new opportunities in many areas, significant changes in the localization mechanisms of SUAVs are taking place. In this section, a set of outstanding issues related to new trends are summarized and discussed, as well as relevant future research directions are highlighted.

- ***Resource Management in SUAVs*** Renewable energies and green communication are promising solutions for power-supplying and energy-saving SUAVs, which

enables them to autonomously operate without any assistance and physical intervention. This presents great potential for their localization system as they provide a self-sustainable ecosystem by harvesting energy from the environment and continuously producing and supplying power to their system [75]. Therefore, the autonomy of the UAVs is no longer hampered by their energy suppliers and it is affordable to improve the localization through additional hardware such as sensors, cameras, etc. Hence, future research must be directed toward efficiently managing the restricted UAV resources by designing hardware and technologies that enhance their endurance, recharging batteries and improved their localization precision [88]. On the other hand, it is also essential to find the best trade-off in energy consumption between SUAV members to increase their flight time with the aim to extract as much information as possible from the available observations to raise their localization accuracy.

- ***Localization over 6G, B5G, 5G and telemetry***. The proliferation of mobile services via B5G/5G/6G technologies will enable SUAVs to use localization via telco

providers rather than GNSS [89]. Usage of telemetry data will be also seamlessly possible for the GCS, by the dual telecommunication channel provided by the telco services [90]. Moreover, mmWave and terahertz communication are new concepts that curtail the spectrum problems and capacity limitations of current communication. In the coming years, these emerging technologies may make it possible to provide accurate localization as they offer larger bandwidth and pervasive high-speed access in complex environments. Therefore, future SUAVs require to support all these leading-edge technologies in the design of their localization systems as they constitute the next generation of networks and communication trends.

- *Intelligent Mobile fog and edge computing (FEC)*. The next-generation computer systems will support edge and fog computing nearby the perimeters of the network to enhance the user experience and decrease the round-trip communication delay [91]. However, the influence of edge/fog computing on localization has not been investigated. For SUAVs, this might be one of the nearest ground stations or one of the UAVs with enhanced hardware installed onboard in order to provide low-latency location and localization solutions [92]. Therefore, there is great industrial and academic potential to integrate edge/fog computing in the localization of UAVs that needs to be further investigated.

- *SUAVs-enabled Internet-of-Everything (IoE)*. The Internet of Everything (IoE) [93], [94] is a paradigm on the cusp of revolutionizing the technological landscape. It enables the delivery of a wider range of information by connecting many ubiquitous devices to the Internet. Then, it uses artificial intelligence to analyze the massive amount of collected data. For example, the work presented in [95] reviews the use of UAVs for the target localization and surveillance applications without addressing the research tackling their integration in the future of IoE. Therefore, the amalgamation of IoE to enhance SUAVs localization systems is still in its infancy and needs to be investigated.

- *SUAVs-supported health and medical services*. The last years have witnessed a continuous and rapid change in the health sector. With the latest COVID-19 outbreak [96], real challenges were raised in terms of exploiting the infrastructure, pandemics-based data, and knowledge to counter this threat and help society to cope with fall-back. For example, the paper [97] has examined the relation between UAVs and multiple BANs in data collection but has not involved the localization aspect of UAVs in their work. Therefore, it is essential to conduct thorough research on the potential of integration SUAVs for the delivery of medical supplies and patients monitoring.

- *Cyber-security and Blockchain*. Cyber-security of information systems has been a great concern in the last decade. For instance, many IDS schemes have been

TABLE 3. List of abbreviations.

Abbreviation	Explanation
AOA	Angle Of Arrival
CL	Cooperative localization
DCAG	Distributed Collaborative Autonomous Generation
DNN	Deep Neural Network
DP	Dynamic Programming
EKF	Extended Kalman Filter
FANET	Flying Ad-hoc Network
GCS	Ground Control Station
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
INS	Inertial Navigation System
IoD	Internet of Drones
IoE	Internet of Everything
IoT	Internet of Things
ITS	Intelligent Transportation System
LDM	local dynamic map
LIDAR	LIght Detection And Ranging
LoS	Line of Sight
IR	Infra-Red
MDS	Multi-dimensional Scaling
FEC	Mobile fog and edge computing
ML	Machine learning
M2M	Machine to Machine (communications, etc.)
OWC	Optical wireless communications
PSO	Particle Swarm Optimization
RF	Radio Frequency
RFID	Radio Frequency IDentification
RSS	Received Signal Strength
SLAM	Simultaneous Localization And Mapping
SMC	Sliding Mode Controllers
SUAV	Swarm Unmanned Aerial Vehicle
TOA	Time Of Arrival
TDOA	Time Difference Of Arrival
UAV	Unmanned Aerial Vehicles
UWB	Ultra Wide Band
VLC	Visible Light Communications
WANET	Wireless Ad-hoc NETwork
WCL	Weighted Centroid Localization
YOLO	You Only Look Once

