UAV-Based IoT Platform: A Crowd Surveillance Use Case

Naser Hossein Motlagh, Miloud Bagaa, and Tarik Taleb

The authors demonstrate how UAVs can be used for crowd surveillance based on face recognition. To evaluate the use case, they study the offloading of video data processing to a MEC node compared to the local processing of video data onboard UAVs. For this, they developed a testbed consisting of a local processing node and one MEC node.

ABSTRACT

Unmanned aerial vehicles are gaining a lot of popularity among an ever growing community of amateurs as well as service providers. Emerging technologies, such as LTE 4G/5G networks and mobile edge computing, will widen the use case scenarios of UAVs. In this article, we discuss the potential of UAVs, equipped with IoT devices, in delivering IoT services from great heights. A high-level view of a UAV-based integrative IoT platform for the delivery of IoT services from large height, along with the overall system orchestrator, is presented in this article. As an envisioned use case of the platform, the article demonstrates how UAVs can be used for crowd surveillance based on face recognition. To evaluate the use case, we study the offloading of video data processing to a MEC node compared to the local processing of video data onboard UAVs. For this, we developed a testbed consisting of a local processing node and one MEC node. To perform face recognition, the Local Binary Pattern Histogram method from the Open Source Computer Vision is used. The obtained results demonstrate the efficiency of the MEC-based offloading approach in saving the scarce energy of UAVs, reducing the processing time of recognition, and promptly detecting suspicious persons.

INTRODUCTION

Unmanned aerial vehicles (UAVs), also known as drones, are expected to provide diverse civilian, commercial, and governmental services. The use of UAVs has currently started in different civilian sectors. UAVs are used for environmental monitoring to monitor land pollution and industrial accidents. In agriculture, they are employed to monitor the general health of plants by showing water and nutritional stress as well as finding insect damage [1]. One of the main applications of UAVs has been in disaster relief and management. In [2], a cloud-supported UAV framework is proposed for disaster sensing applications in disconnected, intermittent, and resource-limited environments. Moreover, during the Japan East great earthquake, UAVs were used:

- To coordinate disaster relief efforts
- To capture images of the damaged reactors at the Fukushima Daiichi nuclear power plant for site assessment
- To provide real-time data of radiation levels at the nuclear power plant
- To assess the state of the cleanup and reconstruction efforts taking place in Fukushima prefecture [3].

In addition to the aforementioned applications, UAVs are used in law enforcement for border control by detecting the locations of people intending to cross national borders. In a rescue and border control use case, UAVs are daily used to rescue migrants in the Mediterranean Sea [4] with the help of video surveillance systems. Furthermore, UAVs are used for public safety, through crowd surveillance, to provide safety for crowds of people through recognizing criminals and detecting any other suspicious human activities. A potential use case of UAVs can be crowd surveillance [5]. In such a use case, cameras are mounted on UAVs; by applying face recognition methods on streamed videos, suspicious people can be detected in real time in an efficient manner.

Due to the computational overhead required by such a use case and given the limited power supply of UAVs, the processing of collected data by a UAV is a challenging issue. Nowadays, depending on the UAV type, batteries available in the market do not allow UAV flights longer than 90 minutes, and that is without doing any processing onboard UAVs [6]. Therefore, in order to ensure a flight time long enough for UAVs, the computational overhead onboard UAVs should be as lightweight as possible. The offloading process of video data processing to an edge cloud may be regarded as a solution. However, depending on the underlying radio access technology (RAT), that is, WIFI or LTE, streaming videos from UAVs to an edge cloud, that is, mobile edge computing (MEC), still requires an important amount of energy. For this reason, it is mandatory to distinguish between the applications that could be executed onboard of UAVs and those that should be offloaded to MEC. In this article, we consider the UAV-based crowd surveillance use case and investigate the benefits (or drawbacks) of the offloading process in terms of energy consumption and processing time. Indeed, along with the ongoing advances in wireless communications technologies, MEC will facilitate the offloading process from UAVs due to its expected wide deployment in the network, meaning that a UAV does not need to travel to carry out the data offload. In this article, a testbed is developed for performing face recognition using the Local Binary Pattern Histogram (LBPH) method from Open Source

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Computer Vision (OpenCV), which is a precise and more accurate algorithm [7].

