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Distributed Collaborative Controlled Autonomous Vehicle Systems over Wireless Networks

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Abstract— **Inspired by military tactical, civil help-and-rescue applications, it is desirable yet challenging to develop networked systems of autonomous vehicles and sensors in dynamic, resource-constrained and adversarial environments. An essential aspect of designing such collaborative systems is to address the communication needs of the vehicles in order to perform a given mission. The vehicles' communication network should maintain a connectivity pattern based on the requirements of the mission.**

In this paper, we consider both the control and communication aspects for coordinated path planning of a group of autonomous vehicles in an adversarial environment. We propose distributed algorithms to control the vehicles' trajectories over a wireless vehicle-to-vehicle network. Distributed control algorithms both with and without collaboration between the vehicles are presented. We study the performance of the wireless network over the distributed controlled autonomous vehicles. Simulation results show that collaboration between vehicles results in better performance for path planning and wireless inter-vehicle communications. However, contention-based communication protocols are likely to fail due to severe channel conditions.

I. Introduction

Collaborative control of groups of autonomous agents (robots, unmanned vehicles, etc.) has gained a growing amount of attention recently. Collaborative robotics, automated highway services, mobile sensor networks, and disaster relief operations are examples of applications in which advances in wireless and other technologies has led engineers to design groups of unmanned mobile vehicles [1]. In all of the above applications there is a strong incentive to come up with efficient decentralized control and decision-making schemes. Decentralization is preferred due to lack of expensive central coordination and robustness to single node failure. A challenging issue in design of collaborative swarms of autonomous vehicles is the need to implement efficient communication mechanisms. In many control theoretic studies, certain communication capabilities are implicitly assumed to hold [2]–[5].

The main contribution of this paper is to explicitly address the effects of communication on the performance of the networked system with emphasis on maintaining group connectivity. We study 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. The mission is to explore the terrain, cover a target area while avoiding any possible obstacles or threats, and finally send information about features of the area to a command center. Building on our earlier work [5], [6], we use gradient flow based artificial potential methods for path planning [7], [8] in a kinematic setup. Despite their limitations, artificial potential based navigation functions have been found lots of applications in collaborative control [2], [3], [9], [10]. Hybrid stochastic methods have been proposed to overcome local minima problems [6]. We study 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 study the performance of the wireless inter-vehicle network based on the IEEE 802.11 media access mechanism. Simulation results show that collaboration between vehicles results in better performance for path planning and wireless inter-vehicle communications. However, contention-based communication protocols are likely to fail due to severe channel conditions.

We address challenges in maintaining group connectivity under such circumstances and suggest some future directions based on our work in [11]–[13]. Related work includes [14] in which the authors consider a localized notion of connectedness and study its relationship to the global connectivity of a network of vehicles, and [15] in which the authors address the problem of controlling the motion of a network of agents while preserving k-hop connectivity, and [16] in which the authors discuss maintaining connectivity between multiple mobile agents with bounded inputs.

This paper is organized as follows. After introducing our system model in Section II, we present our distributed control algorithms and describe the wireless network based on inter-vehicle communications in Section III. We show our simulation results in Section IV. Finally conclusions and future work are addressed in Section V.

II. System Model

We consider a group of n autonomous ground vehicles that are maneuvering within an area $\mathcal{A} \subset \mathcal{R}^2$, e.g. a battlefield or a building with unknown potential dangers. There is very limited knowledge available regarding the internal structure or the topology of $\mathcal{A}$ besides its boundary. In fact, it is the mission of these vehicles to explore $\mathcal{A}$ under little or no direct human supervision, cover some target $\mathcal{T} \subset \mathcal{A}$ 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] Throughout this paper, we assume there is only one target $\mathcal{T}$ for all vehicles.

The main constraints during the maneuvering of the 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 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 the initial position of the target $\mathcal{T}$. However, the position of the target can be changed during the maneuver, which is either because better motion planning results are available after collecting certain amount of information, or a new target is necessary after the environment has changed considerably. 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 all vehicles via vehicle-to-vehicle communications. Since the environment in $\mathcal{A}$ is highly dynamic, we assume 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 vehicle, an obstacle or a moving threat within a distance of R_d.

