

# Information Autonomy: Self-Adaptive Information Management for Edge-Assisted Autonomous UAV Systems

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**Abstract**—Making Unmanned Aerial Vehicles (UAV) fully autonomous faces many challenges, some of which are connected to the inherent limitations of their on-board resources, such as energy supply, sensing capabilities, wireless characteristics, and computational power. The sensing, communication, and computation Internet of Things (IoT) infrastructure surrounding the UAVs can mitigate such limitations. However, external traffic dynamics, signal propagation, and other poignant characteristics of the IoT infrastructure make it an extremely dynamic and incoherent environment, especially in urban scenarios, thus challenging the use of IoT resources for mission-critical UAV applications. Herein, the concept of information autonomy is introduced to extend autonomy to encompass how information-related tasks are handled in this challenging scenario. In this paper, we motivate the need for “Information Autonomy” based on our observations from real-world experiments and present a self-adaptive framework for edge-assisted UAV applications. Through our preliminary evaluation, we show that our “Information Autonomy” framework is capable of handling uncertainties autonomously during run-time.

## I. INTRODUCTION

On-board resources available to commercial Unmanned Aerial Vehicles (UAV) are inherently limited by the airborne nature of these devices. Such constraints affect key sub-systems, such as sensors and computing platforms, which are instrumental for prolonged and autonomous operations. A relevant trend in mobile devices, whose application has been recently extended to include UAVs, is to use resources from the Internet of Things (IoT) and edge infrastructure surrounding the UAVs to enhance their performance [1], [2]. In particular: *a*) wireless cellular networks can be used to extend the communication range of the UAVs and connect them to other edge devices or the internet core [3]; *b*) data streams from ground sensors or devices can supplement those from on-board sensors to extend the information available to the UAVs [4]; and *c*) signal processing tasks can be offloaded to compute-capable devices residing at the network edge, that is, edge servers [5].

Although most of the discussion provided in this paper applies to all the three cases listed above, herein we focus on edge offloading – case *c*, often referred to as edge computing [4] – due to its potential to enable a high degree of operational autonomy to those highly constrained devices. The advantages of edge computing applied to UAV systems

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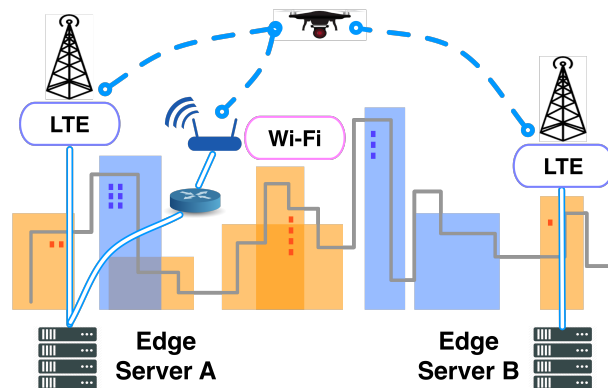


Fig. 1: The scenario considered in this paper: an autonomous UAV leverages the surrounding IoT infrastructure to improve mission performance. Specifically, we focus on offloading computing tasks to edge servers through wireless links.

are rather intuitive: a powerful machine with an unlimited energy supply connected to a UAV through a one hop wireless link can effectively execute complex algorithms beyond the reach of on-board UAV computing platforms and deliver the outcome to the UAV, thus enabling advanced – autonomous – learning, control and planning. The edge server can run simpler algorithms in a shorter time, thus improving the reaction time of the UAV to external stimuli. Finally, we remark that continuous computation requires a substantial amount of energy, a precious resource that should be parsimoniously used to avoid degradation of mission lifetime. By taking over compute-intensive processes, the edge server can significantly reduce energy consumption of the UAV.

Based on the above discussion, edge computing, and in general infrastructure assistance to UAV systems, appears to be an extremely promising component of future UAV systems (see Fig. 1). However, there are several technical challenges to overcome to fruitfully and reliably apply this paradigm to a mission-critical system such as autonomous UAVs. A crucial aspect of the infrastructure assisting the UAVs is that it is shared by a multitude of devices and services. This, together with the characteristics of signal propagation, creates an extremely dynamic environment, where the time needed to transfer data to the edge server, or the time to complete the processing task are highly variable, and governed by extremely complex temporal and spatial random processes [6]. As a result, blindly trusting infrastructure assistance may lead to severe

performance degradation.