We used the algorithm to recognize particular faces from a database of 40 faces, each stored in a separate directory, considering that each person has 10 different facial details and expressions (e.g., open vs. closed eyes, smiling or not smiling, face with or without glasses). To do the experiment, 10 videos of different lengths are taken in real life by a camera, each of which contains a group of people. Thus, we compared the performance of the offloading process against the local processing of the face recognition onboard UAVs. To make this comparison, we performed two experiments. First, we sought to recognize the faces of five suspected people while varying the video lengths. The results of this experiment demonstrate that it is highly efficient to offload the face recognition operation to MEC rather than processing it locally onboard UAVs. Second, we looked for face recognition by setting the video duration to 1 s while the number of suspected people was varied. The results of the second experiment show that the energy required by a UAV and the processing time when the video processing is offloaded remains the same regardless of the number of profiled persons. The envisioned UAV-based crowd surveillance use case is implemented as part of the target UAV-based IoT platform described below.

The article is organized in the following fashion. We describe the envisioned UAV-based IoT platform. We discuss the potential of UAVs and their integral role in fifth generation (5G) mobile systems. We introduce the target UAV-based crowd surveillance use case and discuss the results obtained from a real-life implementation of the use case. The article then concludes.

UAV-Based IoT Platform

While UAVs are used for their original tasks (e.g., parcel delivery by Amazon, power line monitoring by SharperShape), they can be simultaneously applied for offering numerous value added services (VASs), particularly in the Internet of Things (IoT) when they are equipped with remotely controllable IoT devices. In such a way, UAVs will form an innovative UAV-based IoT platform operational in the sky [1]. This shall decrease the capital and operational expenses for creating a novel ecosystem. Through this platform, IoT data can be collected via remotely controllable IoT devices mounted on UAVs whenever triggered on and off at the right time, at the intended positions, and/or per specific events. Based on the required energy, the collected data can be processed locally onboard UAVs or offloaded to cloud servers on the ground. To build an efficient UAV-based IoT platform, there is need for a platform orchestrator (centralized or distributed) that is aware of diverse contextual information about UAVs, such as their flying routes, their IoT equipment, and their battery status. For instance, in a scenario when a police department requests a video record from a specific position, the appropriate flying UAV has to deviate from its original path to execute the task. To do this, knowledge on the current state of the UAV such as its current geographical position and its remaining energy becomes mandatory [8]. Figure 2 shows our envisioned architecture for the UAV-based IoT platform. The figure demonstrates a widespread network of flying UAVs, each assigned to a specific task: some are flying, and some are ready to fly when needed.

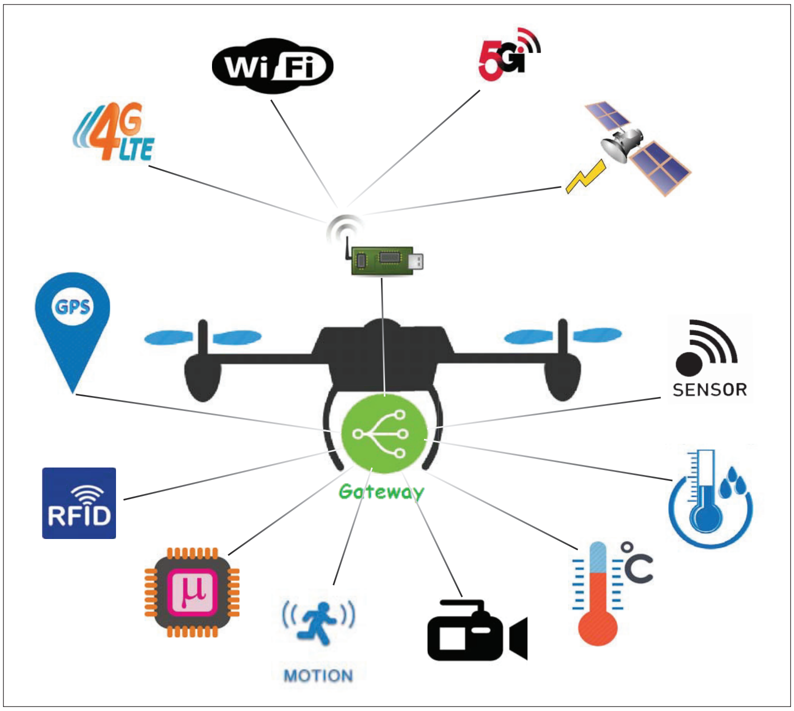

Figure 1. UAVs equipped with diverse IoT devices.

