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Motif-based Communication Network Formation for Task Specific Collaboration in Complex Environments

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Abstract— **Networks of mobile autonomous vehicles rely heavily on wireless communications as well as sensing devices for distributed path planning and decision making. Designing energy efficient distributed decision making algorithms in these systems is challenging and requires that different task-oriented information becomes available to the corresponding agents in a timely and reliable manner. We develop a systems engineering oriented approach to the design of networks of mobile autonomous systems, in which a cross-layer design methodology determines what structures are to be used to satisfy different task requirements. We identify a three-tier organization of these networks consisting of connectivity, communication, and action graphs and study the interaction between them. It is expected that in each functionality of a network, there are certain topologies that facilitate better achievement of the agents' objectives. Inspired from biological complex networks, we propose a bottom-up approach in network formation, in which small efficient subgraphs (motifs) for different functionalities of the network are determined. The overall network is then formed as a combination of these sub-graphs. We show that the bottom-up approach to network formation is capable of generating efficient topologies for multi-tasking complex environments.**

I. Introduction

Design of energy efficient distributed path planning and data dissemination algorithms in networks of autonomous vehicles requires understanding of the system and communication complexity, identifying tasks and their requirements, and trade off analysis of the performance metrics. Performance of a network of vehicles, from the perspective of achieving goals and objectives in a timely and reliable manner is constrained by their collaboration and communication structures and their interplay with the vehicles' dynamics. The safety and efficiency considerations require that these networks are endowed with structures that facilitate efficient information transmission. The objective of this paper is to develop a framework for the design of efficient information transmission structures for collaborative mobile agents.

In the field of collaborative control the flow of information between a group of entities requires different apparatus and is performed for different goals. Therefore the term 'network' is used to describe various structures that cover different aspects of information transmission. In the high level design, networks are often modeled as graphs and graph theoretic analysis is performed to analyze the performance. Several works have considered the effects of graph topology on the convergence of the distributed consensus/gossip based algorithms for collaborative control applications (e.g., see [21], [11], [24], [13] and the references therein). In [2] and [13], we provided a rigorous evaluation of network topology effects on the performance of these algorithms and showed the efficiency of certain small world topologies. The design philosophy behind these works is that of a top-down design, i.e. the graphs that optimize a single performance metric or satisfy a favorable trade-off are selected as the candidates for the system structure. The results of such analysis are often asymptotic and valid for large number of agents [9]. There have also been many works that consider the analysis of network formation, starting from the local level. The focus of this bottom-up approach has been to discover how local preferences and decisions will result in the emergence of real world networks with properties such as heavy tailed degree distributions and small world effect [9]. Using any design philosophy, the intended links are to be realized via low power wireless media. The lower level design addresses challenges emanating from realizing the ideal graph topologies and consists of physical layer, MAC layer and network layer constraints. Some recent works have addressed cross layer design for optimizing energy efficiency in wireless sensor networks for control applications [22], [18]. A crucial point is that the behavior of low power communication links cannot be adequately captured via simple on-off binary models due to asymmetric and unreliable characteristics of wireless communications [25].

We consider the interdependence of these two levels of design and develop a systems engineering framework to capture the design requirements effectively. Our main contribution is two-fold. First, we introduce a three-tier organization of collaborative control networks consisting of connectivity, communication, and action graphs and study the interaction between these graphs. We then design a bottom-up architecture to enhance the performance of such networks and analyze the networks that result in a hierarchical manner by merging efficient sub-networks.

The structural implication of the results of our earlier work on the design of efficient and robust networks as a link augmentation process [3] indicates that efficient topologies emerge as the result of two competing processes: minimizing a notion of distance between the nodes (a global effect) and making the communication requirements of neighboring nodes as symmetric as possible (a local effect), i.e. the local neighborhood of the nodes should be reasonably well-