We contend that to fully harness the benefits of infrastructure assistance while preserving reliable flight and mission control, the notion of “autonomy” needs to be extended from pure mission control to include an advanced layer of intelligence making decisions on how information is handled within the complex UAV-infrastructure system. We refer to this layer as “information autonomy”. We remark that information autonomy could boost the performance of many distributed, and constrained, mission-critical systems. We make our discussion specific to UAVs due to their extreme characteristics in terms of limitations, mobility and complexity of operations.

Herein, we provide a first description of an architecture realizing information autonomy, and a detailed discussion on the many challenges present in the definition of key modules such as state acquisition/tracking, prediction and decision making. The discussion is supported by illustrative results from detailed simulation and real-world experiences and implementations.

The rest of the paper is organized as follows. Section II describes the operational scenario and discusses the lessons learned from real-world experiments. In Section III, we present the motivation and need for information autonomy in the context of UAV systems. Section IV presents the fundamental structure of information autonomy and emphasizes the key challenges in its realization. Section V presents the proposed “Information Autonomy” architecture. We present the preliminary results in Section VI. Finally, Section VII concludes the paper.

## II. LESSONS LEARNED FROM REAL-WORLD EXPERIMENTS ON UAV SYSTEMS

Figure 1 illustrates the infrastructure-assisted autonomous UAV system at the center of this paper. In the edge computing scenario, the UAV is connected to one or more edge servers, compute-capable devices positioned at the network edge to complete computing tasks, through 1-hop wireless links (e.g., Long-Term Evolution (LTE) or Wi-Fi links). Edge computing is expected to reduce latency compared to cloud computing.

In the considered scenario, the edge servers could take over the analysis, and possibly the control, functions of the sensing-analysis-control pipelines typically used to support the operations of autonomous UAVs. In such edge-based pipeline, the input generated by the on-board sensors and the output from the modules at the edge server, need to be wirelessly transferred. Importantly, as compute-intensive tasks often require a large amount of energy, offloading can possibly reduce energy consumption at the UAV, even when considering the additional energy needed to transmit the data to the edge server.

For a successful completion of a mission, all the hardware components of UAV have to continuously generate new data to inform the control algorithms in a dependable and energy-efficient manner. Unfortunately, it is difficult to estimate the resources needed for sensing, actuation, communication, and control before the mission (run-time) since the stability of the UAV is impacted by various environmental, system, and

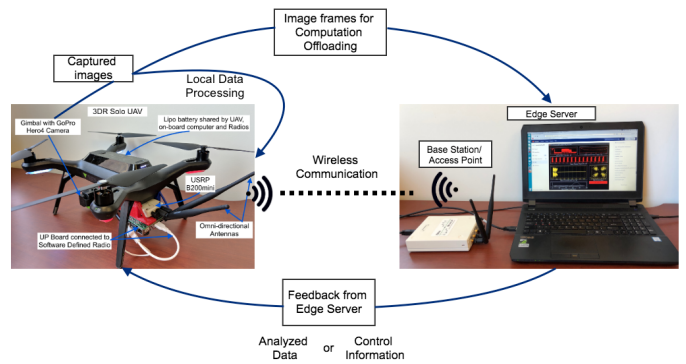


Fig. 2: Experimental setup for UAVs with on-board computing and communication equipments.

network components. In the rest of this section, we report the lessons learned from real-world experimentation.

### A. Run-time Uncertainties in Edge-assisted UAV Applications

We conducted a series of experiments involving UAVs and edge servers using the setup shown in Figure 2. Our goal is to assess the performance and the resource constraints of edge-assisted UAV systems. In these experiments, the UAV is equipped with small on-board computer connected with a WiFi dongle and a USRP B200mini to emulate an LTE interface. The edge server is established using a Laptop with high computational capacity equipped with the same network interfaces. We tested a UAV mission of target tracking based on image classification.

