

Optimized Compression Policy for Flying Ad hoc Networks

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Abstract—Managing energy consumption for computation and communication is a key requirement for flying ad hoc networks (FANET) to prolong the network lifetime. In many applications, the main role of drones is to collect imagery information and relay them to a ground station for further processing and decision making. In this paper, we present a *predictive compression policy* to maximize the end-to-end image quality penalized by the communication and computation costs. The idea is to predict the number of remaining links to the destination for a given routing algorithm and use it to re-compress image frames at intermediate nodes such that the overall energy consumption is minimized. Numerical results confirm that the performance of this method is within 4% of the global optima and higher than the current fixed-rate policies with a significant margin.

I. INTRODUCTION

In *flying ad hoc networks* (FANET), the limited payload and battery size of drones imposes tight restrictions on the total power consumption. In drone-based imagery systems, the final image quality depends on the image resolution influenced by the compression rate. The communication energy cost is directly proportional to the volume of exchanged image frames, whereas the computation cost is proportional to the input file size and the number of re-compression stages. Indeed, there exists an intrinsic trade-off between the energy used for communication and computation [1]. An important challenge in solving this trade-off is that the number of communication hops is not priorly known to the source node to adjust the compression rate accordingly. In [2], we developed a greedy distance-based routing algorithm for unmanned aerial vehicle (UAV) networks with dynamic topology and introduced upper and lower bounds on the number of expected communication hops for given network conditions. In this paper, we propose a *predictive compression policy* that solves this trade-off by adjusting the per-link compression rates based on the expected number of remaining hops for a desired performance metric.

II. SYSTEM MODEL

We consider a network consisting of N nodes $\mathcal{N} = \{n_1, n_2, \dots, n_N\}$ distributed uniformly in a $L \times L$ rectangular area, as displayed in Fig. 1. The communication range of each UAV is represented by a circular area of radius R . Consequently, the set of neighbors for node n_i at time t is defined as $\mathcal{N}_i(t) = \{n_j \in \mathcal{N}, d_{ij}(t) \leq R\}$, where $d_{ij}(t)$ is the Euclidean distance between nodes n_i and n_j at time t .

To simulate drone motion trajectories, we use the *Paparazzi* mobility model (PPRZM) proposed in [3], which uses Markov Process to combine several common mobility patterns such as *linear way points*, *circular*, *oval*, and *eight-like rotations* and *parallel sweeping* with random initial locations and motion parameters.

In this work, we use our previously proposed distance-based greedy routing algorithm [2], where the routing protocol operates as a geographic forwarding approach. More specifically,

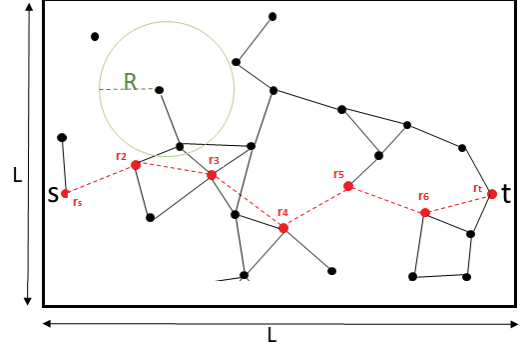


Fig. 1: UAV network with N nodes in a $L \times L$ area. The communication range is represented by a circle of radius R . The red dashed line represents the optimal path based on the utilized distance-based greedy algorithm.

at step i , the packet is passed by the current node n_i to a neighbor node $n_j \in \mathcal{N}_i$, which is closest to the destination t . Also, the packet transmission is constrained by $d_{jt} < d_{it}$, which means that we always make a progress, to ensure a loop-free path. The algorithm is initialized with current node as source: $n_1 = s$, and terminates when the destination node is visited, i.e. $n_j = t$. The red dashed line in Fig. 1 represents an example of the selected path using this algorithm.

Although we implement the proposed compression method on top of the greedy routing in [2], it is general and can be integrated with any routing algorithm, if the expected number of remaining hops is known at each step.

III. PREDICTIVE COMPRESSION POLICY

Here, we present a compression optimization policy to maximize the quality of the image file at destination while minimizing the computation and communication costs. Through investigating different perceptual image quality metrics including [4], [5], we conclude that a sigmoid-like function can best model the impact of compression on degrading the image quality.

Here, we use $Q_A(r) = \left(\frac{1 - e^{-r/A}}{1 - e^{-1/A}} \right)$, where r is the compression rate and A controls the shape of the function. The denominator is the scaling factor to ensure $0 \leq Q_A(r) \leq 1$ for $0 \leq r \leq 1$. We set $0.1 < A < 0.5$ to best comply with the results from the above-mentioned papers.

Suppose that the end to end h -hop path is represented by $\mathcal{P}_h = \{n_1, n_2, \dots, n_h\}$. For a constant transmission power per bit per link, the total energy to send an image of size F is $\sum_{j=1}^h k_c r_j F$, where h is the number of links through the path, r_j is the compression rate at node n_j , and k_c is a constant.

