Joint Optimization of Trajectory Planning and Task Scheduling in Heterogeneous Multi-UAV System

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Abstract

The use of unmanned aerial vehicles (UAV) as a new sensing paradigm is emerging for surveillance and trackingapplications, especially in the infrastructureless environment. One such application of UAVs is in the construction industry where currently prevalent manual progresstracking results in schedule delays and cost overruns. Inthis paper, we develop a heterogeneous multiUAV framework for progress tracking of large construction sites. The proposed framework consists of Edge UAV which coordinates the data relay of the visual sensor-equipped Inspection UAVs ($IUAVs$) to the cloud. Our framework jointly takes into consideration the trajectory optimization of the Edge UAV and the stability of system queues. In particular, we develop a Distance and Access Latency Aware Trajectory (DLAT) optimization that generates a fair access schedule for $IUAVs$. In addition, a Lyapunov based online optimization ensures the system stability of the average queue backlogs for data offloading tasks. Through a message based mechanism, the coordination between the set of $IUAVs$ and Edge UAV is ensured without any dependence on any central entity or message broadcasts. The performance of our proposed framework with joint optimization algorithm is validated by extensive simulation results in different parameter settings. Keyword: Path Planning, Task Scheduling, Data Offloading, Construction Site Monitoring, Unmanned Aerial Vehicles (UAVs), Lyapunov Optimization

1 Introduction

The unmanned aerial vehicle (UAV) based solutions are emerging in various domains such as wireless sensing [1], payload delivery , precision agriculture , help and rescue operations [4], etc. Moreover, with the current trend of automation, sensing and information exchange in Industry 4.0, UAV based applications are also finding their place in the construction industry especially for re- source tracking and progress monitoring using aerial im- agery. Such solutions are helpful in infrastructure-less large construction sites as they provide ease of deployment, quick access to the ground-truth data and higher reachability and coverage [5]. Further, the autonomous or semi-autonomous UAV based solutions could facilitate progress monitoring, building inspections (for cracks or other defects), safety inspections (to find any environ- mental hazards) and many more construction-specific audits automatically. The UAV based visual monitoring of under-construction projects also allows simultaneous observability of ground-truth data by different collaborating entities. Availability of such data and information helps in timely assessments that could reduce schedule delays, cost overruns, resource wastage and financial losses which are not uncommon in construction projects. A plausible solution to address the aforementioned challenges could be a Mobile Edge Computing (MEC) [6] based heterogeneous multi-UAV framework. Such a framework along with the prior geometric knowledge avail- able about the construction site as gathered from a Building Information Model (BIM)[7] could help create an ef- fective multi-UAV based visual monitoring system for con- struction sites. As for any constrained environment, the optimization of computational resources is central to de- velop a solution. The integration of UAVs and MEC into a single framework could facilitate that with efficient data collection/processing from the UAV based dynamic sen- sors in infrastructure-less environments [8]. In addition, an MEC based framework can help to perform partial computation offloading wherein a part of data is processed by the UAVs while the rest gets offloaded to the cloud. An MEC based UAV framework is not new and the de- ployment of the UAVs as base stations or edge servers is widely studied [9, 10]. These studies reflect on the flexibility in deployment of UAV based edge computing components. However, there is a problem of buffer over- flow of UAVs due to the limited on-board processing and the shared bandwidth to transfer data to the cloud which leads to instability in the system. In addition, the dy- namic nature of such systems with varying data traffic and continuous movement of UAVs makes it difficult to stabilize or control the system in a deterministic man- ner. Researchers have used online Lyapunov optimization [11] to address such system instabilities. Lyapunov opti- mization considers the stability of the system with time varying data and optimizes time averages of system utility and queue backlogs. In this paper, we address the challenges of deploying a heterogeneous multi-UAV system for construction site monitoring by the joint optimization of UAV trajectory planning and data offloading task scheduling. The pro- posed framework employs two types of UAVs viz. Inspec- tion UAVs $IUAV$s and Mobile Edge UAVs (Edge UAV). While the former is deployed as visual sensors to collect visual data from different locations of the site, the latter interacts and collects data from $IUAV$ s, and offloads the same to the cloud. The core objective of the framework is to minimize the total energy consumption of the sys- tem while considering the data queue backlogs of $IUAV$ s and Edge UAV and also jointly optimizing the trajectory of the Edge UAV in accordance with the trajectories of I