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connected, whereas long range links should provide global connectivity. To design efficient local connectivity patterns, in this paper we use the idea of network motifs which was first proposed in the context of biological networks [19]. Network motifs are task specific local connectivity patterns, which exist with much higher frequency in real biological networks compared to those in random networks. These are sub-networks of low number of nodes (usually 3-4) whose persistence in networks, imply their efficiency in the sense that they optimize certain performance metric in a local scale. Recently, certain algorithms for determining such sub-networks using convex optimization methods have been proposed, which essentially treat the problem as a system identification problem from equilibrium information [26], [14]. Such approaches can not be taken in the context of collaborative vehicles, since the system can not be treated in equilibrium. Instead, we use a simulation testbed to find network motifs for local communication structures. Here, the group mission consists of several tasks such as search operation, data gathering/processing, target finding and leader follower explorations. Each task gives rise to certain motifs that are specific to that task and the partial knowledge of the environment specifications that the agents operate in. In this way, the most efficient task-specific local topologies are extracted. Switching suitable graphs when the mode of operation is changing can be handled by solving the resulting reachability problem using methods for symbolic planning such as graph grammars [15], [23]. Based on such switchings, we also address the effects of split/merge operations on the spectral characteristics of the resulting connectivity graphs.

The paper is organized into the following sections. The basic set up of the problem, the taxonomy of collaborative control networks and the motif generation algorithm are presented in Section 2. Section 3 addresses the hierarchical network formation design and the effects of merging the motifs on network performance and structure. Simulations and discussion are provided in Section 4. Section 5 concludes the paper.

II. Task-oriented motif selection in the collaborative vehicles framework

In this section, we describe our systems engineering based approach to the design of efficient network topologies for collaborative vehicles. The idea is to capture the task requirements in *action graphs*, form efficient sensing and communication subgraphs based on trade-offs between the tasks' importance, and integrate the topologies in a hierarchical manner. The design procedure is depicted in Figure 1.

We consider a group of n autonomous ground vehicles over an area $\mathscr{A} \subset \mathscr{R}^2$, with unknown obstacles and threats. There is very limited knowledge available regarding the internal structure or the topology of $\mathscr{A}$. The vehicles explore the area $\mathscr{A}$ under little or no direct human supervision, perform collaborative activities, cover a target area $\mathscr{T} \subset \mathscr{A}$, while avoiding any obstacles and threats and exchanging information.

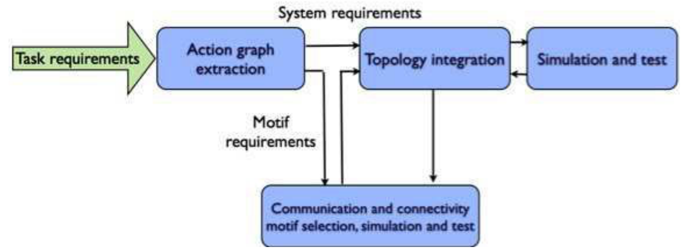


Fig. 1. A systems engineering approach to task oriented topology design

A vehicle detects a moving threat if it is within its R_d distance, and can be destroyed by the threat if their distance is less than R_e ($< R_d$). The vehicles can sense each other and obtain information about each others' positions and velocities if they are within the neighboring distance $R_s = R_d$. There is a desired inter-vehicle distance R_0 (less than R_s). The vehicles are provided with wireless communication radios and can communicate. The wireless channels are vulnerable to fading and interference [20]. In this paper, we consider: (a) Physical layer losses and attenuation (b) Media access layer losses and contention, which occur as the result of interference, when multiple nodes are transmitting data simultaneously.

A. Three essential graphs

There are three graphs that describe the network of moving vehicles: a *connectivity graph*, a *communication graph*, and an *action graph*. The first two graphs describe the information exchange in the network whereas the *action graph* captures the collaborative task specific requirements.

We order the vehicles and identify each one with its index. The *connectivity graph* is modeled as a dynamic graph topology $\mathscr{G}_c = (\mathscr{V}, \mathscr{E}(t))$. The vertices represent the vehicles and there is a bi-directional link between two nodes i and j with corresponding position vectors p_i and p_j at time t if

$$||p_i(t) - p_j(t)|| \leq R_s.$$

By $\mathscr{N}_i(t)$, we denote the set of the (connectivity) neighbors of vehicle i, defined by $\mathscr{N}_i(t) \stackrel{\triangle}{=} \{j \in \mathscr{V}(t) : j \neq i, \|p_i(t) - p_j(t)\| \leq R_s\}$. We also use the notation $j \sim i$, if $j \in \mathscr{N}_i$.