The data delivery from UAVs is performed by any wireless technology that suits the target UAV application such as WiFi and cellular networks (i.e., 4G-LTE, 5G). The choice of wireless technology may depend on diverse factors such as required security, reliability, and system responsiveness. Instead of UAV-to-ground communications, UAVs may also form clusters, in a flying ad hoc networking (FANET) manner, leveraging their short-range wireless communication technologies (e.g., Bluetooth and WiFi) to benefit from sharing their onboard IoT devices, computation resources, and data transmission links. In a cluster, a suitable UAV could be elected as the cluster head to transfer the collected IoT data on behalf of other UAVs to the ground station. Such a clustering approach may be beneficial in situations where UAVs do not have enough individual power/computation resources to accomplish a task or may need to complement each other's IoT devices to carry out an IoT task. Figure 2 depicts the system orchestrator (SO), which coordinates the operations of UAVs and their IoT devices and handles requests from users for IoT services. To satisfy a request for an IoT service, the SO first selects the most suitable UAVs based on many metrics such as UAVs' current routes, their onboard IoT equipment, their residual energy level, and the priority level of their current mission [8]. The SO also coordinates the flying paths of UAVs, ensuring collision-free travel. For secured communications between UAVs and ground stations, the SO instructs UAVs on which access technology to employ and when, and specifies where the data should be delivered (e.g., edge vs. central cloud). The SO is assumed to have all necessary intelligence to be self-capable to autonomous-

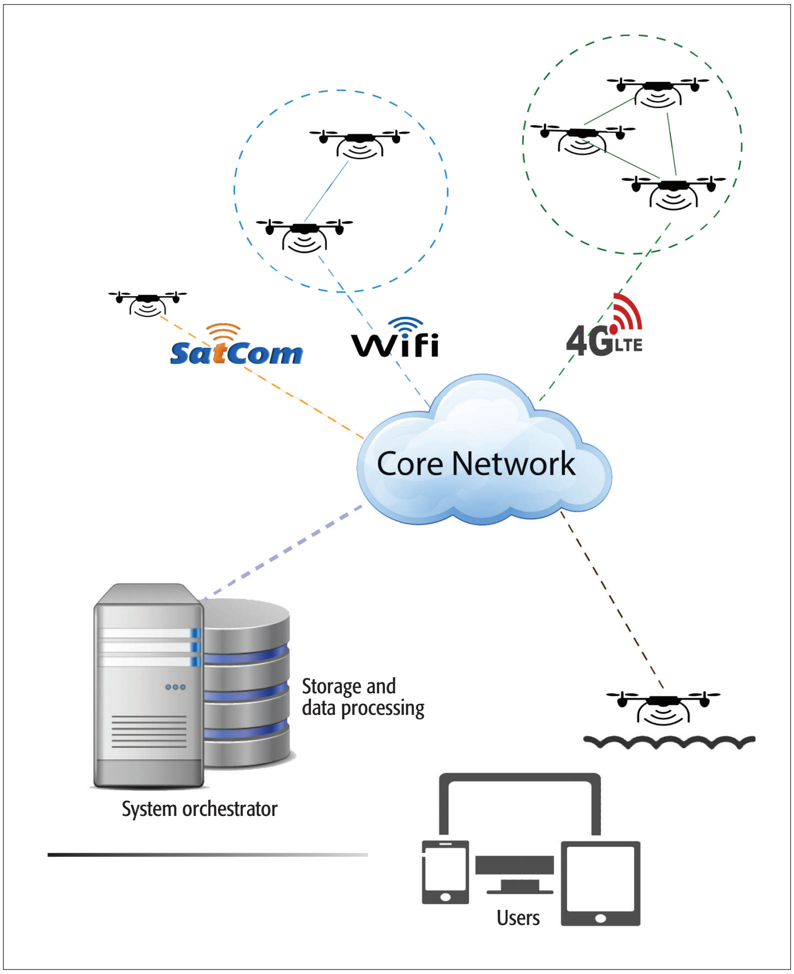

Figure 2. High-level view of the envisioned UAV-based IoT platform.

ly self-operate, self-heal, self-configure, and adequately resolve any possible conflicts from diverse policies [1].