U AV s having minimum access latency and travel dis- tance. The online resource management such as transmission power and processor frequency of the Edge U AV is evolved using Lyapunov optimization (as in [12]). The rest of the paper is organised as follows: Section 2 presents the proposed heterogeneous multi-UAV frame- work for construction site monitoring. The overall system objective is discussed in Sections 3. Sections 4 and 5 dis- cuss the trajectory optimization and Lyapunov based sys- tem stability, respectively. The simulation setup has been presented in Section 6. Section 7 discusses the results gathered from the experiments while Section 8 concludes the paper.

2 Heterogeneous Multi-UAV Frame- work

Figure ?? depicts the overall multi-UAV framework with all its components. The system consists of two hetero- geneous UAVs i.e. a set of Inspection UAVs I U AV = I U AV1, I U AV2, I U AV3, ..., I U AVN and a Mobile Edge UAV (Edge U AV). I U AV s are smaller in size and are more agile. They collect visual data from a set of Point of Interests (PoIs) denoted as L = l1, l2, l3....lk across the construction site. As the construction sites are infrastructure-less environments, there are limited Access Points (AP) available for connectivity to the cloud. Fur- ther, the I U AV s possess limited connectivity range that makes it difficult for them to transfer data to cloud di- rectly. In addition, the I U AV s move in the 3D Cartesian coordinate system. The Edge U AV , which is larger in size and possesses higher computational capabilities, coordi- nates with the I U AV s to relay the data (after partially processing the same) to the cloud. Edge U AV always maintains a constant height and thus its trajectory lies in an horizontal plane. The communication between I U AV and Edge U AV (A2A channel) has limited range and bandwidth. We have assumed the achievable data transmission rate of the I U AVi in a given time slot as dof f i (t). Further, The height of the Edge U AV is h which is dependent on cov- erage range r and line of sight (LoS) loss caused due to environmental effects [13]. The A2A channel power gain $(\zeta) fromIUAVtoEdgeUAVcanbegivenas:$

$$\zeta = g_0 * (\frac{dis_0}{dis_1})^{\theta}$$

(1) where g0 is the path loss constant, dis0 is the reference distance, dist distance between the UAV$_s, and \theta is the path loss exponent.$

2.1 Data collection and offloading

Each PoI (li) is a tuple (¡ di, i ¿) where di specifies the amount of data (images) to be collected and i denotes the coordinates of the site locations in 3D space. The sequence of PoIs to be visited is provided to I U AV s and same is also shared with the Edge U AV . During the traversal along the sequence of PoIs, the limited buffer may make the I U AV wait at some PoIs along the trajectory until it offloads the data to the Edge U AV . The Edge U AV can communicate with one of the I U AVi in a time slot. The data gathered by each of the I U AVi in a time slot t is denoted by Ai(t). Qi(t) represents the queue of the I U AVi and dof f i (t) denotes 2 the amount of data offloaded to the Edge U AV by the I U AVi in time-slot t. The recursive equation to update the Qi(t) is as follows:. Qi(t + 1) = maxQi(t) dof f i (t), 0 + Ai(t) (2) The Edge U AV accepts data from the selected I U AVi in the time-slot t in its queue L(t). The following equation updates L(t) recursively: L(t + 1) = maxL(t) c(t) dof f edge(t), 0 + Aedge(t) (3) where Aedge(t) is the data arrived from the selected I U AVi in time-slot t, c(t) is the data processed by the Edge U AV in time-slot t, and dof f edge(t) is the number of bits offloaded to the cloud in time-slot t.

3 System Objective

n the proposed framework, the offloading of data happens at two stages - 1) from I U AVi to Edge U AV and 2) from Edge U AV to the cloud. Our main focus is to achieve the end-to-end data offloading to the cloud by minimizing the total energy consumption of the whole system (Esystem) which is defined as: Esystem(t) = Etransition edge (t) + EComm edge (t) + NX i=1 (EComm i (t)) ! (4) where Etransition edge (t) is the transition energy of the Edge U AV , EComm edge (t) is a communication energy of the Edge U AV and EComm i (t) is the communication energy of the ithI U AVi. Further, we discuss the various components of Esystem along with the expressions to calculate the same.

