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# Large Scale Multi-Robot Coordination Under Network and Geographical Constraints

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***Abstract*—This paper addresses the problem of coordinating great numbers of vehicles in large geographical areas under network connective constraints. We leverage previous work on hierarchical potential fields to create advanced skills in multi-robot systems. Skills group together various field objectives to accomplish the performance requirements in response to high-level commands. Our framework calculates trajectories that comply with priority constraints while optimizing the desired task objectives in their null spaces. We use a model-based dynamics approach that provides a direct map from field objectives to vehicle accelerations, yielding smooth and accurate trajectory generation. We develop a real-time software system that implements the proposed methods and simulates the coordinated behaviors in a 3D graphical environment. To validate the methodology, we simulate a large exploration task and demonstrate that we can effectively enforce the required constraints while optimizing the exploration goals.**

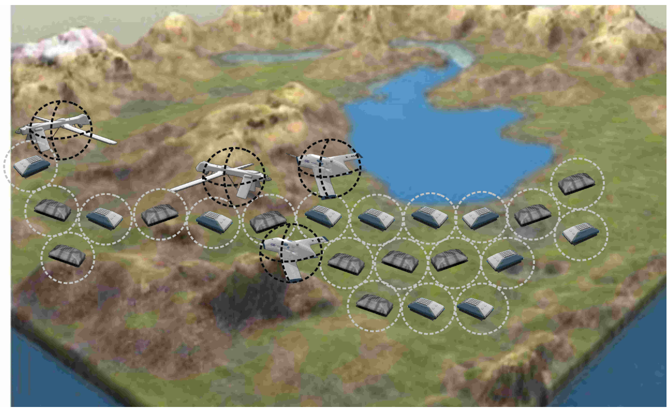
Fig. 1. Illustration of multi-vehicle scenario.

## I. Introduction

The development of technologies for the surveillance, monitoring, and gathering of information in large geographical areas is an important research domain for assessing and planning complex cooperative scenarios. An important problem in this context is the coordination of multitudes of robotic vehicles under network connective and geographical constraints.

One of the main challenges in this domain is the execution of many low level objectives as part of the global coordination strategy. This problem arises in our application, in which we must impose network topology and collision avoidance constraints while simultaneously executing path tracking objectives and formation behaviors. Another challenge we are faced with is the design of an architecture that scales efficiently to very large numbers of vehicles.

To address these challenges, we employ potential field criteria extensively. The main advantages of using potentials is the low computational overhead associated with task representations and the simplicity of using gradient descent controllers. We develop a centralized system, which allows us to guarantee network connectivity, facilitate decision making at the group level, and create vehicle formations based on global criteria. An important characteristic of our methods is its hierarchical structure, which provides a layer to analyze and resolve possible conflicts between task objectives.

To implement potential field strategies, we create a generalized dynamic model of the robotic group that relates vehicle accelerations to control fields. This model provides an effective interface to project artificial potentials into actuator space. The resulting generalized accelerations are then integrated to obtain trajectories that can be tracked by the individual vehicles.

Prioritization is implemented by projecting lower priority objectives into the algebraic null-space of higher priority fields. This technique guarantees that lower priority objectives are constrained and therefore do not interfere with higher priority objectives.

To compensate for potential fields falling into local minima, we complement our framework with $A^*$ search algorithms providing optimal path plans of task behavior.

Potential field techniques in robotics have been widely employed since their introduction in [5]. At the same time, obstacle avoidance techniques have been explored in the context of redundant kinematic-based manipulation [9], [1] operating as soft constraints. Task priorities were later developed to simultaneously achieve multiple objectives [12], [16]. Recently, we have developed model-based prioritized control methods to add rigid constraints to the potential field approach. [15].

In this paper, we leverage potential field methods in the context of multi-robot systems. Multi-robot cooperation goes back to variations of the piano's mover motion planning problem given several robotic entities [14]. In [17], a distributed multi-agent system was presented for multi-robot coordination using subsumption control and the principle of self-organization. A more advanced approach for distributed coordination was developed in [11], addressing collision avoidance and basic formation behaviors.



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Advanced mission specifications with temporal sequencing were explored in [10]. In [2], motor schemas were outlined for the control of UGVs. In [18], the problem of role assignment for robotic teams was tackled.

In recent years, new efforts have been placed on developing low-level control methods for multi vehicle coordination. The integration of geometric planning strategies with reactive formation behaviors was explored in [4]. To create rich behaviors, the concept of competing behaviors was explored in [8]. In [3], non-hierarchical methods to enforce ad-hoc networks were developed.

In this paper we present a comprehensive control methodology that addresses the important problems of (1) ensuring network connectivity between vehicles, (2) enforcing geometric constraints, (3) resolving conflicts between competing objectives, and (4) executing goal tracking and formation behaviors.

