PERSISTENT CROWD TRACKING USING UNMANNED AERIAL VEHICLE SWARMS

A Novel Framework for Energy and Mobility Management

Angelo Trotta, Ufuk Muncuk, Marco Di Felice, and Kaushik R. Chowdhury

Digital Object Identifier 10.1109/MVT.2020.2982244
Date of current version: 16 April 2020

Aerial surveillance systems are a cost-effective and on-demand solution for smart city monitoring. However, the deployment of a swarm of unmanned aerial vehicles (UAVs) for continuous video capture of mobile ground target (MGT) activities poses new research issues in terms of energy management, scenario coverage, and multidevice task coordination. In this article, we address these challenges by proposing Persistent Crowd Tracking Using UAVs (PERCEIVE), a novel framework for continuous video surveillance via UAVs that are periodically replenished through mobile charging stations (MCSs).

Background

Driven by the concentration of resources, economic reasons, and lifestyle preferences, cities are growing into dense population hubs; in fact, two-thirds of the world population will reside in urban areas in the coming decades, per estimates given by the United Nations. In such cases, ensuring the security and protection of citizens from bad actors and natural calamities is a basic expectation [1]. Thanks to the growing popularity of Internet of Things (IoT) sensors and transformative advances in computer vision, we can now monitor specific points in real time through dedicated video surveillance systems. Such systems are often installations of outdoor cameras, with operational examples already existing in cities such as Chicago, Beijing, London, and Moscow. Furthermore, worldwide spending on security solutions is expected to achieve a compound annual growth rate of 9.2% during the period 2018–2022, according to the International Data Corporation.

To overcome the limitations of restricted viewpoints, constant video capture angle, and wired-infrastructure dependence, next-generation video surveillance systems will involve UAVs, which are uniquely suited to monitoring and tracking mobile targets (e.g., pedestrian crowds [2]) due to their freedom of movement, ability to deploy on demand, and power to dramatically decrease hardware costs [3]. At the same time, the deployment of swarms of UAVs for video surveillance applications is nontrivial: tracking a number of MGTs requires jointly addressing research issues related to computer vision (e.g., the localization of the targets [4]) and energy and mobility management. In this article, we focus on the second issue, as outlined in the following.

Challenges to UAV-Based Crowd Surveillance Systems

- *Energy management*: Given that the autonomy of commercial off-the-shelf (COTS) UAVs is limited to the order of tens of minutes, different approaches have been proposed to extend the lifetime of a UAV-based swarm: 1) energy-aware control protocols that aim to minimize unnecessary maneuvers of the mobile devices [5], 2) energy-aware network protocols that reduce the amount of data transmitted or processed on the edge by UAVs, and 3) energy replenishment policies via a ground charging infrastructure [6]. We believe the latter approach is the only viable solution that guarantees the persistence of an aerial coverage service. Hence, a resource allocation policy needs to be formulated for practical situations where the number of charging stations (CSs) is less than the number of available UAVs. While several solutions based on linear programming [7] and learning [8] have been proposed, few works take into account the degradation of the quality of service (QoS) caused by replenishment operations [9]. Similarly, there are very few experimental studies quantifying the lifetime extension offered by wireless charging solutions for UAVs [10].
- *Mobility management*: Tracking a mobile crowd requires periodically adjusting the position of a given UAV, so that the overall aerial coverage of the targets is maximized while minimizing the risk of collisions with peer vehicles. Toward this aim, proposed UAV swarm mobility algorithms are often inspired by natural phenomenon [11], [12]. However, this problem becomes further complicated when there are MCSs in the vicinity. This implies additional coordination between the aerial and ground components, both of which are mobile. The authors of [13] provide one of the few studies on the joint optimization of UAV trajectories and the placement of MCSs. However, given the computational complexity, the work explores only small-scale scenarios.

TWO-THIRDS OF THE WORLD POPULATION WILL RESIDE IN URBAN AREAS IN THE COMING DECADES, PER ESTIMATES GIVEN BY THE UNITED NATIONS.

Proposed Approach

In this article, we present a generic architecture for crowd monitoring through a swarm of UAVs. The proposed PERCEIVE solution addresses the two research challenges previously mentioned; i.e., 1) it guarantees persistent video surveillance through a fleet of MCSs, and, at the same time, 2) it aims to jointly maximize the quality of the tracking and its temporal continuity through novel charging scheduling as well as UAV and MCS swarm mobility algorithms. The PERCEIVE architecture is inspired by recent software-defined networks since it separates the UAV data acquisition and micromobility plane, which is performed on the edge, from the swarm control plane, which is performed on the cloud

Worldwide spending on security solutions is expected to achieve a compound annual growth rate of 9.2%.

through a service chain involving multiple different modules. In more detail, three novel contributions are addressed in the article:

- We describe the implementation of a UAV wireless CS that can be mounted on the roof of a vehicle. We characterize its performance as well as the energy consumption of UAVs performing video surveillance tasks.
- Based on the previous results, we integrate the UAV replenishment service with a probabilistic charging scheduling algorithm, which takes into account both the residual energy of the UAVs and the QoS of the aerial video surveillance system.
- Finally, we address the mobility management of both UAVs and MCSs via swarm mobility algorithms based on the potential field force model to maximize the number of targets covered (for the UAVs) and minimize the overhead of the charging operations (for the MCSs). Crowd mobility prediction mechanisms are designed and evaluated to enhance the positioning of the UAVs and MCSs through time.

