An Orientation Aware Learning MAC for Multi-UAVs Networks

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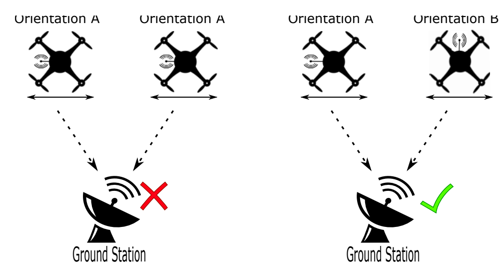
***Abstract*—In this paper, we consider channel access in Unmanned Aerial Vehicles (UAVs) networks where a ground station is equipped with Successive Interference Cancellation (SIC) capability. The problem at hand is to derive a transmission schedule for UAVs to communicate with a ground station frequently, and with minimal collisions. We first formulate a stochastic optimization problem before introducing a novel distributed Learning Medium Access Control (MAC), aka L-MAC, protocol. A key novelty of L-MAC is that it allows UAVs to learn the best orientation that results in the highest decoding success. Our simulation results show that L-MAC achieves a throughput that is 68% higher than the well-known Aloha protocol without SIC, and 28% higher than Aloha with SIC.**

1. Introduction

Unmanned Aerial Vehicles (UAVs) are increasingly being used in many applications such as broadcasting [1], and mobile base stations [2]. In these applications, UAVs are required to communicate with a ground station continuously. Thus, they require a link with a high capacity to the ground station. To this end, we equip the ground station with a Successive Interference Cancellation (SIC) radio [3], which allows it to receive transmissions from *multiple* UAVs simultaneously if their respective Signal to Interference plus Noise Ratio (SINR) is above a certain threshold. This paper focuses on deriving a transmission schedule for use in a multi-UAVs network. As the schedule repeats, coupled with the fact that the ground station supports SIC, a short schedule means UAVs will be able to transmit frequently; equivalently, the network capacity will be high.

The key novelties in our work are that we consider the orientation of UAVs and random channel gains. In particular, a number of works, see [4], have shown that the orientation of a UAV has an impact on the channel condition or gain at a ground station. This is particularly advantageous when the ground station has a SIC radio. UAVs are able to re-orient themselves to improve SIC decoding success. Consider the example scenario with two UAVs in Figure 1. We can see in Figure 1(a) that the two UAVs have the same antenna orientation. Suppose that at this orientation, the received power is not sufficient to cause a difference that allows SIC decoding to be successful. Hence, the transmission from these two UAVs fails. Now consider Figure 1(b), where a UAV changes its orientation, which causes a different receive power at the ground station. In this case, this new orientation allows the ground station to successfully decode all transmissions.



(a) Transmission fails (b) Success

Figure 1. An example transmission scenario.

A number of works have focused on UAVs placement or optimizing antenna heading angles such as [5]. They have a similar aim as ours, i.e., throughput maximization. However, they do not aim to derive a transmission schedule, and their UAVs do not have any learning ability. Additionally, they do not consider a receiver with SIC capability. Many authors have considered nodes with SIC capability; e.g., [6], [7] and [8]. These works, however, consider a different system and problem. References [9] and [8] also aim to derive short schedules. However, they do not employ any learning mechanisms nor consider nodes that can re-orient themselves to facilitate SIC decoding.

From the foregone example in Figure 1, we see that there are two *actions* to be optimized: (i) transmission time, and (ii) orientation. To this end, we introduce an orientation aware MAC scheme for UAVs. Specifically, we address the following optimization problem: given a UAVs network with a ground station that has SIC capability, determine the shortest possible transmission schedule for UAVs. Each UAV is tasked with learning the best transmission policy i.e., to determine the best time slot and antenna orientation. A challenging issue is the random channel gains caused by UAVs mobility. To this end, we formulate a *novel* stochastic optimization problem in Section 3. We then propose a distributed MAC called L-MAC that uses the well-known Softmax based function to determine the said actions; see Section 4. Advantageously, L-MAC does not require the ground station to collect channel state information from each

UAV, and thus making it suitable for use in large-scale UAVs networks. Our results show that L-MAC achieves up to 68% higher throughput as compared to the Aloha protocol. Our conclusions are presented in Section 6.