proposed not only for WSNs [98], but also for the recent IoT networks [99]. SUAVs and their ground stations constitute a flying IoT network, which is vulnerable to various cyber-attacks such as DoS, jamming, network-flooding, etc. Therefore, serious measures need to be employed, using the aforementioned IDS for mitigation, and intrusion prevention mechanisms like authentication and access control. Moreover, as discussed in [100], Blockchain systems are proposed as a security mechanism to be employed by IoT as well as in SUAV for localization purposes. Thus, the application of Blockchain security solutions to SUAVs is an open research area to be investigated, especially for the localization and/or logging of the flight paths.

V. CONCLUSION

In today's automated and enhanced world, everything technological is becoming more autonomous and self-driven,

applications can be thought of ranging from autonomous cars/trucks to delivery drones. In the case of drones and UAVs, when autonomous smart decision and mobility is executed in flocks, it requires execution of commands in a more coordinated and collaborative fashion. As an example, this paper presents SUAVs; a flock of UAVs that are collaboratively moving and executing their preassigned tasks for the goodness of humans. Furthermore, the paper presents communication technologies that are aiding localization, as well as path planning methods and an up-to-date overview of research efforts on localization/positioning systems for SUAVs. Finally, it highlights challenges, issues, and future research directions.

Authors of this article project that SUAVs will be a key tool in providing disrupting services and innovative solutions for the benefit of mankind, such as from automated medicine deliveries by the pharmacies towards providing remote fermentation to the crops of precision agriculture.

APPENDIX
ABBREVIATIONS AND ACRONYMS
List of abbreviations are listed in Table 3.

ACKNOWLEDGMENT

REFERENCES
[1] (Mar. 2021). *Global Market for Commercial Applications of Drone Technology Valued at Over 127bn*. [Online]. Available: https://press.pwc.com/

[2] S.-J. Chung, A. A. Paranjape, P. Dames, S. Shen, and V. Kumar, "A survey on aerial swarm robotics," *IEEE Trans. Robot.*, vol. 34, no. 4, pp. 837–855, Aug. 2018.

[3] M. Coppola, K. N. McGuire, C. De Wagter, and G. C. H. E. de Croon, "A survey on swarming with micro air vehicles: Fundamental challenges and constraints," *Frontiers Robot. AI*, vol. 7, p. 18, Feb. 2020.

[4] G. Chmaj and H. Selvaraj, "Distributed processing applications for UAV/drones: A survey," in *Progress in Systems Engineering: Proceedings of the Twenty-Third International Conference on Systems Engineering*, vol. 366. Springer, 2014.

[5] M. Alwateer, S. W. Loke, and A. M. Zuchowicz, "Drone services: Issues in drones for location-based services from human-drone interaction to information processing," *J. Location Based Services*, vol. 13, no. 2, pp. 94–127, 2019.

[6] W. Zafar and B. M. Khan, "Flying ad-hoc networks: Technological and social implications," *IEEE Technol. Soc. Mag.*, vol. 35, no. 2, pp. 67–74, Jun. 2016.

[7] A. D. Boursianis, M. S. Papadopoulou, P. Diamantoulakis, A. Liopa-Tsakalidi, P. Barouchas, G. Salahas, G. Karagiannidis, S. Wan, and S. K. Goudos, "Internet of Things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review," *Internet Things*, vol. 18, May 2022, Art. no. 100187.

[8] J. N. Yasin, S. A. S. Mohamed, M.-H. Haghbayan, J. Heikkonen, H. Tenhunen, and J. Plosila, "Unmanned aerial vehicles (UAVs): Collision avoidance systems and approaches," *IEEE Access*, vol. 8, pp. 105139–105155, 2020.