All the proposed solutions are evaluated through Object Modular Network Testbed in C++ (OMNeT++) simulations by feeding the simulator with the UAV charging/discharge profile data obtained through the testbed. The results reveal that the PERCEIVE mobility management algorithm is able to increase performance by more than 700% compared to UAV static coverage. Similarly, the energy management strategies (MCS mobility and the scheduling algorithm) guarantee an improvement of +300% compared to a scenario with no CSs and of +23% with charger infrastructure placed at fixed locations.

UAV Charging and In-Flight Measurements

Figure 1 shows the prototype implementation of a wireless charging system that can be mounted on the roof of a vehicle. We include two components in the design to ensure compliance with the industry standard, Qi.

Wireless Energy Transmitter

The transmitter module contains four individual Qi-compliant transmitters placed beneath a plexiglass surface with a thickness of 5 mm. Each transmitter is capable of supplying 45 W of power through magnetic induction-based wireless power transfer, thus complying with the Wireless Power Consortium 1.2 specification. A microcontroller (μCU) in the form of a Raspberry Pi 3 Model B+ coordinates the entire charging process. We use a DJI Matrice 100 in our setup, with a camera-based guidance system for landing. Upon landing, the onboard Robot Operating System (ROS) informs the μCU, which undertakes the following steps:

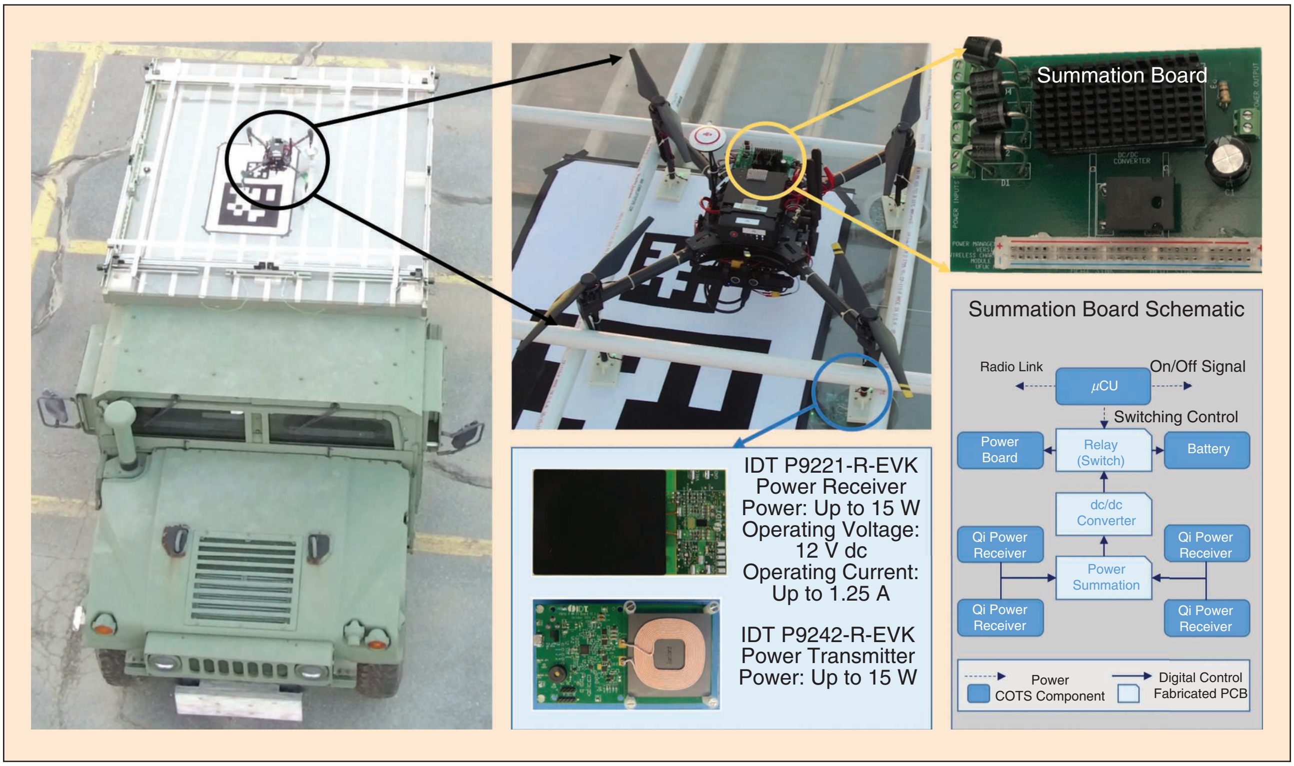

Figure 1 The UAV charging infrastructure, onboard power management fabricated circuit, and schematic. PCB: printed circuit board.