The *communication graph* is also a dynamic graph $\mathscr{G}_{com} = (\mathscr{V}, \mathscr{E}_{com}(t))$ in which the links are uni-directional and exist whenever the communication between the corresponding nodes is successful. In simulation studies, it is usually assumed that based on the allocated energy, the transmission power is set so that in the case where there is no obstacle, a communication radius R_c is covered. This model has been shown to be misleading due to unreliability and asymmetry of real links and models. More realistic models incorporate sending and receiving radio parameters as well as the environmental parameters [25], [16]. It is important to note that the existence of a communication link is meaningful in a statistical sense. Furthermore, any time a node's attempt to transmit data fails, it starts a re-transmission procedure until a time-out happens. We assume that a link between two nodes exists at time t, if and only if the transmission is successful within the specified time limit $[t, t+T_{Timeout}]$, where $T_{Timeout}$ denotes the time-out interval.

The *action graph* determines which node requires access to which node's information for a given purpose at a given time. Action graphs are used to capture the specific requirements of each task. In this work, we impose a minimal constraint of action graphs with strong connectivity for assuring safe operation of the vehicles.

B. Tasks, motifs, and an algorithm for motif generation

We now determine a framework for extracting connectivity and communication network motifs for collaborative control of vehicles. Network motifs were first introduced as building blocks of complex networks in the context of gene transcription networks [19], [1]. A network motif is a subgraph that recurs in complex networks with much higher frequency than in random networks. It is shown that certain subgraphs of 3 and 4 nodes persist in gene transcription networks by an algorithm that compared their occurrence versus random networks. The application of the algorithm to other types of networks (food webs, neuron connectivity, electronic circuits, and World Wide Web) suggested that persistent motifs are task dependent and represent the underlying functionality of the network. For example, similar motifs can occur in electronic circuits and food webs, when the underlying functionality is to provide efficient flow of energy. Also, biological networks are evolved to address multiple tasks in a robust manner, i.e. the topologies in biological networks provide satisfactory performance for conducting multiple tasks rather than optimizing the conduction of a single task.

The motif selection algorithm can be adopted for the collaborative control framework, using a (potential) energy minimization method. The idea is to find small persistent connectivity and communication topologies that evolve in the course of missions using the partial knowledge of the terrain. The algorithm uses the following principles:

1) *Task specifications:* The tasks to be performed should be selected. Typical tasks include search and target finding, tracking, obstacle and threat avoidance, data gathering, exchange and processing information and leader follower explorations. In this step task requirements are translated into constraints on action graphs.
2) *Energy assignment:* Energy functions $\{J^j(i)\}_{(i,j)=(1,1)}^{(n,M)}$ are attributed to each of the M tasks $\{T_j\}_{j=1}^{M}$ for each vehicle. These functions are selected so that minimizing them would result in task achievement.
3) *Task combination:* To account for multiple tasks that each agent should perform, we combine them linearly. Agent i is assigned with an energy function

$$J_{i,t}(p_i(t)) = \sum_{j=1}^{M} \lambda_j J_{i,t}^{j}(p_i(t))$$

The weights determine the importance of the tasks and are used as trade-off parameters in studying the effect of different tasks on the emerging topology.
4) *Randomizing the environment:* The exact specifications of the terrain are often unknown prior to the mission. Using partial knowledge about the environment, (e.g. the number of obstacles and threats and their expected position) expected mission environments are generated.
5) *Running simulations:* The simulations involve each node minimizing its corresponding energy function via gradient descent method,

$$\dot{p}_i(t) = -\frac{\partial J_{i,t}(p_i)}{\partial p_i}. \tag{1}$$

using only information local in time and space to the node [6]. Independent simulations are run to average out the effects of terrain uncertainties.
6) *Analysis:* The resulting connectivity and communication subgraphs are analyzed to determine the most persistent subgraphs in successful missions with valid action graphs.

We will apply this algorithm to a collaborative control problem in Section IV.

