Opportunistic Communications for Networked Controlled Systems of Autonomous Vehicles

Hua Chen, Pedram Hovareshti and John S. Baras

Institute for Systems Research and Department of Electrical and Computer Engineering
University of Maryland, College Park, MD 20742, USA
Email: {huachen, hovaresp}@umd.edu, baras@isr.umd.edu

***Abstract*—Situational awareness requires maintaining a reasonable level of communication connectivity in networks of autonomous vehicles. It is difficult to overcome deep fading from time-varying wireless channels in a dynamic and resource constrained environment. Moreover, other system constraints such as the energy consumption and total operation time make the design of communication protocols for such systems more challenging.**

In this paper, we consider the problem of efficient communications between a group of autonomous vehicles with energy consumption and total operation time constraints in an adversarial environment. We show that the policy of continuously attempting to communicate reliably over the course of the mission may lead to considerable system degradation. We propose an adaptive algorithm to make communication attempts opportunistically, based on the qualities of the wireless channels as the vehicles move throughout the terrain. We compare the proposed algorithm with a non-opportunistic algorithm in which the vehicles blindly attempt to communicate regularly throughout the course of the mission. We show that the proposed algorithm significantly improves the system performance, both in terms of operation time when the agents transmit only situational information and data throughput when additional data transmission is necessary.

I. Introduction

The development of networked systems of autonomous agents has been driven by various applications such as collaborative robotics, automated highway services, mobile sensor networks and disaster relief operations recently [1]. Decentralized control and decision making schemes are desired in all of these applications due to impracticality of centralized coordination and robustness to single node failures. Implementation of efficient communication schemes for collaborative control scenarios is challenging due to distributed nature of the system. Moreover, implicit information transmission capability is often assumed in many control theoretic studies [2]–[5].

In [6], we explicitly addressed the effects of communication on the performance of a networked system of autonomous vehicles with an emphasis on maintaining a certain level of group connectivity. We studied both the control and communication problems for a group of autonomous vehicles that are maneuvering with little or no direct human supervision in an adversarial environment. We use a gradient flow based artificial potential method [5], [7] for motion planning. We studied the effects of communication between nodes on the group's path planning by comparing two schemes. In one scheme the vehicles only process their sensed local information whereas in the second scheme, they collaborate by communicating among themselves. We showed that collaboration between vehicles results in better performance for path planning and wireless inter-vehicle communications. However, simulations also showed that the performance of wireless inter-vehicle network is degraded dramatically under severe channel condition even with collaboration.

In this paper, we look at the joint control and communication problem from a different point of view. When there are other constraints besides maintaining inter-vehicle communications, it is not efficient to attempt reliable communication *regularly*. We address this problem under the constraints of energy consumption and total operation time to perform the mission. We propose an algorithm to seek communication opportunities based on the qualities of the wireless channels and make communication attempts accordingly. We compare our algorithm with a non-opportunistic algorithm, in which a vehicle makes a fixed number of communication attempts at a new position before moving to the next position. We show by simulation that the proposed algorithm reduces the total operation time when there are only position information to be exchanged, and also communicates more packets utilizing the same operation time when there are additional data traffic.

This paper is organized as follows. After introducing our system model in Section II, we present the algorithm for opportunistic communications between a networked group of autonomous vehicles in Section III. We discuss our simulation results in Section IV. Finally, conclusions are drawn in Section V.

II. System Model

We consider a group of n autonomous ground vehicles maneuvering within an area $\mathcal{A} \subset \mathcal{R}^2$, e.g. a battlefield or a building with unknown potential dangers. Besides the boundary of $\mathcal{A}$, there is very limited knowledge available regarding the internal structure or topology of $\mathcal{A}$. The vehicles' mission is to explore $\mathcal{A}$ under little or no direct human supervision, cover a target area $\mathcal{T} \subset \mathcal{A}$ while avoiding any possible obstacles or threats, and finally send information about features of $\mathcal{A}$ to some server, e.g. a command center.[1]

[1]We will use the term server or command center interchangeably throughout this paper.

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We assume there is only one common target $\mathcal{T}$ for all vehicles.