- It activates four beams that secure and drag the UAV to a central spot, aligning it with the charging modules beneath. This mechanical action is visible in the two overhead pictures in Figure 1, with the close-up view showing the legs of the UAV clamped between the mechanical beams.
- It directs the ROS to disconnect the flight motors from the battery and sets a relay switch to direct any power flow into the batteries. This is the switching control function shown in the schematic diagram on the so-called power management board.
- It initializes the wireless transmitter–receiver modules to start the wireless charging. The Qi transmitters begin the standards-specified sensing, followed by the energy transfer. Note that any misalignment exceeding 3 mm for a given transmitter–receiver coil prohibits the charging action from starting.

Wireless Energy Receiver

To increase the overall charging rate, the prototype uses four Qi-compliant receivers, one affixed to each leg. The receiver output voltage and current are 22.5 V and 2 A, respectively. We designed a power management board (mounted on the top of the UAV and magnified in Figure 1), which includes a power summation circuit and a dc/dc converter circuit. The power summation circuit combines all of the dc outputs from the receivers in parallel by keeping the amplitude of the output voltage constant, thus effectively summing up the total current. The adjustable 600/dc converter transforms the output voltage of the power summation circuit to the voltage required to charge the UAV battery. This circuitry makes practical deployments of the proposed power management circuit possible by interfacing with any type of UAV that has a different charging voltage requirement. In our setup, we use a DJI Matrice 100 that requires 27 V to charge the battery, and our overall conversion efficiency is 80%, with a net output power of 144 W.

Table 1 summarizes the charging performance of our proposed system with various UAV models in terms of the charging time. Selected UAVs, such as the DJI M100, Intel Aero, and Yuneec Typhoon H, can be charged to full battery capacity in less than, or approximately, 1 h. Optimizing the charging operation becomes important when the UAV carries a load such as a video camera that is needed for surveillance applications. Our experimental studies reveal a significant reduction in flight time in such cases. For example, a DJI Matrice 100 UAV used in our prototype charging demonstration suffered a 45.7% reduction in flight time, compared to a fully unloaded case, when it was interfaced with a Zenmuse XT camera (270 g) and camera adapter (52.16 g). As a result, proper scheduling policies must be designed in case multiple UAVs performing video surveillance are sharing the same MCS, as described in the following.

NEXT-GENERATION VIDEO SURVEILLANCE SYSTEMS WILL INVOLVE UAVS, WHICH ARE UNIQUELY SUITED TO MONITORING AND TRACKING MOBILE TARGETS.

Scenario and PERCEIVE Architecture

We consider the scenario of Figure 2, composed of MGTs, UAVs, and MCSs. Let $M = \{m_0, m_1, \dots m_{n_m}\}$ indicate the set of MGTs. Similarly, let $U = \{u_0, u_1, \dots u_{n_u}\}$ and $C = \{c_0, c_1, \dots c_{n_c}\}$ represent the set of available UAVs and MCSs, respectively. We abstract from thet physical meaning of the MGTs, i.e., they can be constituted by pedestrians or by vehicles; however, we assume that all of them will follow the same, constrained itinerary defined as a sequence of streets. In view of increasing the protection of individuals and infrastructure in next-generation smart cities, a swarm of UAVs is employed for continuous video recording of the activities of the MGTs: while hovering, each UAV monitors a circular area of radius R on the ground. Given the limited computational capabilities of the UAVs, the video streams are transmitted via a cellular 4G connection to a remote cloud infrastructure where they are merged and analyzed. The experimental results provided in the “UAV Charging and In-Flight Measurements” section demonstrate the limited flight autonomy of the UAVs, which is a severe constraint for applications such as PERCEIVE. For this reason, we consider the presence of MCSs with contact-based charging surfaces that

TABLE 1 ***The performance of the proposed wireless charging surface system with various UAV models.***

UAV Model	*Per-Unit Battery Capacity (mAh)*	*Flying Time, No Payload (min)*	*Charging Duration (min/unit at 45.6 W)*	*Maximum Payload Capacity (g)*
DJI M600	4,500 (×6)	35	51	6,000
	5,700 (×6)	40	64	
DJI M100	4,500	22	51	1,000
	5,700	28	64	
Intel Aero	4,000	20	45	680
Yuneec Typhoon H	5,400	25	60	225
Altura Zenith ATX8	20,000	40	225	3,000

continuously adjust their positions according to UAV and MGT mobility. The PERCEIVE framework aims to orchestrate the operations of the UAVs and MCSs so that two system goals are maximized:

- tracking quality, defined as the total time when the activities of the MGTs are filmed by at least one UAV
- lifetime, defined as the temporal length of the aerial surveillance system until the first UAV runs out of energy.