C. Relays and hierarchical network formation

Our previous work [13], [3] shows that efficient network structures are locally well-connected and also supplied with long range links that provide reasonable global connectivity. Such long range links are implementable using a hierarchical structure. After designing efficient clusters of small number of nodes (motifs), each cluster elects a head-node equipped with multi-mode communication capabilities as well as longer range sensing devices. These cluster-heads maintain the cluster's connectivity with the rest of the network through communicating with aerial platforms (APs) that act as relays in the network (See [4] and [5]).

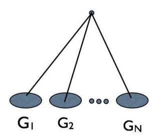
III. Spectral properties of the hierarchical design

A graph theoretic approach is used to study the connectivity of the composite graphs determined by the hierarchical design. The set of n vehicles and their connectivity (or communication) network are modeled by a graph $G = (V, E)$. The nodes of the graph, $V = \{1, 2, ..., n\}$ represent the vehicles and the edges $E = \{l_1, l_2, ..., l_e\}$ represent the links. The connectivity properties of a graph are captured by its *Adjacency* and *Laplacian* matrices and their spectra. The adjacency matrix, A is a symmetric n by n matrix with 1 (*resp.* 0) in the $(i, j)^{th}$ position, if there is (*resp.* is not) a link between nodes i and j. We denote the characteristic polynomial for the adjacency matrix by $\Phi(G) = \det(\mu I - A)$ and its eigenvalues by $\mu_1 \leq \mu_2 \leq ... \leq \mu_n$. The degree of node i, d_i is the total number of edges incident to it. Let D be a diagonal matrix with the i^{th} diagonal entry equal to d_i. The Laplacian of a graph is defined as $L = D - A$. The Laplacian is a positive semidefinite matrix. We denote its characteristic polynomial by Ψ and its eigenvalues by $\lambda_1 = 0 \leq \lambda_2 \leq ... \lambda_n$.

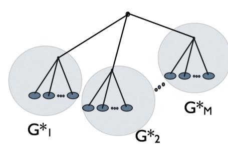
Many structural properties of graphs can be deduced based on the Adjacency and Laplacian spectra [8], e.g. the lower the number of distinct eigenvalues of A, the better the structural properties of the graph [10]. The distance of the

Fiedler eigenvalue $\lambda_2 > 0$ from zero determines how well-connected a connected graph is. For $k-$regular graphs $\lambda_2 = k - \mu_{n-1}$ and therefore small μ_{n-1} is desired. We calculate the characteristic polynomial of the adjacency matrix of the hierarchical graph based on those of the starting subgraphs (ground clusters or motifs) as a generalization of a method of Gutman [12].

Consider a group of vehicles divided into N clusters (motifs) $\{G_1, G_2, ..., G_N\}$. Each cluster consists of a few vehicles and their interconnections. The cluster G_i is connected to one and only one Aerial Platform (AP) in the higher level through one of its members, a designated cluster-head $r(G_i)$. APs and their descendent vehicles can form clusters connected to a higher level AP. The process of going from the $k-1^{st}$ level to the k^{th} level consists of joining each of the APs in the k^{th} level to their descendants by a link with the constraint that each AP in the $k-1^{st}$ level is connected to one and only one k^{th} level AP. This process is continued till the highest level of the hierarchy with only one node is reached. Examples of 2 and 3 hierarchies are depicted in Figure 2. The characteristic function for the adjacency matrix of the hierarchical graph, $\Phi(G)$, is calculated using the following lemma.



(a) A two-level hierarchy



(b) A three-level hierarchy

Fig. 2. The hierarchical graph formation process

Lemma 3.1:
1) If two graphs $G_1(V_1, E_1)$ and $G_2(V_2, E_2)$ are *disjoint*, and their direct sum is given by $G = G_1 \oplus G_2 = (V_1 \cup V_2, E_1 \cup E_2)$, then
$$\Phi(G) = \Phi(G_1).\Phi(G_2) \quad (2)$$
2) If the link (i, j) is a bridge in a graph, i.e. its deletion will add a disjoint component to the graph, then:
$$\Phi(G) = \Phi(G - \{(i, j)\}) - \Phi(G - \{i\} - \{j\}), \quad (3)$$
where, $G - \{(i, j)\}$ is the graph resulting from deletion of the edge (i, j) and $G - \{i\} - \{j\}$ is the graph resulting from deletion of vertices i and j and the links incident to them.