The main constraints of maneuvering the group of vehicles come from the obstacles and moving threats that are distributed in $\mathcal{A}$. An obstacle is a closed area that cannot be entered by any vehicle. A moving threat is an object that moves along an unpredictable trajectory with an unknown speed. A vehicle must keep at least a distance of R_e away from any moving threat, otherwise it will be destroyed. In addition to the obstacles and moving threats, vehicles should keep a safety distance from each other in order to avoid collisions while maintaining communications with nearby vehicles. We further assume that the size of an obstacle is much larger than that of a vehicle or a moving threat, hence we denote a vehicle or a moving threat as a point in $\mathcal{A}$ for simplicity.

Before starting to maneuver, each vehicle is given an initial position of the target $\mathcal{T}$. However, the position of the target can change during the maneuver. This is because either better motion planning results are available after collecting certain amount of information, or capturing a new target is required after the environment has changed considerably. In this paper, we assume the change of the target position can only be initiated from the server. The server sends the message of target update to one or several vehicles depending on links available, and the message is gradually spread to other vehicles via vehicle-to-vehicle communications. Since the environment in $\mathcal{A}$ is highly dynamic, we assume that there is no global information available about the positions of other vehicles, obstacles or moving threats. Instead, each vehicle is equipped with devices for short-range detection, i.e. a vehicle can discover another object (another vehicle, an obstacle or a moving threat) if it is within a distance of R_d.

The vehicles also have other devices such as sensors or cameras to capture various features of the internal structure of $\mathcal{A}$, which are later delivered to the server. However, due to the highly dynamic nature of the environment, the server can only access limited number of vehicles at any time. From time to time, the server may change the vehicles from which data are pulled. Hence it is necessary that a vehicle can deliver its data to any other vehicle via vehicle-to-vehicle communications. On the other hand, since each vehicle only has information about positions of the neighboring objects from local detections, they need to exchange such information between themselves. These information are time-sensitive, since each vehicle can have a better trajectory if it collects more information regarding the position of the target, other vehicles, obstacles and moving threats. We denote these information as *position information*, and other information that are delivered to the server as additional *data traffic*.

It is well known that wireless channels used for communication in such settings are vulnerable to fading and interference. The mathematical modeling of the wireless channels for our application is very challenging due to the highly dynamic nature of the terrain which blocks the line-of-sights (LOS) between the vehicles and results in reflection and scattering among many other physical phenomena which affect the transmitted signals [8]. Interference happen when more than one pair of vehicles attempt to communicate simultaneously within a short distance and thus lead to confliction in the wireless medium. In this paper, we mainly consider the shadowing effects and model the path loss based on the Fresnel zone radius and the obstruction that lie in the first Fresnel zone [9].

III. Opportunistic Communications for Networked Vehicles

In this section, we describe our proposed algorithm for opportunistic communications between a group of networked autonomous vehicles.

A. Model of Motion Planning

In this paper, we use kinematic motion planning based on the artificial potential method developed in [5]. The potential functions are chosen to lead the vehicles towards the target while avoiding collisions or threats. We assume that time is slotted. At time t, let $p_i(t) = (x_i(t), y_i(t))$ be the position of the i-th vehicle at time t. We denote $\mathcal{V}(t)$ as the set of vehicles that are alive, $\mathcal{O}(t)$ as the set of obstacles, and $\mathcal{M}(t)$ as the set of moving threats. We let $\mathcal{N}_v^i(t)$, $\mathcal{N}_o^i(t)$ and $\mathcal{N}_m^i(t)$ be the set of neighboring vehicles, the set of obstacles and the set of moving threats known to the i-th vehicle at time t respectively. We also denote $\mathcal{T}^i(t)$ as the target at time t as far as the i-th vehicle knows. At time t, the following optimization problem is solved locally at the i-th vehicle

$$\begin{aligned} \min_{p_i(t)} \quad & J_{i,t}(p_i(t)) \\ \text{s.t.} \quad & G_k(p_i(t)) \leq 0,\ k \in \mathcal{N}_o^i(t) \\ & \|p_i(t) - p_i(t-1)\| \leq \delta, \end{aligned} \tag{1}$$

where $G_k(p_i(t))$ is the nonlinear constraint corresponding to the k-th obstacle, and δ is the step size.