UAV Potential in Advanced Mobile Communication Systems

UAVs exhibit outstanding characteristics compared to manned airplanes. They have unique features for being dynamic, easy to deploy, easy to reprogram in flight, able to measure anything anywhere, and able to fly in a controlled air space with a high degree of autonomy [9]. As mentioned earlier, UAVs can be used to provision diverse services, ranging from civilian to commercial and governmental. Using suitable IoT devices, cameras, and communication devices, countless use cases can be defined for UAVs. For instance, using high-resolution cameras and a suitable communication system such as LTE, UAVs can be used for crowd surveillance, the core topic of this article. This use case can obviously be considered for security reasons to monitor any suspicious activity among crowds of people. When equipped with suitable IoT devices, UAVs can be used to collect IoT data from great heights. Depending on the energy required for the computation of the IoT data and the urgency of the IoT task, the collected IoT data can be processed locally or delivered to an adequate server using a suitable RAT [10]. The data can be gathered from any sensor (e.g., temperature and humidity) or any imagery device (e.g., digital camera). The latter can be used for surveillance, inspection, mapping, or modeling. Most existing UAVs have the ability to deliver data in real time to a ground control station (GCS). Some have local data storage and processing capabilities, enabling them to carry out computational tasks onboard. Most IoT devices onboard UAVs (e.g., sensors, cameras, actuators, and RFIDs) are remotely controllable (Fig. 1).

In addition, UAVs can employ FANET principles to deliver data to a server/GCS. FANET resolves several design limitations associated with the infrastructure-based architecture approach. It solves the communication range restriction between UAVs and GCS, and provides a certain level of reliability for the communication [11]. An important issue in UAV communications pertains to the type of communication technology to be employed onboard UAVs. Due to the dynamic and mobility features of UAVs, there is a need to guarantee reliable communication among them (i.e., good coverage, stable connectivity, and sufficient throughput). The advanced communication systems (i.e., LTE 4G and 5G mobile networks) will be the communication standard to support the long distance, high altitude, and high mobility nature of UAVs. UAVs will use these communication technologies to transfer or exchange data with diverse IoT devices on the ground in a machine-to-machine (M2M) manner as well as to communicate with GCS. Indeed, current LTE 4G systems are used to increase network expandability up to hundreds of thousands of connections for low-cost, long-range, and low-power machine type communication (MTC)/IoT devices. In addition, 5G networks will be designed to offer high data speed (i.e. exceeding 10 Gb/s) and extremely low latency (i.e., 1 ms) [12]. These networks will provide ubiquitous coverage, including at high altitudes. They will support 3D connectivity; a characteristic referring to the ultra-high reliability, ultra-high availability, and ultra-low latency features of UAVs. One of the most important features of these mobile networks shall be support for extreme real-time communications such as real-time mobile video surveillance and streaming. Furthermore, they shall provide broadband access enabling high-definition video and photo sharing in a densely populated area. These mobile networks are also expected to support UAVs in avoiding physical collisions among them by supporting remote planning and alteration (when needed) of their flying routes.