3.1 Transition energy of Edge U AV

The transition energy of Edge U AV refers to the energy consumed in moving from one location to another. The transition energy of the Edge U AV is given as: Etransition edge = ——vel(t)——2 (5) where is a constant that depends on the total mass of the Edge U AV and vel(t) is the velocity of I U AV

3.2 Communication energy of Edge U AV

Edge U AV offloads the data to cloud through a wire- less channel [14]. The communication energy consumed to transmit the data to the cloud is given as: Ecomm edge (t) = (2 dof f edge(t) W 1) N0W (6) where the parameters are defined in the Table ??

3.3 Communication Energy of I U AV

The energy consumed for offloading the dof f i (t) data bits at time slot t from the selected I U AVi to the Edge U AV using the A2A channel of bandwidth W Hz is given simi- larly to Equation 6 as: Ecomm i (t) = (2 dof f i (t) W 1) N0W (7) As the PoIs are predefined and the I U AV s follow a predetermined path, the energy consumed for the move- ment of I U AV s are not taken into consideration. Given the energy of the system, our goal is to find the optimal parameter values so as to minimize the ex- pected cumulative energy across the time horizon. The system policy in every time-slot t can be given by X(t) = Fedge(t), pi(t), Pedge(t), Sedge(t). Hence, the end-to-end data offloading policy parameters X(t) aims at minimiz- ing total expected energy of the system. As the chan- nel information for the data offloading is not determin- istic and varies in the environment, the amount of bits arrived at the Edge U AV depends upon the channel char- acteristics as well as the current position of the selected I U AVi. Such time-coupling of variables is responsible for the stochastic nature of the system. The overall optimization model for the stable system performance is given as: 3 P1: min X(t) lim T → 1 T TX t=1 E[Esystem(t)] s.t. 0 FM E (t) F max tT (C1) 0 pi(t) pi,max i = 1...N tT (C2) 0 Pedge(t) Pmax tT (C3) dof f i (t) Qi(t) i = 1..N tT (C4) c(t) Fmax edge tT (C5) dof f i W log2(1 + ()pi,max(t) No W) i = 1..N tT (C6) dof f edge(t) W log2(1 + Pmax(t) NoW) tT (C7) lim T → E[Qi(t)] T = 0 i = 1..N tT (C8) lim T → E[L(t)] T = 0 tT (C9) The constraints C1 and C3 defines the maximum frequency and maximum transmission power of the Edge U AV respectively. In addition, C5 defines the max- imum number of bits processed by Edge U AV . Further- more, C4 and C6 upper bound the number of transmitted bits. Similarly, for I U AV , the constraints C2, C4 and C6 bound the number of transmitted bits. The constraints C8 and C9 establish the rate stability of all system queues (I U AVi and Edge U AV). Next we discuss the model to optimize the trajectory of the Edge U AV with respect to the trajectories of I U AV s.

4 Distance and Latency Aware Trajectory

The flexible and dynamic trajectory planning of Edge U AV could help in applications within construction industry where it is hard to reach by terrestrial commu- nication infrastructure. As already mentioned, the po- sition of I U AV s changes in every time-slot since they move through different PoIs to collect data. Hence, the Edge U AV 's trajectory needs to be estimated in such a manner that it can connect and access an I U AVi in a time-slot before the I U AVi's queue overflows. Whenever an I U AVi's queue gets full, it doesn't move to its next designated PoI and sojourns at the same PoI until it is able to offload its data to the Edge U AV and free up some queue space. Hence, in order to choose one of the I U AV s to offload its queue, the Edge U AV would re- quire the real-time information about the queues of all the I U AV s in each time-slot. This information is not avail- able a priori due to the dynamic nature of the system. We use a message passing based approach for estimating the queue sizes of the I U AV s in order to make a selection. Further, the trajectory of the Edge U AV must be opti- mized so as to consume minimal energy. The trajectory optimization model of Edge U AV optimizes the trade-off between transition energy of Edge U AV and access laten- cies of all I U AVis. In addition, the access latency based data offloading generates a fair schedule for the I U AV s to offload data to the Edge U AV . Access latency (Ri(t)) of the ith I U AVi in the time-slot t is the difference be- tween the time of its last access by the Edge U AV and the current time-slot. P2: min X(t) TX t=1 NX i=1 xi(t) ——Sedge(t + 1) Sedge(t)——2 s.t. ——Sedge(t) Si(t)—— vmax , i = 1..N tT (C1) h2 i (t) + ——Sedge(t) Si(t)——2 gopmax(2 dof f i 2W 1)1N 2 o (C2) Qi(t) 0, i1..N (C3) NX i=0 (Ri(t)(1 xi(t) (N