The vehicles also have other devices such as sensors or cameras to capture various features 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 the position of the neighboring objects from local detections, they need to exchange these 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 other vehicles, obstacles and moving threats. We denote these information items as *control information*,[2] and the data that are delivered to the server as *data traffic*.

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

[2] The message regarding target update in Algorithm 2 is also treated as control information.

Practical considerations of the terrain makes it impractical to implement such a system based on wired links. Hence it is desirable to build our networked control system based on wireless media. It is well known that wireless channels are vulnerable to fading and interference. The mathematical modeling of the wireless channels for our application is very challenging due to highly dynamic nature of the terrain which blocks the line-of-sight (LOS) between the communication vehicles and results in reflection and scattering among many other physical phenomena which affect the transmitted signals [17], [18]. We mainly consider the shadowing effects and model the path loss based on the obstruction that lie in the first Fresnel zone and the Fresnel zone radius. Interference happen when more than one pair of vehicles attempt to communicate simultaneously within a short distance and thus lead to conflict in the wireless media.

III. Collaborative Controlled Vehicles over Wireless Networks

We consider the general high level kinematic path planning problem for the group of vehicles over a wireless network. The algorithm generates a sequence of waypoints to follow by each vehicle. The algorithm uses artificial potential navigation functions and is based on our previous work [5]. The potential functions are chosen to lead the vehicles towards the target while avoiding collision and moving threats. In the sequel we briefly mention the framework of [5].

A. Potential Functions

We assume time is slotted. At time t, let $\mathcal{V}(t)$ denote the set of vehicles that are alive, $\mathcal{O}(t)$ the set of obstacles, and $\mathcal{M}(t)$ the set of moving threats. Let $p_i(t) = (x_i(t), y_i(t))$ be the position of the i-th vehicle at time t. We let $\mathcal{N}_v^i(t)$ denote the set of vehicles known to the i-th vehicle at time t[3]

$$\mathcal{N}_v^i(t) = \{j \in \mathcal{V}(t) : j \neq i,\ i \text{ knows the position of } j\}.$$

Similarly, we define the set of the obstacles and moving threats known to the i-th vehicle at time t as

$$\mathcal{N}_o^i(t) = \{j \in \mathcal{O}(t) :\ i \text{ knows the position of obstacle } j\}$$

and

$$\mathcal{N}_m^i(t) = \{j \in \mathcal{M}(t) :\ i \text{ knows the position of threat } j\},$$

respectively. We denote by $\mathcal{T}^i(t)$ the target area at time t as far as the i-th vehicle knows.

To maneuver the vehicles, a potential function is constructed for each vehicle consisting of several terms, each of which reflects a goal or a constraint. The potential function $J_{i,t}(p_i(t))$ for the i-th vehicle at time t is

$$\begin{aligned} J_{i,t}(p_i(t)) &= \lambda_g J_t^g(p_i(t)) + \lambda_n J_{i,t}^n(p_i(t)) \\ &+ \lambda_o J_t^o(p_i(t)) + \lambda_m J_t^m(p_i(t)), \end{aligned} \qquad (1)$$

[3] We define $\mathcal{N}_v^i(t)$ in this way instead of a set of neighboring vehicles within the detection range R_d, i.e. $\mathcal{N}_v^i(t) = \{j \in \mathcal{V}(t) : j \neq i, \|p_i(t) - p_j(t)\| \leq R_d\}$, since the i-th vehicle knows the positions of some vehicles beyond R_d in Algorithm 2.