[9] A. K. Sivakumar, M. H. C. Man, H. Liu, and K. H. Low, "Collision severity evaluation of generalized unmanned aerial vehicles (UAVs) impacting on aircraft engines," in *Proc. Int. Conf. Unmanned Aircr. Syst. (ICUAS)*, Jun. 2021, pp. 1240–1247.

[10] I. Ioannidis, "Unmanned aerial vehicles and remote sensing in search and rescue missions in Sweden," KTH, Stockholm, Sweden, Tech. Rep. TRITA-ABE-MBT 18475, 2018, p. 69.

[11] S. Hayat, E. Yanmaz, and R. Muzaffar, "Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 4, pp. 2624–2661, 4th Quart., 2016.

[12] N. H. Motlagh, T. Taleb, and O. Arouk, "Low-altitude unmanned aerial vehicles-based Internet of Things services: Comprehensive survey and future perspectives," *IEEE Internet Things J.*, vol. 3, no. 6, pp. 899–922, Dec. 2016.

[13] J.-J. Wang, C.-X. Jiang, Z. Han, Y. Ren, R. G. Maunder, and L. Hanzo, "Taking drones to the next level: Cooperative distributed unmanned-aerial-vehicular networks for small and mini drones," *IEEE Veh. Technol. Mag.*, vol. 12, no. 3, pp. 73–82, Sep. 2017.

[14] C. Kanellakis and G. Nikolakopoulos, "Survey on computer vision for UAVs: Current developments and trends," *J. Intell. Robot. Syst.*, vol. 87, no. 1, pp. 141–168, Jul. 2017.

[15] Y. Lu, Z. Xue, G. S. Xia, and L. Zhang, "A survey on vision-based UAV navigation," *Geo-Spatial Inf. Sci.*, vol. 21, no. 2, pp. 21–32, 2018, doi: 10.1080/10095020.2017.1420509.

[16] B. Li, Z. Fei, and Y. Zhang, "UAV communications for 5G and beyond: Recent advances and future trends," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2241–2263, Apr. 2019.

[17] Y. Zeng, J. Lyu, and R. Zhang, "Cellular-connected UAV: Potential, challenges, and promising technologies," *IEEE Wireless Commun.*, vol. 26, no. 1, pp. 120–127, Feb. 2019.

[18] A. Tahir, J. Böling, M.-H. Haghbayan, H. T. Toivonen, and J. Plosila, "Swarms of unmanned aerial vehicles—A survey," *J. Ind. Inf. Integr.*, vol. 16, Dec. 2019, Art. no. 100106.

[19] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, and M. Debbah, "A tutorial on UAVs for wireless networks: Applications, challenges, and open problems," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2334–2360, 3rd Quart., 2019.

[20] H. Shakhatreh, A. H. Sawalmeh, A. Al-Fuqaha, Z. Dou, E. Almaita, I. Khalil, N. S. Othman, A. Khreishah, and M. Guizani, "Unmanned aerial vehicles (UAVs): A survey on civil applications and key research challenges," *IEEE Access*, vol. 7, pp. 48572–48634, 2019.

[21] P. S. Bithas, E. T. Michailidis, N. Nomikos, D. Vouyioukas, and A. G. Kanatas, "A survey on machine-learning techniques for UAV-based communications," *Sensors*, vol. 19, no. 23, p. 5170, 2019.

[22] M. Schranz, M. Umlauft, M. Sende, and W. Elmenreich, "Swarm robotic behaviors and current applications," *Frontiers Robot. AI*, vol. 7, p. 36, Apr. 2020.

[23] O. Sami Oubbati, M. Atiquzzaman, T. Ahamed Ahanger, and A. Ibrahim, "Softwarization of UAV networks: A survey of applications and future trends," *IEEE Access*, vol. 8, pp. 98073–98125, 2020.

[24] L. P. Osco, J. M. Junior, A. P. M. Ramos, L. A. de Castro Jorge, S. N. Fatholahi, J. de Andrade Silva, E. T. Matsubara, H. Pistori, W. N. Gonçalves, and J. Li, "A review on deep learning in UAV remote sensing," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 102, Oct. 2021, Art. no. 102456.

[25] R. Shahzadi, M. Ali, H. Z. Khan, and M. Naeem, "UAV assisted 5G and beyond wireless networks: A survey," *J. Netw. Comput. Appl.*, vol. 189, Sep. 2021, Art. no. 103114.

