Learning based Intelligent IoT Task Offloading and Resource Allocation in UAV-assisted Fog Network

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Abstract
Unmanned Aerial Vehicles (UAVs) are widely used to serve different IoT services and applications in the Fog environment. In order to perform offloading task locally in a specific geographic area, the edge level computing nodes or UAVs require the understanding of the environment and the workload. In this paper, we consider that the UAVs can perform the scheduling of the tasks from the users by creating a network of mobile computing environment. Therefore, first we create a network of mobile Fog nodes such as UAVs based on their features in a certain geographical location and we use Competitive Learning (CL) to create the computing networks. Then, through Reinforcement Learning (RL), different tasks are assigned to the UAV networks so that the close by UAVs in the network can collaborate with each other to serve the user computation tasks. Based on different task loads, the UAVs efficiently allocate the computational resources such as CPU, memory and bandwidth to the users. The simulation result shows the efficiency of the proposed mechanisms of creating the networks and resource allocation for task offloading in the mobile Fog nodes.

1. Introduction
In recent years, Unmanned Aerial Vehicles (UAVs) are used to provide a broad spectrum of IoT applications like delivery system, mobile small cell deployment, disaster management system, energy efficient data collection etc [1][2][11]. Since the UAVs are able to provide higher mobility, a larger coverage area can be provided to the end users so that the edge level tasks can be executed from the height through UAVs [3]. In addition, the cloud paradigm has been effectively shifted towards the edge of the network through Fog that enables low-latency, location awareness, mobility and wireless access capability [4]. Usually, the existing research on Fog computing considers the edge level Fog nodes or devices to be statically deployed in different geographic areas. However, the recent advancement of UAV technology and neural network [13] research ignites new kinds of Fog based IoT services, which demands for not only data collection from a wide area of coverage, but also low cost intelligent task processing at the edge [5]. The idea of task offloading in different networks including Fog has been widely studied in the literature [6] [7] [8] [9]. However, these researches are limited to the task offloading in statically deployed network infrastructure or Fog devices and the mobility issue of the Fog devices is not addressed properly. Therefore, in this paper we propose a IoT task offloading framework in an unknown and dynamic environment which uses the mobile Fog computing nodes such as UAVs to perform the computational tasks at the edge of the network. In our scenario, first, we consider mobile computational networks consist of UAVs and the network is created using Competitive Learning (CL) based on their availability parameter in a certain geographical location. Second, through Reinforcement Learning (RL), different IoT tasks are assigned to the UAV networks so that the close by UAVs in the network can collaborate with each other to serve the user computation tasks by allocating the resources such as CPU, memory and bandwidth.

2. System Overview
The system model for the intelligent task assignment is presented in Figure 1. There are three core components in the envisioned model: i) the UAVs are considered as Fog nodes which are located in a specific geographical area with substantial amount of processing, communication and storage capacity; ii)
The service provider (SP) can manage and plan the flight path of the UAVs in the network and is able to remotely monitor the activity of the UAVs, iii) the communication network includes both cellular and satellite communication where core network and ground station is used to communicate with the cloud based SP. In case of the cellular communication, the UAVs must be inside the range of the cellular base station. However, the UAVs also have the interface to use the satellite communication medium in case of the unavailability of the cellular coverage in the environment. Different IoT service users (marked green in Fig. 1) in the coverage area of UAVs submit their task requests to the UAVs so that the collaborative task processing can be offered locally by the UAVs. In this paper, we provide a solution that can efficiently offload the task load to a network of UAVs (A, B, C in Fig. 1). We consider the mobility of the UAVs during the task processing. The main parameters of the neighboring UAVs are shared with each other and they are able to determine the amount of time two UAVs will stay in range of each other. The predicted time, \( \tau \) is the link expiration time which denotes the amount of time two UAVs will stay in range of each other.

### 3. UAV task offloading network using Competitive learning

In Fig. 2, the competitive learning [12] is implemented in a Neural Network with one hidden layer or competitive layer where the competitive neuron is a weight vector \( w_i = (w_{i1},...,w_{ip}), i=1,...,I \). In Alg. 1, the input data for the input layer is \( X = (x_{11},...,x_{1m})^T \) where the input vector is \( x_u \) which includes the link expiration time, location co-ordinates from GPS of UAVs, UAV speed, and direction angel between the neighboring UAVs and the residual resource profile of UAVs. The similarity measure between different UAVs are calculated using \( X \) and \( w_i \). For every input vector \( x_u \), the competitive neurons compete with each other to find similarity among themselves and create the clusters of similar UAVs based on the linear combinations of the input parameters of the UAVs. The winner neuron set its output \( o = 1 \) and the competitive neurons set the output to \( o = 0 \). The inverse of the Euclidean distance is used to measure the similarity between the input vector and weight vector. In the next section we discuss how the different tasks are assigned to different UAV networks.