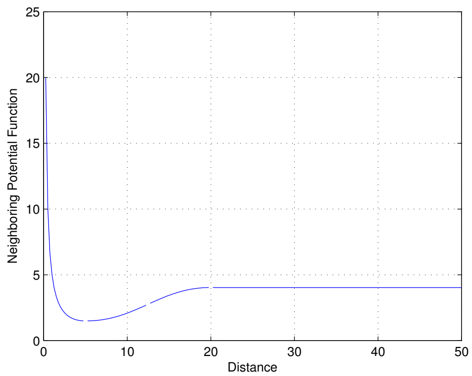


Fig. 1. Neighboring potential function

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 area $\mathcal{T}^i(t)$. Here $f_g(\cdot)$ is a strictly increasing function with $f_g(0) = 0$. This function guarantees that the i-th vehicle will move toward the target $\mathcal{T}^i(t)$ in absence of other objects. We use $f_g(r) = r^2$ in our simulations. The threat and obstacle avoidance potentials are on the contrary strictly decreasing functions of the vehicles' distance to threats and obstacles, and tend to infinity as this distance approaches 0. The neighboring potential is more involved, since it is designed to make the vehicles maintain some optimal distance. Fig. 1 provides the shape of the neighboring potential function that we use. For the detailed discussion of these components and the effects of the weights, we refer the reader to our earlier work [5]. The velocity of the i-th vehicle at time t is derived from the gradient descent equation:

$$\dot{p_i}(t) = -\frac{\partial J_{i,t}(p_i)}{\partial p_i} \tag{2}$$

B. Networked Control of the Vehicles

We now describe two distributed algorithms to control the trajectories of the autonomous vehicles. It should be noted that in both cases the optimization is performed locally at each vehicle. However, we will show later that better performance can be achieved through collaboration even with the same optimization algorithm.

1) Distributed Control of the Vehicles with Only Local Information: We first introduce the distributed algorithm with only local information. In this case, the i-th vehicle performs a local detection and identifies all neighboring vehicles, obstacles, and moving threats within R_d and update its $\mathcal{N}_v^i(t)$, $\mathcal{N}_o^i(t)$ and $\mathcal{N}_m^i(t)$. All other vehicles, obstacles or moving threats which are beyond the range R_d are completely unknown to the i-th vehicle, and thus are not included in $J_{i,t}(p_i(t))$. For the sake of simulations, we have considered discretization of the system with time steps small enough to preserve the stability of the original continuous algorithm. We also assume a prearranged synchronization scheme. The algorithm can be described as Algorithm 1.

Algorithm 1 Distributed Control with Only Local Information

```
The initial position of the target T is loaded into each vehicle;
t ← 0;
while V(t) is not empty and some vehicle in V(t) is outside the target T(t) do
    for all vehicles in V(t) do
        The i-th vehicle identifies its local information set N_v^i(t), N_o^i(t) and N_m^i(t) through a local detection procedure;
        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 N_v^i(t), N_o^i(t) and N_m^i(t);
        The i-th vehicle moves to the new position p_i^*(t);
    end for
    t ← t + 1;
    Update the set of alive vehicles V(t);
end while
```

From Algorithm 1 we can see the local information set $\mathcal{N}_v^i(t)$, $\mathcal{N}_o^i(t)$ and $\mathcal{N}_m^i(t)$ that can be obtained by the i-th vehicle highly depends on the detection range R_d, which is limited by the device and energy constraint. Hence the benefits of the application of Algorithm 1 to highly adversarial environments are limited, since local information may not be sufficient to provide the vehicles with appropriate maneuvering capabilities.

2) Distributed Collaborative Control of the Vehicles: We notice if the i-th vehicle can access the position information of the objects that are beyond its detection range R_d, then a better performance is expected even with the same local optimization procedure to derive $p_i^*(t)$. This can possibly be done through local vehicle-to-vehicle communications. In our algorithm, at each time t, the vehicles exchange this control information before they start to transmit the data traffic. We note that the amount of data for control information is much smaller than that of the bulk data traffic. Hence the control information can spread rapidly among the vehicles, either by using the control channel when the wireless connections are established, or through other local, epidemic or gossip based protocols [19], [20]. The details of the algorithm are shown in Algorithm 2.