## II. Models and control methods

We leverage our previous work on control of multi-dimensional systems under constraints in order to solve the problem of coordinating multi-robot systems. The important issues we address here are: (1) combination of multiple objectives to form rich behaviors, (2) scalability of the algorithms to large numbers of vehicles, and (3) low computational overhead on control and planning processes.

We consider the problem of coordinating the behavior of a group formed by large number of vehicles cooperating in a network. The group must be able to accomplish arbitrarily complex tasks, maintain an optimized network topology, and handle geographical constraints.

To implement potential field techniques, we assign a dynamic model to the group. Consider the vector of generalized coordinates for the 2D positions of $n$ vehicles,

$$p = \langle p_{1x}, p_{1y}, p_{2x}, p_{2y}, \ldots, p_{nx}, p_{ny} \rangle. \tag{1}$$

To apply field potentials onto the vehicles, we assign the following dynamical model characterizing the behavior of the multi-robot group

$$M\ddot{p} = \Gamma, \tag{2}$$

where $\Gamma$ is a $2n$ dimensional vector of generalized forces applied to the group, $M$ is the $2n \times 2n$ diagonal matrix of vehicle masses, and $\ddot{p}$ is the $2n$ vector of vehicle accelerations. This model allows us to treat vehicles as physical objects subject to generalized forces. In particular, the desired generalized forces can be translated into path trajectories by numerical integration, i.e.

$$\begin{aligned} \ddot{p}_{\text{des}} &= M^{-1}\Gamma, \\ \dot{p}_{\text{des}} &= \dot{p}_0 + \int_0^{\Delta t} \ddot{p}_{\text{des}} d\tau, \\ p_{\text{des}} &= p_0 + \int_0^{\Delta t} \dot{p}_{\text{des}}(\tau) d\tau, \end{aligned} \tag{3}$$

where $p_0$ and $\dot{p}_0$ represent the current generalized position and velocity trajectories and $p_{\text{des}}$, $\dot{p}_{\text{des}}$, and $\ddot{p}_{\text{des}}$ represent the estimated output trajectories of the vechicles.

A task criterion in our framework defines a function from $2n$ vehicle coordinates to $m$ task coordinates. Task coordinates are chosen to represent functional quantities as part of the desired action. We represent a $m$ dimensional task with coordinates

$$x \triangleq \langle x_1, x_2, \ldots, x_m \rangle \tag{4}$$

which are defined as a transformation $T$ from generalized vehicle coordinates, i.e., $x = T[p]$.

We then associate a differential representation involving a group-wide Jacobian transformation of task coordinates, i.e. $J = \partial x / \partial p$. Our objective is to create task forces derived from the potential field and apply them on the vehicle actuators. Based on the principle of virtual work, forces that produce work in systems in motion can be translated into generalized forces using the duality

$$\Gamma = J^T F \tag{5}$$

where $F$ is the control force that will optimize the gradient descent policy.

We define potential fields as quadratic functions, i.e.

$$V_{\text{criterion}} \triangleq \| x - x_{\text{des}} \|^2 . \tag{6}$$

Our goal is to develop control policies that minimize the potential field and thus satisfy the criteria we designed. In order to do that, we need to relate the criteria $x$ to the forces $F$ associated with the potentials. This relation can be established by developing a dynamic model of task behavior. By left-multiplying (2) by $JM^{-1}$, we find $\ddot{x} - \dot{J}\dot{p} = JM^{-1}\Gamma$, and by using (5), we derive the dynamic equation

$$\Lambda \ddot{x} + \mu = F. \tag{7}$$

Here we denote $\Lambda \triangleq (JM^{-1}J^T)^{-1}$ to be analogous to a mass/inertial factor and $\mu \triangleq \Lambda \dot{J}\dot{p}$ to be analogous to a Coriolis/centrifugal velocity factor. In view of (7), the choice of the control policy $F$ will enable us to instantaneously guide the task towards the goal.

Ultimately we want to control $\ddot{x}$ so that we can achieve the goal established by the potential field. In view of Equations (5) and (7), our control becomes:

$$\Gamma = J^T(\Lambda F^* + \mu) \tag{8}$$

where $F^*$ is the desired control law that implements the potential field. This choice gives us the linear feedback control law [6]

$$\ddot{x} = F^*. \tag{9}$$

To make the task field converge, we implement proportional-derivative control laws by performing a closed-form gradient descent on the potential field.

To combine multiple objectives, we define $K$ independent fields where each field characterizes a simple stand-alone goal. In [15] we introduced a prioritized architecture for multi-dimensional systems that addresses redundancy by imposing priorities between the control fields. Because we treat groups of vehicles as multi-dimensional systems, we leverage this architecture to the multi-robot problem. Therefore, the mathematical derivations described below are borrowed from this previous work and the reader should refer to the citation to follow the derivations.