Results indicate the following challenges:

- **1. Environmental Uncertainty** - Weather conditions such as wind speed, temperature, and humidity influence control. Harsh conditions may require a significant amount of energy even just to maintain the UAV stable. Due to the unpredictable nature of the weather, it is difficult to predict or allocate in advance a resource budget for flight and motion.
- **2. System Uncertainty** - In surveillance or other edge-assisted UAV applications, the performance depends on the computation capacity, as well as the available energy budget for computation, communication, and sensing. All these quantities are variable that depend on internal and external factors.
- **3. Network Uncertainty** - Wireless links are susceptible to capacity variations due to interference, and channel propagation. Thus, UAV systems relying on edge servers have to carefully manage and select channel and network resources.

The above challenges highlight the need to introduce “Information Autonomy” to react and adapt to the system, network, and environmental uncertainties. Application goals have to be updated dynamically during the mission to maximize the mission duration. In the next section, we formulate the problem goals with respect to the application scenario.

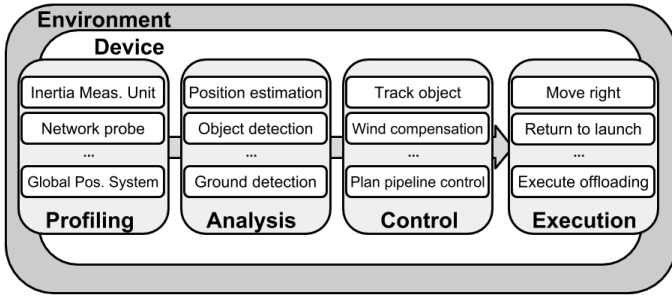


Fig. 3: Profiling-Analysis-Control Pipeline for Mission Autonomy.

### III. PROBLEM FORMULATION AND MOTIVATION

We consider an UAV autonomously operating to accomplish a mission. Here, we do not specifically define the mission, but, instead, assume that autonomous operations necessitates sensor input to be transformed into short- and/or long-term decisions. For instance, video input from on-board cameras can be processed to determine navigation, or to plan the mission. We further assume that our objective is to assure the mission completion, therefore maximizing mission time, while maintaining a high degree of quality of operations, as discussed below.

Figure 3 depicts a basic diagram of the modules involved in the transformation from input vector  $\mathbf{u}_t$  to the output vector  $\mathbf{y}_{t+\Delta}$  given a context or state  $\phi_t$ , where  $t$  is the time at which the sensor input is acquired. The input is first processed in the analysis module to extract relevant features. For instance, in a video-based navigation application, the input is a video frame, and the output of the analysis module, generated by an object detection algorithm, is a set of labeled bounding boxes. The features produced by the analysis module are sent to the control module, which generates the final output  $\mathbf{y}_{t+\Delta}$ . In this particular example, the output are motion and navigational commands.

Formally, we denote the transformation as:

$$\mathbf{y}_{t+\Delta} = f(\mathbf{u}_t, \phi_t). \quad (1)$$

Note that the output is generated at time  $t+\Delta$ , where  $\Delta$  is a random variable corresponding to the time needed for the transformation. We refer to  $\Delta$  as the *capture-to-output* delay.

If the function  $f$  is complex, the delay  $\Delta$  might be large, thus increasing the reaction time of the UAV to input stimuli and possibly degrading mission performance. Moreover, compute intense transformations may require a, possibly large, amount of energy  $E$  to be completed. *Our objective, thus, is to use infrastructure-assistance to reduce  $\Delta$  as much as possible, while also minimizing energy consumption.*

In the edge-based pipeline, the capture-to-output time  $\Delta$  is a function of many variables describing the environment. Let's decompose the delay of the edge-based pipeline  $\Delta^e$  as follows:

$$\Delta^e = \Delta_{\text{data}}^e + \Delta_{\text{computing}}^e + \Delta_{\text{output}}^e, \quad (2)$$

where  $\Delta_{\text{data}}^e$ ,  $\Delta_{\text{computing}}^e$ , and  $\Delta_{\text{output}}^e$  are the delay to transport the data to the edge server, the processing time at

the edge server and the time to transport the output back to the UAV, respectively.