Algorithm 2 shows that not only a vehicle can get the position information of the objects beyond its detection range, but the server can also update the target position by communicating with only one or several vehicles. This is very useful when more accurate position estimates of the target is calculated at the server after collecting more information, or the target position must be changed due to

Algorithm 2 Distributed Collaborative Control

The initial position of the target $\mathcal{T}$ is loaded into each vehicle;
$t \leftarrow 0$;
while $\mathcal{V}(t)$ is not empty and some vehicle in $\mathcal{V}(t)$ is outside 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 information set $\mathcal{N}_v^i(t)$, $\mathcal{N}_o^i(t)$ and $\mathcal{N}_m^i(t)$ accordingly;
    The i-th vehicle updates $\mathcal{T}^i(t)$ if notified;
    The i-th vehicle exchanges the local information set $\mathcal{T}^i(t)$, $\mathcal{N}_v^i(t)$, $\mathcal{N}_o^i(t)$ and $\mathcal{N}_m^i(t)$ with the vehicles that have connections between them, and updates the local information set accordingly;
    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 for
  $t \leftarrow t + 1$;
  Update the set of alive vehicles $\mathcal{V}(t)$;
end while

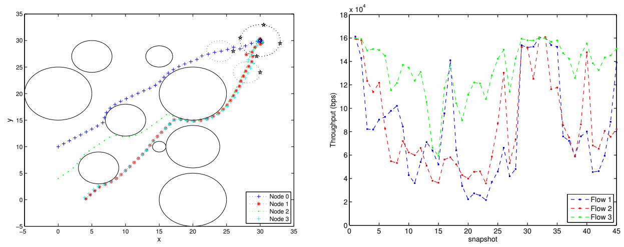
discovery of hazardous objects nearby. Algorithm 2 can be used in more adversarial and highly dynamic situations.

C. Wireless Inter-Vehicle Networks

The communication module in our system is responsible for both inter-vehicle control information and data traffic transmission to and from the command center. Note that the control information is more time-sensitive but needs much less bandwidth compared to the bulk data traffic. In light of that, we assume that either the transmission of control information can be accomplished via control channels, or the bandwidth that is consumed by the control information is negligible compared to that of the bulk data traffic. Hence, in this paper we assume that the exchange of control information can be finished before the transmission of bulk data traffic in each time slot. With this assumption, the transmission of control information and data traffic can be well separated.

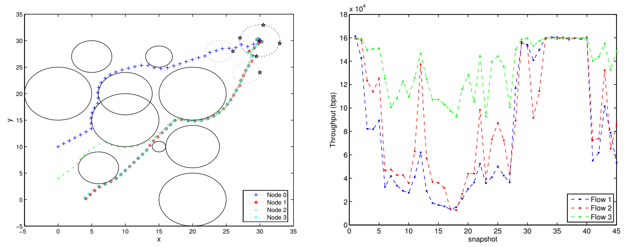
Hereafter we only consider the data transmission when discussing the performance of the wireless vehicle-to-vehicle network. We assume each vehicle always has data to transmit whenever communication opportunities are available.

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 [21], 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 use the IEEE 802.11 based medium access protocol. Under this assumption, the wireless medium is shared between vehicles using the CSMA/CA mechanism. We use an ad hoc routing protocol at the network layer, e.g. Dynamic Source Routing (DSR) routing [22]. We assume UDP protocol at the transport layer. This is because smaller delays are desirable for timely decision making at the server in our application, where certain level of packet transmission errors can be overcome by aggregating data traffic from all vehicles.



(a) Trajectories of the 4 vehicles. (b) Throughputs of the 3 wireless links.

Fig. 2. Simulation results of Algorithm 1, where there are 9 obstacles in the area $\mathcal{A}$.

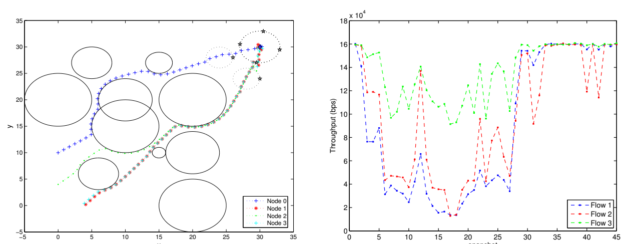


(a) Trajectories of the 4 vehicles. (b) Throughputs of the 3 wireless links.