Priorities are used as a mechanism to temporarily override certain non-critical fields in order to fulfill critical constraints. In this approach, fields are ordered according to their relative importance in the safe and successful accomplishment of the instantaneous actions. We leverage this methodology for the problem of coordinating large numbers of vehicles. By designing behaviors which assign high priority to geographical and network enforcement fields, we guarantee these constraints are satisfied while optimizing the mission goals. To establish priorities between fields, we define the prioritized control structure

$$\Gamma = \Gamma_1 + \Gamma_{2|1} + \Gamma_{3|2|1} + \cdots + \Gamma_{P_K} = \sum_{j=1}^{K} \Gamma_{P_j}, \qquad (10)$$

where the piped notation $i \mid j \mid \ldots$ indicates a prioritized ordering from left to right, $Pj \triangleq \{j \mid j-1 \mid \cdots \mid 1\}$ is the prioritized ordering of the $j$th priority level, and $\Gamma_{P_j}$ represents the projection of the generalized forces of the $j$th field onto the null space of higher priority fields. The control structure for a given field is

$$\Gamma_{P_j} \triangleq J_{P_j}^T \, F_{P_j} \qquad (11)$$

where

$$J_{P_j} \triangleq J_j N_{P_j}, \qquad (12)$$

is the prioritized Jacobian of the $j$th field and $N_{P_j}$ is the prioritized null-space associated with all higher priority fields.

To demonstrate that (11) has the desired decoupling behavior, we determine the dynamic equation of each field and study their mutual coupling. Similarly to (7), by left-multiplying (2) by $J_{P_j} M^{-1}$ we obtain the dynamic equation

$$\ddot{x}_{P_j} - J_{P_j} h_j = J_{P_j} M^{-1} \Gamma. \qquad (13)$$

To design controllers that optimize the gradient descent of the potential fields, we choose control structures of the form

$$\Gamma_{P_j} = J_{P_j}^T \left( \Lambda_{P_j} \, F_{P_j}^* + \mu_{P_j} - \Lambda_{P_j} J_{P_j} M^{-1} \sum_{l=1}^{j-1} \Gamma_{P_l} \right), \qquad (14)$$

where

$$\Lambda_{P_j} \triangleq \left( J_{P_j} M^{-1} J_{P_j}^T \right)^+ \qquad (15)$$

is a prioritized mass matrix, $(.)^+$ represents the Moore-Penrose pseudoinverse, and $\mu_{P_j}$ is a prioritized Coriolis/centrifugal factor.

Substituting (14) into (13) via (10), we obtain a decoupled set of linear behaviors

$$\forall j\,, \quad \ddot{x}_{P_j} = F_{P_j}^*, \qquad (16)$$

which are used to implement feedback controllers that optimize the desired gradient descent policies for the objectives.

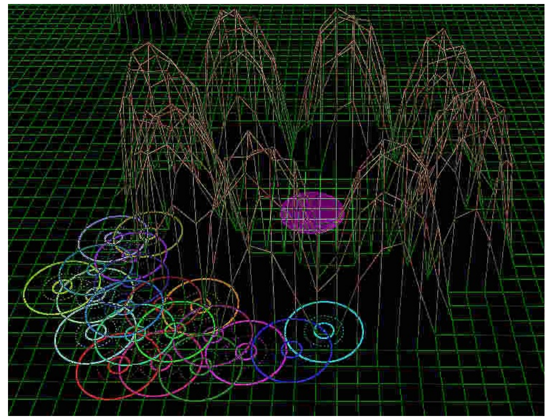

Fig. 2. Conflict scenario: The goal of the group is to reach the centroid, which has been placed in an inaccessible location surrounded by mountains. Because the obstacle field does not let the group through the mountains, the goal field is rendered infeasible.

The above property is only true when all fields are feasible within the group's available redundancy. A common scenario is when two fields have conflicting goals. For example, a field imposing network separation constraints can conflict with a field that attracts vehicles to a geometric centroid, as illustrated in Figure 2. In this particular case we normally assign higher control priority to the network constraint since it guarantees communication at all times. During conflicting scenarios, higher priority fields leave too few degrees of freedom available for the full execution of low priority fields, and the low priority fields are considered only partially feasible. In the representation given in (12), this situation occurs if the null-space matrix $N_{P_j}$ does not span the lower priority field coordinates represented by $J_j$. In turn, the prioritized Jacobian $J_{P_j}$ becomes ill conditioned causing the mass matrix in (15) to become singular. Let us define the Singular Value Decomposition of the term,

$$J_{P_j} M^{-1} J_{P_j}^T = \begin{bmatrix} U_r & U_n \end{bmatrix} \begin{bmatrix} \Sigma_r & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} U_r^T \\ U_n^T \end{bmatrix}, \qquad (17)$$