Along with MEC, these advanced communication systems could lift the computing and storage resource restrictions of UAVs, enabling them to offload intensive computations to the edge cloud. Indeed, MEC aims to place generic storage and computing close to the network edge in a mobile network environment. MEC also aims to enable billions of mobile devices to operate for real-time and computation-intensive applications directly at the network edge. MEC can be applied for different use cases as video analytics, location services, IoT, augmented reality, optimized local content distribution, and data caching. The outstanding characteristics of MEC are its service mobility support, closeness to end users, and the dense geographical deployment of the MEC servers [13]. These capabilities will contribute to wide deployment of UAVs, such as the Unmanned Aerial System (UAS) Traffic Management (UTM) system envisioned by the U.S. National Aeronautics and Space Administration (NASA) [14]. With such wide deployments of UAVs, new business models will appear whereby UAVs can be used as a backbone for the ground Internet and/or to complement the coverage of 5G. In this regard, it is worth mentioning Google's project, SkyBender, which uses UAVs to deliver Internet at speeds 40 times faster than 4G systems in the Mexico desert [15]. However, there is a delivery range restriction as the project employs high-frequency millimeter-wave technology that has shorter communication range in comparison to the traditional wireless communication technologies.

UAV-Based Crowd Surveillance

In public places such as stadiums or during parades, it is important to protect civilians from threats. Indeed, in recent years, the rate of crimes in urban areas, such as street crimes, vandalism, and terrorism, has increased. Therefore, anticipating crimes through detection and recognition of criminals among crowds of people is an important approach. In traditional patrol systems, there is a need for many security guards and a huge amount of human effort to provide necessary safety for people. In this vein, UAVs can be used to assist security guards by remotely surveilling people at places of interest. UAVs can provide immunity from any hazard and help not just to control but to track, detect, and recognize criminals adopting face recognition methods. Employing UAVs with appropriate IoT devices, such as video cameras, can offer an efficient crowd surveillance system; detect any eccentric motion and suspicious action; and recognize criminals' faces. The use of this technology provides a bird's eye view for crowd surveillance and face recognition. Therefore, crowd safety and security can be enhanced, while at the same time, the number of security guards deployed on the ground can be reduced. The process of face recognition consists of well defined steps: facial features extraction, database creation of known faces, and face detection matching videotaped faces with profiled ones. Different video analytic tools are available. Many of them can cope with the high mobility feature of UAVs and can achieve face recognition with high accuracy. Recognition of multiple faces at the same time is also possible. The processing of recorded video for face recognition can happen locally as well as at remote servers, enabling the offloading of the face recognition operation to MEC. OpenCV presents noticeable algorithms for face recognition. It employs machine learning to search for profiled faces within a video frame. Indeed, OpenCV uses LBPH with its associated libraries and databases. The approach of LBPH is to summarize the local structure in an image by comparing the pixels with its adjacent ones. LBPH results in accurate face recognition.

In the remainder of this article, we demonstrate how much impact the offloading of face recognition computation has on the energy consumption of UAVs and the overall processing time. Figure 3 depicts the envisioned experiment scenario. In this scenario, we consider a UAV equipped with a video camera and connected to the GCS through LTE cellular network. Figure 4a shows the UAV used in our experiment. The figure also shows the LTE eNodeB used (donated by Nokia). The underlying LTE network is exclusively used for research, and offers low latency and a high bit rate as well as extended coverage to support a variety of scenarios, where measurements can be carried out horizontally, vertically, at higher altitudes, with line of sight (LoS) and beyond LoS. The network includes edge computing resources co-located with the LTE base stations deployed in the Aalto University campus, thus enabling dedicated high-speed low-latency access to critical resources. This is schematically represented by MEC in Fig. 3. The used UAV is a built-in hexacopter equipped with an LTE modem, a gimbal with a high-resolution digital camera, as well as several computing and sensing resources. They include a flight controller (FC) module for stable flight, equipped with gyroscopes, accelerometers, and a barometer; and an embedded Linux system (i.e., a Raspberry Pi) interconnecting the LTE modem to the FC. To set up an LTE connection, any PC can be used as a GCS. On the PC, flight control software, such as Mission Planner, is installed. The PC is used for controlling the FC via a connected LTE modem.