Proof: The proof is standard and can be found in [8]. ■

In the case of a 2-level hierarchy (Figure 2(a)), there is one AP and the ground clusters $\{G_1, G_2, ..., G_N\}$, are connected to the AP by N links. The spectrum of the composite graph can be obtained using the following theorem.

Theorem 3.1: For a 2-level hierarchical topology, with N clusters $\{G_1, G_2, ..., G_N\}$, the characteristic polynomial is determined by:
$$\Phi(G) = \lambda \prod_{k=1}^{N} \Phi(G_k) - \sum_{i=1}^{N} \prod_{k \neq i} \Phi(G_k).\Phi(G_i - \{r(G_i)\}). \quad (4)$$

Proof: The proof follows by induction on N. If there is only one cluster G_1 and one AP, using Lemma 3.1, results in: $\Phi(G) = \lambda \Phi(G_0) - \Phi(G_0 - \{r(G_i)\})$,

If we add a second cluster G_2, using Lemma 3.1 yields, $\Phi(G) = \lambda \Phi(G_1)\phi(G_2) - \Phi(G_1)\Phi(G_2 - \{r(G_2)\}) - \Phi(G_2)\Phi(G_1 - \{r(G_2)\})$. Therefore the result holds for $N = 2$. Now, if the result holds for $m = N-1$, using Lemma 3.1,
$$\Phi(G) = [\lambda \prod_{k=1}^{N-1} \Phi(G_k) - \sum_{i=1}^{N-1} \prod_{k \neq i} \Phi(G_k).\Phi(G_i - \{r(G_i)\})]$$
$$.\Phi(G_N) - \prod_{k \neq N} \Phi(G_k)\Phi(G_N - r_N) =$$
$$\lambda \prod_{k=1}^{N} \Phi(G_k) - \sum_{i=1}^{N} \prod_{k \neq i} \Phi(G_k).\Phi(G_i - \{r(G_i)\}).$$
■

Extension to higher levels of hierarchy is immediate at the cost of more indexing. Consider the case of the 3-level connectivity hierarchy in Figure 2(b). Each of the gray shaded clusters G_i^* consists of a first Level AP (cluster-head in the new setting) and its descendants. Theorem 3.1 can be invoked again to find the characteristic polynomial for the composite graph:
$$\Phi(G) = \lambda \prod_{k=1}^{N} \Phi(G_k^*) - \sum_{i=1}^{N} \prod_{k \neq i} \Phi(G_k^*).\Phi(G_i^* - \{r(G_i^*)\}),$$
in which the i^{th} cluster, G_i^*, consists of the AP denoted by $r(G_i^*)$ and first level motifs are $G_0, G_1, ..., G_{N_1}$, so that $\Phi(G_i^*) = \lambda \prod_{k=1}^{N_1} \Phi(G_k) - \sum_{i=1}^{N_1} \prod_{k \neq i} \Phi(G_k).\Phi(G_i - \{r(G_i)\})$, and $\Phi(G_i - \{r(G_i)\}) = \prod_{k=1}^{N_1} \Phi(G_k)$.

IV. SIMULATIONS

We illustrate our proposed algorithm by simulating a scenario consisting of 4 collaborating vehicles, and study the connectivity and communication networks emerging in the process for $N = 100$ independent runs over a randomized terrain. The tasks that each vehicle should perform, consist of: reaching a fixed target, obstacle avoidance, collision avoidance, and moving threat avoidance. We assume that the vehicles gather and communicate data for a joint estimation effort. We assume that the action graph needed for this effort contains bi-directional links $\{(v_0, v_3), (v_0, v_2), (v_1, v_2)\}$. The communication attempts are made when vehicles can sense each other or a beacon signal indicating the existence of the others in the range.

The terrain is a 700m $\times$ 700m area $\mathscr{A}$ with the target area being the neighborhood of the point (670,670). Only the number and the approximate size of the obstacles are known before hand. In the simulations 10 obstacles are generated uniformly inside the area $\mathscr{A}$. The vehicles start from around point $(100, 100)$. Six moving threats rotate around the target on two concentric circles. The detection range is $R_d = 50m$, and $R_e = 12.5m$. Each vehicle senses other vehicles in a radius of $R_s = 50m$. A mission is declared 'successful' if the majority of the vehicles safely reach the target.