Intuitively, the components associated with the wireless transfer of data, *i.e.*,  $\Delta_{\text{data}}^e$  and  $\Delta_{\text{output}}^e$ , are a function of the used technology (*e.g.*, LTE or Wi-Fi), channel characteristics (UAV-base station distance, fading and shadowing), and network load. The processing component of the delay, that is,  $\Delta_{\text{computing}}^e$ , is highly dependent on the server load. Importantly, channel gain, and network and server load are highly variable, and have complex spatio-temporal distributions that play an important role in the determination of effective data management and analysis strategies.

#### A. Need for Information Autonomy

To study the dynamics of edge-assisted UAV applications, we used an integrated UAV-network simulator – FlyNetsim [7] which allows the application developers to experiment with simulated UAVs, wireless network(s), and edge servers. The UAVs receive control messages over the widely used MAVLink [8] protocol and exchange telemetry information for specific computation tasks and closed-loop controls. Different from other integrated UAV-network simulators, FlyNetSim is capable of supporting a wide range of application scenarios, centralized or decentralized control approaches, and can simulate the transport of data streams and telemetry-based controls. Additionally, FlyNetSim can emulate a range of network conditions, including multiple heterogeneous networks, device-to-device ad-hoc communications, different types of mobility models and also multipath and multi-hop communications. The simulator makes an efficient use of resources, and, thus, provides excellent scalability and can support complex scenarios. Using this tool, we simulate network conditions with varying load and mobility to evaluate the variations in the time  $\Delta$  triggered by these parameters.

In Figure 4, we show temporal traces of  $\Delta_{\text{data}}$  from the object detection scenario, in which the UAV transfers a picture to the edge server using Wi-Fi. The total time is a function of the number of competing wireless nodes and their transmission rates. It can be observed that as the traffic generated by each node increases (see Figure 3a), not only the average delay increases, but the temporal variations across subsequent frames become more apparent. This is due to the complex interactions between the streams induced by the transmission and transport layer protocols, which manifest especially as the sum traffic approaches the maximum link capacity. Similarly, if we increase the number of competing nodes (see Figure 3b), packet failures or timeouts will eventually induce large variations. The bottom plot (Figure 3c) in the picture shows the abrupt variations in the delay  $\Delta_{\text{data}}$  induced by random motion of the UAV when adaptive rate is used. Importantly, the underlying conditions, channel gain, number of nodes, task load, vary over time and space, presenting different trends in different contexts.

From these examples, it is clear that offloading may not be consistently beneficial, at least from the point of view of capture-to-output delay. Moreover, the dynamics of capture-

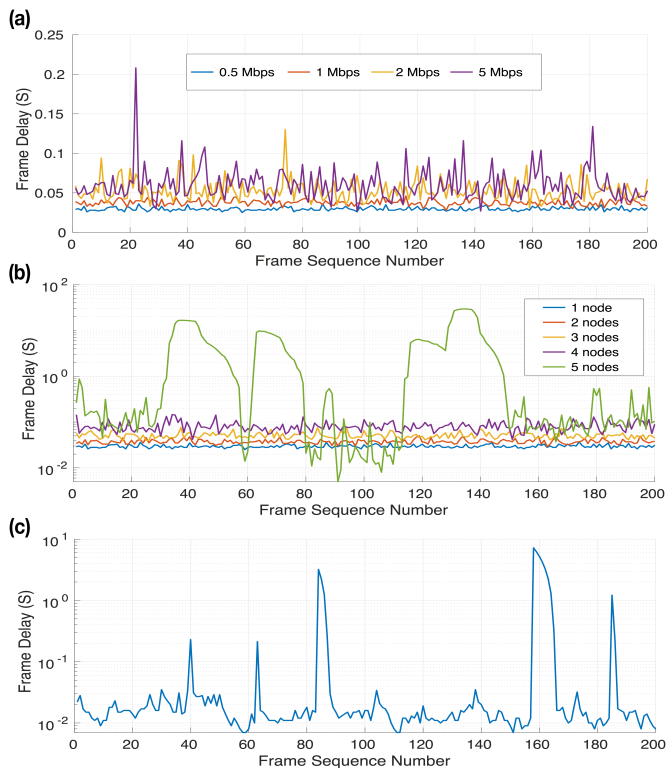


Fig. 4: Frame delay as a function of network load & mobility.

to-output delay highly depend on the characteristics of the surrounding environment.