The hexacopter can carry 1.5 kg of payload, including laboratory equipment and metering devices. With a completely charged battery, its flight time is around 30 minutes with the full payload. It also has a safe landing scheme to cope with unlikely motor failure situations. In the envisioned scenario, security guards access the control station and continuously surveille the people. Upon noticing uncommon behavior from a particular person (or group of persons), they command the UAV to take a video of the person(s) and apply facial recognition on the captured video to identify the suspicious person(s) and verify if he/she/they have any criminal records. To investigate the benefits of computation offloading of the facial recognition operation to MEC vs. its local

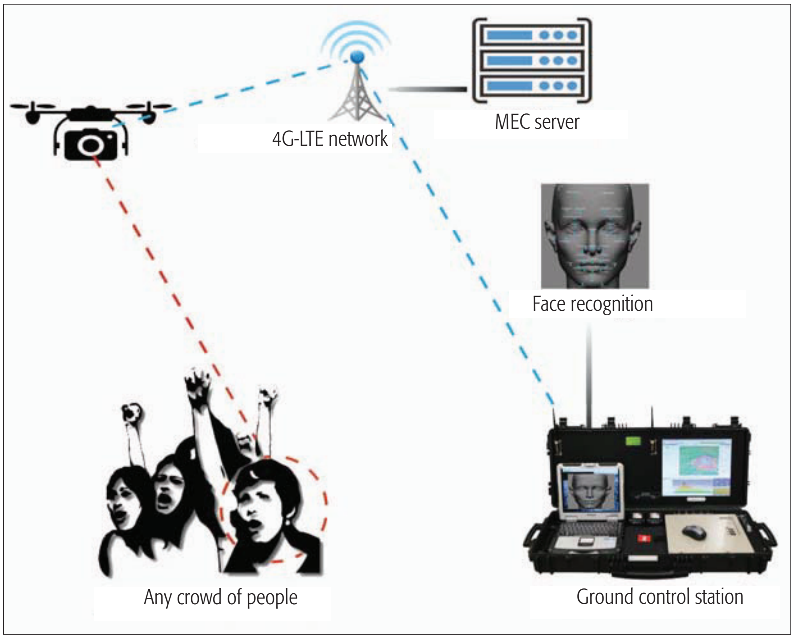

Figure 3. High-level diagram of the envisioned experiment scenario.

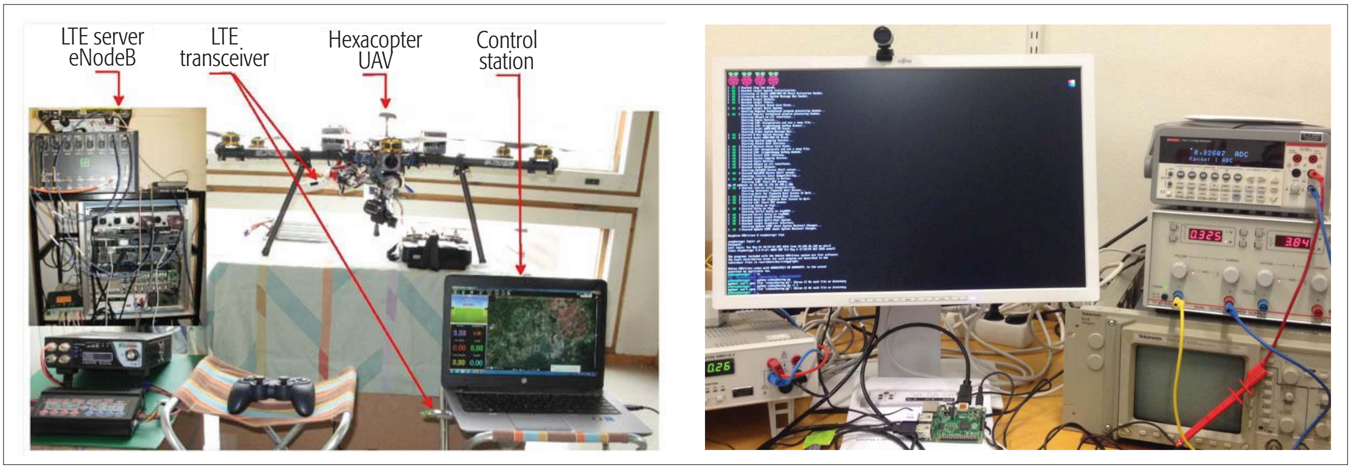

Figure 4. Experiment setup (testbed): a) used UAV along with LTE-based system for UAV control; b) testbed for energy consumption measurement.