[26] A. Rovira-Sugranes, A. Razi, F. Afghah, and J. Chakareski, "A review of AI-enabled routing protocols for UAV networks: Trends, challenges, and future outlook," *Ad Hoc Netw.*, vol. 130, May 2022, Art. no. 102790.

[27] N. Amarasingam, A. S. A. Salgadoe, K. Powell, L. F. Gonzalez, and S. Natarajan, "A review of UAV platforms, sensors, and applications for monitoring of sugarcane crops," *Remote Sens. Appl., Soc. Environ.*, vol. 26, Apr. 2022, Art. no. 100712.

[28] M. F. Aslan, A. Durdu, K. Sabanci, E. Ropelewska, and S. S. Gültekin, "A comprehensive survey of the recent studies with UAV for precision agriculture in open fields and greenhouses," *Appl. Sci.*, vol. 12, no. 3, p. 1047, Jan. 2022.

[29] M. Khelifi and I. Butun, "Swarm unmanned aerial vehicles (SUAVs): A comprehensive analysis of localization, recent aspects, and future trends," *J. Sensors*, vol. 2022, pp. 1–10, Feb. 2022.

[30] M. Khelifi, S. Moussaoui, S. Silmi, and I. Benyahia, "Localisation algorithms for wireless sensor networks: A review," *Int. J. Sensor Netw.*, vol. 19, no. 2, pp. 114–129, 2015.

[31] A. Chakraborty, E. Chai, K. Sundaresan, A. Khojastepour, and S. Rangarajan, "SkyRAN: A self-organizing LTE RAN in the sky," in *Proc. 14th Int. Conf. Emerg. Netw. Exp. Technol.*, Dec. 2018, pp. 280–292.

[32] Y. Li, Y. Zhuang, X. Hu, Z. Gao, J. Hu, L. Chen, Z. He, L. Pei, K. Chen, M. Wang, X. Niu, R. Chen, J. Thompson, F. M. Ghannouchi, and N. El-Sheimy, "Toward location-enabled IoT (LE-IoT): IoT positioning techniques, error sources, and error mitigation," *IEEE Internet Things J.*, vol. 8, no. 6, pp. 4035–4062, Mar. 2021.

[33] F. Gustafsson and F. Gunnarsson, "Positioning using time-difference of arrival measurements," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, vol. 6, Apr. 2003, p. 553.

[34] G. Zhao, D. Wang, and M. Fattouche, "Time sum of arrival based BLUE for mobile target positioning," *Adv. Sci. Lett.*, vol. 4, no. 1, pp. 165–167, Jan. 2011.

[35] F. Zafari, A. Gkelias, and K. K. Leung, "A survey of indoor localization systems and technologies," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2568–2599, 3rd Quart., 2019.

[36] M. A. M. Marinho, R. S. J. Ferreira, J. P. C. da Costa, E. P. de Freitas, F. Antreich, K. Liu, H. C. So, T. Rafael, and R. Zelenovsky, "Antenna array based positioning scheme for unmanned aerial vehicles," in *Proc. 17th Int. ITG Workshop Smart Antennas*, 2013, pp. 1–6.

[37] K. Witrisal, C. Anton-Haro, S. Grebien, W. Joseph, E. Leitinger, X. Li, J. A. D. Peral-Rosado, D. Plets, J. Vilà-Valls, and T. Wilding, "Localization and tracking," in *Inclusive Radio Communications for 5G and Beyond*. Amsterdam, The Netherlands: Elsevier, 2021, pp. 253–293.

[38] J. A. Farrell and M. Barth, *The Global Positioning System and Inertial Navigation*. New York, NY, USA: McGraw-Hill, 1998.

[39] A. Sari, A. Lekidis, and I. Butun, "Industrial networks and IIoT: Now and future trends," in *Industrial IoT: Challenges, Design Principles, Applications, and Security*. Cham, Switzerland: Springer, 2020, pp. 3–56.

[40] S. Vatansever and I. Butun, "A broad overview of GPS fundamentals: Now and future," in *Proc. IEEE 7th Annu. Comput. Commun. Workshop Conf. (CCWC)*, Jan. 2017, pp. 1–6.