where $U_r$ and $U_n$ are eigenvectors that span the rank and null kernels, and $\Sigma_r$ are the non-zero eigenvalues. Then, (15) becomes

$$\Lambda_{P_j} = U_r \Sigma_r^{-1} U_r^T. \qquad (18)$$

In this case, combining (14) with (13) by means of (10) yields the following set of partially controlled dimensions

$$U_r^T \left( \ddot{x}_{P_j} = F_{P_j}^* \right). \qquad (19)$$

Since $U_r$ corresponds to the rank eigenspace, the above equation achieves a linear mapping within the controllable directions. As a result, the potential field acts in the subspace of $U_r$ descending the gradient optimally until it reaches the minimum energy within that space.

## III. Behavior coordination

We consider the problem of using high level commands for controlling large scale robotic systems. An action primitive is

| *Control Field* | *Coordinates* | *Pri* |
|---|---|---|
| Obstacle avoidance | distance to obstacles | 1 |
| Network topology | distance between vehicles | 2 |
| Network graph | distance between clusters | 3 |
| Goal pursuit | distance from centroid to goal | 4 |
| Formation | formation coordinates | 5 |
| Friction | generalized coordinates | 6 |

TABLE I
DECOMPOSITION FOR EXPLORATION PRIMITIVE

our mechanism to encapsulate multiple criteria for executing meaningful group behaviors. It defines a complete ordering where more critical objectives take precedence over less important objectives. The criteria are represented by reactive control fields with the following parameters: (1) coordinates, (2) goals, and (3) control policies.

We develop a case scenario to analyze and develop an action primitive that coordinates an exploration mission in a complex geographical environment. We introduce six criteria that characterize the design specifications of this case scenario as shown in Table I.

In general, the most critical fields are the ones that contribute to the preservation of the group and maintain network connectivity. In our problem, these fields correspond to obstacle avoidance and the two fields that maintain network connectivity. The goal pursuit field comes next in the hierarchy. As such, a simple criterion for controlling the group's centroid will naturally result in vehicle distributions that comply with network and geographical constraints. Next, we place a formation field which uses the residual redundancy to optimize the given geometries. A friction field is placed in the last priority level to dampen the uncontrolled modes. We describe each field of Table I in detail:

**Obstacle avoidance field**

An obstacle avoidance field guarantees that vehicles react to geometric constraints in the terrain. The coordinates defining the field are

$$x = [\ldots\ d_{ij}\ \ldots] \tag{20}$$

where

$$d_{i,\text{obs}} \triangleq \| \ p_i - p_{\text{obs},i}\ \| \tag{21}$$

represents the distance from vehicle $i$ to the perimeter of obstacle $\text{obs}$. The field operates based on the principle of repulsion with repulsion goals equal to

$$d_{ij,\text{des}} = r_i + d_{\text{away}} \tag{22}$$

where $r_i$ is the radius of the vehicle and $d_{away}$ is a safe distance away from the perimeter of the obstacle. To control the field effectively, we set an activation threshold $d_{\text{close}}$ that determines when vehicles are too close to the obstacle, and we require that $d_{\text{away}} > d_{\text{close}}$. Pushing vehicles beyond the activation threshold is needed to prevent the field from bonding the vehicles to the obstacle permanently.

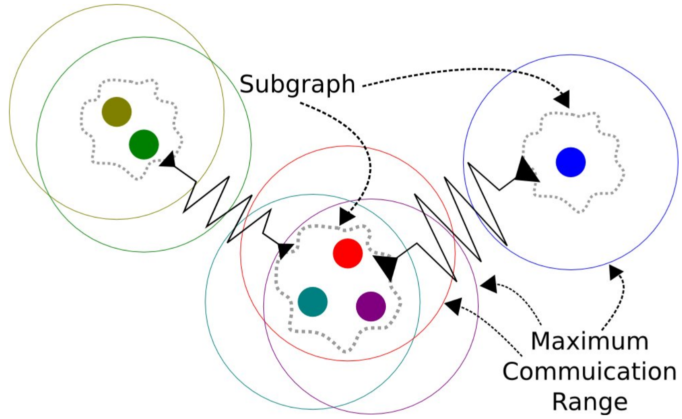


Fig. 3. Network connected field diagram. The nodes (labeled "Subgraph" in the figure) are attracted so that the vehicles remain in communication range and maintain a connected network.

A naive approach is to repel vehicles in the direction of the distance vector. A better approach is to add a tangential component to the avoidance field in the direction of the flow.

**Network topological field**

A network topological field is designed to prevent vehicles from violating proximity conditions that result in communication interference. This field consists of applying repulsion forces between pairs of vehicles in proximity. An activation threshold is defined based on network specifications and a repulsive goal is imposed on every pair of vehicles within range.