A potential function is constructed for each vehicle consisting of several terms, each of which reflects a goal or a constraint. The potential function for the i-th vehicle at time t is

$$\begin{aligned} J_{i,t}(p_i(t)) \quad &= \quad \lambda_g J_t^g(p_i(t)) + \lambda_n J_{i,t}^n(p_i(t)) \\ &+ \quad \lambda_o J_t^o(p_i(t)) + \lambda_m J_t^m(p_i(t)), \end{aligned} \tag{2}$$

where J_t^g, $J_{i,t}^n$, J_t^o and J_t^m are the component potential functions relating to the target, neighboring vehicles, obstacles and moving threats respectively, and λ_g, λ_n, λ_o and λ_m are weighting factors. The potentials are chosen such that they encode the intended behavior of the vehicles regarding obstacle avoidance, keeping distance from neighbors and target finding correctly. For example, the target potential function is $J_t^g(p_i) = f_g(\rho(p_i, \mathcal{T}^i(t)))$, where $\rho(p_i, \mathcal{T}^i(t)) = \inf_{a \in \mathcal{T}^i(t)} \|p_i - a\|$ is the smallest distance from p_i to the target $\mathcal{T}^i(t)$. Here $f_g(\cdot)$ is a strictly increasing function with $f_g(0) = 0$, which guarantees the i-th vehicle moves toward $\mathcal{T}^i(t)$ in absence of other objects. The details of the potential functions used for motion planning can be found in [5], [6].

B. Opportunistic Communications for Networked Vehicles

The wireless communication module in the networked system exchange messages for both position information and additional data traffic between vehicles. Note the position information is time sensitive but needs much less bandwidth compared to the bulk data traffic. In light of that, throughout this paper we assume whenever there is available bandwidth, the vehicles transmit data traffic only if there are currently no position information need to be sent.

We assume *the duration of one snapshot*, i.e. the time elapsed between a vehicle's presence in two consecutive positions, is $T_0 = T_s + T_c + T_m$, where T_s is the time used for local sensing, T_c is the time used for inter-vehicle communications, and T_m is the time used to move from the current position to the next position. When the resources are not strictly restrained, we can choose a large enough T_c such that the vehicles can exchange at least the position information within T_c. However, in other situations there are other constraints such as the total operation time to finish the mission which makes a choice of large T_c unacceptable. On the other hand, even without such constraints, it is difficult to achieve reliable inter-vehicle communications over the wireless medium *at all positions* along their trajectories, since the time-varying wireless links sometimes experience severe degradation due to obstacles, mobility of vehicles and radio interferences. In this case reliability for communications comes with a higher price of increased complexity of the communication algorithms and higher energy consumption. As a result, it is not efficient to make efforts for reliable communications equally at any positions, especially when the qualities of the wireless links are not good enough.

We now address the problem of efficient communications between vehicles under the constraints on energy consumption and total operation time to finish the mission. The proposed communication algorithm is based on opportunistic communications or channel-aware scheduling in some literature [10]–[17]. The general idea is to communicate more when opportunities arise and less otherwise. There has been work on exploiting communication opportunities across time slots [11]–[13] or across multi-users [10], [14]–[17]. In this paper, we explore another communication opportunity, i.e. we seek *communication opportunities across different positions* along the trajectories of the moving vehicles. At those positions where the wireless links are likely to fail, the vehicles proceed with their planned motion, and they attempt to make more communication attempts at positions where the qualities of the wireless links are better. As a result, the vehicles exchange information efficiently at positions with better link qualities and maneuver when the wireless links are severely degraded.

We use energy consumption and total operation time as the metrics for performance comparison. We assume most of the energy is consumed by local sensing, wireless communications and mechanical move.[2] Furthermore, we assume

[2]Here we ignore the energy consumption due to local computation and decision making.