[41] N. Gyagenda, J. V. Hatilima, H. Roth, and V. A. Zhmud, "A review of GNSS-independent UAV navigation techniques," *Robot. Auto. Syst.*, vol. 152, Jun. 2022, Art. no. 104069.

[42] P. Pasnani and M. L. Seto, "Terrain-based localization and mapping for autonomous underwater vehicles using particle filters with marine gravity anomalies," *IFAC-PapersOnLine*, vol. 51, no. 29, pp. 354–359, 2018.

[43] T. N. Lee and A. J. Canciani, "MagSLAM: Aerial simultaneous localization and mapping using earth's magnetic anomaly field," *Navigation*, vol. 67, no. 1, pp. 95–107, Mar. 2020.

[44] D. Hanley, A. B. Faustino, S. D. Zelman, D. A. Degenhardt, and T. Bretl, "MagPIE: A dataset for indoor positioning with magnetic anomalies," in *Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN)*, Sep. 2017, pp. 1–8.

[45] A. Couturier and M. A. Akhloufi, "A review on absolute visual localization for UAV," *Robot. Auto. Syst.*, vol. 135, Jan. 2021, Art. no. 103666.

[46] F. B. Sorbelli, S. K. Das, C. M. Pinotti, and S. Silvestri, "Range based algorithms for precise localization of terrestrial objects using a drone," *Pervasive Mobile Comput.*, vol. 48, pp. 20–42, Aug. 2018.

[47] H.-C. Chen, T.-H. Lin, H. T. Kung, C.-K. Lin, and Y. Gwon, "Determining RF angle of arrival using COTS antenna arrays: A field evaluation," in *Proc. IEEE Mil. Commun. Conf. (MILCOM)*, Oct. 2012, pp. 1–6.

[48] S. M. LaValle and J. J. Kuffner, "Randomized kinodynamic planning," *Int. J. Robot. Res.*, vol. 20, no. 5, pp. 378–400, 2001.

[49] S. Karaman and E. Frazzoli, "Sampling-based algorithms for optimal motion planning," *Int. J. Robot. Res.*, vol. 30, no. 7, pp. 846–894, 2011.

[50] H. Strasdat, J. M. M. Montiel, and A. J. Davison, "Visual SLAM: Why filter?" *Image Vis. Comput.*, vol. 30, no. 2, pp. 65–77, 2012.

[51] M. Samir, C. Assi, S. Sharafeddine, D. Ebrahimi, and A. Ghrayeb, "Age of information aware trajectory planning of UAVs in intelligent transportation systems: A deep learning approach," *IEEE Trans. Veh. Technol.*, vol. 69, no. 11, pp. 12382–12395, Nov. 2020.

[52] A. Bürkle, F. Segor, and M. Kollmann, "Towards autonomous micro UAV swarms," *J. Intell. Robot. Syst.*, vol. 61, nos. 1–4, pp. 339–353, Jan. 2011.

[53] Y. Tang, Y. Hu, J. Cui, F. Liao, M. Lao, F. Lin, and R. S. Teo, "Vision-aided multi-UAV autonomous flocking in GPS-denied environment," *IEEE Trans. Ind. Electron.*, vol. 66, no. 1, pp. 616–626, Jan. 2019.

[54] S. Zhao, Z. Hu, M. Yin, K. Z. Y. Ang, P. Liu, F. Wang, X. Dong, F. Lin, B. M. Chen, and T. H. Lee, "A robust real-time vision system for autonomous cargo transfer by an unmanned helicopter," *IEEE Trans. Ind. Electron.*, vol. 62, no. 2, pp. 1210–1219, Feb. 2015.

[55] J. Zheng, T. Yang, H. Liu, T. Su, and L. Wan, "Accurate detection and localization of unmanned aerial vehicle swarms-enabled mobile edge computing system," *IEEE Trans. Ind. Informat.*, vol. 17, no. 7, pp. 5059–5067, Jul. 2021.

[56] M. Y. Arafat and S. Moh, "Localization and clustering based on swarm intelligence in UAV networks for emergency communications," *IEEE Internet Things J.*, vol. 6, no. 5, pp. 8958–8976, Oct. 2019.

[57] O. Shrit, S. Martin, K. Alagha, and G. Pujolle, "A new approach to realize drone swarm using ad-hoc network," in *Proc. 16th Annu. Medit. Ad Hoc Netw. Workshop (Med-Hoc-Net)*, Jun. 2017, pp. 1–5.