The coordinates defining the field are described as

$$x = [\ldots\ d_{ij}\ \ldots] \tag{23}$$

where

$$d_{ij} \triangleq \| \ p_i - p_j\ \| \tag{24}$$

represents the distance between pairs of close vehicles. The field operates based on the principle of repulsion with repulsion goals equal to

$$d_{ij,\text{des}} = r_i + r_j + d_{\text{push}} \tag{25}$$

where $r_i$ and $r_j$ are the radii of the vehicles and $d_{\text{push}}$ is a safe distance between vehicles. To control the field effectively, we require that $d_{\text{push}} > d_{\text{interference}}$ where $d_{\text{interference}}$ is the threshold that determines when a pair of vehicles is too close.

**Network connected graph field**

Communication specifications in our problem require that there exists at least one path of communication links between any two vehicles in the network. We define another network enforcement field shown in Figure (3) to ensure the existence of communications paths.

We represent the communication network of vehicles using an undirected, weighted graph. A communication threshold

$d_{\text{range}}$ is defined to monitor when vehicles are nearing the limits of communication range. We also characterize the desired optimal communication distance $d_{\text{optimal}}$ between neighbors.

Each node in the graph represents a cluster of vehicles that form a connected sub-network with communication links no greater than $d_{\text{range}}$. Between each pair of nodes, we create an edge with weight equal to the distance between neighbors. The goal is to attract the nodes so that they no longer exceed $d_{\text{range}}$. We apply a minimum spanning tree (MST) algorithm to the graph. Since a MST happens to minimize the length of the longest edge, it guarantees that our entire group reconfigures in minimal time.

We define a network connected graph field that imposes the attraction forces between nodes in the graph. This field has coordinates for every pair of nodes in the graph that are joined in the MST. For each pair of attracted nodes $i$ and $j$, $d_{ij}$ represents the distance between nodes. The coordinates of the field are described as

$$x = \begin{bmatrix} \dots & d_{ij} & \dots \end{bmatrix} \tag{26}$$

where

$$d_{ij} \triangleq \| p_{i^*} - p_{j^*} \| \tag{27}$$

represents the distance between the closest pairs of vehicles $i^*$ and $j^*$ in each node. The field operates based on the principle of attraction with attraction goals equal to

$$d_{ij,\text{des}} = d_{\text{optimal}} \tag{28}$$

When the nodes exceed $d_{\text{range}}$, this field activates and attracts the nodes before they breach the communication range.

### Goal pursuit field

We now design a field to maneuver the group around the geography of the terrain. The goal pursuit field uses only a single coordinate $x$ to represent the distance from the group's geometric centroid to the desired $p_{\text{goal}}$. The coordinate defining the field is

$$x = \| p_{\text{cog}} - p_{\text{goal}} \| . \tag{29}$$

The field operates based on the principle of attraction with attraction goal equal to

$$x_{\text{des}} = 0. \tag{30}$$

As we move the desired centroid, the constraint fields will ensure that the group locally adapts to geometric and network changes as it follows.

### Formation field

Formation fields are tools to distribute vehicles in geometric topologies. The main idea of formations is to enhance group performance in some desired metric. For instance, to maximize the area swept in an exploration mission, we have designed a circle formation field shown in Figure 4 that uniformly distributes vehicles around the group's geometric centroid using the maximal achievable radius. The coordinates defining the field are

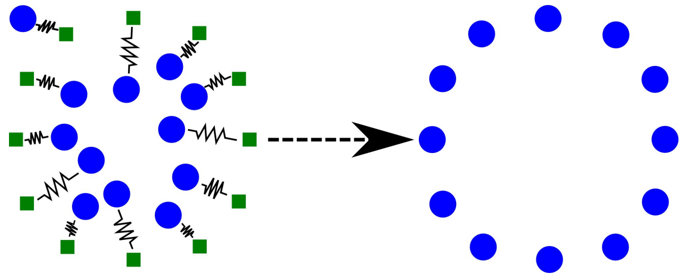

Fig. 4. Circle formation field diagram. Each vehicle is attracted to the closest position on the perimeter of the circle.

$$x = \begin{bmatrix} \dots & \| p_i - p_{\text{circle},i} \| & \dots \end{bmatrix} , \tag{31}$$

where $p_{\text{circle},i} = p_{\text{cog}} + r_{\text{circle}} \begin{bmatrix} \cos \frac{i}{2\pi n} & \sin \frac{i}{2\pi n} \end{bmatrix}$ is chosen so that each vehicle $i$ positions itself to the closest point on the circumference. We compute $r_{\text{circle}}$ offline based on the number of vehicles and their optimal network ranges. The field operates based on the principle of attraction with attraction goals equal to

$$x_{i,\text{des}} = 0. \tag{32}$$

### Friction field

The friction field is designed to dampen uncontrolled modes. The coordinates defining this field are the vehicle generalized coordinates

$$x = \begin{bmatrix} p_{1,x} & p_{1,y} & \dots & p_{n,x} & p_{n,y} \end{bmatrix} . \tag{33}$$

The idea of the friction field is to minimize the uncontrolled movement of the vehicles while pursuing higher priority objectives. The field operates on the velocities $\dot{x}$ by imposing a damped behavior

$$\dot{p}_{i,\text{des}} = 0 \tag{34}$$

causing each vehicle to decrease velocity in its uncontrolled directions.