In the following section, we detail how such goals are addressed by PERCEIVE. We first introduce the notation used in the rest of the article. We assume that PERCEIVE operations are scheduled at fixed time slots of constant length (t_{slot}); the latter denotes the temporal interval between two consecutive executions of the framework. Let $T = \{t_0, t_1, t_2, \ldots\}$ be the system evolution across time slots and $P(m_j, t_i)$ be the GPS position of MGT m_j at time slot t_i. Similarly, let $P(u_j, t_i)$ and $P(c_j, t_i)$ be the GPS positions of UAV u_j and MGS c_j at time-slot t_i, respectively.

PERCEIVE System Components

The operation of the PERCEIVE framework is split into modular services executed in the cloud to minimize the computational effort for the UAVs. The service chain is depicted in Figure 2 and executed at each time-slot $t_i \in T$. First, the video streams of the UAVs are merged and analyzed to identify the presence and current location of the MGTs under video surveillance. Based on the previous MGT positions, the direction of the crowd is estimated. Next, the UAVs with critical residual energy are allocated to the vacant MCSs according to a scheduling policy. The MGT positions and directional flow of the overall crowd are given as input to position-update modules, which determine the next hovering coordinates of the UAVs [i.e., $P(u_j, t_i)$, $\forall u_j \in U$] and MCSs [i.e., $P(c_j, t_i)$, $\forall c_j \in C$]. The details of each service are discussed in the following.

MGT Identification and Tracking

We assume the MGTs to be visually distinguishable from the other scenario objects so that state-of-art object classification algorithms can be applied to the video stream gathered by each UAV. We do not further elaborate on the vision task, since this article focuses on the mobility and energy management of a UAV-based video surveillance system. Similarly, at every time slot, a local map is extracted from the frames gathered by each UAV, estimating the position of all MGTs in the current range of the video camera (stage 1 in Figure are then merged into a single scenario map, which contains the position of all of the MGTs monitored by the swarm as well as the location of the UAVs and MCSs (stage 2).

Crowd Mobility Prediction

When the itinerary of the crowd is not known in advance, the PERCEIVE framework attempts to predict the next positions of the MGTs to better provision the placement of the UAVs and MCSs at each time slot. This is performed via a two-step solution depicted in Figure 3 (stage 3). First, a spatial clustering algorithm is executed on the scenario map, exploiting the observation that crowds are often characterized by the spontaneous formation of clusters. We used the *K*-means algorithm due to its efficiency in spatial clustering. However, we remark that, thanks to the modularity of the PERCEIVE architecture, different clustering schemes might be integrated for crowd estimation. Then, the vector mobility of each centroid is estimated as the difference between the positions at time slot t_i and t_{i-1}. In the "Performance Evaluation" section, we assess the effectiveness of such a mechanism compared to the case where the crowd itinerary is given as input.

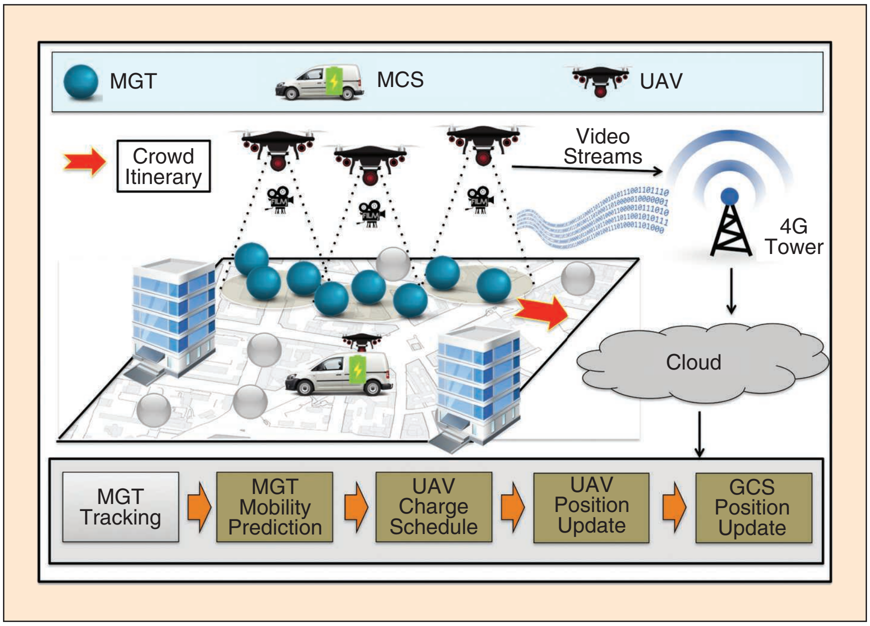

FIGURE 2 The video surveillance scenario and PERCEIVE architecture. GCS: ground control station.