2. Network Model

We consider a network comprising of $|N|$ fixed/mobile UAVs and a ground station, denoted as s, where $N = \{1, 2, \ldots, |N|\}$ is the set of UAVs. Each UAV $i \in N$ is equipped with a radio for communication with ground station s and transmits with power P. In addition, UAVs always have traffic to transmit. Our UAVs network operates in terms of frames. Each frame contains z time slots; each time slot is represented as t, where $t \in \{1, 2, \ldots, z\}$. In each time slot t, if UAV i is scheduled to transmit, it selects an orientation $k \in O$ to transmit data to ground station s, where O is a set of orientations. For example, we can set $|O| = 4$, where $O = \{\text{'North'}, \text{'South'}, \text{'East'}, \text{'West'}\}$. Let G^t_{ik} denote the channel coefficient of UAV i when it transmits in orientation k at time t. Moreover, G^t_{ik} is drawn from a Nakagami-m [10] distribution, which includes the path loss. Also, we denote by $\Gamma^t \subseteq N$ as the set of UAVs that have chosen to transmit in time slot t.

The ground station has a SIC radio. To decode a composite signal, it first decodes the strongest received signal and treats other signals as noise. After that, it subtracts the decoded signal from the composite signal and proceeds to decode the next strongest signal [3]. The received power of UAV i when it transmits over orientation k at time slot t is denoted as $\mathcal{P}^t_{ik} = PG^t_{ik}$. Let $\mathbf{p}^t$ be a set containing the received power of UAVs transmitting in time slot t; i.e., UAVs in Γ^t. Assume that the order of received power in $\mathbf{p}^t$ at ground station s in slot t is as follows: $\mathcal{P}^t_{ik} \geq \mathcal{P}^t_{jl} \geq \cdots \geq \mathcal{P}^t_{mk}$. Then the ground station decodes the transmission from UAVs in Γ^t in the following order: UAV i with orientation k, UAV j with orientation l, and so forth. Let $\varphi^t_i(\mathbf{p}^t)$ return a set containing received power that is less than the received power of UAV i. Formally, the transmission of UAV i is successful if,

$$\frac{\mathcal{P}^t_{ik}}{\sigma^2 + \sum_{p \in \varphi^t_i(\mathbf{p}^t)} p} \geq \gamma \tag{1}$$

where γ is SINR threshold that corresponds to a data rate r_γ, and σ^2 is the noise power, which can also include any residual noise from imperfect SIC. If SIC decoding is successful, the ground station subtracts UAV i's transmission from the composite signal, and proceeds to decode UAV j's signal. SIC decoding is successful if,

$$\frac{\mathcal{P}^t_{jl}}{\sigma^2 + \sum_{p \in \varphi^t_j(\mathbf{p}^t)} p} \geq \gamma \tag{2}$$

Finally, the last transmission is successful provided that the following inequality is satisfied,

$$\frac{\mathcal{P}^t_{mk}}{\sigma^2} \geq \gamma \tag{3}$$

3. The Problem

Our problem consists of two parts: (i) the ground station needs to determine the *best* frame size z, and (ii) for each frame, each UAV i needs to select a transmission slot. In both parts, the aim is to maximize the sum-rate. In part (i), for a given frame size z, each UAV i has two decisions or actions: (a) a^t_i, which is set to one ($a^t_i = 1$) if it selects to transmit in slot $t \in \{1, 2, \ldots, z\}$, and (b) a^t_{ik}, which is set to one if it chooses to use orientation k when transmitting in slot t; i.e., we have $a^t_{ik} = 1$ and $a^t_i = 1$. Define the vector or transmission schedule $\mathbf{a}_z = [(a^t_i, a^t_{ik})]$, with $t \in \{1, 2, \ldots, z\}$, $i \in N$ and $k \in O$, meaning vector $\mathbf{a}_z$ has dimension $z \times |N| \times |O|$. We define $\mathcal{A}_z$ as a collection of all possible transmission schedules $\mathbf{a}_z$; i.e., the set $\mathcal{A}_z$ contains all possible combinations of transmission slots and orientations of all UAVs. Also, each UAV only transmits once in each frame; formally, we have $\sum_{t=1}^{z} a^t_i = 1$. In addition, if $a^t_i = 1$, then at most one orientation can be chosen: $\sum_{k \in O} a^t_{ik} = 1$.

