Privacy-by-Design Task Offloading for UAV-mounted Cloudlets

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ABSTRACT

We consider a network of capacitated Unmanned Aerial Vehicles (UAVs) cooperating as an aerial edge computing system. Due to limited onboard energy and computation capabilities of UAV-mounted cloudlets, a single UAV might not be able to execute a large number of tasks and guarantee their desired quality of services. The overloaded UAV can fulfill its overwhelming workload by offloading its tasks to other UAVs. However, data privacy and accessibility are of critical importance that need to be considered for offloading. We propose a privacy-by-design offloading solution for an overloaded UAV aiming to minimize the offloading cost while satisfying the quality of services.

KEYWORDS

Edge Computing, Unmanned Aerial Vehicles, Data Protection

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1 INTRODUCTION

In mobile edge computing, deploying cloudlet infrastructure at the edge of the network is costly and may not be feasible in many situations (e.g., disaster situations, emergency rescue, unexpected surge in user demand) and regions with sparse or no infrastructure of wireless access points such as remote rural areas. To overcome these problems, considering Unmanned Aerial Vehicles (UAVs) as computational cloudlets is proposed by virtue of their inherent attributes such as aerial mobility, low operating costs, flexible deployment, and wireless communication ability [2, 8, 9]. UAV-mounted cloudlets can provide edge computing services and hence improve quality-of-service (QoS) for ground IoTs [3, 11].

While UAV-mounted cloudlets can bring many opportunities to avoid QoS violations and balance the load, they have often limited computing capacities and energy budgets. To expand the computational capacity and coverage of a single UAV-mounted cloudlet, especially when serving large computational demands, autonomous cooperation and coordination among multiple UAVs are needed

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to form an interconnected computing system and improve quality of edge services [4, 5]. Such a perspective, however, opens new research challenges on account of the current lack of efficient data protection mechanisms for offloading. In particular, the major categories are considered privacy and accessibility restrictions defined as follows: 1) *Privacy restrictions*: If some tasks are offloaded to the same UAV (i.e., cloudlet) for computing, they can reveal sensitive information, which could harm IoT user privacy [7, 10]; 2) *Accessibility restrictions*: There are often some restrictions in offloading a task to a specific UAV due to lack of trust, reliability, or system compatibility/preferences [6, 12].

In this paper, we consider a network of capacitated UAV-mounted cloudlets (NUMC) cooperating as an aerial computing system and propose a privacy-by-design offloading solution for an overloaded UAV aiming to minimize offloading cost while satisfying quality of services and handling both restrictions. We first formulate an optimal offloading mathematical model for this Data Protection Offloading Problem (DROP). DROP is an NP-hard problem. We then propose an iterative algorithm by exploiting graph theory to obtain efficient and computationally tractable solutions. We finally evaluate the performance of our proposed algorithm in extensive experiments.

2 OPTIMIZATION FORMATION

We define u_0 as an overloaded UAV and $U = \{u_1, \dots, u_m\}$ as a set of m UAVs with available computational resources. The set of tasks at u_0 to be offloaded is defined as $K = \{k_1, \dots, k_n\}$, where n is the number of tasks and $n \geq 1$ (u_0 has at least one task to be offloaded). Let F_i be the CPU frequency (i.e., CPU cycles per second) of u_i , and its capacity is denoted by $u_i^{cap} = (C_i^{cap}, D_i^{cap})$ where C_i^{cap} is the number of idle computational cycles of u_i and D_i^{cap} is the available memory size of u_i . Each task $k_i \in K$ has some requirements defined by (C_i, D_i) , where C_i represents the number of computational cycles required to obtain the outcome of k_i , and D_i denotes the data size of k_i .

The total energy consumption for completing k_i via offloading to $u_j \in U$ can be computed by [5]:

$$E_j(i) = \frac{D_i P_0}{B_j} + C_i \gamma (F_j)^2, \quad (1)$$

where P_0 denotes the transmission power of u_0 , γ is the effective switched capacitance (input transition), and B_j represents the bandwidth of u_j .

Similarly, the total delay of completing task k_i by offloading to u_j is calculated by:

$$T_j(i) = \frac{D_i}{B_j} + \frac{C_i}{F_j}. \quad (2)$$

Figure 1: Average cost

Therefore, we define the overhead cost of offloading k_i to u_j , in terms of energy consumption and processing time, as:

$$Z_j(i) = \alpha_i E_j(i) + \beta_i T_j(i), \quad (3)$$

where $0 \leq \alpha_i, \beta_i \leq 1$ represent the relative importance weights of energy consumption and processing time for task k_i according to its required QoS and current battery lifetime of UAVs. This provides a rich modeling flexibility that fits the general case, where each task may have different importance weight values.