UAV Charging Scheduling

At the beginning of each time-slot t_i, the PERCEIVE framework implements the persistence strategy; i.e., it checks for the presence of UAVs to recharge. This is performted through a swarm intelligence-based probabilistic mechanism inspired by the well-known stimulus response model [11]. In more detail, the charging probability (CP) function is computed for each UAV u_j:

$$CP(u_j, t_i) = \frac{S(u_j, t_i)^2}{S(u_j, t_i)^2 + \theta(u_j, t_i)^2}. \quad (1)$$

Here, the numerator (i.e., the stimulus) is a proxy for the recharge need of UAV u_j at time slot t_i, and it is defined as $S(u_j, t_i) = (B(u_j) - E(u_j, t_i))/B(u_j)$, where $B(u_j)$ is the battery capacity of the UAV and $E(u_j, t_i)$ its residual energy at time slot t_i. Vice versa, the threshold θ is a proxy for the QoS decay, i.e., the loss of monitoring quality caused by the departure of UAV u_j, and it is expressed as the number of MGTs uniquely covered by u_j at time slot t_i, normalized between zero and one. It is easy to see from (1) that the CP is maximized when 1) the current UAV is running out of energy and 2) the UAV is not filming an area with a high density of MGTs by itself. For each UAV u_j, the charging operation is scheduled with the probability given by (1); in this case, the UAV is allocated to the closest vacant MCS, if any. The procedure is iterated across all UAVs according to a priority order given by the residual energy of each device.

UAV Position Update

The placement of the UAVs is a complex tradeoff between the requirement of the video surveillance system (e.g., maximal tracking of the MGT activities) and operational safety (e.g., minimal collision risk among the UAVs). For this purpose, the PERCEIVE system employs a task coordination method based on the virtual field force model originally proposed in [14]; for each UAV, the model computes the direction and intensity of the forces acting on the vehicle and governing its mobility, as depicted in Figure 3 (stage 4). Specifically, two force types (attractive and repulsive) are considered: the UAVs are attracted by MGTs to fulfill the coverage task, while they are repulsed by other UAVs in the neighborhood to avoid collisions. The attraction force from each MGT is attenuated by a factor γ in case the latter is already covered by another UAV; the parameter controls the tradeoff between the coverage extension (i.e., the number of MGTs filmed) and coverage redundancy (i.e., the number of UAVs filming each MGT), as demonstrated in the "Performance Evaluation" section. In addition, a third attractive force acts on each UAV, pushing it toward the estimated crowd direction (see the "Crowd Mobility Prediction" section). At time slot t_i, any flying UAV $u_j \in U$ moves according to the field force at its position $P(u_j, t_i)$, which is defined as the result of all of the forces applied to the vehicle and communicated by the cloud service.

THE PLACEMENT OF THE UAVS IS A COMPLEX TRADEOFF BETWEEN THE REQUIREMENT OF THE VIDEO SURVEILLANCE SYSTEM AND OPERATIONAL SAFETY.

MCS Position Update

The mobility of the MCSs is constrained by both UAVs and MGTs; i.e., they must follow the UAV swarm to minimize the length of the charging path while, at the same time, keeping a safe distance from the MGTs. The tradeoff is described again via the previously introduced field force model, so that each MCS is attracted by the UAVs and repulsed by the MGTs in its neighborhood. The intensity of the attractive force originated by UAV u_j at time slot t_i is made inversely proportional to the residual battery level $[E(u_j, t_i)]$. As before, at time slot t_i, any vacant (i.e., not used by any UAV) MCS $c_j \in C$ moves toward the resultant forces applied to this current position (stage 5 in Figure 3).

Performance Evaluation

We evaluate the performance of the proposed PERCEIVE framework via extensive OMNeT++ simulations. To this purpose, we model a city scenario with a pedestrian crowd following a predefined itinerary according to the reference point group mobility model. Unless indicated otherwise, the following parameters