[58] R. Opromolla, G. Inchingolo, and G. Fasano, "Airborne visual detection and tracking of cooperative UAVs exploiting deep learning," *Sensors*, vol. 19, no. 19, p. 4332, Oct. 2019.

[59] M. Saska, T. Báca, J. Thomas, J. Chudoba, L. Preucil, T. Krajník, J. Faigl, G. Loianno, and V. Kumar, "System for deployment of groups of unmanned micro aerial vehicles in GPS-denied environments using onboard visual relative localization," *Auton. Robots*, vol. 41, no. 4, pp. 919–944, 2017.

[60] M. Rubenstein, A. Cornejo, and R. Nagpal, "Programmable self-assembly in a thousand-robot swarm," *Science*, vol. 345, no. 6198, pp. 795–799, 2014.

[61] A. Ledergerber, M. Hamer, and R. D'Andrea, "A robot self-localization system using one-way ultra-wideband communication," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Sep. 2015, pp. 3131–3137.

[62] W. Wang, P. Bai, Y. Zhou, X. Liang, and Y. Wang, "Optimal configuration analysis of AOA localization and optimal heading angles generation method for UAV swarms," *IEEE Access*, vol. 7, pp. 70117–70129, 2019.

[63] A. Wang, X. Ji, D. Wu, X. Bai, N. Ding, J. Pang, S. Chen, X. Chen, and D. Fang, "GuideLoc: UAV-assisted multitarget localization system for disaster rescue," *Mobile Inf. Syst.*, vol. 2017, pp. 1–13, Mar. 2017.

[64] Z. Li, A. Giorgetti, and S. Kandeepan, "Multiple radio transmitter localization via UAV-based mapping," *IEEE Trans. Veh. Technol.*, vol. 70, no. 9, pp. 8811–8822, Sep. 2021.

[65] B. R. Stojkoska, J. Palikrushev, K. Trivodaliev, and S. Kalajdziski, "Indoor localization of unmanned aerial vehicles based on RSSI," in *Proc. 17th Int. Conf. Smart Technol. (IEEE EUROCON)*, Ohrid, North Macedonia, Jul. 2017, pp. 120–125.

[66] M. Chen, F. Dai, H. Wang, and L. Lei, "DFM: A distributed flocking model for UAV swarm networks," *IEEE Access*, vol. 6, pp. 69141–69150, 2018.

[67] A. I. Mourikis and S. I. Roumeliotis, "Performance analysis of multirobot Cooperative localization," *IEEE Trans. Robot.*, vol. 22, no. 4, pp. 666–681, Aug. 2006.

[68] D. J. Pack, P. DeLima, G. J. Toussaint, and G. York, "Cooperative control of UAVs for localization of intermittently emitting mobile targets," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 39, no. 4, pp. 959–970, Aug. 2009.

[69] J. Zhu and S. S. Kia, "Cooperative localization under limited connectivity," *IEEE Trans. Robot.*, vol. 35, no. 6, pp. 1523–1530, Dec. 2019.

[70] A. Howard, M. Mataric, and G. Sukhatme, "Localization for mobile robot teams: A distributed MLE approach," in *Experimental Robotics VIII*, vols. 146–155. Berlin, Germany: Springer, 2003.

[71] A. Martinelli, F. Pont, and R. Siegwart, "Multi-robot localization using relative observations," in *Proc. IEEE Int. Conf. Robot. Autom.*, Apr. 2005, pp. 2797–2802.

[72] E. D'Amato, I. Notaro, M. Mattei, and G. Tartaglione, "Attitude and position estimation for an UAV swarm using consensus Kalman filtering," in *Proc. IEEE Metrol. Aerosp. (MetroAeroSpace)*, Benevento, Italy, Jun. 2015, pp. 519–524.

[73] E. D. Nerurkar, S. I. Roumeliotis, and A. Martinelli, "Distributed maximum *a posteriori* estimation for multi-robot cooperative localization," in *Proc. IEEE Int. Conf. Robot. Autom.*, May 2009, pp. 1402–1409.

[74] S. Rao and D. Ghose, "Sliding mode control-based autopilots for leaderless consensus of unmanned aerial vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 5, pp. 1964–1972, Sep. 2014.