Each vehicle maintains a potential function $J_{i,t}(p_i) = \lambda_g J_t^g(p_i(t)) + \lambda_n J_{i,t}^n(p_i(t)) + \lambda_o J_t^o(p_i(t)) + \lambda_m J_t^m(p_i(t))$,

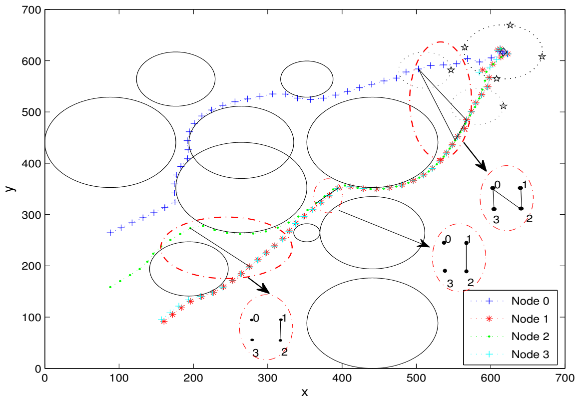


Fig. 3. Sample mission terrain: Communication graphs for snapshots $= 10, 21, 35$

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 the corresponding weighting factors. Each vehicle moves in the gradient descent direction according to Equation (1). The potentials are chosen so that they encode the intended behavior of the vehicles regarding obstacle avoidance, keeping distance from neighbors and target finding correctly. The details for the choice of potential functions can be found in our previous work [6]. The parameters $\lambda_g = 200, \lambda_n = 500, \lambda_o = 1000$, and $\lambda_m = 1000$ are used in this paper.

On the communication side, we model the physical layer path loss by considering the obstructions occurring in the first Fresnel zone [7]. We use the IEEE 802.11 based medium access control (MAC) protocol. The wireless medium is shared between vehicles using the CSMA/CA mechanism. We use the UDP protocol at the transport layer, since smaller delays are desirable for timely decision making, where certain level of packet transmission errors can be overcome by aggregating data traffic from all vehicles. In our simulations, the trajectory determination gradient algorithm (Equation (1)) is implemented in MATLAB, and the simulation of the wireless communication network is carried out in the network simulator software, NS-2.

Figure 3 shows a sample run of the simulation. The resulting communication graphs at 3 snapshots $t = 10, 21$, and 35 are magnified in the figure, where only at $t = 35$ the communication graph is connected. After running $N = 100$ simulation runs, 72 successful runs were identified, in which 3 or 4 vehicles reached the target. We identified a list of the most persistent connectivity and communication motifs. Figure 4 displays the motif "dictionary" list. Figures 5 and 6 respectively show the percentage of occurrence among the most persistent motifs in connectivity and communication graphs in successful missions. We now consider a three level hierarchical network with 4 APs in which all the vehicle motifs are in the form of $m1$ constructed by the method

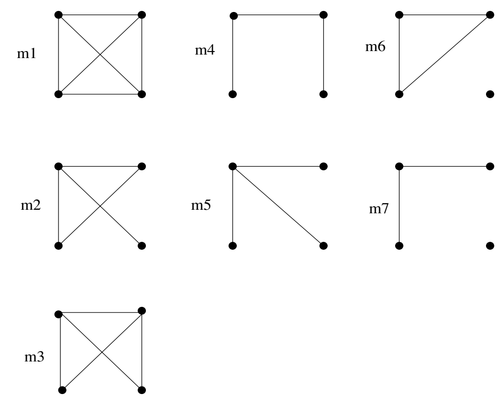


Fig. 4. A dictionary of all the connectivity and communication motifs

of section III. Therefore the graph consists of 69 nodes. Figure 7 shows the eigenvalues of the composite graph. Some observations follow:

1- The emerging connectivity motifs are well-connected, i.e. in the successful runs of simulations, the vehicles maintain a well-connected topology. This confirms our previous assertion [3] that efficient networks are locally well-connected. These locally well-connected graphs should be interconnected using the hierarchical approach of section III to minimize a notion of graph distance between geographically distant nodes as indicated in [3].