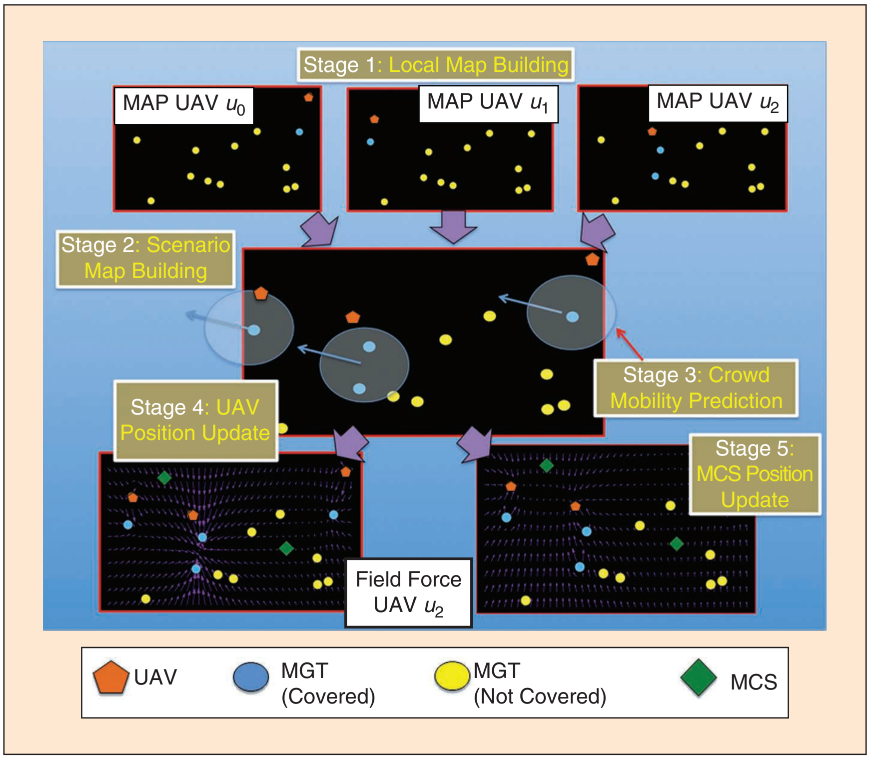

FIGURE 3 The example operations of the PERCEIVE framework.

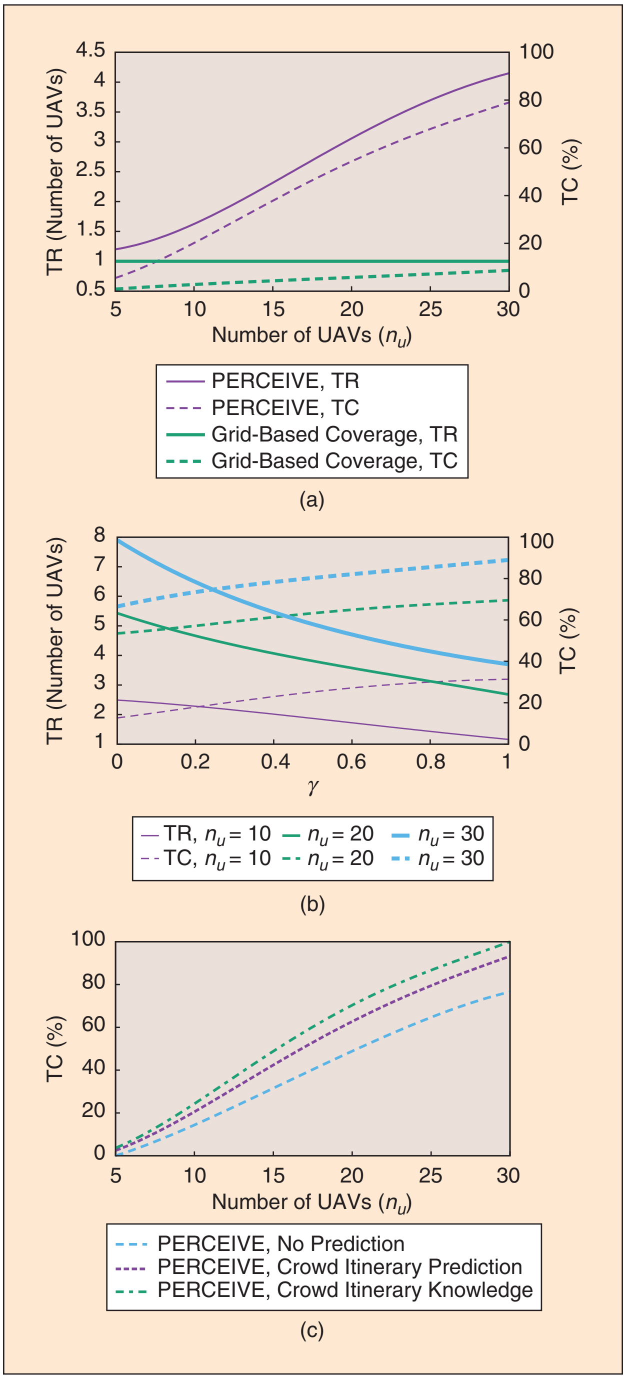

FIGURE 4 (a) The TC and TR for dynamic/static UAV swarm deployments. (b) The tradeoff between the TR and TC metrics when varying the γ parameter. (c) The impact of crowd mobility knowledge of the TC metric.