For a time slot t, the reward for UAV i is defined as,

$$r^t_i(\mathbf{a}_z) = \begin{cases} r_\gamma, & \frac{a^t_i \sum_{k \in O} \mathcal{P}^t_{ik} a^t_{ik}}{\sigma^2 + \sum_{p \in \varphi^t_i(\mathbf{p}^t)} p} \geq \gamma \\ 0, & \text{Otherwise.} \end{cases} \tag{4}$$

Note, if UAV i does not transmit ($a^t_i = 0$), then its SINR will be less than γ, and thus $r^t_i(\mathbf{a}_z) = 0$. Also, we have $\mathbf{p}^t = \{\mathcal{P}^t_{jk} \mid \mathcal{P}^t_{jk} a^t_{jk} > 0, \forall j \in N, \forall k \in O\}$. Using (4), the *total* reward or sum rate is therefore,

$$R(\mathbf{a}_z) = \sum_{t=1}^{z} \sum_{i \in N} r^t_i(\mathbf{a}_z) \tag{5}$$

We are now ready to define part (ii) of our problem. Formally, for a given frame of length z, we aim to identify an action $\mathbf{a}^*_z$ that yields the maximum average reward,

$$\mathbf{a}^*_z = \arg\max_{\mathbf{a} \in \mathcal{A}_z} \mathbb{E}\left[R(\mathbf{a})\right] \tag{6}$$

The expectation is taken with respect to the joint probability distribution of channel gains to UAVs.

We now turn our attention to part (i) of our problem. The ground station aims to determine a frame size z that yields the maximum average throughput. In particular, it seeks to optimize the following quantity,

$$\mathcal{T} = \max_{z \in \mathbb{N}_{>0}} \mathbb{E}\left[R(\mathbf{a}^*_z)\right] \tag{7}$$

where $\mathbf{a}^*_z$ is the optimal joint action for frame size z.

4. A Learning MAC

Our distributed MAC enables each UAV to learn the best time slot in a given schedule and also orientation that yields the highest transmission success. It associates a probability to each time slot and orientation, where a high probability indicates a high reward. Figure 2 shows the steps taken by a UAV to learn the transmission probability of each slot and

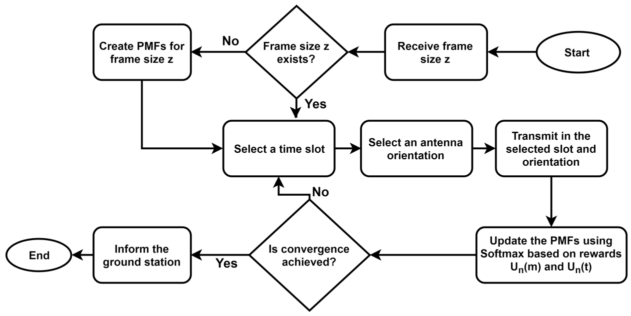


Figure 2. A UAV's learning process.

corresponding antenna orientation for a schedule length z that is transmitted by the ground station.

For a given frame length z, let α_i^z denote the Probability Mass Function (PMF) over time slots $t \in \{1, 2, \ldots, z\}$, and α_{it}^z is the PMF over the set K of antenna orientations for the selected time slot t. We write $\alpha_i^z(t)$ as the probability that UAV i transmits in time slot t, and $\alpha_{it}^z(k)$ is the probability that UAV i will use the k-th antenna orientation in slot t.