1)) Rmax, i1..N (C4) NX i=0 (xi(t) Qi(t)) 1, i1..N (C5) NX i=0 xi(t) = 1 i1..N (C6) The first constraint C1 of optimization model P 2 signifies the distance travelled within a time-slot is limited by the maximum velocity. The following constraint C2 restricts that the selected I U AVi should be in the coverage range of the Edge U AV . Constraint C3 denotes that the queue of the selected I U AVi shouldn't be empty while C4 lim- its the time that has elapsed since the last access of ith I U AVi should be less than Rmax. The constraint in C5 selects the I U AVi which has data to offload whereas C6 4 is a binary constraint to select only one of the I U AVi in a time-slot.

5 Lyapunov Optimization based System Stability

The model presented in P1 in Section 3 is a stochastic op- timization problem. The data arrival at the system queues is random in nature. With the help of online Lyapunov optimization algorithm, we can solve such stochastic opti- mization models and jointly stabilize all queues by finding the optimal X(t) in each time slot [15]. The quadratic Lyapunov function [15] associates a scalar measure to queues of the system. Further, the sta- bility of the system is maintained by a guaranteed mean rate stability of the evolving queues i.e. lim T → E[Qi(t)] T = 0, i 1, 2, ..N (8) lim T → E[L(t)] T = 0 (9) Z(v(t)) = 1 2 " NX i=1 Qi(t)2 + L(t)2 (10) v(t) = [Qi(t)N i=1, L(t)] consists of all backlog queues of the system at time t and Z(.) is quadratic Lyapunov func- tion of system queues. The Lyapunov drift corresponding to above function can be given as: Z(v(t)) = E[(z(v(t + 1)) z(v(t)))] (11) The Lyapunov drift plus a penalty function is minimized to stabilize the queue backlog of the system which is given as: D(t) = Z(v(t)) + V E[Esystem(t)] (12) where V is a positive system constant which controls the trade-off between Lyapunov drift and the expected energy of the system. A high value of parameter V signifies more weight on minimizing energy of the system at the cost of high queue backlog. Hence, V acts as a trade-off param- eter between system's energy and queue backlog. An upper bound on Z(v(t)) can be derived as, (for details see [15, 11]) Z(v(t)) =E[NX i=1 Qi(t) dof f i (t)] E[L(t) (c(t) + dof f edge(t))] + C (13) where C is a deterministic constant. As a result, the upper bound of the drift plus penalty function becomes D(t) C E[NX i=1 Qi(t)dof f i (t) L(t)(c(t) + r(t))] +V E[Esystem(t)—v(t)] (14) Hence, the original formulation P1 is reduced to P3 which bounds the system's drift to keep the system stable as follows: P3 min X(t)E " NX i=1 Qi(t) dof f i (t) E[L(t)(c(t) +dof f edge(t))] + V E[Esystem(t)] s.t. 0 FM E (t) F max tT (C1) 0 pi(t) pi,max i = 1...N tT (C2) 0 Pedge(t) Pmax tT (C3) dof f i (t) Qi(t) i = 1..N tT (C4) c(t) Fmax edge tT (C5) dof f i W log2(1 + ()pi,max(t) No W)i = 1..N tT (C6) dof f edge(t) W log2(1 + Pmax(t) N0W) tT (C7) As can be observed, the constraints in P3 is a subset of the constraints in P1. To further simplify the solution of the optimization formulation, P3 could be reformulated as two separate sub-problems provided the positions of Edge U AV and I U AVi are fixed in a given time slot t.