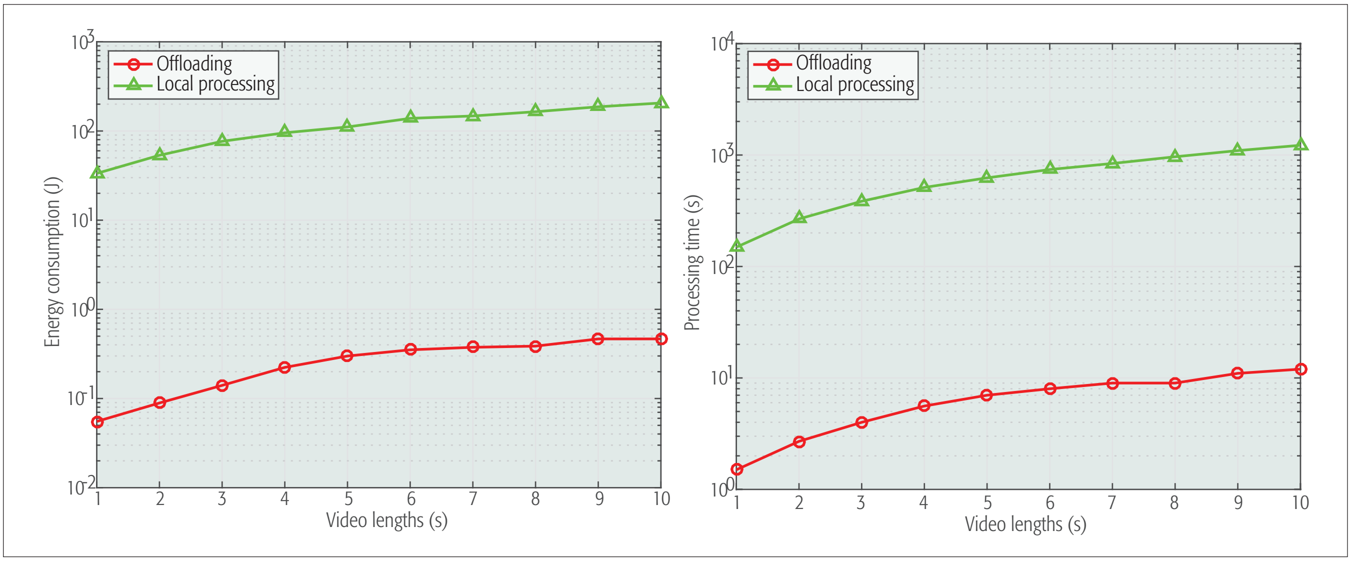

Figure 5. Performance evaluation when different videos of different lengths are processed locally onboard a UAV and when their computation is offloaded to MEC.

processing, we developed a small-scale testbed as shown in Fig. 4b. The testbed environment consists of a Raspberry Pi (RPi) and a laptop that serves as a MEC node. The RPi works as the local processing unit onboard the UAV. In addition, the laptop works as the command and control station of the UAV's gateway for turning the camera on/off, or to command it to locally process the face recognition or offload the processing to the MEC node.

In the experiment and as stated earlier, we used OpenCV's LBPH algorithm to recognize particular faces from a database of 40 faces, each stored in a separate directory. Each person has 10 different faces, varying in brightness/contrast, facial expression (open vs. closed eyes, smiling, not smiling), and facial details (e.g., with or without glasses). The code source in the testbed was developed using the Python programming language. In the experiments, we used TOE8842 dual output power supply as the DC power generator of RPi and set it to 5 V. For the energy consumption measurement, we used a 6-digit resolution digital multi-meter to measure the current (I). In the testbed, 10 videos of different lengths were taken in real life from the camera, each of which contains a group of people. The duration of the *i*th video is *i* s (i.e., duration of the 5th video is 5 s). Therefore, we evaluate the performance in terms of energy consumed and processing time when the facial recognition operation is carried out onboard the UAV and when it is offloaded to MEC. Figure 5 shows the results of our first experiment where we looked to recognize the faces of five suspected people while varying the video lengths. The figure shows that it is far more efficient to offload the facial recognition operation to MEC rather than processing it locally onboard a resource-constrained UAV. Indeed, local processing of the video data consumes a significant amount of energy and drains the UAVs scarce battery. Moreover, the offloading process drastically reduces the processing time compared to performing the facial recognition locally onboard the UAV. From this figure, we observe that the offloading process reduces the energy consumption and processing time more than 100 times compared to performing local processing of video onboard UAVs. Figure 6 shows the results of the second experiment, where the video duration is set to 1 s and the number of suspected people is