## IV. Simulation Results

We perform an experiment of multi-robot coordination on a simulated geographical environment. Using the Python programming language, we have developed a software framework that includes control modules, a simulator, and an OpenGL 3D graphical environment. To efficiently perform the mathematical computations necessary for the controller, we use the Numpy library. The software framework contains a centralized servo control loop that calculates the trajectories of all the vehicles at every iteration.

We simulate 50 vehicles exploring a realistic terrain with an area of $10000\text{km}^2$ which includes various mountains and lakes.

The maximum allowed velocity per vehicle is 110km/hr and a maximum acceleration of $5\text{m/s}^2$. The network specifications impose a maximum communication distance between neighboring vehicles of 2km, and a minimum interference distance of 0.5km.

For this experiment, we use the action primitive described in Table I. The gains and velocity constraints for each field have been empirically tuned to achieve good control performance.

To explore the terrain efficiently, we guide the group's geometric centroid in expanding concentric circles. To enhance the trajectories, we complement the goal pursuit field with a high level $A^*$ planner which optimally steers the centroid around geometric constraints.

An interesting situation arises when the group of vehicles is large enough to surround an obstacle on the way to the goal. In such cases, the natural behavior is to pass the obstacle on both sides and reconnect the sides of the group on the leading fronts. This is accomplished due to the interplay between the goal pursuit field and the network connected graph field. Once the leading fronts of the group pass the obstacle, the back of the group has pressure to split due to the action of the goal pursuit field, causing the connected graph field to reconnect the fronts.

In Figure 5 we present screenshots of the exploration behavior discussed above. The upper-left screenshot shows the vehicles crossing a 12km passage between two large mountain chains. The $A^*$ planner calculates a trajectory through the passage and provides this data to the goal pursuit field. Since the diameter of the formation is 16km, the vehicle group deforms its shape upon entering the passage to cross it. The situation shown in the upper-right screenshot illustrates the navigation around an obstacle much smaller than the group's size, demonstrating the ability of the framework to reconnect fronts after obstacle-induced splits. The screenshot is taken moments before the two fronts reconnect. The lower-left screenshot shows local deformations induced in the group due to the interactions with a large lake structure. Due to the action of the obstacle avoidance field and the goal pursuit field, the group adapts to the contour of the lake. The lower-right screenshot shows a snapshot taken near the end of the exploration experiment, demonstrating that the overall terrain swept by the group (diplayed in dark green) covers almost the entire area.

In Figure 6 we show various data graphs taken during the simulated exploration mission. The overall duration of the mission is 45000s (12.5hr) in simulated time. In the upper-left graph we show the minimum distance measurements between vehicles and obstacles. The safety threshold is represented with a dotted line at the zero ordinate value. As expected, the safety threshold to obstacles is never violated. Similarly, the lower-left graph shows the minimum distances between neighboring vehicles. The optimal distance is set at 1km, which is confirmed by the small variance of movement around this distance. Not shown here is the verification we performed separetely showing that the network always remains connected under the maximum communication range constraint. In the right two data graphs we show tracking data of the group's centroid. The sinusoidal pattern represents the expanding concentric circles. The dotted lines correspond to the resulting goal trajectories. As we can see, the centroid closely tracks the goal trajectory, albeit not perfectly. The errors are induced by the local responses to obstacles which are not modeled.

| *Number of vehicles* | *Controller iteration time* |
|---|---|
| 10 | 0.005 |
| 30 | 0.012 |
| 50 | 0.025 |
| 100 | 0.091 |
| 200 | 0.466 |
| 500 | 5.425 |

TABLE II
SIMULATION BENCHMARK OF WALL-CLOCK TIME PER SIMULATION FRAME FOR VARYING NUMBERS OF VEHICLES.

We benchmark the software performance for a variety of group sizes. In Table II we illustrate benchmarks for 1000 controller iterations. We fit a power-law best fit approximation curve to the data, and find that simulation time grows at a nearly quadratic rate with respect to the number of vehicles. As we can see in the table, the speed to simulate 50 vehicles at 1 simulated second per controller iteration is 40 times faster than real time. Simulating 200 vehicles results in a 2x speedup, demonstrating the capability of our system to scale up to hundreds of vehicles. These results corroborate the efficiency of using potential fields in combination with low-dimensional planners.