We now formulate the data protection offloading problem (DROP) as an Integer Program (IP) as follows:

$$\text{Minimize } \sum_{i=1}^n \sum_{j=1}^m Z_j(i) x_{ij} \quad (4)$$

Subject to:

$$\sum_{i=1}^n C_i x_{ij} \leq C_j^{cap}, \quad \forall j \in \{1, \dots, m\}, \quad (5)$$

$$\sum_{i=1}^n D_i x_{ij} \leq D_j^{cap}, \quad \forall j \in \{1, \dots, m\}, \quad (6)$$

$$\sum_{j=1}^m b_{ij} x_{ij} = 1, \quad \forall i \in \{1, \dots, n\}, \quad (7)$$

$$x_{uj} + x_{vj} \leq 1, \quad \forall \langle u, v \rangle \in E, \forall j \in \{1, \dots, m\}, \quad (8)$$

$$x_{ij} \in \{0, 1\}, \quad \forall i \in \{1, \dots, n\}, \forall j \in \{1, \dots, m\}, \quad (9)$$

where x_{ij} is a decision variable with a value of 1 if k_i is offloaded to u_j and 0 otherwise. To formulate the accessibility restriction, we define an indicator variable, b_{ij} . If k_i can be offloaded to u_j then $b_{ij} = 1$, otherwise $b_{ij} = 0$. To formulate the privacy restriction, we define E consisting a pair of conflicting tasks that cannot be offloaded to same UAV. The objective function (4) is to minimize the overhead cost for all tasks. Constraints (5) and (6) ensure that the assignment of tasks to each resource-rich UAV does not exceed the capacity of that UAV. Constraints (7) ensure that each task is offloaded to exactly one UAV obeying the *accessibility restrictions*. Constraints (8) ensure that any two tasks with *privacy restrictions* cannot be offloaded to the same UAV. Constraints (9) guarantee that the decision variables are binary.

Figure 2: Average execution time

3 GREEDY-RENEW ALGORITHM

Due to the NP-hardness of the DROP, we propose an efficient iterative approach, called *GREEDY-RENEW*.

We first design an UAV Selection Scheme (USS) aiming to decide which task should be selected for offloading at each iteration. USS finds the tasks with minimum number of offloading choices (accessibility). Specifically, if only one task exists, USS selects that task. Otherwise, it selects a task with minimum degree (number of privacy conflicts). After obtaining the target task by USS, we obtain its offloading UAV that has the minimum overhead cost (this step will be enhanced by our *renew rule*). This procedure continues iteratively.

With defining these priorities for offloading, USS can largely reduce the chance of finding infeasible solutions. However, it is still difficult to find a feasible solution for DROP because of being NP-hard. To boost the probability of finding a complete solution, where all tasks are offloaded while satisfying the required restrictions and constraints, we then design a *renew rule*. In doing so, we first sort all accessible UAVs for task k_i , in ascending order of their cost, denoted by $L^s(k_i)$. Then, the first UAV in $L^s(k_i)$ will be selected for the offloading of task k_i . If a complete assignment is not obtained by the USS, *renew rule* updates the offloading decision of task k_i to the next UAV in $L^s(k_i)$. After checking all accessible UAVs of a task if the *renew rule* cannot find a complete assignment for the task, it halts and moves to the next task. Note that the *renew rule* only applies when USS cannot achieve a complete assignment.

4 NUMERICAL EXPERIMENTS

For *privacy restrictions*, we setup a well-known random graph model, the Erdős-Rényi model (N, P) [1], where N is the number of tasks and P is probability of having a conflict with another task. For *accessibility restrictions*, the probability associated with UAVs for each task is P_{01} (the probability of generating 1 using the Bernoulli distribution). Fig. 1 shows that our proposed algorithm obtains near optimal solution. Fig. 2 presents that the proposed algorithm scales well with various number of tasks.

5 CONCLUSION

In this paper, we formulated a general data protection offloading problem (DROP) for offloading tasks among a swarm of UAVs. We

proposed a highly scalable privacy-by-design iterative algorithm that finds near-optimal solutions.

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