2- The emerging communication motifs are mostly disconnected. This primarily points out a major shortcoming of contention-based communication networks for estimation and control purposes in cluttered environments. Unless the number of vehicles and the communication demand are small, IEEE 802.11 based MAC protocols are unable to address the specifications demanded by the action graph. Apparently, the terrain obstructions are fatal in scenarios where the group of energy constrained vehicles need to have reliable communications. This problem can be addressed by the hierarchical design of Section III, where aerial vehicles assist in providing connection between distant parts of the terrain. Another avenue is to consider Stigmergy-based communication, where vehicles moving on the terrain leave "traces" that can be used by other vehicles. This approach has been recently addressed using RFID cards [17].

3-The Fiedler eigenvalue of the composite hierarchical graph is $\lambda_2 = 0.0464$. This is an order of magnitude larger than that of a ring topology over the same number of nodes. For $n = 69$, such a graph has Fiedler eigenvalue of 0.0083. Order of magnitude improvement in Fiedler eigenvalue corresponds to better connectivity [2].

V. Conclusions

In this paper, we provided a three-tier organization of collaborative control networks consisting of connectivity, communication and action graphs. We proposed a bottom-up network formation design methodology based on finding efficient small subgraphs optimized for effective performance. We studied the structural properties of the composite graphs

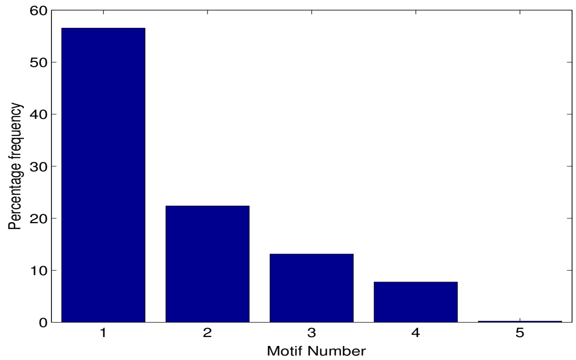


Fig. 5. Connectivity motifs of the highest frequency in successful missions

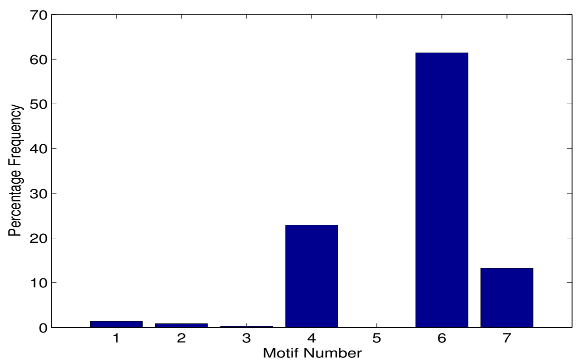


Fig. 6. Comm. motifs of the highest frequency in successful missions

based on the spectral analysis of the emerging networks. We also studied the interconnection of the action, connectivity, and communication graphs in a network of collaborative vehicles and showed that in complex and cluttered environments, these graphs affect each other significantly. An interesting observation is that conventional communication schemes are not efficient for collaborative control applications, where unconventional and implicit communications, use of stationary and mobile relays and hierarchical design are to be implemented for satisfactory operation.

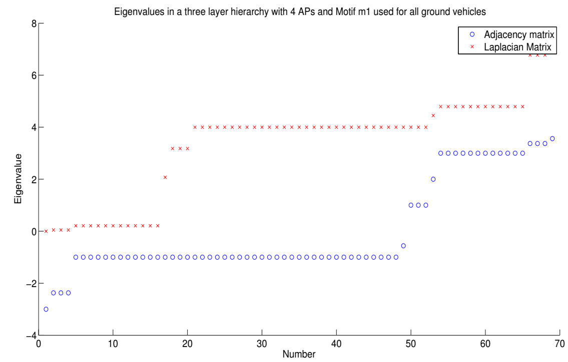


Fig. 7. Eigenvalues in a three level hierarchy with 4APs and motif m1 used for all ground vehicles

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