## V. CONCLUSION

Potential fields provide a modular reactive layer that can individually address the design specifications of complex missions. It is easy to complement our framework with low-dimensional planners to take care of global requirements and handle local minima more robustly.

Contrary to previous methods, our framework handles constraints as rigid prioritized criteria. In feasible situations, it is guaranteed to find a solution for the constraints, while temporarily overriding the execution of less important objectives. Setting priorities enables the design of control strategies that adapt field execution in an optimal manner.

One significant assumption we make in our framework is that the vehicles have global information: because they maintain a connected communication network, we assume they have a communication protocol in which information is exchanged perfectly among all vehicles. Furthermore, we assume vehicles can use triangulation or GPS techniques to determine their relative positions, enabling the design of fields that exploit global information.

Using a model-based approach, we express a direct relationship between potential fields and vehicle accelerations. This representation provides a direct map between behavior and vehicle accelerations, which yields much smoother and accurate responses than in purely kinematic approaches.

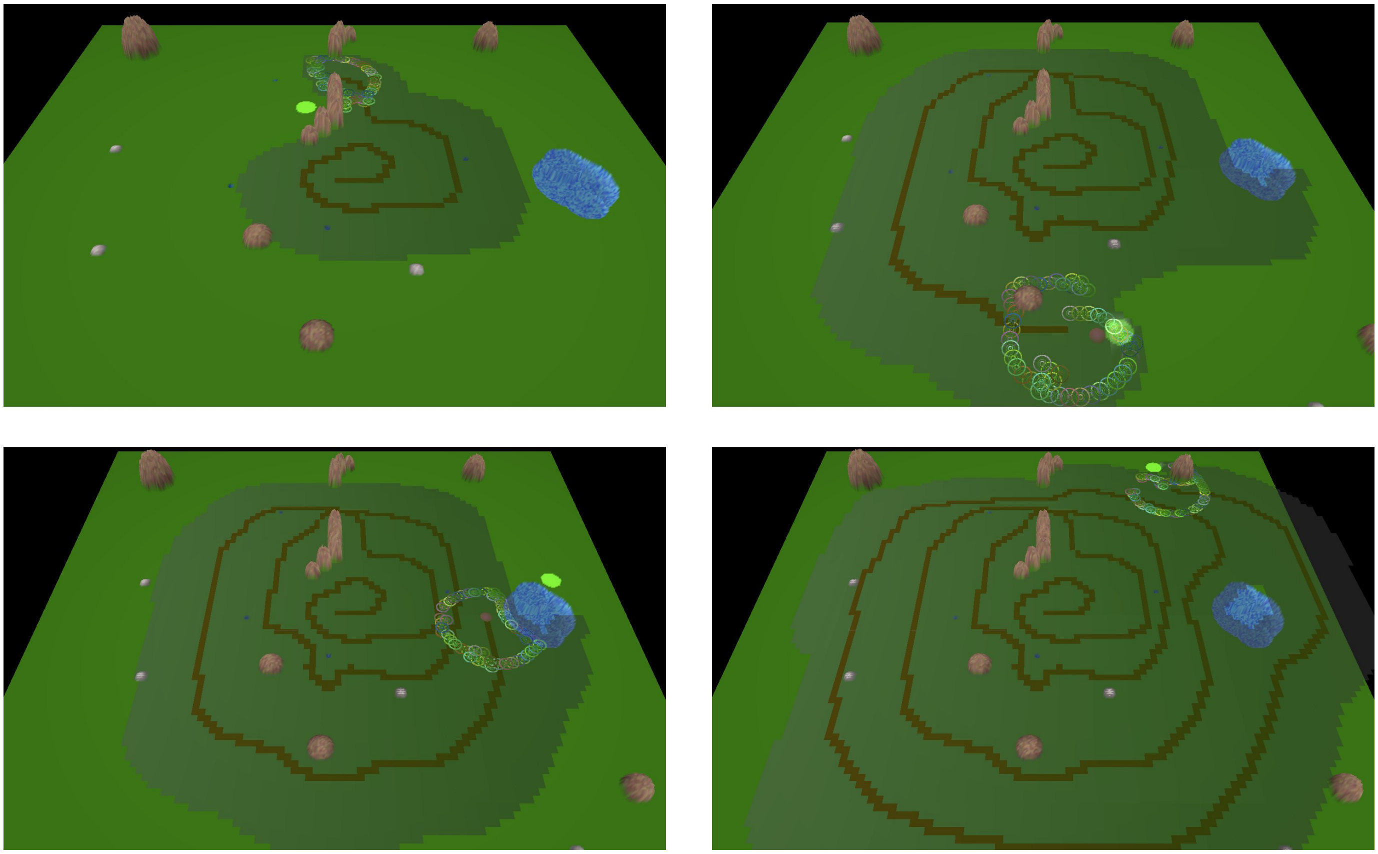

Fig. 5. Screenshots taken during a simulation of 50 vehicles exploring a 100 × 100 km terrain. The bright green spot is the goal of the goal pursuit field, the brown formations are mountains, the blue ellipses are lakes, the small circles are the vehicles maintaining the optimal communication ranges, the dark trace is the trajectory followed by the group's centroid, the dark green area is the terrain visited by the vehicles.