Algorithm 1 Opportunistic Communications between Networked Controlled Vehicles

M ← maximum number of slots for communication without moving;
$t \leftarrow 0$, $\mathcal{V}(t) \leftarrow$ all vehicles that are initially alive;
Load the initial position of the target into each vehicle in $\mathcal{V}(t)$;
$M_i \leftarrow 0$ for each vehicle in $\mathcal{V}(t)$;
while $\mathcal{V}(t)$ is not empty and at least one vehicle in $\mathcal{V}(t)$ has not reached the target $\mathcal{T}(t)$ **do**
  for all vehicles in $\mathcal{V}(t)$ **do**
    The i-th vehicle performs a local detection procedure and updates its local set $\mathcal{N}_v^i(t)$, $\mathcal{N}_o^i(t)$, $\mathcal{N}_m^i(t)$ and $\mathcal{T}^i(t)$ accordingly;
    if the current position is new for the i-th vehicle **then**
      The i-th vehicle attempts to communicate one message;
      $M_i \leftarrow 1$;
    else
      if the last communication at the current position is successful and $M_i < M$ **then**
        The i-th vehicle attempts to communicate one message;
        $M_i \leftarrow M_i + 1$;
      else
        The i-th vehicle starts an optimization algorithm to minimize $J_{i,t}(p_i(t))$ and finds an optimal solution $p_i^*(t)$ based on $\mathcal{T}^i(t), \mathcal{N}_v^i(t), \mathcal{N}_o^i(t)$ and $\mathcal{N}_m^i(t)$;
        The i-th vehicle moves to the new position $p_i^*(t)$;
      end if
    end if
  end for
  $t \leftarrow t + 1$;
  Update the set of alive vehicles $\mathcal{V}(t)$;
end while

local sensing consumes much less energy compared to wireless communications and mechanical move. If we assume energy consumption is proportional to the time duration, we can set $T_s \approx 0$. In order to compare the energy consumption and total operation time using *one single metric*, we further make the following assumptions: We choose a T such that a vehicle can communicate exactly one message with its peer within duration T. We then select a step size δ such that a vehicle spends the same amount of energy on communicating one message or moving a distance of δ, i.e. $T_m = T$.[3]

For the non-opportunistic algorithm, we assume that a vehicle makes K communication attempts in each snapshot regardless of the qualities of the wireless channels, i.e. $T_c = KT$. The duration of a snapshot is thus $T_1 = T_c + T_m = (K+1)T$. For opportunistic communication algorithm, on the other hand,

[3]Here a message can be a chunk of many packets.

we can utilize the time slots with bad channel qualities to maneuver to some other positions with better channel qualities. Hence, unlike the non-opportunistic algorithm, a snapshot may have different number of slots for inter-vehicle communications, which depends on the qualities of the wireless channels. Here an important part is to estimate the qualities of the wireless channels in each position, based on which decisions on whether to communicate or not will be made. However, in practice it is difficult to estimate the wireless channel qualities accurately. Hence, we make the current decision on whether to communicate or not based on the result of the last communication attempt *at the same position*. To find the channel quality at a new position, a vehicle first makes one communication attempt after moving to a new position. Algorithm 1 implements this opportunistic approach.

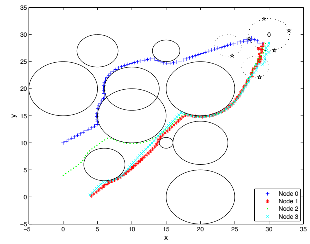
In Algorithm 1, a vehicle first makes one communication attempt at a new position and the further decisions for the following slots are based on the previous outcomings. If the communication attempt is successful, the vehicle continues to communicate until a communication failure happens or the vehicle has communicated for M consecutive slots without moving; otherwise the vehicle moves to the next position. Hence the length of a snapshot is $T_2 = (X+1)T$ where X is an integer-valued random variable depending on the channel qualities. Here M ensures the mission can be finished within a reasonable time. Although the duration of a snapshot can be different from time to time for different vehicles, in this paper we assume time is synchronized by the duration of slot T among different vehicles.

IV. Simulation Results

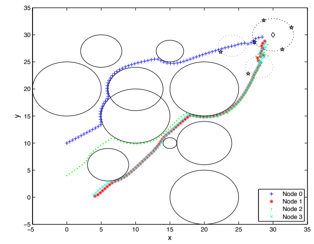
In this section, we show simulation results for the proposed opportunistic communication algorithm between a group of autonomous vehicles.