are used: $n_u = 10$ (number of UAVs), $n_m = 80$ (number of MGTs), $n_c = 4$ (number of MCS), and $\gamma = 0.75$ (redundancy control). The charging and discharging profiles of the UAVs are derived from Table 1 (row 4), and hence we obtained a charging power of 45.6 W and UAV flying power of 191.8 W. The evaluation focuses on the system goals introduced in the "Proposed Approach" section, i.e., the tracking quality and lifetime. The first is measured by two metrics: 1) tracking coverage (TC), defined as the percentage of the time slots in which the MGTs are filmed by at least one UAV, and 2) tracking redundancy (TR), expressed as the average number of UAVs filming each MGT in every time slot.

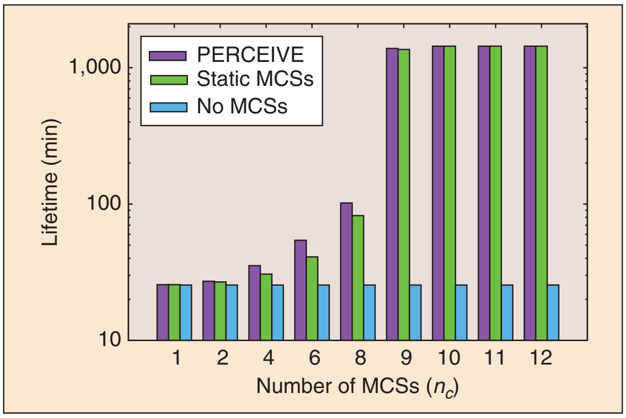

FIGURE 5 The system lifetime for different UAV charging solutions.

Figure 4(a) depicts the TR (full line) and TC (dotted line) metrics when varying the number of UAVs in the scenario. The PERCEIVE framework is compared to a configuration where the UAVs are hovering at fixed scenario positions placed to maximize the full scenario coverage (hexagonal cells). We can see that PERCEIVE provides both higher TC and TR values compared to the static case, thanks to the UAV update module that adjusts the UAV positions as a consequence of crowd mobility. In addition, Figure 4(b) illustrates how the framework can be made responsive to different application requirements (e.g., maximize coverage versus maximize redundancy) by properly tuning the γ parameter. Figure 4(c) investigates the impact of the crowd mobility prediction service on the TR metric. Again, three configurations are tested: 1) the case where the crowd itinerary is known in advance (labeled "itinerary knowledge"), 2) the case where the next MGT's position is estimated through the technique introduced in the "Crowd Mobility Prediction" section, and 3) the case where the itinerary information is not used and the corresponding forces are not instantiated in the virtual field force model. We observe that the UAV video surveillance service benefits from taking into account the MGT mobility; moreover, the results show that the proposed crowd prediction scheme, despite its simplicity, guarantees performance that is close to the case with full knowledge.

Finally, Figure 5 shows the system lifetime when varying the number of MCSs ($n_u = 10$) under three persistence configurations: 1) the case with the MCSs discussed in the "UAV Charging and In-Flight Measurements" section, moving according to the field force model described in the "MCS Position Update" section; 2) the case with fixed CSs placed at the scenario center; and 3) the case without CSs. By shorting the distance with the UAVs, the PERCEIVE solution results in greater energy efficiency than the other solutions, and the performance gain increases with the number of MCSs: for $n_c = 8$, an improvement of +23% compared to the static case and +300% compared to the no-recharge case.

Conclusions and Future Work

In this article, we investigated UAV-based surveillance design that attempts to provide service persistence through MCSs. To this purpose, the PERCEIVE framework was proposed by considering a modular chain of functionalities to perform crowd mobility prediction, UAV charging scheduling, and UAV and MCS mobility updates. We assessed the effectiveness of our approach via experimental measurements of a prototype MCS and extensive simulation results on a city-scale monitoring scenario. Future work includes implementation of the charging scheduling algorithm on a small-case UAV testbed, modeling video quality metrics, extending the model including MCSs equipped with video cameras, and the dynamic orchestration of service tasks between the cloud and the edge nodes.

Acknowledgment

This work is supported by the University of Bologna Alma Idea grant project Bee Drones: Monitoring Systems Based on Ultralow-Power Sensor Nodes and Aerial Communications.

Author Information

Angelo Trotta (angelo.trotta5@unibo.it) is a postdoctoral research fellow in the Department of Computer Science and Engineering, University of Bologna, Italy. His research interests include nature-inspired algorithms for self-organizing multirobot wireless systems, reinforcement learning, the Internet of Things, and the World Wide Web Consortium Web of Things.