Fig. 3. Simulation results of Algorithm 1, where there are 10 obstacles in the area $\mathcal{A}$.

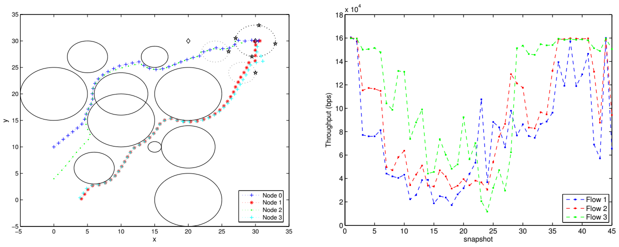
IV. Simulation and Discussion

In this section, we show our simulation results for the distributed control algorithms and the performances of the vehicle-to-vehicle wireless network. In our simulations, the optimization of the trajectories is done in MATLAB, and the simulation of the wireless network is carried out in NS-2.



(a) Trajectories of the 4 vehicles. (b) Throughputs of the 3 wireless links.

Fig. 4. Simulation results of Algorithm 2, where there are 10 obstacles in the area $\mathcal{A}$.



(a) Trajectories of the 4 vehicles.

(b) Throughputs of the 3 wireless links.

Fig. 5. Simulation results of Algorithm 2, where there are 10 obstacles in the area $\mathcal{A}$. The position of the target is initially set to $(20, 30)$, and then set to $(30, 30)$ at snapshot 20.

We consider a group of autonomous vehicles in an $40\mathrm{m} \times 40\mathrm{m}$ area $\mathcal{A}$. We choose a scenario in which there are 4 vehicles maneuvering in an area $\mathcal{A}$ with 9 obstacles randomly distributed for illustration purposes. The target $\mathcal{T}$ is a point, whose position is $(30, 30)$. There are 6 moving threats that are circling around to protect $\mathcal{T}$, 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 the minimum safety distance to a moving threat is $R_e = \sqrt{2}/2$. There are three UDP flows in our simulation, i.e. Flow 1 from vehicle 0 to 3, Flow 2 from vehicle 2 to 0, and Flow 3 from vehicle 1 to 2.

We first show simulation results for the distributed control algorithm (Algorithm 1) in Fig. 2, where the trajectories of the 4 vehicles are shown in Fig. 2(a). We can see that the vehicles are successfully maneuvering to reach $\mathcal{T}$. In particular, two nearby vehicles are maintaining some optimal distance according to the neighboring potential $J^n_{i,t}(p_i)$. When there is enough distance from a vehicle to any other object, the vehicle is almost directly shooting toward the target. However, when a vehicle approaches an obstacle, it then maneuvers along the contour of the obstacle and keeps a small distance to the contour of the obstacle. The trajectory of a vehicle becomes more dynamic whenever it is close to a moving threat. The throughput of the wireless network is shown in Fig. 2(b). We can see that Flow 3 (from vehicle 1 to 2) has the best performance, with very small degradation during the whole maneuver. This is because vehicle 1 and 2 are close to each other, and thus there is no shadowing between them. The other two wireless flows, however, experience significant performance degradation from snapshot 3 to 29. This is due to the shadowing effects which directly come from the obstacles centered at $(6, 6)$, $(10, 15)$ and $(20, 20)$. The second major performance degradation happens between snapshot 35 and 45, where severe interferences arise when 4 vehicles are maneuvering within a very small area.

To better see the impact of shadowing due to large obstacles, we increase the radius of the obstacle centered at $(10, 15)$ from 3 to 5 and add another obstacle centered at $(10, 20)$ with a radius of 4. The simulation results are shown in Fig. 3, where vehicle 0 changes its trajectory significantly to accommodate the topology change in Fig. 3(a). This forces the trajectory of vehicle 0 to move further away from the other vehicles. We can thus expect an even larger performance degradation when vehicle 0 is moving in the shadowing area shaped by the obstacles centered at $(10, 15)$ and $(10, 20)$. Fig. 3(b) supports this observation well. During snapshot 5 and 27, the throughputs of Flow 1 and Flow 2 further drop to 2×10^4 bps, which shows a deeper shadowing compared to Fig. 2(b).