#### 4. Task allocation via Reinforcement Learning (RL)

Let us consider the state space \( S = \{s_1,s_2,\ldots,s_m\} \) which indicates the allocation profiles of the resources at UAV agents based on the IoT task requirements in \( m \) number of states. The set of action \( A = \{a_1,a_2,\ldots,a_n\} \) is the action of assigning the states of resource allocation to each UAV where we consider \( n \) number of UAVs in \( k^{th} \) network as processing nodes. Each valid action means that the task requirements in a state have feasible allocation to the network of UAVs and the agents receives reward values or otherwise the action becomes invalid and the agent receives no reward value. A task set \( T_j \) requires specific amount resources from the UAV network such as CPU, storage and bandwidth. Therefore, the reward value for the actions is defined in generalized form calculated as,

\[
R = \begin{cases} 
\sum_{t\in T_j} R(j), & \text{if } R(j) \leq C \\
0, & \text{otherwise} 
\end{cases}
\]

(2)

where \( R(j) \) is the amount of resource allocated to individual task \( j \) in the task set \( T_j \). \( C \) is the threshold capacity of resources available from the agent.

At time \( t \) the agent takes an action \( a_t \) in state \( s_t \) and updates the Q-value as,

\[
Q(s_t,a_t) = (1 - \alpha)Q(s_t,a_t) + \alpha (r + \beta \min_{a_t}Q(s_{t+1},a_{t+1}))
\]

(3)

\( \alpha = [0,1] \) is the learning rate, \( \beta \) is the discount factor which puts weights to the future Q-values of the state/action pair \( (s_{t+1},a_{t+1}) \).

#### 6. Performance Evaluation

Table I is the simulation parameters for the proposed solution of
task allocation. The flight time $t$ of each UAV is the cumulative distance between the source and destination. The features of each UAV includes location (in Euclidean space), average speed, direction, CPU capacity (in units), Storage capacity (in units), Bandwidth capacity (in units), Expiration time to neighbors. Fig. 3 shows the convergence of the Reinforcement learning algorithm for a network of UAVs. We perform the episodic training for the algorithm and take the output of the CL as input to the RL algorithm. The average number of steps for each UAV in a network is around 16 where the cumulative reward gain is $4.859263\times 10^3$. We observe divergence before 3000 episodes during the training which means the agent has not finished learning the environment and requires more learning in the training. Finally, the algorithm converges to optimal task allocation after 4124 episodes of training.

$$Table I: \text{Simulation parameter(s)}$$

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Tasks</td>
<td>5/UAV network</td>
</tr>
<tr>
<td>Number of UAVs</td>
<td>20</td>
</tr>
<tr>
<td>Coverage Area (x,y)</td>
<td>500,500</td>
</tr>
<tr>
<td>Number of Networks</td>
<td>4</td>
</tr>
<tr>
<td>CPU capacity</td>
<td>10 units/UAV</td>
</tr>
<tr>
<td>Storage capacity</td>
<td>10 units/UAV</td>
</tr>
<tr>
<td>Bandwidth capacity</td>
<td>10 units/UAV</td>
</tr>
<tr>
<td>$\alpha$</td>
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</tr>
<tr>
<td>$\beta$</td>
<td>0.50</td>
</tr>
<tr>
<td>Learning rate</td>
<td>0.25</td>
</tr>
</tbody>
</table>

7. Conclusion
In this paper we have proposed a Learning based Intelligent IoT task offloading and resource allocation in mobile Fog nodes in the Fog Network. We have considered the UAVs as Fog nodes for its coverage benefit over the statically deployed Fog network infrastructure. The use of competitive learning enhances the efficiency in creating the computing network by considering multiple features of the UAVs. The reinforcement learning then uses the output of the competitive learning to allocate resources for necessary tasks in the network. In future, we plan to consider the resource fragmentation problem during resource allocation and interference between tasks in the shared resources.

Acknowledgement
This research was supported by the MSIP(Ministry of Science, ICT and Future Planning), Korea, under the Grand Information Technology Research Center support program (IITP-2017- 2015- 000742) supervised by the IITP(Institute for Information & communications Technology Promotion)*Dr. CS Hong is the corresponding author*

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