UAV-assisted Intelligent Crowdsourcing in Natural Calamity

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***Abstract*—During the natural calamity, it becomes challenging to coordinate the search and rescue operation due to the possible destruction of the static network infrastructure and the lack of sensory observation data support to localize the affected area and victims. Therefore, in this research, we have focused on solving the disaster time intelligent crowdsourcing through UAVs in an energy efficient way for victim localization provided with a quick response to conduct the emergency rescue operation. We have model the energy efficient crowdsourcing through ϵ-greedy Q-learning and the simulation result shows the efficiency and convergence of the modeled algorithm for the proposed energy efficient intelligent crowdsourcing model.**

I. Introduction

The notion of IoT has an immense impact on developing the living situation of people through different innovative and revolutionized applications [8][9][1]. Nowadays, the unmanned aerial vehicles (UAVs) are used in different application such as surveillance system, product delivery system, mobile small cell deployment etc. Because of the higher mobility, the UAVs can provide a larger coverage area than any static network infrastructure deployment. Apart from that, the sensory observation or user data is collected by establishing cooperative and non operative communication in mobile or static sensor network through UAVs[4][5]. Existing research on energy efficient data collection mainly focuses on reducing the energy consumption of the whole network while collecting the environmental sensor data to increase the longevity of the resource constrained WSN or IoT network [6] [7]. Moreover, the existing research on UAV based data collection in a natural calamity mostly focuses on real-time image or video processing to map the affected area without considering the energy efficiency during the flight path of the battery run UAVs [10].
Therefore, in this research, we have focused on solving the energy efficiency in intelligent crowdsourcing for enabling quick response to natural calamity using UAVs and nano data center (NDC). The autonomic crowdsourcing scenario is modeled through the ϵ-greedy Q-learning algorithm and the simulation depicts the efficiency of the proposed model.

II. Proposed System Model

In Figure 1, the nano data centers (NDC) are placed strategically to cover the whole observation area where the NDCs generally collect the sensor observations from the mobile nodes (MN). The mobile nodes are considered as the customer premises equipments (CPE) which produce the crowd data. The NDCs use the base station to send the collected data to the cloud data centers after a certain period of time or when the storage utilization reach to a certain threshold. During the time of any natural calamity, some of the NDCs may become inactive (marked red in Fig. 1) because of the devastating effect of the calamity and therefore the MNs (marked green in Fig. 1) under the inactive NDCs (e.g. D,C) become unable to transmit the sensory observation to the remote cloud data center for the emergency response. Therefore, the UAVs provide the necessary coverage to that infected area so that the environmental data can still become attainable to enhance the efficiency of the rescue operation. The UAVs can communicate with the cellular base station for transmitting the collected sensor data to the cloud data center provided with a seamless and coordinated rescue operation. If the base station becomes unavailable, the UAVs can also transmit the localized crowd data through satellite communication medium and ground station for a quick-response. In our proposed data collection framework, we have considered several scenario which may happen during any natural calamity. For example, during the natural calamity, some of the NDCs become inactive and therefore the MNs are unable transmit the emergency data packet to the cloud. In this case, the UAVs replace the inactive NDCs and collect the observation data from the MNs. However, the UAVs have limited power resource and therefore an energy efficient flight path should be assigned in order to collect the sensory observation from the MNs.

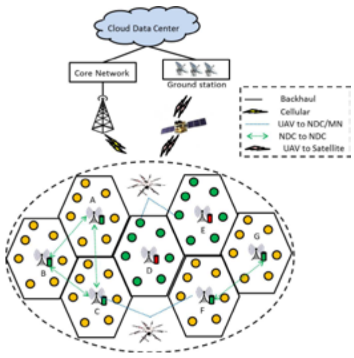


Figure 1: Proposed system model for intelligent crowdsourcing

III. Proposed intelligent energy efficient crowdsourcing

We formulate the energy efficient data collection problem through "model free" ϵ greedy Q-learning algorithm [2] [3]. The Q-learning algorithm provides a faster and reliable energy efficient data collection path in terms of coverage area. We consider there are total m number of NDCs strategically placed in the coverage area where k number of NDCs are currently inactive. Therefore the UAVs provides coverage to the state space $S = \{s_1, s_2, .., s_k\} = \{n_1, n_2, ..n_k\}$ to collect the sensory observations. The agent UAV establishes communication to the MNs which are located to the inactive NDCs and the mobility action is moving from one location state to another. The set of action is $A = \{a_1, a_2, .., a_k\}$ where k is the number of states. The reward value is the residual energy at each state which is defined as,

$$R = w \sum_{1}^{i} \Big(E_{max} - E_i(l, p, d, t) \Big) \qquad (1)$$

In (1), E_{max} is the maximum energy of the UAV, E_i is the energy consumption where l is the received packet length from ith MN, p is the transmission power, d is the data rate and t is the flight time. The priority of any particular state is defined thorugh the weight factor w as in,

$$w = [\frac{i - i_{min}}{i_{max} - i_{min}} \times (h_{max} - h_{min}) + h_{min}]$$

where i is the number of active MN for crowdsourcing, i_{min} is the minimum number of MNs, i_{max} is the maximum number of MNs connected to each UAV. $h = \{1, 2, 3\}^T$ is the priority scale vector where value 1 is the least priority state and 3 the high priority state. The agent UAV explores from one state to another until it reaches the goal state and thus converges. At time t, for each action a_t in state s_t the Q-value is updated as in,

$$Q(s_t, a_t) = (1 - \alpha_{s,t}) Q(s_t, a_t) + \alpha_{s,t} \big(R + \beta \max \big(Q(s_{t+1}, a_{t+1}) \big) \big) \qquad (2)$$

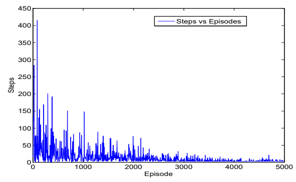
In (2), $Q(s_t, a_t)$ is the Q-value of the current state and $Q(s_{t+1}, a_{t+1})$ is the Q-value of the next state, $\alpha = [0, 1]$ is the learning rate, β is the discount factor. The Q-value is updated with probability ϵ and stored in the Q matrix which acts as the memory of the agent UAV.

IV. Performance Evaluation

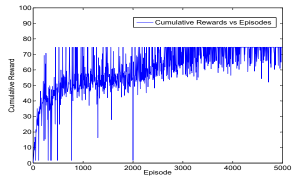
Table I represents the simulation parameter of the proposed algorithm. We choose the initial state of the UAV agent 2 and the goal state is set to 86. The flight time t depends on the cumulative distance between that the agent UAV transverses. In Fig.2, the algorithm converged to the shortest path after 5000 episodes and the number of exploitation is 44080 and the number of exploration is 31027. The UAV transversed 10 states to reach the goal state. The cumulative reward gain of UAV is around 6.029954e+002 at the time of convergence.

Table I: Simulation Parameter

Parameter	Value
MN	500
UAV	1
NDC	100
Penalty, R	-50
ϵ	0.9
α	0.60
γ	0.50
E_{max}	22.2V
p	0.1V
l	4000 bit
Number of Episodes	5000



(a) Steps vs. Episodes



(b) Reward vs. Episodes

Figure 2: Q-learning performance

V. Conclusion

In this paper we have proposed the energy efficient intelligent crowdsourcing during natural calamity through UAVs. In future, we will extend the research by implementing the prototype considering more diverse parameters.

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