5.1 Transmission energy optimization of I U AV s

First sub-problem deals with the optimization of param- eters related to the I U AVi. The variables Sedge(t) i.e. 5 position of Edge U AV and the offloaded bits of the se- lected I U AVi are coupled in particular time interval. The fixed position of Edge U AV decouples these variables. In the optimization model P 3.1, the transmission energy is optimized for a single timeslot given the position of Edge U AV : P 3.1 min pi(t) NX i=1 Qi(t) dof f i (t) + V NX i=1 pi(t) s.t. 0 pi(t) pi,max i = 1..N tT dof f i (t) Qi(t) i = 1..N tT dof f i W log2(1 + () pi,max(t) No W) i = 1...N tT It can be observed that objective function in P 3.1 is a convex function. First constraint is linear and the sec- ond constraint is upper bounded by a concave function. As a result, the stationary point of the objective func- tion can be derived as: p i (t) = minmax No (Qi(t)W V + 1), 0, pmax.

5.2 Transmission energy optimization of Edge U AV

The second sub-problem deals with the optimization of the Edge U AV parameters for the amount of data offloaded to the cloud. Further, here we can ignore the processor frequency parameters and the associated constraints from the optimization as they do not affect the energy opti- mization. The updated optimization model is given as: P 3.2 min Pedge(t)L(t)(dof f edge(t)) + V Pedge(t) s.t. dof f edge L(t) 0 Pedge(t) Pmax r(t) W log2(1 + Pmax(t) NoW) tT The model P 3.2 has a convex optimization objective sub- ject to convex constraints to solve the optimal transmis- sion power of the Edge U AV . The stationary point of the optimization model P 3.2 is Pedge(t) = N0 (L(t)W V 1). The overall solution approach of the proposed hetero- geneous multi-UAV framework is given in Algorithm 1. Algorithm 1 Heterogeneous Multi-UAV Framework Input: Trajectories of all I U AVi and list of PoIs li. Time, t = 0 while t T do 1. Estimate the Qi(t)N i=1and Si(t)N i=1 2. Select the ith I U AVi to offload data using P2 3. Compute and offload dof f i (t) for I U AVi using P 3.1 to Edge U AV 4. Update Qi(t) 5. Transmit status message to Edge U AV 6. Compute and offload dof f edge(t) as using P 3.2 7. Update L(t) 8. t=t+1 (a) (b) Figure 1: (a) 3D Trajectory of UAVs (b) Top View of Trajectory of I U AV s and Edge U AV for 10 times- lots with Latency markers

6 Experimentation

In this section, we present the simulation setup to val- idate the efficacy of our proposed Distance and Latency Aware Trajectory Optimization with Lyapunov based sys- tem utility. The pre-computed trajectories of each of the I U AVi are shared with the Edge U AV before the sim- ulation starts. The simulation parameters are listed in Table 1. We have considered a 100m x 100m square region with PoIs at 2m distance and at heights ranging from 70m to 80m. There are total 2500 PoIs in the region. We sample 500 PoIs uniformly at random. Simulation were performed using three I U AVi and one Edge U AV . All the I U AVi start from randomly selected PoIs of a ge- ographic cluster. The sequence of PoIs visited by each I U AVi is generated using the following steps: 1) Assign all the I U AVi to randomly selected PoIs of a geographic cluster. 2) All the I U AVi select the nearest non-visited PoIs one after the other. This continues till all PoIs are visited. 3) Before proceeding to the next PoI, an I U AVi collects all the data (Ai(t)) from that PoI. In this process of data collection, an I U AVi may remain at the same PoI across multiple time-slots until all the data (Ai(t)) is collected. For each PoI, the visual data to be collected is modelled as the number of bits randomly sampled from a Gaussian distribution with mean as 800 Kb and variance as 200 Kb. We conducted separate experiments for low data and high data scenarios. For low data, the amount of data at each PoI is two times the output of Gaussian distribution while for high data, the amount of data to be collected is 8 times of the Gaussian distribution. The optimization parameter V ranges from 10 to 1015. The length of each time slot is 60 seconds. Figure 1a shows a section of the 3D view of the trajectories followed by the I U AVi and Edge U AV . Figure 1b shows the top view of the same with the access latency depicted at each location point. For better illustration, we have selected a sequence of 10 time slots to draw the trajectory. As can be observed in Figure 1b, for I U AV3 the access latency increases from 5 at location (-26,5.7) to 8 (upper threshold) at location (9,25). Afterwards, the I U AV3 gets accessed by the Edge U AV resulting in the decrease of access la- tency to 1 at location (17,19) in the next time slot. In order to validate the performance of our proposed framework, we created a baseline approach for both the0 50 100 150 200 250 300 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 Transmission Power of Edge$_U AVVinLogScaleDLAT + LyapunovDLAT + MAXDAT + LyapunovDAT+MAX(a)AverageEdgeUAVTrans-missionPowerconsumption0.00E + 005.00E + 071.00E + 081.50E + 082.00E + 082.50E + 083.00E + 083.50E+084.00E+0801234567891011121314NumberofBitsVinLogS$