Next, we explain how UAV i constructs the PMF $\alpha_i^z(t)$ and $\alpha_{it}^z(k)$. Initially, all UAVs set both PMFs to be the uniform distribution. Thus it selects a transmission slot and an orientation uniformly. Assume UAV i selects time slot t, and orientation k. Define the reward corresponding to orientation k as $u_{it}(k)$, which equals the transmission rate r_γ if the ground station indicates UAV i's transmission is successful. Otherwise, it is zero. Then UAV i calculates the probability $\alpha_{it}^z(k)$ using the following Softmax function,

$$\alpha_{it}^z(k) = \frac{e^{u_{it}(k)/\tau}}{\sum_{k' \in K} e^{u_{it}(k')/\tau}} \quad (8)$$

where τ is called the *temperature parameter*, which controls the probability that a UAV exploits the best action or orientation thus far or explore other orientations in O. The PMF α_i^z is calculated in a similar way. Let $u_i(t)$ be the reward, e.g., data rate, for transmitting in time slot t. Then, we have,

$$\alpha_i^z(t) = \frac{e^{u_i(t)/\tau}}{\sum_{t=1}^{z} e^{u_i(t)/\tau}} \quad (9)$$

We deem a PMF to have converged if the change in probability is within a specified tolerance ϵ.

The ground station is responsible for informing UAVs and adjusting the schedule length based on the number of observed transmission successes, failures and idle slots. After informing UAVs of a given schedule length z, it waits for UAVs to achieve convergence. After that, it monitors the performance in terms of the number of success, collision and idle slots for the schedule with length z; see Figure 3. As an example, if there are two collisions, i.e., $c = 2$, then the value 0.2 will be added to the schedule length. If the schedule length changes after rounding up, the ground station informs all UAVs. Note that if UAVs have existing PMFs for a schedule length z, then they simply use these PMFs to select a transmission slot and orientation; i.e., they do not need to learn new PMFs. In Figure 3, the value 0.1 controls the sensitivity in which the schedule length increases/decreases.

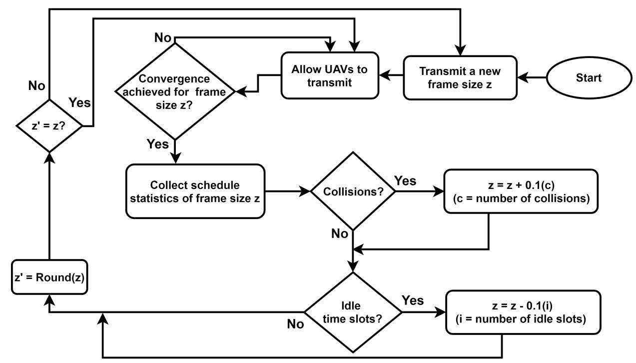
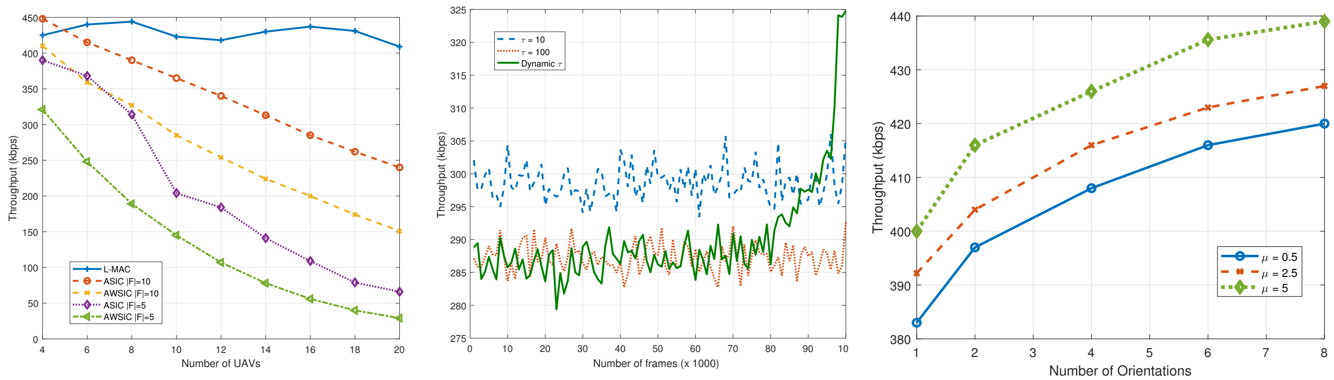


Figure 3. A ground station's schedule length adjustment process.