[75] J. Zhang, J. Yan, and P. Zhang, "Multi-UAV formation control based on a novel back-stepping approach," *IEEE Trans. Veh. Technol.*, vol. 69, no. 3, pp. 2437–2448, Mar. 2020.

[76] F. Hu, Y. Deng, and A. H. Aghvami, "Scalable multi-agent reinforcement learning algorithm for wireless networks," 2021, *arXiv:2108.00506*.

[77] A. I. Khan and Y. Al-Mulla, "Unmanned aerial vehicle in the machine learning environment," *Procedia Comput. Sci.*, vol. 160, pp. 46–53, 2019.

[78] Z. Sui, Z. Pu, and J. Yi, "Optimal UAVs formation transformation strategy based on task assignment and particle swarm optimization," in *Proc. IEEE Int. Conf. Mechatronics Autom. (ICMA)*, Aug. 2017, pp. 1804–1809.

[79] K. Guo, X. Li, and L. Xie, "Ultra-wideband and odometry-based cooperative relative localization with application to multi-UAV formation control," *IEEE Trans. Cybern.*, vol. 50, no. 6, pp. 2590–2603, Jun. 2020.

[80] Y.-H. Tsai, "Vision-based collision avoidance for unmanned aerial vehicles by recurrent neural networks," *Int. J. Comput. Inf. Eng.*, vol. 13, no. 4, pp. 196–200, 2019.

[81] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Las Vegas, NV, USA, Jun. 2016, pp. 779–788.

[82] R. Azoulay, Y. Haddad, and S. Reches, "Machine learning methods for UAV flocks management—A survey," *IEEE Access*, vol. 9, pp. 139146–139175, 2021.

[83] K. Hoshiba, K. Washizaki, M. Wakabayashi, T. Ishiki, M. Kumon, Y. Bando, D. Gabriel, K. Nakadai, and H. G. Okuno, "Design of UAV-embedded microphone array system for sound source localization in outdoor environments," *Sensors*, vol. 17, no. 11, p. 2535, 2017.

[84] N. Kayhani, A. Heins, W. Zhao, M. Nahangi, B. McCabe, and A. Schoellig, "Improved tag-based indoor localization of UAVs using extended Kalman filter," in *Proc. Int. Symp. Autom. Robot. Construct. (IAARC)*, Banff, AB, Canada, May 2019, pp. 21–24.

[85] S. Misra, A. Mukherjee, A. U. Rahman, and N. S. Raghuwanshi, "ROSE: Random opportunistic and selective exploration for cooperative edge swarm of UAVs," in *Proc. Int. Conf. Commun. Syst. Netw. (COMSNETS)*, Jan. 2020, pp. 368–374.

[86] M. Campion, P. Ranganathan, and S. Faruque, "UAV swarm communication and control architectures: A review," *J. Unmanned Vehicle Syst.*, vol. 7, no. 2, pp. 93–106, Jun. 2019.

[87] D.-Y. Kim and J.-W. Lee, "Integrated topology management in flying ad hoc networks: Topology construction and adjustment," *IEEE Access*, vol. 6, pp. 61196–61211, 2018.

[88] S. Sekander, H. Tabassum, and E. Hossain, "Statistical performance modeling of solar and wind-powered UAV communications," *IEEE Trans. Mobile Comput.*, vol. 20, no. 8, pp. 2686–2700, Aug. 2021.

[89] W. Mei, Q. Wu, and R. Zhang, "Cellular-connected UAV: Uplink association, power control and interference coordination," *IEEE Trans. Wireless Commun.*, vol. 18, no. 11, pp. 5380–5393, Nov. 2019.

[90] D. Mishra and E. Natalizio, "A survey on cellular-connected UAVs: Design challenges, enabling 5G/B5G innovations, and experimental advancements," *Comput. Netw.*, vol. 182, Dec. 2020, Art. no. 107451.

[91] F. Zhou, R. Q. Hu, Z. Li, and Y. Wang, "Mobile edge computing in unmanned aerial vehicle networks," *IEEE Wireless Commun.*, vol. 27, no. 1, pp. 140–146, Feb. 2020.