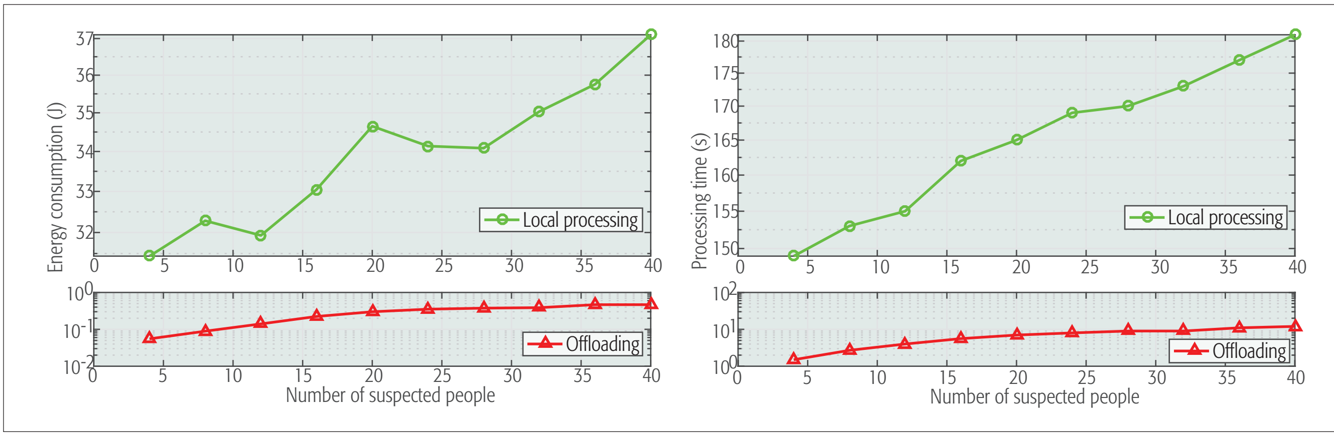

Figure 6. Performance evaluation when a 1s-long video is processed locally on board of UAV and when its computation is offloaded to MEC to recognize different numbers of profiled persons.

varied. The results show that the energy required by the UAV and the processing time if the video processing is offloaded remains the same regardless of the number of profiled persons. However, when the video is processed locally, the required energy and the processing time increase somewhat linearly along with the number of profiled people when the video is processed locally.

Conclusion and Future Work

UAVs are gaining lots of momentum. When equipped with diverse IoT devices, they can be used to form an integrative IoT platform operational in the sky. In this article, we present a high-level view of such a UAV-based IoT platform. As a specific use case of the platform, the article introduces the case of UAV-based crowd surveillance applying facial recognition tools. A testbed is developed using a built-in UAV along with a real-life LTE network. The article compares two cases: when videos are processed locally onboard UAVs and when their processing is offloaded to MEC. The obtained results demonstrate clearly the benefits of computation offloading in saving energy and significantly improving system responsiveness in quickly detecting and recognizing suspicious persons in a crowd. Improvement in the performance becomes more noticeable for longer videos and also when the number of profiled persons is high.

In the future, we will work toward performing crowd surveillance and facial recognition when a cluster of UAVs are employed. In our study, we will investigate the energy consumption by means of local processing when the UAVs share the processing tasks among themselves vs. offloading the computational tasks to MEC. We will also use more than one MEC node to study the efficiency of processing time when the tasks are performed locally by the cluster members vs. when they are offloaded to the MEC nodes. In addition, we are seeking to use more efficient algorithms for testing the crowd surveillance use case.

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