Modeling the physical layer loss for wireless networks of moving vehicles is very challenging. The physical loss is highly environment dependent. Since the vehicles' motion in our scenarios are generally slow enough, we can simplify the problem by only considering the shadowing effects. The concept of Fresnel zone clearance has been used to analyze interference caused by obstacles near the path of a wireless transmission [9], where the first zone must be kept largely free from obstructions. We model the physical layer path loss by considering the obstructions occurring in the first Fresnel zone and the Fresnel zone radius.

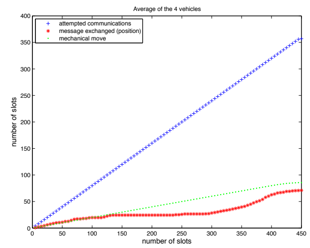
We consider a group of autonomous vehicles in an $40\text{m} \times 40\text{m}$ area $\mathcal{A}$ with 10 obstacles randomly distributed. We choose a scenario of 4 vehicles for illustration purposes, which are indexed from 0 to 3. The target area is a point whose position is $(30, 30)$. There are 6 moving threats circling around to protect the target, where 4 of them are on a circle centered at the target $(30, 30)$, 1 of them is on a circle centered at $(28, 24)$, and 1 of them is on a circle centered at $(24, 28)$. The detection range is $R_d = 3$, and $R_e = \sqrt{2}/2$. The step size for maneuvering is $\delta = 0.5$. There are 4 wireless links in our simulation, where Flow 1 is from vehicle 0 to 3, Flow 2 is from vehicle 2 to 0, Flow 3 is from vehicle 1 to 2, and Flow 4 is from vehicle 3 to 1. In our simulation, we assume the wireless modules of the vehicles are full-duplex. We also assume these devices can detect communication success or failure. As an illustrative example, we set $K = 4$ for the non-opportunistic communication algorithm.



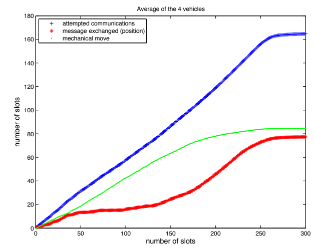
(a) Trajectories of the vehicles for non-opportunistic algorithm.



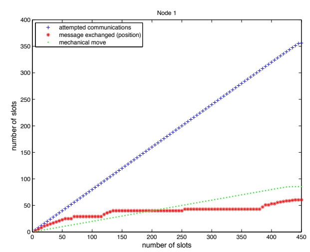
(b) Trajectories of the vehicles for opportunistic algorithm.



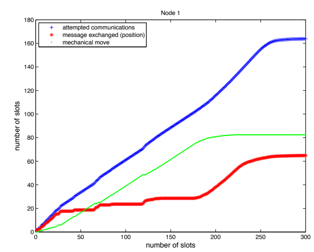
(c) Average performance of the vehicles for non-opportunistic algorithm.



(d) Average performance of the vehicles for opportunistic algorithm.



(e) Performance of vehicle 1 for non-opportunistic algorithm.



(f) Performance of vehicle 1 for opportunistic algorithm.

Fig. 1. Performance comparing of the non-opportunistic and opportunistic communication algorithms, assuming that the vehicles only exchange position information.

In our first simulation, we assume that there are only position information to be exchanged. Since there are no additional data traffic, we are interested in the saving of total operation time that can be achieved by the opportunistic communication algorithm. Hence we set $M = 4$, i.e. the vehicles have at most the same communication opportunities compared to the non-opportunistic algorithm. We run 100 independent simulations for the two algorithms respectively and show the results in Table I and Fig. 1. We compare the means and standard deviations from the 100 simulations in Table I. Table I(a) and I(b) show that the ratios of standard deviation to mean is at most 1.5% for the non-opportunistic algorithm and at most 9.9% for the opportunistic algorithm. We notice that the standard deviations of Table I(b) are relatively larger, which is due to vehicles communicating opportunistically.