$LyapunovDLAT + MAXDAT + LyapunovDAT+MAX(b)AverageEdgeUAVQueuelengthFigure2 : ExperimentalResultsonTransmissionpowerandQueueLength010203$

$LyapunovDLAT + MAXDAT + LyapunovDAT + MAXFigure3 : ComparisonofmaximumAccessLatencybroadcategoriesoftheoptimi$

$1)Tra-jectoryOptimizationand2)TransmissionEnergyandsys-temstability.$

7 Result and Discussions

n this section, we discuss the comparative performances of our proposed approach with other baselines.

7.1 Influence of the trade-off parameter V on Edge U AV

Figure 2a depicts effect of the increase in the parameter V with respect to the transmission power of the Edge U AV . It is evident that DLAT + MAX and DAT + MAX always consume the maximum energy which makes the average energy consumption same across different values of V. For 7 DAT + Lyapunov and DLAT + Lyapunov, a drop in the energy consumption can be observed for V values of 11, 12 and 13. In the Figure 2b, it can be seen that the average Edge U AV queue length stays low for both DLAT + MAX and DAT + MAX at all the values of V. For DAT + Lyapunov and DLAT + Lyapunov, we can observe that the average queue length of Edge U AV starts to increase around V = 11, 12 and 13. It is to be noted that the deflection points in the Figure 2a and Figure 2b align with each other. In the Figure 2b, the average queue length of Edge U AV increases with increase in V as the weightage of the system utility increases. The DLAT and DAT methods with Lyapunov shows similar performance whereas the MAX approach is not affected with the change in the trajectory optimization.

7.2 Per Time slot analysis of I U AV$_i$

As shown in Figure 4 [a], per time slot data offloading schedule of I U AVi based on the trajectory of Edge U AV incurs higher access latency for DAT based approaches. Besides this, Figure 4 [b] shows that the queue of I U AVi is higher for the DAT combinations throughout. It is in- teresting to note from these results that the queue uti- lization in DLAT combinations is well spread out keeping the energy consumption less for optimal V. However, for DAT combinations the queue utilization is more bursty in nature and so is the energy consumption which even touches the MAX baseline for some time-slots as shown in Figure 4 [c]. This behavior can be explained by the fact that in the DAT based approaches, the Edge U AV selects the nearest I U AV which may not have sufficient data to offload at that time instant. On the other hand, the DLAT based approaches select the I U AV s optimally considering the distance as well as the data availability in the I U AV queues. Hence, it can seen that our proposed DLAT + Lya- punov shows consistently better performances with opti- mally balanced trade-off between the trajectory optimiza- tion with low access latencies and minimal transmission power consumption of the system.

8 Conclusion

AV based applications for progress monitoring and re- source tracking are emerging in construction industry.Constructions projects have minimal infrastructure for capture and offloading of ground-truth data. This paper presents a heterogeneous multi-UAV based framework for end-to-end data collection and offloading using a distance and latency aware trajectory optimization. The Lyapunov optimization approach is used to ensure the stability of the system in terms of expected system queue backlogs by breaking the system optimization problem into two sub- problems. The simulation results show that the access latency of our proposed (DLAT + Lyapunov) approach performs better than other baseline approaches. More- over, the analysis of system parameter V has shown a trade-off between the queue stability and the system util- ity.

References

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