Maximizing offloading opportunities for UAV communication

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Abstract

UAVs (Unmanned Aerial Vehicles) built for surveillance must be small and lightweight to go undetected. Therefore, for small surveillance UAVs there is a large dependency on the ground network to provide resources to complete computational demanding tasks in a short time. Thus MEC (Mobile Edge Computing) servers are deployed at base stations to accommodate resource constrained devices. One dilemma that arises is ensuring resources are allocated in a logical process that maximizes the utilization of the local MEC server resources so that the total communication cost incur by additional offloading is reduced. This paper proposes an algorithm that aims to reduce the impact to neighboring MEC nodes by finding the best-fit combination of tasks to be computed at the local MEC server.

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1. Introduction

UAV (Unmanned Aerial Vehicles) oriented demand has evolved dramatically over the last decade and is now a key potential growth market for embedded vision. However, accommodating drones for the next generation network will be challenging task, although, modern drones are semi-autonomous, the biggest revolution is in respect to the content of data sent over the air. The majority of data is now originating from UAVs as raw media such as images, video and sound, in contrast to users' input sending commands to UAVs. The consequence of this shift is the additional load on network infrastructure. Providing computer vision for UAVs is an example which require a large amount of computational resources to identify objects in images and live video while in the air. The challenges for network providers are evident. Network providers must adhere to strict delay requirements and dynamically adapt their resources to provide a high level of service. Installing additional hardware to perform computer tasks on a surveillance UAVs may not be plausible due to the impact the additional weight would have on the agility and performance of the UAV. Therefore, this paper's proposal is to reduce excessive offloading between MEC servers for UAV image data by optimizing the combination of jobs at the local edge server.

2. Related Works

In [1] the authors provide an overview of UAV-aided wireless communication and highlighting the key design considerations of UAVs. In [2] the authors look at the challenges of deploying UAVs to provide 5G coverage to user equipment. In [3] they propose the idea of a cooperative network framework for multi-UAV guided ad-hoc networks, devices with low power may choose to offload their content to a neighboring drone. In [4] authors discuss the potential of UAVs, equipped with IoT devices, in delivering IoT services from great heights. Also the authors present 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.

3. Network Model

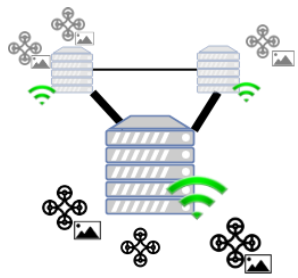

Figure 1: UAVs will depend on MEC servers to complete computational demanding tasks. One example is computer vision.

The above diagram illustrates the communication model between UAVs and MEC (Mobile Edge Computing) servers. The black UAVs contained in set U containing u number of UAVs {1, 2,… , u}. The grey servers are MEC servers located at the base station contained in set M containing m number of MEC servers {1, 2, ... , m}. Each MEC server can dynamically select the subset of image preprocessing tasks to preprocess, denoted as O {1, 2 ,… , o}, until the subset sum of O image sizes exceed the MEC servers capacity C. Each image will be size B in bytes following an exponential distribution. Each UAV in U will send one image i to preform preprocessing following a Bernoulli distribution with probability p since an image may not always be sent from a UAV. The objective is to maximize the MEC server's local utility by finding the best fit combination of O images to preprocess subject to the capacity of the MEC server.

4. Simulation

The following simulation was conducted using Python standard libraries, knapsack optimization package and Numpy. For the purpose of the simulation only one MEC server m receiving images O from a subset of UAVs in U is considered. The capacity C of a MEC server m is set to 200, the probability of an image sent to be preprocessed is 0.8 since a UAV may be in flight travelling to a set location to take a photo. The number of UAVs in set U range from 5 to 35 in our first experiment. In the second experiment the mean image size B ranges from 10 to 40. The sum of all image sizes, including unprocessed images, in O is divided over the sum of image sizes preprocessed at the local MEC server m to determine the utilization. The results are also compared with a randomly selected subset of images to be preprocessed. Thus, we can compare to prove the reduction in B data offloaded to neighboring MEC servers

5. Evaluation

In figures 2 and 3, the knapsack approach starts to outperform the random selection when the subset of O images received exceeds the capacity of the local MEC server. This is due to the fact that the Knapsack can reevaluate its choices until the subset of images minimizes m reaming capacity. The utilization of the MEC server is reduce when the mean image size increases due to the larger images unable to fit into the remaining capacity.

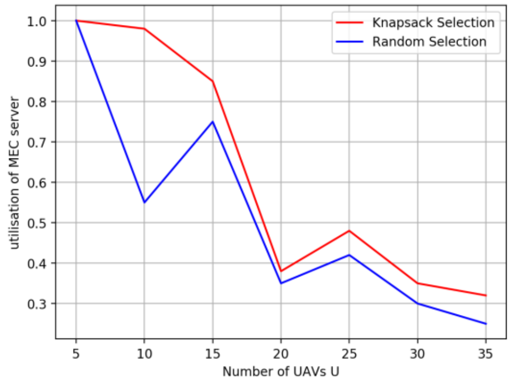

Figure 2: The impact on MEC server utilization in respect to the number of UAVs.

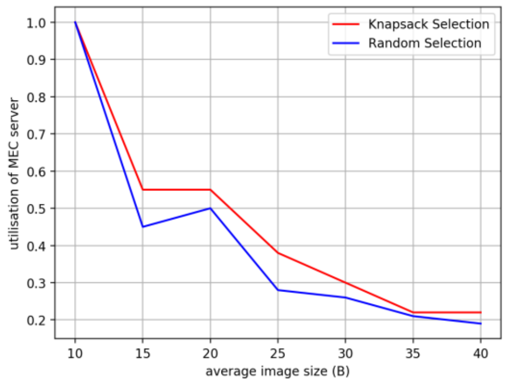

Figure 3: The impact of MEC server utilization in respect to the mean image size.

6. Conclusion

Our results show that the knapsack optimization increases the overall utilization of a MEC server resources over randomly selecting images to preprocess. The results also illustrate the need for a conductor to schedule tasks effectivity in order to further reduce the number of images offloaded to neighboring MEC servers. In light of this, tasks are allocated more effectively than random selection, therefore a reduction in communication costs outside the local MEC server.

7. Future work

Following this paper, our plan is to extend the algorithm so that the offloaded images are sent to the next best MEC server that provides the lowest communication and computational delay available. Furthermore, to create a model to apply Federated Machine Learning fit for computer vision problems in a distributed situation.

8. References

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9. Acknowledgement

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