**Related Work:** the Information Autonomy problem introduced in this paper is a form of Multi-Criteria Decision Making (MCDM) problem [9]. The configuration space for the Information Autonomy consists of multiple parameters that control the wireless communication layer, processor efficiency, energy consumption, and response time of the application with the goal of maximizing mission lifetime and goals. Existing self-adaptation approaches such as Model At Run-time [10], [11] and control theory methods [12] can be applied to solve this class of problems. However, those approaches would need careful formulation and tuning to match the needs of the considered system. A simple optimization framework to control offloading against variations in network rate and server load can be found in [13].

#### IV. INFORMATION AUTONOMY

The simulation results in Section III-A show that a predefined offloading strategy would fail to harness the performance boost granted by infrastructure-assistance, or would possibly even degrade mission performance. We contend that due to the complexity of the involved dynamics, UAVs will need to implement a form of autonomy addressing this relevant aspect of the system. We refer to this layer of autonomy as *information autonomy*. Recall that the goal of information autonomy is to minimize the capture-to-output time  $\Delta$ , by determining how and where information is propagated and transformed within the system. In one of its simplest realizations,

Information Autonomy may just select the best, local or distributed, pipelines to transform sensor feeds into control. As illustrated in Fig. 1, the UAV may have multiple options in terms of network and edge server. We refer to this case in the description that follows.

Structurally, the pipeline to realize information autonomy is analogous to that shown in Fig. 3. However, the modules need to be specialized to the rather difficult problem of managing information in the composite UAV-infrastructure system.

##### A. Profiling

In most autonomous systems, this part of the pipeline is composed of sensors directly collecting signals from the environment. In the context of information autonomy, the Profiling module is assigned the difficult task of extracting information, a signal, from the UAV-infrastructure system to enable the estimation and/or prediction of the state of entire communication-processing sections of the infrastructure. We identify two main strategies, which we refer to as inquiry and probing.

**Inquiry:** The sensing module sends direct inquiries to the infrastructure. For instance, the module can obtain from the network the expected transmission rate, and the number of current tasks – being executed or queued – from the edge server. This method presents two main disadvantages. First, the infrastructure would need to implement protocols to accept requests and compose replies. Additionally, in many network technologies the use of a channel would induce complex interactions with other active data streams, altering the available bandwidth.

**Probing:** A simpler and possibly effective option is to introduce forms of probing, where the profiling module would “test” available pipelines by issuing tasks over the resource. Probing does not require any modification to the infrastructure, but incurs a drawback: the probe will use network and server resources, and for this reason the characteristics of the probes, such as packet number, timing and size, have to be finely tuned.<sup>1</sup>

An interesting tradeoff may exist between the burden imposed to the system and the amount of information extracted by the probes on the state of the system. For instance, a reduced size or frequency of the probes may reduce the amount of information gathered on the state of the pipeline, as a small probe may “traverse” the system unaltered, whereas a sequence of full size tasks may produce informative outcomes while also imposing a large burden to the used channel and server.

##### B. Analysis

The Analysis module transforms the output of the Profiling module – for instance a vector of delays obtained using probes – into features of the sensed pipeline state. Intuitively, as the objective of information autonomy is to select the best pipeline,

<sup>1</sup> Note that if the full task is sent over multiple – independent – pipelines, the UAV can use the output generated in the smallest time, thus reducing the impact of unexpected variations through diversity.

the features should allow prediction of the future performance of available pipelines. Taking as example the traces shown in Section III-A, the Analysis module could attempt to predict future delays or extract properties of their distribution to inform pipeline selection.

A major design aspect in this part of the information autonomy layer is the temporal scale of analysis and prediction. The module could extract a long-term state of the pipeline, corresponding for instance to the number of active nodes and their traffic in our illustrative example. Tracking such state would roughly correspond to mapping samples to a long-term distribution of end-to-end delays, and characterizing their components to plan the appropriate action. Alternatively, the module could maintain a running predictor, continuously predicting future delays from a set of samples. This latter approach allows faster reaction to the variations that exist within the logical states, thus possibly achieving better performance compared to the former approach.