Likewise, the total on-board processing cost to perform compression can be modeled as $\sum_{j=1}^h k_p I(r_j \neq r_{j-1}) + \sum_{j=1}^h k_q r_{j-1} F I(r_j \neq r_{j-1})$, where $I(r_j \neq r_{j-1})$ indicates

a re-compression process at node n_j . The compression cost at node n_j includes a constant part k_p and a part $k_q r_{j-1} F$ proportional to the input file size $r_{j-1} F$. Consequently, the goal is to maximize the following objective function:

$$f(\mathcal{P}_h) = \alpha Q_A(r_h) - \beta \sum_{j=1}^h k_c r_j F - \gamma \sum_{j=1}^h I(r_j \neq r_{j-1})(k_p + k_q r_{j-1} F), \quad (1)$$

where parameters α , β , and γ are used to balance the importance between the quality and cost terms. When a node optimizes this objective function, it makes a simplifying assumption that the adjusted compression rate will not be altered by the subsequent nodes. Therefore, it solves the following problem using the expected number of remaining hops:

$$\begin{aligned} & \text{maximize } g_A(r) = \alpha Q_A(r) - \beta \mathbb{E}[h_i] k_c r F \\ & \quad - \gamma I(r \neq r_{i-1})(k_p + k_q r_{i-1} F) \\ & \text{subject to } r \leq r_{i-1} \end{aligned} \quad (2)$$

This is a convex optimization problem, which admits the following closed form solution, considering the KKT conditions:

$$\begin{aligned} r_\star(i) &= -A \ln \left(\frac{A \beta \mathbb{E}[h_i] k_c F (1 - e^{-1/A})}{\alpha} \right) \\ r_i &= \begin{cases} r_\star(i) & g_A(r_\star(i)) > g_A(r_{i-1}), \\ r_{i-1} & \text{otherwise.} \end{cases} \end{aligned} \quad (3)$$

Due to the dynamicity of the network as well as the uncertainty of $\mathbb{E}[h_i]$, we allow the subsequent nodes to recalculate the compression rate as needed.

IV. SIMULATION RESULTS

To perform simulation results, the network topology is randomly generated using PPRZM model and parameters $N = 100$, $L = 10$ km and $R = 2.5$ km. We use linear and circular motions, where the speed and radii of each pattern are exponentially distributed and the initial directions and phases are uniformly distributed. Other parameters include $\alpha = 5$, $\beta = 1$ and $\gamma = 1$, $k_p = k_q = 0.5$, $k_c = 1$, $F = 1$, $A = 0.3$.

Table 1 compares the achieved end-to-end utility as well as the selected compression rate for the proposed *predictive compression policy* using 5 randomly generated network topologies against the optimal compression rate, and a set of fixed rates with $r = (0.1, 0.2, \dots, 1)$. Here, the *optimal compression rate* is corresponding to the global maximum of (1), when the exact locations of nodes, and the number of hops h are known to the source node ahead of time. It can be seen that the optimal and predicted compression rates are equal for some cases, meaning that the expected number of hops matches the actual number of hops. The improvement in the achieved utility 7.14 is significant and ranges from 13.5% (for 6.29 for constant rate $CR = 0.4$) to 18-fold increase (for $CR = 0.1$). The objective function for the proposed policy (7.14) is only 3.4% less than (7.39) for the optimal policy.

To highlight the importance of the re-compression policy (method A), we compare it against a similar policy, where the designated compression rate by the source node remains unchanged (method B in Fig. 3). It is shown that the proposed

Table I. Comparison of achieved utility for the proposed predictive policy vs optimal policy and fixed-rate policies.

Compression Rate					Objective function	
Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5	CR	Utility
0.1	0.1	0.1	0.1	0.1	CR=0.1	0.40
0.2	0.2	0.2	0.2	0.2	CR=0.2	3.71
0.3	0.3	0.3	0.3	0.3	CR=0.3	5.54
0.4	0.4	0.4	0.4	0.4	CR=0.4	6.29
0.5	0.5	0.5	0.5	0.5	CR=0.5	6.28
0.6	0.6	0.6	0.6	0.6	CR=0.6	5.72
0.7	0.7	0.7	0.7	0.7	CR=0.7	4.76
0.8	0.8	0.8	0.8	0.8	CR=0.8	3.52
0.9	0.9	0.9	0.9	0.9	CR=0.9	2.08
1	1	1	1	1	CR=1	5.50
					Predicted Rate	7.14
					Optimal Rate	7.39

method (A) outperforms method B consistently among all average node velocities. The improvement is more significant (about 75%) for higher node velocities, as expected.

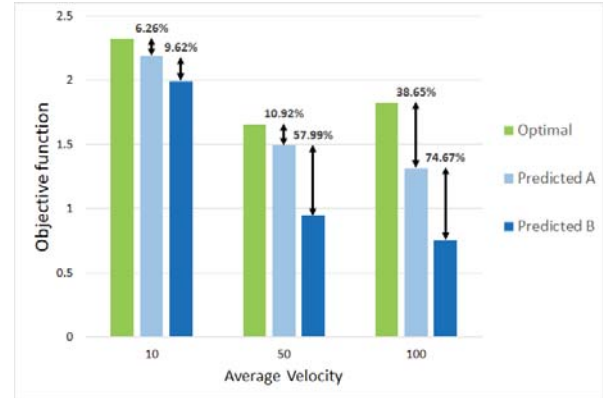


Fig. 3: Objective function for the optimal, the re-compression policy (method A) and optimized but fixed compression policy (method B).

V. CONCLUSION

The results show that the current fixed rate policies are extremely inefficient. One may optimize the accumulated communication and compression cost only by predicting the remaining number of hops per transmission. The improvement depends on the network dynamicity and average node velocities and can be as high as 18-fold increase.

VI. ACKNOWLEDGMENT OF SUPPORT AND DISCLAIMER

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