TABLE I
MEAN AND STANDARD DEVIATION FROM 100 INDEPENDENT SIMULATIONS

(a) Total operation time for non-opportunistic algorithm

Vehicle	0	1	2	3
Mean	407.2	427.0	447.6	433.5
STD	4.5	5.2	4.3	6.6
$\frac{\text{STD}}{\text{Mean}}$	1.1%	1.2%	1.0%	1.5%

(b) Total operation time for opportunistic algorithm

Vehicle	0	1	2	3
Mean	236.9	201.3	259.6	195.4
STD	16.0	14.0	14.1	19.3
$\frac{\text{STD}}{\text{Mean}}$	6.8%	7.0%	5.4%	9.9%

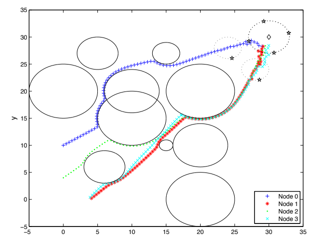
(c) Number of mechanical moves until slot 160 for opportunistic algorithm

Vehicle	0	1	2	3
Mean	63.3	66.6	66.9	71.7
STD	0.52	1.03	0.32	0.68
$\frac{\text{STD}}{\text{Mean}}$	0.8%	1.6%	0.5%	1.0%

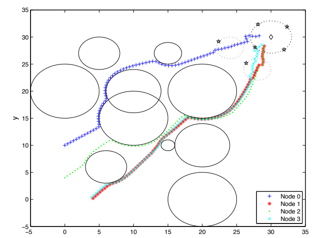
(d) Number of messages for position information exchanged until slot 160 for opportunistic algorithm

Vehicle	0	1	2	3
Mean	35.2	28.6	28.9	16.8
STD	1.2	2.0	0.8	1.3
$\frac{\text{STD}}{\text{Mean}}$	3.4%	7.0%	2.7%	7.7%

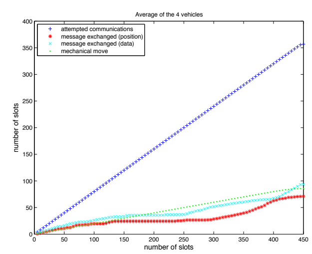
We then show the means and standard deviations for the number of mechanical moves and messages exchanged until the 160-th slot in Table I(c) and I(d) respectively. The largest ratio of $\frac{\text{STD}}{\text{Mean}}$ is 0.8% in Table I(c) and 7.7% in Table I(d). While running more independent simulations provides more reliable results, 100 simulations are enough for our illustration example. We randomly pick one from the 100 simulations and show the vehicles' trajectories for the two algorithms in Fig. 1(a) and 1(b) respectively. We notice that the trajectories of the vehicles are slightly different due to the opportunistic way of communication in the latter case. We then compare the average performance of 4 vehicles from 100 simulations for the two algorithms in Fig. 1(c) and 1(d). The average total operation time of the non-opportunistic algorithm is 428.8 slots in Fig. 1(c). The total operation time of the opportunistic algorithm reduces to 223.3 slots in Fig. 1(d), which is a time saving of 47.9%. On the other hand, the vehicles spend an average of 85.8 and 84.6 slots on actual mechanical move respectively, as shown in Fig. 1(c) and 1(d). Hence there is no additional energy consumption on mechanical move for the opportunistic communication algorithm. Furthermore, the vehicles are able to exchange an average of 71.2 packets in the non-opportunistic algorithm as shown in Fig. 1(c) and an average of 77.8 packets in the opportunistic algorithm as shown in Fig. 1(d). Hence the opportunistic algorithm is able to exchange more position information even though the vehicles give up communication after failures at some positions. We also randomly pick one vehicle and compare the average performance from 100 simulations for the two algorithms. Fig. 1(e) and 1(f) show the performance of vehicle 1 for the two algorithms. The average total operation time of this vehicle is 427.0 and 201.3 slots respectively for the two algorithms, i.e. using opportunistic algorithm the vehicle can save 52.9% of the total operation time compared to the non-opportunistic algorithm. Meanwhile, the average of the actual time used for mechanical move is 85.4 and 82.4 respectively in the two algorithms, and the average number of packets exchanged is 60.5 and 65.2 respectively, as shown in Fig. 1(e) and 1(f). Hence, by utilizing opportunistic communications, the vehicles can maneuver to the target much earlier while there is no



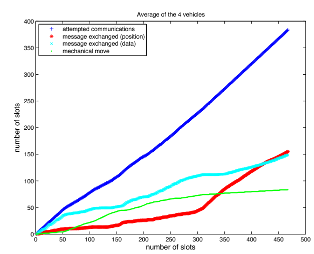
(a) Trajectories of the vehicles for non-opportunistic algorithm.