### C. Control

The Control module transforms the features produced by the Analysis module into decisions. In this context, decisions control the activation/deactivation of pipelines, as well as probing strategies. For instance, if a perceived degradation in the performance of the currently used pipeline, the Control module could activate probing over available pipelines. Minimizing  $\Delta$ , the capture-to-control delay requires continuous tuning of system parameters, such as sampling frequency, offloading strategy and analysis functions. Note that multiple pipelines could be kept active during transitions to avoid mission interruptions.

## V. ARCHITECTURE

In developing a solution for Information Autonomy for UAV systems, we use the well-known Monitoring-Analysis-Plan-Execution-Knowledge (MAPE-K) [14] architecture, and tailor our framework (see Figure 5) to circumvent, at least in part, the run-time uncertainties as described in the previous sections.

Consider an autonomous system with sensors  $s_i$  producing the data point  $(t_j, y_i(t_j))$ , where  $y_i(t_j)$  corresponds to the value read at time  $t_j$ . We introduce the notion of Virtual Sensors (VS), where the  $n$ -th VS is represented by a sequence  $VS_n^\delta = \{r_1, \dots, r_k\}$  of one or more readings from sensors  $\{s_i\}_{i=1, \dots, m}$ . Every sequence is the concatenation of several sub-sequences corresponding to data from the same sensor. The parameter  $\delta$  is the time interval between consecutive sequences. An important challenge is to use algorithms that can combine multi-modal data, combining data produced at different time. Note that from this mapping we compute the minimum update frequency of sensors  $\{s_i\}_{i=1, \dots, m}$  to optimize resource usage.

When a new sequence is produced by  $VS_n^\delta$ , it is encapsulated in a Data Block (DB) that includes some metadata, *e.g.*, type, before it is submitted to the central Buffer (B), implemented as a priority queue, with priority function  $\mathcal{P}$ . The highest priority information in the buffer is then redirected to the next stage using policy  $\mathcal{F}$ , that consists of a map associating every DB of

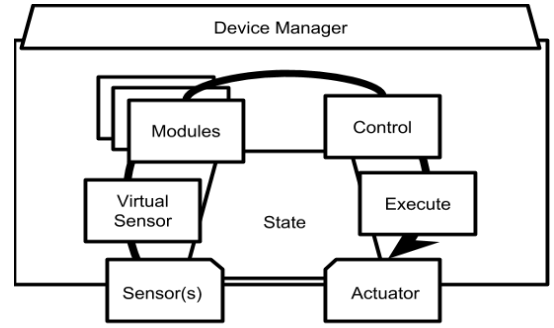


Fig. 5: Graphical representation of the proposed framework and its control flow

type  $\tau$  to the function  $f_a(\cdot)$ . Then, a state update  $X(t) \rightarrow X(t')$  is triggered and *b*) enriches the DB with a selection of state variables  $\chi(t') \subseteq X(t')$  as it appears at time  $t'$ .

We model the data analysis operations as a concatenation of functions  $f_a \circ f_o \dots \circ f_z(\cdot)$ , after each of which a DB is submitted to the buffer B and the priority of such pipeline is re-evaluated. By design (decoupling of input and state) each function isolated and stateless, can be easily offloaded to other devices. These functions are part of the Modules, that include even other pre-control functionalities, such as outgoing communications.

A control mechanism follows the data analysis and allows us to plan (as in MAPE) an action to modify the current state towards the desired one. This can, for instance, consist in selecting a pipeline, activating multiple of them, steering the UAV in a direction or change one of the control parameters, such as the frame rate. The execution module follows, which implements the decision by interacting with drivers of physical or logical components.