Ufuk Muncuk (muncuk.u@husky.neu.edu) is a postdoctoral research associate in the Department of Electrical and Computer Engineering, Northeastern University, Boston. His research interests include design, optimization, and implementation for radio frequency energy-harvesting circuits; wireless energy transfer; system design for joint radio frequency energy- and magnetic coupling-based energy transfer; system design for intrabody transceivers; analog and digital circuit design; wireless sensor networks; and cognitive radio systems.

Marco Di Felice (marco.difelice3@unibo.it) is an associate professor of computer science at the University of Bologna, Italy, where he is codirector of the Pervasive Internet of Things (IoT) System Laboratory. His research interests include self-organizing wireless networks, unmanned aerial systems, the IoT, and context-aware applications.

Kaushik R. Chowdhury (krc@ece.neu.edu) is an associate professor at Northeastern University, Boston. His research interests include systems aspects of networked robotics, machine learning for agile spectrum sensing/access, wireless energy transfer, and large-scale experimental deployment of emerging wireless technologies.

References

[1] R. Du, P. Santi, M. Xiao, A. V. Vasilakos, and C. Fischione, "The sensable city: A survey on the deployment and management for smart city mosnitoring," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 2, pp. 1533–1560, 2019. doi: 10.1109/COMST.2018.2881008.

[2] A. Al-Sheary and A. Almagbile, "Crowd monitoring system using unmanned aerial vehicle (UAV)," *J. Civil Eng. Arch.*, vol. 11, no. 11, pp. 1014–1024, 2017. doi: 10.17265/1934-7359/2017.11.004.

[3] N. H. Motlagh, M. Bagaa, and T. Taleb, "UAV-based IoT platform: A crowd surveillance use case," *IEEE Commun. Mag.*, vol. 55, no. 2, pp. 128–134, 2017. doi: 10.1109/MCOM.2017.1600587CM.

[4] S. Minaeian, J. Liu, and Y.-J. Son, "Vision-based target detection and localization via a team of cooperative UAV and UGVs," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 46, no. 7, pp. 1005–1016, 2016. doi: 10.1109/TSMC.2015.2491878.

[5] Y. Zeng, R. Zhang, and T. Joon Lim, "Wireless communications with unmanned aerial vehicles: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 54, no. 5, pp. 36–42, 2016. doi: 10.1109/MCOM.2016.7470933.

[6] P.-V. Mekikis and A. Antonopoulos, "Breaking the boundaries of aerial networks with charging stations," in *Proc. IEEE Int. Conf. Communications*, Shanghai, China, 2019, pp. 1–6. doi: 10.1109/ICC.2019.8761318.

[7] B. D. Song, J. Kim, J. Kim, H. Park, J. R. Morrison, and D. H. Shim, "Persistent UAV service: An improved scheduling formulation and prototypes of system components," *J. Intell. Robot. Syst.*, vol. 74, nos. 1–2, pp. 221–232, 2014. doi: 10.1007/s10846-013-9970-z.

[8] M. Shin, J. Kim, and M. Levorato, "Auction-based charging scheduling with deep learning framework for multi-drone networks," *IEEE Trans. Veh. Technol.*, vol. 68, no. 5, pp. 4335–4248, 2019. doi: 10.1109/TVT.2019.2903144.

[9] A. Trotta, F. D'Andreagiovanni, M. Di Felice, E. Natalizio, K. R. Chowdhury. "When UAVs ride a bus: Towards energy-efficient city-scale video surveillance," in *Proc. IEEE INFOCOM*, Honolulu, HI, 2018, pp. 1043–1051. doi: 10.1109/INFOCOM.2018.8485863.

[10] N. K. Ure, G. Chowdhary, T. Toksoz, J. P. How, M. A. Vavrina, and J. Vian, "An automated battery management system to enable persistent missions with multiple aerial vehicles," *IEEE/ASME Trans. Mechatron.*, vol. 20, no. 1, pp. 275–286, 2015. doi: 10.1109/TMECH.2013.2294805.

[11] E. Bonabeau, M. Dorigo, and G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems*. London: Oxford Univ. Press, 1999.

[12] A. Trotta, M. D. Felice, F. Montori, K. R. Chowdhury, and L. Bononi, "Joint coverage, connectivity, and charging strategies for distributed UAV networks," *IEEE Trans. Robot.*, vol. 34, no. 4, pp. 883–900, 2018. doi: 10.1109/TRO.2018.2839087.

[13] K. Yu, A. K. Budhiraja, and P. Tokekar, Algorithms for routing of unmanned aerial vehicles with mobile recharging stations and for package delivery. 2017. [Online]. Available: https://arxiv.org/abs/1704.00079

[14] M. Mamei and F. Zambonelli, "Field-based approaches to adaptive motion coordination in pervasive computing scenarios," in *Handbook of Algorithms for Mobile and Wireless Networking and Computing*. Boca Raton, FL: CRC, 2004, pp. 1–31.

VT