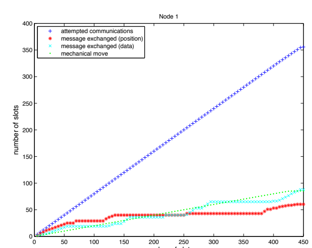
(b) Trajectories of the vehicles for opportunistic algorithm.



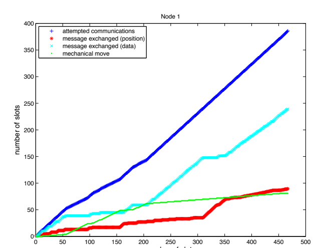
(c) Average performance of the vehicles for non-opportunistic algorithm.



(d) Average performance of the vehicles for opportunistic algorithm.



(e) Performance of vehicle 1 for non-opportunistic algorithm.



(f) Performance of vehicle 1 for opportunistic algorithm.

Fig. 2. Performance comparing of the non-opportunistic and opportunistic communication algorithms, assuming that the vehicles exchange both position information and additional data traffic.

additional energy required for mechanical moving and no sacrifices to the amount of position information exchanged.

In the second simulation, we assume there is additional data traffic besides position information. In this case, we are interested in comparing the number of additional data packets successfully exchanged within the same operation time. Here we adjust the value of M until the total operation times for the two algorithms are close to each other. A value of $M = 12$ is finally used in our simulation. We also run 100 independent simulations. Again, Fig. 2(a) and 2(b) show the trajectories of the vehicles from a randomly drawn simulation from the 100 independent simulations. We compare the average performance from 100 simulations for the two algorithms in Fig. 2(c) and 2(d). The average total operation time is 428.7 slots for the non-opportunistic algorithm in Fig. 2(c) and 406.5 slots for the opportunistic algorithm in Fig. 2(d). Notice the total operation time for the opportunistic algorithm is slightly smaller than that of the non-opportunistic algorithm. The average of the actual time used for mechanical move is 85.7 slots for the non-opportunistic algorithm and 83.5 slots for the opportunistic algorithm. We then take a look at the number of packets exchanged. For position information, the vehicles exchange an average of 71.2 packets for the non-opportunistic algorithm and an average of 155.2 packets for the opportunistic algorithm. For additional data traffic, only an average of 94.2 packets is exchanged in Fig. 2(c) and this number is increased to 148.8 in Fig. 2(d). As a result, the vehicles can exchange more packets for both the position information and additional data traffic in the opportunistic communication algorithm even with a slightly smaller total operation time. Finally, following Fig. 1, we also take a look at the average performance of vehicle 1 from 100 simulations for the two algorithms. The average total operation time of this vehicle is 426.7 slots in Fig. 2(e) and 452.0 slots in Fig. 2(e), which are close to each other. The average of the actual time used for mechanical move is 85.3 and 81.0 slots respectively. Meanwhile, for position information, the vehicle is able to exchange 60.4 packets for the non-opportunistic algorithm in Fig. 2(e), and this number increases to 89.5 in Fig. 2(f). The number of packets for additional data traffic is 87.9 for the non-opportunistic algorithm in Fig. 2(e) and 239.4 for the opportunistic algorithm in Fig. 2(f). Hence by using approximately the same total operation time and the actual time used for mechanical move, there is a considerable increase in the number of packets exchanged for both position information and additional data traffic.

V. Conclusion

In this paper, we considered the problem of communicating efficiently between a group of autonomous vehicles with energy consumption and total operation time constraints in an adversarial environment. We showed that attempting to communicate reliably at all times may lead to considerable system performance degradation. We proposed an algorithm to make communication attempts opportunistically at different positions based on the the qualities of the wireless channels. We compared the proposed algorithm to a non-opportunistic algorithm where a vehicle attempts to make a fixed number of communication attempts at any position before moving to the next position. Simulation results showed that the proposed algorithm reduces the total operation time when there are only position information need to be sent, or exchanges more packets within the same operation time when there are additional data traffic besides position information.

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Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the above-mentioned institutions.

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