Let's now illustrate the behavior of the listed components in a simple scenario involving one UAV and an edge server running the same software architecture. Consider a  $VS_{0.1}^1 = [r_0, r_1, r_2]$ , producing a new sample every 0.1s, containing three readings, where  $r_0$  is a frame and  $r_1, r_2$  are the most recent data points available from accelerometer and gyroscope. First a Data Block is produced by the virtual sensor and enqueued into the buffer B. When it is served, function  $f_a$  is applied, producing a new DB containing the same frame rotated to straighten the horizon. The produced DB is again enqueued in B and ready to be redirected to a pedestrian detection function. Suppose the link with the edge is fairly strong, and therefore the mapping rule  $\mathcal{F}$  calls an offloading function, that sends the DB to a connected edge server. Now the DB is received at the ES, where the same architecture is running. A virtual sensor is listening for incoming DBs, and when receives the data, it enqueues the DB in the local buffer. Thereafter the DB is redirected using the map  $\mathcal{F}_E$ , that is computed taking into account the edge server characteristics and state. The result is then forwarded to the communication module again, now sending to the UAV the resulting DB containing the estimated position of the object to track. The DB is now concatenated with some mission parameters, before being forwarded to the control module. In this case, we use the attached state information to decide if

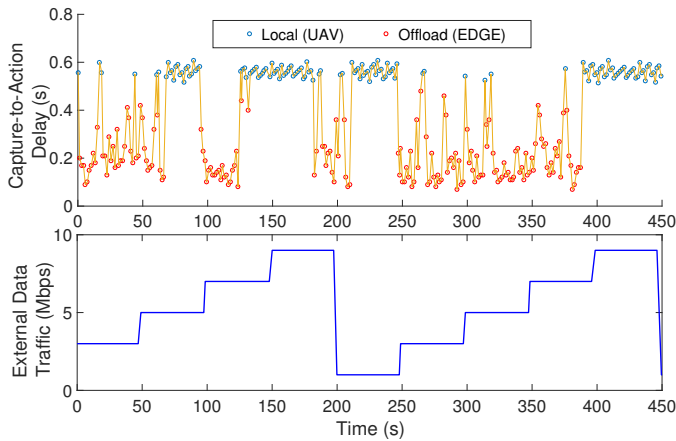


Fig. 6: Temporal variation of frame capture-to-action delay based on instantaneous offloading decisions w.r.t. variations in external traffic load.

the detected object must be tracked or avoided. Finally, the Execute module converts the control DB into an actionable packet that is sent to the motor's driver changing the rotors' speed and performing the required maneuvers.

## VI. PRELIMINARY RESULTS

We experimented with an application scenario where a UAV captures video for object detection based on which it performs control action to follow a target object. The object detection is performed using a Haar-cascade classifier which is executed either by the on-board computer or by the edge server depending on the resource availability. Using a preliminary version of the system described in Section V, and data collected during field experiments, we observe how the system adapts to the environment, and especially to changes in the network load.

We use the FlyNetSim simulator to simulate a network with five nodes: a UAV and an edge Server, and other three nodes competing for the same WiFi channel. Fig. 6 shows the effect of the interfering traffic on the capture-to-control delay, the time interval between when the frame is produced at the virtual sensor, and the beginning of the execution of the maneuver. In this case our goal is to improve control performance by minimizing the end-to-end delay  $\Delta$ . We accomplish this through a simple policy that uses the same object detection algorithm both at the UAV and the ES, selecting for each frame the first control result that reached the executor. It can be observed that in this case, given the deterministic nature of local processing, the resulting maximum delay is always around 0.6s, bounding the worst case to this maximum limit.

We can observe important variations and complex behaviors of the resulting capture-to-control delay. For example, notice the effect of congestion on the capture-to-control delay at  $t = 200s$ , even though the competing nodes are using a small amount of communication resources in the [200, 250]s span. These preliminary results justify how in highly dynamic environments an autonomous system must implement some form of information autonomy to handle information-related tasks.

In our ongoing work, we are developing object detection and RF localization applications using the "Information Autonomy" architecture presented in this paper to further validate the effectiveness of the proposed concept and architecture.

## VII. CONCLUSIONS

In this paper, we presented and discussed the challenges of providing infrastructure-assistance to autonomous systems, and introduced to notion of information autonomy: a layer of autonomy whose objective is to control how information is propagated through the system. The preliminary version of the framework is demonstrated focusing on an object detection application. Results demonstrate the importance of autonomous decision making in this relevant plane of the system.

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