[92] H. Luo, T. Chen, X. Li, S. Li, C. Zhang, G. Zhao, and X. Liu, "KeepEdge: A knowledge distillation empowered edge intelligence framework for visual assisted positioning in UAV delivery," *IEEE Trans. Mobile Comput.*, early access, Mar. 9, 2022, doi: 10.1109/TMC.2022.3157957.

[93] Y. Miao, X. Liu, K.-K.-R. Choo, R. H. Deng, H. Wu, and H. Li, "Fair and dynamic data sharing framework in cloud-assisted internet of everything," *IEEE Internet Things J.*, vol. 6, no. 4, pp. 7201–7212, Aug. 2019.

[94] Y. Liu, H.-N. Dai, Q. Wang, M. K. Shukla, and M. Imran, "Unmanned aerial vehicle for internet of everything: Opportunities and challenges," *Comput. Commun.*, vol. 155, pp. 66–83, 2020.

[95] I. Bisio, C. Garibotto, H. Haleem, F. Lavagetto, and A. Sciarrone, "On the localization of wireless targets: A drone surveillance perspective," *IEEE Netw.*, vol. 35, no. 5, pp. 249–255, Sep. 2021.

[96] M. Angurala, M. Bala, S. S. Bamber, R. Kaur, and P. Singh, "An Internet of Things assisted drone based approach to reduce rapid spread of COVID-19," *J. Saf. Sci. Resilience*, vol. 1, no. 1, pp. 31–35, Sep. 2020.

[97] S. Ullah, K.-I. Kim, K. H. Kim, M. Imran, P. Khan, E. Tovar, and F. Ali, "UAV-enabled healthcare architecture: Issues and challenges," *Future Gener. Comput. Syst.*, vol. 97, pp. 425–432, Aug. 2019.

[98] I. Butun, I.-H. Ra, and R. Sankar, "An intrusion detection system based on multi-level clustering for hierarchical wireless sensor networks," *Sensors*, vol. 15, no. 11, pp. 28960–28978, Nov. 2015.

[99] B. Ismail and O. Patrik, "Detecting intrusions in cyber-physical systems of smart cities: Challenges and directions," in *Secure Cyber-Physical Systems for Smart Cities*. Harrisburg, PA, USA: IGI Global, 2019, pp. 74–102.

[100] I. Butun and P. Österberg, "A review of distributed access control for blockchain systems towards securing the Internet of Things," *IEEE Access*, vol. 9, pp. 5428–5441, 2020.

MANEL KHELIFI received the degree in engineering from the University of Constantine (UMC), the Magister degree, and the Ph.D. degree in computer science (networks and distributed systems) from ReSyD, Doctoral School, University of Bejaia, Algeria. She is currently a Researcher at Fortiss GmbH, Research Institute of the Free State of Bavaria associated with Technical University of Munich (TUM), Germany. She was also an Associate Professor/a Researcher with the Department of Computer Science, Jijel University, Algeria since 2011. From 2014 to 2016, she worked as a Research Assistant with the Université du Québec en Outaouais (UQO), Canada. Her research interests include, but are not limited to, networking, wireless communication, mobile computing, localization, energy efficiency, WSNs, UAVs, and the Internet of Things (IoT).

ISMAIL BUTUN (Member, IEEE) received the B.Sc. and M.Sc. degrees in electrical and electronics engineering from Hacettepe University, and the M.Sc. and Ph.D. degrees in electrical engineering from the University of South Florida, in 2009 and 2013, respectively. From 2014 to 2017, he worked as an Assistant Professor first with the Department of Mechatronics Engineering, Bursa Technical University, and then with the Department of Computer Engineering, Abdullah Gul University. From 2016 to 2021, he worked as a postdoctoral fellow for various universities (University of Delaware, Mid Sweden University, and Chalmers University of Technology). Since 2021, he has been affiliated with the School of Electrical Engineering and Computer Science, KTH Royal Institute of Technology. He has more than 50 publications in peer-reviewed scientific international journals and conference proceedings, along with an H-index of 20. He is a well-recognized academic reviewer by IEEE, ACM, and Springer, who served more than 50 various scientific journals and conferences in the review process of more than 200 articles. He is an Editor of IEEE Access journal, *Sensors* (MDPI) journal, *Journal of Sensors* (Hindawi), and *Nature* (Springer). His research interests include but not limited to computer networks, wireless communications, WSNs, IoT, cyber-physical systems, cryptography, network security, and intrusion detection.

• • •