5. Evaluation

We conduct our experiments in Matlab. Our system consists of up to twenty UAVs. The distance from the ground station to UAVs ranges from 20 to 400 meters. We first train our L-MAC over a period of 100,000 frames. After that, we record the data rate of UAVs over 1000 frames. We set the SINR threshold to $\gamma = 1$ (dB); this corresponds to a rate of 500 kbps. We plot the average of ten simulation runs. The temperature τ decreases linearly after each frame, where it starts from $\tau = 110$ from the first frame and reaches a value of $\tau = 5$ in the last frame; this affords the ground station and UAVs sufficient time to explore their action space before converging onto the best action. The set of antenna orientations is $K = \{0°, 90°, 180°, 270°\}$. We note that as the problem is new, there are no other MACs we could compare against fairly. As a benchmark, we customize the Aloha protocol to operate over a ground station with (i) a SIC radio, labeled as *Aloha with SIC (ASIC)*, and (ii) no SIC radio, labeled as *Aloha without SIC (AWSIC)*.

From Figure 4(a), we see that L-MAC outperforms ASIC and AWSIC. UAVs are able to learn the best time slot and antenna orientation that lead to the highest number of successful transmissions. For example, in case of ten UAVs, the average data rate is approximately 430 kbps for L-MAC. However, ASIC and AWSIC with a frame size of ten achieves 360 kbps and 280 kbps, respectively, for the same number of UAVs. Referring to Figure 4(a), we also see that the average data rate for ASIC and AWSIC decreases as the number of UAVs increases. This is because these protocols have a fixed number of time slots per frame i.e., five and ten. For small number of UAVs, these frame sizes are appropriate. However, with more UAVs, collisions increases, which results in a lower data rate. For example ASIC with a frame length of ten achieves a data rate of 450 kbps for four UAVs, which drops to 240 kbps for twenty UAVs. On the other hand, L-MAC manages to maintain a



(a) (b) (c)

Figure 4. Performance of L-MAC. (a) L-MAC, ASIC vs. AWSIC at $\gamma = 1$ (dB), (b) convergence rate of L-MAC, and (c) number of orientations.

data rate of around 425 kbps as it is able to adjust the frame length based on the number of transmission failures.

Figure 4(b) shows the convergence rate of L-MAC for ten UAVs when τ is either fixed or dynamic. The average data rate is over 1000 frames. We see that when τ is large, i.e., 100, the average data rate is low; i.e., 285 kbps. This is because Softmax is less likely to explore, and thus it may converge onto the local optima solution. If τ is dynamic, the average data rate fluctuates initially as UAVs explore and learn the reward of each time slot and corresponding orientation. Finally, they converge onto the best time slot and orientation; initially, the average data rate is approximately 285 kbps before settling to 325 kbps at the 98-th frame.

Lastly, we investigate how the available number of antenna orientations affect the average data rate. We consider $K = \{0°, 45°, 90°, 135°, 180°, 225°, 270°, 315°\}$. We see from Figure 4(c) that if UAVs more orientations, then the average data rate is higher. That is because of higher diversity in channel gains. Figure 4(c) shows that the data rate for a single orientation is 383 kbps, which increases to 397 kbps for two orientations and 420 kbps when there are eight orientations. We also change the shape parameter μ of the Nakagami-m distribution, where μ controls the fading depth [11]; a lower μ value corresponds to a higher fading depth. From Figure 4(c), we see that the average data rate increases by 2% when we increase the value of μ from 0.5 to 2 and by 5% when $\mu = 5$. Specifically, when $\mu = 0.5$, we obtain 409 kbps. At $\mu = 2.5$, the throughput increases to 416 kbps, and when $\mu = 5$, the throughput is 426 kbps. Advantageously, L-MAC is able to learn the best orientation for all channel conditions or μ values.

6. Conclusion

We have proposed a distributed MAC that enables UAVs to learn the best transmission slot and corresponding orientation, for a given schedule length. Our results show that L-MAC has at least double the average data rate of the Aloha protocol. We find that a dynamic learning rate is necessary, and a higher number of orientations yield better average data rate. Lastly, we note that L-MAC can also be extended to include transmit power control and data rate. We leave this extension as an immediate future work.

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