Next, we compare results from the totally distributed algorithm (Algorithm 1) and the distributed collaborative control algorithm (Algorithm 2). We run simulations using Algorithm 2 under the same settings and show the results in Fig. 4. We observe that the performance of Flow 1 and Flow 2 during snapshot 40 and 43 improves significantly in Fig. 4. This explains the benefit from collaboration between vehicles. However, we can also see that collaboration here doesn't help with the performance drop between snapshot 5 and 27 due to deep shadowing.

Finally we show simulation results where the position of the target changes during the maneuver in Fig. 5. The position of the target is *mistakenly* set to $(20, 30)$ at the beginning of the simulation, which is marked with a diamond in Fig. 5(a). After snapshot 20, the target position is set to the correct coordinate $(30, 30)$. The server sends the message about target change to vehicle 1 at snapshot 20. Vehicle 1 then spreads this information to other vehicles via local information exchange. We can see that the trajectory of vehicle 3 is redirected to the one close to vehicle 0, and all vehicles successfully maneuver to the correct target at the end of the simulation. However, due to the incorrect position information of the target, larger performance degradation is observed in Fig. 5(b). A noticeable performance degradation between snapshots 41 and 44 appears even with collaboration between the vehicles. This shows that the more accurate the target position information is available, the better maneuvering can be achieved.

V. Conclusions and Future Work

In this paper, we presented distributed algorithms to control the trajectories of a group of autonomous vehicles over a wireless vehicle-to-vehicle network. Using potential functions as the objective functions, we proposed distributed algorithms both with and without collaboration to maneuver the vehicles to a target area in an adversarial environment. We studied the performance of the wireless network over the distributed controlled autonomous vehicles. We showed that collaboration between vehicles results in better performance for path planning and wireless inter-vehicle communications. However, our simulations also showed that contention-based communication protocols are likely to fail due to severe channel conditions.

A way around this problem is to use aerial vehicles (AVs) which act as relays in the absence of LOS communication between ground vehicles. Since AVs are expensive, a mechanism should be implemented that 1) requires minimum number of AV interventions, and 2) requests interventions only when necessary. The first requirement, i.e. to find the minimum number of AVs and their locations so that the resultant network (both the network between the ground vehicles and the AVs and the network between the AVs themselves) is connected, is addressed in [11], [12] as a constrained clustering problem with a summation form distortion function $D(K, A)$ involving the distances between the ground vehicles K and the distances between AVs A and a summation form cost function $C_1(A)$ involving only A. The resultant clustering problem was then solved using Deterministic Annealing (DA) to obtain near-optimal solutions. In order for the ground vehicles and the AVs to form a connected network, the following constraints were employed in the DA formulation: a) At least one ground vehicle from each cluster should be within a radius of R_1 from an AV, and b) Each AV should be within a radius of R_2 from some other AV (i.e., the AVs form a connected graph themselves). Here R_1 and R_2 are constant radii determined by the loss exponents characterizing communication link performance decay.

The second requirement is satisfied by an event triggered approach, which is addressed in [13]. The ground vehicles are able to send distress messages (help request signals) to the command and coordinating unit, if they think AV intervention is necessary to save the graph connectivity. However, since AV intervention is costly, it should be considered only if the link losses affect the connectivity in a serious manner. Each agents' problem of whether to call for intervention or not, was addressed in [13] by using neighborhood discovery methods (see [23], [24]) and a collaborative local scheme to find the importance of particular links for the connectivity of the network.

Once the AVs are assigned to maintain the connectivity between ground vehicles, it is necessary that this connectivity is maintained in the course of the whole mission. In a forthcoming paper, we address the dynamic connectivity of the AVs where merging and splitting may occur as a result of the dynamic changes in the terrain.

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