Suggestions for future work include exploring high level behaviors that coordinate multiple action primitives using temporal and event-based models. Because of the modularity of the control abstractons defining fields and action primitives, our methods are well-suited for the design of advanced skills in accordance with mission specifications.

In summary, we have developed a dynamic model of groups of vehicles guided by potential fields. We have established a model-based hierarchical control framework that optimizes the execution of behavioral objectives while enforcing critical constraints. We have developed modular action primitives made of multiple control fields to address the design specifications of a large scale exploration mission. To test the capabilities of our framework, we have implemented a software system that integrates the hierarchical controller, a dynamic simulator, and a 3D graphics environment for outdoor terrain explorations.

## Acknowledgements

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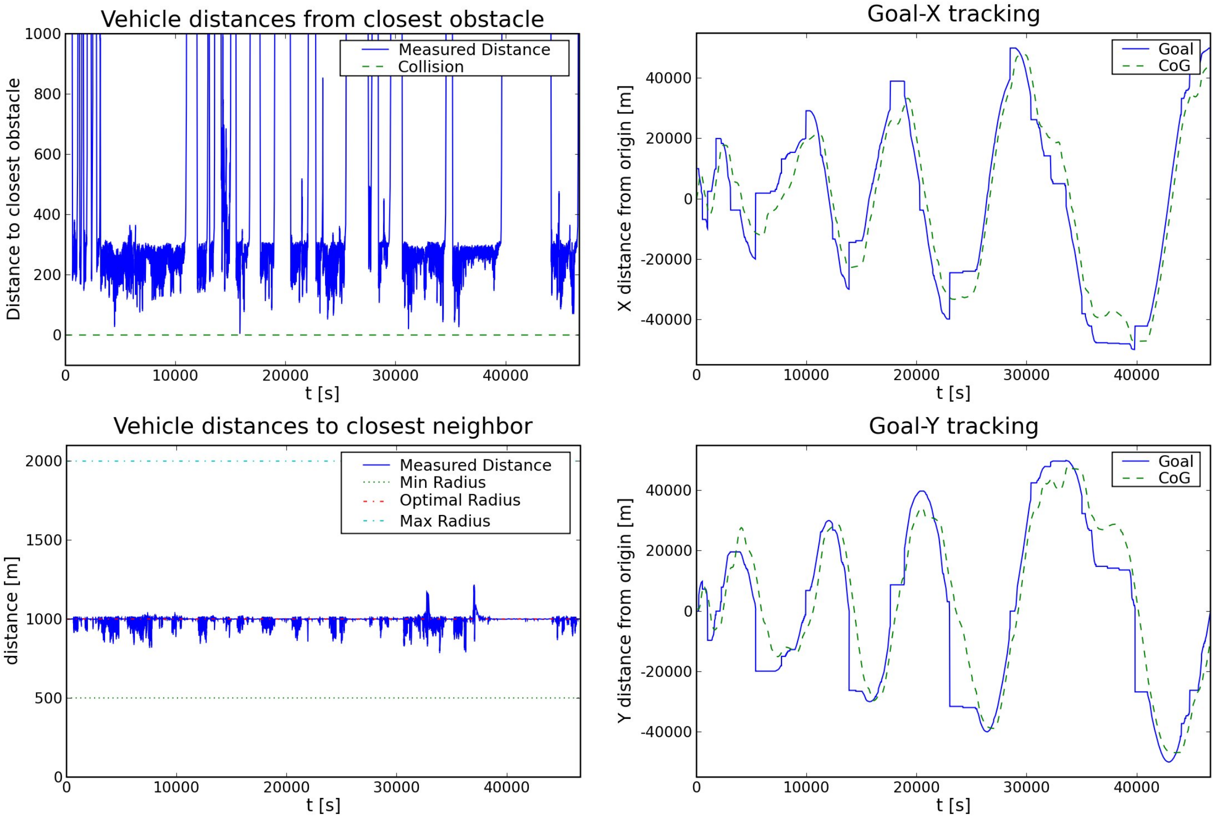


Fig. 6. Data recorded during the exploration behavior of Figure 5.


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